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The authors attempt to assess what has been learned from econometric models about the effect of advertising on sales. Short-term and long-term advertising response as well as model fit are analyzed for 128 econometric models involving the impact of advertising on sales. The approach, a form of meta-analysis called "replication analysis," treats the studies as imperfect experimental replications and uses ANOVA to identify sources of systematic variation. For short-term advertising elasticities, systematic variability is found related to model specification, estimation, measurement, product type, and setting of study. For advertising carryover and model goodness of fit, the "quasi-experimental design" is so imperfect that a high degree of sharing of explained variance among explanatory factors makes it difficult to identify the impact of a particular factor. Because the studies mostly address mature products in the U.S., suggestions are made for research needs crucial to better understanding of how advertising affects sales.

How Advertising Affects Sales: Meta-Analysis of Econometric Results

Estimates of how aggregate advertising affects aggregate sales are available from a variety of econometric models which estimate parameters of general demand functions. We examine systematic variations in the published econometric estimates of short-term and long-term advertising effects using each estimate as a data point in the analysis. The approach configures parameter estimates in a natural experimental design that allows use of analysis of variance to assess systematic effects of particular study characteristics. The approach has been called "replication analysis" (Farley, Lehmann, and Ryan 1981) to indicate that various studies are viewed as imperfect replications of one overall unplanned experiment. Adjustment for systematic effects of the experimental variables allows generalizations about common elements in the studies. The procedure, a form of meta-analysis, attempts to generalize results from a set of existing studies in the spirit of works by Cooper and Rosenthal (1980), Houston, Peter, and Sawyer (1983), Monroe and Krishnan (1983), Reilly and Conover (1983), Sawyer and Peter (1983), and Sudman and Bradburn (1974).

Our analysis proceeds in four steps. First, we describe the published studies used. Second, we develop hypotheses about the effect of different model specifications, measurement procedures, estimation methods, and research environments. We then report the analysis of variance results. Finally, we discuss implications and offer suggestions for future research.

DATA

The analysis is done on estimated parameters from 128 models reported in 22 studies published before 1981.[1] The studies were identified from reviews by Clarke (1976), Dhalla (1978), and Leone and Shultz (1980); we used only those articles reporting results in sufficient detail to be usable in the meta-analysis. About half the studies

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[1]The studies were those of Arora (1979), Clarke (1973), Comanor and Wilson (1974), Cowling and Cubbin (1971), Erickson (1977), Frank and Massy (1967), Parsons (1975), Houston and Weiss (1974), Johansson (1973), Lambin (1969, 1970, 1972), Metwally (1980), Montgomery and Silk (1972), Moriarty (1975), Palda (1964), Parsons (1976), Telser (1962), Weiss (1968), Wildt (1974, 1976), and Wittink (1977).

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are from econometric literature and half from marketing literature. Like the Aaker and Carman sample (1982), this collection (or any collection) does not exhaust all advertising studies and does not represent a random selection of products.

Further, meta-analysis often has a "publication" bias from the use of studies which have passed a reviewing process. This practice may tend to encourage a certain "acceptable" perspective, lessening interstudy variability on key dimensions and increasing collinearity in the meta-analysis by eliminating studies with insignificant or implausible estimates which may make sense in a broader context. Industrial studies, which are mostly unpublished (and classified), also tend to be excluded. The inclusion of results from rejected papers or from industry sources would be very desirable in the future. Nevertheless, the studies we discuss provide a starting point for generalization attempts.

The measures generally common to the studies which are used in comparing results are:

—*short-term advertising effect*,
—*goodness of fit* measured by R, the multiple correlation coefficient[2] calculated for a given model, and
—*advertising carryover* in those cases in which carryover is specified by incorporation of a lagged dependent variable in the model.

Because carryover was not specified in all models and the coefficient of determination was not always reported, sample sizes differ and the three measures must be analyzed separately. We used elasticities to make the short-term advertising effects comparable in terms of unit of measure. In the case of multiplicative models, the coefficients were elasticities; in the case of linear models, elasticities were estimated by multiplying the relevant regression coefficient by the ratio of the means of the dependent variable and the advertising measure.

