FAREENA SULTAN, JOHN U. FARLEY, and DONALD R. LEHMANN*

A meta-analysis of 213 applications of diffusion models from 15 articles relates model parameters to the nature of the innovation, the country under study, model specification, and estimation procedure. The effect of use of the same data by several researchers is examined, as are weighting schemes for improving efficiency of the meta-analysis. A Bayesian scheme is used to combine results from the meta-analysis with new data for estimation of parameters in a new situation.

A Meta-Analysis of Applications of Diffusion Models

Modeling of diffusion processes is a relatively mature research technology, with published work spanning several disciplines and several decades. Because of the importance of such models in theory as well as for "early warning" forecasting for new products, work in the area continues. Enough applications of conceptually comparable diffusion models now have been reported to allow an attempt at quantitative generalizations so that new applications can be compared with reported results rather than with the already discredited hypothesis of zero-valued model parameters. We also examine the effect of repeated use of the same data by different researchers, investigate the use of a weighted least squares estimation procedure for improving the meta-analysis itself, and test a procedure for using meta-analytic results to improve forecasts in new applications.

DIFFUSION MODELS

Diffusion studies generally analyze the development over time of first purchases of a new product or service by a population. They often are couched in a general family of models of diffusion rate at time t (Mahajan and Peterson 1985)

$$\frac{dN(t)}{dt} = g(t)\,[N^* - N(t)] \tag{1}$$

where $dN(t)/dt$ is the rate of diffusion at time t, $N(t)$ is the cumulative number of adopters at time t, N^* is the total number of potential adopters in a population, and $g(t)$ is the rate at which adoption occurs.

Various functional forms for $g(t)$ lead to models that imply different diffusion processes. For example, $g(t) = P$ implies an "external influence" model (Fourt and Woodlock 1960), with diffusion driven by factors such as advertising that are external to the adopting unit. The coefficient P commonly is called the "coefficient of innovation" and this model leads to a modified exponential diffusion curve. When $g(t) = Q\,F(t)$, the model is called an "internal influence" model (Mansfield 1961) where later adopters learn from earlier adopters. Q often is called the "coefficient of imitation" and market growth follows a logistic curve related to the Gompertz function. Finally, $g(t) = P + Q[F(t)]$ is a "mixed influence" model (Bass 1969) in which diffusion is driven by both innovation (P) and imitation effects (Q) and market growth follows a generalized logistic curve. Various extensions of the basic model incorporate flexible families of curves (e.g., Easingwood, Mahajan, and Muller 1983) and marketing mix variables (e.g., Dolan and Jeuland 1981; Horsky and Simon 1983).

DIFFUSION MODEL APPLICATIONS

Our meta-analysis involves 213 sets of parameters from 15 articles (Table 1) published from the 1950s to the 1980s that examine a variety of innovations. Most articles report several sets of parameters involving different products and/or models, so each provides several observations for the meta-analysis. Several innovations appear in more than one study.

Across our 213 applications, the coefficient of inno-

*Fareena Sultan is Assistant Professor, Graduate School of Business, Harvard University. John U. Farley and Donald R. Lehmann are Professors, Graduate School of Business, Columbia University.
The authors thank Sunder Narayanan, Graduate School of Business, Columbia University, for assistance in computer programs for nonlinear estimation and Sunil Gupta, UCLA, for his useful comments.

Journal of Marketing Research
Vol. XXVII (February 1990), 70–7

vation (P) averages .03 and the coefficient of imitation (Q) averages .38, but values vary considerably. Easingwood, Mahajan, and Muller (1983), who apply several different models, report a range of P from .000021 (for black and white TVs using a model in which parameters can vary) to .03297 (for color TVs using a mixed-influence model). Reported values of Q range from .2013 for room air conditioners with a variable parameter model to 1.67260 for black and white TVs. The goal of the meta-analysis reported here is to see what portion of this variation in parameters appears to be systematic and explainable by characteristics of the studies.

