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Marketing Mix Analysis: A Science ... and an Art

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What will happen to sales if I increase the price of my brand? What is the impact of a price promotion? What is the Return on Investment (ROI) from my media spending? How can I optimize my future marketing activity? These are some of the most frequently asked questions we at Millward Brown receive from marketing departments in North America and the rest of the world.

Marketing mix analysis is an excellent tool for addressing these issues. The purpose of this chapter is to review some of the practical considerations facing the modeler when conducting marketing mix analysis in a commercial environment. There is a particular emphasis on the pricing and advertising elements.

An introduction to some of the principles of marketing mix analysis is provided, including an overview of the common modeling tools. We then consider the product categories in which the tools may be applied and focus on the recent development of modeling applications for non-packaged goods brands. Detailed pricing and advertising case histories show how conventional methods can be adapted using techniques such as nonlinear regression (NLR), ridge regression, and multistage modeling in order to provide the client with greater insight and actionability.

However, complex modeling formulations can be inappropriate. To illustrate, we show how good data exploratory techniques have been used in an attempt to understand the longer-term contribution of advertising to sales.

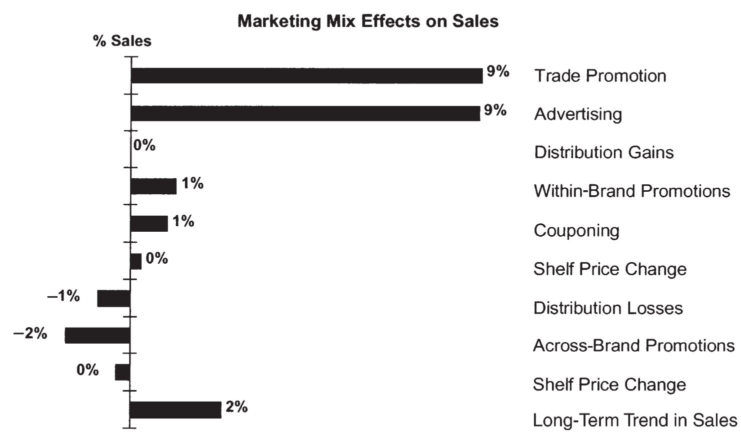
A series of case histories is included, so this chapter should be of interest to both the practitioner and the nonpractitioner. Throughout the chapter, there is a common theme. Marketing mix analysis may be difficult, though not necessarily because of the statistics. There are many issues the modeler needs to address, including data availability, clients' objectives, interpretation, and the application of results. Marketing mix analysis is a science—but it is also an art.

PRINCIPLES OF MARKETING MIX ANALYSIS

Marketing mix analysis identifies and quantifies the impact of key marketing mix components on sales, such as price, promotion, distribution, and advertising (Figure 1). These elements are usually considered for both the modeled brand and competitor brands, because competitor activity can also have both positive and negative effects on sales of the modeled brand. Seasonality is inherent in many categories and, though not a marketing factor, should be incorporated where relevant.

Most models developed in a commercial environment are based on multiple linear regression techniques (general linear models), though other tools are available, including NLR, conventional time-series approaches, and neural networks. These alternative approaches may provide a good prediction of sales, but they can be more computationally

Figure 1
Contribution of Marketing Activity to Sales



demanding or fail to provide the brand manager with an adequate explanation as to *why* there have been movements in sales.

An example of a model for a retailer shows how accurately we are sometimes able to predict sales (Figure 2). The solid line shows weekly sales, and the dashed line is the model prediction of sales.

