MARKETING SCIENCE
Vol. 14, No. 3, Part 2 of 2, 1995
Printed in U.S.A.

EMPIRICAL MARKETING GENERALIZATION USING META-ANALYSIS

JOHN U. FARLEY, DONALD R. LEHMANN, AND ALAN SAWYER
University of Pennsylvania
The Columbia Business School and MSI
The University of Florida

A decade of work in marketing meta-analysis has produced empirical generalizations concerning parameters in models of advertising, price, diffusion, and consumer behavior. Results from these meta-analyses should replace the now discredited zero null hypotheses of such parameters in future work. Probably more important than nonzero "grand mean" average effects is an approach called *Parametric Adjustability*, which provides estimated parameter values for specific conditions reflecting markets and research technologies. Systematic application of the methodology can also help guide research along productive routes and away from repetition of work which has little potential to add new knowledge.

(Generalization; Meta-analysis; Diffusion; Advertising; Buyer Behavior; Pricing; International Marketing)

Introduction

Qualitative generalization focuses on the sign of a relationship, while quantitative generalization focuses on both sign and value. Since parameters of marketing models are unlikely to be universal constants, we need an efficient way to combine and assess parameter estimates made under different circumstances, and (even more useful) to predict parameter values which should occur under yet-unresearched circumstances. Meta-analysis offers one approach to quantitative empirical generalization about parameters of marketing models which should help our field's ability to describe theories, laws, and models which hold for a significant number of situations (Bass 1993). This paper applies generalization to replacing statistically based null hypotheses of zero value for parameters with nonzero null hypotheses based on substantive knowledge in the field and also illustrates methods for tailoring generalizations to specific situations. We also suggest ways that information structures of existing meta-analyses can be used to improve parameter estimates and to help systematically guide new research toward areas potentially most productive in terms of knowledge about both substance and research technology. (For a general discussion of the benefits of and problems with meta-analysis see Wolf 1986; for a discussion focused on marketing, see Farley and Lehmann 1986.)

Meta-analysis in Marketing

While a lively debate continues over the question of whether theory or data do or should come first, it is clear that *accumulating knowledge across studies* to confront

0732-2399/95/1403/0G36$01.25

theory with data is essential to progress. We focus on the role that meta-analysis has played and can play in such knowledge accumulation in marketing. In spirit, our work builds on early attempts at marketing parameter generalization, such as Leone and Schultz (1980).

"Meta-analysis refers to analysis of analyses—the statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings. It connotes a rigorous alternative to the casual, narrative discussion of research studies which typify our attempts to make sense of the rapidly expanding research literature" (Wolf 1986). In marketing, meta-analysis provides a methodological linkage between "tidy and straight-forward" answers studied under experimental conditions and the complex world where environments are difficult to control and common definitions are often not available. The prime benefit of meta-analysis in marketing has been that, with judicious use, it has delivered generalized quantitative estimates of such important measures as price and advertising elasticities, and parameters of buyer behavior and diffusion models, as well as information on the range of accuracy associated with estimated parameters and on how well models fit.

Output from meta-analysis in marketing has included averages of key marketing decision variables like advertising/sales ratios and survey response rates (Yu and Cooper 1983), the relation between salesperson performance and satisfaction (Churchill et al. 1985, Brown and Peterson 1993), and scaleless averages like national per capita consumption rates (Armstrong 1970). These averages have been shown to have quite regular patterns and are forecastable using characteristics associated with a particular measurement. Meta-analysis has also dealt with more general issues related to research design such as the assessment of effect sizes in experiments (e.g., Peterson et al. 1985).

Recently, attention has also turned to more strategically oriented analysis of response parameters—scaleless measures of association between pairs of variables (correlations, Beta coefficients, elasticities) such as price and advertising elasticities (Clarke 1976, Tellis 1988, Assmus et al. 1984), parameters of buyer behavior models (Farley et al. 1982) and parameters of diffusion models (Lawrence and Lawton 1981 and Sultan et al. 1990). Meta-analysis begins with the assumption that different brands and different markets are comparable on a general level and that model *structures* generalize to new research settings, but that model *parameters* to some extent vary systematically over settings in an identifiable manner.

