EDITORIAL

The diffusion of marketing science in the practitioners’ community: opening the black box

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The Guest Editors dedicate this special issue to the memory of Dick Wittink

SUMMARY

This editorial discusses an illustration of the potential hindrances to the diffusion of modern methodologies in the practitioners’ (i.e. the buyers of research, not the consultants) community. Taking the example of classical regression analysis based on store-level scanner data, the authors discuss the potential limitations of the classical regression model, with the example of the occurrence of ‘wrong’ signs and of coefficients with unexpected magnitudes. In an interview with one of the authors, a (randomly picked) Senior Marketing Research Manager at a leading firm of packaged goods reports his/her experience with econometric models. To him/her, econometric models are presented as a ‘black box’ (his/her written words). In his/her experience, they provided results that were ‘quite good’ in a ‘much focused’ context only. There were experimental data obtained with a Latin square design and the analysis included a single brand with only four stock-keeping units (SKUs). The company ‘dropped’ the more ‘ambitious’ studies, which analysed the effect of the retail promotions run by all the actors in a market because of a lack of predictive accuracy (his/her written words are in quotes). The authors suggest that Bayesian methodology can help open the black box and obtain more acceptable results than those obtained at present. Copyright © 2005 John Wiley & Sons, Ltd.

KEY WORDS: regression analysis; Bayesian analysis; latin square design; forecasts

INTRODUCTION

What do practitioners⁸ typically expect from marketing science? They expect ‘answers’ and they are usually ready to pay for those ‘answers’. For example, they may want to know how much to spend on advertising and on trade promotions and/or which brands compete with their own

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⁸In this sentence and in the title of the special issue, by ‘practitioners’, we mean the buyers of research, that is the manufacturers or other users of research, not consultants (the sellers). In the rest of the text, we confound the sellers and the buyers of research when not specified otherwise.

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brands. Can marketing science provide them with those ‘answers’? That is uncertain. It depends on what we mean by ‘answers’. Marketing science is more likely to provide them with documented conjectures, reasonable answers or guidelines for action. Real answers are hard to get if they exist. They are probably beyond human reach.

Typically, theories developed by academics are confronted with single data sets, and clearly the results are often tentative despite the claimed effort for the generalizability of the findings. Of course, the analysis of multiple data sets can strengthen the external validity of the results, but usually, practitioners deal with single markets at a time, and at times, with segments within these markets. They usually operate in specific contexts. Hence, the results obtained by academics may not apply to these niches, these single markets and/or these specific contexts. Still, marketing science can help managers make his/her own decision by identifying the different aspects of a given problem. It can help managers reformulate the problem in a different, perhaps easier way to grasp.

But is it the role of marketing science to provide managers with ‘answers’? In our view, marketing scientists themselves have distinct views on this matter. Some might think that it is the major role of marketing science and, through consultation, academics will contribute to the diffusion and implementation of methodologies in practice. Others might disagree. To them, providing managers with ‘answers’ is only a by-product of marketing science. The major role of marketing science, as that of any science, is to capture the essence of basic phenomena such as the impact of media advertising on sales, the long-run impact of promotion on a brand sales or the diffusion of technological innovations in a market. Other typical examples of basic research might include the separation of individual-level state dependence from heterogeneity in brand choice models (see, for example, Keane [1] who challenges the ‘conventional wisdom in marketing . . . that choice behavior is zero order’ and shows through detailed modelling that the individual-level choice process is state-dependent at least in the product category studied—ketchup). Identifying ‘empirical generalizations’ whether they be on advertising elasticities (see e.g. Reference [2]) or on own price elasticities (see e.g. Reference [3]) might not really help a manager determine his advertising budget or set a product price. Managers can even be tempted to ask the ‘so what?’ question when confronted with so-called ‘empirical generalizations’. Even when ‘empirical generalizations’ are identified, it may remain unclear whether departures from these ‘empirical generalizations’ are random or true, or whether they apply to the situation. In addition, the spirit of scientific articles published in major journals in marketing does not typically seem oriented towards implementation, but rather towards the understanding of basic processes. A user-oriented article would imply a major effort from the authors in terms of the availability of computer codes to facilitate replication, and, more importantly, pedagogical writing. As an example of implementation of a paper published in Journal of Marketing Research, see the website [4]. At the present stage, a strong self-selection process operates among practitioners (and academics) in order to comprehend and to implement the methodologies published in major journals. Consequently, in its current state, marketing

