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The authors conduct a meta-analysis of 751 short-term and 402 long-term direct-to-consumer brand advertising elasticities estimated in 56 studies published between 1960 and 2008. The study finds several new empirical generalizations about advertising elasticity. The most important are as follows: The average short-term advertising elasticity is .12, which is substantially lower than the prior meta-analytic mean of .22; there has been a decline in the advertising elasticity over time; and advertising elasticity is higher (1) for durable goods than nondurable goods, (2) in the early stage than the mature stage of the life cycle, (3) for yearly data than quarterly data, and (4) when advertising is measured in gross rating points than monetary terms. The mean long-term advertising elasticity is .24, which is much lower than the implied mean in the prior meta-analysis (.41). Many of the results for short-term elasticity hold for long-term elasticity, with some notable exceptions. The authors discuss the implications of these findings.

Keywords: advertising elasticity, meta-analysis, empirical generalization, promotion, marketing mix

How Well Does Advertising Work? Generalizations from Meta-Analysis of Brand Advertising Elasticities

Advertising is one of the most important elements of the marketing mix. Controversy rages over whether firms are getting adequate returns on their advertising expenditures (Aaker and Carman 1982; Tellis 2004). One key element in this controversy is how effective advertising is in generating sales. The effectiveness of advertising is often measured in terms of advertising elasticity, or the percentage increase in sales or market share for a 1% increase in advertising. Obtaining generalizable estimates of advertising elasticity and identifying factors that influence advertising elasticity can further the field's understanding of the effectiveness of advertising.

Assmus, Farley, and Lehmann (1984) provide the first empirical generalizations on advertising elasticity. In particular, these authors perform a meta-analysis of 128 estimates of advertising elasticity from 16 studies published between 1962 and 1981 and provide useful generalizations on advertising effect. More than 25 years have passed since that publication. This period (1984–2008) has witnessed significant changes on many fronts that may have an impact on the measurement and effectiveness of advertising. First, the marketing environment has changed as a result of greater competition, globalization, the advent of the Internet, and the ability of the consumer to opt out of television commercials through devices such as TiVo. Second, the data and methods for estimating advertising elasticity are increasing in sophistication with the use of disaggregate scanner data and the application of New Empirical Industrial Organization econometric models. Therefore, it seems prudent to update the empirical generalizations on advertis-

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ISSN: 0022-2437 (print), 1547-7193 (electronic)

Journal of Marketing Research
Vol. XLVIII (June 2011), 457–471

ing elasticity by including data from studies published since 1981.

This study conducts a meta-analysis of 751 short-term brand-level direct-to-consumer advertising elasticities and 402 long-term advertising elasticities from 56 studies published between 1960 and 2008. Our study disconfirms a few of Assmus, Farley, and Lehmann's (1984) findings, validates some of the previous findings, and uncovers several new empirical generalizations and insights, which we summarize in the conclusion of this article.

In this regard, our research is similar in spirit to other follow-up meta-analytic studies in recent times. For example, Bijmolt, Van Heerde, and Pieters (2005) update the meta-analysis of price elasticity conducted previously by Tellis (1988). Hu, Lodish, and Krieger (2007) provide a partial update to Lodish et al.'s (1995) meta-analysis related to television advertising experiments. Our study can also be viewed as a meta-analytic complement to Vakratsas and Ambler's (1999) broad review of advertising literature. They develop a taxonomy, review 250 studies, and provide insights into how advertising works. Our study performs a meta-analysis of econometric estimates of advertising elasticity and provides insights into whether advertising works, the magnitude of the effect, and the factors that influence elasticity. In the process, the study adds to Hanssens's (2009) list of empirical generalizations about marketing's impact.

Our study complements Fischer and Albers's (2010) recent article. Both studies offer insights into the effect of marketing mix on sales. However, whereas Fischer and Albers provide an excellent analysis of the effect of marketing efforts (detailing, journal advertising, and consumer advertising) on primary demand (category expansion) in pharmaceutical products, our analysis focuses on the effect of consumer advertising on selective demand (competitive brand sales) across a wide range of consumer products, including pharmaceuticals.

We organize the remainder of the article as follows: Next, we describe the data. Then, we describe the meta-analysis procedure and present the empirical findings. Following this, we discuss the results and their implications. In the final section, we summarize the results in the form of empirical generalizations and provide some limitations and future research directions.

DATA

This section describes the compilation of the database used in the meta-analysis. The data consist of observations on advertising elasticity (dependent variable) and the potential influencing factors of advertising elasticity (independent variables).

Advertising Elasticity

For this meta-analysis, we selected studies that provide estimates of brand-level, short- or long-term consumer advertising elasticity from econometric models using market data. Thus, our meta-analysis excludes (1) category advertising effects, (2) effects based on experimental or other noneconometric designs, and (3) business-to-business (B2B) advertising. The following paragraphs explain each of these choices.

First, category-level advertising elasticity measures the increase in category sales (primary demand) for a 1% change in total category advertising. In general, these effects are of interest to economists and public policy makers who investigate whether advertising expands category demand in products such as milk, alcohol, and cigarettes (e.g., Gallet 2007). Fischer and Albers (2010) provide a recent comprehensive analysis of the primary demand effects of marketing efforts in the pharmaceutical industry. In contrast, our perspective is that of the brand managers, who are interested in the extent to which advertising of their brands affects their own brand's sales (selective demand).

Second, following the scope of Assmus, Farley, and Lehmann's (1984) meta-analysis, we restrict our analysis to econometric estimates. Lodish and others conduct numerous television advertising experiments and meta-analyze those results (e.g., Hu, Lodish, and Krieger 2007). However, their focus is mainly on whether advertising produces a significant impact on sales in controlled experiments and not in natural market scenarios, which is the purpose of our study.

Third, consistent with Assmus, Farley, and Lehmann's (1984) study, we focus on consumer advertising only. Studies that provide advertising elasticity in the B2B context are few and, in general, pertain to journal advertising to physicians (B2B in the pharmaceutical industry). Fischer and Albers (2010) do a thorough job of analyzing this industry.

We adopted the following procedure for compiling the studies. We began our literature review with Assmus, Farley, and Lehmann (1984) as the base. Then, we used the Social Science Citation Index to identify 132 publications that reference the 1984 meta-analysis. Next, we used keyword searches (e.g., "advertising elasticity", "advertising response", "sales response") in online search engines such as Google Scholar, ABI/INFORM, and Lexis Nexis to identify articles that discuss the subject area. We also reviewed the reference lists in all of the previously mentioned studies. We considered studies that provide econometric estimates of advertising elasticity. Although most studies directly report advertising elasticity, in some cases we had to compute the elasticity according to available data or with inputs from the studies' authors. The process yielded 751 short-term elasticities from 56 publications. We provide details of these studies in Web Appendix A (http://www.marketingpower.com/jmrjune11).

Advertising can affect sales both in the short (current period) and long (current and future periods) run. We define "long-term advertising elasticity" as the percentage change in a brand's current and future period sales for a 1% change in the brand's current advertising.[1] Some studies directly provide estimates of long-term advertising elasticity. Others provide estimates of short-term elasticity and carryover coefficient (coefficient of the lagged dependent variable) from the Koyck model. We calculate long-term elasticity as [short-term advertising elasticity/(1 – carryover coefficient)] (Clarke 1976). A few researchers measure advertising as ad stock, defined as a weighted combination of current and past advertising based on an exponential smoothing coefficient. In this case, the estimate of advertising elasticity is

[1]The combined advertising effect of current and future period is also referred to as cumulative advertising effect.

the long-term elasticity. The short-term elasticity is [long-term elasticity × (1 – smoothing coefficient)] (Danaher, Bonfrer, and Dhar 2008). We obtained 402 long-term advertising elasticities from the 38 studies listed in Web Appendix A (http://www.marketingpower.com/jmrjune11).

