Models for marketing decisions: Postscriptum

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Abstract

The authors of the commentaries on Leeflang and Wittink [Internat. J. Res. Marketing 17 (2000) 105] have generated a welcome set of critical and constructive comments. The content of these papers varies enormously. Most papers advocate a specific perspective or methodology and, except for a few aspects, there is strikingly little commonality. In this postscriptum we categorize the comments, discuss points of contention in four broad areas, and offer a research agenda. © 2000 Elsevier Science B.V. All rights reserved.

Keywords: Model building; Maturity; Econometric models; FPBGs

1. Introduction

We appreciate the interests stimulated by our paper. The comments are provocative, and the authors of the 13 papers provide a wide ranging set of perspectives. In this postscript we categorize and summarize these contributions. We also identify points of convergence and divergence. However, we cannot rebut every argument made by the 23 authors. We focus on what we believe to be the larger and most relevant issues. In Leeflang and Wittink (2000), we represent necessarily a restrictive overview of the extensive model-building literature. Roberts and Winer, in particular, say that our paper does not recognize some important contributions. We refer to Leeflang et al. (2000) for a more inclusive treatment.

In Section 2 of this paper, we introduce a framework which shows our interpretation of major areas of contention. These areas are:

1. the status of model building in marketing (e.g. is it mature?);
2. the philosophy of model building (e.g. what should the model-building process be?);
3. methodology (e.g. how relevant are alternative methods?); and
4. applications (e.g. does e-business require new approaches?)

We discuss our perspectives on these four aspects in Sections 3–6, respectively, and we suggest a research agenda in Section 7.

We use the following descriptors for the 13 comments and our own paper:

<table>
<thead>
<tr>
<th>Author(s)</th>
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<tbody>
<tr>
<td>Albers</td>
<td>Albers (2000)</td>
</tr>
<tr>
<td>B &amp; D</td>
<td>Brodie and Danahar (2000)</td>
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<td>B &amp; W</td>
<td>van Bruggen and Wierenga (2000)</td>
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2. Categorization of divergent perspectives

In L & W, we suggest that there is a level of maturity in model building for marketing decisions. We discuss the model-building process as a systematic approach, and we present recent developments pertaining to distinct stages. Our perspective favors econometric models (methodology) and typical applications refer to markets of Frequently Purchased Branded Goods (FPBGs) (application). We argue that in the future model building efforts will exploit consumer heterogeneity, and we expect the models to contribute to mass customization by integrating soft (e.g., preferences, satisfaction) and hard (e.g., purchases) data.

We categorize the primary comments made in Fig. 1, based on four central aspects of L & W:

1. we claim that model building is mature;
2. we describe a process for model building;
3. the model building is oriented toward FPBGs; and
4. our method of analysis favors econometric applications.

(1) Several authors discuss the present status of model building in marketing. A frequent observation is that the marketing modeling “industry” is not mature. We discuss the arguments by B & W, Roberts, and Winer, and our reaction in Section 3.

(2) Many authors discuss topics that have the “philosophy” of model building as a theme. Suggestions relate to a model’s acceptance rate and ways to improve the impact of models on marketing decision-making. Other suggestions refer to stages of the model-building process such as the formulation of hypotheses, use of hard and soft data, and validation. We critically evaluate the comments of B & D, Laurent, L & R, Roberts and WKB in Section 4.

(3) Model building starts with a recognition of the model builder’s own biases and priors, i.e., the techniques and approaches s/he favors (Naert and Leeflang, 1978, p. 54). There is no doubt that we favor econometric models. Several contributors (Al-

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**Table 1:** Categorization of the perspectives.

<table>
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<th>Status of model building in marketing</th>
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<tr>
<td>• B &amp; W</td>
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<td>• Roberts</td>
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<td>• Winer</td>
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**Philosophy of model building**

<table>
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<th>Emphasis in L &amp; W</th>
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<tr>
<td>maturity</td>
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<td>model-building</td>
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**Methodology**

| • Albers   |
| • D & H   |
| • EBS     |
| • S & B   |
| • WKB     |

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<th>Applications</th>
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<td>web-based</td>
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<td>environment</td>
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Fig. 1. Categorization of the perspectives.

bers, D & H, EBS, S & B, WKB) favor a different methodology and together they sketch a much larger palette of methods, models and approaches that can all contribute to improved marketing decisions. We discuss and evaluate these methods in Section 5.

(4) Several contributors note that most of the applications we discuss are slanted towards FPBGs. We discuss their ideas to redirect model-building efforts to new and underdeveloped areas of application (Gatignon, L & R, M & V) in Section 6.

3. Present status: Maturity or growth

3.1. Arguments

B & W, Roberts, and Winer argue that the marketing modeling “industry” is not mature. They mention:

- the usage rate of marketing models in firms is low (B & W, Winer), and most applications are limited to grocery products and price promotions (B & W, Roberts, Winer);
- managers are not successful in using model-based results for marketing decisions (B & W, Roberts);
- marketing models are not applied to relevant tasks, and there is a discrepancy between the demand for and supply of models (B & W, Roberts);
- there are doubts about the advancement towards standardization (Winer);
- marketing automation will not take place to any substantial extent (B & W), and it would exacerbate the problem of drawing actionable insights from marketing analyses (Roberts);
- modelers cannot give consistent answers to simple questions (Winer);
- marketing is a borrower and not a creator of new methods and models (Winer).

We note that there is disagreement about the definition of a model. B & W define a model as “…a mathematical representation of a marketing problem that aims at finding optimal values for marketing variables”. Our definition is in Leeflang et al. (2000, p. 10): “a model is a representation of the most important elements of a perceived real-world system”. In L & W, we focus on numerically specified representations, and we distinguish descriptive, predictive and normative models. B & W’s definition excludes descriptive and predictive models.

