ABSTRACT
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ANALYSIS OF BRAND PRICE COMPETITION USING MEASURES OF BRAND SIMILARITY

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Cross price elasticities are important to market researchers and managers seeking to understand the differential levels of competition among multiple brands in a category. Elasticities provide two types of information. From a strategic perspective, cross price elasticities provide insights into the market structure of the product category. From a tactical perspective, cross price elasticities help managers quantify the impact of price promotions on competing products.

Obtaining managerially useful cross price elasticities from store-level scanner data is a challenging task (Cooper 1988; Montgomery 1997; Wedel and Zhang 2004). Statistical problems such as multicollinearity often result in cross price effects of unreasonable magnitude or unreasonable sign. Significant progress in elasticity estimation has been made by constraining the pattern of cross-price elasticities using theories from consumer behavior and economics (Allenby 1989; Russell and Kamakura 1994; Bucklin, Russell and Srinivasan 1998). These procedures seek to reduce the number coefficients to be estimated and to require cross price elasticities to obey theoretically desirable patterns. Intuitively, this research argues that the researcher can generate managerially-useful estimates of cross price elasticities from scanner data only by using additional information about market structure.

This work develops a model of brand price competition suitable for the analysis of store-level sales data. Building upon the work of Bucklin, Russell and Srinivasan (1998), we provide a methodology that links the pattern of cross-price sales elasticities to the pattern of brand switching in the market. The goal of this work is the calibration of a demand model which forecasts well and yields useful measures of brand price competition.

Research Approach

The proposed work builds on two key articles in the marketing science literature. Allenby (1989) used the structure of a nested logit choice model to argue that cross price elasticities obey a particular pattern. Let e(i,j) be the percent change in the market share of brand i with respect to a one percent change in the price of brand j. Also, define the symmetrical index S(i,j) as the substitutability of brands i and j. Using this notation, Allenby (1989) argues that

$$e(i,j) = \beta\ S(i,j)\ MS(j) \tag{1}$$

where MS(j) is the market share of brand j and β is a parameter. In this model, the pattern of the S(i,j) coefficients determines the pattern of the cross-price elasticities. By using *a priori* notions about market structure to constrain the pattern of the S(i,j) indices, Allenby (1989) develops a parsimonious method of estimating cross-price effects.

Bucklin, Russell and Srinivasan (1998) generalized the Allenby (1989) model by providing an empirical way of determining the S(i,j) indices. Using an argument based upon a population of heterogeneous logit choice consumers, Bucklin et al. (1998) propose that

$$e(i,j) = \beta\ w(j|i) \tag{2}$$

where w(j|i) is the long-run probability of switching to brand j given a previous purchase of brand i. This equation states that market share cross price elasticities are proportional to the row conditional switching matrix. By comparing equations (1) to (2), it is easily seen that the Bucklin et al. (1998) model defines

$$S(i,j) = Pr(i \text{ and } j)/MS(i)MS(j) \quad (3)$$

where Pr(i and j) is the probability of first buying brand i and then brand j on subsequent purchase occasions.

The strength of the Bucklin et al. (1989) model is its requirement that the cross price elasticity pattern conform to the market structure pattern implied by brand switching behavior in the market. In this way, the researcher makes use of both store-level information (sales and price data) and panel information (brand switching matrix) in developing the model of brand price competition. The weakness of the Bucklin et al. (1989) model is its restriction to market share models. This is due to the fact that the underlying derivation is based solely upon choice behavior.

The present work generalizes the Bucklin et al. (1998) work to deal with sales forecasting models. We begin with a so-called corner solution economic model that predicts both brand choice and purchase quantity for each consumer. By analytically aggregating over consumers, we develop the expression

$$E(i,j) = \beta w(j|i) - \gamma(j) \quad (4)$$

where E(i,j) denotes a sales cross price elasticity and $\gamma(j)$ measures the category expansion effects of each brand. An interesting implication of (4) is that sales cross elasticities can be zero or negative (denoting complementarity) even when market share cross elasticities are all positive (denoting substitution). The explanation is that high quality brands (with a large $\gamma(j)$ value) exert both a substitution effect within the category and a traffic building effect outside the category. Brand price competition in sales data shows the net impact of both these factors.