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4 In a comment on a draft of this paper, Greg Allenby stated that ‘the level of analysis, in practice, is very micro, e.g. at the brand level (not product class level), dealing with specific reasons that people engage in activities, with which specific attributes available from specific offerings provide benefit, or utility, in specific instances and contexts. . . . I don’t think the academic crowd in marketing has taken this on board, and it continues to offer techniques and variables at too high a level of abstraction. In other words, the ax/prax divide largely exists because we academics don’t offer specific solutions’ (personal correspondence dated July 25, 2004). This view is consistent with the arguments made. However, the website [4] provides a counter-example.
science seems to belong to a restricted group mostly composed of academics who essentially interact among themselves with fairly little concern for the trickle-down theory. In addition, typical evaluation procedures in most universities would not necessarily emphasize the implementation of methodologies in practice.

In the following paragraphs, we show, by using an illustration, how marketing science hardly diffuses through the practitioners’ community by taking the case of the use of classical linear regression analysis in practice.

CLASSICAL LINEAR REGRESSION IN PRACTICE

Classical linear regression is a tool that is widely used by both academics and practitioners. In our view, the reasons for its widespread use are as follows: (1) it is quite simple to understand, (2) in principle, it permits to capture the relationship between a dependent variable (e.g. sales) and a series of explanatory variables (e.g. prices, promotion), (3) its parameters can be meaningfully interpreted (see, for example, the discussion by van Heerde, this issue), (4) there exist standard computer packages to implement it, and (5) its use can be automated which is a major advantage to practitioners (consultants). However, its appeal can be quite deceptive when it is used with non-experimental data such as scanner data. For example, practitioners (i.e. manufacturers) can use (buy) the SCAN*PRO model (or a SCAN*PRO-type of model), which is a time series/cross-section linear regression model between store-level brand sales and marketing variables across stores (see e.g. References [5–7]). In the spirit of SCAN*PRO, assuming homogenous response coefficients and fixed but different intercepts across stores and using weekly store-level scanning data for a frequently purchased packaged good, we ran the following linear regression model between log(sales) and log(regular unit price):

$$\log(sales_{ijt}) = K_{ij} + \eta_{i1} \log(rp_{1jt}) + \eta_{i2} \log(rp_{2jt})$$
$$+ \eta_{i3} \log(rp_{3jt}) + \eta_{i4} \log(rp_{4jt}) + u_{ijt}$$  \hspace{1cm} (1)

log(sales_{ijt}) represents the natural logarithm of the unit sales of brand i (i = 1, 2, 3, 4) in store j in week t, uijt is a random variable that is normally distributed with mean 0 and constant variance and log(rp_{ijt}) represents the natural logarithm of regular unit price of brand i in store j in week t. The regular unit price is an ‘imputed value designed to reflect product price in the absence of any discounts or promotions’, see Reference [8]. The coefficients of Equation (1) \eta_{ij} can be interpreted as own and cross-regular price elasticities.

As shown in Table I for an illustrative data set, the own regular price elasticities are consistent with expectations and negative in three cases out of four. However, only one own regular price elasticity is significant at the 95% confidence level (one-sided test). As the products are substitutes, we expect positive cross-regular price elasticities. Out of a total of 12 estimated cross-regular price elasticities, four have an expected sign. Some of the estimated cross-regular price elasticities with a wrong sign even have relatively small standard errors. For example, the estimated cross-regular price elasticity of brand 4 with respect to brand 2 is −1.739 with an estimated standard error of 0.609. These results are consistent with the empirical findings in the literature. For example, Blattberg and George [9] state: ‘The problem is that modelling sales at the chain-brand level often leads to counterintuitive and theoretically
unreasonable estimates of separate elasticities. Coefficients fluctuate too much between
different chain-brand combinations, and frequently have the wrong sign’. They show that
many of the ordinary least-squares coefficient estimates have the wrong sign; see Table I of their
paper.