Early model building in marketing was often of the normative kind with a concentration on the development of solution techniques. Modern model building includes a wide variety ranging from formalized models to numerically specified ones, from descriptive to normative, from simple decision support tools to complete, robust, hierarchical, asymmetric models. B & W’s definitions of marketing information and marketing decision support systems resemble our definitions of descriptive and predictive models.

Whether the penetration or success rate is high or low depends on the definition of models. With regard to managerial success based on model-based results for marketing decisions, we refer to Little et al. (1994) and Parsons et al. (1994). Still, we need a much better understanding of how and why models are or are not used. And we need systematic rather than anecdotal data about the effects of model support for marketing decisions (L & R).

B & W maintain that there are discrepancies between the demand for and supply of models. However, neither the supply nor the demand for models has been documented. Bucklin and Gupta (1999) provide an insightful qualitative perspective on the knowledge generated by models. We agree with Roberts that there needs to be a balance in: (1) understanding the environment; (2) the appropriate tools to use; and (3) the way in which results are applied. It remains to be determined how this balance is achieved, and how it relates to the usage rate.

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2 EBS note that in L & W no explicit reference is made to any actual marketing decision. We have many examples which are subject to confidentiality agreements. Of course, the standardized models we refer to could not have a high usage frequency if there is no impact on decisions.

3 Spring et al. (2000) report that among Dutch direct marketing database companies 40% use models for segmentation and/or targeting.
and the success of model support for marketing decisions.

3.2. Scenarios

For the use of models in practice, we distinguish the following three scenarios: (1) automated use; (2) standardized use; and (3) customized use. Under the category of automated use, we include inventory, direct mail, shelf space and promotion timing applications. For these types of applications, managers need to determine the fit between existing software packages and the characteristics of their business environment. Importantly, there is no need for management to be involved in these model-based applications.

The second category, standardized use, includes the application of models such as ASSESSOR (Silk and Urban, 1978) and SCAN PRO (Wittink et al., 1988). For ASSESSOR, management supplies judgments about the intended marketing plans for a new product, and the model is used to simulate what-if scenarios. SCAN PRO is used for a variety of issues related to promotional activities such as the relative emphasis on display versus feature advertising. The basic model is standardized, based on extensive validation exercises by the supplier, but it can be enhanced to address additional complexities. Albers argues that this is the type of model use that can be implemented on Excel spreadsheets. In practice, this is not straightforward since all sales effects should be decomposed (Gupta, 1988), and the components do not have equal managerial relevance. Recent research shows that lead and lagged effects can be accommodated in models of store data (van Heerde et al., 2000). Semiparametric analyses show that there are threshold and saturation effects as well as complex interaction effects (van Heerde et al., 2001) that require special software.

Customized model building is an activity in which the user plays a pivotal and direct role. In this case, the manager has to identify the proper measures, the relevant variables, the nature of possible effects (non-linear and interactive), etc. Here model building and model use should be intertwined so that management and analyst expertise are fully complementary. We note that for customized applications, we should have a consistent approach even if across domains there does not exist a common answer to a simple question.

3.3. Maturity or growth

The bases for our assessment, that the present era represents a level of maturity in model building for marketing decisions, are:

- the wide applicability of standardized models such as ASSESSOR (> 6000 applications), PROMOTIONSCAN (at least half of FPBG marketers have used it) and SCAN PRO (> 2500 commercial applications);
- model-based automation;
- meta-analyses and empirical generalizations; and
- the application of existing models, developed in one context, to other contexts.

Winer says that maturity of a discipline depends on whether other disciplines adopt its methods. Marketing is still much more a borrower of theories and methods than it is a creator. Indeed, Wansbeek and Wedel (1999) find that the cross references to economic and marketing journals are asymmetric. Since marketing is much more an applied field than economics, this asymmetry will persist, although the asymmetry is much weaker between economics and finance. Nevertheless, areas such as medicine and public policy exhibit considerable interest in our research methods.

We note that the state of model use in marketing is not as well developed as it is in economics and finance. There are several possible reasons. One is that many economics Ph.D.’s find employment in consulting, government and other non-academic areas. Another is that solutions in economics and finance are believed to require a greater amount of systematic analysis. The practice of finance is increasingly also dominated by intermediaries who support mergers, acquisitions, divestitures, initial public offerings, and all varieties of investments. Both managers and consumers find the complexities overwhelming, so that the results generated by black box models in finance find easy acceptance.

By contrast, marketing has many professionals who believe that subjective elements should be cen-
tral to most decisions. A proposal to have managers use models is seen as an infringement of their authority. It is easy for managers to claim that the environment is far more complex than any model is capable of capturing. They have an ingrained confidence that only they can consider all the complexities. The case for models as decision support is not made easier by the lack of quality in the vast majority of statistical and econometric work in practice. In this environment, it is up to model builders to provide convincing evidence both a priori and a posteriori that managers’ decisions are expected to improve with the support of model-based insights.

The maturity phase of a life cycle is, a.o. characterized by: (a) maximum penetration; (b) intense competition; (c) product line extensions; and (d) product modifications. The growth phase shows: (a) growth in sales and revenues; (b) growth in penetration; (c) imitation; and (d) market development.

We believe that the model-building industry shows: (a) intense competition; (b) product line extensions; (c) product modifications; (d) growth in penetration; and (e) market development applications to new contexts. This suggests that model building has characteristics from growth and maturity. Nevertheless, we agree that the industry is not mature in the classic product life cycle sense. We expect with L & R a growth in models and model users in the next several years. Hence, the penetration is not maximal.

