MEASURING CONSUMER RESPONSE TO PRICE USING LOGIT MODELS: IMPLICATIONS OF IGNORING CATEGORY PURCHASE ASPECT

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Logit choice models are popular among marketing researchers. These models are often used to estimate own- and cross-price elasticities as measures of price response behavior. Many of these models, however, focus only on brand choice and do not incorporate the category purchase decision. Using mathematical derivations, numerical examples, and actual estimation results, this article illustrates the errors in price elasticity estimates resulting from the exclusion of the category purchase aspect in logit models. We also discuss the factors that influence these errors and their implications for managers.

INTRODUCTION

Because the marketing research on brand choice provides insights into brand and product line management, understanding the impact of marketing variables on consumer purchase behavior is an important objective. Elasticities of marketing variables (primarily price, but occasionally other variables) are often the outcomes of such modeling efforts. Price elasticities themselves, or expressions derived from elasticities such as clout/vulnerability indices (Kamakura and Russell 1989), are often used to infer important managerial implications in a product market.

The applications of price elasticity are fourfold. First, it is a scale-free measure of the impact of a marketing variable, thus enabling comparison across brands, product categories, consumers, and markets (Tellis 1988). Second, it helps us to understand market structure (e.g., Kamakura and Russell 1989). Third, elasticities are measures of inter-brand competition - how one brand's marketing mix (e.g., price, advertising) affects another brand (Blattberg and Wisniewski 1989). Fourth, as a culmination of the above three applications, elasticities are useful managerial guides for designing optimal marketing strategies (levels of advertising, level of prices and price cuts, etc.) Therefore, it is essential to obtain accurate estimates of elasticities.

Marketing researchers have typically used two general approaches toward understanding the effect of marketing variables on consumer purchases: aggregate store-level data (typically weekly data) and individual (family) level purchase data. Store level data (e.g., Blattberg and Wisniewski 1989) is used to study the effect of store level variables (e.g., shelf-price, store-wide price reductions, display, and feature, etc.). However, in order to arrive at a more fine-tuned understanding of consumer behavior, several researchers have made use of disaggregate level data (e.g., Gupta 1988; Kamakura and Russell 1989). In addition to incorporating all the variables at the aggregate level, disaggregate level models can also incorporate individual specific variables such as brand loyalty, family size, income, use of coupons, etc. Therefore, disaggregate level choice models have been very popular among marketing researchers to arrive at a comprehensive, detailed, and occasionally segment-specific understanding of purchase behavior (e.g., Gupta 1988; Kamakura and Russell 1989). Of the disagregate level choice models, logit models have been the preferred choice among marketing researchers (especially since the seminal work of Guadagni and Little in 1983). This is because of the intuitive interpretation of the logit model based on utility theory (Luce's choice axiom), a well-established research stream in economics and transportation literatures (Ben-Akiva and Lerman 1985), and the simplicity in terms of specification, interpretation, and estimation (compared to, for example, multinomial probit models). The application of logit models in marketing has also been enhanced by the availability of scanner panel data.

These brand choice models are often used to calculate own- and cross-price elasticities or some derivative measures of price elasticities (Gupta 1988; Kamakura and Russell 1989). As elasticities are scale-free, they are commonly used to understand, predict and compare the effect of price on choice, demand, or sales. Many of these models, however, focus only on brand choice (conditional on the occurrence of category purchase) and do not incorporate the decision of whether or not to make a purchase from a category (e.g., Guadagni and Little 1983).

Recent research (e.g., Guadagni and Little 1987; Gupta 1988; Chintagunta 1993; Sivakumar and Raj 1997) has shown that category choice is a very important aspect in explaining the effect of marketing variables in general and price response behavior in particular. However, their research did not focus on the reasons for the possible existence and the amount of differences in estimated parameters of managerial relevance (e.g., price elasticity) between models incorporating and ignoring category choice decision.

This article illustrates the reasons for the differences in elasticity estimates when the category choice aspect of brand choice is modeled versus when it is not modeled, as well as their managerial implications in the context of a nested logit model. By means of mathematical derivations and numerical examples, we discuss the errors that can enter the estimation and discuss two factors that determine the magnitude of errors - the coefficient of inclusive value and the frequency of category purchase compared to non-purchase. The article also demonstrates the issues using actual estimation results from scanner panel data. Finally, managerial implications of the differences in elasticity estimates are discussed.

The contributions of the article are substantive, methodological, and managerial. First, by focusing on the need to estimate accurate price response behavior, this article adds to choice modeling research as well as to pricing research. Second, we demonstrate a method that will enable the calculation of accurate measures of elasticities. We show that although a researcher may only be interested in brand switching, and not in the impact of marketing variables in product category choice or sales, we must incorporate category choice at least as a matter of statistical control. Finally, we show that a managerial understanding of price response behavior as well as managerial pricing strategies will be contingent upon our understanding of the appropriate response behavior. As Sivakumar (2000) argues, methodological issues and managerial implementation are closely linked in the context of understanding brand competition. By enabling managers to understand the exact price response behavior, we will help them to make more appropriate pricing decisions.

