Measuring long-term effects in marketing

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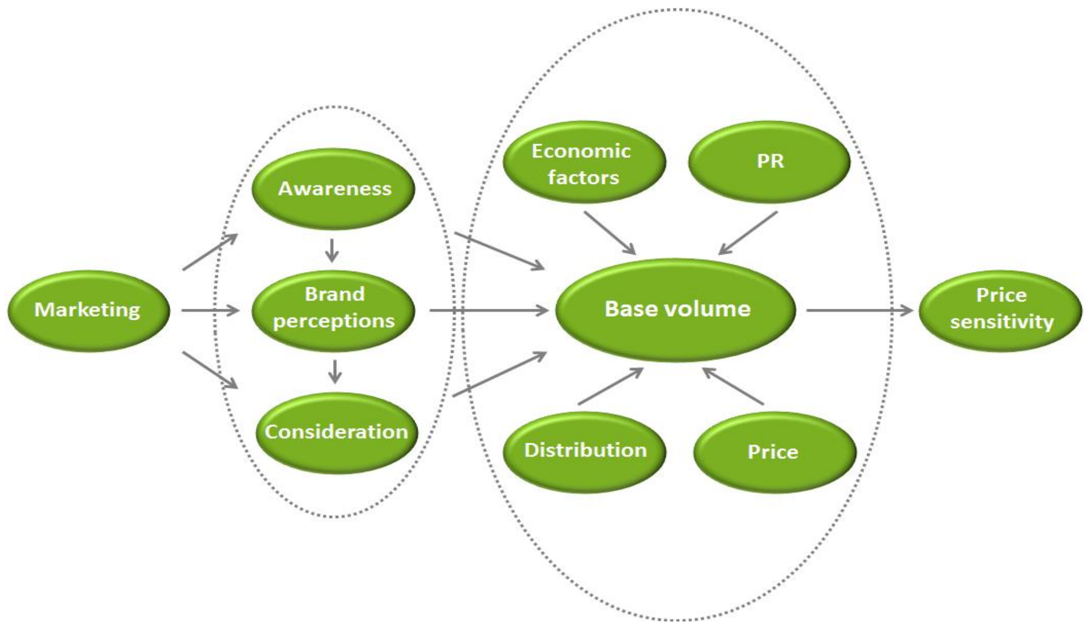
Conventional marketing mix models are typically used to measure short-term marketing ROI and guide optimal budget allocation. However, this is only part of the story as marketing investments do more than simply drive incremental sales volumes. In the first place, successful TV campaigns serve to build trial, stimulate repeat purchase and maintain healthy consumer brand perceptions. In this way, advertising can drive and sustain the level of brand base sales.[1] Secondly, advertising can affect the degree of product price sensitivity – thereby enabling the brand to command higher price premia. Only by quantifying such indirect effects can we evaluate the true ROI to marketing investments and arrive at an optimal strategic balance between them.

Estimation of indirect effects requires four key data inputs: marketing investments, brand perceptions, base sales and price elasticity evolution. Base sales evolution is derived directly from the dynamic time series approach to the mix model (Cain, 2008), indicating the extent to which new purchasers are converted into loyal consumers – through persistent repeat purchase behaviour and lasting shifts in consumer product tastes. This, in turn, can lead to shifts in price elasticity as stronger equity reduces demand sensitivity to price change. Brand perceptions are forged by product experience, driving product tastes and repeat purchase behaviour. Marketing investments, in turn, work directly on product perceptions. This reasoning creates the flow illustrated in Figure 1, where marketing investments are linked to variation in base sales and price elasticity via brand perception data.