Parametric Adjustability

In our discussion of empirical generalization, we focus on a particular branch of meta-analysis related to estimating effect sizes of inter-study differences using analysis of variance and covariance methods. We call this approach "Parametric Adjustability" (Farley and Lehmann 1994), and we find that it offers a very flexible approach to generalize about π_{jk}, parameter j in study k:

$$\pi_{jk} = \pi_j + \sum_{i=1}^{r} \alpha_i X_{ijk} + \epsilon_{jk}. \tag{1}$$

The α_i are the estimated effects on the parameter of r "design" variables representing research environment (product and market), measurement procedures, estimation methods, and model specifications (Farley and Lehmann 1986). Both π_j and the alphas can be estimated using regression or ANOVA techniques, the most common approaches when the Xs are dummy variables.

Parametric Adjustability represents a quantum increase in the "Degree of Difficulty" separating this sort of meta-analysis from the more conventional type, which is based, usually implicitly, on considering various studies as replications over k studies with inter-study differences assigned to the error term,

$$\pi_{jk} = \pi_j + \epsilon_{jk}. \tag{2}$$

This more conventional approach assumes either that there are in fact no material inter-study design differences, that such potential differences are ignored, or that such differences are controlled in experimental design (Ehrenberg and England 1990, Ehrenberg and Bound 1993). Further, measurement and estimation procedures are viewed, at least implicitly, as agreed upon. Another assumption, also usually implicit, is that the variance of ϵ is relatively small in signal-to-noise sense and is primarily due to sampling error.

Parametric Adjustability is important in fields like marketing, where we generally face what might be called "imperfect replication" represented by the α_i, in (1), so that (2) is not the best approach to meta-analysis. Material inter-study design differences almost always exist, measurement is not necessarily agreed upon, and the standard error of ϵ_{jk} is relatively large in a signal-to-noise sense due to potential measurement and specification effects as well as to sampling error.

Generalization Based on Meta-analysis

Meta-analysis has moved furthest in empirical generalization concerning a handful of frequently-used models, so we use results from four models to illustrate the usefulness of Parameter Adjustability. Included are parameters of diffusion, buyer behavior, advertising, and price models. In all cases, ANOVA is used to estimate values of parameters which are specific to (1) product and market, (2) country, (3) estimation method used, (4) other general variables also included in the model, and (5) model-specific parameters included or excluded in the specification.

The Special Role of the Grand Mean in Generalization. The estimated grand mean in (1) gives us our first level of empirical generalization, and values of these are shown in Table 1 for the four meta-analyses. The grand mean from the ANOVA is a weighted average of known values of the parameter. It also plays a special role as it establishes the need for a nonzero value for the null hypotheses for further investigation. In all these cases, it is important to note that if the grand mean is significantly different from 0, tests of a null hypothesis of 0 in future research are not appropriate. Because the grand means are different from the simple arithmetic average of the parameter estimates that went into the ANOVA, a null hypothesis adjusted by the ANOVA for various imbalances in

TABLE 1
The Grand Mean as a "Generalized" Parameter Estimate

	Grand Mean Adjusted for Natural Experimental Design Characteristics[1]	Coefficient of Determination of Meta-analysis	Number of Studies in Meta-analysis
Diffusion Model Coefficients			
Innovation	0.02	0.32	213
Imitation	0.35	0.42	
(Sultan et al. 1990)			
Buyer Behavior Model Coefficients	0.29	0.39	4
(Farley et al. 1982)			
Advertising Model Coefficients			
Short-term elasticities	0.27	0.50	128
Carry-over	0.39	0.60	
(Assmus et al. 1984)			
Price Elasticities	−1.76	0.29	337
(Tellis 1988)			

[1] All are significantly different from 0 at $\alpha = 0.05$.

the "natural" experimental design is desirable. The coefficient of determination of the meta-analysis provides a measure of how much a Parameter-Adjusted meta-analytic estimate can improve on the null grand mean. About half of the variability in estimated parameters can be explained in the relatively well-structured advertising models. By contrast, pricing models, which are especially affected by model specification, produce estimated price elasticities which are harder to predict from the design variables.