Model fit varies both across and within articles for the relatively few studies that report fit measures. For example, Easingwood, Mahajan, and Muller (1983) state that the variance explained, in studies that report fit, ranges from 7.2% for black and white TVs to 96.7% for color TVs, though the predictive accuracy also depends on the estimation procedure used.

SALIENT DIFFERENCES AMONG THE APPLICATIONS

Assmus, Farley, and Lehmann (1984) suggest that four basic categories of study characteristics might help identify systematic patterns in a meta-analysis: (1) research environment, (2) specification, (3) measurement methods and intervals, and (4) estimation methods. All 15 studies used annual data so the measurement intervals were identical and hence are not part of our meta-analysis.

Research Environment

Type of innovation. Table 1 shows that innovations examined include agricultural products, durable goods, industrial products, franchises for fast food restaurants and hotels, medical innovations, and financial investment opportunities. Product type was shown by Assmus, Farley, and Lehmann (1984) to affect estimated values of advertising elasticities.

Country. Most diffusion applications are based on U.S. data, but work also has been done on European data. Advertising elasticities were shown by Assmus, Farley, and Lehmann (1984) to be lower in the U.S. than elsewhere.

Model Specification

Variables included. The basic diffusion model has been extended to include price (Dolan and Jeuland 1981; Kalish 1983; Robinson and Lakhani 1975) and advertising (Dodson and Muller 1978; Horsky and Simon 1983). Inclusion of marketing mix variables in demand functions has been shown to have systematic effects on estimated advertising elasticities (Assmus, Farley, and Lehmann 1984).

There are also basic differences in model structure, as described before. Some diffusion models (Fourt and Woodlock 1960) do not incorporate the coefficient of imitation, whereas others include both parameters (Bass 1969).

Estimation

The effect of estimation method on parameter estimates of some diffusion models has been explored recently (Mahajan, Mason, and Srinivasan 1986; Srinivasan and Mason 1986), though estimation has been shown to be relatively unimportant in at least one meta-analysis (Farley, Lehmann, and Ryan 1982). Estimation procedures used here include OLS, maximum likelihood procedures, nonlinear programming, and numerical solution techniques.

Systematic Effects Induced by Reuse of Data

Eight datasets are used in more than one of our sets of diffusion articles. Reuse of data reduces the number of degrees of freedom and produces a partial repeated measures design, which we address in the manner suggested by Pedhazur (1982, p. 555–7). Eight of the articles report unique datasets.

THE META-ANALYSIS MODELS

The meta-analysis is performed by means of ANOVAs. For the coefficient of imitation, for example,

$$Q_i = \mu + \boldsymbol{\alpha}_1\mathbf{X}_{1i} + \boldsymbol{\alpha}_2\mathbf{X}_{2i} + \boldsymbol{\beta}_1\mathbf{X}_{3i} + \boldsymbol{\beta}_2\mathbf{X}_{4i} + \boldsymbol{\gamma}\mathbf{X}_{5i} + \boldsymbol{\delta}\mathbf{X}_{6i} + \epsilon_i$$

where Q_i is an observed value of the coefficient of imitation, $\mathbf{X}_{ij}$ are vectors of dummy variables representing a particular effect, and $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$ are corresponding vectors of parameters.

Research environment ($\boldsymbol{\alpha}_1$ and $\boldsymbol{\alpha}_2$)
- $\mathbf{X}_{1i}$ represents the type of innovation (three levels: consumer durable, industrial/medical, and other).
- $\mathbf{X}_{2i}$ represents the geographic effect (two levels: U.S. and Europe).

Specification ($\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$)
- $\mathbf{X}_{3i}$ indicates specification of a coefficient of innovation (two levels: present and absent).
- $\mathbf{X}_{4i}$ indicates specification of marketing mix variables (two levels: present and absent).

