Problems With Marketing's 'Decision' Models

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Abstract

This paper raises concerns about marketing's recent endeavours to construct marketing mix decision models. Complex prescriptive marketing mix models are now commonplace in the marketing literature and yet there seems to be a total lack of documented success of such models. This is perhaps explained by the inherent limitations of best fit causal modelling and the lack of validation work. For a model to scientific value it will have had to be validated in many very different situations, this may be impossible to achieve for regression-style models that make causal inferences. The current marketing modelling literature seems to continue to produce many new marketing mix models oblivious to the problems associated with their causal inferences and without any attempts to validate the models. These problems also substantially diminish the practical value of such models to aid decision making.

Introduction

There is now a well established literature presenting marketing mix models, including a number of books which encourage managers to use marketing mix models to guide their decision making (Bucklin et al. 1998; Lilien 1994; Lilien et al. 1992). There is a feeling that marketing is becoming more "scientific" because of the use of increasingly complex statistical modelling of marketing mix effects. Yet, these so called 'decision models' have produced little or no generalised scientific knowledge and there is no documented track record of their practical applications. These two facts are not widely appreciated.

There are practical problems in developing prescriptive marketing mix models that sophisticated (eg non-linear) statistics do nothing to resolve. Current prescriptive marketing mix models are unlikely to predict successfully because they tend to:
Make simplistic and unwarranted causal assumptions,
Make little or no use of the available descriptive knowledge,
Have no predictive track record,
Be complex and are therefore unlike to ever predict.

We are not only concerned with the scientific value of decision models, the issues we raise also have serious implications for the immediate practical value of such models – these problems and their implications seem to be largely ignored in the marketing literature.

Marketing Mix Decision Models

> *"Decision models are for solving problems . . . They should include the variables and phenomena that are vital for the problem at hand, i.e. controllable activities like price, promotions, and advertising. . . The most used choice model is the logit" (e.g. Guadagni and Little 1983) (Little 1994)*

A typical decision model is Guadagni and Little's (1983) classic logit equation (reconstructed here from G&L's Table 1)

y (Sales, as aggregated individual logit-transformed purchase probabilities) =
Brand-size constants + 3.92x_1 (Brand Loyalty) + 2.97x_2 (Size Loyalty) + 2.11x_3 (Promotion) + 29.21x_4 (Promotional price cut)
- 29.94x_5 (Regular depromoted price) - 0.22x_6 (Prior promotional purchase) - 0.46x_7 (Second prior promotional purchase).

This kind of econometric model has been elaborated since (e.g., see Leeflang et al. 2000; Lilien et al. 1992; Little 1994). But the implication remains that *any* such model is expected to show how controllable variables like "promotions" influence sales. However, we doubt if real-life decision problems can ever be successfully resolved by calibrating a single model on one single set of data (see Ehrenberg 1990). Our specific difficulties are broadly three-fold, concerning the nature of the decision variables, their ability to predict, and their causal inferences.

Decision Variables: Completeness and Complexity

The variables used in decision models seldom correspond to, or are detailed enough to reflect, the realities of everyday decision problems. The explanatory variables which are *not* used in such modelling are legion, as briefly illustrated in Table 1. Indeed, Guadagni and Little's (1983) model only covered promotions and two measures of brand-and-size loyalty; they noted that various marketing phenomena are missing … which we know … influence purchases (1983, p 233). Later research addresses some of these omissions but the problems of "completeness" in causal models always remains.

Table 1 Some Potentially Causative Variables

***Consumers*:**	**Needs, Habits, Demographics, etc.**
***Perceptions*:**	**Brand Awareness, Image, Added Values, etc.**
***Promotional*:**	**Advertising, Money-off, Sales promos, etc.**
***Distribution*:**	**Availability, Out-of-stock, Shelf-space, Display, etc.**
***Functional*:**	**Product attributes (Flavours, Formats, etc.)**
***Price*:**	**Absolute or relative, Value for money, etc.**
***Branding*:**	**Differentiated versus Look-alike, etc.**
***Market Structure*:**	**Clustering, segmentation, etc.**
***Brand Equity*:**	**As hypothesized in the literature.**
***Environment*:**	**The Weather, a War, the Web, etc.**
***The Competition*:**	**Manifold.**
***Advertising*:**	**Planning, Creativity, Execution.**
***The Media*:**	**Planning and Buying.**
***Other Publicity*:**	**Word-of-mouth, Sponsorship, etc.**
***Staff*:**	**Their skills, numbers, experience, etc**
***Shareholders, Investors*:**	**Short-termism, etc**

Modelling many such variables would, however, require many functional assumptions and parameters to be estimated (if enough suitable data existed). The resulting complex models would therefore be highly unlikely to have predictive capabilities (e.g., see the assessment by Professor Zellner in García-Ferrer 1998).

What makes it worse, even if particular *x* variables – advertising or price, say – have zero or non-significant regression coefficients in the single data set analysed, this does not mean that managers need make no decisions about advertising or price, or even leave these decisions unchanged.

This is a case of "damned if you do (*put the variables in*) and damned if you don't (*leave them out*)". The paradox is mostly resolved by tackling marketing-mix decision issues more or less separately as in descriptive modelling (e.g., Ehrenberg 2000).

The Need for Predictability

Decision-modelling studies, as reported in the marketing literature, have seldom been directly replicated. Such modelling has, therefore, usually not been exposed to any severe tests of predictive validity, as in the "tedious history" of Food and Drug Administration tests and in clinical trials, or in good science and engineering more generally. In practice, some kind of invariance of results is needed over many substantially different data sets.