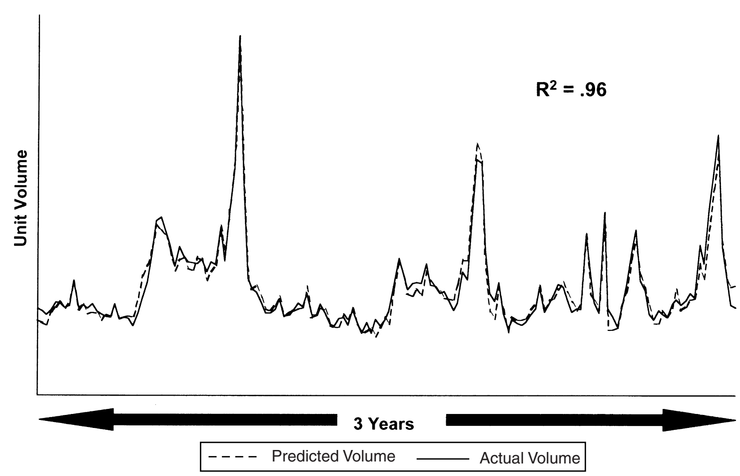
The data were modeled at the store level and then aggregated to present the national picture using general linear modeling of the form:

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_p x_p + \varepsilon.$$

In this example, a "good" statistical prediction of sales was obtained by incorporating the following measures:

- ❏ Regular price and temporary price reduction;
- ❏ Store inventory, store volume per 1000 households in area, type of store (downtown, mall, etc.), selling square footage;
- ❏ Magazine, newspaper, radio, outdoor, and television advertising;

Figure 2
Retail Sales and Model Prediction



- ❑ Seasonality;
- ❑ Underlying trends; and
- ❑ Promotional/store-type interaction.

The accuracy of the model will usually be influenced by the quality of both the sales data and these explanatory measures. If we do not have the data, we cannot expect good models to be produced.

The model inputs will clearly vary by product category, but we can attempt to incorporate any measure, providing adequate detail and timing of an activity is available.

In this example, we can be reasonably satisfied from the modeling perspective. We have a model that has accuracy and that subsequently satisfied two separate validation processes (in process and hold-out sample). We also tested our data to ensure compliance with important statistical assumptions. Diagnostics include residual analysis, leverage statistics, and influence measures. (Refer to any good statistical textbook for further details.)

So, does this scientific part of the modeling development satisfy our clients' requirements? Not on its own (though good statistical fit and validity are obviously important). We must ensure that the model makes sense.

For example, multicollinearity is caused by having highly correlated measures. This can result in a model having good statistical fit but misleading coefficient weight and signs. As modelers, we would lose all respect from a client if we suggested that an increase in price would result in a sales increase, a reduction in distribution would result in a sales increase, the client's television advertising would have a negative impact on sales, and so on. All these scenarios are statistically possible but do not make intuitive sense (and are more likely to be statistical artifacts).

In the retail example, we could have produced an equally good model fit and short-term projection by using conventional time-series approaches such as Box-Jenkins. Such methods tend to be good forecasting tools but fail to meet the client's objectives, in that they are unable to explain *why* there have been movements in sales.

The summary of marketing mix effects on sales (Figure 1) is inherent in presentations produced by almost every agency that specializes in marketing mix analysis. This provides the client with a useful management summary, though it can be too static and almost too simple in nature for the purpose of future application. We have to make every attempt to explain *why* there have been movements in sales and to estimate the expected impact of future marketing activity and the timing of the activity on sales, as well as how sales can be optimized from future activity given a marketing budget. The client wants to use the model to move his or her business forward. We show how to do this subsequently.

To summarize, we should never lose sight of the client's objectives, and throughout this chapter, an important theme is retained: A successful marketing mix analysis requires not only that the modeler have good statistical practice, but also that the modeler gain a good understanding of the client's issues and apply common sense when building and interpreting the model.

CAN I APPLY MARKETING MIX ANALYSIS TO MY BRAND?

Marketing mix analysis is certainly not new and has been successfully applied across diverse brands for many years. The main prerequisite is to have access to reliable and consistent sales data and marketing inputs over time.

Packaged Goods

Historically, most market mix analysis has been conducted on traditional packaged goods brands. The tool has been publicly presented and had a very high profile for at least 30 years, with every product category modeled at some time, ranging from potato chips and candy to deodorants and haircare products (to name just a few).

