

# Limitations of conventional market-mix modelling

**Peter Cain**, Millward Brown Optimor, shows how modelling can enable marketers to account for both short- and long-term campaign effects

**T**HE ULTIMATE OBJECTIVE of all marketing-mix models is to quantify the sales contribution of marketing activities, to calculate return on marketing investment (ROMI). To accomplish this, the models employ econometric techniques to decompose product sales into base and incremental volume. Base sales represent the long-run or trend component of the time series, indicating underlying consumer preferences. Incremental volume, by contrast, is short-run in nature, capturing sales variations driven by temporary selling price, multi-buy promotions and above-the-line advertising. Incremental volumes are converted into incremental revenues or profits, and benchmarked against costs to calculate short run ROI for each element of the mix.

Models that focus solely on incremental volume often recommend a marketing budget allocation skewed towards promotional investment: short-run sales respond well to promotions, yet are less responsive to media advertising - particularly for established brands. This, however, ignores the long-run view: both the potential brand-building properties of successful media campaigns and the brand-eroding properties of heavy price discounts. Acknowledging and quantifying these features is crucial to complete ROI evaluation and more strategic budget allocation.

This article puts forward a unique approach to this issue. Measuring the long-run impact of marketing investments essentially amounts to quantifying their impact on the trend component of sales: the evolution in base sales over time. However, this is not possible in conventional models, since base sales are essentially fixed by construction. To deal with this, the marketing-mix model needs to be restructured to accommodate both short-run and long-run variation in the data. The former is used to calculate ROI on marketing investments in the usual way- The latter generates an evolving baseline, measuring the evolution of brand preferences over time. When combined with marketing investments and consumer tracking information, this allows quantification of long-run ROI.

## Conventional short-term marketing-mix modelling

Market-mix modelling employs econometric techniques to quantify the contribution of a set of driver variables to variations in a sales-response variable. The model-building process involves three key stages:

1. We select key driver variables that represent the full range of the marketing mix. Models are generally specified in terms of distribution, regular shelf price, temporary promoted price, multi-buy promotions,

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features, displays, media advertising, seasonally and competitor marketing.

2. We determine how sales are linked to the driving variables. This may be multiplicative or additive; and variables such as TV advertising or print media can be specified to incorporate saturation effects or diminishing returns to increasing weight.
3. We specify the nature of sales adjustment to changes in the driving variables. A current-period relationship between sales and marketing is known as a static relationship. The implicit assumption is that consumers adjust immediately. However, brand loyalty and habit formation suggest this is unlikely. A preferable formulation is to specify sales in terms of current and past driver values. This is called a dynamic relationship, capturing the time taken for consumers to adjust.

Conventional market-mix modelling introduces dynamics in two ways. First, a one-period-lagged value of sales can be added to the set of drivers. This represents a simplified method of incorporating adjustment to changes in all the drivers. Second, and more usually, dynamics are applied to advertising TVR data alone,



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which traditionally appear in adstocked form to capture the carry-over effects we would expect from successful media campaigns - namely, where effects are felt beyond the period of execution due to product purchase cycles and/or media retention in the mind of the consumer.

**Conventional long-run modelling**

Traditional approaches to modelling the long-run impact of marketing activity build primarily on the basic dynamics outlined above. For example, the long-run effects of television advertising are often estimated using adstocked TVR data with very high retention rates - indicative of heavy persistence of past levels of advertising weight (1). Alternatively, long-run effects are derived simply by multiplying the short-term effects by three, based on results in Lodish (2). Promotion modelling, on the other hand, can be extended to incorporate the negative effects of post-promotional dips (for example, pantry loading).

All such extensions, however, miss a crucial component of the long-run view - namely, how far marketing activity can help - or hinder - the development of underlying brand strength. It is well known that advertising investments tend to generate little incremental return, yet provide a long-run brand-building function. In contrast, excessive reliance on promotions can damage brand image, eroding brand equity. How can we test for and quantify these effects? One approach is to exploit the fundamentals of time-series regression analysis.