Figure 1: The indirect effects of marketing



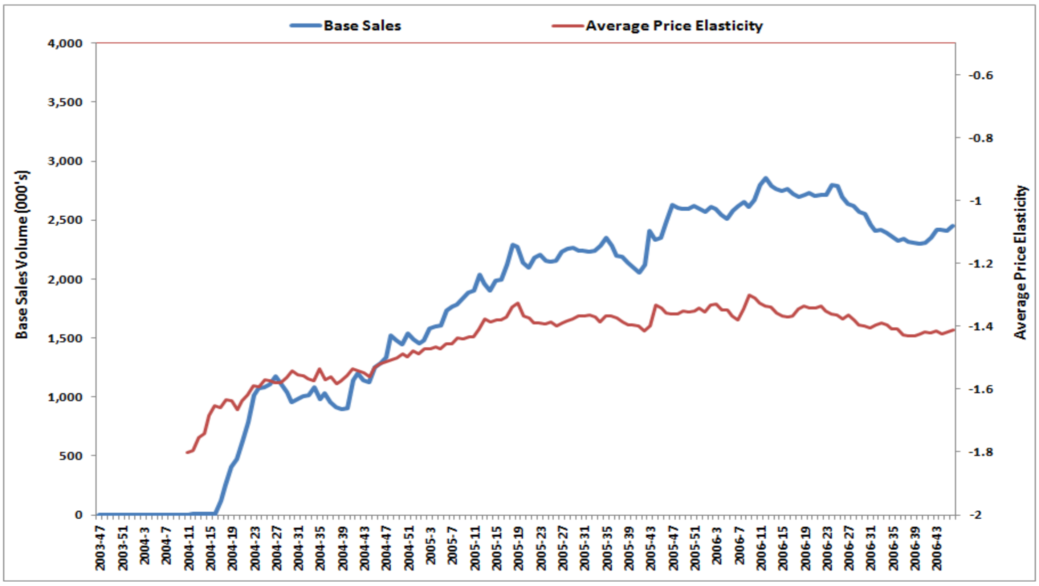
[1]Conversely, excessive price promotional activity can negatively influence base sales evolution – via denigrating brand perceptions and stemming repeat purchase.

Given the evolutionary nature of the base sales (and other) data involved, the appropriate estimation process follows the five key stages outlined in sections 1 – 5 below.[2]

1) Estimating evolution in base sales and price sensitivity

Evolution in base sales and price sensitivity are derived from the time series approach to the marketing mix model. Examples are illustrated in Figure 2. Price sensitivity falls from -1.80 at the beginning of the sample to -1.30 at the beginning of 2006 - in line with a rising loyal consumer base after product launch. Price sensitivity rises thereafter to approximately -1.40 by the end of the sample.

Figure 2: Time series evolution in bases sales and price elasticity



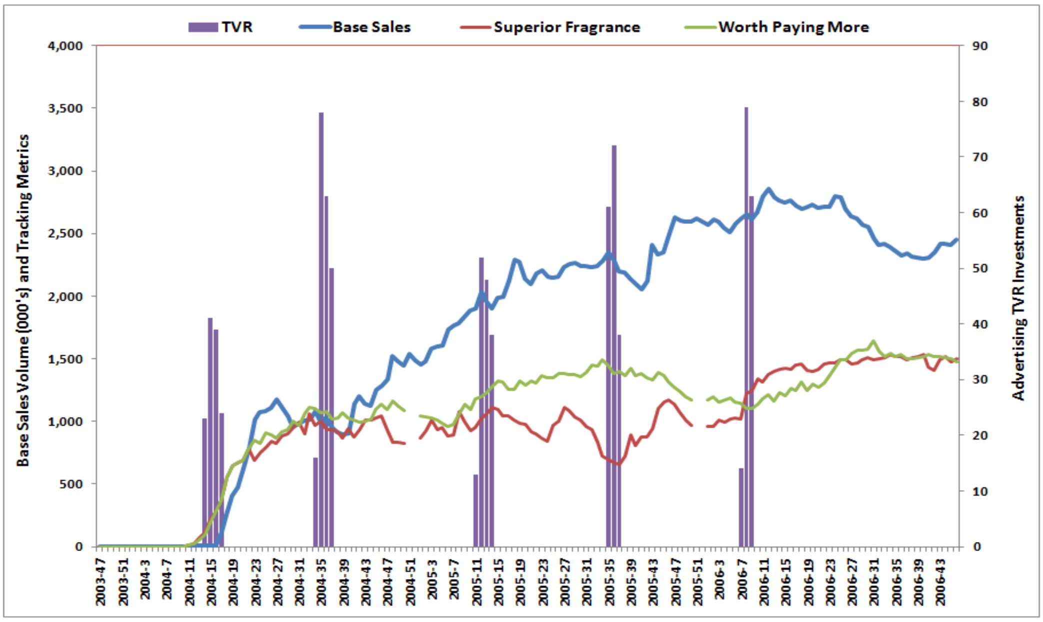
2) Identifying relevant consumer brand perceptions