Packaged goods clients have the luxury of being able to purchase consistent syndicated sales and causal data from ACNielsen or IRI for their own brand and competitor brands by pack size and variant. These data are typically weekly and available for grocery, drug, and mass merchandise sales channels in the United States (though the sales period can vary by category). Any client purchasing ACNielsen or IRI syndicated sales data can conduct or commission marketing mix analysis projects. Models can also be applied on household panel data (see von Gonten 1998; von Gonten and Donius 1996), though this is less common among practitioners and not covered in this chapter.

Even though product categories are diverse and possess their own unique characteristics and purchase cycles, the consistent delivery and detail of data, the fast moving nature of the product, and the common sensitivity to price and promotion often enable a consistent approach to be adopted.

Nonpackaged Goods

A common myth is that marketing mix analysis can be applied only to packaged goods. This is fortunately nothing more than a myth. In recent years, we have worked with diverse clients ranging from automobiles to pharmaceuticals, financial services to retail, lotteries to alcoholic beverages, telecommunications to mail delivery services, gasoline to milk, and so on.

Many of these projects have features or "quirks" unique to their category that make such projects "nonstandard." However, in most cases, we are able to overcome these difficulties through detailed discussion with the client (and provided adequate data are available).

To illustrate, for a recent telecommunications client providing a monthly subscription service, what sales units should we be modeling? This is not as straightforward as it initially appears. Any of the following sales units could be considered:

- New customers,
- Repeat customers,
- Total new and repeat customers,
- The number of telephone calls made, or
- The value of the telephone calls.

This becomes more complex when considering the array of tariffs that range from those targeting the "occasional personal user" with low monthly tariff payments but expensive call rates to those aimed at a "heavy business user" with high monthly payments but less expensive call rates.

We recently assessed the ROI of a direct-to-consumer campaign for prescriptions of a drug. We needed to attempt to disentangle the impact of the campaign on the patient from the influence of the campaign on doctors prescribing the drug. There are inevitable time delays caused by potential users of the drug who are influenced by the marketing activity but subsequently need to make an appointment with their doctor before the drug can be purchased. This adds complexity to the problem at hand (though not necessarily to the analysis).

There are additional considerations for nonpackaged goods. First, a category can be heterogeneous and split into several product fields. For example, one of the most diverse categories is financial services. In recent years, we have modeled bank checking and savings accounts, credit cards, automated payment schemes, life assurance, pension schemes, stock exchange investment products, and car and home insurance. We therefore cannot adopt a blanket approach to the modeling of nonpackaged goods at a category level or within a category. The analytical concepts may be similar, but the factors driving each product field clearly differ.

Second, nonpackaged goods clients do not have the luxury of being able to purchase consistent syndicated data for their brand and competitor brands. Their data arrive in many different formats from many different internal and external data sources. In essence, understanding, making sense of, and manipulating these data is the real challenge when modeling for nonpackaged goods clients

Improving Quality of Client Data and the Growth of Modeling in Nonpackaged Goods

Fifteen years ago, a marketing mix analysis on a nonpackaged good brand could have been conducted but with limited benefit and certainly minimal actionability. Sales data would often be monthly or quarterly, and in some cases, only national data rather than market/regional-level data would be available. Such projects would have a relatively simple model formulation and only be able to provide an estimate of the impact of one medium (usually television). This effect would be directional because of the highly aggregated nature of the data.

In recent years, we have seen a sharp increase in the number of marketing mix analysis projects for nonpackaged goods clients. This is in part attributable to the growth of the service sector, new industries, and technological developments. Many clients now have new, innovative, and powerful management information systems that possess detailed sales and inquiry data on *all* customers, both *locally* and *nationally.*

In many cases, we now have access to more powerful sales data than are available from many of our packaged goods clients that buy syndicated data. For example, a U.S. company was recently able to provide telephone inquiries by day, daypart, and time of day. A financial service organization in the United Kingdom was able to provide the date, time of inquiry, whether a subsequent sale was made, and date of subsequent sale where applicable for each customer/potential customer by market and zip code. Advertising spending was also made available by day and daypart. This quality and level of sales data is very powerful.