Influencing Factors

In addition to advertising elasticity, we collected data on 22 variables that could potentially influence elasticity and classified them into the following six factors:

- *Time and recession factors*: Median year of data and duration of recession during the estimation period;
- *Product and geographic factors*: Product type, product life cycle, and geographic area;
- *Data characteristics*: Temporal interval, data aggregation, dependent measure, advertising measure, and advertising type;
- *Omitted variables*: Omission of lag-dependent variable, lag advertising, lag price, price, quality, promotion, and distribution;
- *Model characteristics*: Functional form, estimation method, incorporating endogeneity, and incorporating heterogeneity; and
- *Other characteristics*: Published versus unpublished work.

Many of these variables correspond to those in Assmus, Farley, and Lehmann's (1984) original meta-analysis. However, availability of new data permits us to investigate several new variables, such as the time trend, presence of a recession, additional product types (service goods and pharmaceuticals), additional continents (Asia and Australia), and additional method factors (incorporation of endogeneity and heterogeneity). Table 1 provides the levels of the independent variables and a detailed description of the expected relationship and the operationalizations of the variables.

PROCEDURE

Univariate Analysis

First, we performed a univariate analysis to obtain an estimate of the mean short-term advertising elasticity, which we then compared with the corresponding value in Assmus, Farley, and Lehmann (1984). We also analyzed the median and distribution of advertising elasticity.

Meta-Analytic Model for Short-Term Elasticity

The purpose of this meta-analysis is to identify the potential influencing factors of advertising elasticity. Prior meta-analytic studies (e.g., Assmus, Farley, and Lehmann 1984; Tellis 1988) have used ordinary least squares (OLS) regression of the following form:

$$A_{sj} = X_{sj}\beta + e_{sj}, \tag{1}$$

where A_{sj} is the jth advertising elasticity from sth study; X_{sj} are characteristics of the market, study design, and model that influence the elasticity (listed in Table 2, Column 3); βs are the meta-analytic parameters of interest, and e_{sj} are the error terms, initially assumed to be independently and identically distributed $N(0, s^2)$. To account for within-study error correlations, Bijmolt and Pieters (2001) point out that unique study-specific characteristics not captured in the independent variables would appear in the error structure. This would result in nonzero correlations leading to nonzero error covariance (within-study), violating the assumptions of OLS regression. Therefore, they suggest using a hierarchical linear model estimated with iterative generalized least squares to allow for a within-study, block nonzero variance–covariance matrix. Specifically, they suggest a model of the following form:

$$A_{sj} = X_{sj}\beta + z_s + e_{sj}, \tag{2}$$

where z_s is the unobserved study-specific effect and is assumed to be distributed with mean zero and standard deviation s^z. Following Bijmolt, Van Heerde, and Pieters (2005), we use Model 2 in our analysis for identifying potential influencing factors.

Alternate Meta-Analytic Models to Test Robustness

There are several issues regarding the estimation of Model 2. First, the advertising elasticities themselves are not true parameters but are estimated with error. We accounted for this uncertainty surrounding the true advertising elasticity using the following procedure: (1) We compiled the estimated advertising elasticity A_{sj}, the jth advertising elasticity from sth study along with its standard error B_{sj}; (2) we assumed that the true parameters lie in the normal distribution $N(A_{sj}, B_{sj})$; (3) we drew $\tilde{A}_{sj}$ observation for each s, j from the corresponding normal distribution; (4) we estimated Model 2 with $\tilde{A}_{sj}$ instead of A_{sj} to get β_k, where β_k is the vector of regression parameters from the kth iteration. Then, we repeated Steps 1–4 for 500 iterations and averaged β_k across all 500 iterations to get an average estimate that takes into account the uncertainty surrounding the advertising elasticity.[2]

A second major issue is collinearity. Several method variables are likely to be correlated. We assessed the extent of multicollinearity through traditional measures such as bivariate correlation, variance inflation factor, condition index, and proportion of variance explained (Belsley, Kuh, and Welsch 1980). However, because most of the method factors are discrete dummy variables, correlation measures often tend to be lower. Therefore, we used cross-tab analysis of pairs of variables and the corresponding chi-square measure to detect deviation from independence of two discrete variables. Using these multiple measures, we identified pairs of variables with potential problems of collinearity. We excluded one of those variables from Model 2 and tested for robustness by inspecting the significance of the other included variable.

Test of Additional Variables

We carried out several analyses to gain additional insights. First, we explored the following four interaction effects[3]:

- *Recession × product type*: A recession may affect advertising elasticity of high-priced durable goods more than low-priced food products;

[2]We thank the associate editor for suggesting this method to account for uncertainty in elasticity estimates.

[3]Numerous other interaction effects are possible, but incorporating all possible interactions would contribute to collinearity and compromise the stability of the model. We included those interactions either for which we had some prior knowledge based on theory or intuition (e.g., product life cycle × dependent measure) or that were otherwise of managerial interest (e.g., recession × product type).

Table 1

FACTORS INFLUENCING ADVERTISING ELASTICITIES: EXPECTED RELATIONSHIPS AND OPERATIONALIZATIONS

Number	*Variable/Level*	*Expected Relationship with Advertising Elasticity*	*Operationalization/How Data Obtained*
Time Trend and Recession			
1	Time trend: Median year of data	Advertising elasticity should decrease over time because of increased competition, ad clutter, the advent of the Internet as an alternate information source, and the consumer's ability to opt out of television commercials through devices such as TiVo.	We used median year of the estimation period to detect time trend. For example, if the study used data from 1982 to 1990 to estimate advertising elasticity, that advertising elasticity observation is said to come from its median year 1986.
2	Recession: Months of recession	During recessionary times, consumers should become more price conscious and tend to ignore generally image-based advertising. Therefore, advertising elasticity should be smaller during recessionary times.	Recession is defined as two quarters of negative gross domestic product growth. Data for the United States and other countries were obtained from the National Bureau of Economic Research and the Organisation for Economic Co-operation and Development websites. When recession data are not identified, we substituted U.S. data. We measured recession variable as the number of months that the economy is in recession as a proportion of total months in the estimation period.
Product and Geographic Factors			
3	Product type: •Pharmaceutical •Durable •Food •Nonfood •Service	No prior expectations.	We obtained category type information directly from the individual studies.
4	Product life cycle: •Growth •Mature	Advertising either provides information or persuades consumers about the advertised brand, both of which are more relevant in the early stage of the life cycle, when consumers know little about the brand or have not formed preferences. Thus, advertising elasticity will be higher for products in the early stage than in the mature stage of the life cycle.	We obtained product life-cycle information directly from the individual studies. When the authors called the studied product "established," we classified it as a mature product.
5	Region: •America •Europe •Other	Europe may have underadvertising due to regulation, short history of advertising, or culture, while the United States may have optimal or overadvertising because of the long history of advertising, intense competition, and advertising wars. If this reasoning is correct, advertising elasticity is likely to be higher in Europe than in the United States.	Region information is based on the continent in which the data for estimation of advertising elasticity are obtained. Most data for the North American continent are from the United States. Many studies that estimate data from Europe state the specific country (e.g., France, Germany). However, we did not analyze at the country level, because there are inadequate country-level observations to obtain credible regression estimates.
Data Characteristics			
6	Dependent measure: •Absolute (sales) •Relative (share)	Absolute sales captures both competitive gains and gains due to primary market expansion. Relative sales captures only competitive gains. Because advertising can increase primary demand, we expect advertising elasticity to be higher when sales are recorded in absolute terms.	We obtained data on dependent measure directly from the estimation model that produced the elasticity. If the model has unit or dollar sales as dependent variable, we considered it absolute. If the dependent variable is market share, we classified it as relative.
7	Temporal interval: •Weekly •Quarterly •Yearly	In general, advertising has a carryover impact. Therefore, the greater the level of temporal aggregation, the more likely it is to capture the sales resulting from the carryover advertising. Thus, we expect current-period advertising elasticity to be larger when data are more aggregated (yearly or quarterly) than less aggregated (weekly or daily) if the model does not capture the carryover effect.	We obtained data interval information directly from the individual studies. We combined some levels because of paucity of data: •Weekly: daily, weekly, monthly •Quarterly: bimonthly, quarterly •Yearly: annual
8	Data aggregation: •Firm •Panel	Estimation of advertising elasticity using firm-level data implicitly aggregates consumer-level information in a linear way. Estimation of advertising elasticity with panel data uses MLE that combines information in a nonlinear way. Therefore, the results may be different, but the direction of change is unknown.	Most of the data are aggregated across consumers at the brand level. These aggregated data are called firm-level data. The panel data type consists of individual consumer–level choice data with corresponding individual advertising data (exposures).
9	Advertising measure: •Monetary •GRP •Relative	Depending on what competitors in the market are doing, changes in absolute advertising may not necessarily reflect the same changes in relative advertising. If competitors tend to match a target firm's advertising, large changes in absolute advertising will translate into small changes in relative advertising. As a result, elasticity estimated with absolute advertising should be smaller than those estimated with relative advertising. The reverse should hold if competitors do not match the advertising.	A brand's advertising may be measured in absolute (monetary values or GRP) or relative (the brand's share of advertising in the market) terms. We obtained data on advertising measure directly from the individual studies. When the researchers used absolute advertising, information is provided as to whether advertising is measured in monetary units or GRP.
10	Advertising type: •Print •Television •Aggregate	It is not clear whether consumers are more responsive to print or television advertising. However, because aggregate advertising is a combination of print and television advertisements, we expect advertising elasticity from aggregate advertising to be between print and television advertising.	We obtained these data directly from the type of advertising described in individual studies. Advertising is aggregate if the advertising is a combination of more than one type of advertising (e.g., print, television, billboards). When nothing is mentioned, we classified it as aggregate advertising.