Estimation method ($\boldsymbol{\gamma}$)
- $\mathbf{X}_{5i}$ indicates estimation method (three levels: OLS, MLE, and other).

Data reuse ($\boldsymbol{\delta}$)
- $\mathbf{X}_{6i}$ indicates use of a particular dataset more than once in the meta-analysis (eight levels indicating repeated use as shown in Table 1).

The ANOVA for P is identical except that $\boldsymbol{\beta}_1$ is absent.

The null hypothesis of zero for each ANOVA coefficient implies that values of diffusion model coefficients do not vary systematically with the design factor—that is, the coefficients of innovation and imitation are equal for all conditions of that factor. A significant ANOVA coefficient indicates a systematic difference in P or Q associated with that particular factor.

The analysis was conducted using dummy variable regression with the variables effect coded. The design

Table 1
STUDIES USED IN META-ANALYSIS OF APPLICATION DIFFUSION MODELS

Authors	*Year*	*Innovation*	*Number of applications used*	*Multiple use of dataset*
Griliches	1957	Hybrid corn	30	Corn
Mansfield	1961	Industrial innovations	11	
Bass	1969	Consumer durable goods	12	Refrigerators, black and white TVs, dryers, air conditioners
Nevers	1972	Consumer durable goods, hotel/ motel franchises, industrial innovations, and hybrid corn	9	Corn, color TVs
Dodds	1973	Consumer durable goods, cable TV subscriptions	2	
Lawton and Lawton	1979	Educational innovations	8	
Bass	1980	Consumer durable goods	6	Refrigerators, black and white TVs, dryers, air conditioners, dishwashers
Heeler and Hustad	1980	Consumer durable goods in Europe	37[a]	
Easingwood, Mahajan, and Muller	1981	CAT scanners	1	CAT scanners
Schmittlein and Mahajan	1982	Consumer durable goods, CAT scanners	8	CAT scanners, air conditioners, color TVs, dryers, dishwashers
Easingwood, Mahajan, and Muller	1983	Consumer durable goods	5	Black and white and color TVs, air conditioners, dryers, dishwashers
Horsky and Simon	1983	Telephone banking	5	
Srivastava, Mahajan, Ramaswami, and Cherian	1985	Financial investments	14	
Gatignon, Eliashberg, and Robertson	1985	Consumer durable goods in Europe	55	
Easingwood	1987	Consumer durable goods in Europe	10	
		Total	213	

[a]Data obtained via personal communication with T. Hustad based on work done by Heeler and Hustad (1980).

matrix of meta-analysis is of course not orthogonal, so regression was used to estimate coefficients (Draper and Smith 1966, p. 244–62) to take account of nonorthogonal factors. The design is also unbalanced, as 112 applications use OLS as the estimation procedure, 202 do not incorporate marketing mix variables, and 133 pertain to consumer durable goods. However, principal components analysis of the covariance matrix of the design variables to check for collinearity showed that the ratio of largest to smallest eigenvalue is about 50, indicating that the design (though not orthogonal) is not singular.

RESULTS OF THE META-ANALYSIS

For the meta-analysis, ANOVA models were fit separately for the coefficients of innovation (P) and imitation (Q). The separate analysis is necessary because P was not specified in all cases. For the models in which both were present, the correlation between P and Q is insignificant (.11). The results are summarized in Table 2. Columns 1 and 3 of Table 2 contain the OLS ANOVA results for the coefficient of imitation using all 213 observations and for the coefficient of innovation using the 161 observations that contain P. (The analysis of Q, the coefficient of imitation, was also run for just the 161 models that specified the coefficient of innovation, P. There were no substantive differences, so the results based on the full sample of 213 observations are reported here.)

Table 2 shows four significant partial effects in the estimated values of the coefficient of imitation in all four categories of the meta-analysis. The estimated coefficients of innovation have significant effects in two categories.