This theory is valuable for two reasons. First, it provides a conceptual link between brand switching patterns and the magnitudes of cross price elasticities. That is, brand switching and cross price elasticities are complementary measures of brand competition. Second, given a brand switching matrix for the product category under consideration, it is possible to constrain cross price coefficients while calibrating a sales response model using store-level scanner data. The result is a model that both yields better forecasts and provides greater insights into brand competition.

Empirical Study

We apply the new theory to the analysis of brand price competition in the soft drink category. Using IRI market level data for a number of Infoscan markets at the package-size level, we develop a multiple-store random coefficients sales response model that constrains the matrix of cross-price elasticities using brand-and-pack-size switching information. In the Appendix, we provide a rough draft of a PowerPoint slide deck that provides details on the empirical findings of the research. Briefly, we find that the market structure of the soft-drink brands in this study is related to package size (number of cans per bundle) and package format (cans versus plastic bottles). By constraining the cross-price effects to the market structure pattern implied by the brand switching matrix, we obtain much better sales model forecasts.

We also consider how a retail manager could use the results to set optimal prices for the soft drink category. Because we can impute the cross-price elasticities facing each store in our sample, we are able to develop a store-specific constrained optimization model in which prices are changed in such a way that the average price in the category remains the same. This optimization has two important practical features. First, because all computations can be carried out in "real-time" using Excel on a laptop computer, this procedure can be regarded as a practical tool for a retail category manager. Second, the constraint on average category prices implicitly acknowledges that the price positioning of the store must be considered prior to any adjustment of item prices (Kahn and McAlister 1997; Corstjens and Corstjens 2002). The optimization procedure is not shown in the Appendix. However, this aspect of the empirical analysis will be discussed in detail during the conference presentation.

Written Paper

We are currently working on a written manuscript describing the methodology and the empirical results. We anticipate no difficulties in having the paper ready by the deadline of February 1, 2008.

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Appendix
ANALYSIS OF BRAND PRICE COMPETITION
USING MEASURES OF BRAND SIMILARITY

Analysis of Brand Price Competition Using Measures of Brand Similarity

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Market Structure

- Defined as the relative substitutability of products within a product category
- Common Measures
  - Perceived product similarity (MDS)
  - Brand switching patterns
  - Cross price elasticities
- Provides insights into tactical and long-run marketing strategy

Brand Price Competition

- Defined as the pattern of cross price elasticities within a given market
- Expected properties
  - Negative own-price effects
  - Positive cross-price effects due to the assumed substitutability of products

E(i,j) = [% Change Sales(i)]/[% Change Price(j)]

Elasticity Estimation

- Simple in theory, but difficult in practice because of severe multicollinearity
  - Looking across brands, price changes are typically highly correlated due to retailer pricing behavior.
  - Estimated cross-price elasticities can be negative (implying complementarity) even though brands are substitutes.

An Attractive Solution

- Merge non-price measures of market structure with item movement data to produce more reasonable measures of cross price effects

Measures of Brand Competition → Cross Price Elasticities
Sales and Price Information → Cross Price Elasticities

Today's Talk

- Develop a new approach for calibrating cross-price elasticities that constrains model parameters using information on market structure
- Evaluate the usefulness of this methodology using store-level item movement data

Prior Research: Allenby Elasticity Model

- Allenby (1989) developed an elasticity model assuming that all consumers in the market follow a nested logit choice model.

$$E(i,j) = \beta\ S(i,j)\ MS(j)$$

$E(i,j)$: $\dfrac{[\%\Delta S(i)]}{[\%\Delta P(j)]}$

$S(i,j)$: Symmetric Index Measuring Market Structure

$MS(j)$: Market Share

Prior Research: Allenby Elasticity Model

- The symmetrical index S(i,j) > 0 is defined according to the partitions assumed to characterize the market.

$$S(i,j) = S[c(i),c(j)]$$

$c(i)$: Index of Submarket Containing Brand i

$c(j)$: Index of Submarket Containing Brand j

Prior Research: BRS Elasticity Model

- Bucklin, Russell and Srinivasan (1998) developed a model based upon the assumption that all consumers follow a logit choice model.

