# Original Article

# Brand management and the marketing mix model

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**ABSTRACT** Brand management is typically defined as the way in which brands are positioned in the marketplace, both in terms of tangibles such as price, packaging and the marketing mix and intangibles such as consumer perceptions and brand equity. The conventional marketing mix model is often used to inform the tangible elements, but is lacking into two key aspects. Firstly, it ignores the role of intangibles. Secondly, the focus is solely on individual brands in isolation. This ignores the wider competitive context, where the decision to choose one brand is the simultaneous decision not to choose another. Successful brand management, however, requires a simultaneous holistic view of all players. To address both issues, this article argues for a dynamic time series version of the discrete choice attraction model. Firstly, the demand system structure treats the entire category as a single unit, capturing competitive steal, cannibalisation, halo and category expansion effects of brand-specific marketing. This provides accurate marketing return on investment and budget allocation, facilitating the manufacturer-retailer relationship. Secondly, the time series approach allows us to quantify the evolution and drivers of consumer brand tastes – critical to understanding brand intangibles. This enables managers to set marketing strategy for optimal long-term brand performance.
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## INTRODUCTION

A key decision facing the brand manager is how best to allocate an often limited marketing budget across a wide set of marketing activities. This is a challenging task in a competitive market place involving complex marketing strategies, where competitor activity can often upset careful planning. In order to identify the best course of action under these circumstances, a good starting point is an understanding of the performance of each marketing mechanic relative to all competing brands in the category. This information may then be used to help reallocate planned marketing resources with a view to maximising brand volume going forward.

The conventional approach is the single equation marketing mix model, which formulates a demand equation as a function of selected marketing drivers. Response parameters are then estimated using classical regression techniques. However, given the highly competitive nature of many categories, ranging from FMCG to consumer electronics and automotive, it is

often preferable to use a framework that can provide a holistic view of all players together – rather than focusing on separate demand patterns in isolation. Such approaches, derived directly from the consumer decision-making process, are known as demand systems.

Demand system approaches take two broad forms: continuous and discrete choice. Continuous choice structures are based on classical utility maximisation ideas where the consumer chooses equilibrium quantities of all goods in the choice set. Discrete choice forms, on the other hand, originate from 'characteristics' theories of utility maximisation (Lancaster, 1966) invoking a binary structure where the decision to choose one good is the simultaneous decision not to purchase any competing alternative. This structure is more prevalent in marketing theory and is ideally suited to quantifying the competitive performance of brand marketing strategies across all players in the market.

In this article, we focus on the application and managerial benefits of the discrete choice demand system. The next section outlines the economic foundations and features of the approach – compared with the somewhat 'looser' forms of the single equation model. The subsequent section examines dynamics and parameter estimation. The penultimate section looks at an application of the model and how it may be used to aid the brand and category management process. The final section concludes.

## DEMAND SYSTEM STRUCTURES AND THE MARKETING MIX MODEL

The marketing mix model is a commonly used tool to evaluate Return on Investment (ROI) and inform optimal allocation of the marketing budget. The model structure is derived from microeconomic theories of consumer demand and econometric techniques are used to estimate demand response to marketing investments. The result is a separation of product sales into base and incremental volume. Base sales represent the long-run or trend component of the product time series, driven by factors ranging from regular shelf price and selling distribution to underlying consumer brand preferences. Incremental volume, on the other hand, is essentially short run in nature, capturing the period-to-period sales variation driven by temporary selling price, multi-buy promotions and off- and online media activity. These are converted into incremental revenues or profits and benchmarked against costs to calculate ROI to each element of the marketing mix.

## Single equation approaches

Conventional marketing mix modelling concentrates on selected items and/or brands in the manufacturer's portfolio. This approach is adequate if we wish to focus on single products at a time and, in the case of the multiplicative form, is a popular choice due to the fact that estimated parameters are immediately interpretable as demand elasticities. However, with simplicity come certain (inter-related) drawbacks:

