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# The Decomposition of Promotional Response: An Empirical Generalization

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**Abstract**
Price promotions are used extensively in marketing for one simple reason—consumers respond. The sales increase for a brand on promotion could be due to consumers accelerating their purchases (i.e., buying earlier than usual and/or buying more than usual) and/or consumers switching their choice from other brands. Purchase acceleration and brand switching relate to the primary demand and secondary demand effects of a promotion. Gupta (1988) captures these effects in a single model and decomposes a brand's total price elasticity into these components. He reports, for the coffee product category, that the main impact of a price promotion is on brand choice (84%), and that there is a smaller impact on purchase incidence (14%) and stockpiling (2%). In other words, the majority of the effect of a promotion is at the secondary level (84%) and there is a relatively small primary demand effect (16%).

This paper reports the decomposition of total price elasticity for 173 brands across 13 different product categories. On average, we find that 25% of the elasticity is due to primary demand expansion (i.e., purchase acceleration) and 75% to secondary demand effects or brand switching. Thus, while Gupta's finding that the majority of promotional response stems from brand switching is supported, the average magnitude of the effect appears to be smaller than first thought. More important, there is ample evidence that promotions have a significant primary demand effect.

The relative emphasis on purchase acceleration and brand switching varies systematically across categories, and the second goal of the paper is to explain this variation as a function of exogeneous covariates. In doing this, we recognize that promotional response is the consumer's reaction to a price promotion, and therefore develop a framework for understanding variability in promotional response that is based on the consumer's perspective of the benefits from a price promotion. These benefits are posited to be a function of: (i) category-specific factors, (ii) brand-specific factors, and (iii) consumer characteristics. The framework is formalized as a generalized least squares meta-analysis in which the brand's price elasticity is the dependent variable. Several interesting results emerge from this analysis.

• Category-specific factors, brand-specific factors, and consumer demographics explain a significant amount of the variance in promotional response for a brand at both the primary and secondary demand levels.

• Category-specific factors have greater influence on variability in promotional response and its decomposition than do brand-specific factors.

• There are several instances where exogenous variables do not affect total elasticities yet significantly affect individual components of total elasticity. In fact, the lack of a significant relationship between the variables and total elasticity is often due to offsetting effects within two or more of the three behavioral components of elasticity. This is particularly true for brand-specific factors, which typically have no effect on total elasticity, yet have important effects on the individual behaviors.

• There is some evidence to suggest that not all promotion-related increases in primary demand are due to forward-buying&mdashin some cases promotions appear to increase consumption.

We use these results to illustrate how category- and brand-specific factors work to drive primary and secondary demand elasticities in different directions.

In short, this paper offers an empirical generalization of a key finding on promotional response—how elasticities decompose across brand choice, purchase incidence, and stockpiling—and new insights into factors that explain variance in promotional response. These findings are likely to be of interest to researchers who are concerned with theory development and the generalizability of marketing phenomena, and to managers who plan promotion campaigns.

**Keywords**
price elasticity, promotion, brand choice, purchase incidence, stockpiling, primary demand, secondary demand, meta-analysis

**Disciplines**
Advertising and Promotion Management | Behavioral Economics | Business | Business Administration, Management, and Operations | Business Analytics | Cognition and Perception | Cognitive Psychology | Marketing | Sales and Merchandising | Strategic Management Policy

# The Decomposition of Promotional Response: An Empirical Generalization

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We use these results to illustrate how category- and brand-specific factors work to drive primary and secondary demand elasticities in different directions.

In short, the paper offers an empirical generalization of a key finding on promotional response — how elasticities decompose across brand choice, purchase incidence and stockpiling — and new insights into factors that explain variance in promotional response. These findings are likely to be of interest to researchers who are concerned with theory development and the generalizability of marketing phenomena, and to managers who plan promotion campaigns.

Key Words: Price Elasticity; Promotion; Brand Choice; Purchase Incidence; Stockpiling; Primary Demand; Secondary Demand; Meta Analysis.

# 1 Introduction

Each year billions of dollars are spent on promotions for a simple reason – promotions work. In an era of increasing competitiveness, however, it has become vital that promotions and promotional response be addressed with sophistication that goes beyond the recognition that promotions enhance sales. Prior research has documented that promotions can enhance sales by: (i) influencing sales of the category (i.e., they have primary demand effects) and thereby sales of the brand, and/or (ii) influencing sales of the brand directly (i.e., they have secondary demand effects).[1]

Managers need more precise answers to the questions: Is the impact of a promotion for the brand(s) they manage on primary demand, secondary demand, or both? If the effect is largely on primary demand, are the sales spikes due to altered timing (purchase incidence) and/or consumer stockpiling? If the effect is on both, what is the split between primary and secondary demand? How do these effects of a promotion differ across brands? Across categories?

Knowledge at this level of detail would allow managers to draw better guidelines for promotion policies, set priorities for promotional dollars, align promotional campaigns, and anticipate the moves and counter-moves of rivals. This paper, through a careful investigation of promotional response for a set of 173 brands across 13 categories, attempts to provide guidance to brand managers involved in addressing these issues. The paper also provides empirical regularities for other researchers working on promotional response.

## 1.1 Research on Price Promotions

There is a wide body of literature employing econometric models calibrated on scanner panel data to evaluate market, segment or household-level reponse to promotions, across some combination of brand choice, purchase incidence or purchase quantity behaviors. Early work demonstrating the impact of promotions on consumer brand choices (Ehrenberg 1972; Guadagni and Little 1983) has given way to more sophisticated models of price promotions (e.g., Neslin, Henderson and Quelch 1985; Rossi, McCulloch and Allenby 1996; Bucklin, Gupta and Siddarth 1998). The

[1]Brand switching corresponds directly to secondary demand. The link between primary demand and incidence and quantity elasticities, however, is less clear. This is because consumers may, over time choose to forward-buy or stockpile, yet not ultimately increase consumption. Thus higher incidence and quantity elasticities are necessary but not sufficient to indicate increases in primary demand. For ease of exposition we will relate incidence and quantity effects to primary demand, and will return to this issue in x4.1.

more complex models either calibrate individual-level response, and/or look at interactions in response across behaviors. A common emphasis, however, is the focus on consumers as the unit of analysis.

A different stream of research that attempts to understand the drivers of promotional response across multiple brands, categories, or market conditions is seen in the work of Bolton (1989) and others that have since followed (Raju 1992; Fader and Lodish 1990; Narasimhan, Neslin and Sen 1996). Here, the focus is typically on a summary measure of brand elasticity as the unit of analysis. Thus, the emphasis in past literature tends to be either on promotions as they affect consumers, or brands, but not both.

Ironically, as pointed out by Blattberg, Briesch and Fox (1995, p.130), the field is in short supply of the general empirical regularities which frame a more integrated perspective of promotions. In a similar vein, Narasimhan, Neslin and Sen (1996) note

> "In the final analysis, ... promotional policy must be set for specific *brands* (their emphasis), and more work is needed to understand how promotional elasticities vary across brands ..."

Our work, which looks at empirical regularities in promotional response across brands *and* at the same time across underlying consumer behaviors, is a step in this direction.

## 1.2 Research Objective and Approach

Bass (1993) describes an empirical generalization as "a pattern or regularity that repeats over many different circumstances" and notes the important role of empirical generalization in (marketing) science. This paper examines the empirical generalizability of previous research on the decomposition of promotional response into primary and secondary demand effects (Gupta 1988; Chiang 1991; Chintagunta 1993). These studies report that secondary demand effects (i.e., brand switching) are the dominant consequence of price promotion.[2]

We begin by examining the decomposition across multiple product categories. Our objective is to determine the extent to which the emphasis on primary and secondary effects varies across

[2]Our analysis takes the perspective of a manufacturer. It is for this reason that the brand switching effect reflects change in secondary demand. From a retailer's perspective, brand switching could reflect a primary demand effect if it is accompanied by store switching as well.

product categories. Second, we formalize, via meta analysis, the linkages between exogenous category, brand and consumer covariates and the three components of a brand's elasticity. Our objective here is to provide a rationale for the effects of the covariates and to demonstrate that they explain a significant amount of the variance in primary and secondary demand elasticities.

To achieve these goals, we estimate the price promotion effect on primary and secondary demand using market basket scanner panel data from 250 households. In all, 519 price elasticities are generated for 173 brands in 13 different product categories. Our household-level choice model allows for dependencies across the purchase incidence, brand choice and purchase quantity decisions within a product category and may be viewed as a variant of Chiang (1991).

To analyze variability in the elasticities, we develop a conceptual framework that captures the consumer's view of the characteristics of individual brands and product categories. Our conceptualization is motivated by Bolton (1989) who notes " ... although market characteristics are associated with differences in price elasticities, customer tastes (i.e., the customers' values for the particular attributes or benefits offered by the category) seem to be important in explaining differences in promotional price elasticities across categories." The key premise is that variability in brand-level price elasticities will be driven by: (1) consumer perceptions of the attractiveness of a price promotion, conditional upon the category environment, (2) the consumer's view of how a price promotion on a given brand influences perceived quality-per-dollar of that brand, and (3) the characteristics of consumers themselves.[3]

The unit of analysis is the *brand-level elasticity* as this is the metric of most interest to the manager. We examine the extent to which variance in a brand's choice, incidence and quantity elasticities can be attributed to three sets of exogenous variables:

- *Category Factors.* Category factors influence the consumer's *budget allocation process*. In particular, they capture consumer perceptions of the assortment and economic benefits associated with buying in a particular product category.

- *Brand Factors*. Brand factors capture consumer perceptions of the brand's *quality-per-dollar*. They include variables which reflect marketing effort and the brand's position in the marketplace.

[3]There is an emerging literature in marketing that examines the issue of whether price-responsiveness of consumers is driven by the environment, consumer traits, or some combination of the two (see, for example, Ainslie and Rossi 1998). Our conceptualization and empirical results allow an additional perspective.

- *Consumer Factors*. Consumer factors reflect the *economic profile* of the brand's clientele. They are summarized by the demographic characteristics of consumers who purchase the brand.

The framework is formalized as a generalized least squares meta analysis in which the brand's price elasticity is the dependent variable.

## 1.3 A Brief Overview of the Key Findings

The substantive findings are:

1. The basic conclusion of Gupta (1988) and Chiang (1991) that the dominant effect of a promotion is on switching (i.e., secondary demand) is valid. The magnitude, however, is considerably lower than previously reported. That is, promotions can have a significant impact on primary demand for a product (i.e., purchase incidence and quantity choice).