A SCENARIO AND AN EXAMPLE

Consider a product market consisting of two brands, A and B. Brand A is offering a price promotion and as a result, the market share distribution between A and B changes. Brand managers of both brands are interested in understanding the manifestations of the brand movements to design future offensive and/or defensive marketing strategies. Three scenarios are possible regarding the market share changes in A and B: (1) the market share change could be contributed entirely by movement from B to A; (2) the market share change could be contributed entirely by movement from non-purchase to A; or (3) the market share change could be contributed by a combination of both. Clearly, the strategies followed will be different for the three scenarios. Managers must understand the exact nature of inter-brand competition to decide appropriate strategies. This article addresses this broad substantive issue in a specific methodological context.

Let us consider a more specific example to motivate the substantive and managerial usefulness of addressing the specific research question. Assume there are two brands in the market with the current period market shares of 60% for brand A and 40% for brand B. Let us say that the prices of these brands are $2.00 and $1.50 respectively. Also assume that when A offers a 10% price cut, the market shares become 72% and 28%. Looking at this data superficially, one would conclude that A has captured 12% of market share from B for a 10% price reduction (a cross elasticity of 3). Although this conclusion appears to be straightforward, the underlying assumption in this interpretation is that the number of consumers purchasing the product category does not change.

However, literature offers evidence to show that the number of consumers who purchase a product category is not constant (a specific manifestation is the phenomenon of cherry picking, in which some consumer enter the market to take advantage of a special price) (Totten and Block 1987).

Suppose that a detailed look at the data indicates that the situation is as follows: only 10% of the total potential consumers purchase the product category during the occasion when there is no price reduction and the choice shares of the brands are 6% and 4% respectively (the market shares being 60% and 40%, the same as in the pre-promotion situation discussed previously). When brand A reduces price, assume that the new choice shares are 8.64 and 3.36, respectively (the market shares being 72% and 28% respectively, the same as the promotion situation discussed previously). This means that the choice share increase of 2.64% to brand A is composed of 2% coming new purchasers of the category and 0.64% coming from brand B (a cross elasticity of 1.6 for brand choice and a cross elasticity of 0.22 for category choice). Thus, identical market share changes may mean different things depending upon the source of the market share changes.

Similarly, the elasticities presented in existing research (e.g., Kamakura and Russell 1989, Table 5) are also based on the implicit assumption that the category choice probability does not change from one choice occasion to the next. However, if this is not the case, the brand choice elasticities reported will be erroneous. As will be explained later, the error will be a function of several factors.

Clearly, the managerial implications of the same change in market share in the two different scenarios are very different.

If the category volume is fixed and all price effects are assumed to be inter-brand movements, a brand's pricing strategy will be aimed more at the competing brands. On the other hand, if category volume can be altered due to price promotions, the focus shifts from attacking the competing brand to building one's own brand. The key issue therefore is to account for category choice probability and to investigate how they influence our understanding of the market and the designing of appropriate strategies.

CONCEPTUAL FRAMEWORK

Components of Elasticity Estimates

From an intuitive perspective, elasticity is always measured as the ratio of relative change in purchases to the relative change in prices. Thus, whether purchase probability is calculated as choice probabilities or whether choice probability is conditional upon category purchase makes no difference, as we are dealing with relative amounts. However, in the case of estimation of elasticities in logit models, this simple intuition cannot be applied in a straightforward manner.

Consumer choice process is hypothesized to consist of two components: whether to buy the product category or not; and if yes, which brand to buy. This structure can be made more complex through an intermediate decision, such as which quality level to buy (e.g., national brand or private label brand) or which variety to buy (e.g., ground coffee or instant coffee; regular or diet cola). However, the analytical treatment for such complicated structures is analogous and, in fact, we do use a more complex structure in our illustrative analysis.

The idea of the choice process defined as category choice followed by brand choice has significant support from the literature. Past researchers such as Guadagni and Little (1987), and Sivakumar and Raj (1997) have used a similar choice structure in their research. Although there has not been any direct evidence that consumers follow the two-state process, the significance of the models and fit and prediction accuracy have demonstrated that at the minimum, the empirical evidence shows that consumers behave as though they follow this process. Further, it must be noted that although the nested logit structure captures the stage-wise choice decision by the consumer, as Hensher (1986) points out, the primary reason for clustering alternatives is the anticipated correlations between the error terms of the alternatives. In other words, nested logit model is one mechanism for modeling the incorporation of category choice and brand choice in a unified framework.

