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Decision models or descriptive models?

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Abstract

This paper contrasts a classic example of a logit decision model with a widely used descriptive model, the Dirichlet.

Decision modeling, reviewed by Leeflang and Wittink in this issue of *IJRM*, aims to help make marketing-mix decisions. However, we have serious doubts about this sort of modeling: its inputs, its outputs, its assumed causality, and its frequent lack of empirically grounded predictability. It also seems to seldom really take account of already well-established marketing knowledge.

In contrast, descriptive modeling more simply aims to depict actual or potential marketing knowledge, and to apply it. Such modeling often deals with marketing-mix factors separately instead of attempting to do so in one overall model.

Keywords: Sales; Marketing mix; Marketing insights; Brand performance measures; Logits; Decision support; Dirichlet; Empirical generalisations

1. Introduction

In this paper, we compare and contrast what is commonly said about decision models and descriptive models in marketing. Do they or don't they help with (a) marketing decisions, and (b) providing insights about consumer behaviour?

Little (1994, p. 155) contrasted the two kinds of models broadly as follows

> *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... but leave out those that are not ('artful incompleteness').... The most-used choice model is the logit.
>
> *Descriptive* models seek to uncover marketing phenomena and to represent them.... This is the classical task of science.... Descriptive models without marketing decision variables...go back to the work of Ehrenberg (1959, 1988)... and others (e.g. the NBD and the NBD-Dirichlet, or Dirichlet for short).

Our purpose here is to elucidate these contrasts: models with or without explicit descriptive knowledge, and models with or without explicit decision variables. What, very briefly, has been claimed for them? What has been their practical use and proven validity?

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We are responding to the Editor's invitation to comment on the lead article "Building models for marketing decisions: Past, present and future" by Leeflang and Wittink (2000a) in this special issue of *IJRM*. However, we also go significantly further and provide our own perspective. As two specific cases, we therefore focus on a classic instance of logit analysis and on a well-established descriptive model, the NBD-Dirichlet.

Our paper assumes that for a model to be credible and usable, it will have shown some kind of demonstrable invariance across many substantially different situations — market conditions, products, brands, SKUs, countries and points in time, mostly with almost totally independent data sets (not just intrinsically similar "hold-out" samples).

2. Decision models

Decision-support models are said to contain marketing variables that a manager can control or at least influence. Such marketing mix models are for solving marketing management problems (Little, 1994). This seems to imply that these marketing variables should have predictive and/or causal powers to affect what will happen when managers change the variables. Leeflang and Wittink (2000b) even speak of automating marketing decisions — the model will make the decisions for the managers. In what follows we question this.

Leeflang and Wittink (2000a) in their current overview of decision models do not actually quote an explicit instance. We therefore refer to Guadagni and Little's (1983) much-quoted logit approach, reconstructed here from Guadagni and Little (1983, p. 218, Table 1), as being a well-known example to illustrate some of the modeling issues here. The model typically relates sales to loyalty and to promotional inputs

$$
\begin{aligned}
&y\,(\text{Sales, as aggregated individual logit-transformed}\\
&\quad \text{purchase probabilities})\\
&\quad = \text{Brand/Size constants} + 3.92x_1\,(\text{Brand Loyalty})\\
&\qquad + 2.97x_2\,(\text{Size Loyalty}) + 2.11x_3\,(\text{Promotion})\\
&\qquad + 29.21x_4\,(\text{Promotional price cut})\\
&\qquad - 29.94x_5\,(\text{Regular depromoted price})\\
&\qquad - 0.22x_6\,(\text{Prior promotional purchase})\\
&\qquad - 0.46x_7\,(\text{Second prior promotional purchase}).
\end{aligned}
$$

This kind of econometric model has been elaborated since (e.g. see Little, 1994; Lilien et al., 1992; Leeflang et al., 2000). However, 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 threefold, concerning the nature of the decision variables, their ability to predict, and their causal inferences.

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.