4. Model building

4.1. The process

The answer to a simple question about the return on marketing investments (Winer) is not straightforward. The effect of an investment in advertising on sales depends on many aspects (such as the type of product, the types of consumers and the purpose of the advertising). But researchers should agree on the process that is suitable for its resolution. In L & W, we provide a detailed description of the model-building process. Roberts argues that cost–benefit considerations must precede model scope in our framework. We agree. Indeed, for commercial applications the (incremental) costs should be compared against (expected) benefits almost continuously during the model-building process.

Roberts also suggests that “time to market dictates that validation must follow use”. His implicit assumption is that validation delays the use of model results. To evaluate this idea consider the three scenarios in Section 3.2. Both automated and standardized applications are based on models that are used repeatedly. Obviously, the commercial acceptance of such models depends on validation prior to use as well as continued evaluations. For customized model building, the only delay in time-to-market occurs if validation cannot proceed until new data are gathered. In a commercial setting, it is extremely rare to have sufficient data for estimation but not for validation. Thus, we see no reason to delay the validation exercise.

The topic of validation takes on greater importance in the new market environment. Data-mining methodologies (L & R) may pick up previously hidden effects. But data-based methods are also prone to converting random patterns into systematic ones. When these methods are applied to new data sources, such as search behavior on the Web, the output is sensitive to peculiarities. Under such conditions meaningful validation is especially critical.

We strongly believe that validation is a key aspect in the model-building process as do Laurent and Roberts. Laurent focuses exclusively on this aspect and he makes an eloquent case for enhanced emphasis. Causality is usually assumed, not tested, exogeneity is often inappropriately assigned to variables that are endogenous,3 and a specific stylized model is arbitrarily adopted. We support his argument, based on Forrester (1961), that any model formulation must represent and capture the critical compo-

3 Laurent argues that Chapter 11 of Leeflang et al. (2000) in which models of competitive reactions are discussed, “casts doubts on a number of models presented elsewhere in the book…” This concern is misplaced since the competitive reaction functions use lagged endogenous variables. The inclusion of such functions in a system of equations show that the equations are recursive. However, we agree that even if the estimated demand functions are valid, managers need to consider competitive reactions so as to avoid overstating the end result of actions.
nents. Far too often, research proceeds without even a superficial understanding of the decision makers for whom the model is intended.

B & D suggest that the state of empirical analysis in marketing requires improvement. They lament the fact that most studies lack competing hypotheses, there is a dearth of empirical support for simple principles, and replication studies are lacking. Recent studies are based on large databases which allow for empirical generalizations (e.g. Bell et al., 1999; Nijs et al., 2001).

4.2. Soft and hard data

In the first step of the model-building process (L & W), we refer to the extensive “models of man” literature. It is well known that a model of subjective judgments of potential outcomes (e.g. academic performance of applicants to a university program, creditworthiness of loan applicants) for repetitive decisions almost always outperforms the judgments themselves. But since these subjective judgments are subject to systematic errors, a model estimated from actual (past) outcomes is expected to generate superior forecasts. Systematic errors result from the order in which folders from, say, applicants are read and from other context effects. For example, an influential source of error emanates from the nature in which feedback about the performance of enrolled students is provided. The faculty responsible for one required course in a graduate program may harass the admission director about the inadequate capacity of students in their area while other faculties do not communicate their experiences. The consequence is that applicant characteristics which are believed to predict performance in this one area will then receive higher weight in future judgments of applicants’ suitability.

By modeling actual performance results for all courses to the same predictor variables available to the decision maker (the admission director), we obtain “optimal” weights that maximize the model’s explanatory performance of past students. If the academic program is stable over time, and other aspects remain approximately the same, then this model will outperform a model of subjective judgments of future performance of current applicants. Importantly, in this setting the context effects that influence a decision maker’s subjective judgments can be removed by substituting actual outcomes. This is an example where we favor hard data (actual outcomes) over soft data (judgments).

We note that the subjective judgments contain systematic and unsystematic errors while the academic performance measures contain unsystematic error (academic success is defined by the grades). Since scores for individual courses are available, these scores can be treated as indicators of a smaller number of constructs. Thus, instead of letting the measurement error be absorbed by the model’s error term, it is possible to quantify it. Srinivasan et al. (1981) use this approach to estimate the true explanatory power of models, separately specified and estimated, for two constructs of academic performance. The predictions from these models are combined to estimate the probability of failure for all applicants in either or both parts of the required MBA program at Stanford University. The model is updated every year, is recalibrated less often, and has been in use for almost two decades.

We do not claim that context effects should always be removed from the model. The example above is of a manager who would make suboptimal decisions, based on judgments, due to systematic errors such as order effects and suboptimal weights. Suppose now that the market environment causes consumers to make decisions that are subject to context effects. If we want to build a model that approximates their decision-making process we want to capture and incorporate the important context effects, as advocated by WKB. In surveys to quantify trade-offs, we favor doing this by incorporating relevant, and potentially idiosyncratic, context effects. There is a research opportunity to demonstrate that such enhanced trade-off models outperform traditional approaches in predicting future marketplace behavior. The impediments that delay the adoption of such enhancements are:

1. commercial researchers would have to study actual purchase behavior and accommodate the observed heterogeneity in relevant contexts, and
2. commonly used predictive validity measures of trade-off results rarely pertain to future marketplace behavior (Wittink and Bergestuen, 2001).
These two impediments mean that even if context effects matter, it will be difficult to obtain incontrovertible evidence of the incremental value of enhanced models.

