Farley, John, Scott Hoenig, Donald R. Lehmann, and David Szymanski (2004), "Assessing the Impact of Marketing Strategy Using Meta Analysis," in *Assessing Marketing Strategy Performance*, eds. Christine Moorman and Donald R. Lehmann, Cambridge, MA: Marketing Science Institute, 145-164.

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Assessing the Impact of Marketing Strategy Using Meta-Analysis

John U. Farley, Scott Hoenig, Donald R. Lehmann, and David M. Szymanski

Introduction

Meta-analysis is a way of using available information from studies to establish the presence or absence of empirical generalizations. The value of meta-analysis lies in its ability to aggregate a potentially large and diverse set of findings into generalizable or typical results and reasons why findings vary across studies and their models. This chapter describes how meta-analysis can be used to assess the impact of marketing strategy and marketing programs.

What Is Meta-Analysis?

Meta-analysis is a term used for a category of approaches that provide a quantitative literature review or summary of a research area. Three types of meta-analyses are typically found in the literature, which focus on (1) the size, (2) explained variance, or (3) statistical significance of an effect. Optimal strategic marketing decisions depend on the magnitude (size and explained variance) of an effect—for example, the impact of advertising on market share or profitability. Statistical significance may be less relevant (because most actions have at least a small nonzero effect on outcomes) and easy to generate (for example, by increasing sample size). Consequently, focusing on the "best guess" (maximum likelihood) estimate of the magnitude of a relationship is more relevant for generating strategic marketing insights (for instance, for forecasting the impact of advertising on sales).

The Formal Model

The starting point for meta-analysis is the identification of the population of studies that report data in, or are convertible to, a common metric. Each study provides one or more data points of the form:

$$Y = \beta X + \varepsilon_1 \qquad (1)$$

where ε_1 represents an error term accounting for various forms of noise in the data.

The object of generalization is β (the estimate of association between X and Y—for example, the association between advertising and sales), with correlations, regression coefficients, and elasticities being acceptable forms. Various statistics related to the above relationship, such as goodness-of-fit measures, might be used as substitutes for β depending on the nature of the literature and the purpose of the meta-analysis.

β is likely to vary across a number of conditions, such as type of offering (product versus service), study setting (industrial versus consumer companies), and the variables specified in multivariate models (such as association between advertising and marketplace performance after controlling for shared variance with price or product features). Each value of β is composed of the overall mean ($\bar{\beta}$), systematic variation due to other factors (Z), and a unique (error) term, i.e.:

$$\beta = \bar{\beta} + \sum_{i=1}^{k} C_i Z_i + \varepsilon \qquad (2)$$

with Z representing the presence/absence or magnitude of various conditions or design elements in the original study, sometimes referred to as moderators of the magnitude of the relationship between X and Y. In meta-analysis, an estimate of the average relationship between X and Y ($\bar{\beta}$) and the impacts of the design elements (C_i) are provided.

The Basic Process

Meta-analysis begins by identifying a relationship between X and Y that has been the subject of repeated empirical study such as the impact of advertising on sales. While only two effects are conceptually necessary for conducting a meta-analysis, areas where many effects are reported and research interest is high add stability to the results and relevance to the findings. These findings evolve from the following steps (Farley and Lehmann 1986), usually performed in an interactive rather than linear fashion:

1. *Identifying and collecting relevant data.* Published studies are the most obvious place to start. Usually their number is not large, ranging from a few dozen to perhaps one or two hundred. It is also desirable to include unpublished studies (working papers, dissertations, company white papers, and so on) so that a more complete set of effects is captured.
2. *Identifying the target measure of association* (β). Sometimes the appropriate measure to summarize is easy to determine, but often it appears in a form requiring adjustment or conversion to another metric. Asking authors for data in a more usable form (for example, correlations) can help overcome this problem.
3. *Estimating the average impact* ($\bar{\beta}$). Simple counts of signs and statistical significance, developing a distribution of effects (for instance, advertising elasticities), and estimating simple means for the target measure (β) are useful. Correcting for sampling error (for example, differences in the sample sizes) and measurement error (such as reliability differences) is common when β is a correlation.
4. *Identifying and coding study differences* (Z). Creativity is needed to fit different model specifications and research frameworks into a common form. Information needs to be as explicit as possible in terms of study design, sample characteristics, and model specification, as well as situation (type of product, geographical location, other variables specified in models). If relevant information is unavailable from the original studies, retrofitting by contacting the authors might be required.
5. *Estimating the impact of study differences* (C). Due to the naturally imperfect design of study differences (Z_i), multivariate analysis is important for determining C_i. Although hypothesizing the signs of the various C_is is unnecessary, results grounded in statistical, psychometric, or substantive theory are less prone to spurious effects. For most meta-analyses, regression (for example, dummy-variable regression analysis) is adequate for estimating the average effect and its contingencies.

Step 1: Identifying and Collecting Relevant Data

This task involves finding as many studies as possible that report data on a particular topic. The process involves a three-tier strategy of searching multiple databases, reviewing references in located articles and other sources, and identifying unpublished studies. The process is typically concluded when it becomes clear that additional efforts to locate additional studies are not producing tangible results.

Multiple Database Search. The fastest way to identify potentially relevant studies is to search titles and abstracts of refereed journals, books, and unpublished dissertations using electronic resources such as ABI-INFORM, EBSCO, LexisNexis, Worldcat, the Library of Congress catalog, and Dissertation Abstracts Online. A keyword search of the Web can generate leads on government or company reports. It is also imperative to review the text of journal articles to identify relevant studies not covered by electronic services or overlooked in keywords or titles. (This can happen when the relationship of interest is only one of many relationships being modeled in a study and therefore not highlighted by the keyword.)

Since different keywords yield different search results, it is important to test several. However, it is easy to get lost in a search. A particular keyword can result in thousands of hits. Often the best way to edit the resulting list is to mark articles of potential interest. While looking at 1,000 article titles may seem to be a hopeless task, in reality it can be done in a few hours.

Searching References in Located Articles. Take advantage of existing searches. Review the references in identified studies, and if qualitative reviews or comparable meta-analyses exist, review their references for useful leads.

Searching for Unpublished Studies. Unpublished studies may contain smaller, nonsignificant effects (since journals may be biased toward publishing statistically significant effects) and studies that have just been completed and are not yet published may offer findings based on improved measures, methodologies, and models. These findings should be part of the meta-analysis, and so a search for papers hidden in people's file drawers should be performed. Contacting published authors in the field and making open requests for papers via electronic list servers or other Web-based communications can be beneficial.

Step 2: Identifying the Target Measure of Association (β)

The data for a meta-analysis have been generated by a "natural experiment" involving different researchers working in different research environments with different research tools, using different terms and different metrics to document their findings. Thus, the precise reason why meta-analysis has value—its ability to take disparate findings and offer insights into their central tendency and situational influences—also makes it difficult to execute.

Many beginners or researchers trained rigorously in hypothesis generation and statistical techniques have an initial tendency to reject potentially useful data if different studies on a topic are not reported identically or if the studies appear deficient on some characteristic. However, seemingly nonidentical studies (for instance, some about services and others examining products) often can still be compared, and contextual or methodological disparities should be examined for their influence as part of the meta-analysis.

One useful approach is to seek measures that have obvious commonalities and to categorize studies according to the metrics used for reporting findings. Regression coefficients can be made comparable by adjusting the units and in some cases by calculating elasticities. Correlation coefficients can be developed from *t*, *F*, and chi-squared values (see formulas in Glass, McGaw, and Smith 1981).

It also helps to consider variables at an abstract (construct) rather than operational (measure) level. For example, while studies reporting the relationship of strategic profiles to performance may use different profile operationalizations, they can often be considered indicators of the same core factors. If measures cannot be adjusted to similar units, the sign of the relationship may be collected as the data for a meta-analysis. Finally, when all else fails, contact the authors of the original studies and ask for needed correlations or standard errors for converting regression coefficients to elasticities.