Building on Blattberg and George [9], Montgomery and Rossi [10, p. 413] write that
‘Unrestricted least squares estimates of own- and cross-price elasticities are often of an incorrect
sign and unreasonable magnitude, particularly if the analysis is performed at a relatively low
level of aggregation, such as the account or store level’. Also, the results show, for example, that
the cross effect of the regular price of brand 3 on the sales of brand 1 is almost three times as
large as the cross effect of the regular price of brand 1 on the sales of brand 3 (1.446 versus
0.531). As the mean regular price of brand 1 is about 15% larger than that of brand 3, this result
seems inconsistent with most of the evidence. However, the literature deals mostly with the cross
effects of temporary price cuts instead of changes in regular prices, see e.g. the discussion in
Reference [11] and the references cited therein. In the same fashion, the cross-regular price
elasticity of brand 4 with respect to the sales of brand 1 is not significant but the estimate of the
cross-regular price elasticity of brand 1 with respect to the sales of brand 4 is statistically
significant at the 95% confidence level and equal to 0.649. As the mean regular price of brand 4
is 19% larger than the mean regular price of brand 1, this result does not seem consistent with
most of the evidence again.

In any event, can the relative sizes of these cross effects be predicted ex ante? If these results
can only be explained ex post, it is unclear whether the explanation has much internal validity.
Overall, how can the results obtained be ‘sold’ to a client (i.e. a manufacturer of packaged goods
or other user of research), assuming here for the moment that diagnostic checks did not indicate
obvious inadequacy of the model? Using two-sided tests instead of one-sided tests for cross-
regular price elasticities leads to drastically different interpretations. But the use of two-sided
tests seems hard to justify when products in a market are substitutes. Given the potential
inconsistency of the results with expectations (if any), what can a consulting firm offer a client in
return for his/her fee? The results shown in Table I appear quite typical of those obtained with
classical linear regression analysis based on store-level scanner data.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Own-regular price elasticity and cross-regular price elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Brand 1</td>
</tr>
<tr>
<td>Log(sales(_{1jt}))</td>
<td>-0.587</td>
</tr>
<tr>
<td></td>
<td>(0.369)*</td>
</tr>
<tr>
<td>Log(sales(_{2jt}))</td>
<td>0.566</td>
</tr>
<tr>
<td></td>
<td>(0.303)</td>
</tr>
<tr>
<td>Log(sales(_{3jt}))</td>
<td>0.531</td>
</tr>
<tr>
<td></td>
<td>(0.285)**</td>
</tr>
<tr>
<td>Log(sales(_{4jt}))</td>
<td>0.649</td>
</tr>
<tr>
<td></td>
<td>(0.382)**</td>
</tr>
</tbody>
</table>

* Standard error in parentheses. Number of observations = 2146, number of stores = 37.
** Significant at \( p < 0.05 \) (one-sided test).
As discussed above, wrong signs occur quite often and the relative sizes of cross-regular price elasticities can be hard to predict \textit{ex ante}. One needs to distinguish cross-regular price elasticities from cross-temporary deal price elasticities. To our knowledge, this distinction has not yet often been made in the literature. The issue of the appearance of wrong signs with the use of classical regression methods has been discussed at length in the literature; see Reference [12] for a recent discussion. Substantial biases that we do not illustrate here can occur with the magnitude of the coefficients of dummy variables. For example, the model predicts that unit sales are multiplied by 30 or 40, under the \textit{ceteris paribus} assumption, when the product is placed in an end-of-aisle display and accompanied with a major advertisement.

One possible next step could be to consider Bayesian methods of analysis. In this paper, we will focus on Bayesian techniques, but there are also various other aspects that could amount to gaps between academics and practitioners. Note that we believe that these gaps are surmountable. For example, it is our experience that, while firms have access to huge databases containing detailed information on the behaviour of their customers, managers (i.e. potential buyers of marketing research) seem to underestimate the enormous potential of such databases, maybe due to information ‘overload’. They do so by still considering basic regression models, of which we can easily understand that they can ‘never’ capture the variation in millions of data points. With more data, one also introduces more heterogeneity, and when such heterogeneity is unobserved, then one usually resorts again to Bayesian methods; see also Reference [13].

We now turn to the specific case of Bayesian methods. Despite its relevance to the analysis of scanner data (among other types of data), Bayesian regression analysis has not yet found its place among practitioners (consultants) and not even among academics. In our view, there are at least two distinct ways to use regression analysis in marketing: (1) regression as a theory-testing tool, and (2) regression as an updating device (Bayesian school).