2.1. 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. Would reduced ad spend, for example, be expected to depress:

- *The Retailer* — Delisting, reduced shelf-space, needing more trade deals, etc?
- *The Salespeople* — Demotivating them? Or making them try harder?
- *Consumers* — Fewer of them buying? Or the same number buying less? Or fewer being retained or converted?

Or would reduced spending encourage the competition, e.g. copycat cutbacks or alternatively, higher spending ("*Now's* our opportunity!")? Leeflang and Wittink (2000a) say little about the level of detail required for decision-making.

In addition, explanatory variables which are *not* used in such modeling 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 (Guadagni and Little, 1983, p. 233). Later research addresses some of these omissions but the problem of "completeness" in causal models always remains.

Modeling many such variables would, however, require many functional assumptions and parameters to be estimated (if enough suitable data exist). 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 for example with the descriptive Dirichlet modeling in Section 3 and the "artful incompleteness" in Little's (1994, p. 155) earlier definition.

2.2. The need for predictability

Decision-modeling studies, as reported in the marketing literature, have seldom been directly replicated. Such modeling 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.

This issue of invariance has been extensively examined in macroeconomic modeling for example, especially by Hendry (1983, 1995). But Leeflang and Wittink (2000a) quote few, if any, invariant results from the classic decision model literature.

How invariant are any of the coefficients in Guadagni and Little's (1983) above equation, say? One does not know. The two very different price-related coefficients of ± 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. However, they certainly show their own "local invariances", like elasticities being consistently lower for big brands than for small ones (e.g. Guadagni and Little, 1983; Scriven and Ehrenberg, 1999; Sethuraman et al., 1999). So, how are such results to be used (e.g. predictively extrapolated) in practice?

In the outcome, the above kind of logit modeling then finds that the most important determinants of sales are brand and size loyalty, i.e. *non-decision* variables (Guadagni and Little, 1983, p. 221). Loyalty has, of course, been known to be key determining consumer behaviour at least from Cunningham (1956) onwards, including a special issue of *IJRM* in 1997 (Vol. 14, No. 5). Loyalty is, however largely by-passed in the decision-modeling literature, as reviewed in this issue of *IJRM*. 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, 2000b). This well-established and dominant finding is rarely, it seems, taken into account by decision modelers.

2.3. 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 $y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + \text{error}$, the mathematics unequivocally says that an increase in x_1 by 5 units increases the value of y by $5b_1$ 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, p. 82):

> Findings... indicate that 'corporate image' [x_2] has a significant but indirect impact on 'customer loyalty' [y] ...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).

However, 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.

2.4. The use of decision models

Leeflang and Wittink (2000a) go little into the actual uses of decision models in the literature, or discussions thereof. Instead, they mainly note various decision models that have been reported, without much comment or evaluation. For example, they quote the Dorfman and Steiner (1954) normative theorem as specifying the optimal values of price, advertising and quality for profit maximisation. This, it would seem to us, is all that a marketing manager might need.

However, what managers have actually used the Dorfman and Steiner (1954) normative predictions (or their later theoretical developments (e.g. see Leeflang et al., 2000, pp. 144–150, 154–155))? So why quote the theorem, and especially without its originators' remarkably self-critical judgement at the time:

> 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).

More generally, Leeflang and Wittink (2000a) list marketing problem areas where decision models have been developed (e.g. in their Section 3.2). However, if there really are many successful applications, why is firms' demand for such models called "latent" (Section 3.2)? Does the literature reviewed by Leeflang and Wittink perhaps only imply that academic decision models must be useful because they have been written about (i.e. "used") by academics?

One apparent exception is Bucklin and Gupta's (1999) report on their industry survey of the use of scanner data. This report claimed specifically that logit analyses had led to reduced spending on coupon promotions, i.e., a strategic marketing decision. However, it gave no modeling specifics and no references. Also, as an exercise in allocating "causes", it seems to us more likely that the roots of the trade's disenchantment with coupons were simply descriptive, namely

- *consumers* hardly using coupons (only some 3% are generally redeemed),
- *retailers* finding them expensive and bothersome to handle,
- *manufacturers* having seen few dramatic sales or profit upturns.

