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The author describes a meta-analysis of econometric studies that estimated the elasticity of selective sales or market share to price. The literature review yielded 367 suitable price elasticities from about 220 different brands/markets. The results indicate that the price elasticity is significantly negative and, in absolute value, eight times larger than the advertising elasticity obtained from a prior meta-analysis. The omission of distribution or quality, the use of only cross-sectional data, and temporal aggregation lead to severe biases in the estimates of price elasticity. The elasticity also differs significantly over the brand life cycle, product categories, estimation methods, and countries.

The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales

Over the last three decades researchers have reported a large number of econometric studies on the price sensitivity of selective demand. These studies usually were motivated by academic curiosity about consumers' price sensitivity or by managerial concern about appropriate price levels. Currently, the development of new estimation methods (e.g., Carpenter and Lehmann 1985; Guadagni and Little 1983; Krishnamurthi and Raj 1988; Tellis 1988b) and the debate about alternative functional forms (e.g., Brodie and de Kluyver 1984; Ghosh, Neslin, and Shoemaker 1984) suggest that the topic is still very relevant. As past studies used a variety of models and measures, in many time periods and environments, a summary of their findings would enhance our knowledge in the area.

This article describes a meta-analysis of these econometric studies in the spirit of similar works by Assmus, Farley, and Lehmann (1984) and to a lesser extent by Clarke (1976) and Leone and Schultz (1980). However, none of these three reviews addressed price sensitivity. Assmus and his coauthors meta-analyzed only estimates of advertising response models, Clarke analyzed estimates of only the duration of advertising's cumulative effect, and Leone and Schultz specifically excluded estimates of price sensitivity.

Meta-analysis provides a mean estimate of price sensitivity and explains its variation by interstudy differences. Meta-analysis is a systematic, "objective," efficient, and precise means of summarizing past results, but does not provide a final statement of truth on the issue (see discussions by Farley and Lehmann 1986; Hedges and Olkin 1985; Hunter, Schmidt, and Jackson 1982; Rosenthal 1984).

RESEARCH DESIGN

Definition of Terms

The term "selective demand" means demand for a particular firm's branded product, measured as its sales or market share, as opposed to "primary" or category demand. The term "brand" is used generically to cover the individual brand, business unit, or firm whose sales or market share is under investigation. Similarly, because market share is a definition of relative sales, the term "sales" refers to both market share and sales, but the analysis explicitly accounts for the difference. The term "price sensitivity" is a latent construct referring to the extent to which consumers vary their purchases of a product as its price changes. The term "price coefficient" is used generically to cover any estimate of price

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sensitivity by regressions of sales on price. It includes dimensionless estimates such as elasticities and those with dimensions that are dependent on the measures of price and sales. If s = sales and p = price, the elasticity of sales to price is defined as $(\delta s/\delta p) \cdot (p/s)$. We can easily show that the coefficient of the regression of s on p is the elasticity if we include the logarithms or percentage changes of s and p in the regression. If the original regression uses natural values of sales and price, the elasticity can be obtained by multiplying the coefficient of the regression by the ratio (mean of p/mean of s).

Selection of Studies

The review includes studies that provide unambiguous estimates of the main effect of a brand's, business', or firm's price on actual market sales or market share for the whole sample of observations under investigation. This definition of the scope excludes studies on the effect of price on primary demand, typically a subject of interest in the economics literature, as well as studies that use nonbehavioral criterion variables, such as attitudes or purchase intentions. It also excludes studies involving the use of overt intervention to elicit consumer response (e.g., laboratory experiments) because they elevate price consciousness. Finally, it excludes studies that provide estimates only by regional or demographic groups and not over the whole sample under investigation. Local or regional differences are not of general interest and demographic differences are infrequently reported.

The literature search covered the 1960–1985 period, which includes the start of the *Journal of Marketing Research,* the primary outlet for models estimating price sensitivity. The previous literature reviews indicate that almost all the studies were done after 1960. The search involved personal collection of papers, prior literature reviews, five relevant marketing journals, and nine relevant business and economic journals, in that order. The search was terminated when increasing efforts yielded few useful studies. A computer search of the ABI/Inform database yielded either too many or too few studies and was not successful. The results of the literature search indicate very clearly that the estimation of price sensitivity is of interest typically to marketers. For example, about 90% of the researchers were in marketing, about 80% of the articles appeared in marketing journals, and about 50% of the studies were reported in the *Journal of Marketing Research.*

Several of the selected studies involved multiple models that differed by product category, brand, life cycle, estimation method, functional form, region, and demographic groups. To enrich the natural design, all the estimates from the individual models were retained unless they differed by local regions or demographic groups. This approach yielded 424 models from 42 studies (Table 1). These models so not fully overlap with the 128 included by Assmus, Farley, and Lehmann (1984) because this review is more recent and focuses on price elasticity.