\textbf{REGRESSION AS A THEORY-TESTING TOOL}

In a pioneering article on the application of simultaneous equation models to the sales/advertising relationship for filter and non-filter cigarette brands, Bass [14] used regression as a theory testing tool. In his article, he develops premises about the range of the coefficients of the structural equation model. Although Bass does not indicate how he obtained these ranges, he provides an illustrative example of the use of regression methods with non-experimental data. The clear advantage of setting the parameter ranges is that the parameter estimates obtained from unrestricted regression analysis can be rejected. Equivalently stated the regression model becomes falsifiable. To our knowledge, this approach has not been pursued despite its potential relevance to the application of classical regression methods to scanning data, perhaps because of the lack of guidance for setting meaningful \textit{a priori} ranges of parameter estimates. Still, one would probably need a rather deep knowledge of a market in order to develop reasonable upper and lower bounds of the parameters. Typically, only the signs of the parameters can be predicted \textit{ex ante}. When the empirical results are not consistent with expectations, marketing scientists usually reject the empirical estimates and resort to improved estimation methods (e.g. Bayesian methods).

Would a client (i.e. a manufacturer or other user of research) be ready to pay for an ‘improved’ estimation method? It seems to us that practitioners (i.e. the buyers of research, not...
the consultants) may be more open to surprising results than academics. For example, following an interview that is reported later, the interviewee wrote that ‘positive own-price elasticity is not necessarily shocking when the brand has a high perceived value’. Still what can a consultant do about an incorrectly signed parameter? How can he/she tell whether the sign is incorrect or not? To him/her, the benchmark can be the expectations from the client whereas to an academic, theory dictates the sign. The error in scanner data is related to the very nature of the data. That is, they are non-experimental data. These data, including scanner data, are usually marred by confounded effects (like measurement errors), which may explain wrong signs and unexpected coefficient magnitudes. Consequently, a potential ‘black-box’ approach may be tempting.

AN APPRAISAL OF BAYESIAN METHODS

Given the practical appeal of Bayesian methods, it seems legitimate to ask the following question: Why isn’t everyone a Bayesian? Here we do not mean Bayesian in a strict ‘science–philosophical’ sense, but more in the sense that it provides helpful tools to summarize data in a useful way. We believe there can be several reasons for not considering Bayesian methods. First, despite its currently increasing diffusion in the overall researchers’ community, its penetration in the marketing science community is still rather low. The Bayesian philosophy and methods are not often taught in doctoral programmes, and even less so in MBA programmes. Classical methods are much more popular than Bayesian methods. Most practitioners with social sciences or business training are familiar with the classical linear regression model. Few of them are familiar with Bayesian methods.

Second, even if Bayesian methods have been taught and their relevance to marketing practice has been demonstrated with real-world examples, their adoption might still be hampered by their relatively high analytical complexity, in particular in the multivariate case.

Third, even when the analytics are comprehended by the user, he/she might still need to parameterize the prior distribution with subjective estimates. This may not be an easy task since it requires prior knowledge of the distribution of the parameters (e.g. own-regular price elasticities and cross-regular price elasticities). Typically, consultants are hardly experts on specific consumer goods markets and they may need their clients’ inputs into the analysis. However, one of the reasons clients may buy these studies is that they lack knowledge about the level of competition in their markets. Hence, they may encounter difficulties parameterizing the prior distributions subjectively. Provocatively, one might even argue that if the client knew the parameters of the prior distribution, he/she would perhaps not buy the study in the first place.

Fourth, even if one can parameterize a prior distribution, one needs to resort to numerical computational methods, as, typically, closed-form expressions of the posterior distributions given the data, are not available (see e.g. Reference [15]). Hence, the issue of automation in the implementation of these algorithms can arise from a practitioner’s (consultant’s) standpoint. If the implementation cannot be automated, the diffusion of the Bayesian methodology in the practitioners’ (i.e. the end users’) community can be slowed. Consequently, the hindrances to the diffusion of Bayesian methodology (as being one of the aspects of empirical marketing research) can occur at various levels in our view, ranging from the conceptual or analytical stage to the implementation stage.
A good introduction to the application of Bayesian methodology is given in Reference [16]. An illustration of the use of Bayesian methods with store-level scanning data appears in Reference [10]. Most of these methods are based on the notion of shrinkage, i.e. a brand/store level parameter estimate is a function of the performance of this brand in a store but also of this brand in other stores. The target of this shrinkage is rather arbitrary although Montgomery and Rossi [10, p. 417] suggest that ‘in many marketing applications, it might not be reasonable to shrink across brands’. Most of the proponents of the Bayesian econometrics in marketing have been exposed to the teachings and writings of Zellner [17] at the University of Chicago, and hence its name ‘The Chicago School’ (see the Acknowledgements in Reference [17]). They introduced these methods to marketing through their applications to store-level scanning data, from the pioneering study of Reference [9] to the more recent work as in Reference [10]. Applications of these methods have been extended to the analysis of individual-level purchase histories [18]. For methods that are closely connected to the Bayesian approach, see the influential study by Swamy [19] and the recent work by Chintagunta et al. [20]. For an introduction to Bayesian modelling of household-level purchasing data, see Reference [21] and for an assessment of the pervasiveness of the Bayesian approach with marketing data, see References [22, 23]. However, consistent with Drèze’s [24] early claim, the number of densities used in an applied setting is still quite limited.