$$E(i,j) = \beta\, w(j|i)$$

$$E(i,j) = \frac{[\%\Delta MS(i)]}{[\%\Delta P(j)]}$$

$w(j|i)$ = Brand Switching Probability Prob(j given i)

Prior Research: BRS Elasticity Model

- The BRS model is a generalized Allenby elasticity model in which the S(i,j) indices are defined by the brand switching matrix.

$$S(i,j) = w(j|i)/MS(j)$$

or equivalently ...

$$S(i,j) = Pr(i \text{ and } j)/[MS(i)MS(j)]$$

This Research: Full Switching Elasticity Model

- Developed as an extension to the BRS model to allow for category expansion and contraction due to promotional activity.
  - Both Allenby and BRS models are more suited to market share data because they assume that relative shares are independent of market size.

Assumptions: Full Switching Elasticity Model

- Consumer Utility
  - **$U = \phi(1)q(1) + \ldots + \phi(B)q(B)$**
    where q = quantity and ϕ = marginal utilities subject to time varying random shocks.
- Budget Constraint
  - **Budget = B / PR^{α}** where PR is a (weighted) geometric mean of current prices
- Model Features
  - Consumer buys only ONE brand in the category.
  - Total expenditure varies over time.

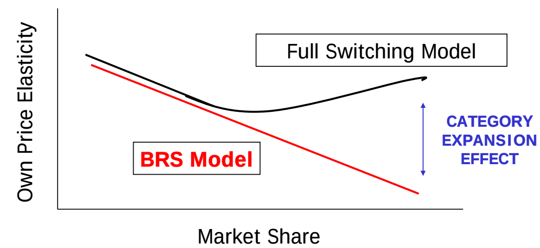
Elasticity Expressions: Full Switching Elasticity Model

- Assuming utility maximization (subject to a budget constraint) and by aggregating over consumers, the market-level sales elasticities are given by …

$$E(i,i) = -[1 + \gamma(i) + \beta(1 - w(i|i))]$$
$$E(i,j) = \beta w(j|i) - \gamma(j)$$

β = Substitution Within Category
$\gamma(i)$ = Category Expansion

Own Price Elasticities in Full Switching Elasticity Model



Cross Price Elasticities in Full Switching Elasticity Model

- Cross-price elasticities *may be negative* (implying complementarity) if a brand is sufficiently elastic.

$$E(i,j) = \underbrace{\beta w(j|i)}_{\text{Substitution Effect} > 0} - \underbrace{\gamma(j)}_{\text{Expansion Effect} > 0}$$

Empirical Application

- Soft Drink Brand Sales in the Columbus, Ohio region
  - 4 National Brands + Store Brand
  - 5 Product Forms/Sizes
    - Cans (6 pack, 12 pack, 24 pack)
    - Bottles (20 oz., 2 Liter)
  - Total of 25 SKU's

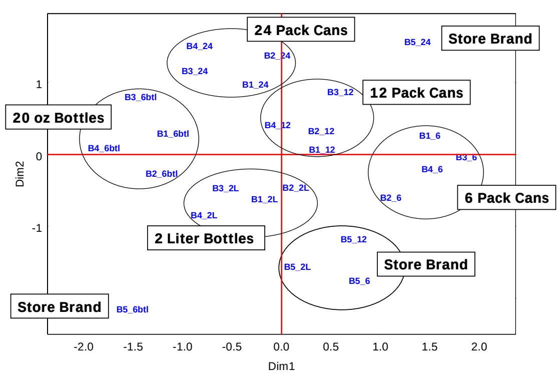
Empirical Application

- 19 Grocery Stores (all members of the same grocery chain)
- 114 weeks of information
- 37,555 total observations
  - 84 weeks for calibration
  - 30 weeks for holdout

Brand Switching Information

- The analysis uses the Row Conditional Switching matrix to constrain the elasticity pattern.
  - Data taken from a national consumer panel
- An MDS map can be constructed from the switching data to help visualize the pattern used to constrain the elasticities.
  - Similarity(i,j) = Prob(i to j)/MS(i)MS(j)

MDS Map of Brand Switching Matrix



Structure of Models

- All models are variants of log-log regressions including prices for all brands as well as variables capturing other factors.

$$\mathrm{Log[Sales(i)]} = \beta_{0i} + \beta_{i1}\,^{*}\mathrm{log(Price[1])} + \ldots$$
$$+\ \beta_{iB}\,^{*}\mathrm{log(Price[B])} + \text{Other Factors}$$

- Most models allow for random effects across stores in brand intercepts and cross-price elasticities.