Separately, we argue in Section 4 (L & W) that in the Web-based environment consumers will benefit from decision support systems. These systems should process marketplace data on alternative products and services efficiently so that a consumer’s utility function can truly be maximized. Currently, consumers are subject to framing effects induced by advertisements and Website characteristics. In traditional outlets, context effects also originate from the manner in which products are displayed (or the order in which the consumer is guided through retail outlets). Instead, we envision a world in which a consumer can either eliminate these effects or can create an idiosyncratic decision-making process. In this scenario, some existing biases will disappear, some will be reduced in magnitude, and some will be modified.

For example, Thaler and Benartzi (2000) suggest how important context effects in saving behavior can be reduced. They provide explanations of suboptimal savings and they also suggest remedies. Their remedy is to have consumers make saving decisions now for future periods (since it is easier for consumers to imagine that future periods allow for savings behavior than it is to implement savings now).

Context effects are receiving increasing interest in marketing in, for example, the deferral of choice. Traditional measures and methods focus primarily on what will be chosen, not whether or when. Thus, market share is a measure that captures share conditional upon category purchases. Choice models capture the effects of marketing and other variables on which alternative is chosen. And conjoint quantifies the trade-offs between alternatives given a category purchase. More recently, choice-based conjoint approaches allow for “no choice”. Based on laboratory experiments, Dhar (1997a) provides rich insights in the phenomena that produce choice deferral. His research results show, for example, that deferral incidence can increase when an (attractive) alternative is added to a choice set. He conducts multiple experiments to test a specific theory and to rule out alternative explanations and proposes how observed phenomena can be incorporated in marketing activities (e.g. Dhar, 1997b).

4.3. Segmentation and customization

We suggest (L & W) that the new marketing will emphasize customization. Advances in computer hardware and software, and in telecommunication bandwidth facilitate production on demand, just-in-time inventory, customized communication, distribution and pricing, etc. Increasingly, marketing activities, including product characteristics, can be mass-customized at low cost.

Our perspective is that the research should not assume that segments naturally exist. We need to explore and exploit heterogeneity in needs, preferences and behavior to the fullest extent. Segmentation applies if the costs of mass customization exceed the benefits. We expect that this is the case for inexpensive goods marketed individually, and for the selection of customers. For selection the criterion is whether a potential customer is expected to be profitable which depends on a match between the individual’s preferences and the firm’s core competencies.

The marketing activities employed to acquire and retain customers are, we expect, increasingly customized. For durable goods, it is now feasible to offer individually tailored items based on individual assessments of benefits sought. Communication can be individualized in content, in media and in timing. Products and services will be bundled, production occurs on demand, and pricing is based on willingness to pay. For nondurables, such as packaged goods, segmentation will continue to be applicable.

WKB mention that consumer goods manufacturers have reduced product assortments, and on the face of it this seems inconsistent with our argument in favor of customization. But customization is not efficiently achieved by enlarging the total number of varieties offered in a conventional retail outlet. Over time, manufacturers simultaneously added to product lines and increased promotions (e.g. the frequency of temporary price cuts). As a result, consumers were faced with excessive complexities in the choice process. However, the reduction in assortments cannot be interpreted as a lack of desire for customization. Procter & Gamble (P & G) now offers infrequently purchased varieties (such as unusual sizes of disposable diapers) only via the Web. But even on the Web, the options are vast and the search process
required can be daunting for the best intended consumer. For that reason, consumers need decision support systems which allow them to maximize their customized utility functions with access to infobots (L & W).

We argue that customization, not segmentation, should be the benchmark in the new environment for several reasons.

1. Consumers differ enormously in needs and wants. Early comparisons of external predictive validity in conjoint showed that individualized preference functions outperformed segment-based functions as much as the latter outperformed aggregate (homogeneous) functions (Montgomery and Wittink, 1980). Subsequently, Hagerty (1985) showed that segment-based functions could, under certain conditions, narrowly outperform individualized ones. However, these results are based on homogeneous attributes and levels and a modest number of judgments. In practice, heterogeneity matters not just for preference or choice function parameters but also for the attributes and levels.

2. It is now possible to estimate the profitability of individual customers. In many industries, firms are in the process of changing accounting and information systems to track individual customers in terms of costs and revenues.

3. Marketing has been product-focused ever since P & G invented the brand management system. The brand management system is segment-based and it depends on effective utilization of the marketing mix for sales and market share. However, the traditional application of the marketing mix does not distinguish between acquisition and retention of customers. Thus, supermarket retailers act as if they have to convince all customers every week again that their outlet is to be preferred. With today’s technologies, firms can optimize the allocation of marketing activities between acquisition and retention efforts (Blattberg and Deighton, 1996). The brand management system should be replaced by a customer management system so that the explicit focus of managers is: what do individual customers need or want, what do they purchase, when and under what conditions do choices occur, how satisfied are they with the purchase process and consumption, what are their intents to repurchase and to expand the portfolios of goods and services purchased from the firm, etc.

In the new environment, it is not meaningful to impose segmentation as a (semi-permanent) fixture. Instead, we propose that all raw, interpreted and inferred data are defined at the individual level so that the benefits of localized and temporary segments can be compared against the costs. This philosophy is consistent with the example of direct marketing efforts (WKB) which are based on individual customer differences.

Although we prefer to frame the problem in terms of customers represented in a database, telecommunication developments will also soon allow, say, a retailer with excess inventory of a perishable good to contact specific consumers through their GSMS. In the US, legislation stipulates that some time in 2001 the location of all GSMS has to be identifiable with an error of no more than 100 ft. This allows for the definition of temporary segments. However, long-term implications should be considered, meaning that even here customized pricing will occur.

The argument that the identification of heterogeneity in, say, choice data is an ill-posed problem (WKB) does not mean that we should favor segmentation. The lack of a unique way to capture heterogeneity is not different from the fact that segments are artificial constructs whose identification requires a series of assumptions. McFadden and Train (2000) show that it is optimal to accommodate heterogeneity within segments. Chung and Rao (2000) find that a model with two latent classes and random effects within each class has superior explanatory power over other models.