WHY IS EVERYONE NOT A BAYESIAN?

The lack of exposure to Bayesian philosophy and methods, the lack of training in analytical and computational methods and the lack of availability of Bayesian regression methods in standard computer packages may represent potential hindrances to the diffusion of Bayesian methods among practitioners and academics.

In the current state of affairs, the development and use of Bayesian and Bayesian-related methods still belongs to a rather small set of academics and practitioners in marketing. Recently, Bayesian scholars took the baton and organized conferences which aim to diffuse Bayesian methodology in the practitioners’ and the academic communities by making software available. Examples are given by the Bayes Applications and Methods in Marketing Conference (BAMMCONF) at Ohio State University and the conferences organized by the Wolfson Conference Center at Imperial College in London using the free Bayesian inference Using Gibbs Sampling (BUGS) software. Other free software such as R can enhance this diffusion. Editors might incite authors: (1) to use free software, and (2) to make it available to potential users for replications, by enhancing the chances of acceptance of their paper substantially.

In addition to the analysis of scanner data, some applications areas such as conjoint analysis have been penetrated by Bayesian methods, thanks in part to a close interaction with academics (see e.g. Reference [25]), and these methods have been adopted by practitioners (see e.g. Sawtooth Software). In our view, the commercialization of these methods requires a fairly high level of training of consultants. In addition, more work on the methods of elicitation of prior distributions of parameters from practitioners (i.e. the buyers of research) is necessary (see e.g. References [26–28]). In a recent study, the parameters of the prior distribution of the parameters were assessed by the researchers themselves based, reportedly, on ‘economic theory’ (see e.g. Reference [10]). It is unclear whether experts in the product category studied (refrigerated
orange juice) would provide similar estimates as those given by the researchers and whether they would feel confident in these estimates. Hence, we see a possible source of a gap, which somehow ‘should’ be bridged. Clearly, a combination of judgment with data to estimate parameters is probably necessary to compensate for the existence of noise (confounding effects) in non-experimental data.

An illustrative assessment of the current attitude towards econometric modelling among practitioners (i.e. the buyers of research) based on an interview with a Senior Marketing Research Manager at a leading manufacturing firm in a consumer packaged goods market.

In the spirit of Reference [29], one of the authors conducted an interview with a Senior Marketing Research Manager at a leading manufacturing firm in a consumer packaged goods market. He/she was a graduate from a prestigious business school and in his/her late 30s (apparently). He/she had been in a marketing research position in the company for about four years. Here are his/her written comments in full sent to us (in English) after the interview:

‘In general, marketing researchers do not use regression analyses for modelling that regularly. They tend to find that they are ‘black box’ kind of studies, where statistical parameters are quite impossible to check. This kind of studies is often one shot. It is supposed to help (among other tools) the build-up of a strategic knowledge upon the media/promotion/price relative contribution to the success of a brand. These studies can be deceiving, not really believable to top management because of their lack of consistency with basic observations on the behavior of the brand in the past. My experience in the area of modelling with multiple regression is very mixed. It was quite good in the case of one single price-elasticity research which was done with a specific experimental design, i.e. a Latin square design, and in a very focused context, i.e. one brand with only four different stock-keeping units (SKUs) in a competitive context. The output was a very strong price elasticity. This result actually prevented the company from possibly taking a dangerous move on its pricing policy. It was confirmed to be a sound recommendation by the market evolution afterwards. My experience is very poor in the case of a more ambitious program which aimed to assess the relative performances of the retail promotions run by all the actors in the market. The analysis was rejected by the sales department. They compared the model’s predictions with the subsequent incremental sales due to the retail promotions and there were lots of inconsistencies. The report was simply not actionable to the marketing research people. This kind of study was completely dropped afterwards’.

