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The importance of pricing decisions for firms has fueled an extensive stream of research on price elasticities. In an influential meta-analytical study, Tellis (1988) summarized price elasticity research findings until 1986. However, empirical generalizations on price elasticity require modifications because of (1) changes in market characteristics (i.e., characteristics of brands, product categories, and economic conditions) and (2) changes in the research methodology used to assess price elasticities. Therefore, the authors present a meta-analysis of price elasticity with new empirical generalizations on its determinants. Across a set of 1851 price elasticities based on 81 studies, the average price elasticity is –2.62. A salient finding is that over the past four decades, sales elasticities have significantly increased in magnitude, whereas share and choice elasticities have remained fairly constant. The authors find that accommodating price endogeneity has a strong (magnitude-increasing) impact on price elasticities. A striking null result is that accounting for heterogeneity does not affect elasticities significantly. The authors also present an analysis that explains the difference between their findings and Tellis's findings, and they indicate which new price elasticity studies are most desirable.

New Empirical Generalizations on the Determinants of Price Elasticity

Because pricing is one of the most important issues in marketing (Gijsbrechts 1993; Monroe 2003), understanding the factors that influence price sensitivities is essential. Therefore, an extensive stream of research on price elasticities has been stimulated. In an influential meta-analysis, Tellis (1988) summarizes research findings until 1986 and provides the contemporary state of knowledge on the overall level of price elasticity and its determinants. However, a single meta-analysis "does not provide a final statement of truth on the issue" (Tellis 1988, p. 331). Because the most recent meta-analysis on price elasticity (Tellis 1988) was published 17 years ago and the literature on price effects has continued to flourish, it is important to examine which empirical generalizations still hold and which need to be revised.

The aim of this article is to update and extend empirical generalizations on price sensitivity by presenting the results of a meta-analysis on the determinants of price elasticity.[1] We update Tellis's (1988) generalizations, which were based on 367 price elasticities published between 1961 and 1985. Our meta-analysis includes 1851 price elasticities, covering the period from 1961 to 2004. In addition, we broaden the scope by studying several important additional determinants. In Figure 1, we distinguish between two broad classes of determinants of price elasticity: market characteristics and the research methodology. The first class entails characteristics of the brand and product category and economic conditions. Understanding how price elasticities vary with market characteristics is important for the development of a successful marketing strategy. We examine the following determinants that were absent in Tellis's (1988) meta-analysis: year of data collection, manufacturer brands versus private labels, household disposable income, and inflation rate. The second class is research methodology, which refers to data and model characteristics. To obtain

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[1]The interpretation of elasticities can be problematic in some cases, such as for comparing cross-brand price elasticities (Sethuraman, Srinivasan, and Kim 1999) and for decomposing sales elasticities into primary and secondary demand effects (Van Heerde 2005; Van Heerde, Gupta, and Wittink 2003). Nevertheless, we use price elasticities as the measure of price sensitivity because elasticities are insensitive to the unit of measurement. Thus, they can be compared across markets, product categories, brands, and model formulations.

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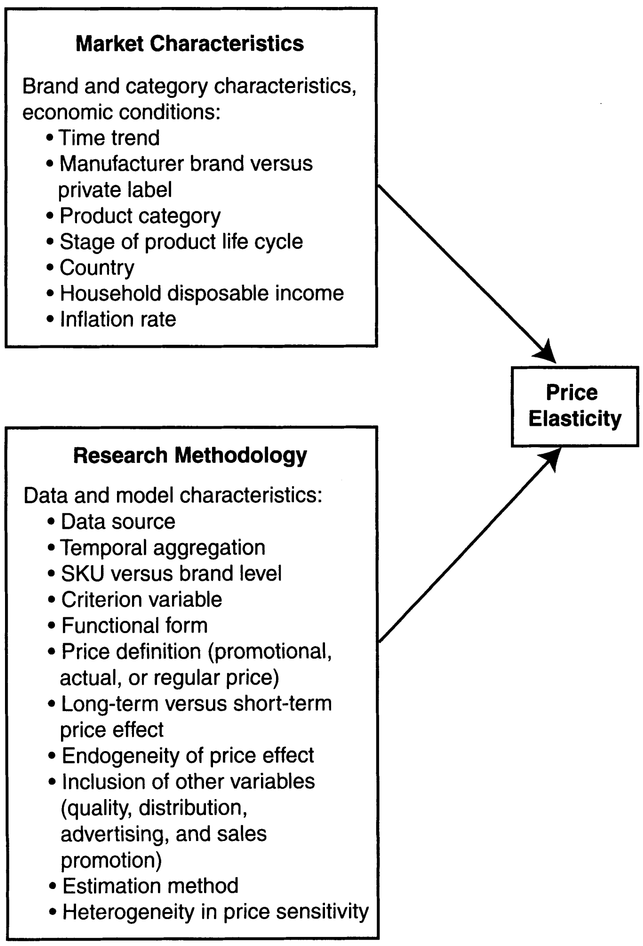
Figure 1
STUDY FRAMEWORK FOR FACTORS INFLUENCING OBSERVED PRICE ELASTICITY



elasticity estimates for a specific situation, models relating performance measures (i.e., sales, shares, and choices) to price are formulated and estimated on empirical data. We examine whether decisions made throughout the research process, from data selection to model specification and estimation, influence the price elasticity. We assess the following new determinants relative to Tellis's (1988) determinants: brand-level versus stockkeeping-unit-level (SKU-level) elasticities; separate elasticities for actual, regular, and promotional prices; long-term versus short-term elasticities; endogeneity of prices; and heterogeneity in price sensitivity.

In the "Methodology" section, we describe the meta-analytic methodology of collecting and analyzing price elasticities. Next, we present our findings on both classes of determinants (see Figure 1), we examine temporal patterns in price elasticity, and we contrast our generalizations with those of Tellis (1988). Finally, we discuss managerial and methodological implications and give directions for further research, particularly on which new price elasticity studies are most desirable.

METHODOLOGY

Data Collection and Coding

To identify publications that report price elasticities, we conducted an elaborate search strategy. First, we examined publications that were cited in previous literature reviews of pricing research (Bolton 1989a; Tellis 1988). Second, we used ABI/Inform, PsycINFO, EconLit, Kluwer Online, and ScienceDirect for a computerized bibliographic search. Third, we examined articles that referred to Tellis (1988), as identified by the Social Sciences Citation databases. Fourth, we conducted an issue-by-issue search of nine major marketing journals (from 1986 forward).[2] Fifth, we searched the Web for working papers. Sixth, we screened the references in the publications that we had already obtained for additional studies with price elasticities.

The decision to include an observation of price elasticity is based on four criteria. First, we examine brand and SKU elasticities only and exclude category sales elasticities (as does Tellis 1988). Second, the elasticity should represent the price sensitivity of a single brand or SKU (not averages across items) because we aim to assess determinants that vary across items. Third, we consider only price elasticities based on actual purchase or sales data. Thus, we omit elasticities based on experimental and judgmental data, such as purchase intentions and preferences. Fourth, we limit our empirical generalization to business-to-consumer markets, and therefore we omit elasticities derived from business-to-business markets.

The quest for price elasticities yields a set of 81 publications (see Table 1) and a total of 1860 price elasticities.[3] Nine price elasticities (.5% of the observations) are outside the interval of the mean elasticity plus or minus five times the standard deviation. These observations have been omitted from further analyses, because they are typically based on small sample sizes (e.g., Simon 1979, p. 447) or are identified as outliers in the original publications (e.g., Bolton 1989b, p. 209). The final numbers of studies and elasticities are 81 and 1851, respectively. The average number of price elasticities reported per publication is 22.9, with a minimum of 2 and a maximum of 264.

