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The authors examine an important influence on the price-advertising tradeoff, the ratio of price and advertising elasticities. Their theoretical analysis stresses the centrality of the elasticity ratio and shows how the pass-through ratio, the fraction of loyal consumers who take advantage of price discounts, and the contribution-price ratio are additional factors that influence the price-advertising tradeoff. Empirical analysis of 262 observations from published studies indicates that the price elasticity is "on average" 20 times the advertising elasticity. The elasticity ratio is higher for mature products than for products in the early stage of the life cycle, and for nondurable goods than for durable goods. These findings suggest that price discounting may be more profitable than an advertising increase for nondurable goods and mature products. The ratio is smaller for elasticities estimated from yearly data than for those based on quarterly or monthly data. This finding raises a question about the appropriate level of aggregation for understanding the relative effects of price and advertising.

An Analysis of the Tradeoff Between Advertising and Price Discounting

Are price cuts more profitable than increases in advertising? On a day-to-day basis, brand management frequently reduces to competition for market share, and managers face a choice between two classes of marketing instruments: advertising that can enhance the brand's nonmonetary attractiveness and price discounts that provide a monetary incentive to buy the brand.

Recent empirical findings have increased the importance of analyzing this tradeoff. Several researchers have discussed the low sensitivity of sales to advertising, and others have shown the strong responsiveness of sales to various types of price cuts. For example, Assmus, Farley, and Lehmann's (1984) review of the marketing literature finds that the advertising elasticity of sales is in the region of .22. Aaker and Carman's (1982) review of research with the ADTEL data suggests that firms may

well be overadvertising. Eastlack and Rao's (1989) experiments at the Campbell Soup Company in the mid-1970s indicate that increases or decreases in advertising generally do not translate into corresponding changes in sales. Abraham and Lodish's (1989) experiments at IRI show that half of the increases in ad intensity have no impact on sales.

At the same time, many studies have shown the strong sensitivity of sales to price cuts. Tellis' (1988a) review of the literature finds that the average price elasticity of sales is -1.76, more than eight times the elasticity of advertising. Recent studies with scanner data also demonstrate the strong response of consumers to various incentives such as price differences, discounts, and coupons (e.g., Guadagni and Little 1983; Gupta 1988; Tellis 1988b). Tellis' (1988b) study in particular created a controversy in the advertising industry and the business press because it showed that brand choices and quantity purchased are much more responsive to price than to the number of TV ad exposures.

Critics have pointed to several factors that favor advertising. For example, a large-share firm may find even a "small" increase in share due to advertising to be very profitable. Similarly, available contribution, though adequate to cover some advertising increases, may not leave

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room for a meaningful price discount. Moreover, price cuts to consumers who otherwise would buy at the high price involve an opportunity loss. In addition, retailers may not always pass on a manufacturer's price discount to consumers, thus reducing the revenues obtainable from a price discount.

Hence, though a growing body of findings suggest that price cuts may be more effective than advertising, the former need not be profitable. Moreover, there is no generalizable test of the effectiveness of these two instruments, nor a formal framework for comparing their relative profitability. Further, the influence of retail pass-through and the availing of discount by loyal buyers have not been considered explicitly in assessing the profitability of price discounts. Our study addresses these issues. It has two broad objectives.

First, we explore analytically what conditions render a price cut more profitable than an increase in advertising. This analysis is similar in spirit to efforts by Dorfman and Steiner (1954), Lambin (1976), and others to determine optimal advertising and price levels, but has two key differences. We attempt not only to determine what levels are globally optimal, but also whether *changes* in advertising or in price are more profitable. Further, we include two factors that affect the profitability of price discounts: (1) the opportunity loss from buyers who would have bought the brand at regular price and (2) the opportunity loss from retailers who pass on only a fraction of the manufacturer's discounts to the consumers. From this analysis, we identify and discuss conditions under which a price discount or an advertising increase will be profitable. We formally establish that the ratio of price to advertising elasticities has a key role in the price-advertising tradeoff.

Second, we try to estimate the actual ratio of the price and advertising elasticities by a meta-analysis of econometric estimates in the literature. The ratio of the price and advertising elasticities should contain valuable information on the responsiveness of consumers and markets to marketing efforts. In particular, such empirical estimates take into account the disposition of consumers, the competitive environment, and the effectiveness of the two instruments. Whereas Assmus, Farley, and Lehmann (1984) analyze only advertising elasticities (from a relatively small sample of 128 estimates) and Tellis (1988a) analyzes only price elasticities, our study (based on 262 estimates) analyzes the ratio of these elasticities *when both are estimated in the same model*. Like previous studies, ours explores how the ratio of elasticities differs across such factors as the life cycle, product durability, and time frame.

Some of the questions we raise have been answered for specific firms or situations. Our study looks for generalizations across firms and markets in the spirit of studies by Assmus, Farley, and Lehmann (1984), Bolton (1989), Leone and Schultz (1980), and Tellis (1988a). Our presentation of the theoretical and empirical results on the ratio of elasticities is arranged in five broad sec-

tions: analytical background, hypotheses, design for the empirical analysis, results, and conclusion.

Generally, price elasticity $[(\Delta q/q)/(\Delta p/p)]$ is negative and advertising elasticity $[(\Delta q/q)/(\Delta A/A)]$ is positive. Because it is easier to interpret and discuss positive numbers, we refer only to the absolute magnitude of the price elasticity. For example, when we say the price elasticity is higher, we mean the magnitude of the price elasticity is higher or the elasticity is more negative. Again, in order to work with positive numbers, we define the *elasticity ratio* as $-\text{price elasticity}/\text{advertising elasticity}$.

ANALYTICAL BACKGROUND

In this section, we analyze a firm's decision to spend in price discounts or advertising. Henceforth, the term "firm" refers to manufacturers only, that must typically choose between advertising and price discounts. Let the firm's current price (to consumers) be p and advertising be A . If the firm sells a quantity $q(p, A)$ with an associated variable cost¹ $C(q)$ and fixed costs F , the firm's current profits are

$$(1) \quad \Pi_0 = pq - C(q) - A - F.$$

The firm could increase profits by either a price reduction (Δp) or an advertising change (ΔA). We show how profitability, and hence the decision to spend in a price change or in an advertising change, is related to the following factors: (1) the ratio of price elasticity to advertising elasticity, (2) the contribution-price ratio, (3) the firm's advertising to sales (A/S) ratio, (4) the fraction of regular-price demand sold at the discounted price, and (5) the retailer's pass-through ratio.

The analytical exercise consists of three steps. The first step pertains to price changes. We introduce the notion of a modified (or effective) price elasticity, which together with contribution-price ratio determines the conditions in which a discount is profitable. The second step pertains to advertising changes where an analogous concept of a modified advertising elasticity provides the conditions for an advertising increase. These two steps identify regions in the price-advertising elasticity space where different strategies would be profitable. Step 3 considers both options together. Here, we address the price-advertising tradeoff by computing the percentage increase in advertising required to match the profits obtained from a 1% price cut.

Price Reduction

Firms introduce temporary price cuts mostly in two ways: (1) indirectly, by *trade deals* (price cuts) to retailers who, in turn, pass on a fraction of the price reduction to the consumer as temporary *price discounts*

¹Variable costs include manufacturing costs, retailer margins, and other variable costs.

(TPDs), and (2) directly, by *on-pack "cents-off" coupons and rebates* that are redeemable by consumers.