Table 1
CONTINUED

Number	Variable/Level	Expected Relationship with Advertising Elasticity	Operationalization/How Data Obtained
Omitted Variables			
11	Lag dependent variable: •Omitted •Included	Lagged sales are likely to be correlated positively with current-period sales and current-period advertising (because current advertising is often set as a proportion of past sales). Therefore, we expect omission of lagged sales to bias advertising elasticity positively.	We obtained these data directly from the model from which the advertising elasticity is estimated.
12	Lag advertising: •Omitted •Included	Lagged advertising is likely to be correlated positively with current-period sales and current-period advertising. Therefore, we expect omission of lagged advertising to bias the advertising elasticity measure positively.	We obtained these data directly from the model from which the advertising elasticity is estimated.
13	Lag price: •Omitted •Included	Lagged price is likely to be correlated negatively with current-period sales and positively with current-period advertising. Therefore, omission of lagged price should negatively bias the advertising elasticity.	See preceding item.
14	Price: •Omitted •Included	Price is likely to be correlated negatively with current-period sales and positively with current-period advertising. Therefore, we expect omission of price to bias the advertising elasticity measure negatively.	See preceding item.
15	Quality: •Omitted •Included	We were unable to predict the sign of correlation between quality and sales and, thus, the direction of the effect.	See preceding item.
16	Promotion: •Omitted •Included	We were unable to predict the sign of correlation between promotion and advertising.	See preceding item.
17	Distribution: •Omitted •Included	Distribution is likely to be correlated positively with current-period sales and positively with current-period advertising. Therefore, we expect omission of distribution to bias the advertising elasticity measure positively.	See preceding item.
Model Characteristics			
18	Functional form: •Double log •Linear, Share •Other	No prior expectations.	We obtained these data directly from the model from which the advertising elasticity is estimated.
19	Estimation method: •OLS •GLS •MLE •Other	No prior expectations.	We obtained these data directly from the model from which the advertising elasticity is estimated.
20	Endogeneity: •Omitted •Included	We had no theoretical reasoning, but Villas-Boas and Winer (1999) find that omitting endogeneity in price elasticity estimation biases the estimate toward zero.	A model incorporates endogeneity if it treats advertising as a dependent variable endogenously determined within the model structure.
21	Heterogeneity: •Omitted •Included	No prior expectations.	A model that allows for differences in advertising response parameters across households or segments in the sample is deemed to incorporate heterogeneity. Both discrete and continuous heterogeneity are included in this measure.
Other Factors			
22	Study type: •Published •Unpublished	Because of the general bias toward publishing articles that produce significant effects, advertising elasticity in published articles should be higher than advertising elasticity from unpublished works.	We obtained these data directly from the studies.

Notes: OLS = ordinary least squares, GLS = generalized least squares, and MLE = maximum likelihood estimation.

- *Product life cycle × product type*: Advertising might be more important in the early stage of durable products because they are less easily known by trial;
- *Product life cycle × dependent measure*: For growth products, advertising may have greater influence on sales than share because of the higher potential for category sales growth, whereas for mature products advertising may influence market share more than absolute sales because firms are competing for a share of fixed total market; and
- *Data interval × omission of lagged sales*: When data are more aggregate (yearly), omitting lagged sales (carryover effect) may not affect advertising elasticity as much as when data are less aggregate (weekly).

Second, we investigate whether some brand characteristics influence advertising elasticity. We collected data on brand market share, brand advertising share, and relative price for 212 of 751 observations. However, Sethuraman, Srinivasan, and Kim (1999) state that the elasticity measure is related to brand share and advertising share by definition. For example, in the linear model, (absolute) advertising effect is measured as d(market share)/d(advertising). To

Table 2

FACTORS INFLUENCING ADVERTISING ELASTICITIES: MODEL 2 REGRESSION COEFFICIENTS (STANDARD ERRORS)

				Short-Term Advertising Elasticity		*Long-Term Advertising Elasticity*	
Number	*Variable*	*Level*	*Expected Sign*	*Main Effect Only*	*Main + Interaction Effect*	*Main Effect Only*	*Main + Interaction Effect*
0	Intercept	All obs.		.07 (.12)	–.08 (.17)	.06 (.2)	–.26 (.21)
Time Trend and Recession							
1	Time Trend	Year of data	–	–.004 (.002)**	–.004 (.001)***	–.005 (.002)**	–.007 (.003)***
2	Recession	Months of recession	–	.01 (.06)	.02 (.06)	.42 (.10)***	.34 (.09)***
Product and Geographic Factors							
3	Product type	Drug	?	.19 (.09)**	.16 (.14)	.14 (.11)	.29 (.13)***
		Durable	?	.29 (.09)***	.26 (.06)***	.27 (.08)***	.48 (.1)***
		Food	?	.03 (.03)	–.15 (.06)**	.08 (.05)	–.13 (.1)
		Service	?	.10 (.07)	–.04 (.11)	–.10 (.08)	–.08 (.08)
		Nonfood	Base	0	0	0	0
4	Product life cycle	Mature	–	–.08 (.05)**	–.08 (.06)*	.08 (.06)	.15 (.12)
		Growth	Base	0	0	0	0
5	Region (continent)	Europe	+	.09 (.05)**	.16 (.06)***	.16 (.05)***	.34 (.08)***
		Other	?	.05 (.05)	.06 (.05)	.09 (.06)	.08 (.05)
		North America	Base	0	0	0	0
Data Characteristics							
6	Dependent measure	Absolute	+	–.03 (.02)	.08 (.07)	–.12 (.04)***	.20 (.10)**
		Relative	Base	0	0	0	0
7	Temporal Interval	Weekly	–	.04 (.03)	.05 (.03)	.05 (.06)	.04 (.07)
		Yearly	+	.08 (.04)**	.09 (.03)***	.10 (.11)	–.03 (.18)
		Quarterly	Base	0	0	0	0
8	Data aggregation	Firm	?	–.20 (.05)***	–.24 (.06)***	.07 (.08)	–.03 (.06)
		Panel	Base	0	0	0	0
9	Advertising measure	Relative	?	.07 (.03)**	.07 (.03)***	–.11 (.07)*	–.10 (.07)
		GRP	?	.16 (.08)**	.16 (.09)**	.16 (.06)***	.30 (.09)***
		Monetary	Base	0	0	0	0
10	Advertising type	Television	?	.19 (.09)**	.21 (.09)**	–.17 (.05)***	–.18 (.05)***
		Aggregate	?	.11 (.06)*	.14 (.05)**	–.03 (.05)	–.01 (.05)
		Print	Base	0	0	0	0
Omitted Variables							
11	Lag dependent variable	Omitted	+	.10 (.07)*	.09 (.06)*	—	—
		Included	Base	0	0	—	—
12	Lag advertising	Omitted	+	.002 (.03)	.01 (.03)	.14 (.04)***	.13 (.03)***
		Included	Base	0	0	0	0
13	Lag price	Omitted	–	.01 (.05)	.03 (.05)	.04 (.08)	.17 (.12)
		Included	Base	0	0	0	0
14	Price	Omitted	–	–.01 (.03)	–.01 (.03)	.03 (.05)	.02 (.07)
		Included	Base	0	0	0	—
15	Quality	Omitted	?	–.02 (.07)	–.04 (.06)	–.15 (.08)*	–.11 (.07)
		Included	Base	0	0	0	0
16	Promotion	Omitted	?	–.03 (.08)	–.01 (.08)	.13 (.08)*	.14 (.07)**
		Included	Base	0	0	0	0
17	Distribution	Omitted	+	.11 (.04)***	.11 (.04)***	.10 (.05)**	.11 (.06)**
		Included	Base	0	0	0	0