Step 3: Estimating the Average Impact ($\bar{\beta}$)

Not all β_is are of equal quality: Estimates grounded in larger samples and developed from more reliable scales tend to be more accurate. Because disparities between the observed and population correlational values caused by sampling and measurement error can be substantial, it is advisable to adjust the β_is to ensure the most accurate effects are available for estimating the impact of study differences (the *C*s), as in Hunter and Schmidt (1990). For correlations, this involves calculating the attenuated correlation (sample size weighted and reliability corrected). Regression coefficients or elasticity adjustments can be adjusted by running a weighted regression model when estimating C_i with sample size or, if available, the inverse of the variance of the estimates of β_is as weights.

Adjusting correlations for sampling errors and reliability differences has an added benefit. It offers the opportunity to assess whether the variance in the correlations is real or artificial (that is, due mainly to sampling and measurement error). When a substantial proportion of the variance (more than 25%) remains after accounting for sampling and measurement error, a search for moderators is better justified because something other than sampling and measurement error accounts for differences across the respective β_is.

Step 4: Identifying and Coding Study Differences (Z)

Elements that vary at the study level (for example, whether the study has an industrial or a consumer setting) and model level (for example, whether certain independent variables are included or excluded in the various studies' regression models) should be examined for their influence on the magnitude of β. Theory or established empirical patterns normally suggest which variables should be included in the set of Z predictors. In most instances, these predictors are either contextual (for example, the study setting) or methodological factors that describe the investigation.

Contextual factors often include the offering (products versus services, industrial versus consumer), the industry (for example, high versus low technology), and characteristics of the researchers (for example, their background discipline) and respondents (such as students versus nonstudents). Some examples of *methodological factors* include the nature of the data (time series versus cross-sectional, from a controlled or natural experiment versus a survey), level of aggregation (brand versus market, aggregate versus individual measurement), model specification (for example, some models include other exogenous factors, carryover effects or time-varying parameters; functional specifications; inclusion of interactions and slope shifts), estimation procedure (possibilities include bivariate versus multivariate, linear versus nonlinear, and single or multiple equations), data collection method (for example, interview, diary, mail questionnaire, scanner, telephone interview), and variable definitions (for example, profitability defined as return on investment, return on assets, or return on equity).

An overlooked benefit of meta-analysis is that it makes possible the examination of design variables not previously examined within a study. These can include country-of-origin effects or temporal effects that can offer insights into whether relationships are applicable across nations and whether effects have diminished or strengthened with time. Hence, design variables should not be limited to those already examined in individual studies.

Coding. The most convenient approach to coding is to assign a column in a spreadsheet to each of the variables in the natural experimental design. Each row represents a particular observation in a given study. Because most of the design variables involve coding for the presence or absence of a particular characteristic, a single dummy variable ($j - 1$ dummy variables where j is the number of levels or

categories that characterize the design factor) can be used to capture whether the element was included ($Z_i = 1$) or not ($Z_i = 0$) in the respective study. Effects coding (see next section) can also be used to increase the interpretability of results, especially when more than two levels describe a design element (for example, performance as market share, profitability, or sales).

It is likely that many revisions will be made before a final design is formed. One useful approach is to begin with a few studies, try a coding scheme, and revise as needed. We suggest being fairly liberal in the coding, but also fairly detailed. Going back to add variables or determine their exact meaning is far more painful than finding out that some are not important and others need to be aggregated to a broader level.

Once the data has been coded, simple inspection often reveals some problems. In particular, some dummy variables may have few observations and slightly different terms may be used by authors to refer to the same phenomenon. It is often useful to combine these variables if the combination makes conceptual sense and effects sizes are similar within the combined categories.

Step 5: Estimating the Impact of Study Differences (C)

For estimating C_i, we consider two fundamental forms: "one at a time" (univariate), and "many at a time" (multivariate), both of which can be estimated using regression.