Overall, the distributions of the estimated parameters summarized in Table 1 are plausible. Equilibrium short-term elasticities should be greater than zero (smaller values imply negative returns to advertising) and less than one (values greater than unity imply increasing returns to scale of advertising and hence imply the firm is underadvertising.) In fact, only one of the 128 estimated elasticities is less than zero and none is greater than one. Similarly, the coefficient of the lagged dependent variable should be between zero and one and all values of the estimates are within this range. The means in Table 1 represent averages of individual estimates which may differ systematically because of the large interstudy differences that are the subject of replication analysis.

[2]Experiments with normalized values of R using the transformation

$$ln = \frac{1 + R}{1 - R}$$

produced virtually identical results, apparently because of the clustering of the values in the .5 to .8 range. The results on R are reported as they are easier to grasp intuitively.

Table 1

SUMMARY OF STATISTICS ON ADVERTISING ELASTICITIES, CARRYOVER EFFECTS, AND GOODNESS OF FIT

	Mean[a]	*Standard deviation*	*Available sample size*
Short-term elasticity	.221	.264	128
Carryover	.468	.306	114
R	.783	.214	109

[a]All significantly greater than zero at $\alpha = .01$

REPLICATION ANALYSIS OF ECONOMETRIC MODELS

The econometric studies do not provide as good an environment for meta-analysis as the 37 highly comparable Fishbein models (Farley, Lehmann, and Ryan 1981), though they afford a larger and more readily comparable set of results than parameters of four consumer decision process models (Farley, Lehmann, and Ryan 1982). Significant problems in configuring results from these models for meta-analysis are related to variation over studies in model structure, measurement, and research environment.

The models are not structurally identical. On a conceptual level, estimates of advertising effects are comparable in the sense that firms attempting to use advertising efficiently should meet the same conditions relating price and advertising impact (Dorfman and Steiner 1954). In contrast, unlike the Fishbein models in Farley, Lehmann, and Ryan's (1982) study, the econometric advertising models differ fundamentally in terms of specification of variables other than advertising and in terms of specification of the pattern of how advertising affects sales over time. The meta-analysis implicitly involves an assumption that "true" model specification is not totally idiosyncratic to each situation.

Measures are not all comparable. Again, on the conceptual level, model parameters appear comparable over studies—for example, the estimates are generally scaleless elasticities or can be converted easily into elasticities. However, significant problems of comparability arise because some models are built on brands and others on products, and some models use market shares and others sales volumes as independent variables.

Research contexts differ in many ways—products, geographic location, definitions of dependent and explanatory variables, estimation methods, measurement time frame, etc. Though variation of factors such as these is necessary to provide the contextual variability required for meta-analysis, the large number of factors in this case implies a very large and complex "natural" experiment. For practical purposes, no exact replications are available in the literature.

HYPOTHESES ABOUT PATTERNS IN ADVERTISING EFFECTS

Hypotheses about patterns in estimates of the three parameters (short-term elasticities, advertising carryover, and goodness of model fit) were developed from literature. The hypotheses divide into two groups, (1) those related to model specification, measurement, and estimation and (2) those related to specifics of the research environment in a particular study. Each hypothesis is related to a "main effect"—i.e., to significant differences that might be expected in model parameters from a study with particular characteristics. In all cases, the hypotheses should be interpreted in an "other things equal" sense because the various factors under consideration are in fact generally correlated. Further, hypotheses about short-term elasticities should not be contradicted by patterns in carryover which lead to opposite effects in long-term and short-term elasticities.[3]

DIFFERENCES RELATED TO MODEL SPECIFICATION, MEASUREMENT, AND ESTIMATION

Choice of specification and estimation techniques is generally under control of the researcher, and various alternatives are likely to be tried before a "best" version is chosen.

Specification

Actual model specifications differ in terms of the variables included, the assumed timing of the advertising effect (especially in terms of carryover of the impact of current advertising into the future), and the functional form of the equation used.