Despite the apparent lack of success stories, decision models are at times thought to be more practical than descriptive models, and academics have claimed that managers have looked to these models rather than to descriptive ones (e.g. Rossiter, 1994). But how many managers have in fact been successfully pushing "if–this–then–that" buttons to tell them instantly to double their ad spend or fire half the sales force?

Our alternative view, which we feel does reflect the realities of managerial life, is that making engineering-type management decisions is slow and laborious. We conjecture that few aeronautical engineers believe Newton's Inverse-Square Law of Gravity $g \cong m_1 m_2 / d^2$ told the Wright Brothers instantly in 1903 how to overcome gravity in order to achieve the first sustained powered flight, or that even now, g is telling Boeing what size engines to put on to their Jumbos.

Instead, technical and management decisions are generally reached by combining many different inputs, about engine thrusts, air-flows, turbulence, gravity, metal fatigue, bursting tyres, traffic forecasts, costs and revenues, and so on. In engineering, this usually involves years of hard calculation and design work, together with many simplifying approximations, guestimates, committee meetings and politics. Similarly in marketing. Hence, in the descriptive modeling of consumer behaviour patterns that is outlined in Section 3, marketing-mix factors are often studied separately, at least in the first instance (as for example in Kathy Hammond's work on promotions reported in Ehrenberg et al., 1994).

Indeed, there are more things in decision-making and its possible modeling than seem to be dreamt of in the philosophies recounted by Leeflang and Wittink (2000a) in their review. All in all, it seems to us that the decision-modeling literature says very little about actual marketing decisions.

3. Descriptive models

Descriptive models of consumers' buying behaviour — e.g. Hendry, first-order Markov, NBD, NBD–Dirichlet, etc., plus their more complex descendants (e.g. Bhattacharya et al., 1996; Sethuraman et al., 1999), receive little coverage in the decision-model literature, let alone are they *used* by most academic modelers (Leeflang and Wittink, 2000a, Section 2.1; Little, 1994, p. 155, are very brief exceptions). The ways in which good descriptions of well-established marketing phenomena can, for example, provide decision-support and marketing insights does not yet seem to have been widely appreciated. Hence, we briefly outline some key aspects.

Table 2, as a specific example, gives nine standard "Brand Performance Measures" (BPMs) for Folgers, P&G's instant coffee brand in the US (quoted from Ehrenberg and Uncles, 2000). Such measures are continually tracked on a vast scale by the world's larger marketing research companies (e.g. AC Nielsen, IRI, TNSofres, GfK, etc.) and their clients.

The resulting statistics are seldom presented in this simple way, but Table 2 describes how Folgers' share of the market of 24% was due to 11% of US households buying the brand in the year, on average 3.2 times. This result helps us go beyond mere description towards explanation: the two numbers — 11% buying 3.2 times — are by definition the mathematical determinants of Folgers' annual sales and of its 24% market share.

Table 2
A brand performance audit

Folgers USA 1992	Brand size			Loyalty-related (annual)					
	Market share (%)	% Buying in		Purchases per buyer	% Buying		Category		100% Loyal
		Week	Year		Once	5+	Purch	SCR[a]	
Observed	24	1	11	3.2	46	18	6.4	50	14%

[a] Share of category requirements.

Three inter-related questions about such "descriptive" findings, which we now discuss, are:

1. Why are such numbers what they are? Why did 11% buy Folgers 3.2 times? Why did half (46%) of its customers buy it only once? Why did Folgers satisfy only half of its customers' instant coffee requirements in the year (an SCR of 50%)? In short, how do these measures vary between brands, and why?
2. What does this tell us, for example, about competition? What marketing insights follow?
3. What does one *do* about it (i.e. what decision applications are there out there)?