Univariate Analysis. As a starting point, it is useful to analyze the impact of design variables one at a time through differences in means or correlations across levels of a design variable. Due to correlation among design factors (Z_i), however, univariate summaries can be misleading or biased. For this reason, we strongly recommend doing "many at a time" (multivariate) analysis.

Multivariate Analysis. To control for the impact of other variables (as well as for common effects within studies that provide multiple data points), a multivariate procedure is needed. For most situations, regression (ordinary least squares) will suffice, and in fact may be more stable than more so-called sophisticated procedures (such as neural networks, hierarchical, or Bayesian approaches) when dealing with minor variations in model specification. Regression also has the advantage of being understood by a reasonably large fraction of potential researchers and readers.

In regression, collinearity among the design measures is often a problem. One way to assess collinearity is to analyze the design matrix using principal components analysis or factor analysis. One can also use collinearity diagnostics (for example, maximum variance inflation values greater than 10 imply that collinearity is influencing the estimates). The researcher can then choose which variables to remove from the analysis or group to form a single construct.

Power. Given the relatively small number of effects (often 100 or less) in many meta-analyses and the large number of design variables to consider, statistical power (the ability to detect significant differences) is limited. This favors the position (null hypothesis) that all effects are of similar magnitude. While this is consistent with the philosophy of meta-analysis, it could overlook consistent, but small, effects.

To ensure adequate power, it is preferable to include only design (dummy) variables with 10 or more observations; doing so has the added benefit of yielding more stable estimates of C_i. Power is easily calculated when analyzing correlations and is therefore recommended for developing a sense of whether adequate power is available for detecting large, medium, or small effects. It may also be worthwhile after initial analysis to reduce the design and increase power by excluding variables that are not impactful or by combining levels of a variable that are similarly impactful. Since a design variable can have several levels, which lead to multiple dummy variables, also see if the variable as a whole has significant impact. One can perform a simple nested (Chow) test to compare the variance explained with and without the set of dummy variables.

Multiple Observations from the Same Study. When multiple observations come from the same study, there is an issue concerning how to deal with them. Selecting a single observation from a study greatly reduces power, as does averaging results of more than one study. The latter in particular can mask study variance and limit the number of design features that can be coded and analyzed. For example, if a single study estimated the relationship of advertising to performance first in a service and then in a product setting, taking the average of these two effects would mean one could not examine the setting as a potential moderator.

When multiple observations are included, the meta-analysis can treat them as independent, weight them by the inverse of the number of observations in the study (to make each study in the meta-analysis have the same weight), or treat them as dependent within the study. A straightforward way to account for multiple effects from the same study is to include a dummy variable for all of the observations that come from that study. If effects coding is used, the data from a hypothetical five-study set might look like:

Observation	Study	Study 1 Dummy Variable	Study 2 Dummy Variable	Study 3 Dummy Variable	Study 4 Dummy Variable
1	1	1	0	0	0
2	1	1	0	0	0
3	1	1	0	0	0
4	1	1	0	0	0
5	2	0	1	0	0
6	2	0	1	0	0
7	2	0	1	0	0
8	3	0	0	1	0
9	3	0	0	1	0
10	4	0	0	0	1
11	5	−1	−1	−1	−1
12	5	−1	−1	−1	−1

(The dummy for Study 5 is deleted because of redundancy.) Of course, this approach uses up degrees of freedom (which may be limited due to small sample sizes) by requiring the estimation of more parameters, and so assessing the appropriateness of using multiple observations a priori is suggested.

The appropriateness of using multiple observations from a study or an average of the observations within a study can be assessed empirically. One approach is the Q-test outlined in Hedges and Olkin (1985), which is used for assessing the degree to which multiple effects within a study are similar in value. Interestingly, including multiple observations is not only superior to using a single one on the basis of increased power and added design features, but the respective means and sampling error variances often are comparable at the individual result and study level (Szymanski and Henard 2001) so that treating multiple observations as independent works quite well (Bijmolt and Peters 2001).