Dependent Variable

Three dependent variables warrant consideration: the estimated t-statistic, the price elasticity, and the price coefficient. (The latter two are not mutually exclusive by definition.) Though the t-statistic is units-free and has a known distribution, it does not provide direct information about consumer price sensitivity and therefore is not the best for meta-analysis. The price coefficient is more easily interpreted than the t-statistic, but it is sometimes dependent on the measures of sales and price used in the study and hence is not suitable for a meta-analysis across studies. The price elasticity is the ideal measure for the meta-analysis, being both units-free and easily interpreted; it represents the percentage change in sales for a 1% change in price. Accordingly, only those models that estimated elasticities, or provided enough data to calculate the elasticity, are used in the meta-analysis. The selection criteria reduced the set of elasticities to 367, which are from about 220 different brands or markets.

Under the assumption of rational and reasonably informed consumers, price elasticity should be negative. Because of the negative sign, the term "greater price sensitivity" correctly means a more negative price elasticity and "less price sensitivity" means less negative price elasticity. (The terms "higher" or "lower" and "bigger" or "smaller" elasticity cause confusion because either could apply, depending on absolute or actual elasticity). When differences in the estimated elasticities are due to errors in estimation (and not to environmental differences), they are called "*biases.*" If the estimate is *more positive* than the true value, it is a *positive bias*. The opposite holds for a more negative estimate.

Independent Variables

The logic of this meta-analysis is to pool estimates of usable price elasticities from sales response models reported in the literature and analyze the differences in elasticities by the characteristics that distinguish those models. Table 2 is a distribution of the elasticities from various models by model characteristics grouped into four categories: model specification, environmental characteristics, data characteristics, and estimation method. For nominal independent variables, only those levels of study characteristics having at least 15 observations are used; the rest are collapsed into broader categories or an "other" category. The model characteristics constitute the independent variables of the meta-analysis. Hypotheses about their potential effects on estimated elasticity follow.

HYPOTHESES

The hypotheses are based on an integration of marketing and econometric theory where available, or else on *ad hoc* reasoning. They are discussed in the order of variables in Table 2.

Model Specification

Model specification involves the problem of omitted variables and the model's functional form. The omission

Table 1
LIST OF STUDIES IN THE META-ANALYSIS[a]

Author	*Year*	*Usable estimates*	*Remarks*
Banks	1961	0	No elasticity available
Bass and Pilon	1980	2	
Bemmaor	1984	20	
Brodie and de Kluyver	1984	24	
Buzzell and Wiersema	1981	0	No elasticity available
Carpenter and Lehmann	1985	0	Multiple estimates
Cowling and Rayner	1970	10	
Cowling and Cubbin	1971	5	
Dalrymple	1968	3	
Gatignon	1984	0	No main effect reported
Ghosh, Neslin, and Shoemaker	1984	8	
Guadagni and Little	1983	8	
Houston and Weiss	1974	6	
Jacobson and Aaker	1985	0	No elasticity available
Jeuland	1980	18	
Krishnamurthi and Raj	1985	0	Estimates only by subsamples
Kuehn, McGuire, and Weiss	1966	1	
Lambin	1969	0	No elasticity available
Lambin	1970	3	
Lambin	1976	103	
Massy and Frank	1965	1	
McCann	1974	0	No elasticity available
Metwally	1974	24	
Moriarty	1975	3	
Moriarty	1985	0	No elasticity available
Phillips, Chang, and Buzzell	1983	0	No elasticity available
Prasad and Ring	1976	0	No main effect reported
Ratchford and Ford	1976	12	
Reibstein and Gatignon	1984	14	
Robinson and Fornell	1985	1	
Schultz	1971	2	
Sexton	1970	3	
Sexton	1974	0	No elasticity available
Simon	1979	74	
Stowsand and Wenzel	1979	1	
Telser	1962a	15	
Telser	1962b	0	Single estimates over BLCs
Varadarajan and Dillon	1981	0	No elasticity available
Weiss	1968	2	
Wildt	1974	3	
Wittink	1977	1	
Total	1961–1985	367	

[a]For references, see Tellis (1988a). This is a comprehensive list of only those studies included in the meta-analysis. A large number of studies were excluded for reasons cited in the text. Some of the latter are listed here as excluded lest readers think they were overlooked.

of a relevant variable from the model biases the estimated price elasticity only if the omitted variable is related significantly to both sales and price. The direction or sign of the bias is the product of the signs of the correlations of the omitted variable with sales and price (Kmenta 1986, p. 443–6).[1] This formula and knowledge of the relationship among the independent variables lead to strong hypotheses about the omission of quality, distribution, lagged market share, and lagged price; ambiguity about the relationship among the remaining variables leads to weak predictions about their omission.

[1]Following Kmenta (1986) and with usual notation we can show these results formally. Let

$$Y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \epsilon_i$$

be the true model, but we wrongly estimate

$$Y_i = \beta_1^* + \beta_2^* X_{2i} + \epsilon_i^*,$$

and let $f(r_{23})$ = some function $f(.)$ of the covariance between X_{2i} and X_{3i}. Then, by definition of the regression estimates, we can show that $\beta_2^* = \beta_2 + \beta_3 f(r_{23})$.