3.1. Compared with what?: Generalisable regularities from brand to brand

Light is thrown on such BPMs by comparing them with (a) the BPMs for other brands, and (b) the theoretical Dirichlet model predictions as well-established norms. Table 3 summarises and verifies such benchmarking comparisons for half a dozen of the BPMs, for each of the top eight brands in a dozen varied product-categories (Ehrenberg and Uncles, 2000).

Four by now well-established invariant patterns are that:

1. market shares and penetrations both decrease steeply (by factors of up to 10 from A to H, i.e. about 1000%);
2. most of the *loyalty-related* measures, however, stay broadly the same across the brands, or decrease far less steeply — the "Double Jeopardy" phenomenon (McPhee, 1963; Ehrenberg et al., 1990);
3. the average rate of *category* buying by buyers of each brand, however, always decreases a little for the larger brands (e.g. from 13 for Brand H to 10 for Brand A);
4. the theoretical NBD-Dirichlet predictions "T" mirror the observed values "O" closely (to within about 4 percentage points or so for the individual brands in each of the categories), i.e. the predictions "do quite well" (Leeflang et al., 2000, p. 234).

These patterns show what competitive markets are like, as found across more than 50 product and service categories, and over several decades (Table 4). Anyone with access to buyer-panel data can check or expand on the generalisability or invariance of the findings.

Table 3
Observed and theoretical performance measures

Annual	*Brand Size*			*Loyalty-Related Measures*							
Brands **(by share)**	Market Share	% Buying		Purchases Per Buyer		% Buying 5+ times		100%-loyal		Cat.Purch Per Buyer	
	O%	**O**	T	**O**	T	**O**	T	**O**	T	**O**	T
Brand A	**28**	**46**	46	**3.9**	3.9	**24**	25	**22**	16	**10**	10
Brand B	**19**	**35**	36	**3.6**	3.5	**21**	20	**16**	13	**11**	11
Brand C	**12**	**25**	25	**3.1**	3.1	**16**	17	**11**	11	**12**	12
Brand D	**9**	**22**	21	**2.8**	2.9	**13**	14	**11**	10	**11**	12
Brand E	**7**	**14**	16	**3.2**	2.8	**19**	14	**12**	9	**12**	12
Brand F	**5**	**12**	11	**2.7**	2.8	**11**	12	**10**	9	**12**	12
Brand G	**4**	**11**	10	**2.7**	2.9	**11**	12	**9**	9	**12**	12
Brand H	**3**	**6**	7	**3.2**	2.6	**13**	13	**7**	9	**13**	12
Av. Brand	**11**	**21**	21	**3.1**	3.0	**16**	16	**12**	11	**12**	12

O = observed; T = theoretical Dirichlet predictions.
Arrows signify decreasing values.

Table 4
Varied replications for Dirichlet-type patterns

Products and services
50 Food, drink, cleaners, and personal care products
OTC medicines, prescription drugs
Gasoline, aviation fuel, cars, PCs, ready-to-mix concrete
Retail stores and chains (including for womenswear)
TV programs and channels
Brands and variants
Large and small brands
Pack-sizes; flavours
Private labels
Price bands
Time, space, and people
Different points in time, 1950–2000
Different-length analysis-periods
Britain, USA, Japan, Germany, Australia, etc.
Light and heavy buyers; demographic subgroups
Household or individual purchases
Market conditions
Near-steady state and non-partitioned markets
Dynamic markets for loyalty measures
Within partitioned sub-markets
Subscription and repertoire markets

Other invariant patterns described in the literature include the nature of consumer heterogeneity (Ehrenberg, 1959), period-by-period repeat-buying including "Conditional Trend Analysis" (Goodhardt and Ehrenberg, 1967), "Natural Monopoly" (McPhee, 1963), the "Duplication of Purchase Law" and "IIA" (Goodhardt, 1966), and the highly predictable effects on the different BPMs of the chosen length of the analysis-period (Ehrenberg, 2000b). In the decision-model literature such descriptive findings are usually conspicuous only by their absence (e.g. the half page or so in Leeflang et al., 2000, p. 234, and Leeflang and Wittink, 2000a, Section 3.3).