Trade deals have been a major form of marketing expenditure and account for more than 35% of total marketing support in the packaged goods industry. Further, past empirical studies of price elasticity (which we subsequently meta-analyze) generally have used market (or shelf) price changes without accounting for firm coupons and rebates. Hence, we consider only manufacturers' trade deals offered as a price discount (Δp_m) per unit for all quantities purchased during the discount period.

A major source of revenue loss to the firm from price discounts has been *low pass through*—retailers pass through to the consumer only a fraction of the deal they receive from the firm (e.g., Chevalier and Curhan 1976). The success of a firm's trade deal depends on how much of the deal's value is passed through. Let g ($0 \leq g \leq 1$) be the fraction of the trade deal that retailers pass on to the consumer. Then, for the consumer to receive a Δp discount, the firm should provide a trade deal equal to $\Delta p/g$.

In passing through an amount Δp of the trade deal as price discounts, retailers attempt to balance the increase in demand (due to brand switching or increase in quantity bought) with the opportunity loss from loyal consumers who would have bought the brand at the regular price. Let Δq be the increase in demand and f be the fraction of the original demand served at the reduced price. Then $f q + \Delta q$ units are sold at the reduced price ($p - \Delta p$), and $(1 - f)q$ units are sold at the regular price, p . Note that the trade deal ($\Delta p/g$) is applied only to the quantity sold at the reduced price. Any quantity bought by the retailer on deal but sold at the regular price is absorbed in the pass-through (g). If the retailer purchases $q + \Delta q$ units at a discount of Δp_m and sells $f q + \Delta q$ units at a discount of Δp and the rest at regular price,

$$\text{pass through, } g = \frac{\text{discount passed on by retailer}}{\text{discount given by firm}} \\ = \frac{\Delta p(f q + \Delta q)}{\Delta p_m(q + \Delta q)}$$

Then the new profits (Π_1) for the firm from a price-change option are $(p - \Delta p_m)(q + \Delta q) - C(q + \Delta q) - A - F$, which can be written by substituting for Δp_m as

$$(2) \quad \Pi_1 = (p - \Delta p/g)(f q + \Delta q) \\ + p(1 - f)q - C(q + \Delta q) - A - F.$$

Let c be the marginal (variable) cost of producing the additional units—that is, $c = [C(q + \Delta q) - C(q)]/\Delta q$. We assume that the firm operates at normal capacity, with fixed and variable costs invariant to changes in price and advertising. We also assume that the marginal cost (c) is constant for small changes Δq . Then $(p - c)/p$ is the proportion of each sales dollar that contributes to fixed costs and profits. We refer to this ratio as the contribution-price ratio (k). We assume the contribution is

positive in the price range. Subtracting equation 2 from equation 1 and ignoring the small $\Delta p \Delta q$ product term, we obtain the increase in profits due to a price reduction (Δp):

$$(3) \quad \Delta \Pi_1 = (p - c)\Delta q - q f \Delta p / g.$$

The first expression on the right side is the gains to the firm from increased sales (Δq) and the second expression represents the losses due to $f q$ demand being sold at the ($\Delta p/g$) decreased price. Multiplying and dividing equation 3 by $q \Delta p$ and simplifying, we get

$$(4) \quad \Delta \Pi_1 = p q (\Delta p / p) (k \epsilon_p - f / g),$$

where ϵ_p is the price elasticity. For a given fractional price change ($\Delta p/p$), $k \epsilon_p$ represents the gains due to increased sales and f/g is the opportunity loss from retailer pass-through and from original demand being served at a lower price. We refer to f/g as the loss ratio. Equation 4 specifies the conditions for a price discount. The firm will increase its profits if $k \epsilon_p > f/g$ or if $k(g \epsilon_p / f) > 1$. The term $g \epsilon_p / f$ has an interesting interpretation. It shows that f , the fraction of original demand served by the discount scheme, and g , the pass-through ratio, are critical factors that modify the profitability of sales responsiveness to price cuts. We refer to $g \epsilon_p / f$ (which is price elasticity/loss ratio) as the "modified" price elasticity (ϵ_p') which, in some sense, measures the effective incremental demand for a (Δp) price cut. This expression, when multiplied by the contribution unit (k), gives the "effective" total contribution for unit cost incurred as a result of a price cut. Hence if $k(g \epsilon_p / f) > 1$, the firm should price discount. The breakeven price elasticity at which the firm makes no additional profits by a price reduction can be obtained from equation 4:

Result 1: The breakeven price elasticity is $\epsilon_p^* = f/gk = fp/g(p - c)$. Above this value ($\epsilon_p > f/gk$), the firm should price discount.

This result goes beyond standard economic theory by showing how four key factors influence the decision to price discount. First, the higher the price elasticity, the more the firm should price discount. Second, a firm should spend more on price cuts if the retailers pass through a major portion (g) of the trade deal. Proponents of price cuts assume that g is high (close to 1) and hence overstate the need for price discounts, whereas opponents assume g is low and understate its importance. As g may well be between 0 and 1, empirical estimation is crucial for the price-change decision. Third, as a smaller fraction (f) of the original demand switches to the reduced price, the firm should spend more on discounts to attract switchers. Proponents of price cuts tend to believe that f is low whereas opponents believe f is close to 1. As f can take any value between 0 and 1, a knowledge of f is important for understanding the profitability of a price cut (Neslin and Shoemaker 1983). Fourth, the decision on price discounts is also intrinsically related to the contribution-price ratio (k), which can range from 0 to 1.

Firms with higher margin or contribution can cut their price and still increase their net profits through additional sales. A relatively high contribution ratio implies a cost structure that has more of total costs fixed and has relatively low marginal (or variable) cost. Such industries (e.g., paper) should be more willing to discount. An appropriate costing system should enable each firm to measure the contribution-price ratio.

Advertising Change

For a small increase in advertising (ΔA), let the sales increase by Δq . Then the new profits are

$$(5) \quad \Pi_2 = p(q + \Delta q) - C(q + \Delta q) - (A + \Delta A) - F.$$

Subtracting equation 5 from equation 1, we find that the increase in profits is

$$(6) \quad \Delta\Pi_2 = (p - c)\Delta q - \Delta A.$$

The first expression on the right side is the gains due to increased sales and the second expression is the advertising expense. Multiplying and dividing equation 6 by pq and simplifying, we get

$$(7) \quad \Delta\Pi_2 = pq(\Delta A/A)(k\epsilon_A - A/S).$$

$k\epsilon_A$ represents the gains due to increased sales and A/S is the advertising expense measure. The firm will increase profits through an advertising increase if $k\epsilon_A > A/S$ or $k[\epsilon_A/(A/S)] > 1$. $\epsilon_A/(A/S)$ can be interpreted as the "modified" advertising elasticity (ϵ'_A), analogous to the modified price elasticity. ϵ'_A is then a measure of the effective demand increase for a ΔA advertising increase. $k\epsilon'_A$ therefore gives the marginal revenue for unit cost incurred as a result of increase ΔA . If $k\epsilon'_A > 1$, the firm gains profits by an advertising increase. From equation 7, we have a result analogous to result 1.

Result 2: The breakeven advertising elasticity at which the firm makes no additional profits from an advertising change is $\epsilon^*_A = (A/S)/k$. If advertising elasticity is higher ($\epsilon_A > (A/S)/k$), a firm should increase advertising (if $\epsilon_A < (A/S)/k$, the firm should decrease advertising).