In our conceptual development, we consider a two-brand market. The probability of brand choice can be decomposed into two parts: the probability of category choice during a choice opportunity (e.g., during a shopping trip) and the probability of brand choice given category choice.
This can be expressed as

$$PROB_{brand} = PROB_{category}\, PROB_{brand/category} \tag{1}$$

The price elasticity of brand choice can also be accordingly decomposed.

$$(\partial PROB_{BRAND}/\partial P)(P/PROB_{BRAND}) = [\partial(PROB_{CATEGORY}PROB_{BRAND/CATEGORY})/\partial P][P/PROB_{CATEGORY}PROB_{BRAND/CATEGORY}] \tag{2}$$

After algebraic manipulation,

$$ELASTICITY_{brand} = ELASTICITY_{category} + ELASTICITY_{brand/category} \tag{3}$$

Brand choice models not incorporating the category purchase aspect can calculate only $ELASTICITY_{brand/category}$. The implications of omitting the category purchase can be illustrated with a numerical example. If a brand has a 30% choice share and the $ELASTICITY_{brand/category}$ is 1 and $ELASTICITY_{category}$ = 0.5, a 10% change in a marketing variable (e.g., price) will thus change the choice share of the brand by 4.5 share points (15% of 30%). In the absence of our knowledge of $ELASTICITY_{category}$, we would estimate the change as only 3 share points (10% of 30%).

We next discuss the impact of ignoring the category choice decision by means of the nested logit model, which has been one of the most well-accepted methodologies used to incorporate the category choice decision in consumer purchase behavior (e.g., Guadagni and Little 1987; Sivakumar and Raj 1997).

Nested Logit Model

A common method of including category choice decision in brand choice models in marketing is the nested logit model (Ben-Akiva and Lerman 1985;Guadagni and Little 1987). Table 1 gives the simple nested logit structure incorporating the category purchase decision in a two-brand market. The table gives elasticity formulas incorporating and ignoring the category choice decision.

Table 2 illustrates the formulae in Table 1 with a numerical example. Specifically, Table 2 shows that the own-price elasticity of brand A is -3.468 when the category purchase aspect is incorporated and -1.2 when the category purchase aspect is omitted from the analysis. The corresponding figures for cross-price elasticities are 0.532 and 2.8 respectively. Table 2 also shows that both own elasticities as well as cross elasticities are susceptible to errors due to the omission of the category purchase decision: the magnitude of own elasticity is underestimated and cross elasticity is overestimated. However, typically, for choice shares of 50% or less, the magnitude of own elasticity is greater than the magnitude of cross elasticity. Therefore, the error will appear to be relatively much larger for cross elasticity than for own elasticity. This insight is significant because cross elasticity deals with inter-brand competition; most brand choice research has the goal of understanding the effect of a brand's strategy on another brand.

TABLE 1.
EXPRESSIONS FOR ELASTICITIES FOR A SIMPLE NESTED LOGIT MODEL

Decision Stage	Alternatives
I. Deciding to purchase	Purchase or not purchase
II. If decided to purchase, which brand to buy	Purchase A or B

Notation
E_{ij} - elasticity giving the effect of brand j on brand i; for own elasticity, i = j
b_i - price coefficient for brand i
$Prob_{i/j}$ - Probability of i given j
I - inclusive value coefficient when modeling stage 1

Note: These elasticity formulae are applicable when logarithm of price is used in the value function. If plain price is used, then the elasticity formulas will need to be multiplied by the respective prices.

Own elasticities incorporating category choice

$E_{AA} = b_A(1\text{-}Prob_{A/PUR}) + I\ b_A\ Prob_{A/PUR}\ (1\text{-}Prob_{PUR})$
$E_{BB} = b_B(1\text{-}Prob_{B/PUR}) + I\ b_B\ Prob_{B/PUR}\ (1\text{-}Prob_{PUR})$

Cross elasticities incorporating category choice

$E_{BA} = \text{-}b_A\ Prob_{A/PUR} + I\ b_A\ Prob_{A/PUR}\ (1\text{-}Prob_{PUR})$
$E_{AB} = \text{-}b_B\ Prob_{B/PUR} + I\ b_B\ Prob_{B/PUR}\ (1\text{-}Prob_{PUR})$

Own elasticities ignoring category choice

$E_{AA} = b_A(1\text{-}Prob_{A/PUR})$
$E_{BB} = b_B(1\text{-}Prob_{B/PUR})$

Cross elasticities ignoring category choice

$E_{BA} = \text{-}b_A\ Prob_{A/PUR}$
$E_{AB} = \text{-}b_B\ Prob_{B/PUR}$

The error in the estimation of elasticity will be directly proportional to (i) the percentage of non-purchase (which is a measure of inter-purchase time or purchase frequency) and (ii) the coefficient of inclusive value (which indicates how the variables at the brand choice level impact the category choice decision). From a modeling perspective, a coefficient of inclusive value is bound in the range of 0 and 1. A value of 0 indicates that the category choice decision is not influenced by variables affecting brand choice. That is, ignoring the category choice decision will not affect the calculation of price elasticities. A value of 1 for the coefficient of inclusive value indicates that the impact of marketing variables at the brand choice level also impact category choice very strongly. In addition, it indicates there is no need to model the choice process as a tree structure, as illustrated; the non-purchase option can be modeled along with the brand choice aspect in a flat structure.