Two judges, neither of whom is an author of this article, independently coded the price elasticities and determinants. Interjudge agreement was greater than 90%, and a third judge resolved inconsistencies. The operationalization of most determinants does not require explanation, with a few exceptions. We obtained growth rates of disposable household income (per capita and corrected for inflation) from the National Accounts Yearbook Database, which is published by the United Nations Statistics Division (see http://unstats.un.org/unsd/). We used the consumer prices indexes that are published in the International Financial Statistics of the International Monetary Fund Yearly to operationalize

[2]We inspected the following journals: *International Journal of Research in Marketing*, *Journal of the Academy of Marketing Science*, *Journal of Consumer Research*, *Journal of Marketing*, *Journal of Marketing Research*, *Journal of Retailing*, *Management Science*, *Marketing Letters*, and *Marketing Science*.

[3]Most often, price elasticity was explicitly reported in the publication. Otherwise, we derived price elasticities from the model parameters (see Hanssens, Parsons, and Schultz 2001, p. 125; Leeflang et al. 2000, p. 173).

Table 1
PUBLICATIONS INCLUDED IN THE META-ANALYSIS ON PRICE ELASTICITY

Authors	*Year*	*Publication Outlet*	*Volume (Issue), Pages*	*Number of Elasticities*	*Average*
Ailawadi, Gedenk, and Neslin	1999	*International Journal of Research in Marketing*	16 (3), 177–98	30	–1.87
Allenby	1989	*Marketing Science*	8 (3), 265–80	18	–4.34
Allenby and Lenk	1994	*Journal of the American Statistical Association*	89 (428), 1218–31	4	–.41
Allenby and Rossi	1991	*Marketing Science*	10 (3), 185–204	40	–3.41
Bajari and Benkard	2003	Working paper		5	–6.64
Bass and Pilon	1980	*Journal of Marketing Research*	17 (4), 486–497	2	–2.02
Bemmaor	1984	*Journal of Marketing Research*	21 (3), 298–308	20	–2.68
Besanko, Gupta, and Jain	1998	*Management Science*	44 (11), 1533–47	12	–2.71
Blattberg and Wisniewski	1989	*Marketing Science*	8 (4), 291–309	40	–5.65
Bolton	1989	*Journal of Retailing*	65 (2), 193–219	31	–2.40
Brodie and De Kluyver	1984	*Journal of Marketing Research*	21 (2), 194–201	18	–.95
Bucklin, Russell, and Srinivasan	1998	*Journal of Marketing Research*	35 (1), 99–113	9	–1.92
Capps and Love	2002	*American Journal of Agricultural Economics*	84 (3), 807–816	13	–2.15
Carpenter et al.	1988	*Marketing Science*	7 (4), 393–412	11	–2.28
Chen, Kanetkar, and Weiss	1994	*International Journal of Forecasting*	10 (2), 263–76	36	–2.38
Chib, Seetharaman, and Strijnev	2002	Working paper		16	–2.71
Chintagunta	1992	*International Journal of Research in Marketing*	9 (2), 161–75	8	–2.95
Chintagunta	1993	*Marketing Science*	12 (2), 184–208	12	–1.62
Chintagunta	2001	*Marketing Science*	20 (4), 442–56	39	–1.21
Chintagunta	2000	Working paper		29	–2.62
Chintagunta and Honore	1996	*International Journal of Research in Marketing*	13 (1), 1–15	16	–1.35
Chintagunta, Jain, and Vilcassim	1991	*Journal of Marketing Research*	28 (4), 417–28	4	–1.99
Christen et al.	1997	*Journal of Marketing Research*	34 (3), 322–34	20	–2.29
Cooper	1988	*Management Science*	34 (6), 707–723	12	–1.78
Cotterill	1994	*Agricultural and Resource Economics Review*	23 (3), 125–39	9	–1.53
Cotterill and Samson	2002	*American Journal of Agricultural Economics*	84 (3), 817–23	8	–2.47
Dhar, Chavas, and Gould	2003	*American Journal of Agricultural Economics*	85 (3), 605–617	16	–3.72
Foekens, Leeflang, and Wittink	1999	*Journal of Econometrics*	89 (1–2), 249–68	9	–2.88
Ghosh, Neslin, and Shoemaker	1983	Conference proceedings	226–30	29	–1.68
Gönül and Srinivasan	1993	*Marketing Science*	12 (3), 213–29	12	–2.03
Guadagni and Little	1983	*Marketing Science*	2 (3), 203–238	16	–2.24
Gupta et al.	1996	*Journal of Marketing Research*	33 (4), 383–98	81	–2.06
Hausman, Leonard, and Zona	1994	*Annales d'Economie et de Statistique*	34, 159–80	15	–4.98
Hildebrandt and Klapper	2001	*International Journal of Research in Marketing*	18 (1–2), 139–59	9	–2.86
Houston and Weiss	1974	*Journal of Marketing Research*	11 (2), 151–55	6	–2.48
Hruschka	2002	*European Journal of Operational Research*	138 (1), 212–25	12	–2.12
Jain, Vilcassim, and Chintagunta	1994	*Journal of Business and Economic Statistics*	12 (3), 317–28	22	–2.18
Jedidi, Mela, and Gupta	1999	*Marketing Science*	18 (1), 1–22	40	–.26
Jeuland	1980	Conference proceedings	20, 310–26	18	–.42
Kadiyali, Chintagunta, and Vilcassim	2000	*Marketing Science*	19 (2), 127–48	6	–3.26
Kadiyali, Vilcassim, and Chintagunta	1999	*Journal of Econometrics*	89 (1–2), 339–63	4	–9.47
Kalyanam	1996	*Marketing Science*	15 (3), 207–221	12	–5.65
Kamakura and Russell	1989	*Journal of Marketing Research*	26, 379–90	4	–3.81
Kim	1995	*Marketing Letters*	6 (2), 159–69	18	–4.41
Kim, Allenby, and Rossi	2002	*Marketing Science*	21 (3), 229–50	20	–2.50
Kim, Blattberg, and Rossi	1995	*Journal of Business and Economic Statistics*	13 (3), 291–303	10	–3.75
Kim and Rossi	1994	*Marketing Letters*	5 (1), 57–67	10	–3.30
Kinoshita et al.	2001	*Agribusiness*	17 (4), 515–25	24	–3.07
Kopalle, Mela, and Marsh	1999	*Marketing Science*	18 (3), 317–32	6	–1.63