- When estimating sets of conventional equations across competitive products, it is perfectly possible that volume steal is either less than or greater than volume gains. Whereas this issue is generally interpreted as category growth or shrinkage respectively, it is simply a consequence of the fact that sets of single equations are unrelated to each other and do not 'add-up', telling us nothing about genuine category effects of product marketing.
- We cannot accurately define how much of the marketing incremental is due to substitution from other brands and how much is due to category expansion effects. This is an important distinction from the point of view of category management and
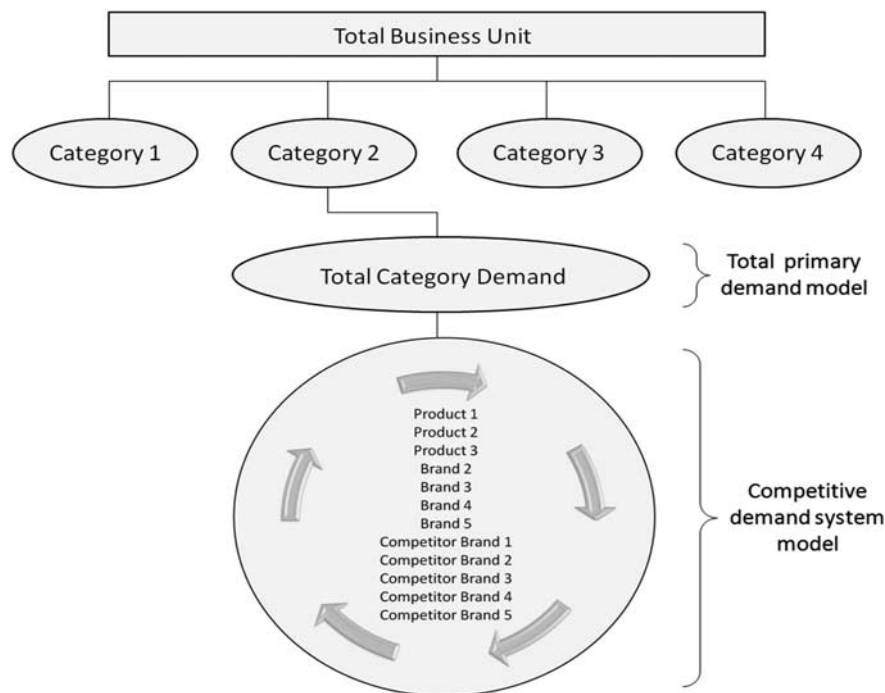
**Figure 1:** Demand system structure.

optimising manufacturer and retailer behaviour.

- Any one brand's volume sales and the impact of its marketing mechanics will be heavily influenced by all simultaneous competitive marketing activity across the category. By ignoring these interactions, the conventional approach does not accurately evaluate the contribution of each marketing mechanic to a specific brand.

## Demand system approaches

One solution to these issues is holistic category level analysis that simultaneously evaluates the interactions between all the players. This gives brand managers a panoramic view of the category and the relative performance of their brand(s) within it. To address this, simultaneous equation demand system approaches are required. Figure 1 illustrates a typical structure, where a manufacturer operates across four distinct categories, competing against differentiated products and brands. Category 2 represents a

case where the firm produces five key brands, which may be split into individual products, competing against five competitor brands. This can be viewed as a stock of consumer demand flowing through the system – with each product/brand competing for share as a function of an (optimised) marketing mix strategy and all other relevant demand drivers. The net result is not necessarily a 'zero-sum' game. Consequently, the system is complemented with a model for total category demand.

There are various mathematical structures that can be used to formalise the structure of Figure 1. On the one hand, we have continuous choice models such as Stone's Linear Expenditure system (Stone, 1954), the Rotterdam model (Theil, 1965; Barten, 1966) and the Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980). On the other hand, there are the discrete choice approaches such as the attraction models illustrated in Nakanishi and Cooper (1974). In this article, we focus on the attraction model due to its more widespread

use in the marketing literature (*inter alia* Cooper and Nakanishi, 1988; Carpenter *et al*, 1988; Fok *et al*, 2003)[1]. Figure 1, for a representative category, is written as follows:

$$\ln\left[\frac{s_{it}}{s_{pt}}\right] = \left[\alpha_i - \alpha_p\right] + \left[T_i - T_p\right] + \left[\delta_{it} - \delta_{pt}\right]$$

$$+ \sum_{k=1}^{M}\sum_{j=1}^{n}\left(\beta_{kij} - \beta_{kpj}\right)\ln X_{kjt} + \left[\varepsilon_{it} - \varepsilon_{pt}\right] \quad (1)$$

$$\ln CV_t = \alpha + T_i + \delta_t + \sum_{j=1}^{n}\sum_{k=1}^{K}\rho_{ij}\ln X_{kj}$$