**Measuring long-run consumer demand**

Time-series regression analysis is a statistical technique that decomposes the behaviour of any time-ordered data series into trend, seasonal, cyclical and random-error components. All marketing-mix models involve sales observations over time and constitute time-series regressions with additional marketing driver variables. The trend component represents the long-run evolution of the sales series and is crucial to a well-specified marketing-mix model.

In the conventional approach, the trend is represented by the regression intercept plus a linear deterministic growth factor - adding or subtracting a proportional amount to or from the regression intercept over each period of the data sample. The result is a sales decomposition with a linear trending base, illustrating how base sales - often interpreted as long-run consumer demand - reflect the underlying trend imposed on the data. If no observable positive or negative growth is present, the base is forced to follow a fixed horizontal line (3).

Trends in sales data rarely behave in such simple deterministic ways. Many markets, ranging from fast-moving consumer goods (frnCG) to automotive, exhibit trends that evolve and vary over time (4). This is ignored in the conventional marketing-mix model. However, for evaluating the long-run brand-building impact of marketing, this is a serious oversight. Quantifying brand-building effects requires an understanding of how the long-run component of the time series - that is, base sales - behaves. This is not possible if base sales are pre-determined to follow a constant mean level or a deterministic growth path, as any long-run variation in the data is suppressed. To overcome this, we need to re-specify the model as a time-series regression with a

modelled trend component. The result is a truly evolving baseline, providing a more precise picture of the evolution of long-run consumer demand and short-run incremental volume (5). An example for an frnCG face-cleansing product is shown in Figure 1 (6).

**Measuring indirect effects of marketing**

Having estimated the behaviour of product base sales, we can now quantify the longer-term brand-building impact of marketing investments. This is because if such investments play a role in driving base-sales evolution they have a long-run or trend-setting impact - over and above any short-run incremental contribution. For example, ROI for TV advertising tends to be small - particularly for established brands. However, successful TV campaigns also serve to build trial, stimulate repeat purchase and maintain healthy consumer brand perceptions, thus driving and sustaining base sales (7). Such indirect effects need to be quantified to evaluate the true ROI for marketing investments (8).

One approach is to construct a model measuring the impact of marketing investments on long-run consumer demand via their impact on underlying brand perceptions. The process is \*

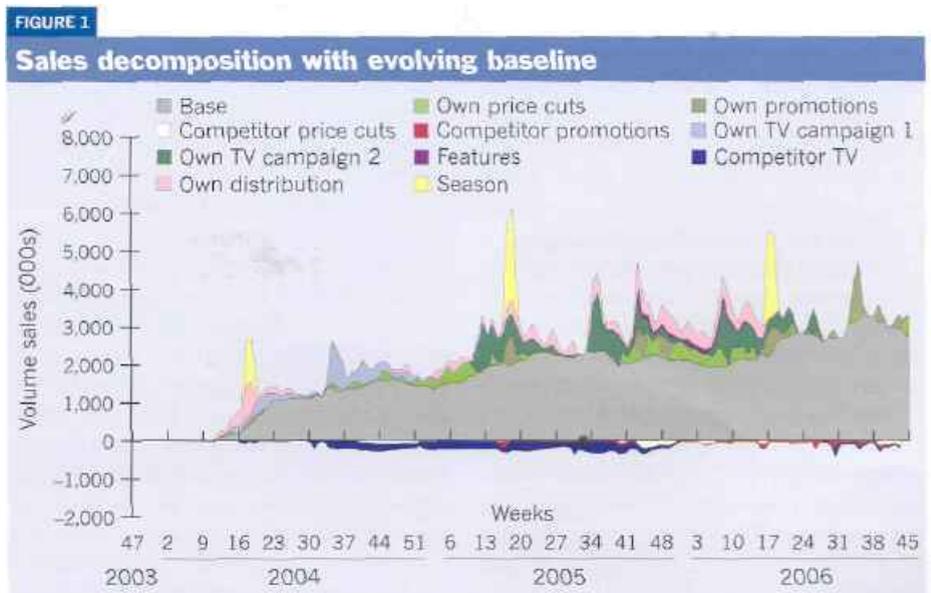
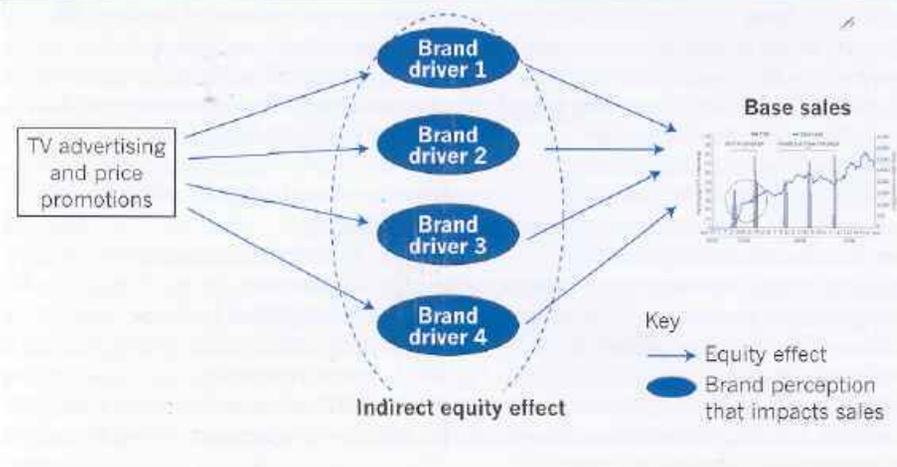


