Recent advances in data gathering through checkout scanners have produced vast amounts of data on the actual behavior of consumers in the marketplace, creating new opportunities for managers and researchers to understand competition and consumers' response to the marketing mix. Previous analyses of this data in the literature have focused either at the household (micro) or store (macro) level. The authors propose a method of enriching the analysis of competitive behavior by combining the in-depth consumer information obtained from a micro-level household scanner panel with the comprehensive market data supplied by a macro-level retail-tracking panel. The approach offers the manager detailed information about consumers (e.g., identification of consumer segments in terms of brand preferences and socioeconomic characteristics) along with strategic diagnostics of the product-market (e.g., the sensitivity of the market to price promotions, impact of a brand's strategy on competitors, vulnerability of the brand to competitive actions).

Understanding Brand Competition Using Micro and Macro Scanner Data

The advent of the checkout scanner at retail stores has led to a flood of consumer and market data once unimaginable to a brand manager. Suddenly, the problem has shifted from finding enough data about consumers and markets to transforming vast amounts of data into useful information for brand management.

Although many researchers have addressed this problem by building models of brand competition, most work has focused on either the detailed analysis of the purchase records of each household in a panel (micro-level analysis) or the aggregate analysis of store-level tracking data (macro-level analysis). Our work extends this research by developing a methodology that addresses the "intelligent joint usage of panel and store data" (Bender 1993). This integration of two data sources provides a means of enriching the managerial interpretation of macro (market) data using diagnostic information from micro (consumer) data.

Macro Versus Micro Analysis

Research on the competitive effects of price and promotions commonly involves analyzing the product market at a macro level using aggregate data (at the store, regional, or market level) on market shares and each brand's price and promotions (Blattberg and Wisniewski 1989; Cooper 1988; Cooper and Nakanishi 1988). Because the sampling unit is often a store or regional market, each observation canvasses the population of purchases at that particular store or region at any given time. Macro-level analyses thus reflect the actual market shares in the markets under study and generally lead to accurate forecasts of the overall impact of a brand's price and promotion policies.

However, the use of macro data to uncover the competitive structure of a market is problematic. Although graphical tools for analyzing brand price competition have been developed (Cooper 1988), natural correlations among the prices and promotions of competing brands often produce unstable model coefficients of limited managerial relevance (Blattberg 1989). For example, Bucklin, Russell, and Srinivasan (1993) report an analysis of aggregate scanner data in which one-third of the cross-price elasticities have inappropriate (negative) signs. Moreover, with the notable exception of the Zenor and Srivastava (1993) unfolding model, macro analyses provide only limited insights on the pattern of brand preferences within different consumer segments.

In contrast, micro-level data (typically from a household scanner panel) are available in a higher level of detail. Analysis of these data leads to a direct understanding of choice behavior, brand preferences, and the relationship between purchase behavior and consumer socioeconomic characteristics (Bucklin and Gupta 1992; Bucklin and Srinivasan...

Extrapolation of micro results to the market level must be approached cautiously. Because the unit of analysis is the purchase event, databases are large and analysis is limited to a sample of households. Even though household-level results can be aggregated to obtain segment- or market-level estimates of marketing mix effects (Grover and Srivinvan 1992), the resulting aggregate estimates will be biased if data collection procedures or household selection criteria yield a sample of households that is not representative of the market under study. Narasimhan and Renken (1991) provide a discussion of the types of biases that can be present in micro analyses of scanner panel data.

Information Availability

From a managerial perspective, micro data are more detailed than macro data but are less readily available. For example, A.C. Nielsen surveys 3000 grocery stores and 40,000 households across 62 market areas in the United States (Davey 1993); but these numbers are deceptive—a manufacturer interested in a single major market area typically would have access to 60–80 stores and 1800 households. Because the stores are sampled on the basis of sales volume, store-level data provide an excellent approximation to the total sales in the region. In contrast, effective panel sizes are quite small once allowance is made for each household’s category usage and continuous panel membership during a selected time period. In one study, a panel data set of 2500 households provided only 243 usable households (Bender 1993). Such sparsity of household panel data relative to the population of households in a regional market (typically 240,000) creates a preference for store-level analysis by marketing managers.

Compounding these issues are questions about the accuracy and availability of causal data on price and promotions provided in micro panel data. In the United States, Information Resources Inc. uses scanner data panels in selected geographical areas, whereas A.C. Nielsen emphasizes national consumer wand panels (Schlossberg 1991). Because in-home consumer wand panels require some causal information to be self-reported, price and promotion information may be inaccurate or missing for certain purchases. (Wand panels, however, do capture information about product category purchases in stores that are not equipped with retail scanning equipment.) Outside the United States, information availability is much worse. In Western Europe, for example, the amount of store-level scanning data is growing, but consumer panel data is still limited (Davidson 1992).

Integrating Micro and Macro Data

These considerations confront marketing managers with an important trade-off between the potential richness of sparse micro data and the econometric difficulties of highly representative macro data (Bender 1989). We respond to this trade-off by developing a store-level analysis that uses household-level information to understand the pattern of brand competition. We first analyze the observed purchase behavior of a household panel to identify consumer preference segments. We then use the substitution patterns observed in this micro-level analysis to assist in the estimation of a market share model based on retail tracking data. The result is a market share model with a flexible pattern of brand competition that is linked explicitly to the pattern of preferences observed in the household panel.

This integrated approach has two attractive features for the marketing manager. First, it recognizes data constraints by using only purchase summaries from consumer panel data to supplement the analysis of readily available store-level data. Because the approach does not require any causal information from the household panel, the researcher can use either scanner data panels or in-home wand panels. If necessary, consumption data taken from a consumer survey could be used instead of consumer panel information. Thus, the approach places light demands on the properties of the micro data.

Second, although the procedure is fundamentally a macro-level analysis, it retains much of the richness of a micro data analysis. The approach provides the manager with insights about market segmentation (obtained from the micro-level data) and aggregate response to the marketing mix (obtained from the macro-level data). The market structure can reveal subsets of brands that compete more closely, and the segmentation structure can uncover the particular segments in which this competition occurs. This detailed information provides the marketing manager with a way of identifying the strengths and vulnerabilities of the firm’s brand with respect to price competition.

We first develop a model of consumer behavior and show how it relates to the market’s preference segmentation and aggregate market shares. We then present a method of calibrating the model and illustrate the approach with data from the powdered laundry detergent category. We conclude with suggestions for further research.

AN INTEGRATED APPROACH FOR MICRO AND MACRO SCANNER DATA ANALYSIS

The purpose of our approach is to uncover the competitive structure in a product category while identifying the market segments leading to such a structure. However, rather than focusing only on macro-level tracking data or micro-level household scanner panels, our procedure uses both sources in a simple, easily implemented two-stage model.