Effects Related to the Research Environment

Data from European countries produce higher coefficients of innovation than U.S. data. Because many of the products introduced in Europe were introduced first in the U.S., possibly the innovation was not risky (i.e., partially presold) and hence was adopted more quickly in Europe. European and American coefficients of imitation are not significantly different.

Industrial/medical innovations have higher coefficients of imitation than durable and other innovations. For industrial/medical innovations, the adopting units may be forced by competitive pressures to imitate quickly.

Effects Related to Model Specification

The presence of the coefficient of innovation is associated with a higher coefficient of imitation. It appears that a complete model should specify both to avoid what may be an important implicit restriction on parameters.

The presence of marketing mix variables leads to lower *coefficients of imitation.* Adoption is apparently not such an "automatic" or mechanically driven process as the simple (underspecified) process models suggest, and much of the diffusion process is driven or at least accelerated by marketing activities. Including such variables in the diffusion model is clearly indicated.

Effect Related to Estimation

The coefficients of innovation and imitation are affected by estimation methods, though the magnitudes of the differences tend to be small. OLS estimation procedures produce higher estimates whereas MLE and nonlinear estimation procedures lead to lower estimates for the coefficients of innovation and imitation. This finding suggests the need for systematic study of estimation methods (Mahajan, Mason, and Srinivasan 1986; Srinivasan and Mason 1986).

Effects of Reused Data

The interpretation of these eight ANOVA coefficients is somewhat complex because they are an inseparable combination of possible substantive differences related to the particular market and possible covarying biases involving such possibilities as correlated error terms across the various models, which we have no way to assess. The effect of the reuse of data by different researchers appears minimal on the coefficients of innovation, as none of the individual coefficients are significant.

The situation is different for the coefficient of imitation. There is a significant positive effect for color TVs (which is a more "continuous" innovation because of high perceived compatibility due to the familiarity of adopters with black and white TVs) and hybrid corn and CT scanners (which may represent demonstration effects for farmers and hospitals, respectively).

Table 2

INCREMENTS IN COEFFICIENTS OF INNOVATION AND IMITATION RELATED TO SPECIFIC CHARACTERISTICS OF DIFFUSION MODEL APPLICATIONS

	Coefficient of innovation (P)		*Coefficient of imitation (Q)*	
	OLS	*WLS*	*OLS*[a]	*WLS*[a]
Grand mean (intercept)	.040[b]	.039[b]	.302[b]	.302[b]
Elements of study design				
Type of innovation				
Industrial/medical			[b]	[b]
Products	.008	.007	.283	.275
Durables	−.016	−.016	−.064	−.062
Other products	.008	.009	−.219	−.213
Country	[b]	[b]		
Europe	.018	.018	.032	.041
U.S.	−.018	−.018	−.032	−.041
Estimation	[b]	[b]	[b]	[b]
MLE estimates	−.009	−.009	−.022	−.032
OLS estimates	.022	.022	.062	.075
Nonlinear estimates	−.013	−.013	−.040	−.043
Specification			[b]	[b]
Coefficient of innovation included			.165	.170
Coefficient of innovation not included			−.165	−.170
Marketing variables included	.001	.000	−.076	−.067
Marketing variables not included	−.001	.000	.076	.067
Effects of reused datasets			[b]	[b]
Refrigerators	−.015	−.014	−.296	−.307
Black and white TVs	.013	.014	−.202	.225
Room air conditioners	.005	.006	−.105	−.103
Dryers	.015	.015	−.196	−.191
Color TVs	.001	−.000	.208	.208
Hybrid corn	NF[c]	NF[c]	.502	.506
Dishwashers	.001	−.003	−,173	−.176
CT head scan	−.008	−.007	.378	.431
Basic data				
Number of observations	161	161	213	203
F-value for model	7.3	7.2	10.8	14.2
Adj R^2	.34	.34	.41	.50
R^2	.39	.39	.45	.53

[a]Includes effect for presence of coefficient of innovation.
[b]Significant effects.
[c]Not feasible to include because it creates a singular experimental design.