EMPIRICAL ILLUSTRATION

Data

The purpose of the empirical illustration is to demonstrate, using scanner panel data, the biases involved in omitting the category purchase aspect. To be consistent with current research in the area, we chose a dataset that has already been used in existing research (albeit for investigating a different substantive issue), slightly modified the variable list and model specification to suit our specific research objectives, and reanalyzed the data.

TABLE 2.
DOES IGNORING CATEGORY CHOICE ASPECT LEAD TO INCORRECT INFERENCES?
(The numbers are for illustration only; they are not results of actual data analysis)

Decision Stage	Alternatives
I. Deciding to purchase	Purchase or not purchase
II. If decided to purchase, which brand to buy	Purchase A or B

NOTATION

SYMBOL	VALUE	EXPLANATION
$Prob_{PUR}$	0.1	Probability of category purchase
$Prob_{PUR}$	0.9	Probability of category non-purchase
$Prob_A$ purchase	0.7	Probability of purchasing A given category
$Prob_B$ purchase	0.3	Probability of purchasing B given category
b_A	-4	Price coefficient for A
b_B	-3	Price coefficient for B
I	0.9	Coefficient of inclusive value

CALCULATION OF ELASTICITIES FOR A AND B

	ELASTICITY OMITTING CATEGORY PURCHASE	ELASTICITY INCORPORATING CATEGORY PURCHASE
E_{AA}	-1.2	-3.468
E_{BB}	-2.1	-2.829
E_{BA}	2.8	0.532
E_{AB}	0.9	0.171

Basing our analysis on existing research has several advantages. First, using a dataset that has already been used will offer our research a certain degree of face validity. Second, an entirely new dataset could be considered too idiosyncratic for the research question, thereby potentially influencing the results in our preferred direction; for this reason, it is helpful to follow existing datasets. Third, using existing datasets and procedures will ensure that the proposed analysis conforms to existing results while offering a new and expanded understanding of price elasticity dynamics.

The chosen dataset is comprised of scanner panel data for tomato ketchup provided by A.C. Nielsen to academic researchers under the auspices of the Marketing Science Institute. The set-up of the data, the operationalization of variables, and the estimation procedure were similar to the ones followed by Sivakumar and Raj (1997); hence, they are described only briefly here. The analysis consisted of four brands, three national brands and one store label.

TABLE 3.
ELASTICITY EXPRESSIONS FOR A TYPICAL MULTI-BRAND MARKET

Decision Stage	Alternatives
I. Deciding to purchase	Purchase or not purchase
II. If decided to purchase, which type to buy	Purchase national brand or store brand
IIIa. If decided to buy national brand, which brand to buy	A, B, and C.
IIIb. If decided to buy store brand, which brand to buy	D

Notation

E_{ij} - elasticity giving the effect of brand j on brand i; for own elasticity, i=j.

b_i - price coefficient for the quality level i; $\text{Prob}_{i/j/k}$ - Probability of i given j given k

I_1, and I_2 are inclusive value coefficients in stage 2 and stage 3 respectively.

Own elasticities incorporating category choice

$E_{AA} = b_H(1-\text{Prob}_{A/H/PUR}) + I_1 b_H \text{Prob}_{A/H/PUR}(1-\text{Prob}_{H/PUR}) + I_2 I_1 b_H \text{Prob}_{A/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{BB} = b_H(1-\text{Prob}_{B/H/PUR}) + I_1 b_H \text{Prob}_{B/H/PUR}(1-\text{Prob}_{H/PUR}) + I_2 I_1 b_H \text{Prob}_{B/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{CC} = b_H(1-\text{Prob}_{C/H/PUR}) + I_1 b_H \text{Prob}_{C/H/PUR}(1-\text{Prob}_{H/PUR}) + I_2 I_1 b_H \text{Prob}_{C/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{DD} = b_L(1-\text{Prob}_{L/PUR}) + I_2 b_L \text{Prob}_{L/PUR}(1-\text{Prob}_{PUR})$