In Figure 1, we present an overview of this integrated approach and its two-stage estimation process. The first stage uses a latent class analysis of household purchase statistics (taken from a consumer panel) to identify preference segments and obtain information regarding brand preferences within each of these segments. Results from this micro-level analysis then are used in conjunction with retail tracking data to estimate a market share model that accounts for the preference segments. In this section, we start with a model of household purchase behavior and show how this model leads to the micro and macro models represented in Figure 1.
Understanding Brand Competition

A Model of Household Purchase Behavior

Our analysis is based on a simple model of the purchases made by each household in each week. Let \( x_{ith} \) be the number of equivalent units (e.g., standard package size) of brand \( i \) purchased by household \( h \) during week \( t \). Assume that the household belongs to a segment \( s \), which is homogeneous in preferences. To simplify exposition, assume also that this purchase volume \( x_{ith} \) has a Poisson distribution\(^1\) with mean

\[
\lambda_{ith} = \lambda_h \lambda_s u_{ith}
\]

where \( \lambda_h \) is a measure of the overall weekly volume purchased by household \( h \), \( \lambda_s \) is a measure of seasonal factors that affect the purchases of all households, and

\[
u_{ith} = \exp(\alpha_{ith}/\sum_s \exp(\alpha_{ish})
\]

is the expected volume share of purchases of brand \( i \) by household \( h \) during week \( t \). Here, the summation runs over the \( B \) brands in the market.

The term \( \exp(\alpha_{ish}) \) represents the attractiveness of brand \( i \) to a member of segment \( s \). We model the log-attractiveness as

\[
\alpha_{ith} = \phi_{ih} + \beta_i p_{ih} + \delta_i d_{ih}
\]

where

- \( p_i \) = the price of brand \( i \),
- \( d_i \) = the in-store promotion intensity of brand \( i \),
- \( \beta_i \) = the brand's price sensitivity parameter,
- \( \delta_i \) = the brand's promotion sensitivity parameter, and
- \( \phi_{ih} \) = the intrinsic attraction of the brand (adjusting for price promotion).

We assume, without loss of generality, that \( \sum_i \phi_{ih} = 0 \).

With this model, purchase volumes depend on household characteristics (\( \lambda_h \)), time varying influences (\( \lambda_s \)), intrinsic brand attraction (\( \phi_{ih} \)) and brand-specific marketing actions (\( \beta_i p_{ih} + \delta_i d_{ih} \)).\(^2\) Note that \( u_{ith} \) depends only on the segment \( s \) to which the household \( h \) belongs. Hence, the relative attraction of a brand during a particular week is an interaction between the marketing actions of the various brands and the intrinsic attractiveness of these brands to the household's preference segment.

To develop the micro and macro models, we aggregate household purchases over both time and households. The resulting models will be logically consistent, because they are derived from the same model of household behavior. To simplify this process, we assume that conditional on the Poisson means \( \lambda_{ith} \) the observed purchase volumes \( x_{ith} \) are statistically independent with respect to brand \( i \), household \( h \), and week \( t \). This conditional independence assumption, which commonly is made in the context of choice modeling (e.g., Bucklin and Gupta 1992; Kamakura and Russell 1989), implies that the correlations among the purchase volumes \( x_{ith} \) are induced solely by the natural correlations among the means \( \lambda_{ith} \). Substantively, this assumption does not rule out correlations among observed purchase volumes; it merely restricts the source of the correlation to the three components: \( \lambda_h \), \( \lambda_s \), and \( u_{ith} \).

The Macro Model: Weekly Volume Shares

First, let us show how the macro model arises from the aggregation of purchases across households. Define \( x_{ih} = \sum_h x_{ih} \) as the total volume of brand \( i \) purchased by all households in week \( t \), and let

\[
y_{ih} = x_{ih}/(x_{ih} + ... + x_{ih})
\]

be the corresponding market share (measured on a volume basis). Furthermore, define

\[
f_i = \sum_{i \in s} \lambda^s_i \lambda_h \lambda_s^s \lambda_{ih} + \sum_{i \in S} \lambda^s_i \lambda_h \lambda_s^s \lambda_{ih}
\]

as the expected relative volume (i.e., relative size) of each of the \( s = 1, 2, ..., S \) segments. Using standard results for the Poisson distribution (e.g., Bickel and Doksum, 1977, p. 340) and the fact that the \( x_{ih} \) are conditionally independent across households and brands, we find that, conditional on the total market volume in week \( t \), the observed market shares \( y_{ih} \) follow a multinomial distribution with mean

\[
MS_{ih} = \sum f_i MS_{ih}
\]

where

\[
MS_{ih} = \exp(\alpha_{ish}/\sum_s \exp(\alpha_{ish})
\]

\( ^1 \)The Poisson assumption is not critical. It is required only to justify the modeling of household share of requirements using a multinomial distribution. The expressions for the means of the macro and micro models remain valid regardless of the distributional form assumed.

\( ^2 \)The model can be modified to consider household dynamics explicitly by writing the Poisson mean as \( \lambda_h u_{ith} \). The only impact of this change is that relative segment sizes may show time variation. However, if we assume that the changes in \( \lambda_h \) of different members of the same segment are statistically independent, then relative segment sizes will be stable, and the macro model will have the same form as shown in Equations 6-8. Dynamics due to marketing variables (e.g., lagged impact of advertising) can be captured by using a cumulative variable (e.g., goodwill of advertising) in the specification of Equation 3.
and

\[ \alpha_{st} = \phi_t + \beta_t d_t + \delta_i d_t \]

is the expected volume share within segment \( s \) at week \( t \).

This representation of aggregate market share as the sum of market shares within segments first was proposed by Bell, Keeney, and Little (1975) and has strong similarities to segmentation models developed by Grover and Srinivasan (1987, 1989) and Kamakura and Russell (1989). As noted by Bell, Keeney, and Little (1975), the model does not imply the proportional draw mechanism associated with simple attraction models. This provides the proposed macro model with considerable flexibility in representing the pattern of brand competition. In particular, the general expression in Equations 6–8 can accommodate the very diverse structures of the Batsell and Polking (1985) market share system.

It should be noted that the macro model in Equations 6–8 requires an understanding of the preference segmentation of the market, that is, the intrinsic brand attractions \( \phi_t \) and the relative size of segments \( f_s \). We show next that summary information from a consumer panel can provide information about both aspects of the macro model.

The Micro Model: Share of Requirements Over a Time Period

Our primary interest in using the micro data is to construct a simple method of identifying intrinsic brand preferences \( \phi_t \) and relative segment sizes \( f_s \), which can be used in the macro model. To develop the micro-level model, we aggregate the purchases of each household over time and calculate the share of requirements for the household in that product category

\[ q_{bh} = \frac{\sum \lambda_i \lambda_{1h} + \ldots + \lambda_{gh}}{\sum \lambda_{1h} + \ldots + \lambda_{gh}} \]

for each brand. This ratio is simply the proportion of the household’s purchase volume for the entire micro data period allocated to a particular brand. Following the household level model, we assume that each household belongs to a homogeneous preference segment \( s \). For expositional purposes, we also assume here that the segment \( s \) to which household \( h \) belongs is known to the researcher. (This assumption is relaxed subsequently.)

Because marketing activity for each brand varies over time and has some impact on choice, we would not expect \( q_{bh} \) to provide unbiased information about the intrinsic attraction of brand \( i \) to the household’s segment \( s \) (\( \phi_{is} \)). However, as we show next, the bias has a special form that still allows us to use the observed \( q_{bh} \) for structuring the macro model.