Table 1
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Authors	*Year*	*Publication Outlet*	*Volume (Issue), Pages*	*Number of Elasticities*	*Average*
Krishnamurthi and Raj	1991	*Marketing Science*	10 (2), 172–83	12	–4.43
Kumar and Divakar	1999	*Journal of Retailing*	75 (1), 59–76	43	–.25
Lambin	1970	*Journal of Business*	43 (4), 468–84	3	–1.38
Lambin	1976	Book		73	–1.80
Massy and Frank	1965	*Journal of Marketing Research*	2, 171–85	4	–2.43
Mehta, Rajiv, and Srinivasan	2003	*Marketing Science*	22 (1), 58–84	8	–1.07
Metwally	1974	*Review of Economics and Statistics*	57 (4), 417–27	24	–2.91
Montgomery	1997	*Marketing Science*	16 (4), 315–37	11	–2.92
Montgomery	2002	*Chapter in book by Franses and Montgomery, eds.*	257–94	12	–2.77
Mulhern, Williams, and Leone	1998	*Journal of Retailing*	74 (3), 427–46	14	–3.52
Murthi and Srinivasan	1999	*Journal of Business*	72 (2), 229–56	12	–2.96
Nevo	2000	*Rand Journal of Economics*	31 (3), 395–421	35	–2.94
Nevo	2001	*Econometrica*	69 (2), 307–342	25	–3.04
Pauwels, Hanssens, and Siddarth	2002	*Journal of Marketing Research*	39 (4), 421–39	49	–5.99
Pinkse and Slade	2004	*European Economic Review*	48 (3), 617–43	8	–4.35
Reibstein and Gatignon	1984	*Journal of Marketing Research*	21 (3), 259–67	14	–1.68
Roy, Chintagunta, and Haldar	1996	*Marketing Science*	15 (3), 280–99	12	–3.09
Russell and Bolton	1988	*Journal of Marketing Research*	25 (3), 229–41	39	–3.09
Russell and Kamakura	1994	*Journal of Marketing Research*	31 (2), 289–303	30	–2.13
Seo and Capps	1997	*Agribusiness*	13 (6), 659–72	264	–2.81
Simon	1979	*Journal of Marketing Research*	16 (4), 439–52	74	–1.63
Sivakumar	2001	*Journal of Marketing Theory and Practice*	9 (2), 1–10	8	–4.21
Song and Chintagunta	2002	Working paper		24	–1.69
Srinivasan, Popkowski-Leszczyc, and Bass	2000	*International Journal of Research in Marketing*	17 (4), 281–305	16	–1.21
Telser	1962	*Review of Economics and Statistics*	44 (3), 300–324	94	–2.91
Van Heerde, Gupta, and Wittink	2003	*Journal of Marketing Research*	40 (4), 481–91	8	–3.65
Van Heerde, Leeflang, and Wittink	2000	*Journal of Marketing Research*	37 (3), 383–95	9	–2.88
Villas-Boas and Winer	1999	*Management Science*	45 (10), 1324–38	12	–5.74
Vickner and Davies	1999	*Journal of Agricultural and Applied Economics*	31 (1), 1–13	10	–5.07
Wagner and Taudes	1991	*International Journal of Research in Marketing*	8 (3), 223–49	6	–.37
Wittink	1977	*Journal of Advertising Research*	17 (2), 39–42	25	–1.02
Wittink et al.	1988	Working paper		12	–2.51
Total				1851	–2.62

country-level inflation rates (see http://www.imf.org/external/pubs/). In our data set, the yearly growth rates of disposable household income range between –2.7% and 6.8%, with a mean of 1.6%. Inflation rates vary between .2% and 14.8%, with a mean of 4.5%.

To examine an autonomous time trend, we used the year in which data were collected, which we obtained for 1667 of the 1851 elasticities. Because the average difference between the year of publication and the year of data collection is 8 years (with a minimum of 2 and a maximum of 18), we imputed the year of publication minus 8 as the year of data collection for the 184 missing values.

Model for the Determinants of Price Elasticities

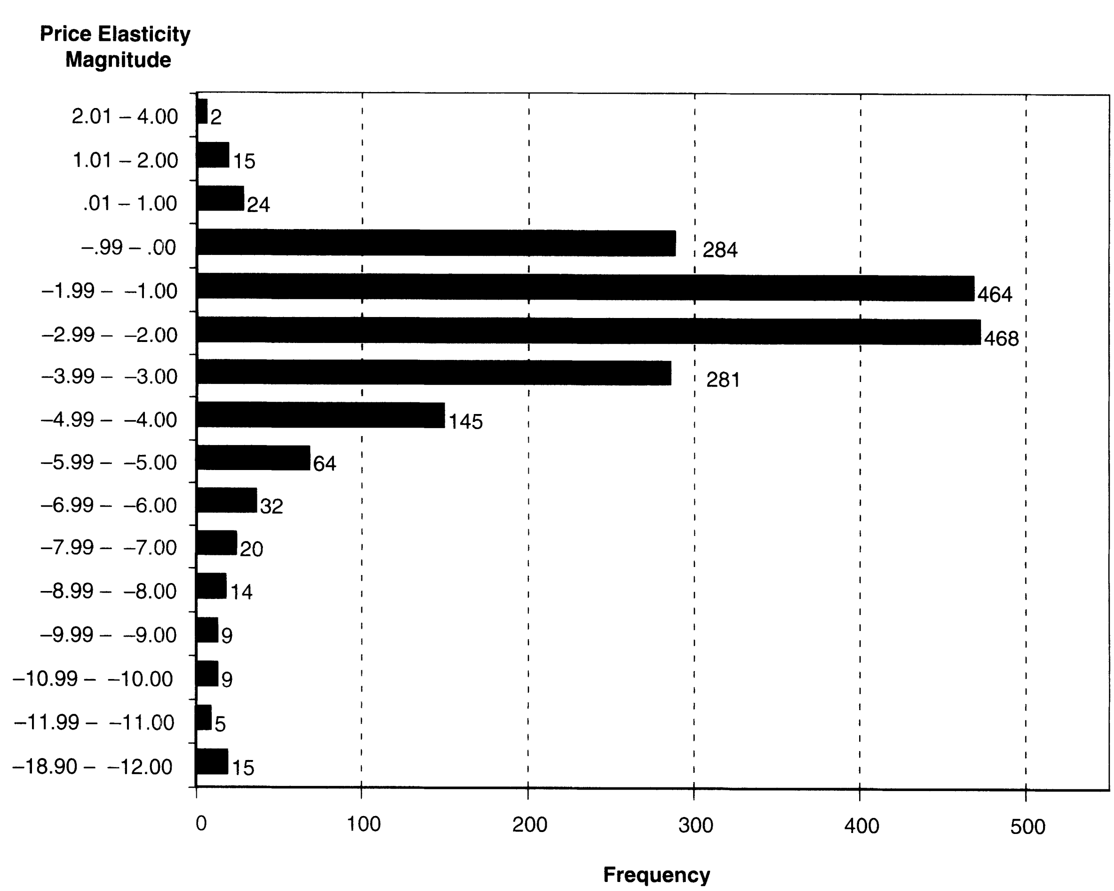
We model price elasticities as a linear function of the determinants (Farley, Lehmann, and Mann 1998). To account for within-study error correlations between price elasticities, we apply hierarchical linear models estimated with iterative generalized least squares, as Bijmolt and Pieters (2001) suggest. Before applying the hierarchical linear model, we examined possible confounds between the 21 determinants using PRINCALS, a principal components analysis for categorical variables. This represents a conservative approach because PRINCALS optimizes correlations between categorical variables. Only 11 of the 210 correlations between optimally transformed determinants were greater than .5, and no correlation was greater than .7. We performed sensitivity analyses, omitting each of the determinants with at least one correlation greater than .5 one at the time. This did not alter the findings regarding the other variables, indicating that the degree of multicollinearity is sufficiently low. Therefore, all determinants were kept in the model to prevent potential omitted variables biases. In addition, we performed a residual analysis to examine assumptions of the hierarchical linear model (Hox 2002, pp. 22–30). Normal probability plots of the standardized residuals and plots of standardized residuals against predicted price elasticities show support for most model assumptions. However, the price elasticities (see Figure 2) and residuals (not shown) display negative skewness. Given the large sample size, the regression coefficients and standard errors of the hierarchical linear model are highly robust against such violations (Maas and Hox 2004).

RESULTS

The Overall Magnitude of Price Elasticity

We present the frequency distribution of the observed price elasticities in Figure 2. The overall mean price elasticity in our meta-analysis is –2.62 (median = –2.22, standard deviation = 2.21). The distribution is strongly peaked; 50% of the observations are between –3 and –1, and 81% are

Figure 2
FREQUENCY DISTRIBUTION OF OBSERVED PRICE ELASTICITIES



between –4 and 0. Furthermore, 2.2% of the price elasticities are positive.

