

Limitations of conventional marketing mix modelling¹

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1) Introduction

The primary function of all marketing mix models is to quantify the sales contribution of marketing activities, with a view to calculating Return on Investment (ROI). To accomplish this, all such models employ econometric techniques to decompose product sales into base and incremental volume. Base sales represent the long-run or trend component of the product time series, indicative of underlying consumer preferences. Incremental volume, on the other hand, is essentially short-run in nature, capturing the week-to-week sales variation driven by temporary selling price, multi-buy promotions and above the line media activity. Incremental volumes are then converted into incremental revenues or profits and benchmarked against costs to calculate short-run ROI to each element of the marketing mix.

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

This article puts forward a unique approach to resolving this issue. Measuring the long-run impact of marketing investments essentially amounts to quantifying their impact on the trend component of the sales series: that is, on 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 problem, the marketing mix model needs to be re-structured 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 measures the evolution of brand preferences over time. This generates an evolving baseline which, when combined with marketing investments and consumer tracking information, allows a quantification of long-run ROI.

¹ Admap (2008).

2) Conventional short-term marketing mix modelling

Marketing mix modelling employs econometric techniques to quantify the contribution of a set of driver variables to the variation in a sales response variable. The model building process for sales involves three key stages.

Firstly, we select the key driver variables. These need to represent the full range of the marketing mix such that sales variation is fully explained. Models are generally specified in terms of selling distribution, regular shelf price, temporary promoted price, multi-buy promotions, features, displays, media advertising, seasonality and extreme events.

Secondly, we determine the way in which sales are linked to the driving variables. This may be multiplicative, yielding constant elasticity demand functions, or additive where response elasticities depend on the level of sales. Variables such as TV advertising or print media can also be specified to incorporate saturation effects or diminishing returns to increasing weight.

Finally, we specify the nature of sales adjustment to the change in driving variables. For example, a current period relationship between sales and marketing variables is known as a 'static' relationship. The implicit assumption here is that consumers adjust immediately to any change in the driver variable. However, factors such as brand loyalty and habit formation suggest that this is unlikely. A preferable formulation is to specify sales in terms of current and past driver values. This is known as a dynamic relationship and is intended to capture the time taken for consumers to adjust to the new level of the relevant driver.

Conventional marketing mix modelling introduces dynamics in two ways. Firstly, a one-period lagged sales value can be added to the set of driving variables. This represents a parsimonious approach to incorporating adjustment to changes in all the driving variables. Secondly, and more usually, dynamics are applied to advertising TVR data alone, which traditionally appear in adstocked form to capture the carry-over effects that we would intuitively expect from successful media campaigns: namely, where the effects are felt beyond the period of execution due to product purchase cycles and/or media retention in the mind of the consumer.

3) Conventional long-run modelling

Traditional approaches to modelling the long-run impact of marketing activity build primarily on the basic dynamics introduced in section 2. 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.² Alternatively, long-run effects are derived simply by multiplying the short-term effects by three, based on results in Lodish *et al* (1995). Promotion modelling can also be extended to incorporate the negative

² Other approaches include auxiliary regressions of base sales - derived from conventional marketing mix models – and adstocked TVR data with high retention rates. However, as outlined below, such approaches are inherently flawed since base sales in conventional marketing mix models are predetermined with no genuine systematic time series variation.

effects of post-promotional dips – reflecting pantry loading, where stocking up in response to promotional deals today cannibalises product sales tomorrow.

All such extensions however – although important in their own right – miss an extremely important component of the long-run view. That is, the extent to which 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 serve to provide a long-run brand-building function. On the other hand, excessive reliance on promotions can denigrate brand image, eroding equity in the brand. How can we test for and quantify these effects? One approach is to exploit the fundamentals of time series regression analysis.

4) Measuring long-run consumer demand

Time series regression analysis is a statistical technique that decomposes the behaviour of any time-ordered data series into a trend, seasonal, cyclical and random error component. All marketing mix models involve time-ordered sales observations and thus 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, then 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 Good (FMCG) to automotive, exhibit trends that evolve and vary over time.⁴ This is ignored in the conventional marketing mix model. However, when it comes to understanding the long-run brand-building impact of marketing on sales, this is a serious oversight. Quantifying brand-building effects requires an understanding of how the long-run component of the time series behaves: that is, how base sales behave. This is not possible if base sales are pre-determined to follow a constant mean level or a deterministic growth path, as any true long-run variation in the data is suppressed. To overcome this, we need to specify the trend component as part of the model itself – in much the same way as classical time series analysis does. This allows us to simultaneously extract both short and long-run variation in the data, giving a more precise picture of the evolution of long-run consumer demand and short-run incremental drivers.⁵ The result is a marketing mix model with a truly evolving baseline. An example for an FMCG face cleansing product is illustrated in Figure 1.⁶