Significant and Insignificant Factors. One consistent result of these meta-analyses is that the majority of hypothesized design factors turn out not to relate to significant differences in estimated parameters (Table 2). In particular, the majority of product class variables in the research environment measures had no significant effect, nor did most types of estimation methodology used. For example, in a meta-analysis of Fishbein studies, measurement procedures, samples, and field of study had no effect on parameter values (Farley et al. 1982). Similarly, only 11 of 34 situational characteristics produced significantly different price elasticities (Tellis 1988), and only seven of 36 potential factors produced significant differences in long and short-term advertising elasticities (Assmus et al. 1984). The overall pattern is one of robustness rather than one of the great differences which many scholars seem to anticipate (Farley and Lehmann 1994), except for model specification which had a significant effect in all four cases.

Estimating a Specific Parameter. The estimated value for a particular parameter is simply constructed by adding the estimates of the appropriate α_i to the grand mean. (The values of $\hat{\alpha}$ are displayed in detail in the four meta-analyses and are not repeated

TABLE 2

Significant and Insignificant "Natural Experiment" Design Variables in Four Meta-Analyses

	Significant Factors	Insignificant Factors
Short-term Advertising Elasticities		
Model Specification	Include carry-over functional form	Include other marketing and exogenous variables
Measurement	Data interval	Media and variable definitions
Estimation	—	OLS, GLS
Research environment	Food, country	Durables, other non-durables
Buyer Behavior Model Elasticities		
Model specification	Endogenous and controllable exogenous variables	Non-controllable exogenous variables
Measurement	—	Interviewing methods, products, countries
Research environment	—	Durables, non-durable
Estimation	—	OLS, 2SLS
Coefficients of Imitation in Diffusion Models		
Model specification	—	Include marketing variables
Measurement	—	Multiples use of data sets
Estimation	OLS	MLE, non-linear methods
Research environment	Country	Product
Price Elasticities		
Model Specification	Include distribution	Include product quality, other variables lagged dependent and independent variables. Functional form
Environment	Detergents, country	Durables, food, toiletries
Measurement	Time series	Aggregation, sample size
Estimation	GLS	MLE, OLS

here.) For example, using Tellis (1988) an adjusted estimate of price elasticity for a European food product from an OLS model which includes advertising in the model is:

Price Elasticity (from Tellis 1988)	Value of ANOVA Coefficient
Grand Mean	−1.76
Food product	−0.63
Early in life cycle	0.78
Europe	0.50
Ordinary least squares estimate	−0.12
Advertising included in model	−0.36
Estimate of price elasticity for this situation	−1.65

Note that both European and new product elasticities are lower, that food elasticities are higher, and that price has a clear interaction with advertising in this case.

Relative Effect Sizes in the Meta-Analyses. The key practical question for empirical generalization is whether the significant effects in Table 2 are relatively "large," which we interpret to mean as large as or larger than other suspected or established sources of variability. In particular, we are interested in whether effects which are relatively hard to study because they require collection of new data (about unstudied products or countries, for example) are large in comparison to effects which are relatively easy to study using data already collected (estimation and model specification, for example).

There is no accepted measure of "effect size" for a particular factor on a particular parameter, so we have proposed a multivariate generalization measure generalizing on Wolf (1986, p. 23–37).

Effect size for factor i on parameter j

$$= \frac{\text{Range of significant ANOVA coefficients related to levels of factor } i \text{ for parameter } j}{\text{Grand mean estimate of parameter } j \text{ from the meta-analysis ANOVA}}. \quad (3)$$

The results for the four meta-analyses are shown in Table 3. Model specification has the most consistently large effect, although product and market differences also matter. International differences tend to be small relative to other effects such as model specification, with one exception in which the denominator of the effect size is very small, indicating that international generalizations offer a useful first approximation (Farley and Lehmann 1994).

While it is clearly worrisome that technical matters—estimation methods and particularly model specification—should have such large effects on parameter estimates, multimethod within-study comparisons offer a low-cost way to help us gain deeper insights on these technical issues. We recommend that editors should encourage researchers to experiment with specification and estimation methods by requiring within-study experiments for publication, rather than continuing with the clearly untenable notion that there is a "best" specification and a "best" method and that the authors of a particular paper have found both. The set of required experiments should be clearly specified, in order to differentiate this activity from conventional data dredging.