As for price elasticity, this result shows that the decision to increase advertising depends on three factors. First, a firm should increase advertising expenditures as the advertising elasticity increases. Second, firms with high contribution-price ratio (k) stand to gain by increasing their advertising. The ratio (k) describes how much is left after meeting the variable cost. When k is high, the total contribution obtained from sales generated through increased advertising will more than offset the fixed advertising costs, resulting in a net increase in profits. Third, the A/S ratio affects the profitability of advertising primarily by definition of advertising elasticity. A 1% increase in advertising costs much more at higher levels of A/S and hence reduces advertising's profitability.

When both price and advertising elasticities are at the

breakeven point—that is, $\epsilon_p = \epsilon^*_p = f/gk$ and $\epsilon_A = \epsilon^*_A = (A/S)/k$ —the firm is at its optimum with respect to both instruments. Notice that in this case $\epsilon_p/\epsilon_A = (f/g)/(A/S)$. In the special case when $f = 1$ and $g = 1$, we obtain the Dorfman-Steiner (1954) result for optimal investments, $\epsilon_A/\epsilon_p = A/S$. This special result has been used by many researchers (e.g., Lambin 1976) to compare optimal and actual marketing investments.

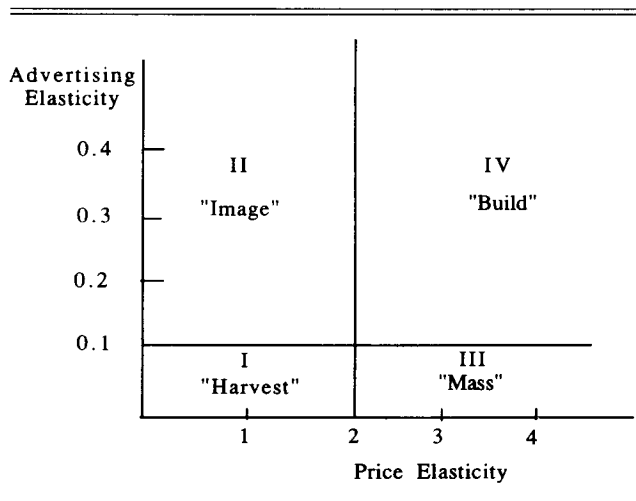
Illustration

To illustrate the price change and advertising change scenarios, we consider an example in the normal range of firms' operation: $k = .5, f = .6, g = .6, A/S = .05$ (5%).² The breakeven elasticities (from results 1 and 2) are $\epsilon^*_p = 2$ and $\epsilon^*_A = .1$. Figure 1 is a plot of price elasticity on the x axis and advertising elasticity on the y axis to show the regions under which different price and advertising strategies should be adopted.

In region I ($\epsilon_p < 2, \epsilon_A > .1$), the market is neither very price elastic nor advertising elastic. This situation could occur in well-established niche markets or markets in the decline stage of the life cycle (Kotler 1988). In these markets, consumers have well-set preferences and

²Though arbitrarily chosen for illustration, these values appear reasonable on the basis of scattered empirical studies. The value of the A/S ratio has been chosen from the normal range of 0–15% observed in the market. The value of pass-through, g , has been chosen on the basis of the Chevalier and Curhan (1976, p. 31) study showing that when retailers do pass through part of the deal, they pass through about 60–80%. There are no direct measures of f , but estimates from related research (Bawa and Shoemaker 1987; Bucklin and Lattin 1990) suggest a value of .6. Contribution ratio (k) is a firm-level accounting measure that we assume to be .5 because of lack of data.

Figure 1
REGIONS OF PRICE-ADVERTISING ELASTICITIES AND RELEVANT STRATEGIES^a



^aAssumptions: $k = .5, f = .6, A/S = .05$.

are neither swayed by price nor persuaded by advertising. Examples include Cutex nail polish, Gillette double-edged razor blades, and Cuticura face powder. In these markets, firms should neither discount prices nor increase advertising, but "harvest" their brands to maximize profits (Day 1984, p. 115).

In region II ($\epsilon_p < 2$, $\epsilon_A < .1$), the market is more advertising elastic than price elastic. This situation applies to image products such as cosmetics, new products, and luxury goods. For new products, consumers are influenced more by advertising that contains information than by price discounts (Nagle 1987). For image products and luxury goods, consumers respond more to advertising that promotes a distinct image or portrays an image of prestige than to price discounts. Thus, for both of these classes of goods, firms should spend relatively more on advertising than on price discounts.

In region III ($\epsilon_p > 2$, $\epsilon_A < .1$), the market is more price elastic and less advertising elastic; several mass or generic products, particularly in the frequently purchased mature consumer goods market, belong here (Kotler 1988; Stern 1966). Consumers are well informed about the various brands on the market, and the lack of real product differentiation causes them to switch on the basis of price. In such markets, to increase profits, a firm should spend more on price discounts than on advertising.

In region IV ($\epsilon_p > 2$, $\epsilon_A > .1$), the market is both price elastic and advertising elastic. Consumers are influenced by persuasive advertising that provides attribute information, but the availability of several competing brands and extensive market information enables them to shop around for a good price. Differentiable goods (e.g., cereals, home furniture) and goods with seasonal sales (e.g., winter clothes, toys) tend to be in this region. Here, a firm can "build" sales and raise profits through both an advertising increase and/or a price discount. This region is of great interest to marketers, who often wonder which strategy to adopt and what the tradeoff is. We provide a precise formula for the tradeoff.

Price-Advertising Tradeoff

One way to understand the tradeoff is to determine what advertising increase (ΔA) would yield the same profits as a given price discount (Δp). To assess the profit-equivalent strategies, we equate the two profits and set $\Pi_1 = \Pi_2$ or $\Delta\Pi_1 = \Delta\Pi_2$:

$$(8) \quad pq(\Delta p/p)(k\epsilon_p - f/g) = pq(\Delta A/A)(k\epsilon_A - A/S).$$

Rearranging equation 8, we have

$$(9) \quad \frac{\Delta A/A}{\Delta p/p} = \frac{\Delta'A}{\Delta'p} = \frac{k\epsilon_p - f/g}{k\epsilon_A - A/S},$$

where $\Delta'A$ and $\Delta'p$ are the fractional (or percentage) advertising and price changes, respectively. If $\Delta'p = 1$, the expression on the right side gives the percentage increase in advertising necessary to match the profits from

a 1% price cut given to the consumer. Result 3 states how this tradeoff is related to the ratio of elasticities.

Result 3: The percentage advertising increase ($\Delta'A$) necessary to match the profits from a 1% price cut is greater than, equal to, or less than the ratio of elasticities when the modified price elasticity is greater than, equal to, or less than the modified advertising elasticity, respectively.

That is,

$$\Delta'A > \epsilon_p/\epsilon_A \text{ when } \epsilon'_p > \epsilon'_A \text{ or } \epsilon_p/\epsilon_A > (f/g)/(A/S),$$

$$\Delta'A = \epsilon_p/\epsilon_A \text{ when } \epsilon'_p = \epsilon'_A \text{ or } \epsilon_p/\epsilon_A = (f/g)/(A/S),$$

and

$$\Delta'A < \epsilon_p/\epsilon_A \text{ when } \epsilon'_p < \epsilon'_A \text{ or } \epsilon_p/\epsilon_A < (f/g)/(A/S).$$

The proof is obtained by simply substituting $A/S = f\epsilon_A/g\epsilon_p$ in equation 9.