FIGURE 2

The indirect effects of marketing



illustrated in Figure 2 and proceeds in three key stages.

1. We identify potentially important consumer beliefs or attitudes towards the brand such as level of trust, personality, and perceptions of value and quality. Data are recorded weekly over time - often rolled up into four-weekly moving average time series to minimise the influence of sampling error. An example is illustrated in Figure 3, which plots the evolving baseline of Figure 1 alongside TVR investments and brand perceptions of product fragrance and perceived product value.

2. We establish the importance of selected brand-tracking measures in driving consumer demand. Tracking data represent the evolution of consumer brand attitudes over time. Extracted base sales from the market-mix modelling phase represent long-run evolution of consumer demand. Examples are given in Figure 3. Time-series regression analysis is used to test for an equilibrium relationship between these variables: that is, a relationship where the series follow a long-run path together over time, which tends to be restored when disturbed. This allows us to avoid spurious correlations, which simply pick up unrelated trending. Only then can we interpret the regression coefficients as valid estimates of the importance of each demand driver(9).

3. We introduce marketing investments: advertising TVRs are shown alongside the data in Figure 3, for example. We then look at how shifts in each marketing investment influence each image statement and, exploiting the equilibrium relationship identified in the second stage, how subsequent shifts in each image statement affect base sales. In this way, a sequential path is identified through the system, as illustrated in Figure 2, measuring the indirect impact of marketing activities on long-run consumer demand (10).

**Calculating the full long-run impact and total ROI**

Estimated indirect impacts of marketing investments are part of the long-run sales trend; as such, they generate a stream of effects extending into the foreseeable future: positive for TV advertising and negative for heavy promotional weight. In order to quantify these effects, we need to establish how far they decay over time. First, the benefit will diminish as loyal consumers eventually leave the category and/or switch to competing brands. Second, future benefits will be worth less as uncertainty increases. Once we have measured the appropriate decay rates, we exploit a standard method in financial accounting known as present value discounting to quantify the current value of the future revenue streams.

The indirect 'base-shifting' impact over the model sample, together with the decayed present value of future net revenue streams quantifies the total long-run impact of advertising and promotional investments (i i). These are then added to the weekly revenues calculated from the short-run modelling process. Benchmarking final net revenues against initial outlays allows calculation of the total ROI for marketing investments.

**Managerial implications**

The long-run modelling process delivers two key commercial benefits.