Secondly, important consumer beliefs or attitudes towards the brand are identified. These will encompass statements about the product, perception of its value, quality and image. Such data are routinely supplied by primary consumer research tracking companies. Data are usually 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 2 alongside advertising TVR investments and brand perception data relating to fragrance and perceived product value.[3]

[2] Note that for any long-term or permanent indirect brand-building effects to exist, brand sales must be evolving. The flow illustrated in Figure 1 is often referred to as a Path Model and estimated using Structural Equation Modelling (SEM) techniques. However, conventional SEM analysis is not suitable for evolving or non-stationary data in levels.

[3] 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.

Figure 3: Evolution of base and consumer tracking statements*



*Source: Cain (2010)

3) Contribution of brand perceptions to brand demand and price sensitivity

Thirdly, we establish the impact of relevant tracking measures on brand demand and price sensitivity. Brand image tracking data represent the variation in consumer brand perceptions over time. Extracted base sales represent evolution of observed brand purchases or long-run brand demand - driven by trends in shelf price, selling distribution and, crucially, brand perceptions. Regression analysis is used to identify relationships between these variables. When evolving variables are involved, 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 base demand drivers. The cointegrated Vector Auto Regression (VAR) model (Johansen, 1996, Juselius, 2006) is used for this purpose and demonstrated with the following model structure.

$$\begin{bmatrix} \Delta X_{1t} \\ \Delta X_{2t} \\ \Delta X_{3t} \\ \Delta X_{4t} \\ \Delta X_{5t} \\ \Delta X_{6t} \\ \Delta X_{7t} \end{bmatrix} = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} & \pi_{14} & \pi_{15} & \pi_{16} & \pi_{17} \\ \pi_{21} & \pi_{22} & \pi_{23} & \pi_{24} & \pi_{25} & \pi_{26} & \pi_{27} \\ \pi_{31} & \pi_{32} & \pi_{33} & \pi_{34} & \pi_{35} & \pi_{36} & \pi_{37} \\ \pi_{41} & \pi_{42} & \pi_{43} & \pi_{44} & \pi_{45} & \pi_{46} & \pi_{47} \\ \pi_{51} & \pi_{52} & \pi_{53} & \pi_{54} & \pi_{55} & \pi_{56} & \pi_{57} \\ \pi_{61} & \pi_{62} & \pi_{63} & \pi_{64} & \pi_{65} & \pi_{66} & \pi_{67} \\ \pi_{71} & \pi_{72} & \pi_{73} & \pi_{74} & \pi_{75} & \pi_{76} & \pi_{77} \end{bmatrix} \begin{bmatrix} X_{1t-1} \\ X_{2t-1} \\ X_{3t-1} \\ X_{4t-1} \\ X_{5t-1} \\ X_{6t-1} \\ X_{7t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix} \tag{1}$$