WKB also raise the issue that heterogeneity and state dependence in choice models are confounded. However, these model components can and should be separated (Keane, 1997; Gupta et al., 1997). For incomplete models, it is common to have definitions that mislead the casual reader. For example, EBS interpret the “loyalty” variables in Guadagni and Little’s (1983) choice model as actual loyalty. In fact, the loyalty variables are household-specific variables which primarily capture heterogeneity in brand preferences and therefore “explain” a large part of the variation in choices.
WKB emphasize that the cost of individualized targeting is not negligible. It is actually instructive to reverse the problem: the costs of current practices are excessive and unnecessary. For example, the automobile companies in the US still attempt without success to forecast demand for individual styles. They maintain an inventory of about 60 days of sales, which means that in total more than 2 million cars are in inventory at any time. At an assumed average cost to the manufacturer/dealer of $15,000 per car, this means $30 billion in inventory. Due to the poor demand forecast accuracy, and also due to escalation of poor marketing practices in the past, the average amount of rebate or other promotion per car is about $2,000. Assuming US sales of 12 million cars per year, the estimated cost of this marketing activity is at least $24 billion! Yet even with the vast promotion (and advertising) expenditures, and a huge inventory, it is extremely rare for customers to find their preferred combination of characteristics. Due to a lack of fit between supply and demand at the individual level, the customer will not pay full price (hence, the rebate). Even at a reduced price the customer will not be satisfied and will therefore require more marketing attention for repeat purchase. It should be clear then that the Web provides customers with an opportunity to select their preferred combination of characteristics. Due to the potential for enhanced customer satisfaction, reduced price sensitivity and increased retention is enormous if mass customization is the norm.

5. Divergence in methodologies

5.1. Introduction

In L & W, we discuss models to support marketing decisions. Little (1994) argues that such models usually “include variables and phenomena that are vital for the problem at hand, i.e. controllable activities like price, promotions and advertising”. Little also claims that descriptive models “seek to uncover marketing phenomena and to represent them”. By contrast, EBS claim an explanatory capacity of descriptive models but apparently rule this out for decision models even though the latter capture the effects of marketing control variables. In practice, the distinction between decision and descriptive models is not necessarily clear. Models intended to support marketing decisions may describe relevant phenomena including relations between variables and descriptive models may or may not contain marketing control variables.

In this section, we focus on the divergence in methodologies. In practice, the methods are often complementary. But the contributors adopt an advocacy position. Albers claims that future models will be estimated with spreadsheet software. B & W argue that decisions depend upon marketing management support systems. D & H illustrate the promise of time-series analyses. And S & B lament our lack of discussion of structural equation models. Finally, EBS take the extreme perspective that only Ehrenberg’s descriptive models depict actual or potential (marketing) knowledge.

The complementarity of these approaches may be apparent from the following. Structural equation methods are promising for theory development and testing, especially for (cross-sectional) survey data with multiple indicators of constructs. Time-series analysis is attractive for a study of long-term effects of a modest number of marketing variables. Marketing management support systems can capture the decision-maker perspective. Econometric models are well-suited for the estimation of relations between variables. In the remainder of this section, we discuss structural-equation models, time-series models and econometrics in some detail.

5.2. Structural equation models

S & B provide an elegant discussion of opportunities and recent developments inherent in structural equation models (SEM). They mention that SEM is largely absent from the marketing models books. However, they acknowledge that SEM is more pertinent for explaining marketing phenomena and theory testing than for predicting outcomes and decision making. Our focus is on “building models for marketing decisions”.

Theory testing can be indirectly useful for decision making, for example with respect to the direction and the nature of interaction effects (see, e.g. Mitra and Lynch, 1995, who use laboratory experi-
ments to demonstrate how and why advertising can both increase and decrease prices and price sensitivities. Such results can be extremely useful to all managers. And SEM can also feed into the specification of econometric models (see Sirohi et al., 1998, for an application).

Although S & B acknowledge that SEM is not directly useful for decision making, they do not discuss why this is so. Fundamentally, the problem is that SEM applications in marketing are dominated by analyses of correlations. The results are then stated in terms of standardized slope coefficients which are rarely appropriate for managerial decisions. For theory testing, these coefficients can be meaningful as long as we deal with constructs that have a natural or meaningful variability. Researchers in psychology focus on constructs that vary across individuals, and this variability usually does not depend on manipulations created for economic gain. By contrast, researchers in economics deal with market variables that are partly under the control of marketing managers and partly a function of competitive forces. As is well known, correlations depend on the amount of variation in variables. Thus, if the focus of study is on economic variables (S & B mention such variables as brand equity, customer satisfaction, competitive rivalry, market orientation and promotional intensity), the amount of variation is determined by strategic and tactical forces.

We have no quarrel with the idea that theory building and testing is a necessary exercise either before or during a model-building exercise. But if the theory testing is based on coefficients which do not have a one-to-one correspondence with either slope coefficients or elasticities, we have the wrong basis for marketing decisions. Recent papers do, however, use SEM based on covariances (Baumgartner and Steenkamp, 1998; Steenkamp and Baumgartner, 1998), and this approach avoids the problems associated with correlations (and standardized slopes). Still, the applicability of SEM to models of marketing mix variables is not obvious. There is usually only one measure of an item’s regular price, of its temporary discount, of other promotional activities, etc. Unless we can justify that consumers do not respond separately to such variables, it is inappropriate to create constructs of which these measures are indicators. However, it does seem meaningful to use multiple measures for a construct such as competitive intensity.