To find out what information can be recovered from the micro data about the intrinsic attraction of each brand \( \phi_{is} \), we first develop an expression for the mean of the share of requirements for each household. Because \( \lambda_{is} \) is a conditionally independent Poisson variable across time, the distribution of \( q_{bh} \) conditional on the total number of purchases of the household, is multinomial with mean

\[ \lambda_i = \sum \lambda_{i1h} + \sum \lambda_{i2h} + \ldots + \sum \lambda_{igm} \]

where the summations run over all weeks \( t \) in the micro data.

To derive the brand intrinsic attraction \( \phi_{is} \), we invoke two assumptions about the temporal elements of the model:

1. Stationarity—The marketing variables \( (p_i, d_i) \) for all brands follow a time series process over all weeks in the micro data. The process can include both stationary and seasonal components.

2. Relative attraction—During any week \( t \), the relative attraction

\[ u_{it} = \exp[\alpha_{it} + \sum \exp[\alpha_{it}]] \]

of each brand is independent of the total attraction \( \sum \exp[\alpha_{it}] \) of all brands. Moreover, relative attraction is independent of the seasonal component \( \lambda_t \).

These two assumptions are quite general. The first implies that firms have particular marketing policies that vary over time but have a stable mean over the time horizon of the micro data. The second ensures that the household’s relative brand attraction is statistically independent of the household’s total product category consumption; looking across the time horizon of the micro data, variations in the total attractiveness of the product category do not differentially favor the relative attraction of any one brand. Empirical evidence supporting this second assumption is presented in Ehrenberg (1988).3

Using these assumptions, we show in Appendix A that as the number of time periods in the micro data increases, the mean of \( q_{bh} \) for a household in segment \( s \) converges in probability to

\[ \text{plim } q_{bh} = \frac{M_i \exp(\phi_{is})}{M_0 \exp(\phi_{is}) + \ldots + M_{gh} \exp(\phi_{is})} \]

where \( M_i \) is a constant that depends on the joint distribution of brand \( i \)’s price and promotion variables \( (p_i, d_i) \) and the response coefficients \( (\beta_i, \delta_i) \). (Here, \( \text{plim} \) denotes probability limit.) Clearly, \( M_i \) depends on the marketing policies of brand \( i \). However, in any particular data set, \( M_i \) can be regarded simply as a brand-specific constant that does not depend on the segment or household. That is, the household share of requirements data are biased indicators of intrinsic brand attraction, but the bias is common across all households.

A more useful way of expressing Equation 11 is to consider the Cooper-Nakanishi (1988) transformation of the share of requirements statistics

\[ \lambda_i = \log(q_{ih}/q_{h}), \]

where \( q_{h} \) is the geometric mean of the \( q_{bh} \). Let \( M \) denote the geometric mean of the brand-specific constants \( M_i \) in Equation 11. Using the assumptions outlined previously (and recalling that \( \sum \phi_{is} = 0 \)), it follows immediately that as the number of weeks in the micro data increases, \( \lambda_i \) converges in probability to

\[ \text{plim } \lambda_i = \phi_{is} - \rho_i \]

where \( \rho_i = -\ln(M/M_i) \) is a brand-specific constant. Thus, for a reasonably long data history, \( \lambda_i \) differs from \( \phi_{is} \) by a con-

3Ehrenberg’s (1988) empirical work indicates that household purchase volume and seasonality do not have an impact on market share for frequently purchased goods.
stant that depends only on the brand—not the household or segment.

These results show that the intrinsic brand attraction within each segment is a simple function of household share of requirements. We now show how the segment sizes $f_i$ relate to these same household-level data. The expected volume of a household can be obtained from the grand total volume

$$V_h = \sum x_{1ih} + \ldots + \sum x_{nh},$$

where, as before, the summation runs over the entire period of the micro data. This expression has expectation

$$E(V_h) = \omega \lambda_h,$$

where $\omega$ is proportional to the mean of the seasonal component $\lambda_i$ over time. Analogous to $p_i$, $\omega$ does not depend on the household or segment under consideration. Note that knowledge of $\omega \lambda_h$ enables the researcher to compute $f_i$, the relative segment size defined in Equation 5; thus, $V_h$ can be used to compute a consistent estimate of $f_i$.

**Summary**

We show in this section how the theoretical model of household purchase behavior sets the stage for linking an analysis of household share of requirements to an analysis of retail tracking data. If segment membership is known, household purchase summaries $I_h$ can be used to obtain consistent estimates of a brand's intrinsic attraction that differ from the true value $\phi_i$ only by a brand-specific constant $p_i$. Following the same rationale, overall household purchase volumes $V_h$ can be used to obtain consistent estimates of relative segment sizes $f_i$. The result is a fully structured (and partially calibrated) macro model suitable for further analysis using retail tracking data.

**ESTIMATING THE MICRO AND MACRO MODELS**

**Micro-Level Analysis**

The key challenge in developing the market preference segmentation is determining the segment $s$ to which each household $h$ belongs. We identify preference segments with a latent class analysis of each household's share of requirements statistics. Details are given in Appendix B. The justification behind the procedure is that biases in the means of the share of requirements are brand specific. Thus, a classification of households into segments using observed volume shares $q_{ih}$ is equivalent to a classification of households into segments using estimates of the true brand attractions $\phi_i$. This latent class analysis generates the total number of segments $S$, the estimated volume-weighted choice probabilities $\theta_i$ and estimated relative segment size $F_i$ for each segment $s$, and the probability $r_{hs}$ that household $h$ belongs to segment $s$.

We use the estimated volume-weighted choice probabilities $\theta_i$ and segment size $F_i$ for each segment $s$ as the definition of the market segmentation in the macro-level analysis.

For this purpose, we define the intrinsic attraction of brand $i$ within segment $s$ as $I_i = \ln(\theta_i/\theta_s)$, where $\theta_i$ is the geometric mean of the purchase probabilities $\theta_{ij}$ in segment $s$. Analogous to the development in the last section, $I_i$ is a consistent estimate of $\phi_i - \rho_i$, where $\rho_i$ captures the marketing activity of brand $i$ in the micro data.

Although segment membership probabilities ($r_{hs}$) are not used directly in the macro-level analysis, they are useful in relating brand-purchase profiles to household sociodemographic characteristics. We show in the empirical work that the sociodemographic profile of each segment can be related to brand preferences ($\rho_i$) observed within the segment.

**Macro-Level Analysis**

The purpose of the macro-level analysis is the estimation of a market-share response model at the market level that takes into account the preference structure identified at the household level. In our previous modeling of household purchase behavior, we show that the aggregation of purchases across households for any given week $t$ is given by the attraction model

$$MS_h = \sum f_i MS_{ih},$$

$$MS_{ih} = \exp(\alpha_{ih})/\sum \exp(\alpha_{ih}),$$

where $\beta_i$ and $\delta_i$ are the brand-specific response coefficients for price ($p_i$) and promotion ($d_i$), respectively. Because $F_i$ is a consistent estimate of $f_i$, and $I_i$ is a consistent estimate of $\phi_i - \rho_i$, we can rewrite the macro model as

$$MS_h = \sum F_i MS_{ih},$$

$$MS_{ih} = \exp(\alpha_{ih})/\sum \exp(\alpha_{ih}),$$

$$\alpha_{ih} = \phi_i + \beta_i p_i + \delta_i d_i,$$

where $p_i$ is a brand-specific intercept that reflects brand marketing activity. By replacing certain parameters with consistent estimates from the micro data, we can use the micro data to constrain the macro model partially. Thus, instead of estimating the full set of parameters in Equations 16–18, we can use the retail tracking data exclusively to estimate the small set of unknown brand-specific parameters in Equations 19–21: intercepts $p_i$, price response coefficients $\beta_i$, and promotion response coefficients $\delta_i$.