Effects of Determinants

We first estimated a full model with main effects of the determinants and a set of ten potentially relevant interaction effects. Because of strong multicollinearity, we could not obtain estimates for this model. Therefore, we tested each interaction effect separately, using a likelihood ratio test to compare the main-effects model and a model adding a specific interaction effect. Next, we estimated a model containing main effects and the four interactions that were significant in the previous step. We report the estimates in Table 2. We mention the six omitted interactions when we discuss the corresponding main effect. The model fit is satisfactory and significant (R^2 = .16; F = 9.65; degrees of freedom = 35, 1815; $p < .01$). In subsequent sections, we discuss the influence of (1) market characteristics (i.e., characteristics of brands and categories and economic conditions) and (2) the research methodology (data and model characteristics) (see Figure 1).

Market Characteristics: Brand and Category Characteristics and Economic Conditions

Year of data collection. The past decades have been characterized by a shift of marketing dollars from advertising to promotions (Mela, Gupta, and Lehmann 1997; Mela, Jedidi, and Bowman 1998; Neslin 2002, p. 57). Because the impact of this shift on sales is tangible and usually immediate, price decreases are attractive to results-oriented managers who want a reliable way to increase sales in the short run (Neslin 2002, p. xi). However, promotions increase price sensitivity in the long run (Boulding, Lee, and Stealin 1994; Mela, Gupta, and Lehmann 1997), whereas (thematic) advertising decreases price sensitivity (e.g., Kaul and Wittink 1995). Given the increasing focus on promotions and the decreasing focus on advertising over the past decades, the magnitude[4] of price elasticity would be expected to increase over time.[5] However, when we control for other determinants in the hierarchical model, the overall time trend is insignificant (p = .79).[6]

However, we find a significant interaction effect between the year of data collection and the definition of the criterion variable (p = .02). The magnitude of the absolute (sales) elasticity has become stronger over time (net change of –.04 each year). Thus, every 25 years, the elasticity of sales to price has become one percentage point stronger, which is a striking result. The relative elasticities (i.e., choice and market share) are quite stable (i.e., no significant change). Thus, the primary demand part of the sales elasticity is increasing over time, whereas the secondary demand part is stable. This finding is consistent with the work of Mela, Jedidi, and Bowman (1998), who find that a long-term exposure to promotions leads to stronger primary demand responses (i.e., purchase incidence and quantity). To shed further light on the changes over time in elasticity levels, we present a detailed additional analysis in the section "Temporal Patterns in Price Elasticity."

Brand ownership: manufacturer brand versus private label. Manufacturer brands tend to be well-known brands with stronger market positions and higher prices than those of private labels. Because brand strength is associated with less price-elastic responses (Bell, Chiang, and Padmanabhan 1999; Bolton 1989a; Boulding, Lee, and Stealin 1994; Danaher and Brodie 2000; Ghosh, Neslin, and Shoemaker 1983), we expect that elasticities for manufacturer brands are closer to zero than are private label brands. However, the effect of brand ownership on elasticity is not significant (p = .64), mirroring Narasimhan, Neslin, and Sen's (1996) findings.

Stage of product life cycle and product category. The literature is ambiguous on how price elasticities vary over the product life cycle. On the one hand, at early stages of the product life cycle, consumers are more involved with the category, and they focus on the benefits of the new product, leading to weak price elasticities (Ghosh, Neslin, and Shoemaker 1983). In later stages, price elasticities could increase in magnitude because price-sensitive consumers are attracted to the category or because the number of competitive substitutes increases (Parker and Neelamegham 1997). On the other hand, in later stages of the product life cycle, product differentiation may make consumers more loyal, which might result in smaller sales responses to price changes (Simon 1979). In addition, the product life-cycle effect may depend on the type of criterion variable (absolute sales versus market shares/choice), as price changes in the early stages more severely affect absolute sales levels (Tellis 1988). Finally, the pattern of price elasticity over the product life cycle may differ across product categories (Parker and Neelamegham 1997; Simon 1979).

We test for the interaction between the product life cycle and the type of criterion variable (sales versus share/choice). In our study, this interaction effect is not significant (p = .85); thus, we exclude it from the model. To assess product category effects, we categorized the products into durables and groceries with high and low stockpiling propensity, using Narasimhan, Neslin, and Sen's (1996) classification. The main effects of product category ($p < .01$) and of product life cycle ($p < .01$) and the interaction between the product category and the product life cycle ($p < .01$) are significant. To understand the magnitude of the predicted effects of product life cycle and product category, we present Panel A in Table 2. It reveals that for all life-cycle stages, the price elasticity magnitude is the highest for durables; this is consistent with the notion that consumers have a stronger incentive to respond to price changes of big-ticket items (durables) than for smaller-ticket items (groceries). We also find that for all product categories, price elasticities are stronger in the introduction/growth stage than in the mature/decline stage, consistent with the product differentiation argument (Simon 1979).

Although we anticipated stronger elasticities for groceries with high (versus low) stockpiling propensities, the opposite result holds for early life-cycle categories, whereas there is no difference for mature/declining categories. A tentative explanation is that for new grocery categories with a short shelf life (e.g., refrigerated microwave food), consumers may be particularly attracted by price reductions as

[4]We use terminology based on the magnitude of price elasticities. For example, we label a change in price elasticity from –1.7 to –2.5 as an increase in magnitude.

[5]We measure the two other determinants (income and inflation) in yearly growth rates rather than levels, which avoids a confound with the year of data collection.

[6]Unless indicated otherwise, we use two-sided tests and α = .05.

Table 2
EFFECTS OF DETERMINANTS ON PRICE ELASTICITY

Group of Determinants	Determinant[a]	Levels	Number of Elasticities	Hierarchical Linear Model: Parameter Estimate[b]	Standard Error	Predicted Value[c]
Constant				–3.79***	.90	
Empirical situation (brand, category, and market characteristics)	Year of data collection	Linear effect		.01	.02	
	Year of data collection × criterion variable (abs. sales)			–.05**	.02	
	Brand ownership	Manufacturer brand	1704			–2.67
		Private label	147	.08	.17	–2.59
	Stage of product life cycle	Introduction or growth (IG)	204			See Panel A
		Mature or decline (MD)	1647	1.48***	.50	
	Type of product category	Groceries, low stockpiling (GL)	453			
		Groceries, high stockpiling (GH)	1365	1.39***	.40	
		Durables (DR)	33	–1.28	1.73	
	Type of product category × stage of product life cycle	GH; MD	1192	–1.37***	.44	
		DR; MD	28	.10	1.82	
	Country	United States/Canada	1583			–2.70
		Europe	191	.35	.61	–2.35
		Australia/New Zealand/Japan	77	–.06	.70	–2.75
	Household disposable income growth rate	Linear effect		.01	.10	
	Inflation rate	Linear effect		–.18***	.06	
Research methodology (data and model characteristics)	Data source	Firm (ex-factory data)	206			–2.78
		Store panel	1032	.08	.51	–2.70
		Household panel	613	.22	.48	–2.56
	Temporal aggregation	Weekly or biweekly	1328	.51	.50	–2.81
		Monthly to yearly	523			–2.30
	Item definition	SKU	633			–2.97
		Brand	1218	.47*	.28	–2.50
	Criterion variable	Relative sales (market share, choice)	1296			–2.92
		Absolute sales	555	–.32*	.20	–2.58
	Functional form	Multiplicative or exponential	810			–2.47
		Attraction	659	–.21	.26	–2.68
		Additive	382	–.56**	.27	–3.03