3.2. Marketing insights

Such invariant findings have, over time, led to many decision-related marketing implications and insights (see again Ehrenberg and Uncles, 2000 and earlier references). Descriptive models seem to become *explanatory* by linking them to different aspects of the market and of marketing, e.g. for Consumers, Brands, Marketing-mix inputs, and Managerial issues. Examples are briefly as follows.

3.2.1. For consumers

Dirichlet implications for experienced consumers are that they mostly have heterogeneous but steady split-loyalty purchase propensities instead of each consumer being constantly buffeted around by various marketing inputs.

These purchase propensities (or probabilities) are usually "zero-order" and "as-if-random" (i.e. purchase feedback or learning will mostly have stabilised long ago with by now highly experienced consumers (e.g. Bass et al., 1984; Ehrenberg and Uncles, 2000).

Markets are unsegmented between competitive brands (but potentially segmented for subcategories or categories, e.g. cat food is bought by cat owners) (Kennedy and Ehrenberg, 2000 — a controversial but double-award-winning and much discussed paper).

3.2.2. For brands

All loyalty-related measures as in Table 3 (e.g. repeat-buying; 100% loyals; share of category requirements SCR; etc.) tend to be highly correlated ($r > 0.9$). They appear to measure the same thing, i.e. "*loyalty*". Loyalty exists but varies little between competitive brands.

In theoretical models like the Dirichlet, brands are by definition closely substitutable, i.e. undifferentiated except for their names and market shares: thus "Brands are Brands", or "The Commodity with a Name". This is also thought to be so in practice for directly competitive brands, because worthwhile competitive advantages are soon copied (see also Ehrenberg et al., 1997).

Functional differences occur *within* brands (pack-sizes, flavours, hatch backs, etc). SKU-level product variants are again much the same for most brands, as noted in Guadagni and Little (1983) for pack-sizes. (Functionally different sub-markets also occur and are usually self-evident, e.g. decaffeinated versus regular coffee, moist versus dry cat food, etc.) All this tends to be accommodated in the broad NBD-Dirichlet approach by allowing for the appropriate functional groupings of stock-keeping units (Singh et al., 2000).

Minor product or emotional differences can also occur between brands (e.g. the bottle-top or the car-door handle). However, they are seldom advertised or featured on packs, or noticed by consumers until after they have chosen the brand in question (e.g. Ehrenberg et al., 1997).

3.2.3. For the marketing-mix

The Dirichlet approach accommodates all such brand differences by generally expecting them to affect the items' different penetrations (i.e. how many consumers have an item in their repertoires or consideration sets). However, marketing inputs would seldom affect average purchase frequencies or other loyalty measures, since these tend to be steady from brand to brand or item to item, as in Table 3, except when penetrations are very high (Singh et al., 2000).

Advertising appears to be largely aimed at competing and hence similar brands. It is thought to act as publicity, largely to remind and reassure the experienced consumer and help to defend the brand's penetration, rather than having to persuade consumers to become more loyal (Ehrenberg et al., 2000; Mills et al., 2000).

Managers may nonetheless pursue loyalty-building aims (e.g. loyalty cards, relationship marketing, etc.). The Dirichlet findings then explain why such efforts do not work as expected (i.e. no major increases in loyalty, see Sharp and Sharp, 1997a).

3.2.4. For marketing management issues

The principal strategy implication stems from the near-steady state which is observed for most markets most of the time. Marketing has therefore mainly to maintain a brand's competitive position in the pecking-order — "running hard to stand still" — with only an occasional gain (a bonus) or loss, as discussed variously in our preceding references.

It is often thought when comparing competing brands that any deviations from the descriptive norms would or should be the prime interest — e.g. the norms being something to "beat" and to "make your brand grow". However, the O–T deviations for established brands as in Table 3 seem generally small or not surprising or not very consequential (e.g. that that particular brand has patchy distribution). In practice the loyalty-related measures are mostly "just right", as Bhattacharya (1997) has put it in this journal.