Variables included. Specification bias may be caused by omission of variables correlated with those included in the equation, the estimated advertising elasticities being biased in the direction of the relation between an omitted variable and sales. Because multicollinearity among the explanatory variables frequently is mentioned in the studies, it is unreasonable to assume that this bias does not exist. For example, inclusion of a price term should produce larger advertising elasticity than would be obtained if no price variable were specified in situations (such as those reported by Farris and Buzzell 1979 and Wildt 1974) when advertising and prices are correlated positively and price has a negative impact on sales. The situation is less clear *a priori* for the impact of exogenous variables, as results depend on both their correlation with advertising and their anticipated impact on sales. Most exogenous variables are macroeconomic measures (GNP for example) or sociodemographics (average family income or family size, for example). They generally should have positive correlations with sales, and their exclusion should bias advertising coefficients upward. Other exogenous measures (seasonality for example) may have a neutral effect on the estimates, although the effect could be negative (positive) should correlation with sales happen to be negative (positive).

A model misspecified by exclusion of important variables should not fit as well as one incorporating those variables unless the excluded variables are very highly correlated with those included in the models.

Carryover effect. Clarke (1976) provides an in-depth examination of carryover coefficients in a set of studies similar to those we discuss. When omission of a carryover effect constitutes misspecification, upward bias of the coefficient for the current advertising will result if current and past advertising are correlated positively and if past advertising has a positive impact on current sales. Palda (1964) shows this effect by applying a model with and one without a carryover variable to the same data. Again, misspecification by exclusion of a carryover term can result in a model which fits less well.

Functional form. The choice of an additive or multiplicative model can affect elasticity. In most multiplicative models, the short-term elasticity is constrained to be constant over the range of the demand function, whereas in linear models the corresponding elasticity varies. For elasticities near unity, the constant elasticity estimate and the average computed elasticity may not differ, though individual values will differ for all but one point. For values of elasticities substantially less than unity (as is generally the case here), the additive model is likely to produce a higher average elasticity than the multiplicative model.

Variable Definition: Share Versus Volume

Dependent and advertising variables are measured in terms of both volume and share. Those specifications using sales volume as the dependent variable imply two effects for advertising—sales gained from a competitor *and* from possible expansion of the market due to advertising. These effects also will be present in those specifications using sales measurement expressed on a per-capita basis. Use of market share as the dependent variable allows the impact of advertising on primary demand to appear in both numerator and denominator, eliminating market expansion from consideration. Similarly, the use of advertising share implicitly assumes no impact of advertising volume *per se*. As a result, share elasticities may be smaller on average than elasticities computed on the basis of volume measurements.

No significant differences in carryover estimates were found in studies using share or volume measures for ad-

[3]Short-term and long-term elasticities are linked. In the case of Koyck models, for example,

$$\hat{\eta}_{\text{advertising,long-term}} = \frac{\check{\eta}_{\text{advertising,short-term}}}{(1 - \text{estimated carryover})}.$$

Because the hypotheses should not be contradictory, larger values of short-term elasticities should not be systematically associated with larger values of estimated carryover. The results involving carryover should be viewed as only a rough approximation because of differences in interpretation of partial adjustment and geometric lag models, both of which contain structurally similar carryover effects.

vertising and/or sales (Weinberg and Weiss 1982), and we expect the same result in our study.

Estimation Method

There is ambiguity about how estimation method might affect estimated parameters. Advertising elasticities estimated with OLS (in contrast to simultaneous equations or multistep estimation procedures designed to address serial correlation in residuals or correlations of residuals and explanatory variables) are biased in the direction of the relationship of current advertising with current sales—a relationship generally expected to be positive. This relationship is likely to be observed for long intermeasurement periods, and "even with quarterly data, adver tising is strongly affected by current sales" (Schmalensee 1972, p. 98). Cowling and Cubbin (1971), however, found a negative relationship between current advertising appropriations and current market share, which they explain as a "compensatory" mechanism whereby the company responds to a short-term decrease in market share by increasing its advertising share and vice versa. Their OLS estimates of the advertising coefficients are thus smaller than the coefficients when a set of simultaneous equations is fit to the same data base.