Adjustments for Omitted Data, Including Publication Bias. Using only studies published in leading journals may exclude working papers just completed, studies which produced weaker results (and hence were not deemed publishable), or studies that do not fit the current orthodoxy (for example, Copernicus' findings that the world is round would not have been published). One approach proposed by Rosenthal (1984) for examining the severity of publication bias is to see how many studies with no effect would be required to reduce a significant $\bar{\beta}$ to nonsignificance. Another approach is to attempt to back-fit the so-called censored (not included) studies based on the pattern of observed results, as in Rust, Lehmann, and Farley (1990).

Making Adjustments for Substantive Variables, Including Omitted-Variable Bias. When the focus is on regression coefficients or elasticities, the moderators (Z_i) can include select substantive variables (for example, price included or excluded in models of advertising with performance) present or absent in the models in the original studies. Greater ingenuity may be required to assess whether failing to consider a substantive factor such as price biases the correlation between advertising and performance. Unlike multiple regression coefficients, bivariate correlations are not corrected for any variance X and Y share with relevant third factors. One corrective approach is to gather data from the original studies or their authors so that (using the example mentioned above) a matrix of the attenuated, mean correlations among price, advertising, and performance can be constructed. From this, a correlation between advertising and performance with price effects partialled out can be estimated. In general, if the difference between the original and partial correlation is significant, then omitted-variable bias is present and should be considered when estimating the relationship between the two variables.

A Sample of Meta-Analyses in Marketing Strategy

The marketing field is increasingly populated with meta-analyses. Of these, a reasonable number focus on issues related to marketing strategy (see Table 1). The breadth of topics covered indicates the potential value of meta-analysis to marketing strategy.

On the topic of *general strategy*, Capon, Farley, and Hoenig (1990) documented the relationship of strategic, customer, and marketing-mix measures to various performance metrics. Other meta-analyses have considered international strategy standardization (Shoham 2002), export performance (Chetty and Hamilton 1993; Leonidou, Katsikeas, and Samiee 2002), and market share (Szymanski, Bharadwaj, and Varadarajan 1993). The levels of evolution and stationarity of various strategic actions have also been analyzed (Dekimpe and Hanssens 1995).

Marketing assets include the customer base, brands, and new products. Customer-related meta-analyses have considered determinants of customer satisfaction (Szymanski and Henard 2001), including those in marketing channel relationships (Geyskens, Steenkamp, and Kumar 1998, 1999), and characteristics of older consumers (Tongren 1988).

While fewer *branding* meta-analyses have been performed, one looked at how branding in conjunction with price and store name affected buyers' perceptions of quality (Rao and Monroe 1989) and a second examined the traits of consumers who tend to buy generics (Szymanski and Busch 1987).

Table 1
Marketing Strategy Meta-Analyses

Author(s) and Study Year	Title
Market Selection and General Strategy	
Shoham (2002)	"Standardization of International Strategy and Export Performance: A Meta-Analysis"
Dekimpe and Hanssens (1995)	"Empirical Generalizations about Market Evolution and Stationarity"
Chetty and Hamilton (1993)	"Firm-Level Determinants of Export Performance: A Meta Analysis"
Szymanski, Bharadwaj, and Varadarajan (1993)	"An Analysis of the Market Share-Profitability Relationship"
Capon, Farley, and Hoenig (1990) (includes summaries of multiple topics)	"Determinants of Financial Performance: A Meta-Analysis"
Marketing Assets: Customers	
Estelami and Lehmann (2001)	"The Impact of Research Design on Consumer Price Recall Accuracy: An Integrative Review"
Estelami, Lehmann, and Holden (2001)	"Macro-Economic Determinants of Consumer Price Knowledge: A Meta-Analysis of Four Decades of Research"
Szymanski and Henard (2001)	"Customer Satisfaction: A Meta-Analysis of the Empirical Evidence"
Geyskens, Steenkamp, and Kumar (1998)	"Generalizations about Trust in Marketing Channel Relationships Using Meta-Analysis"
Geyskens, Steenkamp, and Kumar (1999)	"A Meta-Analysis of Satisfaction in Marketing Channel Relationships"
Tongren (1988)	"Determinant Behavior Characteristics of Older Consumers"
Marketing Assets: Brands	
Rao and Monroe (1989)	"The Effect of Price, Brand Name, and Store Name on Buyers' Perceptions of Product Quality: An Integrative Review"
Szymanski and Busch (1987)	"Identifying the Generics-Prone Consumer: A Meta-Analysis"