If price elasticity is larger or advertising elasticity is smaller, the ratio is larger and hence (*ceteris paribus*) more advertising is necessary to match a price discount. The impact of the ratio is modified by the f , g , and A/S ratios. If the fraction of original demand bought at the regular price (f) is lower and the pass-through (g) higher, f/g is smaller. Hence it is more likely that the elasticity ratio is larger than the right side $[(f/g)/(A/S)]$ and so the advertising increase required to match a 1% price discount is higher than the elasticity ratio. That is, a substantial amount of advertising is necessary to match the profits from a price discount. Similarly, if the firm's A/S ratio is higher, more advertising is necessary to match a price cut.

Extension to Oligopoly

Models of competitive behavior in oligopolistic markets can be classified broadly according to the assumptions made about industry demand (stable or expandable) and competitive behavior (competitive reaction included or excluded). Appendix 1 or Sethuraman and Tellis (1990) extends the analysis to these models.³ First, we analyze models that assume stable industry demand and do not incorporate competitive reaction. Most empirical response models, and all the models we subsequently meta-analyze, belong in this category. Then we analyze models that allow for expandable industry demand and include competitive reaction. In both cases, the basic results remain unchanged.

Summary and Implications of Profitability Analysis

We have identified the conditions under which a firm should price discount (through trade deal) or increase advertising in the short term. When conditions are favor-

³We do not analyze game theoretic models or models with conjectures and leader-follower reactions. Empirical models of this nature are very few and such models are beyond the scope of our article.

able for both a price discount and an advertising increase, managers face a difficult choice between the two options. We show that the price-advertising tradeoff depends crucially on the ratio of price and advertising elasticities and also on the fraction (f) of regular price demand served at the discount price, the retail pass-through ratio (g), and the A/S ratio. Though knowledge of all these factors is essential for making price-advertising decisions, the importance of the elasticity ratio necessitates an empirical assessment of the magnitude of the ratio and an understanding of how the ratio varies across market factors.

Several studies have provided estimates of price and advertising elasticities. Tellis (1988a) meta-analyzed 367 price elasticities and Assmus, Farley, and Lehmann (1984) meta-analyzed 128 advertising elasticities and provided an integration of the studies. However, these authors did not directly address the ratio of the two elasticities. Because of the different samples of the two meta-analyses and because the price and advertising elasticities were from different models, a post-fact computation of the elasticity ratio from the two meta-analyses is inappropriate. We need a separate meta-analysis of the elasticity ratio when both price and advertising elasticities are from the same model. The availability of several published studies with estimates of both price and advertising elasticities makes such a meta-analysis possible. We first develop the hypotheses that relate the elasticity ratio to various factors. Then we present the design and results of the empirical analysis.

HYPOTHESES

The relationship of the elasticity ratio to various marketing, environmental, and method factors depends on the relationship of the individual components—price elasticity and advertising elasticity—to those factors. Our hypotheses are based on marketing and economic theory and the work of Assmus, Farley, and Lehmann (1984) and Tellis (1988a).

Life Cycle

Mickwitz (1959) speculated that price elasticity increases over the first three stages of the life cycle (introduction, growth, and maturity). Lambin (1970) and Kotler (1971) concurred with this argument. There are many reasons for the increase in price elasticity over the cycle. First, consumers are likely to be better informed about products as the products mature. This increased knowledge about the brands, especially their availability, prices, and discounts, makes consumers more price conscious. Second, consumers in the early life cycle (early adopters) are likely to be less price sensitive than later entrants because of their focus on novelty and not economy (Nagle 1987, p. 137; Rogers 1983). Third, because competition is more intense in the mature stage, consumers will be better able to shop around for a good price (Kotler 1988).

Several empirical studies have found evidence of an

increase in price elasticity over time. Liu and Hanssens (1981), using data for inexpensive gift goods, found that price elasticity increases slightly over time. Tellis (1988a), in his meta-analysis of several price elasticity studies, found that the price elasticity is higher for mature products than for products in the early part of the life cycle. In contrast, Lilien and Yoon (1988), using data on industrial chemicals, found that price elasticity decreases over time. They attribute their findings to faster diffusion of the economic benefits of the new product and increasing price trend. Theoretical and empirical evidence, however, seems predominantly to support the idea of a higher price elasticity for mature products.

Advertising elasticity may be higher during the introductory stage for several reasons. In this stage, consumers actively seek information about product attributes and therefore are influenced by informative advertisements. Advertising creates awareness and interest. In addition, a significant number of new customers are brought in as triers (Assmus, Farley, and Lehmann 1984). In the mature stage, most consumers have had considerable experience with the product and have a fairly well-defined preference structure. Hence informative advertising is not very relevant and advertising with puffery has relatively less effect. Assmus, Farley, and Lehmann (1984) and Parsons (1975) find advertising elasticity to be lower in the mature stage.

H₁: Because price elasticity is higher and advertising elasticity is lower, the elasticity ratio is likely to be *higher* in the mature stage of the brand life cycle than in the early stage.

Product Type: Durable Versus Nondurable

Durable goods tend to be higher-unit-cost items that are often complex and difficult for buyers to evaluate. Because of the greater risk inherent in a wrong choice, the purchaser often is willing to pay a premium for ensured/perceived quality. Nondurable goods are generally frequently purchased, low-unit-price items. The risk in buying from a less well known supplier is not high and the purchasers can feel free to shop around for a good price (Buzzell, Gale, and Sultan 1975). Hence, price elasticity is likely to be higher for nondurable goods.

The advertising elasticity for different products varies according to information needs. For durable products, because of the long-term effects of the choice, consumers are likely to seek extensive information from several sources (including advertisements) before purchase. Hence advertising elasticity is likely to be relatively high. For frequently purchased nondurable products, because experience is not costly, consumers are likely to learn from their own or others' experience. Hence advertising elasticity is relatively low. Assmus, Farley, and Lehmann (1984) found that the advertising elasticity was higher for durable than for nondurable products.

H₂: Because price elasticity is lower and advertising elasticity is higher, the elasticity ratio is likely to be *lower* for durable goods than for nondurable goods.

Data Interval (Level of Temporal Aggregation)

Consumers exhibit price sensitivity by responding to price changes at specific times or purchase occasions. Price change therefore is likely to stimulate brand switching within a very short time frame, and temporal aggregation would mask the instantaneous price response. Hence price elasticity is likely to be higher when data are not aggregated (weekly or monthly) than when data are aggregated (bimonthly, quarterly, yearly).

In general, advertising does not translate into instantaneous sales. According to Clarke (1976), 90% of the cumulative effect of advertising for mature, frequently purchased products occurs in six to nine months. Hence the advertising elasticity is likely to be larger for intermediate and possibly higher levels of temporal aggregation (quarterly and yearly) and smaller for lower (less than monthly) levels of temporal aggregation. In addition, there are aggregation biases in the econometric estimates, the direction of which is not clear.

H₃: The elasticity ratio is likely to be *larger* at lower levels of temporal aggregation and *smaller* at higher levels of temporal aggregation.

Measure of Sales

Sales can be measured as absolute volume (dollars or units) or as relative volume (market shares). Absolute sales volume indicates both competitive gains and primary market expansion; market share indicates only competitive gains. Because in most cases primary demand effects are weak, price elasticity may be higher on average for share elasticities than for sales volume elasticities (Tellis 1988a). Advertising elasticity is likely to be higher when absolute sales are recorded because advertising can increase primary demand (Assmus, Farley, and Lehmann 1984).

H₄: The elasticity ratio is likely to be *higher* for share elasticities than for absolute volume elasticities.