Equation (1) represents an unrestricted VAR model, re-parameterised as a Vector Error Correction Model (VECM).[4] Variables X_{1t} - X_{7t} represent base sales, average price elasticity evolution, regular shelf price, selling distribution, two image statements and advertising data.[5] Model (1) is first used to test for *equilibrium* relationships between the variables: that is, relationships which tend to be restored when disturbed such that the series follow long-run paths together over time. Conceptually, this occurs if linear combinations of the variables provide trendless (stationary) relationships, implying that the π matrix of equation (1) is of reduced rank and the variables cointegrate. With *n* trending I(1) variables, the π matrix may be up to rank *n-1*, with *n-1* corresponding equilibrium relationships to be tested as part of the model process.[6] For ease of exposition - and since we are focusing primarily on the drivers of base sales and price sensitivity - we assume a rank of 2 and thus just two linearly independent cointegrating relationships. This allows us to factorise (1) as:

$$\begin{bmatrix} \Delta X_{1t} \\ \Delta X_{2t} \\ \Delta X_{3t} \\ \Delta X_{4t} \\ \Delta X_{5t} \\ \Delta X_{6t} \\ \Delta X_{7t} \end{bmatrix} = \begin{bmatrix} \alpha_{11} \alpha_{12} \, \alpha_{13} \\ \alpha_{21} \alpha_{22} \, \alpha_{23} \\ \alpha_{31} \alpha_{32} \, \alpha_{33} \\ \alpha_{41} \alpha_{42} \, \alpha_{43} \\ \alpha_{51} \alpha_{52} \, \alpha_{53} \\ \alpha_{61} \alpha_{62} \, \alpha_{63} \\ \alpha_{71} \alpha_{72} \, \alpha_{73} \end{bmatrix} \begin{bmatrix} \beta_{11} & 0 & \beta_{31} & \beta_{41} & \beta_{51} & \beta_{61} & 0 \\ \beta_{12} & \beta_{22} & 0 & 0 & \beta_{52} & \beta_{62} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \beta_{73} \end{bmatrix} \begin{bmatrix} X_{1t-1} \\ X_{2t-1} \\ X_{3t-1} \\ X_{4t-1} \\ X_{5t-1} \\ X_{6t-1} \\ X_{7t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix} \tag{1a}$$

Equation 1(a) represents a cointegrated VAR representation of the system – with each first differenced equation driven by (stationary) advertising investments and two cointegrating or equilibrium relationships between base sales, average price elasticity, regular price evolution, selling distribution and the two image statements. The parameters β_{11} – β_{61} and β_{12} – β_{62} represent the cointegrating parameters. If we take the first cointegrating vector, and normalise on base sales (X_1) by setting β_{11} to unity, then β_{31}, β_{41} β_{51} and β_{61} represent the impact of the regular price level, selling distribution and the two image statements on

[4] Whereas the VAR technique is impractical in the context of the fully specified mix model due to the large number of variables generally involved, the focus on base sales evolution allows us to concentrate on a small group of variables, greatly simplifying the approach. Model (1) is derived from a VAR(1) specification – where all the variables appear with a one-period lag. The appropriate number of lags is generally tested such that each equation depicts a statistically congruent representation of the data.

[5] Advertising data often comes in the form of TVR 'bursts' as illustrated in Figure 3. Under these circumstances, given the discrete nature of such data, it cannot be modelled as an endogenous variable in the system. Under these circumstances we would use (continuous) adstocked TVR data in (1) and condition on this (weakly exogenous) variable in estimation. Alternatively, we would transform the TVR data into a continuous Total Brand Communication Awareness variable.

[6] To provide valid cointegrating relationships with base sales, other variables such as regular price, distribution and image statements must also be evolving. Advertising is generally stationary and would not enter the cointegrating relationship, reflected by the zero entries in the last column of the beta matrix above. The variable itself thus represents a stationary 'combination' and is represented by the third row in the beta matrix with *n-1* restrictions, normalised on β_{73}.

base sales.[7] If we then take the second cointegrating vector and normalise on price elasticity (X_2) by setting β_{22} to unity, then β_{12}, β_{52} and β_{62} represent the impact of base sales and the two image statements on price sensitivity. Additional identifying constraints can be placed on the vectors. For example, we would expect base sales evolution to drive average price sensitivity – as per the flow illustrated in Figure 1 - but not vice versa. Thus we would set β_{21} to zero in the first cointegrating relationship. Furthermore, unless we have reason to believe that the level of regular price and selling distribution influences average price sensitivity, we would set β_{32} and β_{42} to zero in the second cointegrating vector.