From this equation we get the following results. First, if the omitted variable (X_{3i}) is not related to the dependent variable ($\beta_3 = 0$), its omission does not bias β_2 and it is "irrelevant." Second, if the omitted variable is uncorrelated with the included independent variable ($r_{23} = 0$), its omission does not bias β_2. Third, if β_3 and r_{23} are of the same sign, the bias is positive; otherwise it is negative.

Table 2
DISTRIBUTION OF ESTIMATED ELASTICITIES BY MODEL CHARACTERISTICS

Model characteristics					
Variable class	*Variable*	*Scale*	*Level*	*Number of models: observations*	*Mean elasticity*
Model specification	Quality	Nominal	Included	68[a]	−2.10
			Omitted	299	−1.69
	Distribution	Nominal	Included	68[a]	−0.91
			Omitted	299	−1.96
	Advertising	Nominal	Included	208	−1.77
			Omitted	159	−1.75
	Promotion	Nominal	Included	19[b]	−2.32
			Omitted	348	−1.73
	Lagged price	Nominal	Included	19[b]	−2.65
			Omitted	348	−1.71
	Lagged sales	Nominal	Included	225	−1.81
			Omitted	142	−1.69
	Other variables	Nominal	Included	193	−1.66
			Omitted	174	−1.88
	Functional form	Nominal	Multiplicative	218	−1.97
			Attraction, choice	41	−1.03
			Additive	108	−1.62
Environmental characteristics	Categories	Nominal	Detergents	25	−2.77
			Durable goods	70	−2.03
			Food	127	−1.65
			Toiletries	48	−1.38
			Others	45	−2.26
			Pharmaceutical	52	−1.12
	National setting	Nominal	Europe	214	−1.62
			Australia/New Zealand	49	−2.07
			U.S.A.	104	−1.91
	Brand life cycle	Nominal	Introduction	18	−2.37
			Growth	106	−1.16
			Maturity	225	−1.98
			Decline	18	−2.01
Data characteristics	Sales measure	Nominal	Absolute	169	−1.73
			Relative	198	−1.79
	Reference frame	Nominal	Times series	213	−1.65
			Time series × cross section	137	−2.08
			Cross section	17	−0.60
	Temporal aggregation	Nominal	Biweekly or less	34	−2.24
			Monthly or more	333	−1.71
	Source	Nominal	Firm	213	−1.81
			Public	47	−1.52
			Panel	107	−1.78
	Price measure	Nominal	Absolute	102	−1.41
			Relative	265	−1.90
	No. observations	Ratio			
	No. cross sections	Ratio			
	No. parameters	Ratio			
Estimation method		Nominal	GLS	93	−1.29
			MLE + MSLS	47	−2.54
			OLS	227	−1.79
Total				337	−1.76

[a]These figures are identical by accident. Only 11 of these 68 observations overlap.
[b]These figures are identical by accident. Only 4 of these 19 observations overlap.

Omission of quality. If consumers are at least minimally informed about product quality, better quality firms would have higher market shares or higher prices. A review of the studies indicates that the coefficient of quality, when present, is positive. Numerous studies on price and quality indicate that the correlation coefficient, though weak, is positive on average (Tellis and Wernerfelt 1987). Because of this positive relationship of quality with price and market share, the omission of quality would bias the price elasticity positively.

Omission of distribution. Wider distribution tends to have a positive effect on sales (Leone and Schultz 1980). The relationship between price and distribution is not as well documented, though a recommended strategy is for high priced brands to have selective or exclusive distribution (Kotler 1984, p. 555). If firms follow this practice, the omission of distribution would negatively bias the price elasticity.

Omission of advertising. The meta-analysis of Assmus, Farley, and Lehmann (1984) shows that advertising has a positive impact on sales and market share. However, the literature is ambiguous about the relationship of advertising with price (Farris and Albion 1980). Some researchers (e.g., Comanor and Wilson 1974) suggest that advertising serves to differentiate products and thus enables firms to avoid price competition and to charge higher prices. Others have argued that advertised products may be higher priced because they provide consumers with information on products and reduce their search costs (Ehrlich and Fisher 1982; Fergusson 1982). If either of these arguments is true, advertising's omission would positively bias the price elasticity.

Alternatively, some researchers (Nelson 1974, 1975; Ornstein 1977) propose that lower pricing firms would advertise more in order to inform consumers about their lower prices. In that case advertising would be associated with lower prices and its omission would negatively bias the price elasticity. Information on the type of advertising would help to discriminate between these hypotheses, but authors did not provide it.

Omission of promotion. The term "promotion" covers a variety of marketing activities, some that give consumers an incentive (e.g., coupons, premiums, and rebates) and others that increase product awareness (e.g., displays, features, and demonstrations). In general, sales have been found to be related positively to promotions (e.g., Neslin and Shoemaker 1983). The relationship between price and promotion is not well documented and may depend on whether the promotion is incentive or informative.