Cross elasticities incorporating category choice

$E_{BA} = E_{CA} = -b_H\text{Prob}_{A/H/PUR} + I_1 b_H \text{Prob}_{A/H/PUR}(1-\text{Prob}_{H/PUR}) + I_2 I_1 b_H \text{Prob}_{A/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{AB} = E_{CB} = -b_H\text{Prob}_{B/H/PUR} + I_1 b_H \text{Prob}_{B/H/PUR}(1-\text{Prob}_{H/PUR}) + I_2 I_1 b_H \text{Prob}_{B/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{AC} = E_{BC} = -b_H\text{Prob}_{C/H/PUR} + I_1 b_H \text{Prob}_{C/H/PUR}(1-\text{Prob}_{H/PUR}) + I_2 I_1 b_H \text{Prob}_{C/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{DA} = -I_1 b_H \text{Prob}_{A/H/PUR}\text{Prob}_{H/PUR} + I_2 I_1 b_H \text{Prob}_{A/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{DB} = -I_1 b_H \text{Prob}_{B/H/PUR}\text{Prob}_{H/PUR} + I_2 I_1 b_H \text{Prob}_{B/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{DC} = -I_1 b_H \text{Prob}_{C/H/PUR}\text{Prob}_{H/PUR} + I_2 I_1 b_H \text{Prob}_{C/H/PUR}\text{Prob}_{H/PUR}(1-\text{Prob}_{PUR})$

$E_{AD} = E_{BD} = E_{CD} = -b_L \text{Prob}_{L/PUR} + I_2 b_L \text{Prob}_{L/PUR}(1-\text{Prob}_{PUR})$

Own elasticities ignoring category choice

$E_{AA} = b_H(1-\text{Prob}_{A/H/PUR}) + I_1 b_H \text{Prob}_{A/H/PUR}(1-\text{Prob}_{H/PUR})$

$E_{BB} = b_H(1-\text{Prob}_{B/H/PUR}) + I_1 b_H \text{Prob}_{B/H/PUR}(1-\text{Prob}_{H/PUR})$

$E_{CC} = b_H(1-\text{Prob}_{C/H/PUR}) + I_1 b_H \text{Prob}_{C/H/PUR}(1-\text{Prob}_{H/PUR})$

$E_{DD} = b_L(1-\text{Prob}_{L/PUR})$

Cross elasticities ignoring category choice

$E_{BA} = E_{CA} = -b_H\text{Prob}_{A/H/PUR} + I_1 b_H \text{Prob}_{A/H/PUR}(1-\text{Prob}_{H/PUR})$

$E_{AB} = E_{CB} = -b_H\text{Prob}_{B/H/PUR} + I_1 b_H \text{Prob}_{B/H/PUR}(1-\text{Prob}_{H/PUR})$

$E_{AC} = E_{BC} = -b_H\text{Prob}_{C/H/PUR} + I_1 b_H \text{Prob}_{C/H/PUR}(1-\text{Prob}_{H/PUR})$

$E_{DA} = -I_1 b_H \text{Prob}_{A/H/PUR}\text{Prob}_{H/PUR}$

$E_{DB} = -I_1 b_H \text{Prob}_{B/H/PUR}\text{Prob}_{H/PUR}$

$E_{DC} = -I_1 b_H \text{Prob}_{C/H/PUR}\text{Prob}_{H/PUR}$

$E_{AD} = E_{BD} = E_{CD} = -b_L \text{Prob}_{L/PUR}$

Methodology

The model assumes that the consumer first decides between purchase and non-purchase. If the decision is to purchase, then the consumer decides which quality to purchase (high-quality national brand or low-quality store label brand). In the third stage, the consumer chooses the brand within a particular quality level.

The structure of the model used in the empirical analysis and the elasticity formulae incorporating and ignoring the category purchase aspect are presented in Table 3. Though the underlying logic is the same as the simple case presented in Table 1, the expressions are complicated by the increase in the number of brands and the number of levels in consumer decision-making.

Models and Variables

The variables used in the brand choice stage of the model are brand loyalty, display, feature, and the logarithm of price. These variables have been consistently used in almost all logit models of brand choice (e.g., Guadagni and Little 1983; Sivakumar and Raj 1997). The variables used in the quality choice stage of the model are quality tier loyalty, inclusive value, and income. With the exception of Sivakumar and Raj (1997), existing research does not model quality choice. However, our variables included in the quality choice are easily justified. For example, quality-tier loyalty is the extension of brand loyalty. We decided to include income because it may influence the choice of a quality level (the expectation being high-income families will prefer high quality brands). The inclusive value is a manifestation of the nested logit structure and is required for all nested logit models. Most importantly, the inclusive value coefficient is the mechanism by which the effect of brand choice variables is carried over to the quality decision. That is, although price (for example) is not separately included at the quality choice level, it does affect quality choice because the effect of price is carried over to the quality choice through the inclusive value coefficient. In the limiting case of the coefficient being zero, the effect will disappear but in all other cases, the model does account for the role of price in quality choice. The variables included in the purchase/ nonpurchase stage of the model are propensity to purchase a category (this is similar to the loyalty variable, but for purchase or non-purchase), inclusive value, family size, income, and inventory. The loyalty variable is similar to brand loyalty and quality loyalty but in this case, it focuses on purchase/nonpurchase.