$$+ \sum_{L=1}^{l}\phi_i Z_t + u_t \quad (2)$$

Equation (1) represents a brand share model, predicting the (aggregated) probability of product choice from a consumer consideration set in terms of a range of explanatory variables $X_{kjt}$, covering marketing and other relevant demand drivers.[2] The model is written as a set of $n-1$ reduced form log-ratio share equations, each as a function of product- or brand-specific effects $\beta_{ki}$ for each explanatory variable and a full set of direct competitor cross effects $\beta_{kj}$.[3] The $p$th numeraire share equation is defined by the model adding-up constraint – which is used to derive the underlying (structural) parameters of all $n$ shares.

Equation (2) gives a model for the logarithm of overall category volume ($CV$), estimated in terms of brand driver variables $X_{jt}$, a range of macroeconomic drivers $Z_t$, trend and seasonal components.

### Benefits and managerial advantages

Together the brand share system (1) and total category volume model (2) give a set of product volume equations providing several advantages over the single equation approach.

- Firstly, the share structure, via the $\beta_{ki}$ parameters for each marketing mix variable contained in the matrix $X_{kjt}$, allows us to identify pure substitution and complement effects. This highlights the extent to which

each product/brand's marketing strategy stimulates cannibalisation and halo effects within the manufacturer portfolio together with steal across competitive products. This effectively solves the adding-up issue highlighted earlier.

- Secondly, the model accurately separates substitution and category expansion effects. Not only does this provide correct estimates of brand switching behaviour, building on the work of Van Heerde *et al* (2003), it also helps evaluate the impact of product-specific marketing effects on total category demand, facilitating the manufacturer-retailer relationship.

- Finally, marketing response and ROI results are provided for each brand in a fully competitive context – allowing a comparison of each client product or brand within the modelled category, improving budget allocation and short-term brand and category management.

## FULL DYNAMIC MODEL STRUCTURE AND PARAMETER ESTIMATION

The next step in the process is quantification of the share and category response to variation in each of the explanatory variables. This is where econometrics enters the picture: a statistical regression-based procedure to estimate the demand system parameters. Estimation requires acknowledgement of the intrinsically dynamic nature of the share and category demand equations and adherence to the adding-up constraint inherent in sum-constrained share systems. Firstly, the conventional econometric approach to estimating the parameters of any mix model is via standard OLS regression techniques, with a fixed long-term baseline component. However, marketing mix models involve time-ordered sales observations and should be represented as time series regressions with (potentially) evolving baseline and seasonal components estimated simultaneously with all

relevant demand driver variables. This generates a more flexible dynamic approach to the mix model, illustrated in Cain (2005, 2008), which can be generalised to systems of demand equations (Cain, 2005, 2010). Secondly, maximum likelihood estimation of the system ensures that the adding-up constraint is preserved and that the demand response estimates are invariant to the choice of *numeraire* share (Barten, 1966). For estimation purposes, the demand system structure is written as:

$$Ln\left[\frac{s_{it}}{s_{pt}}\right] = \mu'_{it} + \delta'_{it} + \sum_{k=1}^{M}\sum_{j=1}^{n}\beta'_{kij}\ln X_{kjt} + \varepsilon'_{it}$$
1(a)

$$LnCV_t = \mu_{nt} + \delta_{nt} + \sum_{j=1}^{n}\sum_{k=1}^{K}\rho_{ij}\ln X_{kj}$$

$$+ \sum_{L=1}^{l}\phi_i Z_t + u_t$$
2(a)

$$\mu'_{i,nt} = \mu'_{i,nt-1} + \lambda'_{i,nt-1} + \eta'_{i,nt}$$
(3)

$$\lambda'_{i,nt} = \lambda'_{i,nt-1} + \xi'_{i,nt}$$
(4)

$$\delta'_{i,nt} = -\sum_{j=1}^{p-1}\delta'_{i,nt-j} + \kappa'_{i,nt}$$
(5)

Equations 1(a) and 2(a) represent the dynamic analogue of Equations (1) and (2), depicting share and category equations structured around evolving baselines. Equations (3) and (4) describe the baseline dynamics using the structural modelling approach of Harvey (1989). Equation (3) replaces the conventional intercept term with a time-varying (stochastic) trend $\mu_t$ for product $i$ and category $n$. This allows the share and category demand baselines to each follow a random walk with a growth factor $\lambda_t$, analogous to the conventional trend term. Equation (4) allows $\lambda_t$ for both shares and the category to also follow a random walk.