Price discrimination models suggest that a strategy of incentive promotions should be carried out concurrently with a strategy of high prices (e.g., high prices for regular buyers with incentives to attract switchers; Narasimhan 1984; Neslin and Shoemaker 1983; Tellis 1986). If that reasoning motivates actual strategies, (high) prices and promotions would be related positively and the omission of promotion would positively bias the price elasticity.

In contrast, conventional marketing wisdom suggests that informative promotions (e.g., displays, features, demonstrations) should be used concurrently with price cuts to maximize consumer awareness. In that case, (high) prices and promotions would be related negatively and the omission of promotion would negatively bias the price elasticity. Unfortunately, because of limited data, authors tended to combine the two types of promotions and their effects could not be separated.

Omission of lagged price. Current sales may be related positively to lagged price because deal-prone consumers synchronize their purchases with firms' discounting patterns, stocking up when a brand is on sale (Blattberg et al. 1978; Narasimhan 1984; Neslin and Shoemaker 1983). This hypothesis is confirmed by the studies in the meta-analysis, which indicate that when lagged price is included its coefficient is generally positive. As a result of frequent price discounting, (current) price would be related negatively to lagged price. (Because of limited data, we consider only short-term price variation and not long-term price trends due to inflation or experience effects.) Therefore, the omission of lagged price would negatively bias the elasticity of (current) price.

Omission of lagged sales. Besides response to marketing variables, lagged sales should be related positively to the current period's sales because of consumer inertia or loyalty (Parsons and Schultz 1976, p. 170–2). The previous period's sales may affect this period's price to the extent that managers lower price if the prior period's sales are low and revert to high prices if sales are high. Hence the omission of lagged sales would positively bias (the current period's) price elasticity.

Functional form. The two most commonly used functional forms are the additive and multiplicative models (because of inadequate observations, exponential and semilogarithmic models were collapsed as multiplicative). The additive model assumes a linear response to price changes whereas the multiplicative model assumes a curvilinear response. Which functional form is valid is an empirical issue and no prior hypothesis can be developed about systematic differences from using either form.

Environmental Variables

This group covers variation due to the brand life cycle, the product type, and the country of origin.

Product categories. Sales of pharmaceuticals should be less price sensitive because they are high risk products, often purchased in an emergency or by prescription. In addition, when shopping for such health-related products, consumers may give more importance to safety and effectiveness than to price.

National setting. No firm hypotheses are possible about differences in price elasticity across national settings. The higher level of disposable income in the U.S.A. may lead to a less negative elasticity in the U.S.A. in comparison with that in other countries. However, stronger antitrust laws coupled with better consumer information (Thorelli and Thorelli 1977, p. 233–60) may lead to a more negative elasticity in the U.S.A.

The brand life cycle and sales measure. Price elasticity could increase over the brand life cycle for two reasons. First, consumers' knowledge about the brand, especially about availability, deals, prices, and promotions, is likely to be higher in the later stages of its life cycle (e.g., Tellis and Fornell 1988). Second, by temperament early adopters are likely to be less price sensitive than later adopters (Nagle 1987, p. 137; Simon 1979). Accordingly, the price elasticity would be more negative in the later stages of the life cycle. This hypothesis is treated as the main effect of the brand life cycle.

However, the measure of the dependent variable may interact with the life cycle hypothesis for two reasons. First, if the price coefficient is estimated over the whole time series and the elasticity subsequently is derived for various stages of the brand's life cycle (e.g., Simon 1979), the elasticity would be affected by the measure of the dependent variable. Recall that price (p) elasticity is defined as $(\delta s/\delta p)\cdot(p/s)$, where s may be sales or market share. Sales are typically low in the introductory stage and high in maturity. So price elasticity, estimated as above with sales as the dependent variable, would be more negative in the earlier stages of the life cycle.

Second, the sales measure can capture both primary and selective demand changes in response to price changes, but the market share measure captures only selective changes in demand because the primary changes in demand are incorporated in both the numerator and the denominator of the market share measure. Therefore, if response is measured as sales and if primary demand effects are strong as in the early stages of the life cycle, the price elasticity would be more negative; conversely, if primary demand effects are weak as in maturity, the sales measure should lead to a less negative elasticity.

The latter hypothesis is tested as the interaction effect of life cycle × sales measure in the regression analysis. In coding the brand's life cycle, if authors did not explicitly provide information on the life cycle, the brand was coded as mature, the modal category. In such cases, other descriptions of the data supported this coding; moreover, authors are more likely to omit the life cycle description if the brand is in maturity. The potential measurement error will weaken the observed effects.

Data Characteristics

Reference frame. The price elasticity from time series data should be more negative than that from cross-sectional data. The reason is that cross-sectional analyses relate a brand's sales or market share with prices, across the brands in a market, often without controlling for reverse causality. Such effects may be due to large share firms charging higher prices because of their superior name recognition, or some other competitive advantage, or a strategy to harvest share. Small share firms could have lower prices for the opposite reasons.