Substantive patterns in parameters are also of interest. For example, intercontinental differences in advertising sensitivities may be due to a number of factors—media differences or restrictions, copy differences, or cultural preferences about advertising.

In the diffusion models, the coefficient of imitation is fairly stable under a wide variety of conditions. However, models fitted to data from European countries have significantly

TABLE 3

Relative Effect Sizes of ANOVA Estimates of Parameters Available for Surprised Generalization

Types of Models and Parameters Studied	Adjusted Grand Mean	Relative Effect Size Measured as Range of ANOVA Coefficient(s) Associated with that Effect Divided by Estimated Grand Mean: Environment		Technical Factors		
		Country	Product Type under Study	Estimation Method	Other Variables Added to Basic Model	Model Specific Parameters[a]
Diffusion Model Coefficients of (Sultan, Farley and Lehmann 1990)						
Innovation	0.02	2.0	0.2	0.1	0.1	NA
Imitation	0.35	0.1	0.8	0.2	0.8	1.8
Buyer Behavior Model Coefficients[d] (Farley, Lehmann and Ryan 1982)	0.29	NS	NS	0.8	4.8[c]	NA
Advertising Model Coefficients (Assmus, Farley and Lehmann 1984)						
Short-Term elasticities	0.27	0.3	0.5	0.1	0.6	1.0
Carry-over	0.39	NS	0.3	0.1	0.4	NA
Price Elasticities[b] (Tellis 1988)	−1.76	0.3	0.7	0.7	0.7	NA

Source: Table and associated text adapted from Farley and Lehmann 1994.
NS Effect is not significant in the original meta-analysis.
NA Not applicable because the model contains no such model-specific parameter.
[a] Model Specific Parameters are, respectively, a coefficient of innovation in the diffusion models and a carry-over coefficient in the econometric advertising models.
[b] Based on Table 2 of Tellis (1988) to assure negative elasticities; coefficient of determination taken from Table 3.
[c] Includes large negative price elasticities and large positive distribution elasticities; removing these controllable exogenous variable reduces this effect size to 1.2.
[d] Represents a combination of coefficients linking various pairs of variables.

larger coefficients of innovation than the U.S. models. This may be due to the very small average parameter, to some factor like relatively dense populations and/or communication systems, or to the fact that the innovations under study were in most cases first introduced in the United States.

Elasticities computed for a wide range of endogenous variables in the buyer behavior models are relatively robust. This is important because this particular set of models involved quite different products and involved two countries outside North America and Europe—one clearly a developing country.

Difficulties in the study of price elasticities, particularly in isolation, are shown by the relatively low coefficient of determination of the meta-analysis (Table 1) and significant overall differences related to product category, national setting, data characteristics, estimation method, and specifications including quality and distribution.

Using Meta-analysis for Marketing Decisions. Meta-analysis can provide a benchmark for average market responses under different conditions which can be used in concert with an optimization procedure such as the Dorfman-Steiner equilibrium. Such an application is discussed in detail in Farley and Lehmann (1994). It would be productive to further develop means to study price, advertising, distribution, and product quality together in one meta-analysis.