The precise nature of the baseline dynamics are determined by $\eta_t$ and $\xi_t$, which represent two mutually uncorrelated normally distributed white-noise error vectors with zero means and covariance matrices $\Sigma_\eta^2$ and $\Sigma_\xi^2$. If both covariance matrices are non-zero, the baselines evolve as a random walk with stochastic drift. On the other hand, if both covariance matrices are zero, the data are trend stationary and we have a static baseline with deterministic drift. Equation (5) specifies seasonal effects, which are constrained to sum to zero over any one year to avoid confusion with other model components. Stochastic seasonality is allowed for using dummy variables, where $p$ denotes the number of seasons per year, $\delta_t$ is the seasonal factor corresponding to time $t$ and $\kappa_t$ is a random error with mean 0 and covariance matrix $\sigma_k^2$. If the latter is zero, then seasonality is deterministic.

The dynamic attraction model presented here represents a more flexible approach to the traditional dynamic forms used by Carpenter *et al* (1988) and Fok *et al* (2003). In the first place, economic time series data are rarely deterministic. Consequently, we typically observe evolving baselines, representing the evolution in brand tastes and consumer loyalty over time. In the competitive context of demand system 1(a)–(5), this provides invaluable insight into the relative long-term behaviour and position of all brands in the consumer consideration set. Quantifying this behaviour is central to successful management of intangible brand elements such as brand equity and consumer loyalty discussed in section 'Quantifying brand intangibles' below.

Secondly, the framework encompasses the standard behavioural dynamics typically seen in conventional approaches. For example, advertising distributed lag effects can be incorporated in Equation 2(a) in the form of conventional Adstock variables (Broadbent, 1979). Improved short- and medium-term dynamic specification here provides a cleaner read on the long-term evolving component of the sales and share series.

Finally, the model estimation framework can naturally accommodate new products

entering the market as indicated in section 'Model estimation' below, representing an alternative approach to those put forward by Franses *et al* (2004) and Howie and Kleczyk (2008).

## BRAND AND CATEGORY MANAGEMENT

Effective brand management requires navigation through a highly competitive landscape, where guidance on short- and long-term marketing strategy in the context of the overall category is of prime importance. The demand system approach provides the ideal framework via a five-step process.

### Model estimation

The first stage involves estimation of the system parameters to determine marketing effectiveness across the product and brand portfolio. Estimation proceeds by setting up system 1(a)–(5) in state space form (*inter alia* Harvey, 1989), where the state vector contains all regression, trend and seasonal effects. The model is then estimated via maximum likelihood, using the Kalman Filter recursions to update the state vector as new observations become available. It is this updating mechanism that gives the model its evolutionary time varying property and is particularly amenable to incorporating the introduction of new products into the market. As observations for new products arrive, so the state vector can expand to accommodate them.[4]

The holistic category focus allows us to decompose brand-specific marketing impacts into primary (category) effects and secondary (switching) effects. Primary effects are of most interest to the retailer: that is, the retailer is interested in stocking products and brands that help grow the overall category. Secondary effects are primarily of interest to the manufacturer: that is, which brands steal from which and the extent of cannibalisation within the brand portfolio. Brands that

feature both types of effect align manufacturer and retailer interests.

Explanatory variables ($X_{kjt}$) are chosen to fully capture consumer demand, ranging from off- and online media, selling distribution and pricing through to PR and macroeconomic factors.[5] Media data are often split up into separate campaigns to isolate differential effectiveness by message. Diminishing returns for increasing media weight are implicitly incorporated into the multiplicative form of Equation 1(a). However, it is preferable to incorporate non-constant elasticities to test for genuine diminishing returns and saturation effects. Distributed lag effects are incorporated in the form of conventional Adstock transforms.