2. The magnitude of primary and secondary demand effects vary substantially across brands and categories. Our framework built on category-, brand- and consumer-specific factors explains a significant amount (up to 70%) of this variance in promotional response.

3. It is important to decompose total promotional response into its primary and secondary components if one is to fully understand the effect of exogenous covariates. There are several instances where exogenous variables do not affect total elasticity, yet significantly affect individual components of total elasticity. In fact, the lack of a significant relationship between the variables and total elasticity is often due to offsetting effects within two or more of the three behavioral components of elasticity. This is particularly true for the brand-specific factors.

4. Category-specific factors explain most of the variability in promotional response. Brand-specific marketing variables play a modest role, and the characteristics of the brand's core clientele have relatively little explanatory power.

5. Promotions result in demand dynamics that vary systematically across categories and this variance is related to the apparent effect on consumption. In particular, some categories (e.g., bacon, potato chips, softdrinks and yogurt) show increased average purchase quantities on promotion but no subsequent change in inter-purchase times, which implies that promotions increase consumption in these cases.[4] In other categories (e.g., bathroom tissue, coffee, detergent and paper towels) stockpiling effects are more consistent with forward-buying only (i.e., increased purchase quantities *and* increased inter-purchase times).

[4] We also test for the presence of a consumption increase by comparing, for each household the *ratios* of average quantity to average inter-purchase time under promotion and non-promotion purchases (as this number is a straight proxy for the rate of consumption) and present the results in x4.1.

An overview of the meta analysis findings is provided by the following matrix. It highlights how exogenous factors operate differently on the separate components of promotional response. Entries in the matrix indicate the relative strength of the effect of the exogenous factors on each consumer behavior.

| | Consumer Behavior | | |
|---|---|---|---|
| | Secondary Demand | Primary Demand | |
| Class of Factor | Brand Choice | Purchase Incidence | Purchase Quantity |
| Category Factors | Strong | Moderate | Strong |
| Brand Factors | Moderate | Moderate | Moderate |
| Consumer Factors | Weak | Weak | No Effect |

The finer details of these effects, along with their managerial implications, are discussed in x5.

## 1.4 Caveats

It is important to note the following caveats. First, while we take a theory-based approach to developing our conceptual framework for the meta-analysis, it is not derived explicitly from the underlying choice models. To date, no such integrated model exists in the literature, although recent work by Lee and Staelin (1999) which seeks to develop multi-category demand systems from consumer utility structures is a step in this direction. Our framework, however, is largely consistent with the spirit of choice models in which consumers seek to maximize utility in the presence of budget constraint.

Second, the unit of analysis is a *single* elasticity for each brand. That is, we do not explicitly model consumer heterogeneity in choice model response parameters *prior* to computing the brand-level elasticities (as in Bucklin, Gupta and Siddarth 1998). We do, however, include preference heterogeneity and purchase event feedback in the model and allow for correlation between the behaviors.[5]

Third, we do not attempt to address store switching. Clearly, the total elasticity can be defined at a higher level of generality by including the consumer's store selection decision (e.g., Bell and Lattin 1998.) An integrated approach to encompass all aspects of these consumer decisions is a

[5] Abramson, Currim and Jones (1996) show that it is most important to account for preference heterogeneity and purchase event feedback, and that "under-specifying ¯ heterogeneity does not result in any significant bias of the parameters estimated" (p. 18). This view is corroborated by Ailawadi, Gedenk and Neslin (1998) who show that inclusion of preference heterogeneity and loyalty variables may be sufficient to ensure reliable estimates.

desirable direction for future research. Fourth, the spirit of the analysis is cross-sectional (i.e., across-brand and category differences in the three types of elasticity). Our model and approach does not address dynamic or long term effects of promotions (e.g., Mela, Gupta and Lehmann 1997). We do, however, use the results of our analysis to inform the issue of whether or not promotions increase consumption.

The remainder of the paper is organized as follows. The next section provides background and develops the conceptual framework which motivates the exonenous variables for the meta analysis. Section 3 describes the data and methodology and we discuss the results and their managerial implications in x4. Section 5 concludes the paper.

# 2 Background and Conceptual Framework

We briefly highlight two streams in the literature on consumer response to price promotions: (1) individual-level models of elasticity decomposition, and (2) regression-based models that relate exogenous variables to variation in elasticities. Subsequently, we develop a framework for conducting the meta analysis and compare and contrast this to existing work.

## 2.1 Elasticity Decomposition and Drivers of Elasticity

Gupta (1988) presents a model to simultaneously capture the primary and secondary demand effects of a promotion and his results, and the subsequent work by Chiang (1991), suggest that the majority of promotional response (upwards of 80%) is due to brand switching – that is, secondary demand effects dominate. Bucklin, Gupta and Siddarth (1998) report an overall primary-secondary breakdown of 58% - 42% in the yogurt category. Given these differences, the obvious question arises: Is there a pattern to the elasticity decomposition? This issue is the focus of the first part of this paper. The second goal of the paper is to then examine variability in the brand-level choice, incidence and quantity elasticities themselves.

Bolton (1989) was among the first to investigate the market characteristics associated with differences in promotional price elasticities. She developed a model that related the differences in promotional elasticities to factors such as brand market share, manufacturer and retailer advertising levels and promotional activity at the brand and category level. Her data tracked sales of three brands in each of four categories across a set of twelve stores. The results indicate that these brand and market characteristics explain a substantial amount of the variation in promotional price elasticities. In particular, brands with smaller market shares, lower levels of category and brand display activity, and higher levels of category and brand couponing are more elastic. Interestingly, she finds that the effects of *category* display and feature activity on promotional elasticities are much larger than the effects of *brand* prices, display and feature activity.

Fader and Lodish (1990) use *IRI Marketing Factbook* data from 331 product categories to explore the relationship between category structure (e.g., purchase cycle, penetration, etc.) and promotional movement (e.g., volume sold on price cuts, display and feature, etc.). They report systematic relationships between category characteristics and promotional policies. For example, high penetration, high frequency products were the most heavily promoted (although they did not receive a disproportionate share of manufacturer couponing). Raju (1992) has a focus similar to that of Fader and Lodish (1990) in that he explores the relationship between category characteristics and category sales. His dependent variable is the standard deviation in category sales over time. He finds that higher variability in category sales is associated with deeper, albeit infrequent, dealing in the category, cheaper products and the ability of consumers to stockpile.

Narasimhan, Neslin and Sen (1996) study the relationship between product category characteristics and promotional elasticity using data from 108 product categories. They consider three types of promotions (regular, featured and displayed price cuts) and seven category characteristics (penetration, inter-purchase time, price, private label share, number of brands, impulse buying and the ability to stockpile). Their measures of promotional response were generated from the *IRI InfoScan Topical Marketing Report* and the category characteristics were generated from IRI's scanner panel data. They report that promotions get the highest response for brands in easily stockpiled, high penetration categories with short purchase cycles. To summarize, factors which have been found to increase elasticities are given in the following table.

| Author | Factors Increasing Elasticity |
|---|---|
| Bolton (1989) | Smaller market shares |
| | Lower levels of display (brand and category) |
| | Higher couponing (brand and category) |
| Fader and Lodish (1990)[1] | High penetration |
| | High frequency of purchase |
| Raju (1992)[1] | Deeper, infrequent dealing |
| | Consumer ability to stockpile |
| Narasimhan, Neslin and Sen (1996) | High penetration |
| | Short purchase cycles |
| | Consumer Ability to stockpile |

[1] They do not study elasticities directly, however their study implies this.

## 2.2 This Research

Our focus on the elasticity breakdown is motivated by Gupta (1988) and by the information needs of category managers. Our model relating variability in elasticities to exogenous brand, category and consumer covariates is closest to Bolton (1989) and Narasimhan, Neslin and Sen (1996). Table 1 summarizes key differences between our study and previous literature.

**[ Table 1 about here ]**

First, we choose to model elasticities using an individual-level choice framework. The rationale is that market-wide assessment of higher or lower elasticities for a brand, can be traced back to the underlying behavior of individuals. Second, we obtain elasticity estimates across brands and categories from the *same* set of household data. Thus, all purchase decisions are subject to the same budget constraints and consumers are exposed to common store environments. Therefore, any potential cross-category substitution effects are implicitly absorbed in the elasticity calculation. A side benefit is that typical store-level sales data are generated weekly by different batches of consumers who happen to shop that week. In this situation, it is impossible to know how this traffic issue affects elasticity estimates, whereas using observations from the same panelists avoids this potentially confounding factor.

Third, as in Narasimhan, Neslin and Sen (1996) we incorporate factors that account for across-category differences. To enhance consistency we calculate these variables directly from our panel data instead of using national averages. Fourth, we use an iterated GLS method (Montgomery and Srinivasan 1996) for our meta analysis to account for potential heteroscedasticity from two sources: measurement errors in the left-hand-side (elasticity estimates), and cross-category modeling errors. This approach leads to better model fits than those found in previous work. Last, we develop a conceptual framework that relates promotional response in the form of primary and secondary demand effects to category, brand and consumer covariates. The variables in the conceptual framework summarize a utility-maximizing consumer's view of the attractiveness of a price promotion given the brand's category environment and the perceived status of that brand in the category.

The "empirical generalization" contribution of the paper takes place at two levels. First, we present findings on the decomposition or promotional elasticity. Second, we explain the variability in promotional response by modeling the elasticities as a function of exogenous factors suggested by our framework.

## 2.3 Conceptual Framework

In building the conceptual framework we rely heavily on the classic notion of a utility-maximizing consumer operating under a budget constraint (Varian 1992) and on the prior literature discussed above. Our rationale is that the derived elasticities come from choice models which assume utility-maximizing consumers; the conceptual framework should also share this view. As noted previously, the conceptual framework incorporates three broad classes of factor (category, brand and consumer) and Table 2 lists the variables and the hypothesized effects of each. (Details of the operational measures are given Appendix A).

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**[ Table 2 about here ]**

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### 2.3.1 Category Factors

*Category Factors* influence the value of the economic opportunity (as perceived by the consumer) that price promotions offer in a particular product class. For example, a price promotion in a storable category might be viewed very favorably because the consumer can manage inventory and time-shift purchases to take advantage of the promotion.