Panel A (Predicted Value)

	IG	MS
GL	–4.10	–2.62
GH	–2.71	–2.60
DR	–5.38	–3.81

Table 2
CONTINUED

Group of Determinants	Determinant[a]	Levels	Number of Elasticities	Hierarchical Linear Model: Parameter Estimate[b]	Standard Error	Predicted Value[c]
	Duration of the effect	Short-term (ST)	1753			
		Long-term (LT)	98	−3.86**	1.85	
	Definition of price	Actual price (AP)	1634			
		Promotional price (PP)	198	−1.27***	.31	
		Regular price (RP)	19	−1.03*	.61	
	Duration of the effect × definition of price	Promotional price (LT)	44	1.87**	.93	
		Regular price (LT)	3	1.85	1.45	
	Duration of the effect × inflation			.83	.74	
	Price endogeneity	Not accounted for	1558			−2.47
		Accounted for	293	−1.27***	.39	−3.74
	Quality effect	Excluded	1642			−2.69
		Included	209	.27	.38	−2.43
	Distribution effect	Excluded	1775			−2.69
		Included	76	.68	.45	−2.01
	Advertising effect	Excluded	1492			−2.83
		Included	359	.84**	.35	−1.98
	Sales promotion effect	Excluded	1031			−3.01
		Included	820	.79**	.32	−2.22
	Estimation method[d]	OLS	459			−2.61
		GSL, WLS, SUR	309	.26	.24	−2.34
		2SLS	281	−.34	.55	−2.95
		MLE	710	−.19	.32	−2.79
		Bayesian methods	92	.45	.50	−2.16
	Heterogeneity in price sensitivity	Not accounted for	1515			−2.66
		Accounted for	336	−.02	.24	−2.68

Predicted Value[c], Panel B (duration of the effect × definition of price):

	ST	LT
AP	−2.36	−3.78
PP	−3.63	−3.17
RP	−3.39	−2.96

*$p < .10$ (two-sided test).
**$p < .05$ (two-sided test).
***$p < .01$ (two-sided test).
[a]Each categorical variable is included by dummy variables; the first category is the base.
[b]A negative parameter estimate means that an elasticity becomes more negative (i.e., it increases in magnitude).
[c]We obtained predicted values for each determinant level while fixing all other determinants at sample average.
[d]OLS = ordinary least squares; GSL = generalized least squares; WLS = weighted least squares; SUR = seemingly unrelated regression; 2SLS = two-stage least squares; MLE = maximum likelihood estimation.

a trial mechanism because the anticipated regret duration in case of a disappointing experience is shorter (in which case the product is thrown away after a few days). A disappointing trial of a new stockpilable product category (e.g., a hair conditioner) looms longer because the consumer has it for a longer period. When the product category matures, consumers may learn to stockpile at price promotions for the stockpilable product, which closes its elasticity gap with the nonstockpilable product. Further research should examine this issue more closely.

Country. The three regions for which price elasticities have been reported (the United States/Canada, Europe, and Japan/Australia/New Zealand) are all quite homogeneous in the sense that they are all highly developed. Our meta-analysis shows that there are no significant effects of the region dummies on price elasticities ($p = .83$).

Income. An increase in household disposable income reduces consumers' motivation and need to look for low prices, because search costs outweigh the expected benefits of examining price information (Estelami, Lehmann, and Holden 2001). Therefore, we expect that an increasing growth rate of disposable household income reduces the magnitude of price elasticities. However, this effect is not significant ($p = .91$). The income effect could be moderated by the product category. For example, Mulhern, Williams, and Leone (1998) find that the price sensitivity for liquor increases with household income, because this specific category requires substantial financial buying power to take advantage of price promotions. However, the interaction effect between the income and the product category is not significant as well ($p = .07$); thus, we exclude it from the model.

Inflation. The effect of inflation on price elasticities is not clear a priori. On the one hand, we could argue that price variation is high in times of inflation, which blurs the information content of prices and reduces consumers' ability and motivation to seek, learn, and use price information. Thus, consumer knowledge of prices is lower in times of higher inflation (Estelami, Lehmann, and Holden 2001), and consumers are more prone to paying whatever prices are charged (Shamir 1985), leading to less elastic demand. However, if consumers use relative (percentage) price information, elasticities are independent of price and thus inflation. Another possible prediction is that high inflation rates may make consumers aware of and sensitive to price changes. Consistent with the latter prediction, we find a significant magnitude-increasing effect of inflation on price elasticity ($p < .01$). The effect is strong, and an increase of 5.6 percentage points in the yearly inflation rate is predicted to lead to a percentage point increase in the price elasticity magnitude.

Research Methodology: Data and Model Characteristics

Data source. Sales and price data can be obtained from various sources, in particular from manufacturers (primarily ex-factory sales data), stores (retail panel), or household panels. Tellis (1988) concludes that the data source effect is negligible. Gupta and colleagues (1996) find only minor differences between price elasticities obtained from household panel data and those obtained from store data. Similarly, Van Heerde, Gupta, and Wittink (2003) conclude from household data that, on average, one-third of the sales promotion bump is attributable to net effects on cross-brand sales, a result that Van Heerde, Leeflang, and Wittink (2004) closely replicated for store data. Our meta-analysis confirms that whether the data are obtained from manufacturers, stores, or households does not have a significant impact on the price elasticity ($p = .82$).

Temporal aggregation. Prices and sales typically fluctuate at fairly high rates. If data have been aggregated across time, such fluctuations will be lost to a large extent. Price promotions lead to intertemporal movements of sales (Van Heerde, Leeflang, and Wittink 2000), because a sales increase in the promotional week is offset to some extent by sales decreases before and after promotions. Thus, total sales across a longer time period fluctuate much less than weekly sales do. An average price across a longer period also fluctuates less than weekly prices do, but the extra reduction in variation due to intertemporal movements is absent for price. Thus, price elasticities based on data aggregated to longer periods should be closer to zero. However, we find that the effect of temporal aggregation ([bi-]weekly versus longer periods) on price elasticity is not significant ($p = .31$).

Item definition: SKU versus brand. Researchers have a choice between modeling at the SKU and at the brand level. In response to a price change, a consumer may switch between SKUs. If the price effect is assessed at the brand level, such a switch will not be observed if these SKUs are from the same brand, whereas at the SKU level, the switch is observed. Therefore, we expect that the price elasticity magnitude is higher at the SKU level than at the brand level (Christen et al. 1997). A one-sided test (justified as the result of a strong theoretical expectation) for the effect of item definition on price elasticity yields $p < .05$. The average predicted price elasticity is -2.97 for SKUs versus -2.50 for brands.

Definition of the criterion variable. The criterion variable that assesses price elasticity reflects absolute (sales) or relative attractiveness of the brand or SKU (market share or choice probability).[7] The sales elasticity can be decomposed into market share and category elasticity (Leeflang et al. 2000, pp. 170–71) or into brand choice, purchase incidence, and purchase quantity elasticities (Gupta 1988). The absolute and relative elasticities are the same if price changes involve just brand switching and no primary demand effects. However, because primary demand elasticities are often not zero (Bell, Chiang, and Padmanabhan 1999; Walters and Bommer 1996), relative elasticities should be smaller in magnitude than the absolute elasticity. In our meta-analysis, the effect of the definition of the criterion variable (absolute versus relative) on price elasticity has the expected sign ($\beta = -.32$) and is significant at the .05 level (one-sided testing, which is appropriate given strong expectation). The secondary demand (relative) elasticity is approximately 89% of absolute elasticity ($-2.57/-2.89$), which is only slightly higher than the percentage that Gupta (1988) obtains. This result does not mean that 89% of the

[7]We excluded elasticities of purchase quantities to price because they are reported infrequently.

sales increase due to a price reduction comes from other brands (Van Heerde 2005; Van Heerde, Gupta, and Wittink 2003). Van Heerde (2005) and Van Heerde, Gupta, and Wittink (2003) demonstrate that the transformation of absolute and relative elasticities into net sales effects implies that, on average, less than 50% of the own-brand sales increase is attributable to cross-brand sales reductions, whereas the majority is due to temporary category expansion.