Measure of Price and Advertising

Prices could be measured in *absolute* terms (as seen by the consumer) or in *relative* terms, that is, scaled in some way by competitors' prices (as consumers probably process prices). The price elasticity should be higher if the price variable is defined in relation to competitors because in brand choice contexts, consumers are likely to respond to relative rather than absolute price (Monroe and Petroschius 1981). For example, a decrease in price may not lead to a gain in sales if competitors also decrease prices in that period. In general, failure to account for competitive price would lead to weaker (lower) price effects. The price measure is unlikely to affect the advertising elasticity. Hence,

H₅: The elasticity ratio is likely to be *higher* when relative price is used.

Advertising share does not indicate advertising volume increase, an important factor influencing purchase

behavior. On average, advertising share elasticities are likely to be smaller than advertising volume elasticities (Assmus, Farley, and Lehmann 1984).

H₆: The elasticity ratio is likely to be *higher* when advertising is measured in relative terms.

Omission of Lagged Variables

The omission of a relevant variable biases the price (or advertising) elasticity when the omitted variable is related significantly to (current) sales and price (or advertising). The direction and sign of the bias is the product of the signs of the correlations of the omitted variable with sales and price (or advertising) (Kmenta 1986, p. 443-6).

Lagged sales should be related positively to current period sales because of consumer inertia or loyalty, and they should be related positively to current price because managers usually decrease (increase) price when previous period sales are low (high). Hence, omission of lagged sales would positively bias the price elasticity (Tellis 1988a). In other words, because price elasticity is negative, omission of lagged sales would decrease the magnitude of price elasticity.

Omission of lagged sales would positively bias (or increase) the advertising elasticity. Lagged sales are likely to be correlated positively with both current period sales (explained previously) and current period advertising (as current advertising budgets often are determined as a proportion of past sales).

H₇: Because omission of lagged sales produces systematically lower price elasticity (in magnitude) and higher advertising elasticity, the elasticity ratio would be *lower* when lagged sales are omitted.

Because of ambiguity of the signs of correlations of lagged price and lagged advertising with current sales, price, and advertising, and their possible interaction with level of aggregation, no hypotheses are developed about the effect of omission of lagged price and lagged advertising on the elasticity ratio.

Other Variables

We coded the studies on nine other variables (indicated in Table 1). As we do not have specific hypotheses about the effect of these variables on the elasticity ratio, we report only the significant results.

DESIGN FOR THE EMPIRICAL ANALYSIS

This section describes the selection of studies, the data, and the method of testing the hypotheses.

Selection of Studies

We performed an extensive literature search of leading marketing, business, and economic journals published during the period 1960-1988. Because we were simultaneously comparing price and advertising elasticities, we reviewed only studies in which both elasticities were estimated in one model. The 16 studies that met this

Table 1
DESCRIPTIVE STATISTICS BY GROUPS

Category	Class	N	Mean ratio	s.d. ratio	Median ratio	Mean price elasticity	Mean advertising elasticity
Total	Overall	260	389.3	3042.1	19.5	-1.61	.11
Product type	Durable	43	18.8	29.8	5.5	-2.01	.23
	Nondurable	217	462.7	3326.3	25.7	-1.54	.09
PLC	Early	45	15.6	201.0	17.7	-1.10	.11
	Mature	215	467.6	3340.0	22.2	-1.72	.11
Data interval	≤monthly	135	551.7	3916.0	17.9	-1.45	.08
	Bimonthly and quarterly	41	587.1	2853.0	36.3	-1.56	.04
	Yearly	84	31.9	39.3	9.6	-1.92	.19
Lag sales	Omitted	127	523.1	4027.5	11.6	-1.63	.15
	Included	133	261.6	1625.4	28.8	-1.60	.07
Lag price	Omitted	233	185.3	1352.7	17.7	-1.48	.11
	Included	27	2150.7	8501.0	43.9	-2.86	.08
Lag advertising	Omitted	182	247.7	1520.9	27.7	-1.70	.11
	Included	78	719.9	5053.1	13.6	-1.42	.13
Sales measure	Relative	193	515.2	3523.0	17.7	-1.52	.09
	Absolute	67	26.6	177.1	31.9	-1.90	.15
Price measure	Relative	171	228.3	1538.5	25.7	-1.74	.11
	Absolute	89	698.7	4745.4	13.1	-1.37	.11
Advertising measure	Relative	132	226.2	1717.6	16.7	-1.66	.13
	Absolute	128	557.6	3971.7	26.4	-1.57	.09
Quality	Omitted	221	459.5	329.5	23.0	-1.52	.09
	Included	39	-8.2	181.1	8.9	-2.09	.25
Promotion	Omitted	251	401.2	3095.6	17.9	-1.58	.11
	Included	9	59.3	37.7	45.7	-2.46	.05
Distribution	Omitted	203	381	3199.1	23.6	-1.81	.11
	Included	57	419	2425.9	5.4	-0.88	.11
Other variables	Omitted	205	488.8	3419.5	17.7	-1.61	.11
	Included	55	18.8	194.3	31.9	-1.60	.10
National setting	USA	107	168	910.1	19.5	-1.38	.09
	Europe	101	9.5	147.1	6.2	-1.51	.17
	Other	52	1582.7	6587.5	70.4	-2.27	.04
Estimation method	OLS	119	520.6	4089.4	19.5	-1.82	.12
	GLS	112	261.6	1778.8	16.7	-1.15	.09
	TSLS + MLE	29	343.9	1563.9	53.5	-2.51	.12
Data type	Time series	91	242.5	1930.3	13.5	-1.63	.11
	Cross-sectional	169	468.4	3500.5	23.0	-1.60	.11
Advertising type	Print	48	2.5	176.5	3.5	-1.14	.13
	TV	64	1401.3	5957.0	59.6	-1.46	.03
	Aggregate	148	77.3	703.8	15.7	-1.83	.14
Functional form	Multiplicative	42	1681.5	6942.7	13.7	-1.46	.05
	Other	218	140.4	1246.4	22.8	-1.64	.12

standard were those of Bemmaor (1984), Brodie and de Kluyver (1984), Carpenter et al. (1988), Cowling and Cubbin (1971), Ghosh, Neslin, and Shoemaker (1984), Houston and Weiss (1974), Jeuland (1979), Kuehn, McGuire, and Weiss (1966), Lambin (1970, 1976), Metwally (1974), Moriarty (1975), Sexton (1970), Weiss (1968), Wildt (1974), and Wittink (1977). Nine of these studies were reported in the *Journal of Marketing Research*.

Several studies used multiple datasets, each of which in turn covered different markets and brands. Thus the 16 studies had a total of 61 independent databases covering more than 130 separate brands or markets. Some studies had estimates for multiple models that differed by life cycle stage, estimation method, geographic re-

gion, and other factors. Following Assmus, Farley, and Lehmann (1984), Farley and Lehmann (1986), and Tellis (1988a), we considered each estimate an observation. This rule yielded a total of 262 observations from more than 130 separate brands/markets. Though multiple estimates for the same brand/market are not independent because they differ by only one factor, they provide a strong test of the importance of that factor. Subsequently, we discuss the tradeoff between replication and independence.

Description of Elasticities

Economic and marketing theory suggests that the price elasticity should be negative and that the advertising elasticity should be positive and less than one. This as-

sertion is based on the premise that demand (sales) will decrease with price, and increase with advertising at a decreasing rate, in the economic region of a firm's operation. Most observations have elasticity measures in the expected direction (i.e., negative price elasticity and positive advertising elasticity). However, several elasticity measures have unexpected (or perverse) signs and one observation has advertising elasticity greater than one.