In any case, researchers should be aware of the existence of these systematic effects related to multiple use of the same data. Obvious remedies include use of new data, as well as interpreting the results of any work reusing these databases in light of the coefficients in Table 2.

Goodness of Fit

The goodness of fit of meta-analysis ANOVA models must be examined in context. Overall, our meta-analysis explains a third to half of the variation in estimated parameters of the diffusion models. The fits of this meta-analysis compare with those of meta-analyses in other relatively mature areas of investigation such as consumer behavior models (Farley, Lehmann, and Ryan 1982) and advertising elasticities (Assmus, Farley, and Lehmann 1984). In comparison, a meta-analysis of homogeneous studies with few systematic interstudy differences will explain little variability in parameters; this was the case with a meta-analysis of Fishbein models (Farley, Lehmann, and Ryan 1981) in which practically none of the design variables were significant.

META-ANALYSIS EFFICIENCY AND WEIGHTED LEAST SQUARES ESTIMATES

Some sort of weighted least squares procedure may improve efficiency of the meta-analysis if adequate information is available on quality differences among studies. For example, we might weight each parameter estimate by the inverse of its variance or by some proxy based on reported significance levels. Unfortunately, estimated standard errors are available directly for only 34 of the 213 diffusion models. Using a weighting procedure on only 34 observations would not only lower efficiency, but also completely destroy the experimental design. A measure of fit (usually R^2) is available for only 130 observations, again for only a small part of the experimental design.

As a crude test to see whether weighting would make any difference, WLS was performed weighting each estimate used in the meta-analysis by the number of observations used—that is, with the length of the annual time series as a crude proxy for reliability. The number of observations used in estimation is reported for most of the models. There is a slight increase in the coefficient of determination when this crude WLS procedure is used on those observations for which the sample size is available. For the innovation parameter (columns 1 and 2 in Table 2), we find practically no difference in coefficient values or significance between the OLS and the WLS results. For the imitation parameter (columns 3 and 4), we find some differences in coefficient values but not in patterns of significance.

Though even this crude weighting improves efficiency slightly, our inability to apply a more appropriate scheme (based on the variance of the parameter estimates) speaks to the importance of full reporting of measures of variability associated with parameter estimates to make possible more efficient generalization of results over studies.

USING THE RESULTS OF THE META-ANALYSIS

Durations of Diffusion Processes

For the mixed influence model, the predicted time to the maximum rate of adoptions is (Bass 1969)

$$T^* = (P + Q)^{-1} \ln (Q/P).$$

Predicting this point is important, as market growth falls off after that time and managerial action generally is needed. The reported parameter values imply a wide range for T^*. For example, with the average values of coefficient of innovation $P = .03$ and coefficient of imitation $Q = .38$, $T^* = 5.3$ years. With the minimum observed values of both P and Q (.00002 and .00003), $T^* = 80$ years whereas with the maximum observed feasible values of P and Q (.23, .99), T^* = one year (an almost instantaneous peak). These are just arbitrarily chosen examples, but they help establish the wide range in time frames that may be involved in diffusion processes.

Forecasts Using Diffusion Models

Probably the most important application of diffusion models is in early forecasting (Mahajan and Wind 1986). Estimating a diffusion model with few early datapoints has been shown to produce unstable parameter estimates. For example, Tigert and Farivar (1981) concluded, in an industrial application, that early parameter estimates are very sensitive to the number of available datapoints and that one-step-ahead forecasts resulted in "serious problems," a conclusion reinforced by Mahajan and Sharma (1986).

One way to address such instability is to use a Bayesian scheme that utilizes meta-analysis results as "priors" for the new situation. The Bayesian estimation technique used here relies on the Goldberger-Theil approach of "mixed estimation," based in turn on work by Durbin (see Johnston 1972). Prior results from the meta-analysis are mixed with data-based estimates to obtain posterior estimates of the parameters, with weights equal to the inverses of the variances of the two estimates.