Author(s) and Study Year	Title
Marketing Assets: New Products	
Henard and Szymanski (2001)	"Why Some New Products Are More Successful Than Others"
Kalyanaram, Robinson, and Urban (1995)	"Order of Market Entry: Established Empirical Generalizations, Emerging Empirical Generalizations, and Future Research"
Szymanski, Troy, and Bharadwaj (1995)	"Order of Entry and Business Performance: An Empirical Synthesis and Reexamination"
Montoya-Weiss and Calantone (1994)	"Determinants of New Product Performance: A Review and Meta-Analysis"
Kerin, Varadarajan, and Peterson (1992)	"First-Mover Advantage: A Synthesis, Conceptual Framework, and Research Propositions"
Sultan, Farley, and Lehmann (1990)	"A Meta-Analysis of Applications of Diffusion Models"
Marketing Programs: Price and Price Promotion	
Krishna, Briesch, Lehmann, and Yuan (2002)	"A Meta-Analysis of the Impact of Price Presentation on Perceived Savings"
Estelami and Lehmann (2001)	"The Impact of Research Design on Consumer Price Recall Accuracy: An Integrative Review"
Estelami, Lehmann , and Holden (2001)	"Macro-Economic Determinants of Consumer Price Knowledge: A Meta-Analysis of Four Decades of Research"
Nijs, Dekimpe, Steenkamp, and Hanssens (2001)	"The Category-Demand Effects of Price Promotions"
Sethuraman, Srinivasan, and Kim (1999)	"Asymmetric and Neighborhood Cross-Price Effects: Some Empirical Generalizations"
Compeau and Grewal (1998)	"Comparative Price Advertising: An Integrative Review"
Crouch (1996)	"Demand Elasticities in International Marketing: A Meta-Analytical Application to Tourism"
Kalyanaram and Winer (1995)	"Empirical Generalizations from Reference Price Research"
Kaul and Wittink (1995)	"Empirical Generalizations About the Impact of Advertising on Price Sensitivity and Price"

Author(s) and Study Year	Title
Lal and Padmanabhan (1995)	"Competitive Response and Equilibria"
Sethuraman (1995)	"A Meta-Analysis of National Brand and Store Brand Cross-Promotional Price Elasticities"
Biswas, Wilson, and Licata (1993)	"Reference Pricing Studies in Marketing: A Synthesis of Research Results"
Andrews and Franke (1991)	"The Determinants of Cigarette Consumption: A Meta-Analysis"
Sethuraman and Tellis (1991)	"An Analysis of the Tradeoff Between Advertising and Price Discounting"
Rao and Monroe (1989)	"The Effect of Price, Brand Name, and Store Name on Buyers' Perceptions of Product Quality: An Integrative Review"
Tellis (1988)	"The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales"
Eastlack and Rao (1986)	"Modeling Response to Advertising and Pricing Changes for 'V-8' Cocktail Vegetable Juice"
Marketing Programs: Distribution	
Geyskens, Steenkamp, and Kumar (1998)	"Generalizations about Trust in Marketing Channel Relationships Using Meta-Analysis"
Geyskens, Steenkamp, and Kumar (1999)	"A Meta-Analysis of Satisfaction in Marketing Channel Relationships"
Reibstein and Farris (1995)	"Market Share and Distribution: A Generalization, A Speculation, and Some Implications"
Marketing Programs: Advertising	
White and Allen (2000)	"A Meta-Analysis of Fear Appeals: Implications for Effective Public Health Campaigns"
Vakratsas and Ambler (1999)	"How Advertising Works: What Do We Really Know?"
Abernethy and Franke (1998)	"FTC Regulatory Activity and the Information Content of Advertising"
Brown, Homer, and Inman (1998)	"A Meta-Analysis of Relationships Between Ad-Evoked Feelings and Advertising Responses"
Compeau and Grewal (1998)	"Comparative Price Advertising: An Integrative Review"