How invariant are any of the coefficients in the Guadagni and Little's (1983) above equation, say? One does not know. The two very different price-related coefficients ±29 are, however, rather like two sides of the same coin: when a price promotion ends, sales generally revert to the pre-promotion level (a special form of negative collinearity). But predicting pricing responses more generally as being fixed ("constant coefficients") would go against all the evidence that price elasticities depend greatly on their pricing context. So how are such results to be used (e.g., predictively extrapolated) in practice?

In the outcome, the above kind of logit modelling then finds that the most important determinants of sales are brand and size loyalty, i.e., *non-decision* variables (Guadagni and Little 1983, p221). Loyalty has, of course, been known to be a key in determining consumer behaviour at least from Ross Cunningham in 1956 onwards but is, however, largely bypassed in the decision-modelling literature (see Leeflang et al. 2000). There is, for example, little mention of the predictable finding over the last 30+ years that measures of loyalty vary little either over time or between brands (e.g., Ehrenberg 2000). Well-established and predictive findings are rarely, it seems, taken into account by decision modellers.

The Assumed Causal Connections and Correlation

Decision models' claimed "insight into marketing effectiveness" mostly seems to assume that a regression equation implies causation. In the equation $y = b_0 + b_1 x_1 + b_2 x_2 + \ldots + \text{error}$, the mathematics unequivocally says that an increase in x_1 by 5 units increases the value of y by 5b numerically, plus or minus a bit. The (usually) tacit assumption that this kind of correlation also reflects something in the real world is exemplified by a recent journal article that reported a cross sectional study of correlations between corporate image questions and questions concerning likely repurchase (Andreassen and Lindestad 1998):

> *"Findings...indicate that [y] 'corporate image' has a significant but indirect impact on [x] 'customer loyalty'….in conclusion loyalty is driven both by disconfirmation of expectations [x_1] and corporate image [x_2]."*

The notion that changes in x_1, and x_2 will cause changes in y is also already entailed by the traditional language of *a priori* dependent (the y) and independent variables (the x's).

But nobody truly believes that correlation = causation, just like that. So, what do such findings mean? While a sales change is typically thought to have been caused by its correlated price-cut, it could also be due to a change in retail distribution, or to a new marketing director, or to any other omitted variables such as in Table 1.

Real World Decision Making

A fairly common (but unrealistic) view is that for a model to be useful, it must provide managers with prescriptive output. By pushing an "if-this-then that" button, the model should tell the manager to double the ad spend or fire half the sales force. Indeed some authors go so far as to speak of automating marketing decisions (Bucklin et al. 1998). Yet, in spite of such confidence, there appears to be no published case histories of how such models have been regularly applied to (even just assist) marketing decision making. This is perhaps not surprising given the total lack of reported validity testing for such models. For managers to act on a newly-estimated regression model would be like imbibing a potion which a medicine man had just "whipped up on the spot", with no tedious history of previous Food and Drug Authority clinical trials.

Managers do not rely on models to give them 'the answer'. In reality, making technical decisions (in marketing and elsewhere) is slow and laborious, and draws on as much descriptive knowledge as possible. When aeronautical engineers use descriptive scientific knowledge, such as Newton's inverse-square law of gravity, they do not expect $g = m_1 m_2/d^2$ to have told the Wright Brothers how to overcome gravity when first achieving powered and sustained airplane flight in1903, or to be telling Boeing now what size GE engines to put on a Jumbo.

Instead, such technical and management decisions are generally reached by combining many different inputs, usually involving years of hard work, about gravity, engine thrusts, air-flows, turbulence, metal fatigue, traffic forecasts, costs and revenues, and so on, together with many simplifying approximations, guesstimates, and politics. There are more things in decision-making and its modelling than seem to be dreamt of by decision modellers.

Conclusion - Description Before Prescription

As far back as 1954 Dorfman & Steiner presented a (still cited see Leeflang et al. 2000) model that specified the optimal values of price, advertising and quality for profit maximisation (Dorfman and Steiner 1954). If true, this would be just about all that a marketing manager ever needs. But who has actually *used* the Dorfman-Steiner theorem, or even now knows about it? If these models really do work why are they never used - not even by academics ?

As Dorfman and Steiner themselves self-critically noted:

> *"There are good grounds for doubting the economic significance of the whole business of writing down profit functions (or drawing curves) and finding points of zero partial derivatives (for graphical points of tangency). Such devices are merely aids to thinking about practical problems and it may be an uneconomical expenditure of effort to devote too much ingenuity to developing them." (Dorfman and Steiner 1954, p.836).*

Causes have many and varied effects, and effects have many and varied causes. Tiny changes in initial conditions lead to massively different outcomes. Developing models that accurately quantify the causal effects of marketing mix changes is a huge, perhaps futile, task – there is unlikely to ever be a cookbook guide to getting rich that works. The idea that fitting an econometric model to a single set of data will lead to a genuinely predictive model seems to us to be wishful thinking in the extreme.

Decision models are supposed to show why particular marketing actions should be undertaken. But Ross Cunningham (1956) already said long ago that "The 'why'of [consumer] behaviour can be effectively attacked only *after* we know its 'what', 'where' and 'how much'." Otherwise we simply have John Bound's soothsayers who try to foretell eclipses (which often had enormous consequences) without knowing of the movement of the planets (Ehrenberg and Bound 2000).

Recently two ACR presidents (see Richins 2000) have bemoaned the lack of descriptive research in marketing. We have many complex causal models and a dearth of formal descriptive knowledge of marketing mix activity. It seems that we need empirical generalisations that can form the basis of descriptive theories and models, eg the Dirichlet (Ehrenberg 2000), before we embark on ambitious attempts to model the marketing mix determinants of market-share. Or at very least we should begin building some descriptive knowledge about the successful performance or otherwise of our decision models.

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