We apply the Bayesian scheme to estimating the coefficients of innovation and imitation in a basic Bass model for room air conditioners using the data reported by Mahajan, Mason, and Srinivasan (1986). We calculate the prior values of the coefficient of innovation (P) and the coefficient of imitation (Q) using the estimates in Table 2, columns 1 and 3, respectively. (A starting point that disregards characteristics of the new application would be the means and variances reported before.) The meta-analysis priors for a U.S. durable good in a nonlinear estimation method are

$$P_0 = .00 \text{ and } Q_0 = .30.$$

To estimate P and Q from the data, we used the NLIN procedure in SAS and formula 22 from Mahajan, Mason, and Srinivasan (1986). The posterior parameter estimates are those suggested by Zellner (1971, p. 15), with the calculations being done by the analogous matrix formula which accommodates correlation between P and Q (Leamer 1978, 182–6).

The Bayesian scheme appears to produce more robust estimates (Table 3), particularly early in the product history when forecasts are most useful. The estimates gradually switch from the meta-analysis priors (P_0 = .00, Q_0 = .30) to the data-based results as the variance of the data-based parameters decreases. When seven years of data are available, the prior information has almost no impact. However, when only four observations are available, the Bayesian estimate is still closer to the meta-analysis prior than to the data-based estimates.

SUMMARY

The summary of our analysis of 213 applications of diffusion models has substantive implications for the study of diffusion and technical implications for meta-analysis.

What We Have Learned About Diffusion

The coefficients of innovation average .03 and the coefficients of imitation average .38 for the 213 applications used here. These findings suggest that the diffusion process is affected more by such factors as word of mouth than by innate innovativeness of consumers. The coefficient of innovation is fairly stable under a wide variety of conditions, though models fit to data from European countries do seem to have higher coefficients of innovation than the U.S. models. The coefficient of innovation also is influenced by method of estimation used. Because, by definition, the coefficient of innovation captures the chance of adoption of an innovation by an individual independent of other members of the adoption unit, the stability of the parameter to external factors such as marketing mix variables is understandable. In contrast, the coefficient of imitation varies widely with the type of innovation being examined, the estimation procedure employed, and the presence of other variables such as marketing mix variables. (Reuse of sets of data from successful diffusion studies to test other diffusion models may also tend to affect estimated diffusion rates.)

The meta-analytical models explain 30 to 50% of the variability in estimates of the parameters in the diffusion models. This explanatory power is much better than that of the meta-analysis of 37 very similar Fishbein models (Farley, Lehmann, and Ryan 1981) and about the same as that of the meta-analysis of 128 heterogeneous advertising sales models (Assmus, Farley, and Lehmann 1984). Most reported studies fit into a particular category: they use an OLS estimation procedure to study durable goods in the U.S., do not consider marketing mix variables, exclude parameters other than the coefficients of innovation and imitation and a maximum potential, and use diffusion curves that are not flexible. Because our meta-analysis does find systematic effects, there is a need to explore other models that will fill the empty or nearly empty "cells" in the natural experiment—that is, untested combinations. It should be noted that the diffusion models are based on products that had at least some degree of market success and the results presented here may not extend to unsuccessful products, about which little has been reported. An interesting avenue for future research would be to estimate diffusion models for such failed innovations.

What We Have Learned About Meta-Analysis

Repeated use of the same data by different researchers may affect substantive results in a systematic way. Weighted least squares estimation procedures have some promise and should be investigated further, but their usefulness for our meta-analysis is limited because only half of the studies report either the standard errors or goodness-of-fit measures necessary to develop the weights.