Functional form. Tellis (1988) finds no significant elasticity differences between alternative functional forms. However, Bolton (1989b) finds small yet significant differences between price elasticities that are obtained with linear, multiplicative, and exponential models. In our analysis, the overall effect of alternative functional forms on price elasticities is not significant ($p = .13$).

Definition of price and duration of the effect. The price elasticity may strongly depend on the definition of price. It is essential to distinguish among actual, regular (base), and promotional price (price index) (Srinivasan, Popkowski-Leszczyc, and Bass 2000; Wittink et al. 1988). The actual price is the price a consumer pays at the checkout. The regular price is the price in regular (i.e., nonpromotional) conditions. The price index is the ratio of actual price to regular price (Van Heerde, Leeflang, and Wittink 2000; Wittink et al. 1988). It is equal to one in nonpromotional weeks, and it is smaller than one in promotional weeks. Thus, variation in the price index variable reflects promotional price discounts only. A promotional price elasticity measures the percentage sales change due to a 1% promotional price cut.

We first focus on the short-term sales impact of the variables' actual price, regular price, and promotional price. Because a promotional discount is available only for a short period, consumers know that they must respond immediately (Jedidi, Mela, and Gupta 1999). Therefore, we expect a strong promotional price elasticity. In contrast, consumers know that a regular price decrease will also be available in future periods, so the necessity to stockpile or purchase accelerate is absent, potentially leading to weaker regular price elasticities. Fluctuations in actual prices reflect both temporary price discounts and regular price changes, and as a result, we expect their effects to be in between.

In the long run, we expect price promotions to have a somewhat negative effect on consumers' reference prices and quality perceptions (Davis, Inman, and McAlister 1992). Similarly, if the promotion sales spike is followed by a postpromotion dip, the total elasticity is closer to zero than is the short-term elasticity. Time-series studies on the persistence of marketing-mix effects (Dekimpe, Hanssens, and Silva-Risso 1999; Pauwels, Hanssens, and Siddarth 2002) support this expectation. In contrast, regular price changes cause long-term consumer response changes in perceptions and purchase behavior (Ghosh, Neslin, and Shoemaker 1983). Therefore, we expect the long-term regular price elasticity to be larger than the long-term promotional price elasticity. Again, we anticipate that the actual price has a middle position.

The definition of the price effect has a significant impact on price elasticity. Because the number of observations for the short- and long-term elasticities of regular price is small, we only interpret actual versus promotional price elasticities, which have larger sample sizes. In Table 2, Panel B, we show that, as we expected, the short-term elasticity magnitude is lower for the actual price elasticity (–2.36) than for the promotion price elasticity (–3.63), whereas the long-term elasticity magnitude is higher for actual price (–3.78) than for promotional price (–3.17).

In addition, we examine whether the inflation effect is different for short- and long-term elasticities. Although the interaction effect is significant when it is tested relative to a model with main effects only, it is not significant in the model with the three other interaction effects ($p = .26$).

Endogeneity. A model that assumes that prices are exogenous when they are not induces a correlation between price and the error term, leading to a bias in the price elasticity estimate (Besanko, Gupta, and Jain 1998; Chintagunta 2001; Villas-Boas and Winer 1999). The direction of this bias depends on the sign of the price–error term correlation. If a manager decides to decrease price for situations in which some factor (unobservable for the researcher) causes a positive demand shock (Chevalier, Kashyap, and Rossi 2003), the price elasticity magnitude becomes inflated if price is assumed to be exogenous. However, if a manager increases price at a positive demand shock (e.g., to reap profits), the price elasticity estimate is biased toward zero under the exogeneity assumption (Besanko, Gupta, and Jain 1998; Chintagunta 2001; Villas-Boas and Winer 1995). Consistent with the latter reasoning, our meta-analysis shows that accounting for price endogeneity has a substantial and significant effect on price elasticity ($\beta = -1.27$; $p < .01$). In particular, the elasticity is larger in magnitude if endogeneity has been accounted for (–3.74) than when it has not been accounted for (–2.47). If price is indeed endogenous, the price elasticity obtained when accounting for endogeneity is likely to describe more accurately the reaction of demand to price. If endogeneity is ignored, the resulting price elasticity represents the net sales response given demand-side and supply-side reactions, leading to an elasticity that is closer to zero.

Omitted variables. In addition to endogeneity, omitted variables are another driver of correlation between price and the error term. If a regression equation omits a certain relevant predictor variable, parameter estimates of included variables may be biased (e.g., Greene 2000, pp. 334–37), depending on the coefficient of the omitted variable and the correlation between the included and omitted variables. In our meta-analysis, the effects of including product quality ($p = .49$) and distribution ($p = .13$) are not significant, whereas including advertising ($\beta = .84$; $p = .02$) or sales promotion (feature and/or display; $\beta = .79$; $p = .01$) decreases the price elasticity magnitude significantly. In other words, part of the presumably positive sales effects due to advertising and sales promotions is unduly attributed to price reductions when the former two variables are omitted.

Research has shown important interaction effects between price and other marketing-mix variables (e.g., Hanssens, Parsons, and Schultz 2001, pp. 339–40; Kaul and Wittink 1995). Thus, if other marketing-mix variables are omitted, potential interaction effects are omitted as well. The interaction term must be included explicitly in additive models, which has not been done in the studies included in our meta-analysis, whereas the other functional forms (i.e., multiplicative, exponential, and attraction) automatically capture some interaction effects between the marketing-mix variables. However, in our meta-analysis, including interaction effects between omitted marketing-mix variables and functional form does not yield significant results for the quality variable (p = .19), distribution (p = .56), advertising (p = .05), or sales promotions (p = .32). Therefore, we exclude the four interactions from the final model. We conclude that though there are often interactions between price and other marketing-mix variables, omitting the interactions does not result in a systematic upward or downward bias in price elasticity.

Estimation method. Our meta-analytical findings reveal that the effect of the estimation method on price elasticities is fairly small and nonsignificant (p = .49). Although two-stage least squares (2SLS) tends to be the primary estimation method to accommodate price endogeneity, there are several cases in which 2SLS does not go hand in hand with endogeneity. Thus, the level of confounding between the corresponding determinants is sufficiently low.

Heterogeneity in price sensitivity. Consumers are heterogeneous in their price sensitivity as a result of a multitude of factors, such as brand loyalty, product involvement, income, and inventory costs. Accounting for heterogeneity may theoretically increase or decrease the elasticity estimate, depending on the heterogeneity pattern (Hutchinson, Kamakura, and Lynch 2000). The majority of empirical studies find that accounting for consumer heterogeneity leads to higher price elasticity magnitudes (e.g., Chintagunta 2001; Gönül and Srinivasan 1993; Jain, Vilcassim, and Chintagunta 1994). However, Ailawadi, Gedenk, and Neslin (1999) find that though price response parameters might be affected, price elasticities are largely independent of whether consumer heterogeneity is modeled. Our meta-analysis supports the latter finding (p = .93).