- *Share of Budget.* Given that all product categories on the consumer's shopping list are subject to the same budget constraint, we anticipate that consumers are more likely to accelerate their purchase for items that have a higher share of budget. The hypothesis is that consumers are likely to adjust incidence and purchase quantity to take advantage of a promotion in this type of category. This is analogous to the idea that heavy users in a category are likely to be the most responsive to promotions. The impact of share of budget on secondary demand is less clear. Consumers are more likely to have well-formed preferences for items that constitute a large share of budget. This suggests less switching.[6]

- *Brand Assortment (breadth of variety).* Narasimhan, Neslin and Sen (1996) utilize number of brands as an independent variable in their study of promotional elasticities. They observe a negative effect on total elasticity which they attribute to brand switching. The rationale for this result is the presence of many brands reflects broader product differentiation. This, in turn, protects an individual brand from "the enticement offered by a competitor's promotion (p 20)." Bawa, Landwehr and Krishna (1989) find that larger assortments tend to generate higher trial for new products. Thus, we expect the primary demand effect to increase with brand assortment.

- *Size Assortment (depth of variety).* Consumers should be more elastic in categories that offer a broad variety of size assortments, because they have more options and more refined information about the unit (Russo 1977 indicates that unit-price knowledge increases price sensitivity). Furthermore, consumers may either buy larger sizes, or switch brands depending on the way in which unit price information is presented and/or processed. Guadagni and Little (1983) also find that, when offered price promotions, consumers switch up to larger sizes. Thus we expect positive primary and secondary demand effects.

- *Storability.* Storable products facilitate stockpiling and therefore inter-temporal purchase displacement (Litvack, Calantone and Warshaw 1985; Raju 1992; Narasimhan, Neslin and Sen 1996). That is, consumers can purchase at irregular intervals in response to deals, which means they can buy more, but are not compelled to buy on any particular trip. We therefore expect a higher overall primary demand response to promotions. The effect on secondary demand is not as clear. If, however, the storable product is also a non-food item (e.g., detergent) we might expect to see a positive effect on secondary demand too. This is because consumers appear more willing to switch brands in categories where they are not consuming the product directly, and are therefore less vulnerable to taste incompatibilities.

- *Perceived Differentiation.* This construct is a refinement of the brand assortment constructs presented earlier. Assortment is determined by the retailer – all consumers are exposed to the same degree of assortment within a given category, but may perceive it

[6] Raju (1992) utilizes expensiveness in his study of sales variability. The share of budget variable here captures similar information.

differently. Perceptions of differentiation are based on consumer experience with different brands. Categories where brand alternatives are perceived as highly differentiated will be characterized by greater responsiveness in primary demand and less responsiveness in secondary demand.

- *Necessity.* Narasimhan, Neslin and Sen (1996) hypothesize that promotional elasticity is higher for categories that are characterized by a higher degree of impulse buying. The notion is that impulse buying is an in-store response often attributable to promotional activity. We therefore expect non-impulse (i.e., relative necessity) products to be less elastic with respect to purchase incidence and stockpiling and hence, exhibit a lower primary demand effect. Given that a product is a necessity and as such consumers have little flexibility to adjust primary demand, their only outlet for saving money is via brand switching. This suggests a higher secondary demand effect.

- *Purchase Frequency*. We expect to see greater switching effects for more frequently purchased products, but less stockpiling (Fader and Lodish 1990).

### 2.3.2 Brand Factors

*Brand Factors* influence the consumer's perception of how brand characteristics interact with promotions to affect the perceived quality-per-dollar assessment for a brand. For example, a price promotion on a market leader might be viewed more favorably than a price promotion on a lesser brand.

- *Relative Price Position.* The consumer's perspective on whether or not a given brand is a "premium" brand will influence elasticity. Blattberg and Wisneiwski's (1989) finding on asymmetric switching — that premium brands draw more consumers when they promote — implies a higher primary demand effect due to increased incidence and a higher secondary demand effect due to increased switching.

- *Price Variability.* From the consumer's perspective, relative price stability improves the ability to distinguish between regular and promoted prices, and therefore take advantage of price promotions by strategically accelerating purchases or switching brands. This leads to Bolton's (1989) suggestion that greater price variability will be associated with lower response. Consequently, we expect greater price variability will lead to a lower primary demand effect and lower secondary demand effect.

- *Deal Frequency.* More frequent dealing leads to more opportunities for the consumer to exploit price promotions. All other things equal, however, very frequent dealing implicitly reduces the attractiveness of any individual deal in any time period. Prior research shows that consumers are able to accurately detect promotion frequency (Krishna, Currim and Shoemaker 1991). Furthermore, Thaler (1985) and Winer (1986) imply that frequent promotions will lead to lower reference prices. Consequently, brands with more frequent deals should have lower elasticities.

- *Deal Depth.* A higher percentage discount from the base price greatly improves the quality-per-dollar equivalent of a brand. Consequently, greater depth should be accompanied by higher purchase acceleration (Golabi 1985; Ho, Tang and Bell 1998). Raju (1992) hypothesizes that deep discounts can induce some consumers who are loyal to competing brands to switch to the promoted brand. Hence, greater deal depth should also be associated with a positive secondary demand effect.

- *Brand Experience.* A promotion on a brand that has been tried by a large fraction of consumers, will, all else equal, have higher primary elasticities of demand, due to higher drawing power. "Double jeopardy" suggests that these brands with high trial also experience more frequent purchase and higher than expected repeat, and "excess" behavioral loyalty (Fader and Schmittlein 1993). As discussed below, higher brand loyalty leads to lower secondary demand elasticities.

- *Brand Loyalty.* Brands with more repeat purchasing and a more loyal franchise will be less elastic in brand choice and more elastic with respect to purchase quantity (Krishnamurthi and Raj 1991). This is also conjectured by Tellis (1988). We might also expect these brands to have a higher drawing power and as such generate higher incidence elasticities.

### 2.3.3 Consumer Factors

*Consumer Factors* influence the ability or disposition of the brand's core clientele to respond to a price promotion. For example, a brand with a predominantly higher income clientele might see less response to its promotions.

- *Income.* Brands with higher income consumers should be less sensitive to price in brand choice (Ainslie and Rossi 1998). Conversely, they may experience stockpiling because their consumers have more ability to take advantage of deals when the opportunity arises.

- *Age.* To the extent that older households should have more time available to shop and search for deals, one could argue that they should be more elastic. Ainslie and Rossi (1998, p99) however, find directional support for the idea that older consumers are in fact less price sensitive, which leads us to expect lower elasticities for brands with older clienteles.

- *Education.* More educated consumers are expected to be more diligent in taking advantage of price variability. Brands with a more educated clientele will see more response to their price promotions.

# 3 Methodology and Data

## 3.1 Choice Models and Price Elasticity

In deriving the choice models, we assume consumers (households) have a linear additive utility function and for each product category there is a set of brands available which consumers perceive to be substitutes. To conserve space, we simply describe the essence of the model and our modeling decisions here, and place the details in Appendix B.

Gupta (1988) modeled the category decision using inter-purchase time. Our dataset allows us to model the "buy/no buy" decision directly. In addition, while some authors (e.g., Bucklin, Gupta and Siddarth 1998) have modeled quantity as a discrete variable, we adopt a continuous formulation. We make this trade-off in order to allow for correlation between the choice and quantity decisions (e.g., Krishnamurthi and Raj 1988).

We assume consumer i at each purchase occasion t has to decide whether to purchase, respectively, in each of the product categories, and if so, which brand to choose and what amount to buy. For brand choice, we assume that, conditional on purchase incidence, a brand is selected if and only if it yields the highest indirect utility in that category. Furthermore, consumers can forego purchasing in the category if the purchase utility threshold is not crossed.

In specifying the purchase quantity equations, we employ either a system of log-log or semi-log demand equations in which each demand equation corresponds to a selected brand. For a given category, we choose among alternative formulations of the purchase quantity model on the basis of model fit. It is important to note that in integrated choice, incidence and quantity models of this type, the quantity portion of the model typically generates the least reliable parameter estimates and the poorest model fits of the three behavioral pieces. A poor-fitting model, may in turn, lead to a downward bias in the estimated quantity elasticity.

Given the choice model structure just described (and laid out in Appendix B), we can derive the exact expression for each elasticity component (see Appendix C), and it follows immediately that the total elasticity is given by the sum of the three component elasticities: ´$_T$ = ´$_C$ + ´$_I$ + ´$_Q$ (Gupta 1988). Given that our focus is on examining the elasticity differences across brands and categories, we have to first ensure that these elasticities are indeed comparable. To establish consistency, we first normalize all sizes within a category by the most commonly purchased size in that category (prices are adjusted accordingly). In this way, we ensure that all categories are measured in their respective purchase units and eliminate any potential “magnitude” problem in the meta analysis which follows. Once the coefficients of the model have been estimated, the elasticities are calculated for each observation and household and then averaged over all households.[7]

## 3.2 Meta Analysis Explanatory Model

Let $\tilde{e}_{bjc}$ denote the elasticity *estimate* for consumer behavior $b$ (i.e., choice, incidence or quantity) for brand $j$ in category $c$. The following equations detail our application of the Montgomery and Srinivasan (1996) Generalized Least Squares approach to meta analysis. Their approach is predicated on the notion that errors across observations in the meta analysis will not be i.i.d. This intuition is relevant in our setting for the following reason. Our elasticity estimates are generated from choice model parameter estimates that have been estimated with error (we apply the Delta Method to derive the standard errors for the elasticity estimates), therefore the relationship between the *true* and *estimated* elasticities is given by (where the *b* subscript is dropped for ease of exposition)

$$\tilde{e}_{jc} = e_{jc} + \epsilon_{jc}; \quad \epsilon_{jc} \sim N(0; \sigma_{\epsilon}^2) \tag{1}$$

Furthermore, the true model that relates the elasticity to exogenous factors that determine that elasticity is

$$e_{jc} = \alpha + \sum_{f=1}^{F} \sum_{k=1}^{K_f} \beta_{fk} X_{fkjc} + \nu_{jc}; \quad \nu_{jc} \sim N(0; \sigma_{\nu}^2) \tag{2}$$

where $\sigma_{\nu}^2$ is the unique variance in the true elasticity measure, $f$ indexes the classes of exogenous factors, and $K_f$ the number of variables in each class of factor. We assume that the estimation errors (equation 1) and unique errors (equation 2) are uncorrelated so that the total error is partitioned into the sum of these two components: $\psi_{jc} = \epsilon_{jc} + \nu_{jc}$ and $\psi_{jc} \sim N(0; \sigma_{\epsilon}^2 + \sigma_{\nu}^2)$.