### Sales decompositions

The second stage combines the estimated parameters and data to decompose brand sales into its component parts, providing a snapshot of historical performance and a bird's eye view of competitive structure. A key factor here is the choice of reference point. That is, how do we want to represent the incremental performance of marketing investments for each brand? For single brand studies, this is typically calculated as deviations from some minimum investment level over time. However, given the holistic nature of the demand system approach, a natural choice is the category average which creates relative incremental volume decompositions. An example is illustrated in Figure 2, which focuses solely on the marketing contributions for one brand from an application of system 1(a)–(5) to a Fast Moving Consumer Good (FMCG) category (Cain, 2010). It is immediately apparent that the client brand is underperforming in terms of its advertising, selling distribution and regular price strategy. On the other hand, the brand's promotional positioning is pitched correctly and performs well during category-wide seasonal high points.
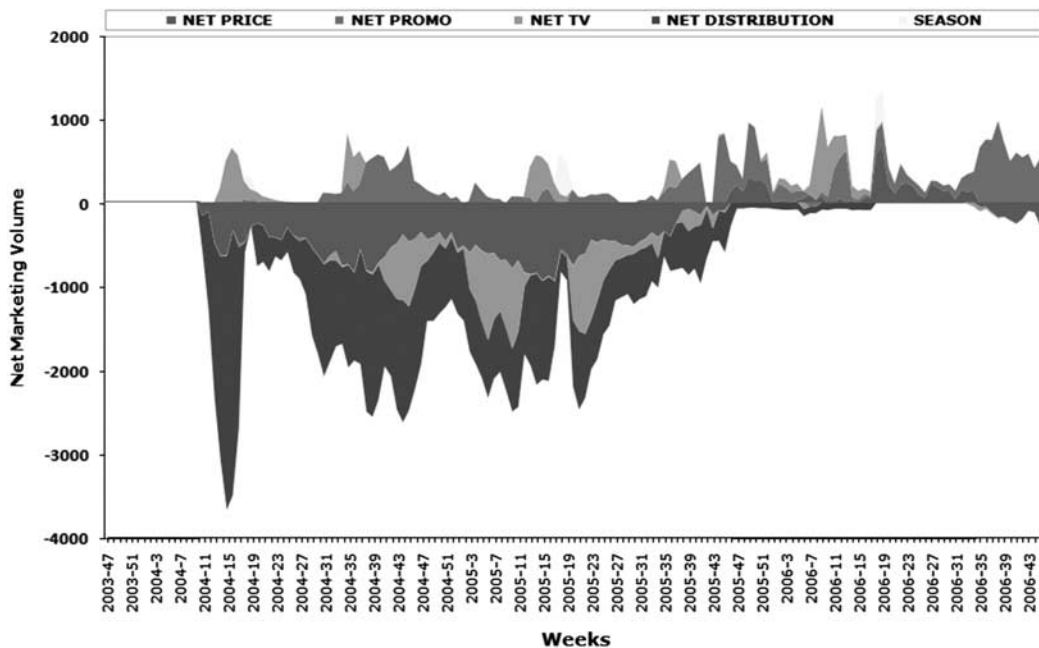
**Figure 2:** Incremental marketing contributions.
*Source*: Cain (2010).

## Short-term ROI

The third stage combines the switching effects quantified in the decomposition process with any category expansion contributions for each mechanic. Together with associated costs and margins, this provides short-term net ROI. Given the holistic and competitive nature of the quantified sales effects – with coherent gains and losses – calculated returns are more accurate than those derived from the conventional single-equation approach.

## Quantifying brand intangibles

The fourth stage quantifies the behaviour and drivers of brand intangibles. Successful marketing investments shift awareness, consideration and brand perceptions which drive repeat purchase behaviour, directly impacting base sales evolution. Firstly, this can feed back into brand perceptions via positive brand experience. Secondly, it can lead to shifts in price elasticity, as changing equity alters demand sensitivity enabling higher price premia. This flow is captured in a self-contained eco-system illustrated in Figure 3 – a flow structured around long-term equilibrium (cointegrating) relationships between brand survey data and brand base volumes or the evolving trend components of model 1(a)–(4).

The brand equity eco-system represents a coherent time series approach to estimation of long-run marketing effects. That is, the system is specifically designed to test for any in-sample evidence of permanent evolution in brand perceptions and sales due to marketing activity. Full details of estimation methodology are given in Cain (2010). The results allow us to rescale marketing impacts to reflect brand-building activity. This takes us to the final stage in the process: optimal allocation of resources to maximise revenues and profits and guide brands to success.