Table 2

CONTINUED

Number	Variable	Level	Expected Sign	Short-Term Advertising Elasticity: Main Effect Only	Short-Term Advertising Elasticity: Main + Interaction Effect	Long-Term Advertising Elasticity: Main Effect Only	Long-Term Advertising Elasticity: Main + Interaction Effect
Model Characteristics							
18	Functional form	Double log	?	.14 (.07)**	.14 (.08)*	.16 (.07)***	–.07 (.09)
		Linear	?	.26 (.10)***	.24 (.09)***	.07 (.10)	.12 (.10)
		other	?	.23 (.09)***	.22 (.08)***	–.28 (.09)***	–.13 (.10)
		share	Base	0	0	0	0
19	Estimation method	GLS	?	–.02 (.03)	–.04 (.03)	–.17 (.05)***	–.18 (.04)***
		MLE	?	.05 (.05)	.02 (.05)	.12 (.08)	.18 (.09)**
		OLS	?	.004 (.02)	–.01 (.02)	–.10 (.06)*	–.12 (.07)*
		Other	Base	0	0	0	0
20	Endogeneity	Omitted	–	–.16 (.08)**	–.16 (.08)**	–.01 (.07)	.04 (.07)
		Included	Base	0	0	0	0
21	Heterogeneity	Omitted	?	–.06 (.06)	–.04 (.07)	.07 (.09)	.09 (.10)
		Included	Base	0	0	0	0
Other Characteristics							
22	Study type	Published	–	.09 (.10)	.07 (.12)	–.02 (.17)	–.16 (.16)
		Working	Base	0	0	0	0
Interaction Effects							
1	Mature life cycle × durable		?	—	–.34 (.13)***	—	–.39 (.11)***
2	Mature life cycle × food		?	—	–.10 (.18)	—	.21 (.14)
3	Mature life cycle × nonfood		?	—	.12 (.12)	—	—
4	Life cycle × absolute sales		–	—	–.13 (.09)*	—	–.40 (.14)***

*$p < .10$.
**$p < .05$.
***$p < .01$.

Notes: OLS = ordinary least squares, GLS = generalized least squares, and MLE = maximum likelihood estimation. We used a one-tailed test if expected sign is unambiguous (+ or –) and a two-tailed test if expected sign is ambiguous (?). Expected sign: + = positive relationship (compared with base level); – = negative relationship; ? = ambiguous relationship; and — = coefficient not included or not estimable. We rounded all coefficient estimates to two decimals.

convert into (percent) elasticity measure, we multiplied the effect by mean brand advertising and divided by brand market share. Because market share is in the denominator and advertising is in the numerator, by definition, advertising elasticity tends to be larger for brands with low market share and high advertising share. Therefore, we only test whether advertising elasticity is higher for high-priced brands by reestimating Model 2 with brand relative price included.

Third, we estimate the following logit model to identify the conditions when the advertising elasticity is significantly greater than zero ($p < .05$, one-tailed test):

$$P(A_{sj} \text{ is significantly} > 0) = \frac{\exp(V_{sj})}{1 + \exp(V_{sj})}, \quad (3)$$

where $V_{sj} = X_{sj}\gamma + \varepsilon_{sj}$, where X_{sj} is the set of influencing variables listed in Table 2, and γ is the coefficient vector measuring the influence of the variable on the statistical significance of advertising elasticity.

Analysis of Long-Term Advertising Elasticity

As with short-term elasticity, we first performed univariate analysis to obtain an estimate of the mean advertising elasticity and compared it with Assmus, Farley, and Lehmann's (1984) value. Next, we obtained insights into the median and distribution of long-term advertising elasticity. Then, we estimated Model 2 to identify factors that influence long-term elasticity. We did not conduct robustness checks, because we did not have sufficient data and because standard errors are not available for long-term elasticity.

RESULTS

Univariate Analysis

Figure 1 presents the distribution of short-term advertising elasticity. There are 751short-term brand-level advertising elasticities with magnitudes ranging from –.35 to 1.80. More than 40% of the elasticities are between 0 and .05. Approximately 7% of advertising elasticities are negative, though in general, we expected advertising elasticity to be positive. In the spirit of meta-analysis, we retained the negative elasticities because the meta-analytic model reveals whether any method or environmental variable is responsible for such negative estimates.

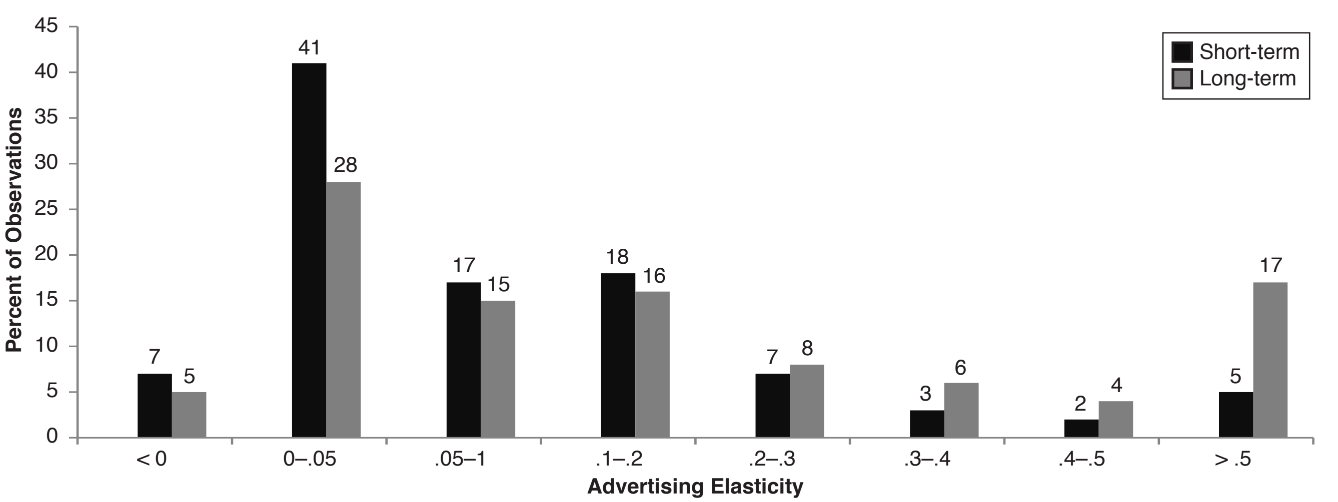
The mean short-term advertising elasticity across the 751 observations is .12, which is substantially lower than Assmus, Farley, and Lehmann's (1984) mean of .22 from 128 observations. We attribute the difference to (1) reduction in advertising elasticities over time; (2) Assmus, Farley, and Lehmann's inclusion of 32 product-level elasticities, which are in general higher than the brand-level elasticities; and (3) Assmus, Farley, and Lehmann's omission of Lambin's (1976) estimates, which are, in general, below the previously stated mean of .22. Our estimate is closer to the mean advertising elasticity of .104 that Hu, Lodish, and Krieger (2007, Table 1) report from 210 real-world television advertising tests. Our estimate is also similar to that of Sethuraman and Tellis (1991), who find that the mean brand-level advertising elasticity across a wide range of categories is .11.