The results of meta-analysis can be used also to aid in "early warning" forecasting before sufficient data be-

Table 3
PARAMETER ESTIMATES FOR ROOM AIR CONDITIONERS

Years of data	Nonlinear least squares P	S_P	Q	S_Q	Bayesian P	S_{PBAYES}	Q	S_{QBAYES}
3	.0725	—	1.09	—	—	—	—	—
4	.0004	.0390	.44	.462	.0001	.0210	.3185	.1677
5	.0008	.0350	.50	.750	.0003	.0203	.3109	.1750
6	.0030	.0027	1.07	.276	.0030	.0027	.5298	.1508
7	.0047	.0020	.88	.132	.0047	.0020	.6772	.1064
8	.0070	.0015	.52	.147	.0070	.0015	.4320	.1139
9	.0069	.0016	.56	.093	.0069	.0016	.5052	.0826
10	.0077	.0014	.50	.071	.0077	.0014	.4731	.0660
11	.0086	.0012	.43	.064	.0086	.0012	.4154	.0603
12	.0089	.0011	.40	.051	.0089	.0011	.3926	.0491
13	.0094	.0009	.38	.043	.0094	.0009	.3757	.0418
Priors	.00	.025	.30	.185				

come available to develop stable parameter estimates. Estimates obtained via a Bayesian scheme that mixes results of the meta-analysis and data are more stable than one-step-ahead forecasts that employ a basic diffusion model and do not explicitly use results of previous research on diffusion. A meta-analysis prior can be estimated even for a condition (a particular combination of the design variables) that has not been studied previously by combining estimates for each element of the combination from different studies. Research is needed on the value of such forecasts.

REFERENCES

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

Bass, Frank (1969), "A New Product Growth Model for Consumer Durables," *Management Science,* 15 (January), 215–27.

——— (1980), "The Relationship Between Diffusion Rates, Experience Curves, and Demand Elasticities for Consumer Durable Technological Innovations," *Journal of Business,* 53 (July), part 2, 51–67.

Dodds, Wellesley (1973), "An Application of the Bass Model in Long-Term New Product Forecasting," *Journal of Marketing Research,* 10 (August), 308–11.

Dodson, Joe A. and Eitan Muller (1978), "Models of New Product Diffusion Through Advertising and Word-of-Mouth," *Management Science,* 24 (November), 1568–78.

Dolan, Robert J. and Abel P. Jeuland (1981), "Experience Curves and Dynamic Demand Models: Implications for Optimal Pricing," *Journal of Marketing,* 45 (Winter), 52–62.

Draper, Norman R. and Harry Smith, Jr. (1966), *Applied Regression Analysis.* New York: John Wiley & Sons, Inc.

Easingwood, C. J. (1987), "An Analogical Approach to the Long-Term Forecasting of Major New Product Sales," *International Journal of Forecasting,* forthcoming.

———, Vijay Mahajan, and Eitan Muller (1981), "A Nonsymmetric Responding Logistic Model for Technological Substitution," *Technological Forecasting and Social Change,* 20, 199–213.

———, ———, and ——— (1983), "A Nonuniform Influence Innovation Diffusion Model of New Product Acceptance," *Marketing Science,* 2 (Summer), 273–95.

Farley, John U. and Donald R. Lehmann (1986), *Meta-Analysis in Marketing: Generalizing From Response Models.* Lexington, MA: Lexington Books.

———, ———, and Michael J. Ryan (1981), "Generalizing from 'Imperfect' Replication," *Journal of Business,* 54 (4), 507–610.

———, ———, and ——— (1982), "Patterns in Parameters of Buyer Behavior Models: Generalizing from Sparse Replication," *Marketing Science,* 1 (2), 181–204.

Fourt, Louis A. and Joseph Woodlock (1960), "Early Prediction of Market Success for New Grocery Products," *Journal of Marketing,* 25 (October), 31–8.

Gatignon, Hubert, Jehoshua Eliashberg, and Thomas S. Robertson (1985), "Determinants of Diffusion Patterns: A Cross-Country Analysis," Working Paper No. 85-121, The Wharton School, University of Pennsylvania.