## Optimal budget allocation, forecasting and simulation

ROI calculation is an important aspect of performance management – by providing a retrospective view into marketing impacts. However, brand and category managers also
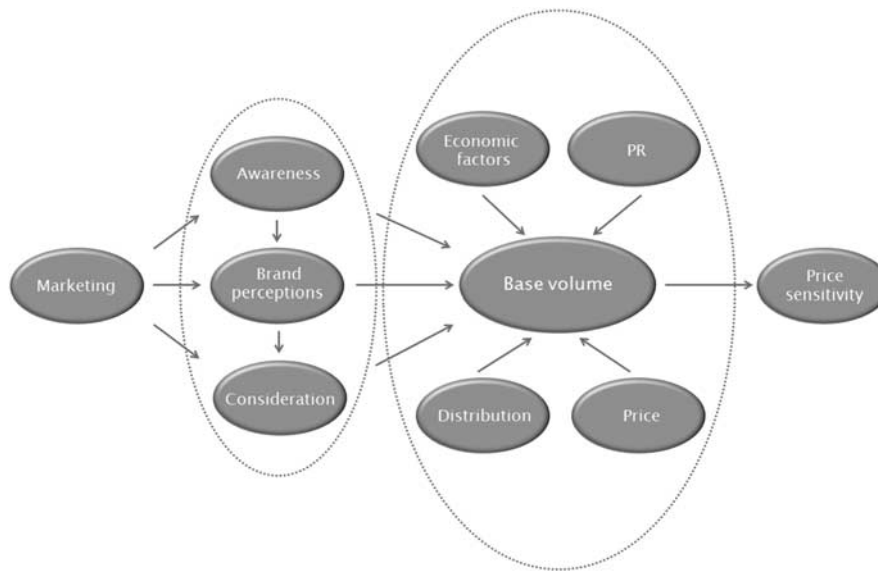
**Figure 3:** Brand equity eco-system.

require advice on how best to plan and deploy future marketing strategies. This is where budget allocation, forecasting and simulation enter the picture.

## Marketing budget allocation

Marketing budget allocation is concerned with the optimal redistribution of promotional and media resources in order to maximise a chosen business objective subject to a defined constraint. This typically involves revenue maximisation under fixed marketing budgets, minimisation of total budget to achieve desired revenues or straight profit maximisation. Marketing response curves, such as those illustrated in Figure 4, lie at the heart of the process. Advertising response is typically concave, reflecting diminishing returns with increasing media weight and is a natural consequence of repeated exposure to a given target audience. The higher the rate of initial reach for a given investment, the more rapid the rate of increase and the steeper the slope. The upper limit quantifies the maximum attainable impact and is equivalent to complete saturation. Any long-run base building effects identified in the brand equity modelling phase serve to re-scale the curves,

crucial to a complete ROI evaluation and a more strategic budget allocation.

Owing to the holistic nature of the demand system approach, model results can be used to inform optimal short- and long-term budget allocation from both a manufacturer and a retailer perspective. For manufacturers, optimisation deals solely with the correct mix across their product and brand portfolios. Consequently, optimisation focuses on a subset of the overall category. Retailers, on the other hand, are interested in maximising total category revenues and profits. This can be achieved by collecting estimated marginal response curves across the modelled category and ascertaining the correct mix across all products and brands to generate maximum revenue or profits. Brands with primary (category) demand effects (and sufficient base sales) tend to receive more budget in allocation, maximising both retailer and manufacturer revenues. It is these brands that align manufacturer and retailer interests.