Normalisation restrictions are quite arbitrary – and reflect assumptions on which variables are adjusting in the system: that is, the endogenous variables and direction of causality. For example, by normalising on X_1 and X_2 in each of the cointegrating vectors, we pre-suppose that image statements drive base sales and price sensitivity. However, it may be that causality runs in the other, or both, directions. The significance of the parameters α_{11}, α_{51} and α_{61} in the equations for ΔX_1, ΔX_5 and ΔX_6 provide the relevant information for base sales. Suppose α_{11} is negative and significant in the equation for ΔX_1, yet α_{51} and α_{61} are zero in equations ΔX_5 and ΔX_6. This tells us that base sales adjust (error correct) to shifts in image statements X_5 and X_6, at a rate α_{11} weighted by β_{51} and β_{61} respectively. However, image statements do not adjust to movements in base sales. Brand perceptions are (weakly) exogenous and *Granger* cause base sales (Granger, 1987). However, if α_{51} and α_{61} are positive and significant in equations for ΔX_5 and ΔX_6 then image statements do adjust to movements in base sales. Causality is bi-directional: from image to base and vice versa. Similar reasoning applies to the equation for ΔX_2, where, for a causal relationship from image statements to price sensitivity, we would expect α_{22} to be negative and significant with α_{52} and α_{62} equal to zero in the equations for ΔX_5 and ΔX_6. A negative and significant estimate of α_{12} would also tell us that base sales Granger cause price sensitivity.

4) Linking marketing investments to base sales

Finally, model 1(a) is used to estimate the full (long-term) impact of advertising on brand perceptions and the impact of the latter on base sales and price sensitivity. To do this, we make use of the Moving Average representation of the cointegrated VAR model 1(a) – written in matrix form as follows:

$$X_t = A + C\sum_{i=0}^{t}\varepsilon_i + \sum_{i=0}^{\infty} C_i^* \varepsilon_{t-i} \qquad (2)$$

Equation (2) shows that the model can be broken down into three components: initial starting values (A) for the variables, a non-stationary permanent component and a stationary component – represented by the cointegrating vectors themselves. The non-stationary C matrix – known as the Moving Average impact matrix – is illustrated in Figure 4 and provides the long-term impact of base sales on price sensitivity, image statements on base sales and advertising on image statements: each may then be combined to predict the net indirect impact of advertising on base sales and price sensitivity.

[7] Note that the regular price parameter estimate is distinct from the average price elasticity derived from the short-term mix model.

Figure 4: Moving Average Impact Matrix

	ε_{X1}	ε_{X2}	ε_{X3}	ε_{X4}	ε_{X5}	ε_{X6}	ε_{X7}
X_1	C_{11}	C_{12}	C_{13}	C_{16}	$\mathbf{C_{15}}$	$\mathbf{C_{16}}$	0
X_2	$\mathbf{C_{21}}$	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	C_{27}
X_3	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}	C_{37}
X_4	C_{41}	C_{42}	C_{43}	C_{44}	C_{45}	C_{46}	C_{47}
X_5	C_{51}	C_{52}	C_{53}	C_{54}	C_{55}	C_{56}	$\mathbf{C_{57}}$
X_6	C_{61}	C_{62}	C_{63}	C_{64}	C_{65}	C_{66}	$\mathbf{C_{67}}$
X_7	0	0	0	0	0	0	0

Each column of Figure (4) represents the cumulated empirical shocks to each equation of the VECM system 1(a).[8] Reading across in rows, the parameters indicate the long-term (permanent) impact of such cumulated shocks on the levels of the variables in the system. For example, the first row indicates that the long-term behaviour of X_1 is determined by shocks in X_2 – X_6 with weights C_{12} -C_{16}. Shocks in X_7 have no direct impact since base sales do not contain any of the direct impact of TV advertising by construction.[9] The final row is populated with zeros, indicating that shocks of all variables in the system have no long-term impact on advertising. This follows by construction since X_7 is a stationary variable.