Griliches, Zvi (1957), "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica,* 25 (October), 501–22.

Heeler, Roger M. and Thomas P. Hustad (1980), "Problems in Predicting New Product Growth for Consumer Durables," *Management Science,* 26 (October), 1007–20.

Horsky, Daniel and Leonard S. Simon (1983), "Advertising and the Diffusion of New Products," *Marketing Science,* 2 (Winter), 1–17.

Johnston, Jack (1972), *Econometric Methods.* New York: McGraw-Hill Book Company.

Kalish, Shlomo (1983), "Monopolist Pricing with Dynamic Demand and Production Costs," *Marketing Science,* 2 (Spring), 135–180.

Lawrence, Kenneth D. and William H. Lawton (1981), "Applications of Diffusion Models: Some Empirical Results," in *New Product Forecasting,* Y. Wind, Vijay Mahajan, and Richard C. Cardozo, eds. Lexington, MA: Lexington Books, 529–41.

Lawton, Steven B. and William H. Lawton (1979), "An Autocatalytic Model for the Diffusion of Educational Innovations," *Educational Administration Quarterly,* 15 (Winter), 19–53.

Leamer, Ed E. (1978), *Specification Searches: Ad Hoc Inference with Non-Experimental Data.* New York: John Wiley & Sons, Inc.

Mahajan, Vijay, Charlotte H. Mason, and V. Srinivasan (1986) "An Evaluation of Estimation Procedures for New Product Diffusion Models," in *Innovation Diffusion Models of New Product Acceptance,* V. Mahajan and Y. Wind, eds. Cambridge, MA: Ballinger Publishing Company.

——— and Robert A. Peterson (1978), "Innovation Diffusion in a Dynamic Potential Adopter Population," *Management Science,* 24 (November), 1589–97.

——— and ——— (1985), *Innovation Diffusion Models and Applications.* Beverly Hills, CA: Sage Press, University Paper Series.

——— and Subhash Sharma (1986), "A Simple Algebraic Estimation Procedure for Innovation Diffusion Models," *Technological Forecasting and Social Change,* 30 (December), 331–45.

——— and Yoram Wind (1986), *Innovation Diffusion Models of New Product Acceptance.* Cambridge, MA: Ballinger Publishing Company.

Mansfield, Edwin (1961), "Technical Change and the Rate of Imitation," *Econometrica,* 29 (October), 741–66.

Nevers, John V. (1972), "Extensions of a New Product Growth Model," *Sloan Management Review,* 13 (Winter), 78–89.

Pedhazur, Elazar (1982), *Multiple Regression in Behavioral Research.* New York: Holt, Rinehart and Winston.

Robinson, Bruce and Chet Lakhani (1975), "Dynamic Price Models for New Product Planning," *Management Science,* 21 (June), 1113–22.

Schmittlein, David and Vijay Mahajan (1982), "Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance," *Marketing Science,* 1 (Winter), 57–78.

Srinivasan, V. and Charlotte H. Mason (1986), "Nonlinear Least Squares Estimation of New Product Diffusion Models," *Marketing Science,* 5 (Spring), 169–78.

Srivastava, Raj J., Vijay Mahajan, S. N. Ramaswami, and J. Cherian (1985), "A Multi-Attribute Diffusion Model for

Forecasting the Adoption of Investment Alternatives for Consumers," *Technological Forecasting and Social Change,* 28 (December), 325–33.

Tigert, Douglas and Behrooz Farivar (1981), "The Bass New Product Growth Model: A Sensitivity Analysis for a High Technology Product," *Journal of Marketing,* 45 (Fall), 81–90.

Zellner, Arnold (1971), *An Introduction to Bayesian Inference in Econometrics*. New York: John Wiley & Sons, Inc.

Reprint No. JMR271106