Price elasticity	Advertising elasticity		
	(+)	(-)	(0)
(-)	217	21	4
(+)	16	2	0
(0)	2	0	0

The dependent variable of interest is the ratio of elasticities ($-$ price elasticity/advertising elasticity). In general, this ratio will be a positive number. The higher this number, the higher the price effect in relation to the advertising effect. When the advertising elasticity is zero this ratio will become infinity. To avoid this occurrence, we set the advertising elasticity to .0001 in such cases. When either price elasticity is positive or advertising elasticity is negative, the ratio is a negative number (has a perverse sign). Nevertheless, these observations are valid with potentially important information and we retain them. Two observations that have both a positive price elasticity and a negative advertising elasticity (perverse signs) yield a positive ratio value indistinguishable from that of observations that have the right signs. Deletion of these observations left a total of 260 for computing the descriptive statistics (see Table 1).

The elasticity ratio ranges from -1321 to 41800 . The large values occur because several advertising elasticities (denominator) are close to zero (of the order of .001). The mean and the standard deviation are also large. Because the distribution of the ratio is highly skewed, with large positive and negative values, we conclude that (1) the median is a better measure of central location than the mean and (2) to test the hypotheses, we need to transform the raw data as explained in the method section.

Method of Testing Hypotheses

The dependent variable (ratio of elasticities) is continuous and the independent variables are categorical. We used OLS dummy variable regression (analysis of variance) to test the hypotheses. The independent variables were dummy coded, and the coefficient from the regression equation reflects the difference in the mean ratio between the hypothesized level of the variable (e.g., nondurable) and the base level (durable). We used a one-tailed t -test to assess whether this difference is in the hypothesized direction and is significantly different from zero at the 95% confidence level ($p = .05$). Where the direction is not specified, a two-tailed t -test was used.

Because the raw data indicated large means associated with large standard deviations, and a skewed distribu-

tion, we used the logarithmic transformation (Dixon and Massey 1969). Perverse signs produce negative ratio values, however, for which the logarithmic transformation is not possible. To overcome this problem, we set all positive price elasticity values to $-.0001$ and all negative advertising elasticity values to $.0001$, producing positive ratio values for all 262 observations. We might also have deleted the observations with perverse signs, but would have lost useful information.

The method we used for testing the hypotheses has some limitations. The censoring of the data, the choice of transformation, the shared variance, and the collinearity among the independent variables may produce spurious results. We subsequently discuss these limitations and assess their impact on the results. Because of these potential problems, we supplemented the regression analysis with some univariate tests. In the first we used the raw data; we performed an extended test of the median using the Kolmogorov-Smirnov D -test and the chi square test (Dixon and Massey 1969). The second supplementary test we performed was the univariate test of the mean using the log-transformed ratio data.

RESULTS AND DISCUSSION

We discuss the results of the empirical analysis in three parts: descriptive statistics, regression results, and test of biases.

Descriptive Statistics

The average price elasticity of the 260 observations is -1.609 , close to the value (-1.76) obtained by Tellis (1988a). The average short-term advertising elasticity is .109, which corresponds closely to the findings of Lambin (1976) and Leone and Schultz (1980). Lambin found the average short-term elasticity of 40 significant advertising coefficients to be .101, with more than 60% of the coefficients less than .1 ($p = .98$). Leone and Schultz, summarizing previous studies, stated that the advertising elasticity ranged from .003 to .482, with most elasticities being below .2. Our estimate is much lower, however, than the value (.221) obtained by Assmus, Farley, and Lehmann (1984). This discrepancy may be due to the difference in the samples. The ratio of the mean price elasticity and the mean advertising elasticity is 14.62.

The descriptive statistics of the elasticity ratio variable (Table 1) indicate large means and large standard deviations. The median measure of central location is 19.5. We can say, then, summarizing published studies, that on average the price elasticity is about 20 times the advertising elasticity. This value is higher than the estimate of 8 reported by Tellis (1988a). Lambin (1976) found the ratio to range from 7 to 80.

Regression Results

The regression estimates and the level of significance are reported in Table 2. The R^2 is 19.8% ($F = 2.55$, $p = .00$). This figure, though lower, compares favorably with those from prior meta-analyses—Tellis (1988a) 28%,

Table 2
MEANS AND REGRESSION RESULTS (log of ratio)

Category	Class	Mean	s.d.	Expected sign	Regression results		
					Coefficient	t-statistic	Significance
Product	Nondurable	3.4	3.7	+	.27	.22	.82
	Durable	2.2	1.7				
PLC	Early	2.1	4.8	-	-2.62	-2.46	.01
	Mature	3.4	3.2				
Data interval	≤ monthly	3.4	3.7	+	4.64	3.5	.00
	Bimonthly and quarterly	4.1	4.0	+	2.84	2.56	.01
	Yearly	2.2	2.6				
Lag sales	Omitted	2.5	4.2	-	-.82	-.16	.12
	Included	3.7	2.6				
Lag price	Omitted	3.0	3.6	0*	.58	.48	.63
	Included	4.5	2.5				
Lag advertising	Omitted	3.2	3.4	0	1.63	2.02	.05
	Included	3.1	3.7				
Sales measure	Relative	3.3	3.7	+	-.36	-.72	.84
	Absolute	2.8	3.0				
Price measure	Relative	3.4	3.1	+	-.49	-.53	.59
	Absolute	2.7	4.2				
Advertising measure	Relative	2.9	3.4	+	.34	.46	.65
	Absolute	3.4	3.7				
Quality	Omitted	3.3	3.7	0	-1.96	-1.99	.05
	Included	2.3	2.4				
Promotion	Omitted	3.1	3.6	0	-1.75	-1.00	.32
	Included	3.9	0.6				
Distribution	Omitted	3.4	3.4	0	1.5	1.91	.06
	Included	2.4	3.8				
Other variables	Omitted	3.2	3.4	0	.07	.08	.94
	Included	3.0	4.0				
National setting	USA	3.3	3.4	0	-4.45	-3.01	.00
	Europe	2.3	3.8	0	-2.28	-2.14	.03
	Other	4.6	2.7				
Estimation method	OLS	2.9	3.4	0	-.16	-.17	.86
	GLS	3.5	3.6	0	.46	.44	.66
	TSLS + MLE	3.0	3.3				
Data type	Time series	3.0	4.2	0	.00	.00	.99
	Cross-sectional	3.2	3.1				
Advertising type	Print	2.8	3.1	0	2.85	3.42	.00
	TV	4.6	2.8	0	.32	.33	.74
	Aggregate	2.7	3.8				
Functional form	Multiplicative	3.5	4.8	0	-1.0	-1.11	.27
	Other	3.1	3.2				

*Hypotheses not developed for these variables.

Assmus, Farley, and Lehmann (1984) 36%, Farley, Lehmann, and Ryan (1982) 34%. The lower value probably occurs because our dependent variable is the ratio of two elasticities and the resulting variance in the data is much higher. Among the variables for which hypotheses were developed, life cycle and data interval have a significant impact on the ratio of elasticities. In addition, the univariate tests suggest that the product type and omission of lagged sales are significant determinants of the ratio. We now discuss the results and implications for each of the hypothesized market characteristics.

Product type. The mean and median of the elasticity ratio are significantly higher for nondurable goods than for durable goods. For nondurable goods, the price elasticity is "on average" 25 times larger than the advertising

elasticity. For durable goods, the price elasticity is only about five times the advertising elasticity. However, the difference in means is not found to be significant in the regression context, perhaps because of problems of censoring and multicollinearity discussed subsequently.