Because OLS procedures minimize squared error, models estimated with this method should fit better, other factors being equal.

DIFFERENCES IN ADVERTISING EFFECTS RELATED TO THE RESEARCH ENVIRONMENT

Even for a correctly specified model with appropriately estimated parameters, qualitative features of market environments might affect results.

Products

There is no reason to expect that advertising response *per se* will vary among products, but there is reason to anticipate that it will vary according to information needs related to particular products and to the state of development of particular markets.

Product types and information needs. Nelson (1974) has suggested that products be categorized as "experience goods" and "search goods" in terms of patterns of consumer information search. For experience goods, which are predominantly frequently purchased and frequently used products, experience is the major source of information and hence advertising elasticity may be relatively low, other things being equal. For durables and new products, a search for sources of information (including advertising) is more likely to accompany purchase. For very expensive and high-risk purchases, however, the buyer tends to rely more on other types of communication, and advertising may be relatively less effective. System models of consumer decision processes generally fit less well for durables than for nondurables (Farley and Lehmann 1977), apparently because of greater variability between timing of advertising exposure and purchase, though there are indications that carryover patterns in endogenous variables for durables are similar to those for nondurables (Farley et al. 1982).

Product lifecycle. Elasticities should be higher during the early growth phase, when a significant number of new customers are brought in as triers, than during the maturity phase of the product lifecycle, when most customers have substantial experience. Because sales during the early phases of the product lifecycle are relatively small, sales increases due to advertising should represent a large percentage gain in contrast to the gain in later periods when more sales are repeat purchases (Parsons 1975).

National Setting

Though some evidence suggests that ratios of advertising to sales for individual products do not differ among countries (Leff and Farley 1980), differences in preferences, restrictions on advertising, and production cost structures may cause advertising elasticities to differ among geographic markets.

Level: Brand Versus Product

A given advertising elasticity should be smaller at the brand level than at the product level because at the product level the impact of advertising has a component due to increase in total sales as well as gains in sales of other brands. Further, advertising increases in oligopolistic markets are likely to be matched by competitors, and this action tends to influence brand-level elasticities downward.

In contrast, advertising (especially in the mature markets which predominate in the studies we used) generally focuses on differentiation from competing brands. This sort of advertising may lead to sales increases for the individual firm without significant product sales increases, thus mitigating the effect of product versus brand in this environment.

Data Interval

Mounting evidence indicates that the measurement interval has a significant impact on coefficients of econometric models involving advertising (Bass and Leone 1981; Vanhonacker 1982), largely because of problems in matching time frame of advertising measurement and advertising effect on sales. As a rule, advertising does not translate into instantaneous sales. According to Clarke (1976), 90% of the cumulative effect of advertising of mature, frequently purchased, low priced products occurs within three to nine months of the advertisement. Hence, maximum elasticities should occur for intermediate levels of time aggregation for the nondurables that predominate in the studies we used. There are indications that carryover coefficients are relatively invariant in relation to measurement period (Weinberg and Weiss 1982), although the implied duration interval clearly varies.

Time Series Versus Cross-Sections

Regressions used to fit models to time-series data often cannot distinguish between lagged advertising effects and positive serial correlation in disturbances (Clarke and McCann 1973; Houston and Weiss 1974; Maddala and Vogel 1969). Because cross-sectional data are not subject to this problem, advertising elasticities estimated with time-series data should be smaller. Further, cross-sectional analysis captures level effects rather than dynamics, again suggesting that time-series elasticities may be smaller.

Media Definitions

Aggregate advertising measurements average the impact of very effective media with that of less effective media. Specific media might produce either higher or lower elasticities than those shown by aggregate measurement which combines media of different effectiveness.

RESULTS

Characteristics of the "Quasi-experimental" Design

The basic analytical approach is to consider the categories in Table 2 (a summary of 50 study classifications) as design variables in a "quasi-experiment" and to use ANOVA in an attempt to assess the impact of each factor. Because the studies were not laid out according to any prior research plan, we have no reason to expect that this "quasi-experimental design" would have anything resembling desirable properties in terms of either the number of available studies or how the studies that are available are configured.