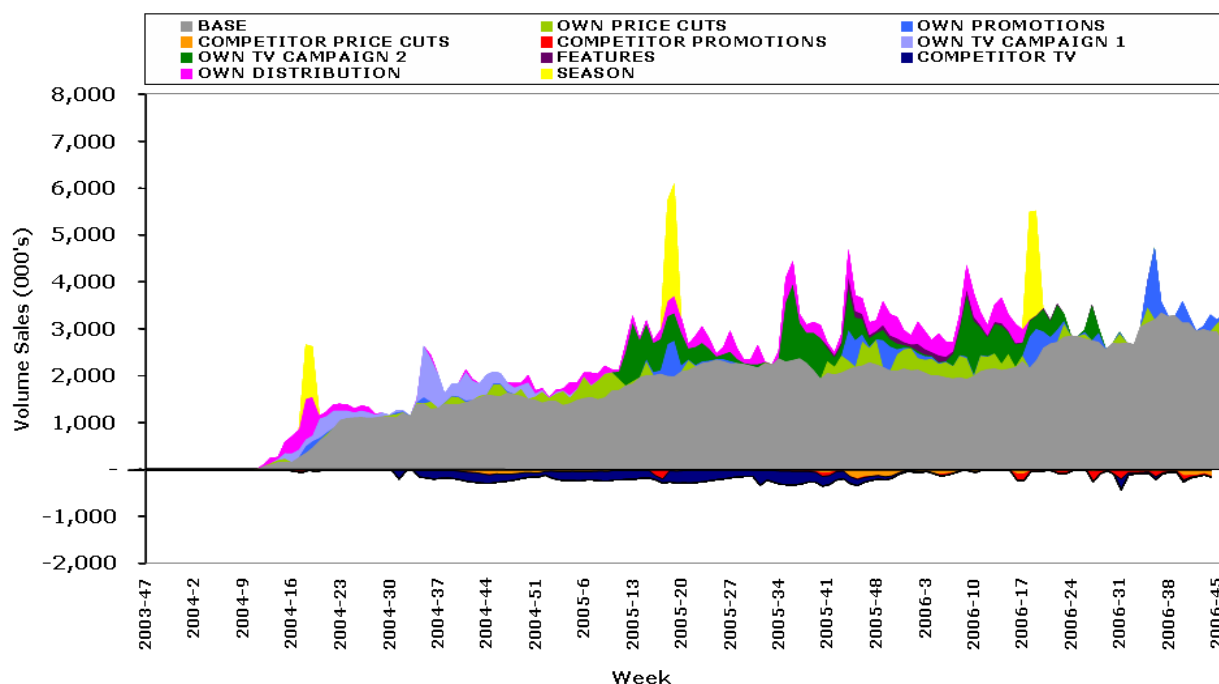
³ Base sales in conventional marketing mix models often appear erratic and evolving. This is purely an artefact of the sales decomposition process.

⁴ See Dekimpe and Hanssens (1995) for a survey.

⁵ See Cain (2005) for a technical development of the approach.

⁶ Evolving base models essentially capture the *stochastic* trend present in the data and can be applied to any time series - both established brands as well as new products. Evolution is not forced on the data, but tested for model adequacy - encompassing the conventional deterministic model as a special case.

Figure 1: Sales decomposition with evolving baseline



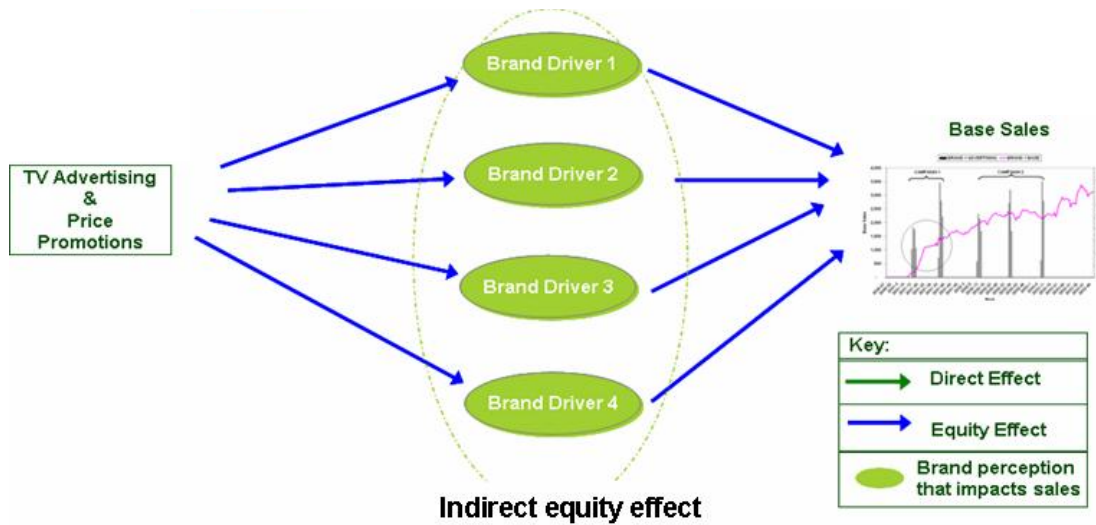
5) Measuring the indirect effects of marketing