[7]Note that due to non-linearities in the elasticity expression this method is preferred to the method where one simply inserts average values of the covariates into the analytical expression for the elasticity. See Ben-Akiva and Lerman (1985).

From the conceptual framework in §2 we have three sets of variables: (1) Category Factors, (2) Brand Factors, and (3) Consumer Factors which contribute the exogenous variables for the meta equation

$$\epsilon_{jc} = \alpha + \sum_{k=1}^{K_1} \beta_{1k} X_{1kjc} + \sum_{k=1}^{K_2} \beta_{2k} X_{2kjc} + \sum_{k=1}^{K_3} \beta_{3k} X_{3kjc} + \psi_{jc} \qquad (3)$$

where the subscripts $1; 2$ and 3 denote the three categories of exogenous variables and $\psi_{jc}$ denotes the *total* error in the elasticity estimate. This partitioning of the meta regression error is especially important when estimates of the left hand side variable are drawn from many studies conducted under different conditions.[8] While in this paper the elasticity estimates are developed from the same choice models and households, the estimates do come from a wide range of product categories. A further conceptual and practical advantage of the GLS procedure is that it allows us to control somewhat for heterogeneity in the meta analysis model rather than in the parameters of the underlying choice models. That is, we recognize that the brand's elasticity estimate follows a distribution that varies by brand and category and take this into account in performing the meta analysis. Estimates of the coefficient vectors, and the variance partitioning are obtained iteratively, with standard errors of the elasticities serving as GLS weights in the initial estimation. Subsequent weights are obtained by further iteration and we find that in all cases convergence occurs rapidly in 5-6 iterations.[9]

## 3.3 Data

*Source and Description.* The data were generated from a market basket database provided by *IRI*. Purchase records for a random sample of 250 panelists, shopping in three supermarkets over a period of 78 weeks were used in the analysis. The 250 panelists were chosen at random from a total pool of 494 households. These panelists reflect the underlying demographics of the larger pool (which, in turn, was selected by IRI to be representative of the whole market). The first 26 weeks of data were used to initialize within-household market share variables; the remaining 52 weeks were used for calibration of the choice models derived in Appendix B.

[8] For example, meta analyses often combine work from several different authors, conducted over many different time periods and datasets.

[9] The interested reader is referred to Montgomery and Srinivasan (1996) for complete details on this iterative scheme.

*Category Selection and Explanatory Variables.* The selection of product categories for the analysis was deliberate. We sought to include a range of categories heterogeneous on several dimensions (e.g., share of budget, storability, etc.). Our chosen products cover 3 out of 4 PROMCLUS and PURCLUS groups, respectively, as defined in Fader and Lodish (1990). Table 3 presents some basic descriptive information on the product categories in the dataset.

**[ Table 3 about here ]**

# 4 Results

Recall that this paper has two goals: (1) to investigate variability in the elasticity percentage decomposition across product categories, and (2) to analyze more formally, via meta analysis, the variability in the brand-level elasticities themselves.

## 4.1 Elasticity Percentage Decomposition

*Dispersion in Elasticities.* We report the mean and variance of the brand-level elasticities for all 13 categories in Table 4.

**[ Table 4 about here ]**

Examination of the results reveals the following. First, there is considerable *across* category variation in brand-level elasticities. Second, there is variation across behaviors, within a category, but the pattern is consistent: choice elasticities are much larger than either incidence or quantity elasticities. The choice (i.e., secondary demand) elasticities are all greater than one and the incidence plus quantity (i.e., primary demand) elasticities are generally less than one. The exceptions are liquid detergents, coffee and dryer softeners.

The overall pattern of results is consistent with our expectations for mature packaged goods. That is, it seems unlikely that promotions in most of these types of categories will expand primary demand, although recent empirical and analytical studies (e.g., Assuncao and Meyer 1993; Ailawadi and Neslin 1998; Ho, Tang and Bell 1998) that link consumption dynamics to promotion response, have shown that there can be important primary demand effects even for these types of products. We return to this issue shortly.

*The Decomposition of Elasticities.* Table 5 shows the percentage decomposition due to choice, incidence and quantity for each of the 13 categories.

**[ Table 5 about here ]**

With the exception of sugar, the breakdowns for a number of categories differ from those reported in Gupta (1988) and Chiang (1991). The choice elasticity varies from a minimum of 49% of total elasticity for butter to a maximum of 94% for margarine; the incidence elasticity ranges from a minimum of 1% of total elasticity for liquid detergents to a maximum of 42% for butter; the quantity elasticity ranges from almost zero for margarine to a maximum of 45% for coffee.[10] These ranges are reflected in the overall average of 75/11/14 which places less emphasis on choice and more on quantity, relative to previous work.

*Role of Storability.* Further sorting of the estimates in Table 5 reveals: (1) all refrigerated products (margarine, yogurt, ice cream, bacon and butter) have much higher proportions for the incidence effect than for the quantity effect, and (2) all storable products (softdrinks, paper towels, bathroom tissue, dryer softeners, liquid detergents and coffee) have just the opposite pattern. Both observations have intuitive appeal and are consistent with the experimental findings of Litvack, Calantone and Warshaw (1985). The result is highlighted in Table 5 where even though the choice percentage is constant between storable and non-storable products (75% in both cases), the quantity effects are much higher for storable products (21% versus 8%). (We discuss the two categories – potato chips and sugar – that do not fall into these two groups, shortly.)

*Role of Consumption Dynamics.* Further analysis is required in order to understand whether promotions: (a) increase consumption, (b) cause stockpiling but no consumption increase, or (c)

[10] Our results for the coffee category differ somewhat Gupta (1988). We attribute this to two factors: (i) we have newer and different data, and (ii) while Gupta's model addresses the "when" question of purchase timing, we focus on the "whether" decision of purchase incidence.

have no appreciable effect on either stockpiling or consumption. All three results have been observed in the literature. For instance, Ailawadi and Neslin (1998) show that promotions lead to increased consumption in yogurt and Krishnamurthi and Raj (1991) document stockpiling by brand loyal consumers. Krishna, Currim, and Shoemaker (1991) show that when promotions are very frequent, consumers do not need to stock up on deals.

To make this issue more concrete, consider the decompositions for sugar and potato chips. Neither category is refrigerated, yet both are non-storable due to freshness considerations — the decompositions suggest that consumers purchase more potato chips but not more sugar when these products are on sale. Our speculation is that consumers' buy more potato chips because they want to consume more and this is less likely to occur with sugar. Softdrinks is another interesting category. It is well known that softdrinks is one of the most frequently promoted categories[11], yet Table 5 shows that softdrinks have a somewhat small stockpiling effect (8%), despite being a storable item. In addition, Lal (1990) provides a theoretical explanation for alternating promotions by major softdrink brands (e.g., Coke and Pepsi) – this ensures that rival store brands are effectively kept out of the market.

In order to investigate consumption dynamics in more detail, we analyzed panelist purchases in all product categories during promotion and non-promotion. One important observation here is that the elasticity estimates themselves are insufficient to determine whether or not consumption increases as a result of promotion. This is because one needs a temporal analysis to uncover this — the elasticity estimates reflect how consumers respond to price changes at given points in time, but do not indicate how long it takes before these consumers return to the market.

To ascertain whether consumption increases were occuring we computed summary statistics from the data. First we measured average quantities on promotion and non-promotion and also measured average inter-purchase times subsequent to promotion and non-promotion purchases. In addition, we computed the averages for household ratios of quantities to inter-purchase times under both promotion and non-promotion purchases.[12]

[11]Totten and Block (1987) report that Coke promotes 41% of the time and Pepsi 47%. In our data the comparable figures are 50% and 58%, respectively. We should also note here that it is possible that the switching effect for this category is overstated. It is well known from the Totten and Block data and other studies, that deal-to-deal buying for softdrinks is widespread. If it is also the case that quantities on deal-to-deal purchases are relatively unchanged, the model will account for the large swings via the brand choice part of the model.

[12]This ratio is an estimate of the rate of consumption.

The following table is based on this exploratory analysis and therefore only indicative of presence and absence of consumption increases — a thorough examination of this issue requires additional research.

| Category | Promotional Purchases | | | Non-Promotional Purchases | | | t-ratios | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\overline{Q}$ | $\overline{IP}$ | $\overline{Q=IP}$ | $\overline{Q}$ | $\overline{IP}$ | $\overline{Q=IP}$ | Quantity | Time | Cons. |
| Stockpiling Only | | | | | | | | | |
| Bathroom Tissue (roll) | 6.76 | 27.65 | 0.30 | 4.83 | 22.38 | 0.28 | 4.47 | 1.59 | 0.53 |
| Coffee (oz) | 35.71 | 58.84 | 0.80 | 24.76 | 43.75 | 1.19 | 4.45 | 1.67 | -1.15 |
| Detergent (oz) | 132.42 | 77.32 | 2.37 | 82.70 | 48.12 | 2.71 | 4.05 | 2.35 | -0.52 |
| Paper Towel (roll) | 2.00 | 45.12 | 0.08 | 1.40 | 34.77 | 0.08 | 4.98 | 1.71 | 0.20 |
| Increased Consumption | | | | | | | | | |
| Bacon (oz) | 27.23 | 46.57 | 0.92 | 19.92 | 47.49 | 0.68 | 4.42 | -0.12 | 1.47 |
| Potato Chips (oz) | 10.25 | 44.63 | 0.64 | 7.37 | 41.78 | 0.41 | 4.44 | 0.32 | 1.62 |
| Softdrinks (oz) | 240.32 | 45.28 | 9.18 | 135.86 | 45.86 | 6.27 | 5.69 | -0.06 | 2.02 |
| Yogurt (oz) | 33.12 | 37.69 | 1.43 | 25.12 | 38.32 | 1.10 | 3.75 | -0.08 | 1.85 |
| "No Effect" | | | | | | | | | |
| Butter (oz) | 21.09 | 41.96 | 0.70 | 20.62 | 38.67 | 0.83 | 1.03 | 0.70 | -1.08 |
| Dryer Softeners (sheets) | 45.83 | 69.50 | 0.88 | 41.24 | 67.63 | 0.81 | 1.02 | 0.15 | 0.42 |
| Icecream (oz) | 66.63 | 38.76 | 1.72 | 66.33 | 35.79 | 1.85 | 0.28 | 0.67 | -0.64 |
| Margarine (oz) | 19.27 | 40.01 | 0.59 | 18.46 | 38.65 | 0.67 | 1.21 | 0.28 | -1.10 |
| Sugar (lb) | 5.42 | 59.37 | 0.18 | 5.41 | 58.21 | 0.23 | 0.09 | 0.13 | -0.69 |

In the table, $\overline{Q}$, $\overline{IP}$ and $\overline{Q=IP}$ represent average quantities, inter-purchase times and rates of consumption, respectively, and all three quantities are calculated for both promotion and non-promotion purchases.