This market-share model is similar to previous market share models (Brodie and Kluvner 1984; Bultez and Naert 1975; Cooper 1988; Ghosh, Neslin, and Shoemaker 1984). Note that we use a differential-effects formulation within each segment. Even though the price and promotion coefficients for each brand are the same over segments, price and promotion elasticities are segment specific because of the differences in the intrinsic brand attractions ($p_i + I_i$) across segments.

Because of potential model misspecification, it is advisable to allow for random error in the relationship between the market shares expected by the model and actual market shares observed in the retail tracking data. We assume that
the retail tracking market shares $Y_{it}$ ($i = 1, 2, ..., B$) during any week $t$ are distributed independently (over time) as Dirichlet with means $MS_{it}$ and covariances

$$\text{Cov}(Y_{ij}) = |\text{diag}(MS_{i}) - MS_{i}MS'_{i}|/(\eta + 1),$$

where $Y_{ij}$ and $MS_{i}$ denote vectors of observed and expected market shares and $\text{diag}(MS_{i})$ denotes a diagonal matrix. In this Dirichlet model, $\eta$ is a nonnegative shape parameter that becomes large as the error variance becomes small (i.e., when the model fits well). The covariance for the Dirichlet also allows for error heteroscedasticity, which varies over time depending on the mean.

Estimation details are given in Appendix C. The use of consistent estimates for the segment-level parameters ensures that this maximum likelihood procedure will yield asymptotically unbiased estimates of brand intercepts $\beta$ and marketing response parameters $\delta$. It should be noted that the consistency of the macro-level parameters is critically dependent on the assumption that the sample of households in the micro analysis is representative of the population of households generating the store-level tracking data. In the empirical illustration reported subsequently, we work to ensure consistency by drawing the household sample from the market area defined by the stores under study.

**ANALYSIS OF BRAND COMPETITION**

The result of our two-step procedure is a market share model consisting of a small number of consumer segments, each with a set of associated parameters: segment sizes ($P_{s}$) and (biased) intrinsic brand attractiveness ($I_{bs}$) estimated in the micro analysis; and brand intercepts ($\beta$), and price and promotion sensitivities ($\delta$) estimated in the macro analysis. This unique blend of disaggregate and aggregate information presents the manager with two principal ways of studying brand competition: segmentation analysis and cross-elasticity analysis.

**Segmentation Analysis**

Segmentation information can be used directly to analyze a brand’s distribution of preferences across the population and understand market response to the brand’s marketing activity. Because the micro analysis enables us to classify households into segments (using the membership probabilities $\pi_{bs}$), these preference segments can be linked directly to household characteristics (e.g., demographics). Combining this information with the brand-specific response parameters ($\beta$ and $\delta$) estimated using the retail tracking data, we obtain a complete description of a brand’s positioning measured in terms of intersegment differences in purchase volumes, brand preferences, demographics, and marketing mix elasticities.

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3In the previous section, we showed that the aggregate market shares in the panel data $Y_{it}$ follow a multinomial distribution. However, the tracking data market shares $Y_{it}$ are a census of all households shopping at the store and consequently have no sampling error. The Dirichlet distribution is used here as a parsimonious way of representing model misspecification in the macro data.

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**Cross-Elasticity Analysis**

Market share cross elasticities are convenient measures of overall brand strength and of the relative substitutability of brand pairs. Define $e(i,j)$ as the percentage change in market share of brand $i$ with respect to a 1% change in the price of brand $j$. These market-level elasticities can be computed as

$$e(i,j) = \beta_{ij}P_{j}/MS_{ij}[\Sigma_{s}f_{s}MS_{is}(1 - MS_{is})]$$

where $P_{j}$ denotes the average price for brand $j$, $f_{s}$ is the relative size of segment $s$, $MS_{is}$ is the brand’s market share within segment $s$, and $MS_{ij}$ is the aggregate market share. Segment-level elasticities also can be computed using similar formulas, if desired.

The elasticity formulas in Equations 23 and 24 provide useful insights on a brand’s market strengths. The cross-elasticity formula, for example, shows that brand $j$’s impact on brand $i$ will be greater when the latter has a small market share and the two brands appeal (i.e., have high shares) to the same market segments. The own-elasticity formula, on the other hand, shows that a brand $i$ will be less affected by competitors when it has a large market share and extremely large or small shares within the various market segments (i.e., competes within specific market niches with a dominant presence in each).

An appealing feature of our model is that the cross elasticities in Equation 24 can be decomposed into simple components, facilitating managerial interpretation. This decomposition is a special case of the LSE utility elasticity model proposed by Russell (1992). Using Russell’s model, the cross elasticities in Equation 24 can be rewritten as

$$e(i,j) = M(j)S(i,j), \quad i \neq j,$$

where

$$M(j) = -\beta_{ij}MS_{ij}P_{j},$$

is the momentum of brand $j$, and

$$S(i,j) = \Sigma_{s}f_{s}R_{is}R_{js}, \quad i \neq j,$$

is a symmetric substitution index ($S(i,j) = S(j,i)$). In these expressions, $R_{is}$ is the ratio between brand $i$’s share within segment $s$ and its aggregate share ($R_{is} = MS_{is}/MS_{i}$). Thus, two brands will be close substitutes when they hold large share (relative to their aggregate) in the same segments (i.e., they compete directly for the same consumers).

The momentum $M(j)$ defined in Equation 26 measures the general impact of brand $j$ over its competitors. Price changes by brands with large momenta tend to have a stronger impact on competitors’ shares. Note that the relative impact of one brand’s price promotions on another is given by the ratio of momenta ($e(i,j)/e(j,i) = M(j)/M(i)$). Hence, momentum determines the pattern of asymmetry in brand competition.

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4Segment-level own price elasticities are defined as $\beta_{ij}(1 - MS_{ij})P_{j}$. Because $MS_{ij}$ varies across segments, the price elasticity of a given brand $i$ will vary across segments as well.
Understanding Brand Competition

In contrast, the substitution index $S(i,j)$ in Equation 27 is a generalized measure of switching between brands $i$ and $j$ that adjusts for segment size and relative brand preference within each segment. Substitution indices provide a measure of the draw pattern expected during a price promotion. For example, suppose that brand $j$ is more substitutable with brand A than brand Z (i.e., $S(A,j) > S(Z,j)$). Using Equation 25, we find that $e(A,j) > e(Z,j)$ (because $e(A,j)/e(Z,j) = S(A,j)/S(Z,j)$). Hence, a price reduction of brand $j$ will draw proportionally more share from brand A than brand Z.