METHODS

Marketing mix analysis can be a very emotive topic, and there are many schools of thought on the correct methodology, ranging from the statistical purists to those who push the statistical validity to its limits (though sometimes through ignorance) in an attempt to get the answer they want. Fortunately, the latter form the minority, and most practitioners usually balance the desire for sensible results with good statistical practice.

Those of a more academic nature may strive for the most statistically complex solution. Although commendable, this can often be impractical in a commercial environment where tight time constraints are imposed by clients. For example, on a recent project, we attempted to use a structural equation modeling approach. This proved to be very time consuming and then difficult to replicate on products in different markets. Moreover, the results were no more meaningful or insightful than those produced within a shorter time period using a general linear model.

A whole book could be devoted to methodological and data issues surrounding marketing mix analysis approaches. Some argue that store-level data is needed to model packaged goods, others argue that modeling can be conducted at the market level, some argue that there is disaggregation bias at the store level, others argue that there is aggregation bias at the market level, some argue that they have the “best” model because they have the better data, others argue that they have the better model because their model has a more complex formulation or is more flexible … and so on.

There are clearly no definitive answers to this debate (though those with their own prejudices may not accept this comment). Because the purpose of this chapter is to focus on modeling applications, we do not enter the debate at this stage other than to say that the “best” approach should be governed by the client’s objectives and the available data.

Papers discussing methodological issues are referenced for the interested reader. We also make observations on methodology in a subsequent discussion.

PRICE AND PROMOTIONAL ISSUES

Price and promotion invariably have the largest *immediate* effect on sales for packaged goods brands, particularly in the grocery sector. Examples of pricing related promotion include

- ❑ Temporary price reductions ("For this week only, the price is reduced from $1.99 to $1.49"),
- ❑ Extra value ("Get 20% extra for the same price"),
- ❑ Extra packs ("Buy one outer pack containing 12 bars and receive 2 free bars"), and
- ❑ BOGOF ("Buy one get one free").

Promotional incentives can also be provided in the form of free or discounted gifts, instant wins, and so on. Irrespective of the nature of the promotion, its effectiveness will be boosted when supported with a combination of "shelf-talkers" and in-store displays.

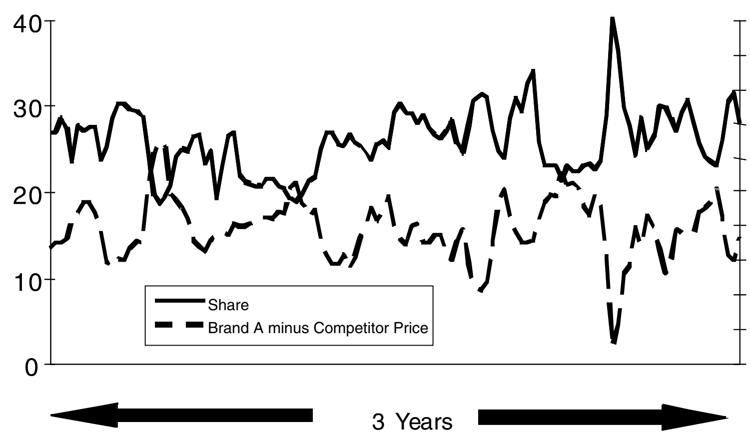
There can be a large amount of bias in price and promotion through the aggregation of store-level data to the market/regional level. Some stores promote, whereas others do not, and the promotional effect therefore can be considerably diluted. ACNielsen and IRI specialize in modeling this micro-level trade activity. They have access to detailed store-level data and have developed proprietary models that enable them to model at the store level and report precisely on the impact of such trade promotions. This is done by comparing the impact of sales on stores with and without the different forms of trade activity.