The median short-term advertising elasticity is even lower at .05, but it is closer to the uncorrected mean short-term elasticity of .04 in Fischer and Albers's (2010, Table W1) recent comprehensive study on pharmaceuticals. The standard errors (or t-values) are reported for 437 of the 751 observations. Advertising elasticities are significantly greater than zero at the 95% confidence level in 57% of the cases.

Overview of Meta-Analytic Results

Table 2 (Column 5) presents the results for the main meta-analytic Model 2 for short-term advertising elasticity. The model explains 37% of the variance in advertising elasticity, which is comparable to Assmus, Farley, and Lehmann's meta-analysis (36%). Coefficients corresponding to 12 of the 22 independent variables are statistically significant at least at $p < .10$: year of data, product type, product life cycle, region, temporal interval, level of data aggregation,

Figure 1
DISTRIBUTION OF SHORT-TERM (N = 751) AND LONG-TERM (N = 402) ADVERTISING ELASTICITIES



measure of advertising, advertising type, omission of lag sales, omission of distribution, functional form, and omission of endogeneity.

We accounted for uncertainty in advertising elasticity by compiling the 437 observations in which information on uncertainty (standard error) is available. We drew 500 random data sets using the method described in the "Procedure" section, estimated Model 2, and computed the average of the estimates for each variable (reported in Web Appendix B at http://www.marketingpower.com/jmrjune11). All significant variables in the main regression model except advertising measure are also significant in this new model. In addition, recession is positive and significant.

We assessed the extent of collinearity by inspecting the variance inflation factors, condition indexes, bivariate correlations, and cross-tabulations. All but one of the variance inflation factors are lower than 5, and all condition indexes are less than 20. Some correlations are high (> 5); therefore, we deleted one variable at a time and inspected the robustness of other results. We also estimated stepwise regression. Almost all the original results are robust, except in two cases: The variable recession is positive and significant in a few alternate models, and omission of endogeneity is not statistically significant in a few models. (Details of these results are available on request.)

We included each interaction effect mentioned in the procedure section one at a time, and we retained them if they were significant. Two effects—product life cycle × product type and product life cycle × dependent variable—are statistically significant. The percentage of explained variance increases from 37% in the model with only main effects to 40% in the model incorporating interaction effects. Table 2 presents the regression results (Column 6).

To ascertain whether a brand's relative price affects advertising elasticity, we used 212 observations for which information on price was available and estimated Model 2. The coefficient of relative price is positive (.03, SE = .05) but not statistically significant.

Which factors influence the statistical significance of advertising elasticity? There are 437 observations for which information on statistical significance (t-values) was available. In 249 of the observations (57%), advertising elasticity is significantly greater than zero. Web Appendix B (http://www.marketingpower.com/jmrjune11) presents results of the Logit Model 3. Because of a lack of data, we did not include interaction effects. The results reveal fewer significant coefficients than in the original model. Advertising elasticity is more likely to be significantly greater than 0 in Europe than the United States, for panel data than aggregate firm data, and for television than print advertising. Some coefficients are marginally significant. A possible explanation for the lack of significance in this model is as follows: A significant advertising elasticity, whether .1 or .5, is taken as 1. A nonsignificant coefficient, whether .001 or .05, is deemed to be 0. This recoding absorbs meaningful variation in the data, which can result in fewer significant estimates than in the original model, with magnitude of advertising elasticity as the dependent variable. In the next section, we present the results on short-term advertising elasticity for significant variables.

Time Trend and Recession

Median year of data. Given the increased competition in consumer products, the advent of the Internet as an alternate information source, and the ability of consumers to opt out of television commercials, we would expect consumers to be less responsive to advertising in more recent times than in the past. Consistent with our expectations, the corresponding regression coefficient of time (median year of data) is negative. This result is robust across models. (We also tested a quadratic effect of time; the coefficient was nonsignificant.)

Assmus, Farley, and Lehmann's (1984) meta-analysis uses pre-1980 data, whereas ours includes post-1980 data. Therefore, we compared advertising elasticity for pre-1980 data (1940–1979) with that for post-1980 data (1980–2004). Instead of treating year of data as a continuous variable, we included a dummy variable to indicate pre- and post-1980 periods. The regression coefficient for after 1980 is –.11 (SE = .06), indicating a significant decline between the two time periods. The mean advertising elasticity is .13 before 1980 (n = 463) and .10 after 1980 (n = 288).

Temporal differences in advertising elasticity can occur because of differences in consumer response to advertising over time or differences in market characteristics and research methods. To explore the impact of market/method factors on the temporal differences in predicted advertising elasticity, we followed Bijmolt, Van Heerde, and Pieters's (2005, p. 151) approach and computed the contribution of various factors to the difference. Table 3 presents the five key contributing factors that influence difference in the advertising elasticity between pre-and post-1980 periods.[4]

[4]We thank one of the anonymous reviewers for suggesting this analysis.

Table 3

KEY CONTRIBUTORS TO CHANGES IN SHORT-TERM ADVERTISING ELASTICITY: PRE- AND POST-1980

Variable	*Level*	*Model 2 Main Effect Coefficient*	*Percentage in Group After 1980*	*Percentage in Group Before 1980*	*Contribution to Advertising Elasticity*
Aggregation	Firm	–.195	46.5	93.3	.09
Ad type	Television	.193	59.7	21.4	.07
Region	Europe	.086	1.1	48.4	–.04
Data interval	Yearly	.083	3.8	36.3	–.03
Life cycle	Mature	–.083	87.9	57.5	–.03

Notes: Sample interpretation and illustration for aggregation: The regression coefficient from main effects Model 2 for data aggregation (firm vs. panel) is –.195; that is, advertising elasticity estimated from firm data is .195 lower than that from panel data. Panel data are rarely used, and firm-level data are predominantly used before 1980: About 93% of short-term advertising elasticity observations before 1980 are from firm data, whereas 47% of the observations after 1980 use firm data. This difference in data representation results in an increase in mean predicted advertising elasticity of .09 in the post-1980 period compared with the pre-1980 period (computed as –.195 × [46.5 – 93.3]/100 = .09, rounded to two decimals).

Firm-level aggregate data constitute the primary database before 1980 (93% use); in contrast, because of the advent of scanner data, post-1980 databases use panel data and firm data is substantially reduced (47% use). This difference in database results in a .09 increase in advertising elasticity after 1980 compared with before 1980. Television advertising is used more in the estimation after 1980 (60%) than before 1980 (21%), resulting in an increase in advertising elasticity of .07 after 1980. Europe is grossly underrepresented after 1980 (1%) compared with before 1980 (48%). Because advertising elasticity in Europe is higher than in the United States, this difference causes a reduction in post-1980 predicted advertising elasticity by .04.

Early researchers tend to use more temporally aggregate (yearly) data, while later researchers use less yearly and more weekly data. This difference causes advertising elasticity to decrease by .03 after 1980 compared with before 1980. Because markets in general have matured over time, approximately 88% of products studied after 1980 are mature products, compared with 58% before 1980. Because mature products have lower advertising elasticity, there is a .03 reduction in advertising elasticity after 1980.

In summary, changes in estimates of advertising elasticity over time can be attributed to changes in market and method characteristics. The observed negative regression coefficient for year of data suggests that the effect persists even after accounting for these factors. Why might advertising response be lower in recent times? Researchers point to advertising clutter and competitive advertising, both of which result in reduced recall and evaluation of the brand being advertised. For example, Kent (1995) documents that the average number of network advertisements per hour tripled from 6 in the 1960s to 18 in the 1990s. Danaher, Bonfrer, and Dhar (2008) report that advertising elasticity declines in the presence of high competitive clutter.