Prior to interpreting the data in this table, several facts need to be noted. First, all of the calculations in the table have been performed *conditional* on a purchase having taken place. We know, however, that consumption may increase as a result of greater consumption by a fixed number of consumers, or, through expansion to additional consumers. Hence, we use the label "No Effect" with some caution, and with this in mind, return to discuss the case for icecream shortly.

Second, there are several ways to infer consumption increases from the data in the table. The most direct would be to simply compare our estimates of the consumption rate (i.e., $\overline{Q=IP}$) under promotion and non-promotion purchases. There are, however, two potential difficulties here. The first is simply statistical – the estimates of the consumption rates are created by averaging ratios across trips and households – and this process makes it more difficult to detect effects. The second reason that we want to look beyond just the consumption rate estimates is substantive. It could be the case that even though the estimates of the consumption rates are not different from each other, there is still some inter-temporal purchase displacement as a result of promotion. Consider bathroom tissue. In this instance, the average consumption rates of 0.28 and 0.30 rolls of tissue per day under promotion and non-promotion are not significantly different from each other. Looking at the average purchase quantities and average inter-purchase times *separately* does, however, provide additional information. The average purchase quantity at regular prices is 4.83 rolls and consumers take about 22.38 days before buying again, yet when faced with promotion, consumers buy an average of 6.76 rolls, but take much longer (27.65 days) before purchasing again. That is, they buy significantly more, but take significantly longer before buying again, which suggests that promotions on bathroom tissue encourage consumers to stockpile.

Beginning at the top of the table, we list four storable categories (bathroom tissue, coffee, detergent, paper towels) that show evidence of stockpiling. In each case, average quantities are significantly higher and average inter-purchase times significantly longer following a purchase on promotion. The second grouping contains four categories (bacon, potato chips, softdrinks and yogurt), which show some increase in average consumption rates across the non-promotion and promotion conditions (for bacon $p < 0{:}10$ and for the other three categories $p < 0{:}05$ on a one-tailed test). The probable consumption increases that result from promotions is also manifest in the fact that average purchase quantities are significantly higher, but average inter-purchase times are *not* significantly longer. It is interesting to note that the only storable category which seems to experience increased consumption is softdrinks. We speculate that this could be due to the extraordinarily high levels of promotion documented earlier.[13]

The "No Effect" group warrants one further comment. As noted above, the statistics in the table are computed conditional upon a purchase having occurred. Thus, they are only able to detect consumption increases for a fixed group of consumers. If, however, promotions also draw additional consumers into the category, overall consumption may increase too. For example, while we classify icecream in the "No Effect" category, we note from Tables 4 and 5 that icecream has a relatively large incidence elasticity. Our calculations suggest that when icecream goes on promotion, overall penetration for the category is up by about 2%. In a way, this implies increased

[13]We do not address the "reverse causality" or endogeneity issue here. That is, firms may promote more because they realize that consumers will consume more. For an analysis of the endogeneity issue in a brand choice context, see Villas-Boas and Winer (1997).

consumption as more consumers are moved from “no buy” to “buy,” although it does not allow us to say whether the average consumption for the *individual consumers* increases.

This final point also highlights the advantages and disadvantages of this sort of exploratory analysis vis-a-vis model-based analysis. While the elasticity estimates do not fully capture inter-temporal consumption changes (which must be captured in order to make statements about ultimate primary demand increases), they do have the advantage of being model-driven and calculated with everything else constant. Furthermore, they capture the inter-relationship between the three consumer behaviors. The sample averages on the other hand provide a preliminary indication of consumption effects, but any differences in these raw estimates could be due to a host of uncontrollable factors. Despite these offsetting benefits, we would expect the data-based proxies in the table and the model-based proxies of primary demand expansion (i.e., the quantity elasticities) to be positively correlated. For our data, the correlation between the thirteen quantity elasticities in Table 4 and the percentage change in average quantities under promotion and non-promotion is about 0.47.

To summarize, the results from the investigation of the elasticity decomposition reveal that the majority of the promotion effect (75%) is due to brand switching. This proportion is smaller than previously reported and suggests a larger than expected primary demand component. Storable products have a proportionally greater quantity effect than do non-storables. Further examination of this issue shows that most storables are simply stockpiled (i.e., even though promotions increase average purchase quantities, inter-purchase times also increase so that there is no apparent increase in total consumption). Blattberg, Eppen and Lieberman (1981) perform an analysis very similar to ours and find evidence of stockpiling in aluminum foil, facial tissue, liquid detergent and waxed paper (Tables 1 and 2, p124-25). They also derive a theoretical model to explain conditions under which storable products are dealt in order to transfer inventory carrying costs to the consumer. For softdrinks and some food products, promotions do appear to increase consumption. Thus, our empirical findings for the yogurt category parallel those of Ailawadi and Neslin (1998). Our more general evidence for promotions increasing consumption is consistent with the models of Assuncao and Meyer (1993) and Ho, Tang and Bell (1998) who show that rational consumers increase consumption when faced with promotions. As highlighted above, this is a very important and complex problem and will require a different type of model to fully investigate it. Silva-Risso, Bucklin and Morrison (1999) develop a decision support system for determining optimal promotion calendars – their model captures all three consumer decisions (choice, incidence and quantity), and has the potential to estimate consumption effects and their relationship to promotional effectiveness.[14]

## 4.2 Meta Analysis Results

For ease of exposition and brevity we do not focus on the effect of each and every variable on all three consumer behaviors. Rather, we: (i) discuss the general pattern of findings as they relate to the conceptual framework and hypotheses (Tables 1 and 2), (ii) highlight results that are consistent with prior literature, and (iii) address some counter-intuitive findings. x4.3 expands on the managerial implications of the framework.

### 4.2.1 An Overview of Main Findings

Table 6 reports the standardized GLS parameter estimates for each of the three behaviors, and for the total elasticity.

**[ Table 6 about here ]**

The model fits are substantially higher than those found in previous work and we are better able to explain brand choice and purchase quantity elasticities, than we are able to explain purchase incidence elasticities. Category-specific factors are especially powerful in explaining variability in brand-level elasticities and brand-factors somewhat less so. Consumer factors have relatively little explanatory power. Nevertheless, we do observe two small but significant effects.

Bolton (1989) speculates that the reason for weaker effects of the brand factors (e.g., relative price levels) is that their values tend to be similar across categories, making it difficult to detect any effect in the regression. For example, the degree of variance in relative normalized prices in

[14]Their empirical application, however, used data from the tomato sauce category – a category which is unlikely to exhibit consumption increases due to promotions.

category A might be very similar to that in category B.[15] Thus, we believe that Bolton (1989) is correct, if one is looking only at the effects of brand-specific factors on *total* elasticities. Total elasticity, however, fails to tell the full story. It is interesting to note that the number of significant effects for the brand factors is much higher when we look at individual behaviors. Here the number of significant brand factors (8/18) approaches one half, in constrast to 1/6 for total elasticity.

A comparison of the hypotheses expressed in Table 2, with the empirical findings in Table 6, yields the following.

- Hypotheses relating six of the sixteen variables (*Share of Budget, Storability, Perceived Differentiation, Necessity, Price Variability* and *Loyalty*) to the primary and secondary demand effects are supported. For example, brands in high share of budget categories see less switching in response to promotions ($\beta_C = -0.599$ $t = -10.93$), but more stockpiling ($\beta_Q = 0.148$, $t = 2.68$).

- Hypotheses relating another six of the sixteen variables (*Brand Assortment, Purchase Frequency, Deal Depth, Brand Experience, Age* and *Education*) to one of the two effects (i.e., either primary or secondary demand) are supported. That is to say we have one finding significant in the expected direction and the other non-significant. For example, increased brand assortment leads to higher primary demand elasticities ($\beta_Q = 0.583$, $t = 8.64$), but does not lead to the expected reduction in secondary demand elasticities ($\beta_C = -0.031$, $t = -0.45$).

- We have null results for *Deal Frequency*[16] and *Income*. The remaining two results for *Size Assortment* and *Relative Price Position* are somewhat counter-intuitive and require additional explanation. We discuss these shortly.

### 4.2.2 Relationship to the Literature

A total of twelve of the sixteen variables influence primary and secondary demand elasticities in a manner consistent with our expectations and the results in prior literature. This suggests that we have a relatively stable and internally-consistent pattern of results that are informative for explaining variability in brand-level elasticities.

[15] We examined the cross-category variability in the one variable, *Deal Frequency*, that was non-significant for all behaviors. A $\chi^2$ test for equality of variances across categories for this variable fails to reject the null hypothesis.

[16] The null result is different from Mela, Gupta and Lehmann (1997). They examine the impact of promotional frequency on a *given brand over time* and find that consumer sensitivity increases. In our case, we examine deal frequency cross-sectionally for a variety of brands and categories in a shorter time horizon. It is possible that our null result is due to aggregation and the shorter time span.

Although increased size assortment produces the expected positive effect on secondary demand elasticities and a positive effect on stockpiling, it is hard to interpret the negative effect for purchase incidence. One possible explanation is that consumer size loyalty (e.g. Guadagni and Little 1983; Bucklin and Gupta 1992) undermines the ability of promotions to increase purchase acceleration. We predicted that brands with a relative price premium would, on average, have higher switching. This argument follows the Blattberg and Wisneiwski (1989) conjecture that lower-tier buyers switch up when given the opportunity. One alternative interpretation of our opposite result is simply that buyers of relative premium brands are less price-sensitive and that these brands therefore have lower switching elasticities — it might be the case that these regular premium brand buyers who are relatively price-insensitive in choice, outnumber the potential number of buyers who trade up.