The relatively higher elasticity ratio for nondurable goods seems to stem primarily from differences in advertising elasticities. The mean price elasticities (Table 1) of durable goods and nondurable goods are not significantly different, but the mean advertising elasticity is considerably lower for nondurable goods.

Given these average elasticity ratios, the decision to reduce price or increase advertising also depends on values of the other variables, k , A/S , and in particular the loss ratio, f/g . To illustrate, we consider a reasonable

case, $k = .5$, $A/S = .05$, $\epsilon_p = 3$. The percentage advertising increase ($\Delta'A$) necessary to match the profits from a 1% price discount and the optimal A/S ratio follow for various values of f/g .

f/g	$\Delta'A$ (%)		Optimum A/S (%)	
	Nondurable goods	Durable goods	Nondurable goods	Durable goods
.5	100	4	2	10
1.0	50	2	4	20
1.4	10	.4	5.6	28
2.0	discount not profitable		8	40

On average, g appears to be about .6 (Chevalier and Curhan 1976). Preliminary estimates based on related research (Bawa and Shoemaker 1987; Bucklin and Lattin 1990) suggest that the values of f may be about .3 to .6. Hence, the average loss ratio (f/g) is likely to be about .5 to 1.5. The following implications can be drawn from our findings.

1. For nondurable goods, when both price cut and advertising increase are profitable, price discounting appears to be a relatively more profitable option than an advertising increase.
2. In contrast, for durable goods, when both price discounting and advertising are profitable, neither of them is clearly superior.
3. Given that the elasticity ratio is 25 and that the advertising elasticity is low, our result implies that perhaps the actual industry A/S ratio (7–11%) for nondurable goods (Table 3) is higher than optimum. Further, in some firms and industries, A/S has increased over the years. Our analysis supports the contention of Aaker and Carman (1982) that a substantial amount of advertising for frequently purchased consumer brands today may represent "overadvertising," advertising under conditions of saturation.
4. For durable goods, the actual A/S ratio (Table 3) suggests that firms are not advertising as much as they should. This discrepancy can be partially explained as follows. The advertising in our model can be interpreted as any nonprice promotional expenditure that does not depend on quantity sold (enters as a fixed cost). For durable products particularly, advertising must be supplemented by other forms of nonprice support such as technical assistance and salesforce support. If these costs are included, the discrepancy may not be very high. Alternatively, f/g may be lower than assumed values.

However, these implications are tentative, and further knowledge of f and g would enable us to draw more precise conclusions about the tradeoff between advertising and price discount.

Life cycle. Of the 262 observations, 212 were for brands in the mature stage of the life cycle, five were for brands in the decline stage, 45 were for brands in the growth stage, and none were for brands in the introductory stage of the life cycle. Because of this unbalanced distribution, we merged observations in the de-

Table 3
ADVERTISING-TO-SALES RATIOS^a

Industry	1982	1985	1989	
<i>Nondurable goods</i>				
Food and kindred products	4.2	5.2	7.8	
Meat products	3.1	1.7		
Dairy products	4.3	5.1	4.7	
Canned preserved fruit/vegetables	4.8	5.3	6.9	
Prepared feed for animals	7.8	8.9		
Bakery products	1.7	1.5	1.7	
Candy and confectionery	6.1	6.5	10.6	
Malt beverages	7.0	8.4	8.4	
Distilled beverages	7.9	7.2	9.5	
Soft drinks	5.7	6.6	7.4	
Soap and detergents	6.8	7.9	7.7	
Perfume and toiletries	8.4	13.1	10.4	
<i>Durable goods</i>				
Apparel/clothing	2.8	2.3	2.9	
Wood products	.3	.3	1.8	
Household furniture	1.7	2.6	4.8	
Radio, TV	4.0	2.4	2.8	
Phonograph records	13.0	9.1	8.3	
Watches	2.1	1.6		
Musical instruments	2.4	3.9		
Toys	10.5	10.0	14.2	
Pens and office supplies	5.9	5.3	5.4	
Firms	1984	1985	1986	1987
Borden Dairy	2.4	1.7	1.99	1.6
Campbell Soup	6.7	6.4	5.83	6.33
CPC International	6.9	6.8	7.25	7.21
Heinz	8.6	9.5	7.86	8.03
Kellogg	17.1	17.6	16.37	21.05
Kraft	6.7	6.7	8.12	5.31
Pillsbury	10.1	8.8	8.99	8.86
RJR Nabisco	11.6	8.7	7.89	7.17
United Biscuits	7.4	5.8	5.46	6.81
Colgate-Palmolive	12.8	11.7	11.34	11.25
Procter & Gamble	15.3	15.6	12.71	11.17
Unilever	11.1	9.9	12.20	10.09

^aSource: *Advertising Age*.

cline and mature stages and called the category the "late" stage of the life cycle. In contrast, we called the observations in the growth stage the "early" stage of the life cycle.

Products in the early stage of the life cycle have a median elasticity ratio of 17.7 and mature products have a median ratio of 22.2. After we account for all other factors, the ratio of price elasticity to advertising elasticity is significantly lower for products in the early life cycle stage (by -2.62 in log terms) than for mature products. This finding confirms the traditional marketing belief that mature products have higher price elasticity in relation to advertising elasticity. The higher elasticity ratio seems to be driven more by differences in price elasticity than by differences in advertising elasticity. The mean price elasticity is significantly higher for mature products than for products in the early stage. The im-

plication is that price discount may be more profitable than advertising for mature products.

Temporal aggregation. The ratio of elasticities is significantly smaller for yearly data than for quarterly and weekly data, as hypothesized. For many durable and most nondurable goods, retailers offer temporary price discounts for a duration of one or more weeks; thus the effective price usually fluctuates on a weekly basis. As data are aggregated above the weekly level, they are less likely to capture variation due to price changes. However, the differences in the ratio seem to arise more from differences in advertising elasticity. Advertising remains constant for a longer period and the effect of advertising is shown only in three to nine months. Hence the advertising elasticities are typically larger and the ratio is smaller in the yearly data. This finding raises a question about the appropriate level of aggregation for comparing the price/advertising impacts. This econometric question awaits more theoretical and empirical work.

Omission of lagged sales. Omission of lagged sales did not have a significant impact on the elasticity ratio in the regression analysis, perhaps because of problems of multicollinearity. Univariate tests showed that the ratio is significantly lower when lagged sales are omitted, as hypothesized. This finding implies that models estimating price and advertising elasticities should include lagged sales as an explanatory variable.

Variable measures (absolute vs. relative). Measures of sales, price, and advertising did not turn out to be significant in the regression analysis or in the univariate tests. The surprising result is that the share elasticities are not different from sales volume elasticities. Most of the studies that analyzed market share (relative sales) models also included relative price and relative advertising. Hence, because of multicollinearity and inseparability of these effects, the individual coefficients may have turned out to be insignificant. Another possibility is that these effects cancelled out. For instance, if the relative sales measure increased the estimated elasticity ratio and the relative price measure decreased it, the two opposing effects may have cancelled each other if they occurred jointly.

Other variables. Among other variables (for which hypotheses were not developed), omission of lagged advertising, omission of quality, national setting, and advertising type show significant results. Omission of lagged advertising and quality resulted in a significant downward bias of the estimated elasticity ratio, which underscores the need for their inclusion in econometric models. The United States and Europe have significantly lower elasticity ratios than other countries (mostly Australia). The elasticity ratio with print advertising is lower than the ratio computed when TV or aggregate advertising was used.