An interpretative parallel to such near-steady market structure is again provided by gravity: what overwhelmingly matters when we walk on the earth, fly in aeroplanes, or play ball, is that gravity is approximately constant, i.e. $g \cong 32\ \mathrm{ft/s^2}$ near the surface of the earth. However, it is predictably a little higher down a mine and a little lower up a mountain, and with other tiny variations, which *very occasionally* indicate oil under the surface and can make one rich. However, mostly both fact and theory say that gravity is pretty much constant. And similarly for buyer behaviour: the facts and the descriptive models say that loyalty measures hardly vary from brand to brand other than directly with market share (Double Jeopardy), and this can have numerous managerial and conceptual marketing applications as we have noted.

Well-grounded descriptive models (i.e. knowledge based on empirical generalisations of invariance) thus can play the classic role of building-blocks for predictive and explanatory theory (Hunt, 1991) and for decisions. They can provide both managers and academics with benchmarks to interpret and to help in assessing the impact of marketing decisions on BPMs. Without this, it seems difficult to make sense of the vast volumes of marketplace data that are available today.

3.3. Practical applications

As we now briefly list for the Dirichlet approach as an instance, a well-grounded descriptive model can have many practical applications. For example:

(i) Brand Audits: Evaluating the performance of individual brands, as in routine tracking studies. Many hundreds of cases of benchmarking and normative analyses have been covered, usually showing that most brands are "normal" as in Table 3 (e.g. Ehrenberg and Uncles, 2000 and the earlier references again). This is well worth checking routinely (i.e. tracking studies mostly tell us that things are as before, i.e. as expected).

(ii) Extensions to New Conditions: The model has been widely used to establish whether the same invariant patterns apply for other conditions altogether, for example, in strange countries or atypical categories such as cars and gas with solus site distribution, as summarised in Table 4.

To learn what any previously unknown market was like, a simple approach was benchmarking against the Dirichlet: are the new data like the other markets which are already known, or are they different (and if so, how and why)? Insofar as understanding their market does affect what managers do, it will affect their decisions and how they evaluate their effects.

(iii) New Brands: A recent example is that new brands have unexpectedly been found to gain near-instant normal loyalty (Ehrenberg and Goodhardt, 2000). This would not have been possible without the already known near-invariance for established brands as in Table 3, i.e. that they in effect do not differ in loyalty.

(iv) Market Partitioning: A major use of the Dirichlet norms has also been in establishing the "non-Dirichlet" clustering of brands by functional or other attributes (e.g. decaffeinated and regular coffee; leaded and unleaded gasoline; luxury cars). Working out which brands compete more/less closely is a typical goal of many traditional clustering, U&A, and segmentation studies. It has here again been made easy by applying well-based benchmarks (see for example Sharp and Sharp, 1997b).

(v) Dynamic Brands or Markets: Short-term advertising responses, seasonalities, stock-outs, promotional blips, longer-term trends, etc., have also increasingly been covered by using the Dirichlet steady-state norms (e.g. Ehrenberg, 2000a). A deeper question is how market dynamics show up — are increased sales due to more buyers, more per buyer, more heavy buyers or fewer 100% loyal ones than expected, and so on (see Ehrenberg, 2000a).

Various researchers have also pursued other applications of the Dirichlet such as, very briefly, (vi) Brand or Line Extensions (Ehrenberg and Goodhardt, 2000), (vii) Cannibalisation (Lomax et al., 1996), (viii) Price Sensitivities (Scriven and Ehrenberg, 1999), (ix) Loyalty Programs (Sharp and Sharp, 1997a), (x) Subscription markets (Sharp and Wright, 1999). In all cases, the studies compared and evaluated what happened with what could be expected from the known descriptive empirical and theoretical Dirichlet-type benchmarks.