For example, in a pooled cross-sectional × times series analysis, Weiss (1968) found that the price coefficient was initially positive. He attributed this effect to omitted-variable bias from pooling cross-sections, such as not accounting for quality inferences, shelf-space allocations, or more effective advertising of the higher priced brands. After controlling for these effects with brand-specific dummy variables, he found the reestimated price coefficient to have the right sign. Similarly, in a simultaneous model estimated with cross-sectional data, Robinson and Fornell (1985) found that market share had a positive effect on relative price.

Temporal aggregation. At any one time, consumers' price elasticity has a within-brand component (reflecting responses to a brand's prices over time) and a between-brand component (reflecting responses to interbrand differences). Consumers exhibit price sensitivity by responses to price at specific times (i.e., purchase occasions). Temporal aggregation of such observations leads to a loss of the within-brand component. If between-brand sensitivity is less negative, as suggested in the previous hypothesis, temporal aggregation would positively bias the elasticity.

Measure of price. The price elasticity would be more negative if the price variable is measured in relation to competitors. The reason is that in brand choice contexts consumers would respond to relative rather than to absolute prices (Monroe and Petroshius 1981). For example, an increase in price may not lead to a loss of sales if competitors also raise prices in that period. In general, failure to account for competitive price would lead to weaker price effects or elasticities that are closer to zero.

Other data characteristics. After we account for the factors previously discussed, the data source and competitive level should not systematically affect the price elasticity. Besides, observations were inadequate to test the effect of competitive level, that is, whether the data were interbrand (or intermodel for durable goods), interbusiness, or interfirm. Similarly (after taking into account the previous characteristics of the data), the number of observations, cross-sections, or parameters should not affect the estimated price elasticity.

Estimation Method

There are roughly four classes of estimation methods: ordinary least squares (OLS), generalized least squares (GLS, including weighted least squares and adjustments for autocorrelation and seemingly unrelated equations), multistage least squares (MSLS, including two- and three-stage least squares), and maximum likelihood estimation (MLE, including limited and full information approaches). Method-induced biases, if any, on the price elasticity are not easily predicted.[2] Because of inadequate observations, the last two categories, both of which estimate simultaneous models, were collapsed.

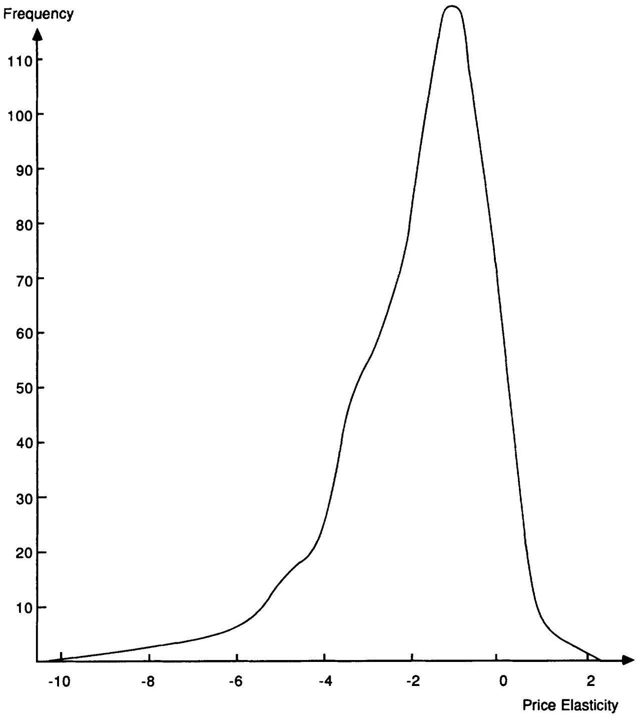
RESULTS

Descriptive Statistics

Figure 1 is a distribution of the dependent variable, the price elasticity estimated in various studies. The mean

[2]In the presence of autocorrelation and heteroskedasticity, OLS estimates relative to GLS and MLE estimates are inefficient but unbiased (Kmenta 1986, p. 269–96). In nonrecursive structural equation models, MLE and MSLS estimates are unbiased, but OLS estimates are biased (Kmenta 1986, p. 711–19); the direction of the bias depends on the patterns of correlations across the equations. Though admitting that the issue is ambiguous, Assmus, Farley, and Lehmann (1984) suggest that estimation by OLS may bias coefficients in the direction of estimated effects.

Figure 1
SMOOTHED DISTRIBUTION OF THE ESTIMATED PRICE ELASTICITY



Mean = -1.76; mode = -1.5; Std. Dev. = 1.74; N = 367;
t-statistic = -19.37 for hypothesis that mean=0.

is -1.76, the mode is -1.5, and the estimates concentrate around these measures of central tendency. The elasticity is significantly negative (t-statistic -19.4, $p =$ 0001). Thus, *on average*, a 1% change in price would lead to a 1.76% change in sales in the opposite direction. The "file drawer hypothesis" suggests there may be many studies that are unpublished because their results are not consistent with the normal expectation of a significantly negative price elasticity. The negatively skewed distribution of elasticities in Figure 1 seems to support this hypothesis. However, because of the higher negative t-statistic, a test of this hypothesis[3] indicates that at least 50,000 estimates of a zero elasticity (t-statistic > -1.645) are needed to accept the null hypothesis that the elasticity is not negative!