This testimonial is highly valued, to us at least. We obtained the contact with the interviewee through a student who was doing a traineeship in the company at the time. Hence, the interviewee can be considered as being ‘randomly picked’. The interviewer had no prior idea about the interviewee’s attitude towards marketing studies, and in particular, towards regression analysis. He had never met him/her before and did not even know his/her name. The interviewer did not select the company as he was the tutor of the student at the time. He contacted the student to have an appointment to learn about the types of marketing studies carried out by the company along with the ensuing experience. The student led him to ‘the’ relevant person. Once the appointment was made, the interviewer sent a questionnaire to the interviewee so that he/she could prepare for the interview. The interviewee had ‘weight’ as a buyer of marketing research in the company and we found afterwards from an (unsolicited) oral testimony that he/she was ‘courted’ by consulting firms. Therefore, his/her view matters.
The ‘mixed feelings’ about regression analysis he/she expressed are consistent with our view about the existence of potential ‘errors’ in parameter estimates obtained via classical regression analysis. The ‘black box’ he/she claims (complains about?) can be explained by the potential existence of apparently ‘odd and hard-to-sell’ results. Like any other buyer in the market place, marketing researchers want to know what they buy. Transparency becomes a key attribute to buy a methodology, especially when the buyer is an ‘expert’ and the stakes are high. To our knowledge, there has not been any published conjoint analysis run on the key attributes of a marketing study, even by consultants selling conjoint analysis. We suspect that the levels of transparency, from ‘black box’ to ‘the equations and the estimation method are published in a major scholarly journal’ would turn out to be very important.

Of course, this testimony comes from a single individual, but he/she works for a major international player with a strong marketing orientation and his/her view is probably far from being an isolated one. This hypothesis of a ‘rational’ buyer can be tested further. For further possible evidence, see the article by Montgomery in this issue, which refers to the slow diffusion of pricing decision support systems in the retailers’ community. We conjecture that Bayesian methodology, although probably more difficult to explain to clients (i.e. the manufacturers or the users of research) than classical regression, can help open the black box. Parameter estimates are more likely to be consistent with expectations and more apt to be shown. For other proponents of the application of Bayesian methodology to other contexts, see the articles by Drèze and by Fader and Hardie in this issue. As is well known in the diffusion of innovation literature, new results and ideas are all the more likely to be adopted as they are consistent with prior beliefs and experience. We focused on the case of econometric models as a ‘black box’ but we might have carried out a similar discussion with (so-called) simulated market tests or other decision support tools that companies might or might not use.

THE CONFERENCE AND THE SPECIAL ISSUE OF ASMBI

Given the potential gap between academia and practice as discussed above, we invited a set of high-profile scholars in marketing to discuss the current issues in their area of expertise in a few pages for publication in a special issue of ASMBI on ‘Bridging the Gap Between Academic Research in Marketing and Practitioners’ Concerns’. We asked them to give us the names of practitioners (whether they are buyers or sellers of research) who could act as discussants of their paper. We stressed that we considered the practitioners’ comments as data in (partial or complete) support of the relevance of their work. In the set of practitioners, some of them may not be clearly identified as the so-called ‘practitioners’. But, when asked for their approval, they accepted to be labelled as ‘practitioners’. The discussants were free to discuss any aspect of the paper, including the methodological ones and the substantive ones. We did not ask them to assess the relevance of the academic contribution, or, equivalently put, to wear a ‘practitioner’s hat’ in their comment. To us, relevance is a subjective, time-dependent and perhaps context-dependent concept. We cautioned them that they were not invited as representative of their firm and that we expected them to provide us with their personal viewpoint on the academic contribution. This viewpoint may not necessarily be that of their firm and inversely the viewpoint of their firm may not necessarily be theirs. Of course, consistent with a scholarly journal, any kind of promotion of private interests was strongly discouraged. We mentioned to the academic contributors that we would send their paper out for review to academics. Also, we
told them that we were organizing a conference in Rotterdam at the Erasmus Research Institute of Management (ERIM) in Rotterdam on the same topic as the special issue. However, participation in the conference was not a prerequisite to the submission of a paper. They all reacted enthusiastically to the project and they provided us with the names of potential discussants of their paper. In a few cases, we made suggestions as to the names of discussants and these names were all accepted by the academics. At this stage, we would like to thank Greg Allenby at Ohio State University who permitted us to locate a discussant and Michel Wedel at the University of Michigan at Ann Arbor who gave us the names of former doctoral students of his who are now in practice, and the name of a consulting client, to act as discussants. Once contacted by us, all these practitioners readily agreed to discuss the academic contributions. Some of them even felt honoured, as they stated it, that this opportunity was offered to them. One of them (Herb Sorensen) took time off to travel from Troutdale, Oregon to Europe to discuss Vicki Morwitz’ paper.