First, Table 2 shows that the empirical design is highly unbalanced. More than 100 of the 128 studies were done in the U.S., treat mature products, or use models which incorporate a carryover effect, respectively. Similarly, for 13 of the potentially interesting factors the sample size is less than 10. Despite this imbalance, and using only those variables with at least 10 observations to preserve at least minimal within-cell sample size, we performed univariate t-tests comparing mean values of estimates from studies with a given characteristic against all other estimates. Many more are significant than would be expected by chance.

	Number of significant differences		
Number of tests	*Short-term elasticity*	*Carryover coefficient*	*Goodness of fit*
29	20	16	15

(These t-tests cannot be considered independent because of other defects in the experimental design discussed subsequently).

Second, as an empirical matter, a natural "quasi-experiment" generally will not have orthogonal factors, one of the major benefits of formal experimental design. When nonorthogonal factors are present, statistical testing of individual effects must address the problem of "shared variance" which is common to two or more effects. In the extreme, the design matrix may be singular, as it was in the study of consumer behavior models (Farley, Lehmann, and Ryan 1981), meaning that some reduction of design variables is required even to make the ANOVA feasible. Principal components analyses on design variables in Table 2, transformed by the Draper and Smith (1966, p. 243–62) procedure so that each subset of ANOVA coefficients sums to zero, are shown in Table 3. In comparison with the ideal orthogonal experimental design for which all the eigenvalues are equal, the design using all the variables clearly involves almost insurmountable collinearity problems. Some relief is given by combining into "all other" classes those variables which occurred for less than 10% of the sample. Although some possibly interesting factors are excluded when this is done, the short-term elasticities design appears to meet minimal conditions for inversion. However, the designs for the carryover coefficients and transformed goodness-of-fit measurements indicate more severe problems. The degree of shared variance in the resulting ANOVAS, also shown in Table 3, indicates that assessing the effects of specific factors on carryover and goodness of fit will be difficult. Though the ANOVAs account for half to three fifths of the variance in the three dependent variables (all three coefficients of determination are significant), five sixths of the explained variance in the lag coefficients and two thirds of the explained variance in goodness of fit are shared. Several approaches are available for allocating shared explanatory power among factors and for estimating the effects of groups of variables (Green, Carroll, and De Sarbo 1978), but we do not use them because our main goal is to assess the impact of individual factors (e.g., to estimate the significant ANOVA coefficients).

Finally, "natural" experiments commonly have problems related to the number of interstudy differences in relation to the number of studies available. Though the 128 studies provide enough degrees of freedom to assess all direct effects (the sum of the numbers of levels shown for the categories in Table 2), a full factorial experiment implies approximately 7 million cells (the product of the numbers of levels). Even the experiment using only design variables with 10% of the sample contains about 140,000 cells. In both cases, replication also is required to estimate all factorial ANOVA parameters. The data needed for analysis of all main effects and interactions or even a substantial fraction of them greatly exceed the relatively small number of available observations.

ANOVA Results

Overall ANOVA results are reported in Table 4, which shows the proportion of variance of each dependent variable explained by each factor. Because of different sample sizes (Table 1), we fit a separate ANOVA for each of the three dependent variables and used only those design variables represented in at least 10% of the sample

Table 2

CHARACTERISTICS OF THE STUDIES AND UNIVARIATE TESTS ON WITHIN-GROUP MEANS OF STUDIES WITH THOSE CHARACTERISTICS VERSUS ALL OTHER STUDIES