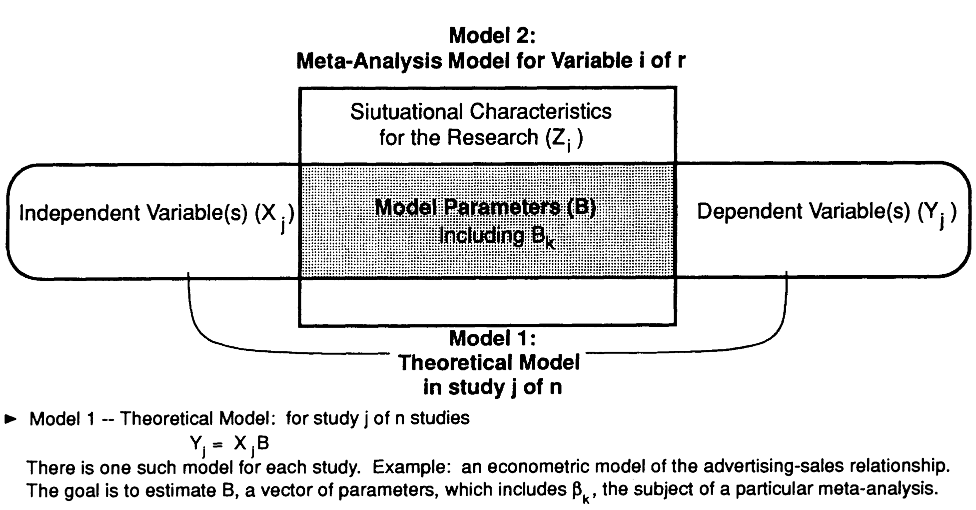
Estimation of Parameter Adjustments

Estimating the αs—the key task for generalizations using Parameter Adjustability—appears to be a relatively straightforward application of regression ANOVA or ANCOVA. In practice, estimation is plagued by the fact that the few available cases produce "sparse" replication in the "natural experiment," and estimation must be done in an environment far from any efficient experimental design. This makes the power of tests to assess differences relatively low. The sparseness can also contribute to confounding and nesting in the "natural" experimental design. Complications are also caused by possible unknown effects and by situations as yet unstudied, as well as nonreporting of basic data like sample sizes or standard errors of parameters or estimates. Further, when the sampling frame is published research, publication bias may be caused by systematic exclusion of insignificant or "unwelcome" results in the review process (Rust et al. 1990). On the positive side, we have already shown that situational characteristics often have less-than-anticipated effects on estimated parameters.

The "Natural" Experimental Design. The relationship of within-study parameter estimation and across-study meta-analysis is shown in Figure 1. The figure focuses on a particular parameter. Two different models are involved:

• *Model* 1 is the Structural Model in study j of n studies. It provides a single estimate of a parameter for variable i, β_{ij}, along with estimates of other parameters which are also specified in that model.

• *Model* 2 is the Meta-Analysis Model. β_{ij} becomes a single observation for the meta-analysis, along with a row of r situational factors about study j. The matrix Z is composed of n rows containing variables (usually dummy variables) representing the situational characteristics for each study. Elements of the rows of Z vary over the n studies. Averages



► Model 1 -- Theoretical Model: for study j of n studies

$$Y_j = X_j B$$

There is one such model for each study. Example: an econometric model of the advertising-sales relationship. The goal is to estimate B, a vector of parameters, which includes β_k, the subject of a particular meta-analysis.

► Model 2 -- Meta-Analysis, where Z contains r ANCOVA design elements for parameter i over n studies

$$B_k = Z_i A_i$$

There is one such model for each observed parameter subjected to meta-analysis for the n studies. Example: B is a set of short-term advertising coefficients from n studies. The goal is to estimate A, which contains the α's in (1). A set of parameters, β, produces a set of meta-analyses.

FIGURE 1. The Respective Roles of Model Estimation and Meta-analysis.

of β_{ij} provide base level estimated values of parameters, and Parametric Adjustment provides even better estimates for the particular situation.

Information in Z. The design matrix Z has not received very much research attention; when it has been analyzed, the goal generally has been to remove pathologies (like singularity as in Farley and Lehmann 1986, Chapter IV). We have paid little attention to the fact that the matrix Z provides a picture of the state of knowledge in a field at a point in time in terms of the design of a "natural" (that is, undesigned) experiment. Each row represents a particular parameter estimate, and multiple results from a given study or multiple uses of the same data also may characterize a particular design (Sultan et al. 1990). Each column of Z represents an environmental factor (product, country, time period) or technical factor (measurement methods, sampling and interviewing methods, and model specifications). Column sums represent sample sizes for individual factors, and these affect the quality of estimates for the effect of a particular factor.

In practice, a great many of the entries in Z are 0—that is, the Z matrix is likely to be quite sparse. Formal characteristics of Z pose real limitations on our ability to do meta-analysis, and the actual structure of Z at any point in time provides guidance to what kind of research is likely to add materially to our degree of knowledge. For example, our knowledge of advertising elasticities is dominated by mature U.S. packaged goods and time series models, since many columns of Z representing other markets and other kinds of models are almost empty. More work related to these near-empty columns is likely to create more knowledge, i.e., reduce uncertainty about the αs.