The arithmetic mean of price elasticity is eight times larger in absolute value than the mean advertising elasticity of .22 obtained by Assmus, Farley, and Lehmann (1984). The unavailability of an environmental "control group" or "null group" makes comparisons of adjusted means difficult. However, after taking into account the predictable method-induced biases (discussed subsequently), the mean price elasticity is about -2.5. In comparison, the mean advertising elasticity of .22 may be inflated because of method biases, though a precise estimate is not available in Assmus, Farley, and Lehmann's article.

Regression Results

The regression explains the variance around the mean of the elasticities due to intermodel characteristics (e.g., Farley and Lehmann 1986, p. 59 ff.; Hedges and Olkin 1985, p. 168 ff.; Raudenbush, Becker, and Kalaian 1988). The analysis is by least squares (ANCOVA or dummy variable regression) with allowances for violations of assumptions as described in the appendix of Tellis (1988a). All tests of significance are against the null hypothesis of homogeneity of the price elasticity across the relevant variable at the .05 level. The two-tailed test is used except for a directional hypothesis. For the categorical independent variables, if the hypotheses are against a particular level, dummy coding is used, that level is dropped, and the coefficients and t-statistics of the remaining levels are interpreted in relation to the one dropped. In other cases effects coding is used and the coefficients are interpreted against the grand mean. However, the F-statistic and significance level for differences across levels of the categorical variable are independent of the type of coding. Because of the many levels of some variables, the F-statistic may not be significant though the t-test may indicate significant differences for particular levels.

Table 3 reports the results along with the hypothesized effects. Ten of the variables show significant differences across levels; for eight of these 10 effects the hypotheses are unambiguous and the results are in the predicted direction. A detailed discussion of the results follows.

Omission of quality. The omission of quality from the model leads to a positive omitted-variable bias of .59 in the price elasticity. This result is consistent with the hypothesis that high quality is related positively to both market share and price. Omitting it from the model results in higher priced products being associated with higher market shares, a relationship actually due to the firms' superior quality.

Omission of distribution. The omission of distribution leads to a negative bias of -1.35 in the price elasticity. This result confirms the expectations that higher priced brands are more selectively distributed and that wider distribution results in higher sales across all brands.

Reference frame. Elasticities based on only cross-sectional data have a positive bias of 2.78 in relation to those based on time series data and 2.42 in relation to those based on time series × cross-sectional data. This effect is expected because cross-sectional analyses relate market share and prices across brands. Such comparisons do not take into account the fact that larger share firms may have higher prices because of either their bet-

[3]With usual notation, $t = \bar{X}/(s/\sqrt{n})$, and t_1 and n_1 from the current studies are -19.4 and 367, respectively. Therefore, to get a joint t greater than -1.645, we need at least n_2 studies, where $n_2 = (t_1/1.645)^2 n_1 - n_1$.

Table 3
REGRESSION RESULTS[a]

Class	Variable	Scale level		Expected sign	Coefficient	T-statistic	Significance
Model specifications	Quality	Nominal	Omitted	+	.59	1.66	.05
	Distribution	Nominal	Omitted	−	−1.35	−4.15	.00[b]
	Advertising	Nominal	Omitted		−.36	−1.18	.24
	Promotion	Nominal	Omitted		.18	.31	.76
	Lagged price	Nominal	Omitted	−	.09	.20	.42
	Lagged sales	Nominal	Omitted	+	−.32	−1.20	.12
	Other variables	Nominal	Omitted	0	−.12	−.39	.70
	Functional form (1.2, .30)	Nominal[c]	Multiplicative		−.24	−1.04	.30
			Attraction		.45	1.49	.14
			Additive		−.21	−.75	.45
Environment	Product category (4.0, .00)	Nominal	Detergents	−	−1.63	−4.22	.00
			Durable goods	−	−1.23	−1.90	.03
			Food	−	−.63	−1.09	.14
			Toiletries	−	−.48	−0.77	.22
			Others	−	−.68	−0.98	.16
			Pharmaceuticals				
	National setting (8.5, .00)	Nominal[c]	Europe		.54	1.88	.06
			Australia/		−.94	−4.06	.00
			New Zealand		.40	1.28	.20
			U.S.A.				
	Brand life cycle	Nominal	Early	+	.78	2.02	.02
			Mature				
	Brand life cycle × sales		Early	−	−1.34	−3.02	.00
			Mature				
Data	Sales measure	Nominal	Absolute	+	.77	2.10	.02
	Reference frame (5.5, .01)	Nominal	Time series	−	−2.78	−3.27	.00
			Time series × cross-section	−	−2.42	−3.23	.00
			Cross-section				
	Temporal aggregation	Nominal	>Biweekly	+	.83	1.71	.05
	Source (.94, .39)	Nominal[c]	Firm	0	.08	.37	.72
			Public	0	−.38	−1.37	.17
			Panel	0	.29	.96	.34
	Price measure	Nominal	Absolute	+	.25	.82	.20
	No. observations	Ratio		0	−.00	−.29	.77
	No. cross-sections	Ratio		0	−.00	−.24	.81
	No. parameters	Ratio		0	−.01	−1.34	.18
Estimation	Method (3.3, .04)	Nominal[c]	GLS		.41	2.35	.02
			MLE + MSLS		−.30	−1.23	.22
			OLS		−.12	−.79	.43
Intercept					1.24	.94	.35