I. Descriptors of model specification and estimation	*No. of studies*	*Short-term elasticities*	*Carryover*	*Goodness of fit*
A. *Model configuration*				
1. *Variables included* (5 levels)				
Exogenous variables	74		−	
Price	72	+	−	+
Other marketing variables	23		−	
Product quality	7	×	×	×
Distribution	4	×	×	×
2. *Pattern of timing* (2 levels)				
Carryover in advertising effect	114	−	+	+
Time-varying advertising effect	12	×	×	×
3. *Functional form* (2 levels)				
Multiplicative	72	−		−
Additive	56	+		+
B. *Variable definition*				
1. *Dependent variable* (3 levels)				
Share	65	−	+	+
Volume	60	+		
Per capita	3	×	×	×
2. *Advertising variable* (3 levels)				
Share	40			
Volume	72	+	−	
Per capita	16	−	+	
C. *Estimation methods* (4 levels)				
Ordinary least squares	46			+
Nonlinear single equations	46	+	+	−
Multiple-step single equations	28	−		
Multiple equations	8		×	×

II. Descriptors of measurement and the research environment	*No. of studies*	*Short-term elasticities*	*Carryover*	*Goodness of fit*
A. *Product*				
1. *Product type* (9 levels)				
Frequently purchased	71		+	
Food	26	−		−
Durables	20	+		−
Other nondurables	17		+	+
Detergents and cleaners	11	×	×	×
Pharmaceuticals and toiletries	10	×	×	×
Gasoline	7	×	×	×
Cigarettes	4	×	×	×
Lydia Pinkham	3	×	×	×
2. *Position in lifecycle* (4 levels)				
Introductory	10	×	×	×
Growth	5	×	×	×
Maturity	109			
Decline	4	×	×	×
B. *National setting* (3 levels)				
U.S.	105	−		+
Europe	14	+		−
Elsewhere	9	×	×	×
C. *Level* (2 levels)				
Brand	86	−		−
Product	42	+		+
D. *Data interval* (3 levels)				
Monthly	41			
Bimonthly and quarterly	32	−	+	
Weekly and yearly	55	+	−	+
E. *Data include cross-sections* (2 levels)	38		+	+
F. *Media definitions* (6 levels)				
Aggregate	90	+		
TV	24	−		
Journals	4	×	×	×
Direct mail	4	×	×	×
Retail	4	×	×	×
Sampling and promotion	2	×	×	×

Note: + or − indicates sign of significant univariate *t*-test at $\alpha = .05$. × indicates sample too small to allow testing or inclusion in later ANOVAS. In some cases these are grouped into an "all other" category for binary comparison.

(Table 2). The deficiencies in the natural experimental design discussed before cause significant sharing of explained variance among factors.

For goodness of fit and carryover, the variable set as a whole has significant explanatory power but shared variance dominates the results. Further analysis of the type suggested in the Discussion section is needed to sort out the effects of individual variables. It is important to recognize that calibration of shared variance is a product rather than a deficiency of meta-analysis.

Shared variance is a lesser problem for the short-term elasticities (for which seven ANOVA variables are significant), probably for reasons related to the principal components results in Table 3. Numerical values of the individual ANOVA coefficients for short-term elasticities significant in Table 4 represent systematic effects associated with particular studies and modeling practices, everything else being equal. These differences have methodological and substantive implications for advertising.

Grand mean. The grand mean in the short-term elasticity ANOVA is .695, significantly greater than zero and also significantly greater than the arithmetic mean of the elasticities unadjusted by the ANOVA for other factors (Table 1). This finding indicates that advertising may be generally more effective in the short run than the

Table 3
IMPACT OF DESIGN IMPERFECTIONS IN THE NATURAL EXPERIMENT

	All design variables from Table 2	Design variables with nonzero values for at least 10% of the sample — Dependent variables: Short-term elasticity	Carryover	Goodness of fit
Principal components analysis of experimental design matrix				
Number of nonzero observations	128	128	114	109
Number of nonredundant variables	42	25	24[a]	25
Ratio of largest to smallest eigenvalue	45,326	663	1800	1555
Determinant	6×10^{-20}	$.29 \times 10^{-12}$	$.58 \times 10^{-15}$	$.1 \times 10^{-15}$
Variance explained by corresponding ANOVA				
Fraction of variability explained by individual variables	NA	.361[b]	.073	.215
Shared variance	NA	.140	.526[b]	.376[b]
Fraction of variability explained by ANOVA (R^2)	NA	.501[b]	.599[b]	.591[b]

Note: NA indicates inversion not practical.
[a]One design variable lost as all equations are specified to include a lagged dependent variable.
[b]Significant at $\alpha = .05$.

average estimated elasticities in Table 1 suggest (Aaker and Carman 1982; Bass 1980).