The next step is to evaluate whether marketing activity plays a role in driving base sales evolution. If so, then it can be said to have a long-run or trend-setting impact - over and above any short-run incremental contribution. For example, it is well known that incremental returns to TV advertising tend to be small. However, successful TV campaigns also serve to build trial, stimulate repeat purchase and maintain healthy consumer brand perceptions. In this way, advertising can drive and sustain the level of brand base sales.⁷ Conversely, excessive price promotional activity tends to influence base sales evolution negatively – via denigrating brand perceptions. Only by quantifying such indirect effects can we evaluate the true ROI to marketing investments and arrive at an optimal strategic balance between them.

To estimate these effects, we link marketing investments to brand perceptions from primary research tracking studies through to long-run consumer demand from secondary research marketing mix analysis. The overall process is illustrated in Figure 2 and proceeds in three key stages.

⁷ Note that such effects are consistent with the ‘strong’ theory of advertising as expounded by Jones (1990). The ‘weak’ theory advocated by Ehrenberg (2000) posits that TV serves solely to build trial, with product performance and other marketing factors driving repeat purchase. Recent evidence from Binet *et al* (2007) tends to confirm the weak theory. However, much of this evidence is based on conventional marketing mix model results, which are not designed to measure long-run brand building effects.

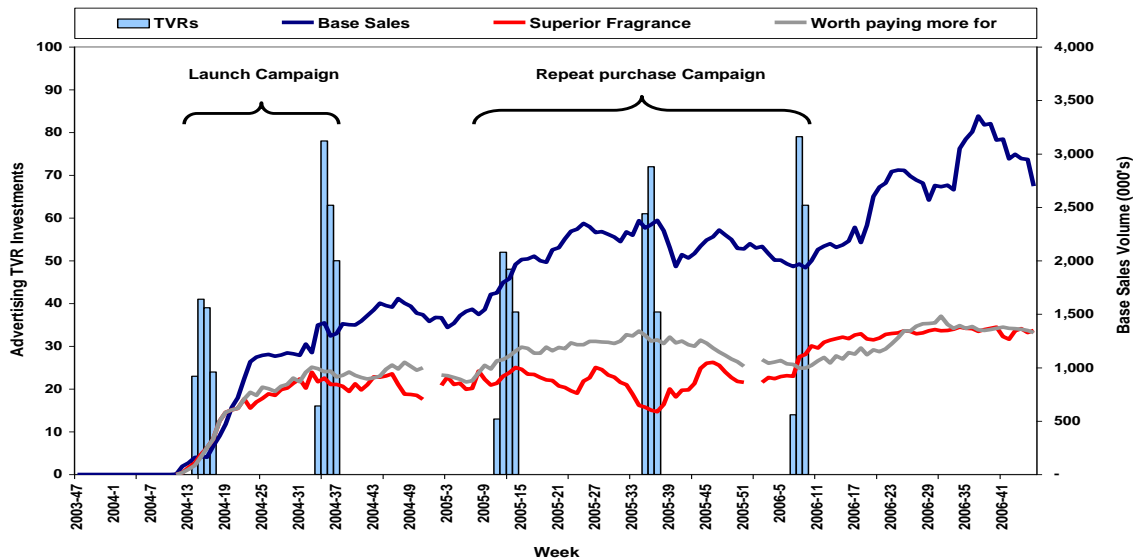
Figure 2: The indirect effects of marketing



5.1) Which consumer beliefs and attitudes are important in brand-building?

Firstly, we identify potentially important consumer beliefs or attitudes towards the brand. These will encompass statements about the product, perception of its value and quality, the brand’s personality and some overall brand statements such as trust. 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 below, which plots the evolving baseline of Figure 1 alongside TVR investments and brand perception data relating to product fragrance and perceived product value.⁸

Figure 3: Evolution of consumer tracking image statements



⁸ Selected brand image statements are often highly collinear. Consequently, preliminary *factoring* analysis is usually undertaken to separate out the data into mutually exclusive themes or groups prior to modelling.