4. Discussion

The long-standing divide between what have been called decision and descriptive models in marketing is, we think, both unnecessary and unhelpful.

Some decision-modelers have denigrated mere description. For example, echoing Little and Anderson (1994), Dyson et al. (1997, p. 13) criticise descriptive models by saying:

> The Dirichlet model describes aspects of buyer behaviour in steady markets.... These are not conditions that the marketing team necessarily want to exist. In fact their job is to change the situation to the benefit of their brand. Unfortunately, the Dirichlet does not allow any real insight into how to affect these changes.

We think of the first part of this as rather naïve, "I wish my brand was bigger/better/etc.", thinking (and the last sentence as wrong). Coming down to earth, Leeflang and Wittink (2000a, Section 3.4) noted, and we agree, that

> The complexity of real-world decisions often makes it difficult to identify the unique role attributable to [decision] models when strategic decisions are made.

In contrast, many applications of descriptive Dirichlet-type patterns are quite easy to identify, as we have illustrated. The model tells us that usually a brand can grow through gaining additional loyal customers as in Table 3, and not through making its customers more loyal. This may seem lacking in ambition, but is what the facts appear to say ("Don't blame the messenger") and certainly shows how mere description need not be "simple". Indeed, the systematic and thoughtful depiction of marketing phenomena usually leads to many insights, decision-support, and informed action and evaluation, as in other scientific and engineering endeavours.

Protagonists of decision models say or imply that decision models (or even only decision models) will show how and why particular marketing actions should be undertaken. However, Cunningham (1956) already noted long ago that the "why" of consumer behaviour for instance (e.g. extra sales) can be effectively attacked only *after* we know its "what", "where" and "how much". Otherwise one ends up with John Bound's soothsayer who tries to foretell an eclipse without knowing of the movement of the planets round the sun (Ehrenberg and Bound, 2000).

Yet, the known descriptive simplicities of buyer behaviour as illustrated in Section 3 are hardly even mentioned in decision modeling, e.g. that competitive markets are of necessity mostly in a state of competitive near-equilibrium, and that loyalty-related measures hardly differ from brand to brand after allowing for the effects of underlying market-share.

This well-established descriptive knowledge is hardly used in the marketing model literature, nor yet explicitly criticised and dismissed. This is so not only in Leeflang and Wittink's (2000a) lead-paper in this issue of *IJRM*; but also in Bucklin and Gupta's (1999) recent survey specifically of the commercial use of scanner-panel data; in most of the major consumer-behaviour treatises (e.g. Engel et al., 1993; Solomon, 1992); and in the countless marketing-management texts (from Kotler, 1999, downwards).

Authors who *do* describe the known descriptive realities of buyer behaviour are still rare (e.g. East, 1997; Foxall and Goldsmith, 1994; Lilien et al., 1992; McDonald, 1992; Weilbacher, 1993). Though there is evidence that some in industry appreciate the explanatory capacity of descriptive modeling — recently Mike Duffy of Kraft contrasted Kraft's own decision-modeling unfavourably with our descriptive approach:

> Their descriptive approach can provide insights into *why* things happen, as opposed to our mix-model approach to determine *what* things happened... (Ehrenberg, 2000a).

The key point of "why-orientated" descriptive modeling such as the Dirichlet is that it can show how and why sales increase when they do increase. From this we can learn.

To summarise, we have sought in these comments to rehearse our view that dedicated prescriptive or decision models are unlikely to predict successfully because they usually:

- make little or no use of the large amount of well-established descriptive knowledge that exists,
- tend to be complex, with many parameters,
- have no solid track-record of predictive practical applications,
- make unsubstantiated causal assumptions.

In contrast, good descriptive models

- provide insights and predictable benchmarks for evaluating change,
- are simple, with few or invariant parameters,
- have a long track-record of published replications and applications,
- help us slowly to learn about causes and their effects.

As in many other areas of engineering, models which successfully describe generalisable marketing phenomena first show us what, where, how, and how much. However, they can then also help in deciding what to do and why.

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