Recession. The current economic environment highlights the need to understand how marketing strategies should be modified in the face of recession. In particular, should advertising budgets be curtailed or increased during recession (for a recent survey of relevant literature, see Tellis and Tellis 2009)? If advertising elasticity is lower during recession, both the impact factor and budgetary considerations would suggest a reduction in advertising. However, if recession advertising elasticity is equal to or higher than expansion advertising elasticity, the decision is not clear. Our meta-analysis reveals that advertising elasticity is not lower during recessionary times. On the contrary, advertising elasticity is higher during recession, though not significant.

Product and Geographic Factors

Product type. We tested for difference in advertising elasticity among many types of product categories—pharmaceutical, food, nonfood, durable, and service goods (e.g., banks, movies). However, we did not have prior expectations for the relative magnitudes of these effects. Regression coefficients (Table 2) and comparison of means reveal that durable goods have the highest advertising elasticity, followed by pharmaceuticals and service goods. Frequently purchased food and nonfood products have the lowest advertising elasticity. In general, nonfood, nondurable products tend to be low-involvement items, such as household cleaners, whose purchase behavior advertising might not significantly influence.

Product life cycle. Advertising either provides information or persuades consumers about the advertised brand. In either case, it is likely to be more relevant and useful in the early stage of the product life cycle, when consumers know little about the brand or have not formed preferences. Thus, advertising elasticity will be higher for products in the early stage of the life cycle than in the mature stage. Consistent with this expectation, products in the growth stage of the life cycle have a higher advertising elasticity (.16) than products in the mature stage (.11), and the coefficient is significant in the regression model (Table 2).

We also find an interaction between product life cycle and product type, as Figure 2 shows. Declining advertising elasticity from the growth stage to the mature stage of the life cycle seems to be more prominent in durable goods, moderate in food products, and nonsignificant in nondurable, nonfood products.

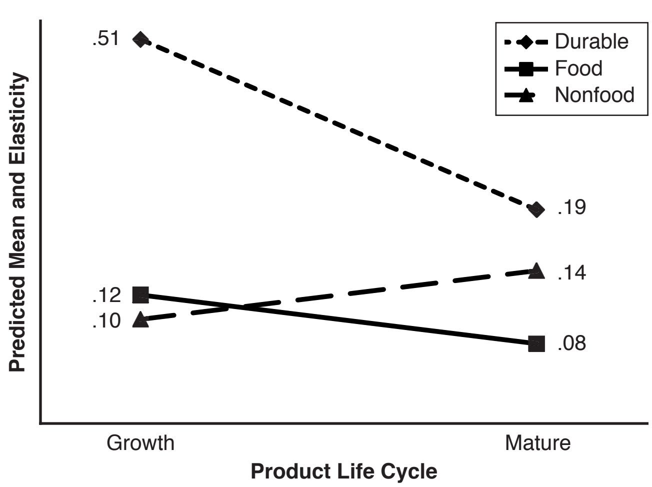
Geographic region. Europe may underadvertise because of regulation, the short history of advertising in the region, or culture. The United States may have optimal or overadvertising because of the long history of advertising, intense competition, and advertising clutter. If this reasoning is correct, advertising elasticity is likely to be higher in Europe than the United States. This is indeed the case: We find that Europe has a significantly higher mean advertising elasticity (.17) than the United States (.11), and this effect holds in the regression model after accounting for other factors (Table 2).

Data Characteristics

Dependent measure. Sales can be measured in either absolute (unit sales or dollar revenues or purchases) or relative (market share) terms. Absolute sales capture both competitive gains and gains due to primary market expansion. Relative sales capture only competitive gains. Because advertising can increase primary demand, we expect adver-

Figure 2

MEAN SHORT-TERM ADVERTISING ELASTICITY BY PRODUCT LIFE CYCLE AND PRODUCT TYPE



Notes: Pharmaceutical and service goods not reported due to small sample sizes (< 10).

tising elasticity to be higher when sales are recorded in absolute terms. Advertising elasticity is slightly higher for (absolute) sales elasticity (.13) than for relative (share) elasticity (.11), but the difference is not significant in the regression model.

However, we find a marginally significant ($p < .10$) interaction effect between product life cycle and dependent measure in the regression model (Table 2). Figure 3 presents the predicted means. In growth products, advertising elasticity is higher when measured with sales as the dependent variable than when share is the dependent variable. This result is intuitive because the potential for an increase in primary demand (which is better captured in the sales model) is higher in the growth stage of the life cycle.

Temporal interval. In general, advertising has not only an instantaneous impact on sales but also a carryover impact. Therefore, the greater the level of temporal aggregation, the more likely it captures the sales resulting from the carryover advertising. Moreover, the greater the level of aggregation, the greater is the bias caused by wrongly capturing the carryover effect. Thus, we expect current period advertising elasticity to be greater when data are more aggregate (yearly or quarterly) than less aggregate (weekly or daily) if the model does not fully and correctly capture the carryover effect. Researchers typically estimate the carryover effect with the Koyck model. However, using aggregate data leads to a positive bias in this model's estimation of carryover effect (Tellis and Franses 2006).

It is noteworthy that we find a nonmonotonic relationship between advertising and data interval; this effect holds when lagged sales (carryover effect) are both included and omitted. Advertising elasticity is lowest with quarterly data and higher with weekly and yearly data.

Data aggregation. Before the advent of scanner data, researchers estimated advertising elasticity using predominantly firm-level aggregate data. Scanner data prompt the use of panel data and the estimation of advertising response at the individual level. Individual-level data seem to be a more appropriate unit of analysis for measuring response to advertising. Although the univariate means are not different between the two groups (both approximately .12), after accounting for other factors, advertising elasticities estimated at the aggregate firm level are significantly lower than those at the disaggregate consumer panel level. This result is consistent with Christen et al.'s (1997) findings.

A plausible explanation for this effect is that aggregate data are a linear combination of individual purchases, whereas panel data estimation uses nonlinear combination of purchases. Gupta et al. (1996, Tables 3 and 4) show that the price elasticity from a linear approximation to a logit model (without heterogeneity) is biased toward zero. Thus, linear approximations using aggregate data may tend to downwardly bias advertising elasticity.

Advertising measure. A brand's advertising may be measured in absolute (e.g., monetary value, gross rating points [GRPs]) or relative (e.g., the brand's share of all advertising in the market) terms. Depending on what competitors in the market are doing, changes in absolute advertising may not necessarily reflect the same changes in relative advertising. If competitors tend to match a target firm's advertising, large changes in absolute advertising will translate into small changes in relative advertising. As a result, elasticities estimated with absolute advertising will be smaller than those estimated with relative advertising. The reverse holds if competitors do not match a target firm's advertising or if they react in the opposite direction. Thus, from the differences in elasticity between relative and absolute advertising measures, we can infer how competitors match a target firm's advertising strategy.

With respect to GRP and monetary (dollar) advertising measures, we offer the following explanation: Advertisers buy GRPs using dollars—one GRP being 1% of target audience (reach) given one exposure. Let a 1% increase in advertising dollars increase GRPs by v% and sales by w%. Then, by definition, dollar advertising elasticity = w, and GRP advertising elasticity = w/v. It follows that, all else being equal, dollar elasticity is greater than GRP elasticity if $v > 1$, and GRP elasticity is greater than dollar elasticity if $v < 1$.