Carryover. The largest numerical effect is that short-term elasticities are .336 higher in models without a carryover coefficient than in models with one. This difference is not significantly different from the arithmetic average of the carryover statistics (.468, Table 1). Thus the effect of an unspecified carryover is picked up largely in the estimate of the short-term elasticity. The fact that models with and without a carryover term fit equally well also indicates that the larger short-term elasticity captures both effects when carryover is not specified.

Exogenous variables included. Models containing exogenous variables have short-term elasticities .103 smaller than those of models lacking exogenous variables. Equations including exogenous variables also have estimated carryover coefficients .162 less than those of equations without them, indicating that longer term elasticities may be overstated even further in models lacking exogenous variables. As most exogenous variables (income, family size, etc.) should be related positively to sales, their omission appears to overstate the effect of advertising.

Functional form. As predicted, elasticities in additive models are a significant .247 higher than elasticities estimated under the more restrictive multiplicative specification in which they are assumed equal over the range of the data. The analytical convenience afforded by models linear in logarithms appears to have an asymmetrical effect of averaging down estimated advertising elasticities. It is important to recognize that this result is an approximation at one point associated with one "average" arc elasticity for each additive function.

Data interval. The increasing attention to the impact of measurement timeframe on advertising effect is supported. In relation to the grand mean, short-term elasticities based on various measurement periods differ as follows.

Weekly or monthly	−.068
Bimonthly or quarterly	.072
Annual	−.004

Though this finding is consistent with our prior hypothesis, clearer interpretation of these results must await further results in the study of aggregation.

Type of data. As anticipated, pooled data (involving cross-sections) produced elasticities .176 larger than those of straight time-series data. Equations fit to pooled data also fit significantly better than those fit to straight time series. These results suggest there is usefulness in disaggregating data (e.g., by geographic areas, purchasing units) whenever possible (Farley, Lehmann, and Winer, 1983).

Products. Explicit product identification is not possible for many studies, but food products (presumably from among the most heavily advertised in that category) have an elasticity .101 higher than that of the other categories. As expected, equations fit to data for durable goods fit significantly less well than other equations.

Locations. Estimated short-term advertising elasticities for Europe are .385 greater than the grand mean, but average .087 smaller than the grand mean for the U.S. This difference may reflect a more restrictive me-

Table 4

FRACTION OF VARIABILITY IN THREE STUDY OUTPUTS EXPLAINED BY VARIOUS STUDY CHARACTERISTICS

Study characteristic	Degrees of freedom	Dependent variable: Short-term elasticity	Carryover coefficient	Goodness of fit
Model specification				
Variables included				
Exogenous variables	1	.022[a]	.021	.002
Price	1	.007	.000	.000
Other marketing variables	1	.000	.005	.006
Advertising carryover included	1	.094[b]	NA	.016
Functional form	1	.037[a]	.000	.019
Variable definitions				
Dependent variable	1	.018	.008	.009
Advertising variable	1	.004	.004	.014
Measurement				
Data interval	2	.035[a]	.005	.005
Pooled data	1	.029[a]	.008	.051[b]
Media definitions	3	.013	.000	.000
Estimation	3	.026	.011[a]	.023[a]
Research environment				
Product type				
Frequently purchased	1	.005	.001	.005
Food	1	.034[a]	.002	.004
Other nondurables	1	.000	.002	.020
Durables	1	.006	.000	.023[a]
Mature product	1	.004	.000	.012
National setting	2	.027[a]	.005	.002
Brand or product	1	.002	.001	.004
R^2		.501[a]	.599[a]	.591[a]

Note: NA indicates not applicable.
[a]Significant at $\alpha = .05$.
[b]Significant at $\alpha = .01$.

dia environment in Europe which may lead to less than optimal expenditures on advertising. Historically, lower incomes also may have kept the advertising industry from reaching the level of maturity that it did in the U.S. through the 1950s and 1960s (Leff and Farley 1980).