However, this does not imply that other agencies, individuals specializing in commercial modeling, or academics cannot develop meaningful models that provide insight on price and other marketing issues. We therefore focus on how the majority of practitioners can address pricing issues, even though the sales data may only be made available at the market/regional level. We are unable to disentangle the specific impact of all trade promotion, but we can show how the brand reacts to price and pricing-related promotion.

Price Elasticity

Figure 3 shows the power of conducting exploratory analysis before we begin to attempt the modeling process. The solid line is weekly volume share of a leading packaged goods brand in the grocery sector over a three-year period. We refer to this as $\text{Brand}_{\text{mod}}$. The main competitor for

Figure 3
Volume Market Share and Price Difference



this Brand is Brand$_{comp}$. The dashed line is the price of the modeled brand minus the price of the key competitor brand and is simply given by

$$\text{Price Difference} = \text{Brand}_{mod}(\$\text{Sales}/\text{Volume Sales}) - \text{Brand}_{comp}(\$\text{Sales}/\text{Volume Sales}).$$

We observe a very strong relationship and almost symmetrical pattern between apparent reductions in price and increase in market share.

Not surprisingly, the inclusion of this price difference term in the model is highly significant. Changes in relative price have a strong influence on sales. For Brand$_{mod}$, we find that a 1% increase in relative price will result in an 0.8% decrease in market share. This is a price elasticity of –0.8.

The elasticity for an additive model can be calculated from the model coefficient, volume, and price:

$$\text{Price Elasticity} = (\text{coefficient for price difference}/\text{Brand}_{mod}\text{average volume}) \times (\text{Brand}_{mod}\text{average price}).$$

For a multiplicative model, the input is a price ratio ($Brand_{mod}$price/ $Brand_{comp}$price). The elasticity is obtained directly from the coefficient.

The price elasticity provides an indication of the sensitivity of the brand to changes in price. The elasticity is also useful as a standardized measure, enabling a meaningful comparison of the impact of price changes across all brands, adjusted for the size of the brand (big brands lose more volume in real terms).

In general, the price elasticity implies that if you increase price by 1% and sales volume decreases as a result by this negative percentage, then you would make the same profit as before. Refer to Broadbent (1997) for a more detailed discussion on the concepts of price elasticity.

We typically find that larger, established brands are less sensitive to price changes than smaller or new brands. We also find that price elasticities are not consistent over the different sales channels. For example, a candy product is likely to have greater sensitivity to price in a grocery store, where there is a wide choice of products and a larger amount of promotional activity, than in a convenience store, where the purchase decision is often made more on impulse and products typically demand a higher price.

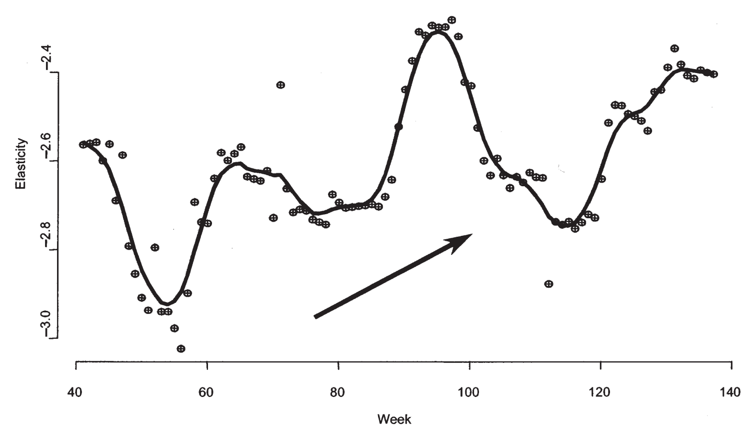
This leads to a simple consideration that should be applied across all marketing mix analysis projects. We should never assume that the elasticities for promotional spending (or any other marketing mix measures) remain constant over the modeling period. Many agencies specializing in marketing mix analysis present bar charts/pie charts in order to summarize the contribution of the various components of the marketing activity to sales (Figure 1). Although such charts provide a useful overview, they should also specify whether the elasticities have remained constant or changed over time. Failure to do this could lead to misleading conclusions and inappropriate marketing decisions being made.