**1. Improved strategic budget allocation**

Market-mix models are used to inform budget-allocation decisions. However, such decisions are short-run focused, often favouring intensive promotional activity over media investments. This often leads to a devaluation of brand equity in favour of short-run revenue gain. Factoring in long-run revenues allows us to redress this balance in favour of strategic brand-building advertising activity.

**2. Improved media strategy**

The equilibrium relationship between consumer brand perceptions and long-run brand sales illustrated in Figure 2 can be used to test for causal links.

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Understanding which key brand characteristics drive brand demand can help to inform the media creative process for successful long-run brand building.

Neither of these benefits is possible using conventional market-mix modelling, which demonstrates the power of combining primary consumer research with modern econometric analysis of secondary-source data.

## Conclusions

This article has put forward an alternative approach to conventional market-mix modelling which explicitly models both the short- and long-run features of the data. Not only does this provide more accurate short-run results but, when combined with evolution in intermediate brand-perception measures, allows an evaluation of the long-run impact of marketing activities. This framework demonstrates two key issues:

1. If we wish to measure long-run marketing effects, it is imperative that econometric models deal with the evolving trend or baseline inherent in most time series: conventional marketing-mix models are not flexible enough to address this issue.

2. Intermediate brand-perception data can be causally linked to brand sales, and used to predict and improve long-run business performance. This directly addresses reservations over the use of primary research data, such as those raised by Binet and Field.

1. Other approaches include regressions of base sales from conventional marketing mix models on adstocked TVR data with high retention rates. However, as outlined below, this is inherently flawed since base sales in such models are predetermined, with no genuine systematic time-series variation.
2. L M Lodish et al: How TV advertising works: a meta-analysis of real world split cable TV advertising experiments. *Journal of Marketing Research*, 32, May 1995.
3. Base sales in conventional marketing-mix models often appear erratic and evolving. This is purely an artefact of the sales decomposition process.
4. See Dekimpe and Hanssens for a survey. (M Dekimpe and D Hanssens: Empirical generalisations about market evolution and stationarity. *Marketing Science*, 14, 3 1995-)
5. See Cain for a technical development of the approach. (P M Cain: Modelling and forecasting brand share: a dynamic demand system approach. *International Journal of Research in Marketing*, 22, 2005.)

6. Evolving base models essentially capture the stochastic trend in the data and can be applied to any time series - for established brands as well as new products. Evolution is not forced on the data, but tested for model adequacy.
7. Such effects are consistent with the 'strong' theory of advertising. (J P Jones: Ad spending: maintaining market share. *Harvard Business Review*, 68, i, 1990.) The 'weak' theory, advocated by Ehrenberg (A Ehrenberg: Repetitive advertising and the consumer. *Journal of Advertising Research*, 40, 6, 2000), suggests that TV solely builds trial, with product performance and other marketing factors driving repeat purchase. Recent evidence from Binet and Field (L Binet and P Field: *Marketing in the Era of Accountability*, WARC, 2007) tends to confirm the latter. However, much of their evidence is based on conventional market-mix model results, which are not designed to measure long-run brand-building effects.
8. The reverse is true for excessive price promotion, which tends to damage brand perceptions, negatively influencing base-sales evolution.
- g. Technically, the trending regressor variables must co-integrate to provide a meaningful equilibrium relationship between stochastic trending variables. This information can then be used to evaluate whether the tracking variables are exogenous 'driving' variables, implying genuine causality from brand-tracking metrics to business performance.
10. The process linking marketing investments indirectly to base sales is estimated using a vector error correction model (VECM) - widely used in the econometrics literature.
11. This may not capture all potential long-run effects. For example, TV investments may simply maintain base sales - with no observable impact picked up using time-series econometric modelling. This can be dealt with by using estimates of base decay in the absence of advertising investments. Further, it is possible that successful TV campaigns reduce price sensitivity, enabling brands to command price premia. This can be estimated by measuring the contribution of TV advertising to the evolution of regular price sensitivity in the market-mix model.

FIGURE 3

### Evolution of consumer tracking image statements



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