Perhaps as important as the significant results are main effects that are not significant. In particular, no significant differences in short-term elasticities are found in models using shares versus levels of sales or in models using brand versus products. This point deserves considerable attention, perhaps in experiments of alternative model specifications in situations where both kinds of data are available. The lack of significance may be related to the fact that the vast majority of products studied are relatively mature and advertising has a relatively minor impact on product class sales.

Similarly, the lack of significant effect of estimation method on short-term elasticities does not deny the importance of appropriate estimation. For example, among the few significant results on the carryover parameters, multiple-step single-equation methods produce significantly lower coefficients for the lagged dependent variable and multiple-equation methods produce significantly higher values. Also related to estimation is the finding that OLS methods produced better fits than other methods as hypothesized.

DISCUSSION

Ideally, meta-analysis should give substantive information about the net result of a body of research, provide implications about methodological issues, and lead to suggestions for future research.

Substantive Implications

Overall, the studies seem to produce estimates which are plausible and which differ surprisingly little over product classes.

Short-term elasticities in models which incorporate carryover effects are significantly smaller, short-term elasticities in models containing exogenous variables are also lower, and long-term elasticities are even lower. Most models involve data on mature, frequently bought products and these results indicate that an appropriate model in these circumstances generally should incorporate exogenous factors and carryover effects.

Cross-sectional data produce higher short-term elasticities than time series, indicating that cross-sectional disaggregation of time series should be done whenever possible.

Elasticities differ among products and settings, being higher for advertised food products and higher in Europe than in the U.S. It appears, for example, that either Europeans underadvertise because of media restrictions or companies in the U.S. overadvertise for some unspecified reason.

Short-term elasticities vary systematically with data interval, indicating, as Clarke (1976) suggests, that results from the high level of current research activity in this area are needed to provide better assessment of advertising effects. In particular, within-study variation of the data interval (when feasible) would be very useful.

Methodological Implications

Tests of hypotheses in future models should use null values for short-run advertising elasticities and lag effects other than zero. In particular, the mean values of the studies (short-term elasticity of about .3, carryover coefficient of about .5, and multiple correlations of about .7) provide good initial estimates.

One value of a meta-analysis is that it can help provide predictions (testable later) for specific situations which have not been studied in actual combination, but whose elements have been assessed individually. Actual estimated values may be larger or smaller depending on the specific situation, and predictions about the impacts of these specific factors can be made by using ANOVA coefficients related to them.

Implications for Future Research

The major implication for future research is that, in general, programmed research should be used to help remedy the defects of the "natural" experimental design. The univariate tests suggest several factors related to significant differences in short-term and long-term advertising response coefficients as well as how well models fit, but whose impact may be obscured by a high degree of common or shared variance in the experimental design. New data are needed to expand available combinations of characteristics of the research environment. Other results can be filled out by experimentation with alternative specifications and estimation procedures on existing data. In the former case, as Aaker and Carman (1982) also suggest, more studies are needed for relatively new products, in locations other than the U.S. and Europe, and for products other than packaged goods—e.g., durable goods and industrial products. In the latter case, systematic within-study comparison of alternative model specifications and alternative estimation procedures would help isolate the model-related and procedure-related sources of differences in estimated parameters without requiring new studies to address these issues. This comparison might be done now with a collection of raw information used in some of the studies we cite. Cast in the framework of meta-analysis, these within-study experiments should not be viewed as "fishing" but as systematic assessment of the impact of various available modeling options on results.

In addition to studies in other research settings, it would be useful to expand the available data base by surveying academic and industrial sources for models which for some reason have not been published. Such studies have been done in industry where they were classified or withheld for other reasons, or they might have produced no results or negative results and hence were deemed unacceptable by the authors or by reviewers.

Finally, a more comprehensive overall model of advertising effectiveness would be helpful in generating theoretical predictions about the impact on advertising effectiveness under specific market conditions. Such a model also would help provide a more explicit and comprehensive basis for hypotheses of the type we discuss.

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