Temporal Patterns in Price Elasticity

In this section, we study the temporal patterns in price elasticity and its determinants. We already highlighted the finding that the autonomous time trend suggests that sales elasticities increase .04 in magnitude each year. In addition, market characteristics and research methodologies have changed dramatically throughout the past decades, which may have enhanced or reduced temporal patterns in price elasticities. As Kayande and Bhargava (1994) suggest, we split the sample into two periods on the basis of the year of data collection. We chose 1956–1979 (the prescanning data era) and 1980–1999 (the scanning data era). Scanning was introduced in the 1970s, and it diffused quickly in the United States by 1980, having an enormous impact on marketing research (Bloom 1980; Mason and Mayer 1980). During the mid-1980s, marketing scientists began publishing empirical studies that used scanner data (Bucklin and Gupta 1999) that had been collected since the beginning of the 1980s. Another rationale to pick 1980 as a split-sample year is that Tellis's (1988) meta-analysis on price elasticity used data that had been collected up to 1979.

For both eras, we report the average observed and model-predicted price elasticities and averages for the determinant variables (see Table 3). We compute the influence on the predicted elasticity by multiplying the pre- and post-1980 determinant averages by the corresponding parameter value, as Narasimhan, Neslin, and Sen (1996) do. We present the ten determinants with the strongest influences.

Table 3

TEMPORAL PATTERNS IN PRICE ELASTICITY AND ITS DETERMINANTS

	Period 1: Prescanning Data Era 1956–1979	*Period 2: Scanning Data Era 1980–1999*	
Number of observed price elasticities	499	1352	
Average observed price elasticity	–2.17	–2.79	
Average predicted price elasticity	–2.29	–2.81	
Determinant[a]	*Average Determinant Value*		*Difference Between Periods in Contribution to the Average Predicted Price Elasticity (Period 2 – Period 1)*
Product life cycle: mature or decline	.60	1.00	.58
Product life cycle × product category: groceries, high stockpiling; mature or decline	.35	.75	–.55
Temporal aggregation: monthly to yearly	.79	.10	–.35
Advertising effect included	.46	.10	–.31
Sales promotion effect included	.16	.55	.30
Inflation rate	5.61	4.05	.28
Price endogeneity: accounted for	.00	.22	–.28
Year of data collection[b] × criterion variable: absolute sales	–4.71	1.27	–.28
Duration of the effect: long term	.10	.03	.26
Functional form: additive model	.49	.10	.22

[a]Determinants are ordered in descending absolute contribution to the difference between periods, and only the ten determinants with the largest contributions are listed.

[b]Mean centered.

The main effect of the product life cycle and the interaction effect with the product categories are the strongest factors that contribute to the temporal change in price elasticity. In the period from 1980 to 1999, virtually all elasticities correspond to mature or decline stages of the product life cycle. This introduces an effect toward weaker price sensitivities (.58), except for groceries with a high stockpiling propensity (–.55). The next most important distinction between the two periods is the temporal aggregation of the data; in the first period, most data sets are monthly to yearly, and in the second period, most are weekly or biweekly (often scanning data). This results in stronger price elasticities (–.35) in the second period. Whereas during the first period advertising is included in the models more often than are sales promotions, the opposite holds for the second period. The two differences in determinant averages cancel each other out, because the impact of omitting advertising and sales promotions is similar (see Table 2). On average, inflation is lower in the scanning era (4.1 versus 5.6), leading to weaker price elasticities (.28) for this period. Whether price endogeneity is accounted for has a large impact on the predicted elasticity (see Table 2). The predicted price elasticity is stronger in the second period (–.28), because in that period, 22% of the elasticities have been estimated while correcting for endogeneity, whereas this is never the case in the first period. The interaction between the time trend and the definition of the criterion variable is also an important driver of the temporal changes in price elasticity. In the 20 years between the midpoints of the prescanning and scanning eras, the trend variable captures an increase in magnitude of the sales elasticity of .28 percentage points (–.28 more negative). Next, the lower number of long-term elasticities in the scanning era decreases the magnitude of the predicted price elasticity (.26). Finally, the additive model was applied frequently in the pre-1980 period but rarely in more recent years, which decreases the magnitude of the predicted price elasticity (.22 less negative). We conclude that longitudinal changes in the determinants play important and sometimes contradictory roles in explaining longitudinal changes in price elasticities.

DISCUSSION

Conclusions

We offer new empirical generalizations on the determinants of price elasticity based on a meta-analysis of 81 price elasticity studies, and we extend the range of potential determinants from Tellis's (1988) landmark study. The average price elasticity that Tellis (1988) finds in his meta-analysis of 367 elasticities is –1.76. Our meta-analysis, which is based on 1851 elasticities, finds an average price elasticity that is substantially larger in magnitude: –2.62. Our figure closely resembles average price elasticities that Bolton (1989a, p. 162) and several other studies (e.g., Hanssens, Parsons, and Schultz 2001, p. 333) report.

We summarize our main conclusions in Table 4 and contrast them with those of Tellis (1988). For several determinants, we reach the same conclusions as Tellis. In particular, we reconfirm that consumers are more price elastic for durables than for other products. In addition, price elasticity magnitudes are higher if sales is the criterion variable than if either share or choice is. Furthermore, we find no significant differences between price elasticities from different data sources (i.e., firms, retail panels, and household panels) or between alternative functional forms. Yet for other determinants, we find that previous generalizations need revision. We no longer find significant price elasticity differences between countries, between levels of temporal aggregation, between models including or excluding quality or distribution, or between estimation methods. Our conclusion that demand for products is significantly more price elastic in the introduction/growth stage than in the mature/decline stage opposes Tellis's (1988) results.

We find several new significant determinants. Although there is no significant overall trend in the price elasticity across the data sample period (i.e., 1956–1999), the difference between absolute and relative elasticities increases over time. Price elasticities become much stronger if endogeneity is accounted for. We find strong effects of omitting advertising and sales promotions as predictors. Therefore, two factors associated with correlations between price and the error term (endogeneity and omitted variables) are influential determinants. Another new finding is that inflation leads to substantially larger price elasticities, especially in the short run. We also find that the promotional price elasticity is larger in magnitude than is the actual price elasticity in the short run and that the reverse is true in the long run. Finally, we find that price elasticity is higher at the SKU level than at the brand level.

Some of our new determinants are not significant. We find that average price elasticities do not differ significantly between private labels and manufacturer brands. Our results also indicate that accommodating consumer heterogeneity does not lead to different price elasticity estimates.

A notable question is why our results differ in some respects from Tellis's (1988). Possible explanations include the sample sizes (we have five times as many elasticities), the analysis methods (we use generalized least squares [GLS], whereas Tellis uses ordinary least squares [OLS]), and the values of the determinants. Although a larger sample size tends to decrease the standard errors of parameter estimates, the application of GLS accounting for dependency between multiple elasticities obtained from a single study (Bijmolt and Pieters 2001) tends to lead to larger standard errors. The net impact of these two effects on parameter reliability is undetermined. Furthermore, GLS yields parameter estimates that are similar to those of OLS (not shown). Thus, the analysis method is not the key distinguishing factor between our study and Tellis's (1988) study.