5.2) Evaluating the contribution of brand attitudes to long-run brand demand

Secondly, we establish the importance of selected tracking measures in driving long-run evolution of brand demand. Image tracking data represent the evolution of consumer brand attitudes over time. Extracted base sales from the marketing mix modelling phase represent long-run evolution of observed brand purchases or long-run brand demand. Examples are given in Figure 3. Time series regression analysis is used to test for an *equilibrium* relationship between these series: that is, a relationship where the series follow a long-run path together over time and one which tends to be restored whenever it is disturbed. It is important to bear in mind that such regressions analyse relationships between trending variables. Under these circumstances, we must be careful to avoid spurious correlations, where the analysis is simply picking up unrelated trending activity. Only then can we interpret the regression coefficients as valid estimates of the importance of each of the demand drivers.⁹

5.3) Linking marketing investments to base sales

Finally, we introduce marketing investments into the system: advertising TVR data are illustrated alongside the data in Figure 3 for example. We then look at how shifts in each marketing investment impact each image statement and, exploiting the equilibrium relationship identified in the second stage, how subsequent shifts in each image statement impact 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

6) Calculating the full long-run impact and total ROI

Estimated indirect impacts of marketing investments are part of the long-run sales trend and as such generate a stream of effects extending into the foreseeable future: positive for TV advertising and negative for heavy promotional weight. These must be quantified if we wish to measure the full extent of any indirect effects.

To do so, we first note that in practice we would not expect future benefit streams to persist indefinitely into the future. Various factors dictate that such benefits will decay over time. Firstly, the value of each subsequent period's benefit will diminish as loyal consumers eventually leave the category and/or switch to competing brands. Secondly, future benefits will be worth less than current ones as uncertainty around future benefits increases. To capture these effects, we exploit a standard method used in financial accounting known as discounting,

⁹ Technically, the trending regressor variables must cointegrate to provide a meaningful equilibrium relationship. Unlike more conventional correlation analysis, 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 to base sales is estimated using a Vector Error Correction model (VECM) – widely used in the econometrics literature for the purpose of measuring long-run or persistent impacts.

which quantifies the current value of future revenue streams. The calculation used for each marketing investment is written as:

$$PV_i = \sum_{t=1}^N \frac{C_{i0} * d_i^t}{(1+r)^t} \quad (1)$$

Where PV_i denotes the Present Value of future indirect revenues accruing to marketing investment i , C_{i0} represents the indirect benefit calculated over the model sample, d represents the per period decay rate of subsequent indirect revenues over N periods and r represents a discount rate. The decay rate serves to re-weight the value of each subsequent period's benefit as loyal consumers eventually leave the category and/or switch to competing brands. The discount rate serves to reflect increasing uncertainty around future revenue.¹¹

The indirect 'base-shifting' impact over the model sample, together with the decayed PV of future revenue streams quantifies the total long-run impact of advertising and promotional investments.¹² 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 to marketing investments.

7) Managerial implications

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

i) Improved strategic budget allocation

The results from marketing mix models are used to inform budget allocation decisions. However, such decisions are very short-run focused, often favouring intensive promotional activity over media investments. This often leads to a denigration 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 marketing activity.

¹¹ The final PV of indirect marketing revenue streams will depend critically on the chosen values of d and r . The benefit decay rate can be chosen on the basis of established norms or estimated from historical data. The discount rate is chosen to reflect the client's internal rate of return on capital: a higher discount rate reflects greater uncertainty around future revenue streams.

¹² Note that this may not capture all potential long-run effects. For example, TV investments may serve to simply maintain base sales – with no observable impact picked up using time series econometric modelling. This effect can be dealt with by using estimates of base decay in the absence of advertising investments. Furthermore, it is possible that successful TV campaigns reduce price sensitivity, enabling brands to command price premia. This effect can be estimated by measuring the contribution of TV advertising to the evolution of regular price sensitivity in the marketing mix model.

ii) Improved media strategy

A key part of the process illustrated in Figure 2 is the equilibrium relationship between consumer brand perceptions and long-run brand sales. This relationship can be used to test for causal links between key brand image statements and long-run brand demand. Understanding which key brand characteristics drive brand demand in this way can help to inform the media creative process for successful long-run brand building.

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

8) Conclusions

This paper has put forward an alternative approach to marketing mix modelling which explicitly models both the short and long-run features of the data. Not only does this provide more accurate short-run marketing 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.

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

Secondly, it demonstrates that intermediate brand perception data can be causally linked to brand sales and used to improve long-run business performance. This directly addresses the reservations over the use of primary research data raised by Binet *et al* (2007).

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