An important feature of our work is that we relate variability in elasticities to the underlying behaviors.[17] Table 6 shows seven instances in which an analysis of *total* elasticity reveals that an exogenous variable has no influence, yet significant effects can be seen for one or more of the underlying behaviors. As noted above, this is especially true for the brand-specific factors. Our result is important because if managers simply examined total elasticities, they could be misled into thinking their actions have no impact. For example, increased *Deal Depth* affects primary demand through stockpiling ($\beta_Q = 0.131$, $t = 2.81$), yet no effect appears for total elasticity. Similarly, the null result for *Loyalty* with respect to the total elasticity is due to the countervailing effects on secondary ($\beta_C = -0.164$, $t = -2.71$) and primary demand ($\beta_Q = 0.191$, $t = 3.13$). These primary and secondary effects are consistent with what one would expect given the findings of Krishna (1992) and Krishnamurthi and Raj (1991).

## 4.3 Implications

The results can be used to: (i) better inform managers and researchers of general patterns in promotional response, and (ii) project consequences of managerial decisions regarding promotional activity.

We illustrate the first point in two different ways. First, note that the overall elasticities for

[17] Narasimhan, Nelsin and Sen (1996) develop hypotheses based on underlying consumer behaviors (e.g., brand switching, purchase acceleration, etc.) but their data only allow analysis of effects on total elasticity.

coffee and softdrinks reported in Table 4 are approximately equal. A more careful analysis of the breakdown in elasticity reveals that a relatively large fraction (47%) of the coffee elasticity is attributable to primary demand, while the analogous figure for softdrinks is only 15%. The managerial implication is that promotions on coffee might encourage forward-buying and therefore generate very little in the way of incremental sales. Although forward-buying does not lead to incremental sales, it does produce desirable competitive effects — a consumer with a pantry full of Maxwell House has little need for Folgers. On the other hand, if all promotions on softdrinks were to do is increase switching, then the benefits of the promotion (to the manufacturer) may be shortlived. Recall, however, that in this particular case of softdrinks, we also obtained evidence that promotions increase consumption (see x4.1), but did not find this effect for coffee.

Second, the results allow us to make directional statements regarding how promotions are likely to affect elasticity components for a particular brand.[18] Among the exogenous factors listed in Table 6, it is likely that the manager has immediate access to proxies for the share of budget his category consumes, and the extent of brand loyalty. Furthermore, it is straightforward to assess storability for the product in consideration. The following 2 X 2 X 2 table illustrates how each of these forces push primary and secondary demand elasticities in different directions. The entries in the table refer to the primary/secondary percentage decomposition.

| | High Share of Budget | | Low Share of Budget | |
|---|---|---|---|---|
| | High Loyalty | Low Loyalty | High Loyalty | Low Loyalty |
| Storable | 31/69[1] | 25/75[2] | 22/78[3] | 15/85[4] |
| Non-Storable | 19/81[5] | 28/72[6] | 19/81[7] | 21/79[8] |

Several comparisons are possible from this table. First, comparing cells 1 and 2 of the matrix, we see that for high budget share, storable products, higher loyalty reduces the relative impact of secondary demand elasticities and increases the impact of primary demand elasticities. Second, a comparison of the breakdowns in cells 1 and 3 illustrates that high share of budget categories will see greater primary effects. Third, a comparison of cells 1 and 5 highlights our finding that storability leads to greater primary demand effects. Clearly, several such tables and comparisons

[18]In developing the example, we note that this is just one of many possible illustrations of how our framework can be used. Our intention is not to list all in detail, but merely illustrate the usefulness of the meta analysis results. We believe that such speculation is fruitful given the high level of agreement between the underlying results and those from prior research, and the high meta analysis model fits.

can be drawn out of our framework. This illustrative example shows how a manager or researcher might use the matrix to: (1) make an educated guess as to how market conditions and other factors influence elasticities, and (2) understand the likely reward from marketing efforts (e.g., efforts to increase loyalty).

A final application of the framework takes a “decision support” approach. In this case, we use explicit knowledge of the values of the exogenous variables to simulate changes in elasticity, given certain managerial actions.

For example, assume that the brand manager for Dannon yogurt is considering a change in promotional policy for the 8oz size. At present the brand promotes 30% of time, and offers an average discount of 15%. The corresponding elasticity breakdown is 79%, 14% and 7% for choice, incidence and quantity respectively. Now imagine that he considers reducing deal frequency by 50% and at the same time increasing the deal depth by 50% over the current value. Using the parameter estimates in Table 6, we estimate the new breakdown is closer to 63%, 24% and 13%. Thus, the increased emphasis on depth of promotion sees a shift in favor of primary demand effects. This may be an important insight for the Dannon manager, given our earlier finding that this category appears to experience increased consumption, and the similar empirical result of Ailawadi and Neslin (1998). That is, the Dannon brand manager might be better off stimulating consumers to accelerate purchase and stock up, as this leads to increased consumption, rather than focusing as much on encouraging switching. This is especially true in our Dannon example, where the brand already has a healthy share position. Finally, this change in policy might also be palatable for retailers who have private label yogurt (as many do), as they could potentially benefit from a reduction in brand switching to Dannon.[19]

# 5 Conclusion

One of the significant advances in the promotions literature was the development of a methodology for decomposition of promotional response into primary and secondary demand components. To date, this methodology has been applied to only two categories, so the generalizability of the substantive finding from this work is unknown.

[19] We thank Dick Wittink for this insight.

Our research has two goals. First, to document cross-category differences in the decomposition of brand-level promotional response, and in particular, differences in the relative importance of primary and secondary demand elasticities. Second, to formalize via meta analysis, a consumer-based framework for understanding the impact of exogenous factors on variability in brand-level elasticities.

The important takeaways from this research effort are:

1. *Primary and Secondary Demand.* We confirm that, with the exception of butter (where the split is approximately 50/50), the largest percentage of the elasticity decomposition falls on secondary demand, or brand switching. This is consistent with the findings of Leeflang and Wittink (1996) who show that managers tend to overreact (relative to a normative benchmark) to the promotional activities of competitors, thus reinforcing the switching effects.

2. *The Decomposition.* The earlier breakdown of 84=14=2 appears to be an exception. Within the spectrum of these decompositions, we find that a 75=11=14 split is about the average across all product categories. Storability is an important moderator. We find that the decomposition becomes 75=3=22 for storable products versus 75=17=8 for non-storable products.

3. *Elasticity Drivers.* Category-specific factors are more powerful than brand-specific factors in explaining the variability in elasticities. For example, share of budget and storability are two category characteristics that play a large role. Share of budget decreases the switching elasticity, but increases the quantity elasticity, while storability increases both. Price variability and deal depth are important brand-specific factors, but they have less marginal impact. Variability decreases all three types of elasticity, whereas increased deal depth increases the quantity elasticity. Consumer-factors (as measured in terms of demographics alone) have relatively little impact in explaining across-brand differences in elasticities. It is the case, however, that for a given brand, elasticity response might differ across consumers (Bucklin, Gupta and Siddarth 1998). Furthermore, variables that describe consumer shopping patterns might be more valuable in capturing price response than are demographics

alone (e.g., Ainslie and Rossi 1998; Bell and Lattin 1998).

4. *Total Versus Component Elasticities*. It is insufficient to simply examine drivers of total elasticity. In many instances a variable has no effect on total elasticity because it has countervailing effects on primary and secondary demand elasticities. This is particularly true in the case of brand-specific factors.

5. *Promotions and Consumption*. There is evidence that promotions increase consumption in some categories (e.g., bacon, potato chips, softdrinks and yogurt). Conversely, we observe that other categories (e.g., bathroom tissue, coffee, detergents and paper towels) experience forward-buying, yet they see no apparent corresponding increase in consumption. As noted in our discussion in x4.1, this is a complex issue and likely to be a very fruitful avenue for future research.

To summarize, the words of Bass (1995) on the state of marketing knowledge are relevant to the status of the choice literature

> "... the field has matured to the point where it seems desirable to take stock of where we are, what we have learned, and fruitful directions for extending the knowledge base."

We show that there are regularities in the decomposition of brand-level price elasticities and that they can be explained by variables derived from a framework that reflects the consumer's view of price promotions. The empirical regularities identified in this paper should be useful to researchers developing models of promotional response, and as an aid to managers in making better-informed promotion allocation and execution decisions.

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# A Operational Measures

- Category Factors
  - *Share of Budget* is computed by determining total dollars spent in the category by each panelist and then expressing this as a fraction of total grocery expenditures. The resulting fractions are then averaged across all households.
  - *Brand Assortment* is the total number of brand alternatives offered in the category.
  - *Size Assortment* is the total number of size alternatives offered in the category.
  - *Perceived Differentiation* is computed from the household-level choice data. First, we compute the within-household market shares for each brand in the product category under consideration. Each element of the household's choice-share vector is then squared and all elements are summed together.[20] This measure is then weighted across all users in the product category, to obtain a category-specific measure of the consumers' view of inter-brand substitutability. Higher values mean that consumers perceive the brands in the category to be more differentiated, less substitutable.
  - *Storability* is a dummy variable indicating whether the category is storable.
  - *Necessity* is a dummy variable indicator of the whether or not the category is a necessity product according to accepted IRI definitions.
  - *Purchase Frequency* reflects likelihood that a product appears on the shopping list on any randomly selected trip. It is the fraction of all trips and individuals who buy the category.
- Brand Factors
  - *Relative Price Position*. We estimate the extent to which a brand is perceived as a premium brand in its product category by first computing brand-specific average prices. These brand-specific prices are then normalized within the category to create a measure that is comparable across categories.
  - *Price Variability* is the coefficient of variation of the brand's price. Higher values indicate *more* variability.
  - *Deal Frequency* measures the proportion of times a brand is found on deal, normalized according to relative deal frequency in the category.
  - *Deal Depth* gives the average percentage discount for a brand, conditional upon the brand being on promotion. This variable is normalized with respect to category activity.
  - *Brand Experience* is the fraction of consumers who have tried the brand, of all those who have bought in the category.
  - *Brand Loyalty* is the average number of purchases of the brand, by all consumers who purchase the brand. This variable is normalized across categories to take into account different purchase rates of different categories.
- Consumer Factors
  - *Income* reflects the modal income level of consumers who purchase the brand. Empirically, we found the mode to be a better discriminator than the mean — this is consistent with recent work by Dhar and Hoch (1997).
  - *Age*. The modal age of panelists who purchase the brand.
  - *Education*. The modal education (higher values indicate higher levels of education) of the panelists who buy the brand.

[20] This calculation provides a household-specific version of the Herfindahl index and varies from $\frac{1}{n}$ to 1, where n is the number of choice alternatives in the category.