The "Ideal" Natural "Experimental" Design—A Factorial Design. A factorial design represents a sort of "ideal" for the natural design represented in Z. In practice, a factorial design, which would allow estimation of all direct effects and interactions, is more a reference point than an achievable goal. For example, a very simple meta-analysis of Fishbein models mentioned earlier had five binary design variables, which would require 32 (2^5) observations to fill the entire factorial design once; of course, at least partial replication is also required. The 37 observations that were available would appear to be adequate, but were not, because nearly half of the specific combinations were missing, e.g., the actual observed design of Z was highly unbalanced.

In actual practice, the number of studies required for a full factorial analysis in a more complex meta-analysis becomes very large as the factors increase even modestly. For example, the meta-analysis of advertising mentioned earlier had several levels each of products, market characteristics, and technical situations; the corresponding factorial design would require thousands of observations compared to the 100 plus available. In general, only direct effects plus selected interactions can be estimated in actual application.

Singularity. Absolute singularity of $Z'Z$ is not unusual in practice. Certain combinations in the actual design may be linearly dependent (i.e., effects are nested) so that only combinations of effects can be estimated—as, for example, in Farley et al. 1982. In these cases, manipulation of $Z'Z$ to remove the singularity is a necessary first step in the meta-analysis, and this necessarily involves reduction of the size of the natural design.

How Many Observations? Even within a nonsingular $Z'Z$ matrix and a fairly large number of studies, the number of nonzero elements in a column of Z (in effect, the number of times that a particular environment, model, or method occurs in the literature) constitutes a sort of partial sample size. Our experience is that the ratio of the largest to smallest eigenvalues of $Z'Z$ must be in the range of 50 or less for inversion to be practical; this, in turn, generally means that 5% or more of the sample should involve a particular column of Z for reliability of generalization of a particular effect—a sample requirement well above that suggested by several authors elsewhere in this volume. We do not disagree, for example, with the conclusion that at least three studies must confirm a result before it is a generalization; we would stress, however, that such a generalization probably applies to a narrowly defined set of conditions represented by similar or identical rows in the Z matrix. Broadening the range of applicability of empirical generalization by adding factors clearly broadens sample size requirements. Relevant minimum sample sizes can sometimes be constructed by combining columns of Z into larger aggregates which produce more stable coefficients, although specificity is lost by doing so. Finally, the issue of whether parameters are stable over time requires consideration and potentially statistical adjustment for changes (Kayande and Bhargava 1994).

Bayesian Approaches to Hypothesis Testing and Meta-analysis

Meta-analysis makes it obvious that a single study is only one data point and, by itself, "proves" little. Knowledge is an accrual process in which evidence across many studies accumulates, and Bayes' Theorem can be used to describe this accrual process. Although any single study is inconclusive, it can and should affect our beliefs about a particular relationship or set of relationships. Bayesian analysis has had limited application to meta-analysis in marketing (Sultan et al. 1990), but it holds considerable promise for future work.

Bayesian meta-analysis of several studies can begin by analyzing them one at a time. (Brinberg et al. 1992). Multiple data points from a series of studies can increase the belief in a particular relationship. This may not be apparent from only a single study, but could be indicated by a series of studies, each of which produced a relationship in the hypothesized direction but not "significant" in the classical sense (Schmidt 1992). Such a situation has arisen, for example, in a study of factors affecting financial performance of firms (Capon et al. 1994).

The Bayesian approach is also well suited to testing the credibility of the null hypothesis of no relationship. Greenwald (1975) demonstrated the ability of the Bayesian approach to examine a null relationship in his reanalysis of the results of two experiments of Layton and Turnbull (1975), in which two similar experiments produced only one small nearly significant main effect. Greenwald's Bayesian reanalysis defined a minimum effect size that would be of interest and then formulated a flat prior probability distribution that was not biased in favor of either the null or alternative hypotheses. The final posteriors produced odds of 7.8 to 1 for the null effects of one independent variable and 23.3 to 1 for the other—greater than the 20 to 1 odds typically considered necessary to disprove a null hypothesis in classical statistical significance testing. The ability of a Bayesian analysis to assess both null and alternative hypotheses is an important advantage. When used in a meta-analysis, this advantage over the classical approach is even more formidable.