When momentum and substitution indices are combined, we obtain the observed pattern of brand price competition. A brand will have the most impact on competitors with which it is highly substitutable and will be most vulnerable to price changes by highly substitutable competitors that also hold high momentum. As we show subsequently, this decomposition of elasticities into momenta and substitution indices is useful in creating a visual display of the asymmetries of brand competition.

Summary

Aside from producing information on the pattern of price competition at the market level, our approach also provides insights into the reasons behind brand differences. Note that momentum in this model is dictated by market-level statistics (share and average price), whereas substitutability is dependent on segment-level preferences. Thus, there is a logical link between the aggregate measures of brand price competition and a brand’s positioning relative to the preference segments.

EMPIRICAL ILLUSTRATION

To illustrate our approach, we study brand competition in the powdered detergent product category. We first develop a representation of the market’s preference segmentation using the share of requirements of each household. We then use the retail tracking data to estimate price and promotion coefficients for each brand.

Data Description

The example discussed here is based on supermarket scanner data for powdered detergents, provided by A.C. Nielsen. The data cover a 42-week period spanning September 1987 through June 1988. The eight national brands with largest market share were selected for analysis. In addition, two composite categories were constructed to represent small-share national brands (Nfl) and private label brands (PL).

The analysis was based on two different data sets. The micro-level data consisted of the volume (expressed in equivalent units of 32 ounces) purchased of each of 12 brands of detergent by a panel of 1361 households. These volumes were calculated with respect to the entire 42-week period.

The second data set consisted of the retail tracking data for 27 stores in one market over the same period. These stores and weeks correspond to the same market and time period in which the panel shopped. However, the tracking data reflect the purchases of all shoppers at that store, and the panel data reflect the purchases of a relatively small sample of households. Equating the household panel and store-level data with respect to time period and market area is necessary to ensure that the panel is a representative sample of the households generating the macro data. The representativeness of the micro data is a key assumption of our approach.7

We selected the first 22 weeks of retail tracking data for model calibration and set aside the remaining 20 weeks for validation purposes. In preparing the data, we eliminated store-week combinations in which the entire set of 10 brands was not available for purchase. This process led to 442 store-week units for calibration and 409 store-week units for validation.

For each store and week, we obtained the following information from the retail tracking data:

1. Market share (in volume) for each of the ten brand categories,
2. Average price per ounce (net of discounts) for each brand category, and
3. Promotion intensity of each brand during the current week (measured in terms of the share-weighted percentage of brand sizes for which feature and/or display conditions were present).

As shown in Table 1, brands differ considerably in price dispersion (measured by the coefficient of variation for price) and promotion intensity (measured by the percentage of volume sold during promotion conditions).

Micro Analysis: Segment Identification

We applied the latent class analysis to the 1361 sampled households. Using the Consistent Akaike Information Criterion (Bozdogan 1987), we obtained an eight-segment representation. Estimated volume shares for each segment and relative segment sizes (measured in equivalent units) are listed

7To examine this assumption, we regressed the volume shares from the store-level analysis (Table 1) on the volume shares from the sample of households. The correlation between the micro and macro shares is .95. Moreover, t-tests of regression coefficients fail to reject the hypothesis that the regression line linking micro and macro volume shares has an intercept equal to zero and a slope equal to one.
in Table 2. Because the standard errors of these estimates are small, the preference structure appears to be well determined by the micro data.

The segment shares reported in Table 2 preview the competitive strengths and weaknesses that will transpire in the macro-level analysis. Compare, for example, the segment preferences for Tide and Surf. Tide draws 90% of the volume within the largest segment (B) and substantial volume (greater than 10%) from five of the eight preference segments; together, these segments account for 72% of the total market volume. In contrast, Surf is purchased by most segments, but does not have a dominant position in any segment. The highest shares of Surf are obtained in one segment (F), in which Surf competes directly with Dash. We show subsequently that these differences in positioning imply a pattern of brand price competition in which Tide has a strong impact on all competitors and Surf is highly substitutable with Dash.

Table 2 also presents the demographic profiles of the eight segments, computed as weighted averages of the house-

| Table 2 |

| POWDERED DETERGENT PREFERENCE SEGMENTS |

<table>
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<tr>
<th>Volume Shares</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
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<td>10.4</td>
<td>4.8</td>
<td>12.8</td>
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| Demographics |

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<th>Age</th>
<th>Segment</th>
<th>Size</th>
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<td>15.4%</td>
<td>9.0%</td>
<td>23.4%</td>
<td>11.3%</td>
</tr>
<tr>
<td>35.2%</td>
<td>22.7%</td>
<td>25.5%</td>
<td>28.7%</td>
<td>37.5%</td>
<td>26.7%</td>
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</table>

| Error Structure |

| Dirichlet Scale Parameter (γ) | 55.1 |

*Estimate is statistically significant at the .05 level.
**Estimate is statistically significant at the .01 level.

Note: The U² fit statistics for the model are .77 (calibration data) and .78 (validation data).

hold demographics using segment membership probabilities \( \pi_n \) as weights. For example, households switching between the low-priced brands All and PL (segment E) are older, smaller in size, and less likely to have young children. Additional descriptions of the preference segments—useful in developing advertising and promotion strategies—could be obtained if data were available on a richer set of consumer characteristics (e.g., psychographics).

**Macro Analysis: Dirichlet Regression Model**

As discussed previously, we restricted the model in two ways. First, the segment sizes \( (f_{i}) \) were set to the values obtained in the micro-level analysis (Table 2). Second, the segment volume attributes \( \phi_{mn} \) were assumed to be equal to \( I_{kn} + \alpha \), where \( I_{kn} \) is obtained from the micro data and \( \alpha \) is estimated from the macro data.

The model was estimated using the maximum likelihood procedure described in Appendix C, leading to the estimates listed in Table 3. All price coefficients were statistically significant and with the expected sign. One of the promotion coefficient estimates was negative but nonsignificant at the .05 level. The estimate for the Dirichlet scale parameter was relatively large (\( \gamma = 55.1 \)), suggesting a small error variance. In Table 3, we also report U² measures of fit and predictive fit (on the holdout sample). These entropy-based measures (see Urban and Hauser 1984) have similar interpretation to the more commonly known R².

As discussed previously, the brand intercept \( \beta \) represents a bias correction for the intrinsic brand attractions \( I_{kn} \) estimated in the micro analysis and should capture the effect of marketing activity during the sampling period of the micro data. Appendix D shows that if the brand intercepts \( \beta \) actually do capture the effect of prices and promotions during the micro sampling period, then these estimates should be related directly to the mean, variances, and covariance of the
brand's price and promotion (see Equations D3–D4). An empirical test of this theoretical relationship yielded a correlation of .94 between the estimated brand intercept $\rho_i$ and the expected value based on each brand's price and promotion policies. The evident linearity of this relationship supports the use of $\rho_i$ as a correction for biases in the micro-level estimates of intrinsic brand attractiveness. In other words, the brand intercepts $\rho_i$ capture the effect of marketing activity in the micro analysis, and $\rho_i + I_{in}$ captures brand preferences within each segment.