Structure of Models

- Other Factors
  - Trend and Seasonality
  - Feature and Display Indices
  - Residual Category Sales (brands not in analysis)
- Estimation is implemented using the PROC MIXED software in SAS.

Benchmark Elasticity Models

- Naive Model
  - Individual brand by store regressions without pooling or parameter constraints.
- Equal Model
  - Random Effects
  - Equal cross elasticities **E(i,j) =** β

Benchmark Elasticity Models

- Base Model
  - Random Effects
  - Cross elasticities follow the simple logit model pattern **E(i,j) =** β**(j)**
- Share Model
  - Random Effects
  - Cross elasticities proportion to market share within store **E(i,j) =** β**(i)MS(j)**

Switching Based Elasticity Models

- Simple Switching (BRS) Model
  - Random Effects
  - Cross elasticities are proportional to the row conditional switching matrix **E(i,j) =** β **w(j|i)**.
  - Assumes that market shares remain stable when category size changes.

Switching Based Elasticity Models

- Full Switching Model
  - Random Effects
  - Cross elasticities depend upon w(j|i) and expansion effects **E(i,j) = β w(j|i) - γ(j)**.
  - Model allows for complementarity as well as substitution due to the influence of the γ(j) coefficients.

Results: Forecasting to Holdout Data

	MAPE
BENCHMARK MODELS	
Naïve (no pooling)	**95.37**
Equal	**9.10**
Base	**4.96**
Share	**12.28**
SWITCHING MODELS	
Simple Switching (BRS)	**8.59**
Full Switching	**3.47**

MAPE = mean absolute percentage error

How Important are Category Expansion Effects?

- To study this issue, define a Hybrid elasticity structure in which the cross elasticity ratio E(i,j)/E(j,i) depends only upon the substitution ratio w(j|i)/w(i|j).

$$E(i,i) = -[1 + \gamma(i) + \beta(1 - w(i|i))]$$
$$E(i,j) = \beta w(j|i)$$

for $\beta > 0$, $\gamma(j) > 0$

Model Features

	BRS	Hybrid	Full Switching
Own Price Elasticities	**Constrained**	**Free**	**Free**
Cross Price Elasticities	**Substitutes ONLY**	**Substitutes ONLY**	**Substitutes and Complements**

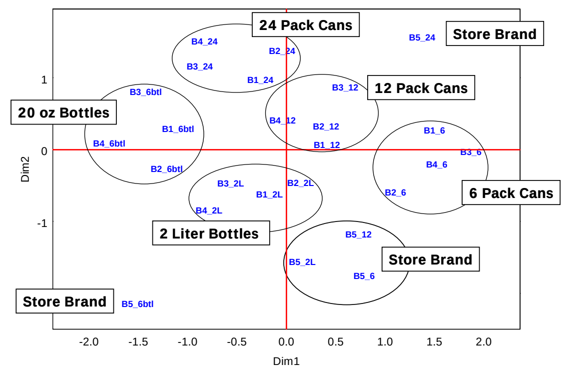
BRS is a share model.
Hybrid and Full Switching are sales models.

Holdout Sample MAPE Statistics for Various Models

γ(i) Pattern	Hybrid	Full Switching
Unconstrained	4.78	3.47
Brand	3.22	2.92
Form	3.10	**2.60**
Brand + Form	4.13	3.11

MAPE of BRS model is 8.59

Elasticity Structure Follows Market Structure



Summary of Results

- Proposed approach yields a model with better forecasts and with greater face validity.
- Methodology has three key features
  - Price competition reflects true market structure.
  - Complementarity of products is allowed when a brand has strong category expansion effects.
  - Model estimation can be carried out using standard software (PROC MIXED in SAS).

Conclusions

- The estimation of cross-price effects can be improved by using *a priori* information on market structure.
- The key challenge in developing a realistic model of brand competition is introducing complementarity in a realistic and parsimonious manner.