The values of the determinants represent a key difference from Tellis's (1988) results, because dramatic changes have occurred in the relative frequency of the various determinant levels when comparing the period that Tellis analyzes with the period that we analyze (see also the section "Temporal Patterns in Price Elasticity"). For the period from 1956 to 1979, we lack observations (1) of price elasticities of private labels, (2) that account for endogeneity and/or heterogeneity, (3) with low temporal aggregation, (4) from models that include sales promotion effects, and (5) that are estimated by Bayesian methods. For the period from 1980 to 1999, we have no or only a few observations (1) of price elasticities for durables, (2) for the introduction or growth

Table 4

OVERVIEW OF UPDATED AND EXTENDED META-ANALYTIC GENERALIZATIONS ON PRICE ELASTICITY

		Effect on Magnitude of Price Elasticity	
Group of Determinants	*Determinant*	*Tellis (1988)*	*This Study*
Empirical situation (brand, category, and market characteristics)	Brand ownership		No significant difference
	Product category	Durables > food > pharmaceuticals	Durables > groceries
	Stage of product life cycle	Mature/decline > introduction/growth	Mature/decline < introduction/growth
	Country	Australia/New Zealand > the United States > Europe	No significant differences
	Household disposable income		No effect
	Inflation		Positive effect
	Year of data collection		Absolute sales elasticity increases; Relative elasticity does not change significantly
Research methodology (data and model characteristics)	Data source	No significant differences	No significant differences
	Temporal aggregation	Negative effect	No significant differences
	Item definition		SKU level > brand level
	Criterion variable	Absolute > relative	Absolute > relative
	Functional form	No significant differences	No significant differences
	Definition of price		Short term: promotional > actual price; Long term: actual price > promotional
	Price endogeneity accounted for		Positive effect
	Quality effect	Included > omitted	No significant differences
	Distribution effect	Omitted > included	No significant differences
	Advertising effect	No significant differences	Omitted > included
	Sales promotion effect	No significant differences	Omitted > included
	Estimation method	GLS < other methods	No significant differences
	Heterogeneity in price sensitivity		No significant effect
Overall average		−1.76	−2.62

stages, (3) with firms as the data source, and (4) from models that include distribution. As we discussed previously, changes in the moderator values have a considerable impact on differences between elasticities that Tellis (1988) considers and those that we consider.

Implications for Managers

This meta-analysis suggests several key learning points for managers who set prices. The gap between sales elasticities and choice/share elasticities is increasing over time, suggesting that primary demand elasticities are increasing. This replicates Mela, Jedidi, and Bowman's (1998) findings. A major implication is that the fraction of the sales promotion bump attributable to cross-brand effects is decreasing over time, because this fraction is a monotonically increasing function of the decreasing ratio of the choice/share elasticity to the sales elasticity (Van Heerde, Gupta, and Wittink 2003). In other words, consumers seem to base their timing and quantity decisions increasingly on price (promotions). Managers may not appreciate the implied deal-to-deal buying behavior because products are decreasingly sold at full margin, but a possible way to avoid this is to reduce the frequency of price promotions. However, cutting back on deals does not necessarily lead to profit increases, as Procter & Gamble found out in the 1990s (Ailawadi, Lehmann, and Neslin 2001).

Another managerially relevant finding is that price elasticities are the strongest in the growth stage of product categories, both for durables and for groceries. This suggests that when managers introduce a new category, a penetration pricing strategy (low to high) is more effective than a skimming price strategy (high to low). An important null result is that the effect of brand ownership on price elasticities is not significant. In other words, manufacturer brands are not necessarily more differentiated than are private labels if brand differentiation is operationalized as the own-brand price elasticity (Boulding, Lee, and Staelin 1994).

The environment in which the manager operates has some ramifications for pricing. If a country's inflation rate is high, demand becomes more price elastic in the short run. This suggests that a brand gains additional sales or share if the item is promoted or if it keeps its regular price increases at a pace that is low relative to the inflation rate. The effect of economic growth rate on elasticities is not significant. This implies that during economic booms, managers should not be tempted to believe that price increases are less harmful than they are during recessions. Finally, the absence of significant effects of region dummies (North America, Europe, Japan/Australia/New Zealand) on price elasticities may provide an argument for price strategies that are similar in developed countries across the globe.

Implications for Researchers

Our results imply that accommodating endogeneity has a strong impact on price elasticity estimates, consistent with Chintagunta's (2001) results. Therefore, we recommend that at a minimum, researchers test for price endogeneity before estimating price elasticities. Furthermore, besides a price variable, researchers should aim to include advertising and sales promotions (features and/or display) as predictor variables in response models. It is also essential to specify which definition of price is used. Preferably, price is decomposed into regular price and price index (actual divided by regular price), which allows disentanglement of the (short- and long-term) effects of both components. To some extent, our results are reassuring for marketing researchers, because several factors pertaining to the data set and model options (i.e., data source, temporal aggregation, functional form, estimation method, and heterogeneity) do not have a significant effect on price elasticity estimates.

Further Research

Because meta-analysis is limited to the issues on which there is a sufficient set of empirical results, it also signals areas that warrant further study. Farley, Lehmann, and Mann (1998) describe how one new observation helps reduce multicollinearity in the meta-analysis design matrix $\mathbf{Z}$ by reducing the trace of $(\mathbf{Z'Z})^{-1}$. We examine this in a follow-up analysis of the current meta-analytic study. Therefore, we generate all possible combinations (nearly five million) of determinant levels (main effects only). Then, for each new design—that is, our original study and a single new observation—we compute trace $([\mathbf{Z'Z}]^{-1})$. The single most desirable new observation, which reduces trace $([\mathbf{Z'Z}]^{-1})$ the most, is a complex combination of many determinant levels, and it is not realistic to expect a researcher to study such an ideal situation. Thus, we examine how the various determinant levels are related to the reduction in trace $([\mathbf{Z'Z}]^{-1})$ and therefore are most essential to enhance further knowledge of determinants of price elasticity. Notably, an analysis of variance shows that only a small set of determinants critically affects the improvement achieved. The largest collinearity reduction is achieved by adding a new observation on the long-term elasticity of regular price, followed by its short-term elasticity. Product category, price endogeneity, and estimation method have a considerable but much smaller effect on the collinearity reduction. New observations that correspond to durables or models that ignore endogeneity or that are estimated with 2SLS or Bayesian methods yield relatively large improvements of the meta-analytical design matrix. Note that the results are largely consistent with the idea of adding observations in sparse determinant categories, such as regular price effects and durables. All other determinants have virtually no impact on the amount of collinearity reduction, because each of the remaining meta-analysis design elements explains less than 1% of the variance in potential reduction.

Beyond the range of the current meta-analytic design, research that extends the scope of knowledge of price elasticities is necessary. First, additional model specification factors may influence the price elasticity, such as whether and how the model accommodates dynamics, state dependence, preference heterogeneity, type of promotion (e.g., feature, display), consumption rates, and cross-store effects. To investigate this, researchers would need to focus exclusively on scanner-data-based studies of the past two decades that examine primarily groceries. We leave this issue for further research.

Second, the effect of price is known to be asymmetric in many circumstances in which price elasticity is larger for price increases than for price decreases (see Hanssens, Parsons, and Schultz 2001, p. 334; Monroe 2003, p. 149). To date, virtually all empirical studies have neglected this issue. When empirical studies assess separate elasticities for price increases and decreases, empirical generalizations on the size of the price elasticity asymmetry and the potential effect of determinants are possible.

Third, the database that underlies our meta-analysis contains only periods and countries that are economically fairly stable. Therefore, the range of observed values of household income growth rate and inflation is limited. For example, we lack observations of price elasticities that correspond to situations with substantial income decreases, hyperinflation (Grewal and Zinn 1996), or hypergrowth, and further empirical research could examine price elasticities in those situations. Fourth, our elasticities are relevant to bricks-and-mortar situations, and investigating whether they are systematically different for Internet situations is an intriguing topic for the next meta-analysis on price effects.

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