### Cross-Elaticity Analysis

It should be noted that the price and promotion coefficient estimates in Table 3 are not elasticities and cannot be interpreted meaningfully or compared across brands. Similarly, the brand intercepts do not have a direct meaning and must be combined with the intrinsic attractions $I_{in}$ within each segment. However, an understanding of brand competition can be obtained by calculating and analyzing cross-price elasticities.

In Table 4, we show that the cross-elasticity pattern predicted by the proposed model departs substantially from the proportional draw structure generated by simple market share models. Note, for example, that the impact of Surf on Dash (1.61) is very different from the impact of Surf on other brands (see Surf column of the elasticity matrix). This departure is because Surf and Dash compete directly within a particular preference segment (F).

In Table 4, we also display the decomposition of the cross elasticities into momentum $M_{ij}$, a measure of brand strength, and substitution indices $S_{ij}$, a representation of market structure. A simple display of the overall pattern of brand price competition can be obtained by using this decomposition and the procedure of Appendix E to develop a competitive map. A two-dimensional example of this map, for four brands only, is shown in Figure 2.
Figure 3  
VULNERABILITY PATTERN FOR CHEER

This map represents each brand by a vector whose length is proportional to the brand's momentum. The cosine of the angle formed by two vectors is proportional to the degree of substitution between the two respective brands. Thus, vectors pointing in the same direction represent brands that compete directly. Take Cheer as an example. Figure 2 shows that a Cheer price promotion would have proportionally more impact on Surf than Tide. Note that the angle between Surf and Cheer is smaller than the angle between Tide and Cheer.

To identify the most threatening competitors (i.e., brands that have the most impact on Cheer), we must consider simultaneously the competitor's momentum and the substitution index between the brand and the competitor. A brand will be most vulnerable to a competitor whose vector has the longest projection onto its own vector. Figure 3 indicates that Cheer is equally vulnerable to Tide and Surf. Thus, in this illustration, Cheer is not a major threat to Tide (Figure 2), but Tide is a major threat to Cheer (Figure 3). Clearly, asymmetry is a characteristic of brand price competition.

A complete competitive map in three dimensions, for all brands considered in our study, is presented in Figure 4. Two major elements of brand price competition can be observed in this map. First, brands with the longest vectors (Tide, Cheer, Ntl, and Surf) are the strongest competitors in the market. In head-to-head competition with weaker brands (such as Bold, Dash, PL, and Purex), the strong brands have a major impact on competitors but are not affected strongly by competitive price changes.

Second, the clustering of the vectors representing each brand reflects the competitive structure identified with the micro analysis. Recall that the substitution index becomes larger if two brands have high relative share in the same consumer segments (Equation 27). (Relative share, $R_{ij}$, is the ratio of brand share within a segment to the overall brand share in the market.) The relative share pattern shown in Table 5 indicates that the high-share brands Tide, Oxydol, and Cheer appeal to segments A, B, C, and H, which generally do not purchase less popular brands. Surf provides an interesting contrast to this pattern. Although Surf is a high-share brand (Table 1), it competes in segments that favor the small-share brands.

The map in Figure 4 captures these features by placing the Tide, Oxydol, and Cheer vectors in the vertical plane and small-share brand vectors in the horizontal plane. Note that the vectors of Tide, Oxydol, and Cheer are aligned closely and point away from the Surf vector. Moreover, the Surf vector is located close to the plane of the small-share brands. Thus, the market structure implied by brand price competition is a reflection of the substitution pattern found in the micro data.

Figure 4  
ELASTICITY MAP FOR POWDERED DETERGENTS

Table 5  
RELATIVE SEGMENT SHARES $R_{ij}$

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
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<td>+</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oxydol</td>
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<td>+</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
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<td>+</td>
<td></td>
<td>+</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bold</td>
<td>+</td>
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<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Relative shares > 1.0 are shown as a "+".

---

8 Consider the projection of competitor j's vector on the vector of our brand i. The length of this projection is equal to the product of two elements: the competitor's momentum M(j) and the substitution index of the brand pair S(i,j). Equation 25 shows that this product is equal to e(i,j), the cross elasticity reporting the impact of the competitor's price changes on the sales of our brand.
Table 6
SUMMARY OF MCI MODELS

<table>
<thead>
<tr>
<th></th>
<th>Tide</th>
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<th>Oxy</th>
<th>Cheer</th>
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U² Fit Statistics: .78 (calibration), .80 (validation)

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U² Fit Statistics: .82 (calibration), .80 (validation)

Note: Elasticities are expressed as the percentage change in the market share of the row brand with respect to a 1% change in the price of the column brand.

Comparison with MCI Models

We also computed the cross price elasticities and U² fit statistics (Urban and Hauser 1978) for two MCI (multiplicative competitive interaction) models drawn from Cooper and Nakanishi (1988). Each of the MCI models was calibrated using the same price, in-store promotion, and market share data as our Dirichlet regression model. Results are displayed in Table 6.

The Differential Effects model is a simple attraction model with brand-specific price and promotion coefficients. This model has 28 parameters, compared with 30 in our model. It implies that a brand draws share in proportion to the market share of the competitor (i.e., cross elasticities in each column are identical). This structure may be acceptable within a market segment, as assumed in our model, but is too restrictive to represent brand competition at the market level.9

In contrast, the Cross Effects model allows for an extremely flexible cross elasticity pattern. The cost of this flexibility is the need to estimate 122 parameters from the retail tracking data. Instability in estimation leads to inappropriately signed (negative) cross elasticities, implying that a price cut by one brand leads to increases in shares in competing brands.10

The different competitive structures implied by these alternative approaches highlight a key feature of our modeling effort. Our analysis develops a flexible elasticity pattern at the market level (varying degrees of substitution among different sets of brands) that is consistent with the preference structure identified at the household level. This provides the estimated elasticity matrix with a high degree of face validity for the brand manager. Moreover, the fit of the proposed model is comparable to the MCI baseline models. Although the MCI models fit slightly better in the calibration data period (U² equal to .78 and .82 for the MCI models versus .77 for the proposed model), differences in fit during the validation period (.80, .80, and .78 respectively) are very small.

CONCLUSIONS

The widespread use of scanners at retail checkout counters and wide availability of household scanner panels has provided retailers and manufacturers with a vast amount of data at the market and household levels. We attempt to in-

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9 A more flexible structure could be obtained by first standardizing price and promotion using a zeta transformation (Cooper and Nakanishi 1988). However, the resulting formulation would not be a differential effects model in terms of the raw price and promotion data. Thus, the competitive structure obtained would be dictated largely by the properties of the zeta transformation.

10 The elasticities predicted by both the proposed model and the MCI models are dependent on the brand prices used in the calculation. In Tables 4 and 6, average brand prices are used. The number of inappropriate (negative) cross elasticities in the fully saturated MCI model could be less if another price point were selected.
tegrate both sources of information. We first identify preference segments from a household panel. This information about the preference structure observed at the household level then is incorporated in a market share response model, calibrated on retail tracking data.