Price is the paid or faced price in cents per 32 ounces, the typical pack size for ketchup. This was converted into a logarithmic form to account for diminishing marginal utility for price. We also use dummy variables for feature and display (defined as 0 if absent and 1 if present). To control for consumer heterogeneity, loyalty is used as a variable. Loyalty is defined as the cumulative proportion of purchases devoted to a given alternative (brand share, quality share, or purchase share respectively for the model stages) before each purchase opportunity. Variables such as family size in the category choice level and income at the quality choice and category choice level are included to obtain further statistical control of other variables. To incorporate a variable to account for inventory, we calculate the inventory of each household prior to purchase and standardize the variable within each family. The inclusive value is the logarithm of the denominator from the previous stage of the logit model.

RESULTS

Estimation Results

Estimation results are presented in Table 4. The coefficients of the variables are of the right sign and are consistent with the results of existing research. The model fit is also similar to existing research. For example, U^2 value for the model compares favorably with those of the other logit models in the literature (e.g., Guadagni and Little 1987).

It has to be noted that from a theoretical perspective, the coefficient of the inclusive value must be in the interval 0-1. The coefficient of the inclusive value is statistically significant. Thus, the significant inclusive value coefficients in the third stage (0.93) show that modeling the non-purchase option significantly affects the results.

Calculation of Elasticities

The estimated price coefficients and the actual market shares from the estimation sample are used to calculate own- and cross-price elasticities of brands. Elasticities are also calculated for the model that does not incorporate the category purchase component

TABLE 4.
RESULTS OF ESTIMATION

	Model Stage 1	Model Stage 2	Model Stage 3
	H_1, H_2, H_3	H, L_1	Purchase, Non-Purchase
Price	-5.99	-2.20	
Loyalty	3.21	3.46	3.32
Feature	1.59	1.54	
Display	0.91[a]	2.67	
Income**		0.08[a]	-0.10
Inclusive Value		1.01[@]	0.93
Family Size**			0.11
Inventory**			-0.46
Model U^2	0.69	0.45	0.34

* Stage 1 refers to brand choice with alternatives being H_i and L_i. Stage 2 refers to quality choice between H and L and stage 3 refers to choice between category purchase and non-purchase

** These variables are entered in the utility function of the first alternative in the choice set.

[@] Not significantly different from 1.0. In all further calculations the value of 1.0 is assumed because the coefficient of the inclusive value must lie in the 0-1 range to be consistent with utility theory.

Coefficients without a superscript are significant at a p value < 0.01; [a] significant at p=0.05 level.

of the decision process. This can be considered to be similar to a model used in Guadagni and Little (1983) or Kamakura and Russell (1989). As explained previously, the error in the estimation of elasticities is a function of several factors. These elasticities (incorporating and ignoring the category choice) are presented in Table 5. In some sense, this table uses the same data set to compare results using methods in existing research and the proposed approach.

There are substantive differences in the two sets of elasticity estimates. For example, the own-price elasticity of brand A is -2.83 for the model incorporating the category choice decision and -1.66 for the model ignoring the category choice decision. Similarly, the cross elasticities of brand A's price on other brands are 0.74 and 4.32 respectively for the models incorporating and ignoring the category choice aspect. Clearly, the impact of ignoring category choice aspect is qualitatively and quantitatively different for own and cross price elasticities. The magnitude of own-price elasticities are underestimated and the magnitude of cross-price elasticities are overestimated by models not incorporating the category choice decision (These results are consistent with those reported by Chintagunta (1993), although his focus was not on explaining the reasons for the differences). Further, Table 5 demonstrates that minor brands' own-price elasticities are less affected by omission of category purchase although cross-price elasticities are more seriously affected. Next, we describe a specific example from existing research that might be affected as a result of ignoring the category choice aspect.

Comparisons can be conceptualized for published existing results (e.g., Kamakura and Russell 1989). For example, based on the details in Table 5 of their article, the cross elasticity of brand A on brand B in segment 1 will be more than the reported magnitude of 0.53. Similarly, the magnitude of own elasticity of

TABLE 5.
ILLUSTRATION OF ELASTICITY ESTIMATES
(entries represent effect of row brand on column brand;
(underlined elasticities incorporate category choice; others do not)

Effect of Brand	Share	Effect on Brand H_1	H_2	H_3	L_1
H_1	.722	-5.25,-1.66	0.74, 4.32	.74, 4.32	.74, 4.32
H_2	.115	0.12, 0.69	-5.87, -5.30	.12, .69	.12, .69
H_3	.074	.08, .45	.08, .45	-5.91, -5.54	.08, .45
L_1	.089	.03, .20	.03, .20	.03, .20	-2.17, -2.00

brand A for segment 1 will be less than the reported magnitude of -1.46. Kamakura and Russell (1989) also compute clout and vulnerability indices based on their elasticity estimated. Clearly, the positioning of brands in the competitive market structure depiction will be different if the elasticity computations change. As they do not consider the notion of category choice probabilities, it is likely that the market structure depiction must be suitably modified to represent the full picture. The exact amount of changes will of course depend upon the specific product category analyzed and other parameters such as the coefficient of the inclusive value, the probability of category non-purchase, and so on.