Another area of concern is the advocacy by S & B that SEM can accommodate a rich set of flexible error structures. For example, SEM can accommodate “errors that are correlated between adjacent time periods” (S & B). Econometrics also offers a very rich array of error specification options. A danger is that we accept the mathematical demonstration (in econometrics) that serial correlation does not cause bias in parameter estimation, assuming that the model is correct. The problem is that serially correlated errors invariably exist because of model misspecification. It is well known that omitted variables and incorrect functional forms invalidate parameter estimates. This argument appears to be very similar to Laurent’s call for a verbal model that becomes the basis for a mathematical one.

5.3. Time-series models

Time-series (TS) models received little attention from marketing model builders and users. D & H attribute the limited diffusion of TS concepts to the following factors:

1. marketing scientists’ lack of training in TS methods and lack of access to user-friendly software;
2. a resistance to data-driven approaches;
3. a lack of adequate data; and
4. the absence of a substantive area for which TS modeling is a primary research tool.

D & H mention that these obstacles have been attenuated. Marketing scientists are better trained in time-series analysis, and there are several user-friendly PC-based packages. Databases cover longer time spans, and D & H expect applications to data at disaggregate time periods and entities. Techniques such as cointegration analysis, unit root testing, error correction modeling and persistence estimation proved their value in quantifying the long-run impact of marketing decisions. TS models have also contributed to the development of empirical generalizations in marketing (Dekimpe and Hanssens, 1995).

We agree with D & H that TS models deserve a prominent place, especially because the models can separate short-term from long-term effects. Unit root
tests allowing for structural breaks are used to determine market shake-ups, i.e. systematic changes in market structures. Empirical results focus, for example, on total market volume, (re-)distribution of market shares, or competitive reaction functions. Such shake-ups may result from the introduction of a new brand (Kornelis et al., 2000).

With D & H, we believe that the most productive use of TS models in marketing is still to occur. Barriers to wider use include the following.

1. The software is not yet sufficiently user-friendly. Our experience with Eviews is that user-friendliness is an inverse function of the number of equations of the system. In TS analysis, the selection of the appropriate number of lags is often based on a statistical criterion. Eviews, however, does not provide such a selection procedure, which makes working in Eviews time consuming.

2. Inference in cointegration models is not straightforward. The resolution of questions involving seasonality (Franses, 1991, 1996) in practical cointegration analysis is neither simple nor easy for most users.

3. The VAR models calibrated for persistence estimation do not have many endogenous variables, and it is not clear how uncertainties associated with more complex models will be resolved (Dekimpe and Hanssens, 1999; Bronnenberg et al., 2000).

4. TS techniques have contributed to the development of empirical generalizations (Dekimpe and Hanssens, 1995) and the enhancement of marketing theory (Dekimpe and Hanssens, 1999; Dekimpe et al., 1999; Bronnenberg et al., 2000). Still TS techniques are data driven and lack foundations in marketing theory.

5. Finer time grids, entity disaggregation and longer time series confront time-series modelers with the problem of what information to use or to discard. D & H indicate that research is needed on how to make the trade-off between statistical-power and managerial-relevance considerations.

In L & W (Section 4.2), we specify a framework in which we identify models that are especially suitable in the future. TS techniques can play an important role in this framework. We agree with D & H that attitudinal variables should be matched with transactional observations and that the dynamic flexibility of TS techniques should be integrated with multinational logit and probit models. We also support D & H’s ideas about research topics such as the functioning of the marketing mix in a non-stationary environment and the effect of the high-information economy on competition and on competitive reactions.

5.4. Econometrics

Although we use a variety of methods in our own research, including experiments, stochastic models, structural equation models and time-series analysis, we often use econometrics as is evident in L & W. Several contributors argue that econometrics is subject to limitations and that other methods are or can be superior. The nature of many of the observations suggests there is some misunderstanding.

S & B mention that typical econometric applications do not take measurement error into account. This is a limitation in the applications not in the methodology. More often than not, the quality of an application leaves a lot to be desired. However, there is a long tradition in econometric theory that deals with errors in variables. Consistent with S & B’s observations, this literature shows that random errors in predictor variables bias the estimated effects toward zero. There exists also a rich discussion of estimation methods such as instrumental variables which can overcome this problem. On the other hand, error in a criterion variable does not create such a bias but, unlike the assertion in S & B, it does decrease the coefficient of determination.

Some of the criticism focuses on the data. For example, scanner data give a “false sense of security” (S & B) and contain a “presumed objectivity” (WKB). Scanner data are indeed not necessarily complete nor without error, and aggregation issues can be severe. Interestingly, many of our papers focus on these issues. For example, we show aggregation can be examined, and we offer solutions (Leeflang and Olivier, 1985; Gupta et al., 1996; Christen et al., 1997). Our work fits the perspective offered by WKB that data difficulties represent opportunities “…to understand such biases and devise technologies that reduce their impact”.

The most contentious comment is by EBS. Much of their criticism of L & W appears to be based on an inadequate understanding of econometric theory and practice. For example, EBS claim that model builders assume that regression equations and correlations imply causation. They refer to a single study in which cross sectional survey data appear to be the basis for causal claims. Apparently this ominous quote proves that all regression models are wrong-headed.