R^2 = 29%; F = 4.51; d.f. = 30/336; p = .00

[a]Dependent variable: estimated price elasticity of selective demand. F-statistics and p-values for multilevel nominal variables are in parentheses.
[b]$p < .0001$.
[c]Effects coding.

ter name recognition or a strategy to harvest market share (Robinson and Fornell 1985; Weiss 1968). A true estimation of price elasticity requires one to take into account the dynamics of consumer response to price changes over time. Though the result is not sensitive to multicollinearity (Tellis 1988a), the size of the bias (especially in relation to the univariate comparison in Table 2) and the small number of estimates with cross-sectional data suggest the need for more research on the issue.

Temporal aggregation. Because of a nonlinear effect of data aggregation, this variable is reclassified into two categories, biweekly or less and more than biweekly. As hypothesized, the estimation of the model on data aggregated above the biweekly level leads to a positive bias of .83 in the price elasticity. Casual observation may confirm the validity of this finding. The prices and sales of competitive brands are in a state of constant flux. Temporal aggregation loses much of the temporal component of price elasticity resulting from short-term price variation. In addition, temporal aggregation may lead to greater reliance on the cross-sectional variation, which causes a positive bias as discussed before.

The brand life cycle and sales measure. Because of instability in coefficients from few observations, the introduction and growth stages are reclassified as "early" and the maturity and decline stages as "late." Price elasticity is less negative (by .78) in the early than in the late stages of the life cycle. As hypothesized, the reason is probably that consumers have better price information in the late stages or that there are more price insensitive innovators in the early stages.

However, when the dependent variable is sales, the elasticity is significantly more negative in the early stages by 1.34. As hypothesized, this effect may be due to the derivation of the elasticity for various life cycle stages from a coefficient estimated over the whole series; because sales are typically lower in the introduction, growth, and decline stages than in maturity, such a computation would result in a more negative elasticity. This effect could also have a substantive explanation. Primary demand effects would be stronger in the early stages of the life cycle, so the use of sales (instead of market share) as the dependent variable would lead to a more negative price elasticity. Consistent with these explanations, the main effect of the sales measure (interpreted as use of the sales measure in the late stages) has a positive effect of .77 on the price elasticity.

Product categories. As hypothesized, price elasticity is more negative for all other product categories than for pharmaceutical products. The difference is significant and particularly large for detergents and durable goods in comparison with pharmaceutical products (after correction for heteroskedasticity, the difference is also significant for food and other categories; see Tellis 1988a). As hypothesized, the reason is probably consumers' concern with the safety, effectiveness, and timing rather than with the price of pharmaceutical products.

National setting. Elasticities from Australia and New Zealand are more negative than those from other countries, whereas those from Europe are more positive. The results could be due either to consumer information and behavior differences or to differences in competitive structures. These differences warrant further study.

Estimation method. Models estimated by generalized least squares lead to price elasticities of .41 above the grand mean. No satisfactory explanation for this difference is apparent.

Measure of price. Contrary to the hypothesis, the price measure is not significant. A possible reason may be that the ANCOVA in the primary models already takes into account variation around means, so the impact of specific price measures is less salient. Alternatively, the reason may be that most of the studies were not at the consumer choice level and did not take into account consumers' reference price, zones of indifference, and so on (Monroe and Petroshius 1981). This issue warrants further scrutiny.

Omission of promotion and lagged price. Unambiguous conclusions about the omission of marketing variables are not possible, perhaps because of data limitations. The effects of promotion and lagged price may be masked by multicollinearity (Tellis 1988a, appendix). Promotion itself is very loosely defined in the original studies. The effect of lagged price may be lost by data aggregation. A proper test therefore would require a data aggregation × lagged price interaction. In addition, in the growth and decline stages, prices and sales may have definite trends, which could mask the hypothesized effects. Inadequate data hindered a separation of all these effects.

Omission of advertising. The insignificant effect of the omission of advertising may be due to problems of variance instability (Tellis 1988a, appendix) or problems of measurement because authors did not give details on the type and competitive context of the advertising.

Other effects. For five other variables we have no reason to find any differences in the price elasticities: the number of observations, parameters, or cross-sections, the omission of "other variables," and the data source. Differences by functional form and omission of lagged sales also are insignificant, though the results may be due to variance instability (Tellis 1988a, appendix).