Figure 4 shows a rolling price elasticity for a packaged goods brand. The average elasticity (the one commonly reported) is –2.7. Focusing on the underlying trend, there has been a slight decrease in the sensitivity of the brand to increases in price. Further investigation showed that this coincided with an increase in both the weight and quality of the television advertising campaigns over the modeling period. This is effectively an indirect long-term impact of advertising on sales of the brand. Price increases are now having a smaller negative impact on sales than they were at the start of the modeling period.

Reporting the average elasticity of –2.7 alone is not incorrect from a statistical viewpoint, but we are failing to provide the brand manager with a true reflection of what is happening to his or her brand due to marketing activity *over time*.

There are also periods of short-term fluctuation. The period around week 95 coincided with a television advertising campaign and strong brand support in-store, though no price promotions. We found that the combined strategy reduced the price sensitivity of the brand for the duration of the campaign.

Figure 4
Rolling Price Elasticity



Modeling by Pack Size—Pricing Case History

We now present a detailed case history for a leading brand in the snack category to demonstrate how the concepts on price elasticity can be applied.

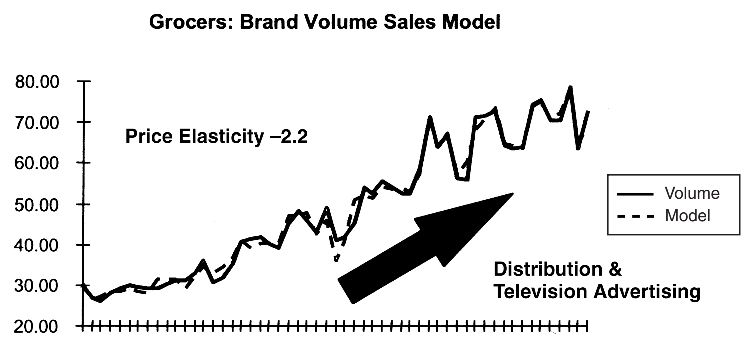
Model 1: Total Brand Sales

Total brand sales in the grocery sector were predicted over a three-year period. The primary focus was to understand the contribution of television advertising to sales. A good statistical fit of total brand sales was produced, and we were able to demonstrate that the growth in sales was primarily driven by both excellent television advertising and increased distribution (Figure 5). The average price elasticity for the brand was –2.2.

Model 2: Pack Size Sales

During the next two years, the client obtained improved sales data, and pricing became the primary issue. The key objectives were to determine the combination of pack size promotions that would generate maximum sales for the brand overall and identify the brand's competitor set by pack size.

Figure 5
Brand Model



Therefore, three refinements were made to the original modeling approach:

- ❏ Model pack size,
- ❏ Use straight price, and
- ❏ Adopt a multistage modeling approach.