The Greenwald (1975) study illustrates how a Bayesian approach to meta-analysis can address issues of statistical significance as expressed by the final posterior probabilities of various relationships. However, the prime focus of meta-analysis is on effect size, and not on yes-no hypothesis testing. Meta-analysis priors can also serve as input into estimation procedures for model parameters in a given study (Sultan et al. 1990, Vanhonacker et al. 1990, Zellner and Hong 1989).

What Next for Meta-analysis in Marketing?

We should recognize both the current contribution and the potential of meta-analysis in providing empirical generalizations about the complex of markets that characterize our research field. A current contribution is content-based null hypotheses for parameters of common econometric, behavioral, and diffusion models. A potential approach is through formulating formal priors—especially formal "noise" indices on parameter estimates. We know, for example, that price elasticities should be about -2, advertising elasticities about 0.25, and elasticities of buyer behavior models about 0.3. Meta-analysis also gives us, through the process of assembling coefficients from the ANOVA, the powerful ability to make credible estimates for specific unstudied combinations of situations, methods, and model specifications.

Methodologically, we think that the most important need for marketing meta-analysis is to identify empirical research needs in the "natural" experimental designs discussed in this paper. Developing such a research stream might use adaptive conjoint measurement methods on the "natural design" matrix (Z in Figure 1) to identify the most important next study or set of studies. This amounts to managing a research program in a field of marketing by looking only for studies which expand knowledge—that is, which somehow improve the natural experimental design represented in Z. We believe the current priorities for such improvement are to:

(1) Establish standards for reporting results which require sample sizes and standard errors as well as the estimated value of parameters.

(2) Conduct methodological "within-study" experiments to control for estimation and specification effects without extensive additional data collection.

(3) Experiment with other approaches to estimation of the meta-analysis model in Figure 1, including nonlinear forms of the meta-analysis itself. For example, we might view observations as variables and form latent variables instead of prespecifying the ANOVA. Similarly, neural network approaches could be applied to the data.

(4) Add important environmental factors—international markets, for example.

(5) Fill "sparse" rows and columns of Z with studies using untested combinations of other factors.

(6) Build experience with Bayesian procedures and extend them to analysis of "experimental design" to help guide future research.

(7) Fill empty cells.

(8) Replicate key within-cell combinations.

Perhaps simple awareness of where the new knowledge is needed will be sufficient to guide further work of researchers toward expansion of our knowledge, but it is probable that some leadership, as from a major journal, would be needed to lead the research meta-program down productive routes reflected in points (1), (2), and (3). Such leadership would require a more rigorous definition of contribution to knowledge concerning model parameters to include quantitative comparison with earlier results.

Finally, from a managerial point of view, it is now important to find ways to make Parameter Adjustment procedures more accessible and understandable. There is a natural tendency of managers to think of markets for which they are responsible as unique; this tends to limit search for information to perfect or near-perfect matches with the problem at hand, and has so far robbed many managers of a strategically important research tool. In our experience, this situation can be remedied, but only when in-depth work with particular managers on particular problems in particular markets is carried out in the framework of meta-analysis.

References

Armstrong, J. S. (1970), "An Application of Econometric Models to International Marketing," *Journal of Marketing Research*, VII (May), 190–198.

Assmus, G., J. U. Farley, and D. R. Lehmann (1984), "How Advertising Affects Sales: Meta-Analysis of Econometric Results," *Journal of Marketing Research*, 21 (February), 65–74.

Bass, F. M. (1993), "The Future of Research in Marketing: Marketing Science," *Journal of Marketing Research*, 30 (February), 1–6.

Brinberg, D., J. G. Lynch, Jr., and A. G. Sawyer (1992), "Hypothesized and Confounded Explanations in Theory Tests: A Bayesian Analysis," *Journal of Consumer Research*, 19 (September), 139–154.

Brown, S. P. and R. A. Peterson (1993), "Antecedents and Consequences of Salesperson Job Satisfaction: Meta-Analysis and Assessment of Causal Effects," *Journal of Marketing Research*, 30 (February), 63–77.