Our procedure is fundamentally a macro-level approach that structures the interpretation of store-level data using consumer purchase summaries. This procedure represents a compromise between choice models based on household level data (e.g., Bucklin and Srinivasan 1991) and market share models based on aggregate data (e.g., Cooper and Nakaniishi 1988). By incorporating segment information from the micro-level analysis, our macro-level analysis generates a flexible market structure while permitting the calibration of an aggregate market share model with a small number of parameters. Furthermore, by placing weak demands on the micro data, the procedure recognizes that household-level data is sparse relative to store-level data and that household-level causal information may not be available.

This integrated approach provides the brand manager with a wide range of market diagnostics. At the segment level, this approach can identify preference segments, measure the segment sizes (in equivalent units and number of households), describe the pattern of brand preferences, and describe the demographic and psychological profile of each segment. At the aggregate (market) level, the brand manager can measure the overall impact of a brand on competitors, its substitutability with other brands, and its direct impact over a particular brand. For a broader sense of the market competitive structure, the manager can rely on the competitive map derived from the macro analysis.

Limitations

In developing our model, we make the fundamental assumption that the sample of households is representative of the population of households generating the store-level data. Clearly, biases in household sampling procedures will generate biases in the estimated pattern of brand competition. We address this issue in our analysis by drawing the household sample from the same market area and time period as the macro data. Another approach is to make the weaker assumption that the types of consumer segments in the micro data are representative of the population, but that the relative segment sizes in the micro data are biased. Under this weaker assumption, the researcher would rely on the retail tracking data to estimate both segment sizes and marketing mix response parameters. If this weaker assumption was also untenable, the present approach would have to be abandoned. In such cases, a method of structuring the aggregate cross-elasticity pattern without using household data must be adopted (e.g., Zenor and Srivastava 1993).

Researchers applying this approach also should be aware that the model application presented here does not capture purchase dynamics. Marketing mix dynamics (e.g., lagged effect of advertising) can be incorporated easily into the current framework by allowing cumulative variables (e.g., the goodwill of advertising) to affect brand attraction (Equation 3). Household dynamics (e.g., product inventory, choice event feedback) present more complex challenges. Our analysis of the model logic indicates that household dynamics will not have an impact on the micro analysis. However, depending on the distribution of these effects across the consumer population, time variation in relative segment size is possible. One way of capturing this effect is to posit a random coefficients distribution that generates a different set of relative segment sizes during each time period.

During the course of this research, we developed an alternative model in which segment size varied over time in response to the total attraction of the category for the segment. The alternative model implies that marketing activity (e.g., price promotions) may affect differentially the interest of certain segments and lead thereby to a link between marketing actions and relative segment size.11 Empirical investigation provided no evidence for this relationship in our data. However, empirical work in other product categories is needed to study this issue.

Clearly, this methodology can be refined further in other ways. For example, Bayesian procedures could be developed to obtain the final elasticity pattern from the tracking data, using the household level preference structure to form reasonable priors. In addition, the relative mix of preference segments shopping at each store (computed from the household panel) could be used as weights, allowing the elasticity pattern to differ across stores. Finally, if household panel data is not available, other sources of information such as survey data could be used to determine the preference segments and the expected brand shares within segments. Again, the issue of representativeness of the data for the relevant consumer population must be addressed.

We view this work as a first step in building models that bridge micro and macro data. Given the increasing interest in store-level analysis by marketing managers, we believe that the approach provides a potentially useful new tool for studies of interbrand competition at the segment and market levels.

APPENDIX A: PROBABILITY LIMIT OF $\theta_{ab}$

To understand the connection between the mean of the household's share of requirements mean and the intrinsic brand attraction of the household's preference segment, we allow the $T$ periods of the micro data to approach infinity and consider the probability limit of $(1/T)\Sigma \lambda_{ab}$. Because the seasonal component is independent of the relative brand attraction (and $\lambda_{ab}$ is time invariant),

\[(A1) \quad \text{plim} (1/T)\Sigma \lambda_{ab} = \lambda_{a}E[\lambda_{b}][E[u_{ab}]],\]

where $E[.]$ denotes expectation with respect to an infinitely long time horizon. Furthermore, because relative brand attraction is independent of total brand attraction,

\[(A2) \quad E[u_{ab}] = E[\exp(\alpha_{ab})]/[E[\exp(\alpha_{ab})] + \cdots + E[\exp(\alpha_{b=1})]].\]

Each of these terms can be expressed as

\[(A3) \quad E[\exp(\alpha_{ab})] = M_{e}\exp(\phi_{a}),\]

where $M_{e} = E[\exp(\phi_{p} + \delta_{a}d_{i})]$, is finite because the brand's price and promotion policies have only stationary and sea-

\[11\text{Details are available from the first author.}\]
sonal components. Inserting Equations A1–A3 into the probability limit expression
\[
\text{plim } \theta_{ih} = [\text{plim}(1/T) \Sigma \lambda_{ih}][\Sigma [\text{plim}(1/T) \Sigma \lambda_{ih}]]
\]
yields Equation 11 in the text.

**APPENDIX B: LATENT CLASS MODEL**

We define segments by using a standard latent class procedure based on \( X^*_h = [x_{1h}, x_{2h}, \ldots, x_{nh}] \), where \( x_{ih} \) is the total volume of purchases of brand \( i \) during the entire micro history of household \( h \). We assume that each household arises from a single preference segment whose long-run volume-weighted choice probabilities are given by
\[
\theta_{ih} = \{\theta_{1h}, \theta_{2h}, \ldots, \theta_{nh}\},
\]
where \( B \) is the number of brands. Conditional on household \( h \)'s membership in a particular segment \( s \) and the total volume of purchases \( V_m \), the theory presented in the main body of the paper indicates that \( X^*_h \) follows a multinomial distribution with choice probabilities \( \theta_{ih} \).

The conditional likelihood of the observed choice frequencies \( X_h \) is given by
\[
L(X_h | \theta_s) = \prod \frac{w_s L(X_{ih} | \theta_s)}{\Sigma w_s L(X_{ih} | \theta_{ih})},
\]
where \( F_s \) is the relative size (in number of households) of segment \( s \). (The relationship between \( w_s \) and the volume-weighted segment size \( F_s \) is explained subsequently.)

Consumer segments are identified by estimating the relative sizes of the segments \( w_s \) and choice probabilities within each segment \( \theta_{ih} \). These can be obtained by maximizing Equation B2 (multiplied across all households) using the E-M algorithm (Dempster, Laird, and Rubin 1977) or using a nonlinear grid search with a trust-region global strategy (Dennis and Schnabel 1983; Makakura and Mazzon 1991).

Once estimates of segment size and choice probabilities are obtained, we can compute \( \tau_{ih} \), the probability that household \( k \) is assigned to segment \( s \) as
\[
\tau_{ih} = \frac{w_s L(X_{ih} | \theta_s)}{\Sigma w_s L(X_{ih} | \theta_{ih})}.
\]

Membership probabilities can be used to transform the segment sizes \( w_s \) into volume equivalents \( F_s \). The relative volume size \( F_s \) is obtained from
\[
F_s = \frac{\Sigma w_{is} \tau_{is} S_{is}}{\Sigma w_{is} \tau_{is} S_{is}},
\]
where \( S_{is} \) is the price of segment \( s \).