Comparison of elasticities for absolute versus relative advertising reveals mixed results. Advertising elasticity with relative advertising is higher than advertising elasticity with a dollar measure of absolute advertising but lower than

Figure 3
MEAN SHORT-TERM ADVERTISING ELASTICITY BY PRODUCT LIFE CYCLE AND DEPENDENT MEASURE

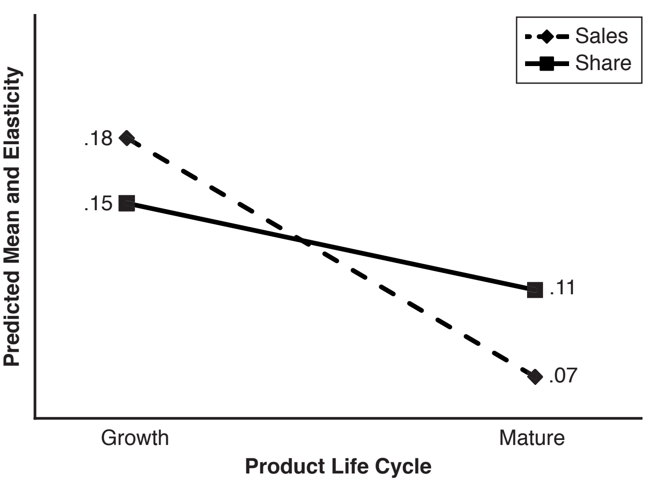


Table 4
OPTIMAL ADVERTISING FOR DIFFERENT VALUES OF ADVERTISING ELASTICITY

Basis for Advertising Elasticity	*Advertising Elasticity*	*Optimal Advertising as a Percentage of Sales*	*Percent Advertising Increase Needed to Match 1% Price Cut*
Prior Meta-Analysis: 1984			
Mean short run	.22	8.5	5
Current Meta-Analysis: 2010			
Mean short run	.12	4.6	30
Median short run	.05	1.9	—[a]

[a]Not computable because the denominator in Equation 4 is zero or negative. The denominator being negative implies that the incremental profits from an advertising increase are negative. Therefore, the firm should reduce its advertising.

with a GRP measure of absolute advertising. However, in absolute advertising, elasticity measured with GRP is higher (.21) than advertising elasticity with monetary value (.09); this difference is significant in the regression model (Table 2). As we stated previously, this finding indicates the possibility of $v < 1$, on average. That is, firms may be operating in a region in which a 1% increase in advertising dollars yields a less than 1% increase in GRP. Further research can assess whether this inference holds. We also investigated whether the difference between dollar and GRP elasticity was due to the correlation between advertising measure and other model factors. We find that GRP elasticities were primarily in nondurable and mature products. However, the results on advertising measure did not change when we excluded these variables from the model.

Advertising Type. Even though mean television advertising elasticity (.12) is not significantly greater than print advertising elasticity (.11), after accounting for other factors, we find print advertising has a lower short-term advertising elasticity than television advertising in the regression analysis (Table 2). One reason for this effect is that television advertising, with its ability to arouse emotions, may be more effective than print advertising, which relies primarily on information appeals (Tellis, Chandy, and Thaivanich 2000).

Omitted Variables

Omission of lagged sales. The omission of a variable biases advertising elasticity, if that omitted variable is correlated with both the dependent variable (sales) and the included independent variable (advertising). The direction of the bias is the product of the signs of the correlations of the omitted variable with sales and advertising. Lagged sales are likely to be correlated positively with both current-period sales and current-period advertising (because current advertising is often set as a proportion of past sales). Therefore, we expect the omission of lagged sales to positively bias advertising elasticity. Consistent with this expectation, we find that, after accounting for other factors, the omission of lagged sales significantly increases advertising elasticity. Put another way, lagged sales picks up the carryover effect of advertising. Omitting lagged sales ensures that the current advertising picks up some of this carryover effect.

Other omitted variables. Among other variables, we find that omission of distribution significantly increases advertising elasticity, perhaps because advertised brands are better distributed. Thus, distribution is positively related to both sales and advertising, resulting in a positive omission bias. The effects of the exclusion of other variables are nonsignificant.

Model Characteristics

Functional form and estimation method. Linear and double log models tend to produce higher advertising elasticity than share models. We find that, overall, functional form has greater influence on short-term advertising elasticity than estimation method.

Incorporating endogeneity and heterogeneity. A more recent trend in estimation of marketing mix is to incorporate endogeneity. We find that, in many models, omission of endogeneity induces a negative bias in the estimates, which is consistent with the belief that omitting endogeneity can bias the estimates toward zero (Villas-Boas and Winer 1999). That is, advertising elasticity is lower when endogeneity is not incorporated.

Recent modelers have also incorporated heterogeneity by allowing for differences in parameters across households in the sample, through either random effects or Bayesian models (Allenby and Rossi 1999). However, we found that the effect of omission of heterogeneity on advertising elasticity is not significant; in other words, omitting heterogeneity does not significantly alter the advertising elasticity estimates.

Results on Long-Term Advertising Elasticity

Figure 1 presents the distribution of long-term advertising elasticities. There are 402 long-term brand-level advertising elasticities. Their magnitudes range from –1.2 to 4.5. More than 40% of the elasticities are between 0 and .1. About 5% of advertising elasticities are negative. The mean long-term advertising elasticity across the 402 observations is .24, which is much lower than the mean of .41 in Assmus, Farley, and Lehmann (1984).[5] The median long-term elasticity is even lower than the mean, at .10.

Table 2 (columns 7 and 8) presents the meta-analytic results for the long-term advertising. The variables in the main effects model explain 29% of the variance in long-term elasticity. The omission of lagged sales is not included as an independent variable, because we use the coefficient of lagged sales to estimate long-term elasticity (dependent variable). Six variables that are statistically significant in the short-term elasticity models are also significant in the long-term model: year of data, product type, region, measure of advertising, omission of distribution, and functional form.

Four variables significant in the short-term model are not significant in the long-term elasticity model: product life cycle, temporal interval, data aggregation, and omission of endogeneity. One reason for the lack of significance is that because long-term elasticity is computed using the formula [short-term elasticity/(1 – carryover effect)], the influence of a variable on long-term elasticity depends on its influence on both short-term elasticity and carryover effect. These two effects acting together may enhance or dampen the resultant coefficient. For example, mature products tend to have smaller short-term advertising elasticity but may have equal or smaller carryover effect compared with growth products. Thus, the effect of product life cycle on long-term elasticity may not be significant.

A surprising finding is that television advertising has higher short-term elasticity but lower long-term elasticity than print advertising. The higher long-term elasticity for print advertising may be because information in print (especially magazines) remains in memory for a longer period than television advertising. Some variables that are not significant in the short-term model are significant in the long-term model: Long-term advertising elasticity is higher during recessions than in expansions; omitting lagged advertising and promotion is also significant in the long-term elasticity models.

[5]The short-term advertising elasticity in Assmus, Farley, and Lehmann (1984) is .22 and the mean carryover is .468, leading to mean long-term advertising elasticity of .414 [= .22/(1 – .468)].

IMPLICATIONS

Implications for Managers

Advertising budgeting. We find the mean short-term advertising elasticity across all observations (1940–2004) is .12, the median elasticity is .05, and elasticity is declining over time. The finding that advertising elasticity is "small" may upset many practitioners, especially those in the agency business. This number seems even more troubling compared with price elasticity, which meta-analyses suggest is more than 20 times larger at –2.62 (Bijmolt, Van Heerde, and Pieters 2005; Tellis 1988). However, comparing absolute elasticity may miss some pertinent issues. First and most important, price cuts affect revenues and profits immediately. Therefore, while a small price cut can greatly enhance sales, it does not necessarily increase profits. Second, advertising has the potential to support a higher price. Third, price cuts can be selectively directed to only some consumers to minimize harm to the bottom line. Fourth, price cuts given to retailers might not be passed on to consumers.