## Forecasting and simulation

Simulation concerns 'what-if' scenario testing. There is overlap with budget allocation insofar as the latter provides a
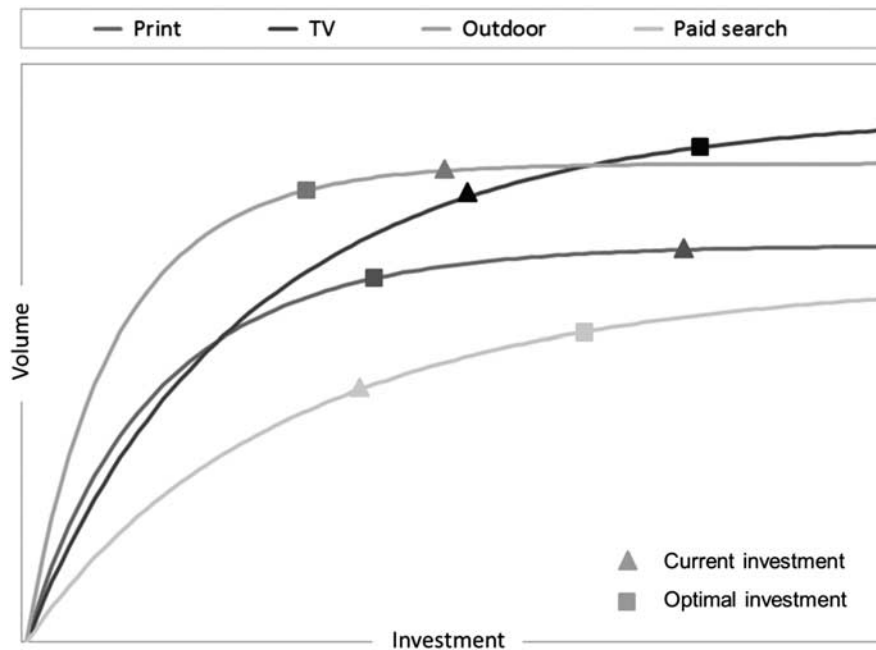
**Figure 4:** Response curves.

simulated revenue or profit amount corresponding to optimal marketing resource allocation. This can be used to evaluate how far the client's planned marketing strategy is from the optimal mix, or simulate the marketing budget needed to achieve desired revenue and profit objectives. However, this presupposes fixed levels of other key business drivers, such as pricing, distribution and economic activity. Forecasting and simulation goes further by using the entire model structure to forecast likely performance and simulate the business impact of alternative scenarios, together with competitor reactions.

For example, suppose the prevailing macroeconomic environment, pricing, distribution and marketing strategy predicts a relatively poor brand performance over the forthcoming planning period. Implementing the optimal recommended media and promotional mix sees decent revenue gains due to brand switching and category growth. However, achieving the required revenue targets through media alone is prohibitively costly due to diminishing returns and excessive promotion is denigrating brand equity. Depending on estimated elasticities,

brand managers may be able to fill the revenue or profit gap by adjusting other levers at their disposal. For example, dropping the planned regular price and increasing selling distribution – given assumed levels of competitor activity – increases the underlying level of base sales. Given the interactive nature of model base and incremental, this boosts the effectiveness of the overall short-term marketing plan. The brand manager can then repeat the process for a range of alternative marketing plans and competitor reactions, picking the optimal strategy to meet desired revenue targets.

## CONCLUSIONS

This article has illustrated an alternative approach to the traditional marketing mix model that provides several key modelling and managerial benefits.

Firstly, the economic demand structure accurately represents the underlying consumer choice process, providing a panoramic view of the performance of each brand in the competitive context of the overall category. This provides insight into

the tangible elements of brand management by delivering a full range of competitor steal, cannibalisation and halo effects, enabling incremental volume and profit maximisation across the manufacturer brand portfolio.

Secondly, measured category expansion effects of brand-specific marketing can facilitate the manufacturer-retailer relationship. As such, the model is also perfectly placed to aid the category management process, with budget optimisation and simulation enabling joint–profit maximisation for both parties.

Finally, the econometric state space structure provides a modern time series framework for the mix model that accurately splits sales into short- and long-term elements. In contrast to the conventional approach where baselines are fixed by construction, the evolving long-term component explicitly incorporates the intangible elements of brand management into the modelling process, enabling measurement of long-term marketing ROI and brand building budget optimisation.

## NOTES

1. For an analysis of the dynamic AIDS model, see Cain (2005).
2. The log-centred form of the attraction model is fully discussed in Nakanishi and Cooper (1974). The log-ratio approach used in the text provides equivalent parameter estimates and is easier to work with (see Houston *et al*, 1992).
3. Note that the parameter estimates of (1) are reduced form in that they are a composite of structural and residually defined parameter estimates of the *p*th product. Cross effect parameter restrictions can also be applied to simplify the model structure and reduce potential collinearity problems.
4. This is fully in keeping with the discrete choice model structure, which naturally handles new product introductions. This is because the model form is based on indirect utility as a function of product characteristics (Lancaster, 1966), where preferences are over the attributes and not the product *per se*. Consequently, it is natural to introduce a new product with marketing attributes that already exist in the marketplace.
5. Note that online drivers such as paid search and display are essentially outcome variables to be explained simultaneously with sales and thus endogenous. This follows directly from the modern offline-online consumer purchase journey as outlined in Cain (2014).

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