Based on the demonstrated empirical results presented in Table 5, the increase in cross elasticities more than compensates for the decrease in own elasticities for minor brands. Therefore, the brands will be actually farther apart in reality compared to the positioning depicted by Kamakura and Russell (1989), reflecting a less intense competition between brands. This conclusion is consistent with the earlier insight that exclusion of category choice makes the competition appear more intense than the actual situation.

DISCUSSION AND MANAGERIAL IMPLICATIONS

Interpretation of Price Response Behavior

What inferences can managers make about the differences in elasticity calculations? While there are substantive differences in the elasticity estimates between models incorporating and ignoring the category purchase aspect, the practical implications can be better understood when we consider estimates of market share changes as a result of price changes. Figure 1 presents scenarios for a price reduction of 10% by brand H_1. The Figure presents these scenarios both for absolute choice shares incorporating the non-purchase option as well as choice shares calculated conditional on category purchase. There are substantial differences in inferences between the models incorporating and ignoring the category choice aspect.

The first conclusion to be drawn from these results is that ignoring the category purchase aspect results in serious errors in the estimation of the effect of marketing variables. This finding is observed in all of the four brands analyzed in this article.

Implications of Interpretation

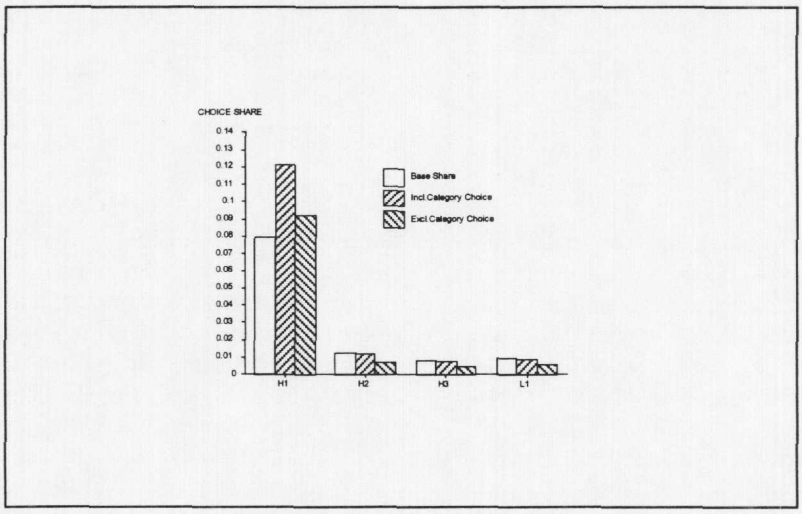
Ignoring the category choice aspect seriously underestimates own-price elasticities and overestimates cross-price elasticities. Underestimation of the magnitude of own-price elasticities may mislead the marketing manager into underestimating the impact of a promotional price cut on the company's brands. As other research (Sivakumar and Raj 1997) has demonstrated, a substantial impact of price promotions is their ability to affect category purchase behavior. Thus, underestimation may lead to more conservative strategies.

Overestimation of cross-price elasticities will mislead the manager into believing that competing brands will be unduly affected by his or her company's promotions, and vice versa. The danger of such misguided strategies is that they will inspire overly mild offensive strategies and/or overly strict defensive strategies - both of which will affect market shares as well as profitability.

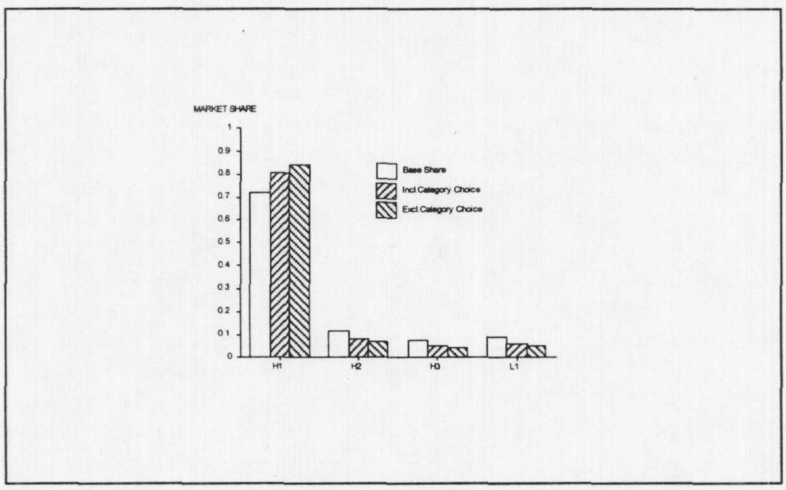
The understanding that category choice changes are also instrumental in affecting market share changes has a number of implications for managerial strategies. First, the competition between two brands need not be direct (i.e., switching between brands) and can be indirect (i.e., moving from and to nonpurchase). In fact, it is quite possible that the brand switching aspect may be less important than category choice aspect in some product categories. This has a number of interesting insights to offer. If market share changes can happen in ways other than brand switching, it means that price competition may not be a zero sum game and that profitability of promotional pricing may not be at the expense of the competing brands. The extent of the distribution of course will depend upon how much of the interbrand movement is contributed by brand choice, how much is contributed by category choice changes, and whether the sales advantage translates into profit advantage. More broadly, the notion of category choice influencing market shares may lead to a peaceful coexistence of manufacturers and retailers because all of the increase during the price promotions does not come from competing brands (we are focusing on short term changes here). All these points clearly highlight the coresubstantive purpose of the article: it is important to decompose the brand share changes into its sub-components and it is equally necessary to estimate these components using an appropriate methodological procedure.