Author(s) and Study Year	Title
Grewal, Kavanoor, Fern, Costley, and Barnes (1997)	"Comparative versus Noncomparative Advertising: A Meta-Analysis"
Riskey (1997)	"How T.V. Advertising Works: An Industry Response"
Trappey (1996)	"A Meta-Analysis of Consumer Choice and Subliminal Advertising"
Batra, Lehmann, Burke, and Pae (1995)	"When Does Advertising Have an Impact? A Study of Tracking Data"
Kaul and Wittink (1995)	"Empirical Generalizations about the Impact of Advertising on Price Sensitivity and Price"
Lodish, Abraham, Kalmenson, Livelsberger, Lubetkin, Richardson, and Stevens (1995)	"How T.V. Advertising Works: A Meta-Analysis of 389 Real World Split Cable T.V Advertising Experiments"
Woodside, Beretich, and Lauricella (1993)	"A Meta-Analysis of Effect Sizes Based on Direct Marketing Campaigns"
Andrews and Franke (1991)	"The Determinants of Cigarette Consumption: A Meta-Analysis"
Sethuraman and Tellis (1991)	"An Analysis of the Tradeoff Between Advertising and Price Discounting"
Hite and Fraser (1988)	"Meta-Analyses of Attitudes toward Advertising by Professionals"
Eastlack and Rao (1986)	"Modeling Response to Advertising and Pricing Changes for 'V-8' Cocktail Vegetable Juice"
Assmus, Farley, and Lehmann (1984)	"How Advertising Affects Sales: Meta-Analysis of Econometric Results"
Marketing Programs: Sales Force	
Vinchur, Schippmann, Switzer, and Roth (1998)	"A Meta-Analytic Review of Predictors of Job Performance for Salespeople"
Brown and Peterson (1993)	"Antecedents and Consequences of Salesperson Job Satisfaction"
Churchill, Ford, Hartley, and Walker (1985)	"The Determinants of Salesperson Performance: A Meta-Analysis"

New products, meanwhile, have received more attention. Henard and Szymanski (2001) and Montoya-Weiss and Calantone (1994) used meta-analysis to assess the characteristics that lead to success for new products and services. The impact of order of entry, especially first-mover advantage, was considered by Kalyanaram, Robinson, and Urban (1995); Szymanski, Troy, and Bharadwaj (1995); and Kerin, Varadarajan, and Peterson (1992). Parameters associated with diffusion effects were documented by Sultan, Farley, and Lehmann (1990).

Pricing and price promotion meta-analyses have examined elasticities in general (Tellis 1988) and for international tourism specifically (Crouch 1996). Meta-analyses have also addressed the impact of promotions on product demand at the category level (Nijs et al. 2001) and the impact of promotions on maintaining market share in a competitive setting (Lal and Padmanabhan 1995). Cross-price effects from competing brands were considered by Sethuraman, Srinivasan, and Kim (1999); Sethuraman (1995) also examined the special case of national and store brands. Consumer perceptions of pricing, meanwhile, include the effects of price presentation on perceived savings (Krishna et al. 2002), macroeconomic determinants of price knowledge (Estelami, Lehmann, and Holden 2001), and the impact of research design on the accuracy of price recall (Estelami and Lehmann 2001). The general characteristics of reference pricing were summarized in studies by Biswas, Wilson, and Licata (1993) and Kalyanaram and Winer (1995).