Tests of Regression Assumptions

The interstudy characteristics constitute a quasi-experimental design that has the problems of nonindependence of observations (error), multicollinearity, and heteroscedasticity. Further, the skewed nature of the data and the presence of large positive and negative ratio values necessitated censoring and logarithmic transformation of the data. These problems could compromise the findings. Appendix 2 of Sethuraman and Tellis (1990) assesses the extent of these problems and their impact on the findings. Here, we briefly state the results of the tests.

Nonindependence of observations occurs when two or more estimates that vary by only one of the method factors come from the same database. Nonindependence increases the strength of the natural design; it does not by itself bias the estimates, but aggravates the problem of heteroscedasticity. Farley and Lehmann (1986, p. 106) believe the problem of nonindependence of observations will not prove nearly as serious as the autocorrelation problems in econometric models using time-series data. Hunter and Schmidt (1990, p. 452) also point out that if the number of estimates contributed by each study is small in comparison with the total number of estimates, there is little error in resulting cumulation. In our case, 262 elasticities come from 132 independent brand/market studies (average of two estimates per study).

To account for lack of homogeneity of variances (heteroscedasticity), Hedges and Olkin (1985, p. 170) suggest reestimating the model by weighted least squares. The results of the regression model obtained by weighting the observations by their (estimated) standard errors (Kmenta 1986, 269–83) do not differ from the original results. To assess the effects of multiple counting, we ran another regression by weighting the observations by the number of replications. That is, if there were two observations from a single brand/market study, each of those observations was given a weight of .5. The regression results do not differ from the original results. In addition, visual inspection does not show high correlation among residuals from the same study. These findings indicate that, in our data, the results are fairly robust to violation of the assumption of independence.

Multicollinearity is present, but not severe. A jack-knife test of the stability of coefficients indicates that only the estimate of product type is sensitive (reverses in sign or increases in magnitude) to the exclusion of life cycle and data interval. The coefficient of life cycle remains stable throughout.

Data modifications such as the reciprocal transformation and the normal (z) transformation do not improve the model fit. These transformations lead to unstable results, as evidenced by low R^2 , high standard errors, and wrong signs of the coefficients. Analysis of observations with negative (perverse) ratio values indicates that no single variable is uniquely responsible for the perverse sign. Though the model fit (R^2) improves considerably when the 45 perverse observations are deleted, the substantiality and usefulness of the information lost render the deletion inappropriate. Deletion of extreme cases (ratio values above 1000 and below -100) does not obviate

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the need for logarithmic transformation and does not change the basic results.

CONCLUSION

Economists have long known the optimal price and advertising levels for certain types of competition (e.g., Dorfman and Steiner 1954). Actual price and advertising levels may not be close to the optimum because of tradition, uncertainty, or competitive pressures. In such scenarios, managers often can make only small changes in price and advertising levels, or they must allocate the marketing budget between price discounts and increases in advertising. We evaluated this tradeoff through theoretical and empirical analyses.

Theoretical Results

The theoretical analysis provides the following insights into the tradeoff between advertising and price discount.

1. Five key factors determine the profitability of a price discount and an advertising increase. Of these, the elasticity of price and advertising is a major factor. In contrast to past studies, ours incorporates two new factors into the analysis: the fraction, f , or regular-price demand bought at the discounted price and the retail pass-through ratio, g .
2. Precise formulas define when changes in price and advertising are profitable.
3. These formulas yield four key types of marketing strategies based on the levels of price and advertising elasticities: harvest, build, mass, and image (Figure 1). Some of these strategies are well known in the normative literature, but they have not been related formally to each other and to marketing investments.
4. In the "build" strategy, when price discount and advertising increase are profitable, the ratio of elasticities (in conjunction with other factors) plays a key role in the price-advertising tradeoff. Specifically, the amount of advertising necessary to match the profits from a 1% price cut increases with the ratio of elasticities, advertising-to-sales ratio, and pass-through ratio (g) and decreases with fraction of original demand (f) bought at the discounted price.

Empirical Analysis

Because price and advertising elasticities are central for evaluating changes in the two instruments, and because we have a large number of published estimates of the elasticities, we carried out a meta-analysis of the ratio of these estimates in the literature. The results of the meta-analysis provide some broad insights and help to evaluate better the relative worth of advertising and price cut. The key results from this analysis follow.

1. The price elasticity is "on average" 20 times the advertising elasticity.
2. The elasticity ratio is about 25 for nondurable goods, suggesting that for those products, a substantial amount of advertising may be necessary to match the profits obtainable from a 1% price discount. Our finding also suggests that the optimal advertising-sales ratio for nondur-

able products may be about 4–8%. The actual ratio is in general higher than this value and has been increasing in some industries. Our analysis therefore cautions managers against overadvertising, in the same spirit as the study by Aaker and Carman (1982). More research on f and g is required to address these issues fully.

3. The elasticity ratio is only 5 for durable goods, suggesting that price discount and advertising increase may be equally good options for increasing profits.
4. The ratio of elasticities is higher for mature products than for products in the early stage of the life cycle, confirming the traditional marketing thought that mature products are more responsive to price discounts. Both price discounting and advertising increase are probably profitable means of promoting products in the early life cycle stage.
5. The elasticity ratio is different for different levels of temporal aggregation, underscoring the importance of finding the appropriate data interval for estimating the ratio. Analysis at the most disaggregate level is appropriate for capturing price effects and increases the appeal of panel data.
6. Omission of lagged sales produces systematically lower ratio values, a finding that underscores the need to include lagged sales in models estimating elasticities.

Limitations

When interpreting these results, we must realize that the concept of elasticities is applicable only for small changes in decision variables and that our measures are only short-term elasticities. Advertising may have longer term effects, such as improving brand image and creating brand loyalty. Given these beneficial effects, our analysis suggests that advertising researchers must develop good copy and techniques to bolster the short-term impact of advertising, as was stressed in the debate reported by Lipman (1989a,b) in *The Wall Street Journal*.

The limitations of the empirical analysis arise primarily from the scope of the original studies. First, many of the original studies did not explicitly specify the product name, so we could not classify our observations into more precise categories than durable goods, frequently purchased goods, and so on. Further, because of having few observations, we had to collapse some classes (e.g., mature and decline stages were collapsed into late life cycle stage). Further, we did not include estimates from experiments and choice models because of their substantially different design and the small number of studies published within the time period sampled. Though the general thrust of the latter studies is consistent with our conclusions, the added observations would have enriched our analysis. Like other meta-analyses in the area, ours did not include unpublished studies such as conference proceedings, doctoral dissertations, and corporate reports. Similarly, we did not analyze higher order interaction effects among our independent variables, nor did we meta-analyze the effect of advertising on price elasticity, a topic on which there is a small but growing body of published studies.

Future Research

Though the limitations can be fruitful areas of future research, we believe the substantive issues uncovered in our analysis warrant further study. First, why does advertising for nondurable products have a relatively low current effect? Is it because of the high noise level, the overadvertising by individual brands, the repetition of old copy, or the lack of creativity? Second, what are the values of f and g for product markets today? Researchers generally have focused on estimating elasticities, so our knowledge of f and g is very limited. Third, how can firms ensure that price discounts to the trade are passed on to the consumers—through stricter contracts, better timing, or by going directly to those consumers? Fourth, how can price discounts and advertising be targeted only to consumers who are sensitive to the particular marketing instruments? The sophisticated scanner databases, which simultaneously track the actions of manufacturer, retailer, and the consumer at different levels of aggregation, provide rich sources of information for answering these questions. For example, segmentation analysis of household purchases on promotion could provide estimates of f .

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