For the permanent indirect impacts of advertising on base sales, the parameters of interest are C_{15}, C_{16}, C_{57} and C_{67}. The latter two parameters measure the impact of advertising shocks on image statements X_5 and X_6 respectively. Parameters C_{15} and C_{16} on the other hand measure the impact of shocks in image statements X_5 and X_6 on base sales. The net indirect impact of 1% changes in advertising and both image statements on base sales is, therefore, %{(C_{15}* C_{57}) + (C_{16}* C_{67})}. The impact of base sales on price sensitivity is given by parameter C_{21}. The impact of advertising on base sales is thus augmented with %C_{21}*[%{(C_{15}* C_{57}) + (C_{16}* C_{67})}] to incorporate the impact of advertising on price sensitivity.[10]

[8] Note that shocks have to be identified as *structural* to ensure that they derive from the variable of interest and are not contaminated by effects from other variables in the system (see *inter alia* Juselius, 2006).

[9] Short to medium-term marketing effects are orthogonal to the baseline. Thus, direct long-term marketing effects are zero by construction and any long-term effects are indirect – working through brand perceptions. An alternative approach, as discussed in Cain (2005) and exemplified in Osinga *et al* (2009), is to specify the trend transition equation of the dynamic marketing mix model directly as a function of marketing effects thus allowing endogenous trend evolution.

[10] Note that significant MA impact coefficients imply permanent or *hysteretic* indirect effects. Non-significant or zero MA coefficients do not, however, imply zero indirect effects. Even though the impulse response functions may decay to zero in the limit, any short to medium-term impulse effects are still evidence of indirect marketing effects – in addition to those measured in the short-term model.

5) Calculating the full long-run impact

Estimated baseline 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 (potentially) negative for heavy promotional weight. These must be quantified if we wish to measure the full extent of such 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 impact will diminish as loyal consumers eventually leave the category and/or switch to competing brands. Secondly, future benefits will be worth less as uncertainty increases. To capture these effects, we exploit a standard discounting method used in financial accounting which quantifies the current value of future revenue streams. The calculation used for each marketing investment is written as:

$$PV_i = \sum_{t=1}^{N} \frac{C_{i0} * d_i^{\,t}}{(1+r)^t} \qquad (3)$$

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 reflecting increasing uncertainty. 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 product manufacturer's internal rate of return on capital: a higher discount rate reflects greater uncertainty around future revenue streams.

The indirect 'base-shifting' impact over the model sample, together with the decayed PV of future revenue streams quantifies the long-run base impact of advertising and promotional investments. The value created by the impact of advertising on price elasticity, on the other hand, derives from the fact that the brand can now charge a higher price for the same quantity with less impact on marginal revenue. The reduced impact of price increases on revenues, weighted by the advertising contribution to price elasticity evolution, provides the additional value impact of advertising. Both the base and price elasticity revenue effects may then be combined with the weekly revenues calculated from the short-run modelling process. Benchmarking final net revenues against initial outlays then allows calculation of a more holistic ROI to marketing investments.[11]

[11] Note that TV investments may serve to simply maintain base sales – with no observable impact picked up using time series econometric modelling. This can be dealt with by incorporating estimates of base decay in the absence of advertising investments – based on prior 'norms' or 'meta' analyses across similar brands in similar categories. Note also, that excessive price promotion may serve to increase price sensitivity by changing the consumer's price reference point. This constitutes an additional negative impact of price promotions on net revenues.

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