Capon, N., J. U. Farley, and S. Hoenig (1994), *Why Some Firms Perform Better Than Others*, Working Manuscript, Columbia University.

Churchill, G. A., N. M. Ford, W. Hartley, and O. C. Walker, Jr. (1985), "The Determinants of Salesperson Performance: A Meta Analysis," *Journal of Marketing Research*, 22 (May), 103–118.

Clarke, D. G. (1976), "Econometric Measurement of the Duration of Advertising Effect on Sales," *Journal of Marketing Research*, 13 (November), 345–357.

Dorfman, R. and P. O. Steiner (1954), "Optimal Advertising and Optimal Quality," *American Economic Review*, 44 (December), 826–836.

Ehrenberg, A. S. C. and J. A. Bound (1993), "Predictability and Prediction," (with Commentary) *Journal of the Royal Statistical Society*, Series A, 156, Part 2, 167–206.

——— and L. R. England (1990), "Generalizing A Pricing Effect," *The Journal of Industrial Economics*, 39 (September), 47–68.

Farley, J. U. and D. R. Lehmann (1986), *Generalizing about Market Response Models: Meta-Analysis in Marketing*, Lexington Books.

——— and ——— (1994), "Cross-National 'Laws' and Differences in Market Response," *Management Science*, 40 (January), 111–122.

———, ———, and M. J. Ryan (1982), "Generalizing from Imperfect Replication," *Journal of Business*, 54 (October), 597–610.

———, ———, and ———, (1982) "Pattern in Parameters of Buyer Behavior Models: Generalization from Sparse Replication," *Marketing Science*, 1 (Spring), 181–204.

Greenwald, A. G. (1975), "Significance, Nonsignificance, and Interpretation of an ESP Experiment," *Journal of Experimental Social Psychology*, 11 (March), 180–191.

Kayande, U. and M. Bhargava (1994), "An Examination of Temporal Patterns in Meta-Analysis," *Marketing Letters*, 5, 141–152.

Lawrence, K. D. and W. H. Lawton (1981), "Applications of Diffusion Models: Some Empirical Results," in Y. Wind, V. Mahajan, and R. C. Cardozo (Eds), *New Product Forecasting*, Lexington, MA: Lexington Books, 529–541.

Layton, R. D. and B. Turnbull (1975), "Belief, Evaluation, and Performance on an ESP Task," *Journal of Experimental Psychology*, 11 (March), 166–179.

Leone, R. P. and R. L. Schultz (1980), "A Study of Marketing Generalizations," *Journal of Marketing*, 44 (Winter), 10–18.

Peterson, R. A., G. Albaum, and R. F. Beltramini (1985), "A Meta-Analysis of Effect Size in Consumer Behavior Experiments," *Journal of Consumer Research*, 12 (June), 97–103.

Rust, R. T., D. R. Lehmann, and J. U. Farley (1990), "Estimating Publication Bias in Meta-Analysis," *Journal of Marketing Research*, XXVII (May), 220–227.

Schmidt, F. L. (1992), "What Do Data Really Mean? Research Findings, Meta-Analysis, and Cumulative Knowledge in Psychology," *American Psychologist*, 47 (October), 1173–1181.

Sultan, F., J. U. Farley, and D. R. Lehmann (1990), "Meta-analysis of Application of Diffusion Models," *Journal of Marketing Research*, XXVII, 70–77.

Tellis, G. J. (1988), "The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales," *Journal of Marketing Research*, XXV (November), 331–342.

Vanhonacker, W. R., D. R. Lehmann, and F. Sultan (1990), "Combining Related and Sparse Data in Linear Regression Models," *Journal of Business and Economic Statistics*, 8 (July), 327–335.

Wolf, F. M. (1986), *Meta-Analysis: Quantitative Methods for Research Synthesis*, Newburg Park: California Sage Press.

Yu, J. and H. Cooper (1983), "A Quantitative Review of Research Design Effects on Response Rates to Questionnaires," *Journal of Marketing Research*, 20 (February), 36–44.

Zellner, A. and C. Hong (1989), "Forecasting International Growth Rates Using Bayesian Shrinkage and Other Procedures," *Journal of Econometrics*, 40, 183–202.