# B Model and Likelihood Function

For each product category, let $I_{it}$ denote a dichotomous indicator so that $I_{it} = 1$ if consumer $i$ purchases that category at occasion $t$ and $I_{it} = 0$ otherwise. Furthermore, let $B = \{1, \ldots, J\}$ denote the set of brands so that $D_{ijt} = 1$ indicates that brand $j$ is chosen by the consumer and $D_{ijt} = 0$ otherwise. Thus, $\sum_{j=1}^{J} D_{ijt} = 1$ conditional on a purchase.

Following the spirit of Hanemann (1984) and Chiang (1991), the choice decisions and the interdependence between decisions are described as follows

$$
Q_{ijt} = \begin{cases} X_{ijt}\beta_j + \varepsilon_{ijt} & \text{if} \quad \nu_{ijt} + \eta_{ijt} > \mathrm{Max}\{\nu_{ikt} + \eta_{ikt}; \forall k \neq j\} \ \& \\ & \qquad \nu_{ijt} + \eta_{ijt} > \nu_{i0t} + \eta_{i0t} \\ 0 & \text{if} \quad \nu_{i0t} + \eta_{i0t} > \mathrm{Max}\{\nu_{ikt} + \eta_{ikt}; \forall k\} \end{cases}
$$

where $j \in B$, $Q_{ijt}$ is the quantity demanded for brand $j$, $X_{ijt}$ denotes the associated covariates, $\beta_j$ contains the corresponding coefficients, $\nu_{ijt}$ represents the perceived benefits of brand $j$ per dollar, $\nu_{i0t}$ is the utility threshold for category purchase, and $\varepsilon_{ijt}$ and $\eta_{ijt}$ are unobservable error terms. To reflect the interdependency between decisions, $\varepsilon_{ijt}$ and $\eta_{ijt}$ are assumed correlated. Moreover, $\nu_{ijt}$ may contain variables also in $X_{ijt}$.

Note that to avoid unnecessary estimation complications, we assume decisions across categories are independent except they are all subject to the same budget constraint.[21] By assuming $\varepsilon_j$ and $\eta_j$ are correlated, the model in effect can be viewed as a hybrid of Krishnamurthi and Raj (1988) and Chiang (1991).

We assume $\varepsilon_j$ is normally distributed and $\eta = (\eta_{i0t}, \eta_{i1t}, \ldots, \eta_{ijt}, \ldots \eta_{iJt})$ are jointly GEV distributed and i.i.d across all households and occasions. Specifically, let $H(\eta) = \exp(-G(-e^{-\eta}))$ denote the joint cdf such that $G(-e^{-\eta}) = [\sum_{k\in B} \exp(-\eta_k/(1-\delta))]^{(1-\delta)} + \exp(-\eta_0)$ where $0 < \delta < 1$. Given the model structure and these assumptions on the errors, the incidence and the choice probabilities can be derived, respectively, as

$$
\Pr(I_{it} = 1) = \frac{e^{(1-\delta)\cdot \ln[\sum_{k\in B} e^{\nu_{ikt}/(1-\delta)}]}}{e^{(1-\delta)\cdot \ln[\sum_{k\in B} e^{\nu_{ikt}/(1-\delta)}]} + e^{\nu_{i0t}}}
$$

$$
\Pr(D_{ijt} = 1 | I_{it} = 1) = \frac{e^{-\delta\cdot \ln[\sum_{k\in B} e^{\nu_{ikt}/(1-\delta)}] + \nu_{ijt}/(1-\delta)}}{e^{(1-\delta)\cdot \ln[\sum_{k\in B} e^{\nu_{ikt}/(1-\delta)}]}}
$$

This specification is equivalent to a nested logit model (McFadden 1978) in which the "inclusive value" has a special form of $\ln \sum_{k\in B} \exp[\nu_{ikt}/(1-\delta)]$ and its corresponding coefficient is $(1-\delta)$. $\delta$ is interpreted as the degree of similarity between brands.

Let $J^+ = \{0, 1, 2, \ldots, B\}$ denote the option set (including the non-purchase option), and let $J^+_{-j} = \{0, 1, \ldots, j-1, j+1, \ldots, B\}$ denote the set without the $j$th option. The joint condition of $D_{ijt} = 1$ and $I_{it} = 1$ can be re-written as follows ($i$ and $t$ are suppressed)

$$
\begin{aligned}
\nu_j + \eta_j &> \mathrm{Max}\{\nu_k + \eta_k; k \in J^+_{-j}\} \\
\nu_j &> \mathrm{Max}\{\nu_k + \eta_k; k \in J^+_{-j}\} - \eta_j \\
\nu_j &> \eta^*_j
\end{aligned}
$$

[21] This is not a serious flaw because we eventually adopt a Generalized Extreme Value (GEV) distribution for $\eta$ error terms. Chiang and Lee (1992) show that the GEV distribution satisfies the necessary and sufficient conditions which ensure the unbiasedness of the estimates when other categories are intentionally omitted.

Given $\eta \sim$ GEV as described above, it is straightforward to show that $\eta^*_j \sim F_j(\cdot)$ such that

$$F_j(\cdot) = \frac{\left(e^{\frac{\eta^*_j}{1-\delta}} + \sum_{k \in J; k \neq j} e^{\frac{\Upsilon_k}{1-\delta}}\right)^{-\delta} \cdot e^{\eta^*_j/(1-\delta)}}{e^{\Upsilon_0} + \left(e^{\frac{\eta^*_j}{1-\delta}} + \sum_{k \in J; k \neq j} e^{\frac{\Upsilon_k}{1-\delta}}\right)^{1-\delta}}$$

We assume $(\epsilon_k, \eta^*_k), k = 1, ..., B$ has a pairwise joint distribution denoted by $B(\epsilon_k, \eta^*_k; \rho_k)$, where $\rho_k$ represents the correlation. Though we do not know the shape of $B(\cdot;\cdot;\cdot)$, we know both marginal distributions. Thus, the following transformation identity, which maintains the same correlation coefficient can be established (Lee, 1983)

$$B(\epsilon_k, \eta^*_k; \rho_k) \equiv BN(\xi_{1k}, \xi_{2k}; \rho_k)$$

where $BN$ is a bivariate normal distribution, $\xi_{1k} = \Phi^{-1}(\Phi(\frac{\epsilon_k}{\sigma_k})) = \frac{\epsilon_k}{\sigma_k}$, and $\xi_{2k} = \Phi^{-1}(F(\eta^*_k))$. For any observation $Q_{ikt}, k \in J$, the corresponding sample likelihood function is

$$L_{ikt} = \int_{-\infty}^{\Phi^{-1}(F(\Upsilon_{ikt}))} f_{bn}\left(\frac{Q_{ikt} - X_{ikt}\beta_k}{\sigma_k}; \xi_{2k}\right) d\xi_{2k}$$

where $f_{bn}(\cdot;\cdot;\cdot)$ is the bivariate normal density. The evaluation of $\Phi^{-1}(F(\cdot))$ can be carried out numerically during the MLE iterations. The sample likelihood for $I = 0$ is $1 - \Pr(I = 1)$. Thus, the log likelihood function is

$$LL = \ln \prod_i \left\{ \prod_{T_i} \left[ \Pr(I_{it} = 0)^{1-I_{it}} \cdot \prod_{k \in J} (L_{ikt})^{D_{ikt} \cdot I_{it}} \right] \right\}$$

## B.1 Variables

Variables included in $X_{ijt}$, $\Upsilon_{ijt}$, and $\Upsilon_{i0t}$, respectively, are

- $X_{ijt}$ = (constant, log price, feature, display, inventory, family size, log expenditure, family* log price)
- $\Upsilon_{ijt}$ = (brand constant, log price, feature, display, last brand purchased, last size purchased, brand loyalty, size loyalty, family size*log price)
- $\Upsilon_{i0t}$ = (constant, log expenditure, inventory, family size)

# C Price Elasticities

It is straightforward to show that the purchase incidence, brand choice and purchase quantity elasticities are

$$\begin{aligned} e_I &= \theta^p \cdot p_j \cdot \Pr(D_j|I) \cdot (1 - \Pr(I)) \\ e_{D_j|I} &= \frac{\theta^p}{(1-\delta)} \cdot p_j \cdot (1 - \Pr(D_j|I)) \\ e_{Q_j|D_j,I} &= \frac{p_j}{E(Q_j|D_j, I)} \cdot \Bigg( \beta^p_j + \sigma_j \frac{\phi(\Phi^{-1}(\Pr(D_j))}{\Pr(D_j)} \cdot \end{aligned}$$

$$\left[\Phi^{-1}(\Pr(D_j))\frac{\partial\Phi^{-1}(\Pr(D_j))}{\partial p_j} + \frac{\theta^p}{(1-\delta)}(1-\delta\Pr(D_j|I) - (1-\delta)\Pr(D_j))\right])$$

where $\theta^p$ is the price coefficient in $\Pr(D_j|I)$. The variance of each elasticity estimate is calculated via the delta method (Rao 1973). Furthermore, it can be shown (Gupta 1988) that the total elasticity is the sum of the elasticities of the three components.