Another critical comment is that the models used are necessarily incomplete (EBS). Our perspective is to use a model with the most critical components, based on principles advocated by Little (1970). EBS argue that because the world is awfully complex, it is impossible to include all relevant variables properly. They assert that if all relevant variables were included the resulting model would not predict well anyway. This point is based on interview remarks by Zellner (Garcia-Ferrer, 1998) who advocates that (regression) model building start with a simple model. He does not define simplicity but does say that the model’s performance should be checked empirically. If the model fails it should be remedied. His recommendation is consistent with Little’s arguments (Little, 1970). And our work with SCAN PRO fits these criteria. The original specification (Wittink et al., 1988) is simple, and has been the basis for thousands of commercial applications. Recently, creative innovations (Foekens et al., 1999; van Heerde et al., 2000, 2001) have shown that refinements in specification and estimation improve explanations and predictions. These evaluations, again consistent with Zellner’s observations, have taken place across many different data sets. We note that today’s marketplace provides an almost infinite number of observations. Recent econometric applications are based on multiple data sets (e.g. Bell et al., 1999; Nijs et al., 2001).

EBS will be interested to know that models containing complex nonlinear and interaction effects, estimated with nonparametric estimation methods, predict well and outperform traditional parametric models in multiple categories (van Heerde et al., 2001). AC Nielsen, IRI and other research suppliers have completed vast numbers of commercial applications of standard econometric models for virtually all consumer goods manufacturers.

We find Ehrenberg’s intolerance for alternative approaches curious. The claims in EBS that dedicated decision models are unlikely to predict successfully are without merit and unsubstantiated. Little et al. (1994) and Parsons et al. (1994) provide many successful applications. It is also curious that EBS illustrate their approach with an example of Folgers. Their measures (EBS, Table 2) are based on a myopic definition of the market: coffee sold in supermarkets. Based on personal interviews, we know that P & G management regrets very much that this myopic definition prevented it from recognizing the threat of Starbucks. The preoccupation with traditional markets and existing retail outlets, implicit in the measures advocated by EBS, made P & G a late party in the market for upscale high-quality coffee. The measures do not uncover market opportunities. In contrast, we advocate the collection of a broad set of measures for individual consumers, including preferences (unmet needs), purchases and satisfaction. In today’s dynamic markets much more is required than appears to be available in Ehrenberg’s toolkit. Consider also how he would investigate whether competitive reaction effects are consistent with consumer response effects (Leeflang and Wittink, 1996).

6. Models in new contexts

6.1. New applications

In marketing, much model building has focused on FPBGs. In most cases, these models support marketing decisions of manufacturers. The scanning revolution directed the attention towards pricing and promotion decisions. In L & W, we expect to see growth in applications in new contexts, such as service marketing, retailing, B2B marketing and electronic marketing (Section 4.2). We expect shifts such as:

- from models covering “metropolitan areas”, regions and countries to models for international marketing activities;
- from models for tactical decisions to models for strategic decisions (Gatignon, L & R);
- from single brand models to models of multiple own- and other-brand items;
• from horizontal competition to horizontal and vertical competition (and interdependencies between channel partners); and
• from models specified at the retail chain to models at the individual store level (micro marketing).

Wind and Lilien (1993) indicate that marketing strategy models are not commonly used by management. Their research indicates that most of the strategy models are not user friendly, do not address key concerns of top managers, do not facilitate the process of making strategic choices, and are more directed to brand strategies than to corporate strategy. However, in the last decade models and tools have been developed that offer better opportunities for support of strategic decisions:

• models that quantify the long-run impact of strategic decisions (D & H, Gatignon);
• models of cooperation and vertical competition in a channel (e.g. Krishnan and Soni, 1997; Kim and Staelin, 1999);
• tools such as Excel’s Solves and @Risk (Add-In) (Albers); and
• other concepts and tools such as those in Lilien and Rangaswamy (1998).

6.2. Web-based developments

There are opportunities to develop integrated systems of models which put a logically linked set of models in the hands of decision makers. The emerging flexible modeling environment of the Web will greatly expand the deployment and use of marketing decision models (L & R). These systems integrate organizational processes and databases and can be used as a basis for important common decisions. Because decision makers may not be present at the same location, Web-based models also offer opportunities to support international marketing decisions (Gatignon).

Web-based developments facilitate the collection of enhanced data. These developments offer opportunities for new “values” such as hybrid products (M & V) and offshoots of e-business (e.g. a search engine or a recommendation agent/infobot). Research is needed to evaluate consumers’ perceptions of the differences between values provided online and corresponding ones offline. Although we may or may not need to revisit existing theories of consumer behavior (M & V), we do need models that capture the unique effects of new shopping environments on consumer behavior. The digital economy generates more data including aspects such as customers’ order processes that previously were difficult to observe.

A similar reasoning applies to modeling international markets. Web data offer enhanced opportunities for the study of international consumer behavior and this medium can overcome the comparability problems of international market research data (Craig and Douglas, 1999, p. 44). We agree with Gatignon that this area has been neglected, although several studies on international marketing recently appeared (Steenkamp et al., 1999; ter Hofstede et al., 1999). Given:

• the developments in international markets, particularly in Europe, with:
  - an increasing number of EU-member countries,
  - the introduction of a common currency unit (Euro),
• increases in international trade, and
• increased communication via the Web,

the demand for international marketing models will increase.

Modeling effects related to Web-driven products and activities on B2C markets are discussed by M & V. For example, Balasubramanian (1998) models competition between retailers and e-tailers. Relations with specific target groups and research on customer relationship management and (mass) customization are treated in L & W. Our perspective (L & W) on the future emphasizes that marketing variables tend to become endogenous at the customer level. As a result, (field) experimentation has to become a standard tool for managers to update their understanding about customers.

M & V suggest that current theories and approaches are insufficient for e-business. Yet it is not clear whether we just need to expand the tools (current work is insufficient but expandable) or need to do a complete revamping (current work is inappropriate). The former interpretation means that we
enhance existing models by, for example, accommodating search processes, browsing, use of recommendation agents and order procurement.