Several meta-analyses have considered the interaction of pricing with other parts of the marketing mix, most frequently advertising. They have examined the sales impact of advertising prices (Compeau and Grewal 1998); price advertising and price sensitivity (Kaul and Wittink 1995); the combined impact of advertising, price, and income on cigarette sales (Andrews and Franke 1991); the tradeoff effects between advertising and price discounting on sales (Sethuraman and Tellis 1991); and the sales response of the vegetable juice drink V8 to changes in advertising and pricing practices (Eastlack and Rao 1986). In addition, Rao and Monroe (1989) considered the combined impact of price, brand name, and store name on perceptions of product quality.

With regard to *distribution*, Reibstein and Farris (1995) summarized the impact of retail distribution characteristics on market share. In addition, meta-analyses have documented the impact of conflict and trust on satisfaction in marketing-channel relationships (Geyskens, Steenkamp, and Kumar 1999) and the effects that various economic outcomes and trust in the channels have on relationship marketing success (Geyskens, Steenkamp, and Kumar 1998).

On the topic of *advertising*, Assmus, Farley, and Lehmann (1984) summarized general elasticities and Vakratsas and Ambler (1999) considered general characteristics of advertising. Category, brand, and copy effects were studied by

Batra et al. (1995). Other subjects that have been addressed include the effects of comparative and noncomparative advertising (Grewal et al. 1997), the use of fear appeals in public health campaigns (White and Allen 2000), the impact of regulation on information availability (Abernethy and Frankle 1998), general characteristics of TV advertising (Lodish et al. 1995; Riskey 1997), the use of various direct-marketing techniques (Woodside, Beretich, and Lauricella 1993), positive and negative ad-evoked feelings (Brown, Homer, and Inman 1998), and use of subliminal advertising (Trappey 1996). Hite and Fraser (1988) documented the determinants of attitudes toward professional people's use of advertising.

Finally, *sales force* meta-analyses have considered the impact of job satisfaction on performance measures (Brown and Peterson 1993) and predictors of job performance (Vinchur et al. 1998; Churchill et al. 1985).

Using Meta-Analysis Results

Meta-analysis results can be used in many ways, including:

1. *Estimating the impact in other situations.* Since strategy experiments are costly and time-consuming, having an estimate of potential impact can be a significant advantage in strategic planning. It is also useful to have insight into stability across situations and into when a strategic variable is likely to have more or less impact.
2. *Evaluating budget proposals.* Budget proposals all look good in PowerPoint. One way to impose some discipline on them is to compare the proposal's implied impact (for example, of advertising spending on sales) with the best knowledge of likely impact, gleaned from the meta-analysis results. This encourages questioning of outliers (for example, what makes your advertising so special?).
3. *Guiding future studies.* In order to improve knowledge, additional studies in an area are usually called for. One approach is to create studies in settings with few past studies. An alternate and more efficient approach involves performing a study that has design elements orthogonal to the most common existing studies by changing about half the characteristics (Farley, Lehmann, and Mann 1998).

Conclusion

In addition to outlining the processes and procedures found to be beneficial in executing meta-analyses, we have cataloged a large number of meta-analyses that

focus on marketing strategy. Our intent is to provide insight into the informal practices that are needed to conduct an effective meta-analysis but that are not necessarily well documented in texts on meta-analysis. We hope that this overview saves time and frustration for future researchers who want to perform a meta-analysis. We also hope we have demystified the technique and process enough to encourage readers to try conducting a meta-analysis.

John U. Farley is C.V. Starr Senior Research Fellow, Tuck School of Business Administration, Dartmouth College.

Scott Hoenig is Visiting Professor, Fox School of Business and Management, Temple University.

Donald R. Lehmann is George E. Warren Professor of Business, Graduate School of Business, Columbia University.

David M. Szymanski is Professor of Marketing and JC Penney Chair of Retailing Studies, Mays Business School, Texas A&M University.

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