Table 1: A Comparison of Frameworks for Promotional Response

| *Study* | *Exogenous* | *Endogenous* | *Data* | *Objective* |
|---|---|---|---|---|
| Bolton (1989) | Market Characteristics | Brand elasticity | Store | Explanatory |
| | Category Price Activity | | | |
| | Brand Market Share | | | |
| | Mfr Advertising | | | |
| | Coupon Magnitude | | | |
| | Display Activity | | | |
| | Ret Advertising | | | |
| Fader and Lodish (1990) | Structural | Promotional | Aggregate | Exploratory |
| | HH Penetration | % Vol on Feature | | |
| | Purchases per HH | % Vol on Display | | |
| | Purchase Cycle | % Vol on Price Cut | | |
| | Private Label Share | % Vol on Mfr Cpn | | |
| | Price | % Vol on Ret Cpn | | |
| Raju (1992) | Category Characteristics | Variability in sales | Aggregate | Explanatory |
| | Expensiveness of Cat | | | |
| | Bulkiness of Cat | | | |
| | Competitive Intensity | | | |
| | Magnitude of Discounts | | | |
| | Frequency of Discounts | | | |
| Narasimhan, Neslin | Category Characteristics | Price elasticities | Aggregate | Explanatory |
| and Sen (1996) | Cat penetration | Featured price cut | | |
| | Inter-purchase Time | Displayed price cut | | |
| | Price | Featured price cut | | |
| | Private Label Share | | | |
| | Number of Brands | | | |
| | Impulse Buying | | | |
| | Ability to Stockpile | | | |
| Our Study | Category Characteristics | Price elasticities | Panel | Explanatory |
| | Share of Budget | Total elasticity | | |
| | Brand Assortment | Brand elasticity | | |
| | Size Assortment | Incidence elasticity | | |
| | Storability | Quantity elasticity | | |
| | Perceived Differentiation | | | |
| | Necessity | | | |
| | Purchase Frequency | | | |
| | Brand Characteristics | | | |
| | Relative Price Position | | | |
| | Price Variability | | | |
| | Deal Frequency | | | |
| | Deal Depth | | | |
| | Brand Experience | | | |
| | Brand Loyalty | | | |
| | Consumer Characteristics | | | |
| | Income | | | |
| | Age | | | |
| | Education | | | |

Table 2: Summary of Meta Analysis Hypotheses[1]

| | Secondary Demand | Primary Demand |
|---|---|---|
| (1) Category Factors | | |
| Share of Budget | - | + |
| Brand Assortment | - | + |
| Size Assortment | + | + |
| Storability | + | + |
| Perceived Differentiation | - | + |
| Necessity | + | - |
| Purchase Frequency | - | - |
| (2) Brand Factors | | |
| Relative Price Position | + | + |
| Price Variability | - | - |
| Deal Frequency | - | - |
| Deal Depth | + | + |
| Brand Experience | - | + |
| Loyalty (Repeat Purchase) | - | + |
| (3) Consumer Factors | | |
| Income | - | + |
| Age | - | - |
| Education | + | + |

[1] ¡ (+) indicates this variable leads to lower (higher) elasticities.

Table 3: Description of Product Categories

| *Category* | *Alternatives*[1] | *Purchases* | Storable | Necessity | *Price Range*[2] |
|---|---|---|---|---|---|
| Bacon | 6 | 844 | No | No | (1.60, 2.69) |
| Margarine | 10 | 1504 | No | Yes | (0.55, 1.44) |
| Butter | 4 | 388 | No | Yes | (1.30, 1.85) |
| Ice Cream | 11 | 1168 | No | No | (1.60, 4.01) |
| Paper Towels | 10 | 1442 | Yes | Yes | (0.54, 1.08) |
| Sugar | 6 | 686 | No | No | (1.61, 2.15) |
| Liquid Detergents | 25 | 886 | Yes | Yes | (4.41, 9.80) |
| Coffee | 18 | 750 | Yes | No | (4.65, 8.97) |
| Softdrinks | 15 | 967 | Yes | No | (0.22, 6.99) |
| Bath Tissue | 20 | 2192 | Yes | Yes | (0.92, 2.11) |
| Potato Chips | 20 | 1179 | No | No | (1.09, 2.82) |
| Dryer Softeners | 18 | 288 | Yes | No | (1.49, 2.76) |
| Yogurt | 10 | 318 | No | No | (0.33, 2.35) |
| **Totals** | 173 | 12,612 | | | |

[1] Number of unique brand-size alternatives.
[2] In the model estimation, prices are normalized to a common unit.

Table 4: Mean and Variance of Elasticity Estimates[1]

| *Category* | *Total* $(\bar{X}_T; \sigma_T)$ | *Choice* $(\bar{X}_C; \sigma_C)$ | *Incidence* $(\bar{X}_I; \sigma_I)$ | *Quantity* $(\bar{X}_Q; \sigma_Q)$ |
|---|---|---|---|---|
| Bacon | (1.57, 0.078) | (1.25, 0.216) | (0.20, 0.143) | (0.13, 0.009) |
| Margarine | (2.34, 0.003) | (2.22, 0.064) | (0.11, 0.116) | (0.01, 0.051) |
| Butter | (1.98, 0.004) | (1.24, 0.075) | (0.57, 0.456) | (0.17, 0.382) |
| Ice Cream | (2.58, 0.004) | (1.89, 0.206) | (0.58, 0.524) | (0.10, 0.319) |
| Paper Towels | (4.74, 0.061) | (4.00, 0.179) | (0.22, 0.255) | (0.52, 0.122) |
| Sugar | (4.60, 0.026) | (4.03, 0.498) | (0.46, 0.727) | (0.11, 0.241) |
| Liquid Detergents[2] | (5.66, 0.600) | (3.95, 0.704) | (0.07, 0.306) | (1.63, 0.139) |
| Coffee[2] | (3.06, 0.049) | (1.65, 0.060) | (0.06, 0.065) | (1.36, 0.036) |
| Softdrinks | (3.09, 0.066) | (2.66, 0.108) | (0.11, 0.106) | (0.31, 0.062) |
| Bath Tissue | (4.66, 0.214) | (3.85, 0.308) | (0.09, 0.488) | (0.71, 0.079) |
| Potato Chips | (3.38, 0.046) | (2.50, 0.089) | (0.07, 0.105) | (0.81, 0.054) |
| Dryer Softeners[2] | (5.28, 0.097) | (4.08, 0.128) | (0.12, 0.359) | (1.07, 0.187) |
| Yogurt | (1.92, 0.069) | (1.57, 0.084) | (0.15, 0.139) | (0.20, 0.114) |

[1] Based on raw (unweighted) elasticities
[2] Primary demand elasticities > 1.

Table 5: Elasticity Decomposition Across Categories[1]

| | Percent of Total Elasticity Due to | | | Demand | |
|---|---|---|---|---|---|
| Category | Choice | Incidence | Quantity | Secondary | Primary |
| Margarine | 93.9% | 5.7% | 0.4% | 93.9% | 6.1% |
| Softdrinks | 85.6% | 5.8% | 8.5% | 85.6% | 14.4% |
| Sugar | 84.1% | 13.3% | 2.5% | 84.1% | 15.9% |
| Paper Towels | 83.2% | 6.0% | 10.8% | 83.2% | 16.8% |
| Bathroom Tissue | 81.2% | 3.6% | 15.2% | 81.2% | 18.8% |
| Dryer Softeners | 78.9% | 1.4% | 19.7% | 78.9% | 21.1% |
| Yogurt | 78.4% | 12.2% | 9.4% | 78.4% | 21.6% |
| Ice Cream | 77.4% | 18.9% | 3.7% | 77.4% | 22.6% |
| Potato Chips | 72.0% | 4.5% | 23.5% | 72.0% | 28.0% |
| Bacon | 71.6% | 20.3% | 8.2% | 71.6% | 28.4% |
| Liquid Detergents | 69.6% | 0.7% | 29.7% | 69.6% | 30.4% |
| Coffee | 52.6% | 2.8% | 44.6% | 52.6% | 47.4% |
| Butter | 48.8% | 42.3% | 8.9% | 48.8% | 51.2% |
| | | | | | |
| Average | 75.2% | 10.6% | 14.3% | 75.2% | 24.8% |
| Std Deviation | 0.13 | 0.11 | 0.12 | 0.13 | 0.13 |
| Minimum | 48.8% | 0.7% | 0.4% | 48.8% | 6.1% |
| Maximum | 93.9% | 42.3% | 44.6% | 93.9% | 51.2% |
| | | | | | |
| Storable | 75.2% | 3.4% | 21.4% | | |
| Non-Storable | 75.2% | 16.7% | 8.1% | | |
| | | | | | |
| Necessity | 75.3% | 11.7% | 13.0% | | |
| Non-Necessity | 75.1% | 9.9% | 15.0% | | |

[1] Based on share-weighted brand elasticities.

Table 6: Standardized GLS Parameter Estimates

| | Secondary Demand | | Primary Demand | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Choice | | Incidence | | Quantity | | Total | |
| Variable | Parameter | t-ratio | Parameter | t-ratio | Parameter | t-ratio | Parameter | t-ratio |
| (1) Category Factors | | | | | | | | |
| Share of Budget | -0.599 | -10.93[a] | 0.001 | 0.01 | 0.148 | 2.68[a] | -0.409 | -7.74[a] |
| Brand Assortment | -0.031 | -0.45 | 0.079 | 0.87 | 0.583 | 8.64[a] | 0.278 | 4.30[a] |
| Size Assortment | 0.097 | 1.82[b] | -0.340 | -4.48[a] | 0.386 | 7.33[a] | 0.177 | 3.38[a] |
| Storability | 0.586 | 8.34[a] | 0.105 | 1.07 | 0.486 | 6.84[a] | 0.676 | 9.99[a] |
| Perceived Differentiation | -0.196 | -2.59[b] | 0.305 | 2.92[a] | 0.295 | 3.85[a] | -0.010 | -0.14 |
| Necessity | 0.328 | 5.22[a] | -0.185 | -1.86[c] | -0.018 | -0.31 | 0.247 | 4.11[a] |
| Purchase Frequency | 0.003 | 0.05 | 0.097 | 1.03 | -0.294 | -4.54[a] | -0.122 | -1.97[b] |
| (2) Brand Factors | | | | | | | | |
| Relative Price Position | -0.099 | -2.38[b] | -0.027 | -0.46 | 0.016 | 0.38 | -0.016 | -0.39 |
| Price Variability | -0.129 | -2.11[b] | -0.185 | -2.40[b] | -0.146 | -2.62[a] | -0.157 | -2.88[a] |
| Deal Frequency | 0.025 | 0.59 | 0.028 | 0.47 | 0.025 | 0.59 | 0.074 | 1.64 |
| Deal Depth | 0.076 | 1.56 | -0.007 | -0.11 | 0.131 | 2.81[a] | 0.035 | 0.85 |
| Brand Experience | -0.059 | -1.17 | 0.540 | 7.98[a] | -0.068 | -1.41 | -0.016 | -0.33 |
| Brand Loyalty (Repeat Buying) | -0.164 | -2.71[a] | 0.096 | 1.10 | 0.191 | 3.13[a] | -0.022 | -0.37 |
| (3) Consumer Factors | | | | | | | | |
| Income | -0.070 | -1.59 | -0.025 | -0.41 | -0.018 | -0.41 | -0.066 | -1.53 |
| Age | -0.087 | -1.78[c] | -0.043 | -0.63 | 0.044 | 0.92 | -0.066 | -1.39 |
| Education | -0.011 | -0.23 | 0.135 | 2.10[b] | -0.047 | -1.04 | 0.008 | 0.19 |
| Willet-Singer (1988) $R^2$ | 0.74 | | 0.38 | | 0.69 | | 0.75 | |

a = p < 0:01; b = p < 0:05; c = p < 0:10