M & V argue that the types of products studied in the new environment differ from, say, FPBGs. They believe that researchers will (finally) model a broader set of products, and they provide a review of recent research on e-business. However, many of the findings seem to be variations on existing themes. For example, Lynch and Ariely (2000) find that consumers’ price sensitivity of merchandise may or may not increase online, dependent upon its uniqueness. This result is related to Mitra and Lynch (1995) who find that advertising increases consumers’ price sensitivity if the consideration set expands but decreases it if an item’s unique qualities show. Similarly, lower search costs online increase price sensitivity. But consumers will also choose simplified processing so that Degeratu et al. (2000) find that price sensitivity of Peapod customers can be lower online than offline if they use self-restricted consideration sets.

The findings reviewed by M & V are instructive. The most interesting result, however, appears to be that while the new environment has new elements, theoretical arguments that have been applied previously still seem to hold. Even the fact that on-line advertising efforts can be evaluated based on sales results (Hoffman and Novak, 2000) is not much different from direct marketing practices. The new environment offers enhanced opportunities for the estimation of advertising effects. In the traditional environment, advertisers claim that they can only be held responsible for exposures. Hoffman and Novak are correct that the new environment facilitates the construction of a much more comprehensive set of measures. A new challenge is to target just the right customers who will become advocates and maximize positive word of mouth.

M & V’s review suggests that the digital economy offers opportunities for managers and researchers. Proactive management requires a much more detailed understanding of customer needs, preferences and choices. Customers will appreciate having bundled products and services that solve their problems. Such a focus implies mass customization on a grand scale. Price sensitivity will decrease and margins increase if managers provide what customers want and do so in a manner that is difficult to duplicate.

7. A research agenda for marketing model building

In the past 50 years, there has been an enormous productivity in marketing model building by academics and practitioners. Models have been developed to advance marketing knowledge and to aid management decision making. In the past two decades especially, the use of information in marketing decision making has undergone revolutionary change. There are important developments in the availability of new data sources, new tools, new methods, new models and new applications. We are very optimistic about the potential of models to be a support tool for marketing decision making. Our optimism may explain why we described the present era to be mature when it has many features of the growth phase in a life cycle.

The contributions to this special issue suggest rich opportunities for model building. We summarize the research issues and we suggest a research agenda.

(1) Document model use and non-use in practice. This should include the usage rate by product category, by type of firm and by type of industry. Other relevant characteristics include the type of marketing decision, the user’s experience with models, the type of decision maker and model type (both descriptive, predictive versus normative and automated, standardized versus customized).

(2) Determine success and failure rates in practice. Include repeat use, and relate this to the model-building process, the use of verbal models as a basis (Laurent), the balance in components (Roberts), model adaptation, model validation, understanding of the decision maker’s perspective (for customized models), the involvement of the decision maker (e.g. combination of model and judgment) and the source(s) of data (e.g. observation, experiment, survey). Success implies a positive return on investment, where the return should include both direct and indirect benefits.

(3) Quantify real-world validation results. This can be done at an absolute level if there is no benchmark. However, it is desirable to show how a model compares against, for example, a traditional approach such as judgment-based predictions. The quality of validation may depend on model-building components such as the inclusion of causality tests,
the accommodation of endogeneity and model specification characteristics. Related to this is the determination of incremental performance attributable to context effects such as BDT phenomena in conjoint and choice models (on questions that focus on “whether” or “when” as well as “what”).

(4) Identify the critical aspects on which international models can provide unique insights. For example, we imagine a need for models that explain and predict differences in response to marketing variables across countries. And as international commerce and trade increases, we imagine that such differences become smaller. At the same time commonalities between subgroups across countries may become (more) obvious.

(5) Pursue model-building efforts in areas that are underserved. Apart from international marketing, these areas include strategic marketing, B2B marketing, micromarketing and e-business. For the latter, it is important for researchers to examine whether extant theories need to be revised or (merely) enhanced.

(6) Examine whether SEM applications can be enhanced for decision-making purposes. For example, the analysis of satisfaction survey data is likely dominated by regression analysis even though most survey instruments appear to include multiple indicators of various constructs. Do properly-executed SEM analyses suggest different decisions than the best possible econometric models? Similarly, do time-series analyses provide superior insights and do they allow for higher-quality decisions than the closest econometric methods? For example, how do time-series analyses of long-term effects compare with econometric models that include time-varying parameters?

(7) Document the use of decision-support systems by managers and consumers. Is successful model use by managers dependent upon its incorporation into a decision support system? Can consumer decision-support systems improve consumers’ decisions, for example by eliminating or reducing undesirable context (BDT) effects? Will managers be more eager to use models if consumers adopt decision-support systems?

(8) Compare the quality of decisions when managers have access to continuous data from individual customers on preferences, choices, satisfaction levels, etc., with that of decisions in traditional environments. What is the incremental benefit from a larger set of measures? What is the incremental benefit from integrated measures? What is the incremental benefit from an explicit customer focus at the individual level over a segment focus?

(9) Contrast the pros and cons of customization and segmentation in the selection of customers, the acquisition of customers and the retention of customers. What are the benefits and costs? Do the results depend on the product category?

(10) What is the optimal amount of field experimentation with marketing activities for learning or updating consumer response, when marketing activities are customized based on estimated parameters from earlier data?

(11) Determine the opportunity to exploit data mining methods. Does its usefulness relative to traditional methods depend on the strength of extant theories? Does it depend on the type of methodology traditionally used? Does it depend on product category or other data characteristics?

(12) Investigate the applicability of dynamic game-theoretic models to study optimal strategic competitive behavior. Does enhanced understanding of the customer reduce the intensity of competitive reactions? Does it enhance the pursuit of differentiated strategies, resulting in better separation of markets? Do multi-period simulations of consumer response to actions and reactions of competing firms reduce managers’ tendencies to imitate competitive behavior?

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References