Sethuraman and Tellis (1991) develop a model to integrate these factors and draw managerial implications about how advertising and price elasticities should affect managers' trade-off between advertising and price discounting. In particular, they show that the advertising increase (ΔA) that would yield the same profits as a given price cut (Δp) in the short term can be computed using the following equation:

$$\frac{\Delta A/A}{\Delta p/p} = \frac{k\varepsilon_p - f/g}{k\varepsilon_A - A/s}, \tag{4}$$

where p is the price, A is advertising, k is contribution to price ratio, f is the fraction of consumers taking advantage of the discount, g is retail pass-through of discount, S is dollar sales, and ε_p and ε_A are price and advertising elasticities, respectively. The optimum advertising-to-sales ratio is given by $(A/S)^* = (f/g)(\varepsilon_A/\varepsilon_p)$. Table 4 presents optimal results using the preceding formulas for different values of advertising elasticity with the following illustrative values: ε_p (absolute) = 2.6 (Bijmolt, Van Heerde, and Pieters 2005), f = .5, g = .5, k = .5, and A/S = .05 (Sethuraman and Tellis 1991).

Table 4 suggests a reduction in budgets allocated to conventional advertising in keeping with the declining trend in advertising elasticity. Alternatively, a firm can take steps to increase advertising elasticity. Kent (1995) suggests creating unique messages, negotiating for noncompete coverage, and more precise targeting of advertising as some ways to overcome the harmful effects of advertising clutter and increase consumers' responsiveness to advertising.

Advertising and recession. The conventional belief is that advertising should be reduced during recession because sales are lower and consumers are more price sensitive and less likely to be influenced by advertising in periods of recession than expansion. First, our results reveal that neither short- nor long-term advertising elasticities are lower during recession, measured as the percentage of the estimation period under recession. Therefore, at a minimum, managers need not reduce advertising in a recession because they falsely believe that the sales impact of advertising will be lower than in expansion periods.

Second, while the coefficient of recession for short-term advertising elasticity is positive, though not statistically significant, the coefficient for long-term elasticity is positive and significant, suggesting that, in general, advertising elasticity is higher during recession. Possible reasons for this effect are that during recession compared with expansion, (1) advertising clutter is lower due to cutbacks in advertising, (2) consumers pay more attention to ad messages to be astute buyers, and (3) ad budgets are supported by higher price and promotional incentives. One reason for the positive effect of long-term elasticity may be that the reduced clutter and increased attention to advertising during recession may not translate into immediate purchases (short-term), because of the tight economy at that time, but may translate into purchases at a later point (long-term) when the economy improves (for supporting evidence from other studies, see Tellis and Tellis 2009).

Conditions favoring advertising. Our finding of higher advertising elasticity suggests that, all else being equal, advertising should be higher for durable goods than nondurable goods and for products in the early stage of the life cycle than mature products. The higher advertising elasticity in Europe than in the United States calls for a broader understanding of whether there is overadvertising in the United States (Aaker and Carman 1982) and underadvertising in Europe.

Implications for Researchers

Temporal interval. Advertising elasticity is significantly different depending on if weekly, quarterly, or yearly data are used. These significant differences underscore the need for determining and using the "correct" data interval for estimating advertising elasticity. The conventional view is that the best data interval matches the interpurchase time for the product category. Recently, Tellis and Franses (2006) have shown that the optimal data interval that provides an unbiased estimate of advertising elasticity is the unit exposure time, defined as the largest calendar period such that advertising occurs at most once and at the same time in that period. This could be minutes or hours in television advertising or days or weeks in print advertising. Furthermore, these authors show that more temporally disaggregate data does not bias the estimates. These findings suggest that, if data are available, less aggregate daily or weekly data may be better than quarterly or yearly data for obtaining unbiased estimates of advertising elasticity.

Incorporating endogeneity. We find that in many models, omitting endogeneity induces a negative bias in advertising elasticity. One implication is that endogeneity should be taken into account when appropriate for the model and context; however, it should not be added as a "checklist" item to the research (Shugan 2004). For example, there is some question whether price is truly endogenous for panel models estimated at the daily level because retailers may not be able to determine optimal prices and change them every day (Erdem, Keane, and Sun 2008). Similar arguments could be made for advertising response because it is unlikely that brand manufacturers can detect and/or adjust their advertising levels quickly enough to adjust for weekly shifts in consumer demand; they can detect and respond to shifts in demand over longer periods of time (quarterly or yearly).

Other factors. We find that the omission of distribution has a positive effect on advertising elasticity, while functional forms such as linear or double log may produce different elasticities. Researchers should be cognizant of these differences and take the following steps when estimating advertising response: (1) Include as many relevant covariates (e.g., price, promotion, quality) as are available, and (2) understand the right econometric approach for the problem at hand or assess the sensitivity of their estimates of the elasticity to estimation procedures.

Nonsignificant variables. Several variables are not significant in the regression model. Does this mean that these factors can be ignored while estimating advertising elasticity? We note that the absence of evidence of effects in the meta-analysis should not be taken as evidence of the absence of an effect. The lack of significance could be due to the lack of proper data, noise in the data, the aggregation effect, or other procedural reasons. Our view is that the "correct" data and procedure must be used when possible. For example, the omission of heterogeneity does not significantly influence advertising elasticity in our meta-analysis. This does not mean researchers can safely ignore heterogeneity. In general, it is appropriate to account for it in advertising response, especially when estimating with panel data.

CONCLUSION

We meta-analyzed 751 brand-level short-term advertising elasticities and 402 long-term advertising elasticities. Our objective is to update Assmus, Farley, and Lehmann's (1984) meta-analysis and to add to Hanssens's (2009) inventory of empirical generalizations. We obtain several useful generalizations, which we list in the following section. Then, we present the limitations and future research directions.

Key Empirical Generalizations

The average short-term advertising elasticity across the 751 observations is .12, which is substantially lower than Assmus, Farley, and Lehmann's (1984) mean of .22 from 128 observations. The median advertising elasticity is even lower at .05. The average long-term advertising elasticity across the 402 observations is .24, which is lower than the implied mean of .41 in Assmus, Farley, and Lehmann (1984), from 128 observations. The median long-term advertising elasticity is even lower at .10.

There is a decline over time in both short- and long-term advertising elasticity. These results suggest a reduction in conventional advertising if the firm was advertising optimally in the past. On average, advertising elasticity does not decrease during recession. If anything, there is a positive relationship between months of recession and long-term advertising elasticity. This result suggests that a firm does not need to cut back on advertising in a recession because its managers believe customers will not be responsive to advertising. Advertising elasticity is higher for durable goods than nondurable food and nonfood products. This finding favors advertising for durable goods, all else being equal.

Short-term advertising elasticity is higher for products in the early stage of the life cycle than those in the mature stage. This effect is especially prominent in durable goods. This result supports focusing on advertising during the early stage and price during subsequent stages of the life cycle, especially for durable goods. In general, advertising elasticity is higher in Europe than in North America, raising a question of whether there is underadvertising in Europe and overadvertising in the United States.

There is a nonmonotonic relationship between advertising elasticity and temporal interval. The elasticities estimated from both weekly and yearly data are higher than those from quarterly data. This result reinforces the need for using the appropriate data interval as Tellis and Franses (2006) derive.

In general, television advertising elasticity is higher than print advertising elasticity in the short run, but print advertising elasticity is higher than television advertising elasticity in the long run. This finding calls for a careful consideration of cost and effectiveness when allocating budgets between the two media.

Advertising elasticity is lower when endogeneity in advertising is not incorporated in the model. When appropriate, researchers should attempt to incorporate endogeneity using recently developed New Empirical Industrial Organization models (Nevo 2001) or acknowledge that the estimate may be lower because of the omission.

Limitations and Further Research

Our study has some limitations that are typical of most meta-analytic research. First, while we have tried to be exhaustive in our literature review, we may have overlooked some publications that estimate advertising elasticity. Second, in identifying the factors that influence advertising elasticity, we are limited by the variables that are available in the original studies. For example, we could not collect data on all four stages of the life cycle or individual country of origin, so we could not estimate influences of these variables on advertising elasticity.

These limitations provide potential directions for further research. On a more substantive level, researchers in the future should try to analyze more growth products, durable goods, industrial goods, and service goods. Further research could also measure the effects of online advertising, incorporate them in meta-analyses, and perform a meta-analysis of the duration of advertising—the period during which the effect of advertising lasts.

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