The conference took place at Erasmus University in Rotterdam on November 21, 2003 under the joint sponsorship of Erasmus Research Institute of Management (ERIM) in Rotterdam, The Netherlands, the Center for Research in Management and Economics at ESSEC in France and the Teradata Center for Customer Relationship Management at Duke University in the United States. We limited attendance to the conference to 100 participants. The composition of the participants was roughly 60 per cent academics and 40 per cent practitioners. The conference included a set of eight presentations with ten discussants.

To our knowledge, this initiative looked like quite an innovative project for a conference and a special issue. Based on the reaction of all the individuals contacted, it seemed that it met the often claimed request for greater interaction between academics and practitioners. The project provided empirical evidence of the relevance of the work of marketing scientists, not through marketing scientists’ own testimony as is typically the case, but through practitioners’ comments on the academics’ work, which is less typical. As we recall, in its early years of its publication, Marketing Science set up a practitioners’ Board and some papers were discussed by these practitioners. However, this initiative did not seem to have stood the test of time. Currently, practitioners may belong to the Editorial Board in the same fashion as academics.

In our view, the project required (some) modesty and self-assurance of the invited academics who accepted to have their work commented upon by active players in the market place. In total, there are 45 contributors to the special issue: 22 of them are academics and 23 are practitioners. Fifteen of these practitioners hold a PhD degree or an equivalent degree. Many of them have published in major scholarly journals as shown in the biographies. Some of them have a publication record commensurate with an academic stature.

The line-up of the papers is as follows. Wu and DeSarbo propose a method for a graphical representation of consumer satisfaction heterogeneity. Bradlow discusses issues he wishes were ‘solved’ in conjoint analysis. In the footsteps of Matheron [30, 31] Bronnenberg reviews the recent literature on spatial models and its potential applications. Vakratsas discusses recent modelling efforts in the sales/advertising relationship and suggests areas for research. Montgomery presents developments in the area of decision support systems for retailer pricing decisions. Campo and Gijsbrechts report the methodological challenges in the area of retail management. Van Heerde proposes an additional measurement of sales promotion effects, which in his view, corrects possible ‘misinterpretations’ (his wording). Pursuing Hanssens’ path
[32], Dekimpe and colleagues discuss persistence modelling in marketing and its application to promotion effects. Hanssens, Leeflang and Wittink develop an alternative view of the relationship between marketing science and marketing practice. Drèze reflects on the changes in the customer/firm relationship due to internet and the potential information overload. Morwitz discusses the potential biases due to the ‘mere measurement’ effect. Are purchase intents predictors of subsequent behaviour? Or, are they self-fulfilling prophecies [33, 34]? Or, are they a little bit of both? Finally, Fader and Hardie bring out their definition of ‘simplicity’ in modelling, in light of the recent book edited by Zellner et al. [35]. They give examples of (so-called) ‘simple’ models, which can potentially bridge the gap between academic research and practice.

Overall, we would like to thank the sponsors, the academic colleagues who contributed to the special issue and those who contributed to the conference, the practitioners who commented on the contributions made by the academics in the special issue and those at the conference. Finally, we thank the reviewers for their punctuality and their constructive comments. We would like to thank the Editor-in-Chief of ASMBI, Jef Teugels, for his initiative to publish a special issue on marketing and for his trust in us. He kindly accepted our request to include the short biographies of the contributors and the list of the reviewers at the back of the issue, thereby allowing a special treatment to a special issue. He was a constant source of support for us. Rob Calver and Sian Jones at Wiley-UK and Sanyin Siang at the Teradata Center for Customer Relationship Management were also very helpful and answered our questions with diligence and punctuality. Also, we would like to thank the administrative staff at the Econometric Institute and at ERIM who contributed to the organization of the Conference, in particular Elli Hoek van Dijke and Tineke de Vhee. In total, about 80 individuals were involved in various capacities in the manufacturing of the special issue, excluding the conference participants whose comments and questions enriched the discussion. Without the contribution and support of all these parties, and undoubtedly without each other’s encouragement, the special issue would not have been published. Overall, it was about a three year project, from the time of launch to the time of (planned) publication.