FIGURE 1.
MANAGERIAL INFERENCES WHEN H1 DECREASES PRICE BY 10%

(a) Changes in Choice Share



(b) Changes in Market Share



Role of Category Purchase Probability

The probability of category purchase inversely affects the errors in the elasticity estimates: in general, the higher the probability of category purchase, the smaller the error. In other words, the errors in elasticity estimates are different for product categories with different purchase cycles and the flexibility in the purchase cycles. As an extreme situation, imagine that the consumer buys the product category on each and every shopping trip; in this case, the error disappears because there is no change in the category purchase probability from purchase occasion to purchase occasion. If the category purchase occurs very infrequently but at fixed intervals (e.g., every eight weeks) and not affected by the marketing actions, then also, the error disappears because all the movement during price reduction is due to movements between brands and not between brands and non-purchase. However, if the category purchase probability is small and it changes with changes in price, the error in elasticity estimates are inversely proportional to the category purchase probability.

With categories that are impulse purchases, if these impulse purchases are driven by price promotions, then again we can see very large errors in elasticity estimates because of the fluctuations in category purchase patterns. Further, the way we define the purchase opportunity also determines error in elasticity estimates. Though we have considered the shopping trip as a purchase opportunity, other operationalizations, such as the week (Gupta 1988), can be adopted. From the perspective of minimizing errors, the larger the window considered as a shopping opportunity, the smaller the error. However, if this window is so large to include different pricing cycles, then, the utility of the analysis is limited because it is not possible to measure the impact of a specific price change.

This research has also shown that modeling category choice should be considered as a necessary statistical control. As the variable "loyalty" is included in any logit choice model (even when the focus of study may be price effects), category choice must be included in any brand choice model, even if the primary objective of the model is inter-brand effects and not category choice aspect (unlike Chintagunta (1993) who argue that if the purpose is only to focus on brand shares, one need not incorporate category choice aspect).

Nested Logit vs. Other Approaches

Although our focus in this article has been the nested logit model, the approach and implications of the nature of the errors in elasticity estimates will be applicable for other disaggregate choice models such as multinomial probit models or mother logit model (Krishnamurthi, Raj, and Sivakumar 1995). In some sense, the implications will be the same for any modeling procedure that does not code non-purchases as a separate entity. However, regression models (e.g., using store level data as in Blattberg and Wisniewski) incorporate all sales (category choice, brand choice, and quantity choice). In these instances, the estimated elasticities are for sales and therefore, it is not possible to decompose the same into brand choice, quantity choice, and category choice components. As we discussed previously, the focus of managerial strategies will be different for different decompositions of the price response behavior and therefore the necessity for adopting disaggregate modeling with specific incorporation of category choice.

Quantity Choice or "How Much to Buy" Decision

Also, in this article, we did not focus on the third aspect of brand choice normally considered in choice models, "how much to buy" or "quantity choice." Although the impact of the "quantity" choice aspect has been demonstrated to be only minor (Gupta 1988) and our approach will be applicable when the quantity purchased is typically one unit of the same size (e.g., saltine crackers), further research that incorporates quantity choice will be the next step to enhance the utility of this stream of research.

CONCLUSION

The main message of this article has been that appropriate conceptualization and methodology in brand choice elasticity estimates are a prerequisite for their managerial utility. Using conceptual derivations, numerical simulations, and empirical results, we have demonstrated that incorrect methodology will result in erroneous estimates of response behaviors, which will in turn lead to inappropriate marketing strategies. Although more product categories must be analyzed before valid generalizations can emerge, we hope that we have made a contribution toward a meaningful understanding of the effect of marketing variables so that managers' actions can be based on correct rather than erroneous estimates.

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ACKNOWLEDGEMENT

The author thanks the *Marketing Science Institute* for providing the data. He also appreciates the guidance of the editors and useful comments from the reviewers.

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