Model Evaluation

The multiple regression explains 29% of the variation in the dependent variable. This percentage compares favorably with that from past studies (e.g. Assmus, Farley, and Lehmann 1984; Farley, Lehmann, and Ryan 1982), especially given the large number of observations (367; the F-value is significant at the .0001 level). Multicollinearity is present, but not severe; it compromises conclusions about only a few variables. The nonindependence of replications on the same data increases the strength of the natural design, does not by itself bias the estimates, limits the generalizability of the results, and may aggravate the problem of heteroskedasticity. Some of the results in Table 3 are sensitive to heteroskedasticity. (Details on all these issues are given by Tellis 1988a)

SUMMARY AND IMPLICATIONS

A long tradition of sales modeling has resulted in a large number of estimates of the price elasticity of selective demand over a variety of conditions. The meta-analytic approach is well suited to summarizing the findings from these studies and determining the factors that systematically affect the estimate of price elasticity. One unambiguous conclusion from the analysis is that the price elasticity is significantly negative. This finding is expected if one assumes rational, informed consumers, but is still noteworthy given the complexity of consumers' information processing and competitive efforts to reduce price sensitivity with advertising and product differentiation. Another reassuring conclusion is that the various estimates cluster around the mean and systematic differences from the mean are consistent with theoretical expectations. An important finding is that the absolute value of the mean price elasticity is eight times larger than that Assmus, Farley, and Lehmann (1984) obtained for advertising elasticity. Hence markets in general are much more responsive to changes in advertising than in price. A growing realization of this fact may explain the more rapid increase of expenditures on various forms of discounting than on advertising.

The omission of quality from market share models positively biases the price elasticity. In other words, managers using such estimates would believe their markets are less price sensitive than they actually are. Given that market leaders in several industries have undergone market share erosion from higher quality entrants (e.g, Japanese entrants in the automobile industry), the finding underscores the importance of measuring quality accurately and incorporating it into market share models.

The omission of distribution leads to a negative bias in the price elasticity. The direction of the bias suggests that higher priced brands are less widely available; however, direct evidence on this relationship is needed to confirm the finding. Good measures for distribution coverage and shelf space are difficult to obtain even with scanner data, but their omission is not without cost.

The greater sensitivity to prices in the latter stages of the life cycle confirms a hypothesis often suggested in marketing. However, estimation method and measures can affect the results. Elasticities with sales as the dependent variable are much more negative in the earlier stages of the life cycle. Following Simon (1979), one reason is that sales at that time are lower. Another explanation is that primary demand effects are stronger and are captured better with sales as the dependent variable.

The findings of systematic biases from temporal aggregation or cross-sectional data increase the appeal of scanner data and its analysis at the most disaggregate level available. This benefit may not have been stressed before. The findings may also explain why market share models based on the PIMS data commonly arrive at insignificant or positive price coefficients (e.g., Buzzell and Wiersema 1981; Jacobson and Aaker 1985; Phillips, Chang, and Buzzell 1983; Robinson and Fornell 1985; Varadarajan and Dillon 1981; because of the unavailability of elasticities, only the Robinson and Fornell study is in the meta-analysis). Because the PIMS data are aggregated over one to four years and frequently involve only cross-sectional data, estimated elasticities could be positively biased by as much 3.5.

Though concerns of efficiency motivated past research on alternative estimation methods, the results of this study suggest that inappropriate methods may lead also to biases in the elasticity. However, the results do not definitely indicate the superiority of any one approach, mostly because each problem requires a specific method and functional form. As the sample included few models of consumer purchase (e.g., Guadagni and Little 1983), such models were not compared with the traditional linear, multiplicative, and attraction models, though the former may be preferable. For example, because purchase models analyze disaggregate choices, they can eliminate the biases from cross-sectional and temporal aggregation discussed before while incorporating behavioral theory for model specification (e.g., Gurumurthy and Little 1986). In addition, they can analyze elasticity differences across purchase stages while avoiding the biases that result from dependencies across these stages (e.g., Krishnamurthi and Raj 1988; Tellis 1988b).

Price elasticity appears homogeneous across some research settings. In particular, it is reassuring that no significant differences in elasticity occur across data sources, functional forms, and numbers of observations, cross-sections, and parameters. However, the failure to determine biases from the measures of price and the omission of promotion, lagged price, and advertising could be due to limitations of the data and should not lull researchers into a false sense of security. In addition, the analysis does not explore the joint effects of the omission of two or more variables, which may be captured by interactions among the independent variables.

The effects of price interactions are not pursued in the study. The one most commonly tested is the effect of the price × advertising interaction. Because studies on this topic are few and employ different designs, they are not pooled with the current set. Another important effect not covered because of inadequate data is the impact of brand share or brand loyalty on price elasticity. A plausible hypothesis is that brands with larger shares have greater loyalty among buyers. Such brands therefore may have a less negative price elasticity. All these topics are promising avenues for future research.

In addition, a direct extension of the meta-analysis would be to test for the effects of higher order interactions among the independent variables. Another extension would be to expand the review to unpublished studies by firms, doctoral dissertations, and conference proceedings. A more extensive search of international studies could provide information about the extent and causes of differences in price elasticity across countries. A third extension would be to test the results by simulation or by manipulation of sufficiently rich market data.

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