We would like to point out one limitation of the project which gives room for further effort. The Conference and the special issue have mostly attracted consultants as ‘practitioners’, that is, the sellers of research, not the users (the buyers) of research. There are three exceptions in the special issue. There was another at the Conference, a Lead Scientist with the Consumer Science group at a major manufacturer of packaged goods, but because of clearance issues, he decided to pull out from the special issue. He presented a study with a hypothetical data set. The mere fact that consultants (i.e. sellers of research) contributed to the Conference and to the special issue does not imply any value judgment, either from the Guest Editors or from the academic contributors, on the quality of their company services. As marketing ‘experts’, we know that the buyer’s (and user’s) viewpoint is critical. As Guest Editors, we brought a (written) viewpoint from a (key) buyer of research in this editorial. Strangely enough, this seems to be quite a rare experience where a producer of marketing science goes out to listen to a buyer (without avowed or un-avowed intent to ‘sell’ marketing science to him/her but with the sole aim to transmit his/her verbatim message to his peers). But there appears to be (much) room for additional input from the market. The next conference and/or special issue can be entitled ‘Marketing Science: The Voice of the Buyer’. We hope that all these efforts will bear fruit. That is, they will bring academics and practitioners (hopefully, the buyers) closer to each other’s interests, with consultants and other sellers of research, including
academics, making the bridge. The marketing discipline will gain from this enhanced intertwinement.\textsuperscript{1,2}

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REFERENCES


\textsuperscript{1}The Guest Editors thank Bruce Hardie for bringing a study by Dossabhoy and Berger [36] to their attention. The authors address the issue of ‘bridging the gap’ from a different perspective by having deans, a selected set of academics, recent and current executive MBA students and senior business executives rate the ‘importance’ of various dimensions of a research project. They focus on the area of Business Policy and Strategy. They give the names of the faculty and of the deans but they do not specify whether the senior business executives act as consultants, that is, as sellers of research, or as buyers of research (manufacturers or other users of research).

\textsuperscript{2}The problem of ‘black box’ occurs in other areas such as finance. An exception due to coincidence is the Black and Scholes formula for pricing options. Its success and the ensuing Nobel Prize may be due to the fact that, at about the same time as the time of the publication (1973), Texas Instruments ‘brought out (an) affordable hand-held electronic calculator that permitted any trader to use (it)’ [37]. One possible reason that consultants often sell ‘black boxes’ is that the model (the black box) makes up their unique selling proposition (USP), not the data collected. Pricing is mostly determined by the model. For obvious reasons, they do not wish their role to be reduced to collecting the data to feed the model. The model would then be available on their client’s desk. To some extent, these middlemen can be considered as potential hindrances to the diffusion of marketing science in the practitioners’ (end users’) community rather than diffusers.

It may happen that models that are published in major scholarly journals are sold with a different name than the name in the publication. Of course, for consultants, a more positive role of the practitioners’ community consists of implementing and selling methodologies that are published in major journals such as \textit{Econometrica}, \textit{Journal of the American Statistical Association}, \textit{Psychometrika}, \textit{Journal of the Royal Statistical Society} (Series A or B), \textit{Applied Statistics}, and possibly \textit{Journal of Marketing Research}, \textit{Marketing Science} and others. They would openly state the source of their software to the client for transparency. So far, they have refrained from doing this and it does not seem they plan to do so. At the moment, typically the authors take care of the implementation and of the diffusion of their own methodology which means that very little happens past the publication [38]. Perhaps, an association such as the INFORMS Society for Marketing Science (ISMS) may grant a prize to applied researchers (consultants or otherwise) who implement a published methodology with a software and make it available to the practitioners’ community. Ease of replication (and of the checking of input and output) in addition to transparency is key to the diffusion of innovations. The consequence of the current state of affairs is that a publication in a major journal can become a self-serving exercise. It boosts one’s career only. Social welfare is hardly enhanced.