Approximations for the variance-covariance of the estimates are obtained using the inverse of \( -H \), a numerical approximation for the negative of the Hessian (H) matrix evaluated at the point corresponding to the MLEs (see, e.g., Seber and Wild 1989).

**APPENDIX C: ESTIMATING THE DIRICHLET REGRESSION MODEL**

Define these symbols as the following:
\[
Y_{it} = \text{the dependent variable (0 < } Y_{it} \leq 1; \Sigma Y_{it} = 1), \quad i = 1, 2, \ldots, B; \quad t = 1, 2, \ldots, T
\]
\[
S_{kt} = \text{the } k\text{-th independent variable for brand } i, \text{ week } t.
\]
\[
\eta = \text{shape parameter for the Dirichlet distribution,}
\]
\[
u_{it} = \text{MS}_i, \text{ where MS}_i \text{ is the expected market share of brand } i \text{ in week } t.
\]

Assume that the expected market shares \( \text{MS}_i \) depend on a vector of response coefficients \( \beta \). Then, the log-likelihood of the observed sample of T vectors \( Y_{it} \) is given by
\[
\ell(Y; \eta, \beta) = \sum \log G(n) + \sum \Sigma \nu_{it} \log G(n) - \ln G(n)
\]
where \( G(\cdot) \) represents the gamma function.

**Specific Formulation**

Suppose that the market shares obey the simple attraction model
\[
\text{MS}_i = \exp(G_n \beta_i) / \Sigma \exp(G_n \beta_i)
\]
where \( \exp(G_n \beta_i) \) is the response coefficient for the \( k \)th predictor. Then, the likelihood equations for the \( \eta \) and \( \beta \) parameters are
\[
\delta \ell / \delta n = D(\eta) T + \Sigma \Sigma \nu_{it} C_{it} = 0
\]
\[
\delta \ell / \delta \beta_k = \eta \Sigma \Sigma \nu_{it} (C_{it} - C_{jt}) Z_{kt} = 0,
\]
where
\[
D(\cdot) = \text{digamma function},
\]
\[
C_{it} = \log Y_{it} - D(\eta), \text{ and}
\]
\[
Z_{kt} = \eta \Sigma \Sigma \nu_{it} (C_{it} - C_{jt}) Z_{kt} = 0.
\]

Equations C3 and C4 define a system of nonlinear equations in terms of \( \eta \) and \( \beta \), which can be solved using iterative search procedures. The solution corresponds to the maximum likelihood estimates (MLE) for \( \eta \) and \( \beta \). Approximations for the variance-covariance of the estimates are obtained using the inverse of \( -H \), a numerical approximation for the negative of the Hessian (H) matrix evaluated at the point corresponding to the MLEs (see, e.g., Seber and Wild 1989).

**APPENDIX D: TESTING THE BIAS CORRECTION FACTOR \( \rho_i \)**

As shown in Equations 12 and 13, the true intrinsic attraction \( \phi_{is} \) is related to the the micro analysis estimate \( I_{is} \) as
\[
\phi_{is} = \text{plim } I_{is} + \rho_i
\]
where \( \rho_i = -\ln(M_i) + \ln(M) \). When the marketing policy var-
\[ \ln(M_i) = [\beta_i \mu_{pi} + \delta_i \sigma_{2i}] + [\beta_i^2 \sigma_{pi}^2 + \delta_i^2 \sigma_{2i}^2 + 2\beta_i \delta_i \sigma_{pi,2i}] / 2 + e_i, \]

where \(\mu_{pi}\) and \(\sigma_{pi}^2\) are the mean and variance of the price for brand \(i\), \(\mu_{si}\) and \(\sigma_{si}^2\) are the mean and variance of promotions for brand \(i\), \(\sigma_{pi,2i}\) is the covariance between price and promotion for brand \(i\), and \(e_i\) is a function of higher order moments of the joint price-promotion distribution. (If the joint distribution of price and promotion is bivariate normal, then \(e_i = 0\).) Note that the first term on the right of Equation D2 is a weighted sum (using the response coefficients as weights) of the average price and promotion, and the second term is a weighted sum of variances and covariance.

Inserting Equation D2 in the definition of \(\rho_i\) and neglecting the terms represented by \(e_i\), we obtain the expression

\[ \rho_i = K + Z_i, \]

where

\[ Z_i = -[\beta_i \mu_{pi} + \delta_i \mu_{si}] + [\beta_i^2 \sigma_{pi}^2 + \delta_i^2 \sigma_{si}^2 + 2\beta_i \delta_i \sigma_{pi,si}] / 2 \]

and \(K = \ln(M)\) is an intercept. This relationship provides an opportunity for empirically verifying the validity of the brand intercept \(\rho_i\) as a bias correction. If the correction is valid (and \(e_i\) is small enough to be ignored), we should expect an approximate linear relationship between the estimated correction \(\rho_i\) and the price and promotion statistics (weighted by the response coefficients \(\beta_i\) and \(\delta_i\)) for each brand.

Using price and promotion statistics (means, variances, covariance) from the micro data and the response coefficients from the macro data, we calculated \(Z_i\) by inserting the appropriate estimates of parameters into Equation D4. A simple regression of the brand intercept \(\rho_i\) (from the macro analysis) on \(Z_i\) yields a regression line with a slope not significantly different from 1. The correlation between the estimated \(\rho_i\) and the estimated \(Z_i\) is .94. These results strongly support the theoretical interpretation of the brand intercepts as corrections for brand marketing activity during the micro period.

**APPENDIX E: DECOMPOSITION OF ELASTICITY MATRIX**

To develop a display of the elasticity matrix, we make use of the fact that the cross elasticities for this model can be written as \(e(i,j) = M(i)S(i,j)\), where \(M(i) = \pi[\beta_i MS_P, i] > 0\). For any value of \(\pi\), we can define the matrix \(Q\) with typical elements

\[ Q(i, j) = M(i)M(j)S(i, j) = M(i)e(i, j), \quad i \neq j. \]

Our objective is to produce a vector map portraying the decomposition in Equations E1 and E2 so that each brand will be displayed as a vector of length \(M(i)\), and the substitution index \(S(i, j)\) for a pair of brands will be represented by the cosine of the angle formed by their respective vectors. To do so, choose \(\pi\) so that \([\max S]\), the maximum of the \(S(i, j)\), is less than one. Then, an eigenvalue decomposition of \(Q\) yields the representation \(Q = R^T R\) where \(R^T\) is the transpose of \(R\), contains the vector coordinates of brand \(i\). By construction, the length of \(R\) will be \(M(i)\) and the cosine of the angle between \(R\) and \(R\) will be \(S(i, j)\).

To create the best visual representation in three dimensions, \(\pi\) is selected to maximize the sum of the three largest eigenvalues. This can be done by first defining \(S(i, j)\) assuming that \(M(i) = MS_P, i\). Then \([\pi S]\) is computed, and the analyst conducts a simple grid search in which \(1/\pi\) is varied between 0 and \([\pi S]\). For each value of \(\pi\), the matrix \(Q\) is redefined using Equations E1–E2 and the eigenvalues of \(Q\) are recomputed.

**REFERENCES**


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