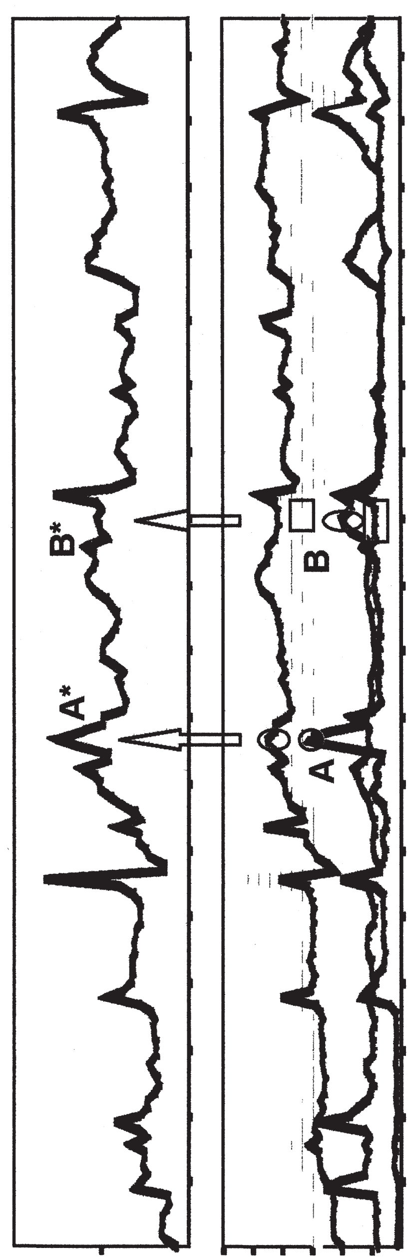
These allow greater insight and actionability for the brand manager by quantifying and explicating the impact of individual elasticities and the extent of cannibalization across pack size. We consider the three model refinements in turn.

Brand Sales Versus Pack Size Sales. Modeling at the total brand level is clearly inappropriate, and we are able to show that this can "hide" potentially key findings (Figure 6). The top chart is total weekly volume sales for the brand—our original unit of measurement. The bottom chart is sales split by the four key pack sizes (small, medium, large, and very large). Points A and B represent two different price promotions.

At point A, the net effect of promoting the small and very large packs results in a positive increase in sales over the promoted period (A*). This is favorable. At point B, the promotion successfully generates sales of the very large pack, but most of these sales appear to be taken from the medium and large packs, and the net effect is minimal (B*). This is unfavorable.

The first refinement was therefore to disaggregate the sales data and model by pack size. This should allow the assessment of pack size inter-

Figure 6
Total Brand and Pack Size Sales



action or cannibalization and indicate where promotions are having the largest impact.

Straight Price. At the same time, we were also considering the merits of using relative price for this new project. Although relative price was adequate for modeling brand sales, this approach does have limitations, particularly as we disaggregate the data. Relative price assumes that a 1% increase in the modeled brand will have the same impact as a 1% decrease in the competitor brand. This tends to work, but conceptually, we would expect a different effect on sales from changing the price of the modeled brand than from changing the price of the competitor brand; the effect is not symmetrical. The second refinement was therefore to use straight price for the client's brand and competitor brands. We should now be able to see the individual contributions of price change.

Competitor Index. We incorporated a straight price term for the modeled brand but were only able to build in the one competitor term. The model worked but was still an unsatisfactory solution for the client who still wanted to know the *competitor set* by pack size and not just the impact of one competitor.

A two-stage modeling approach was therefore adopted. The first phase of the process was to build a model as normal using straight price for the main brand but excluding the competitor prices. The second phase was to model the residuals with only the competitor prices and feed this back into the original model. So, how successful was this approach? Consider the following three observations:

First, a series of pricing terms could now be incorporated across the four models (Table 1). We could also build in a series of other measures (Table 2). Four models were developed explaining between 94% and 96% of variation in sales.

Second, price elasticities are now available for each of the four pack sizes. These are

- ❏ Small pack, –3.6;
- ❏ Medium pack, –3.8;
- ❏ Large pack, –2.8; and
- ❏ Extra large pack, –2.9.

At this stage, we note that the smaller packs appear to be more price sensitive. This is counterintuitive, as we would expect larger packs to be more price sensitive (most consumers buy in bulk to save money rather than for convenience). We were able to explain this apparent discrepancy. The small and medium packs had been predominantly supported with pricing promotions (temporary price reductions). The larger pack sizes had also been heavily supported with other forms of promotional activity (extra packs for same price). When we combine the price and promotional

Table 1
Model Inputs—Price

Client Brand	*Own Label*	*Other Brands*
Small	Small	Brand A Small
Medium	Medium (2 sizes)	Brand A Medium
Large	Large (2 sizes)	Brand B Small
Extra Large	Extra Large (2 sizes)	Brand B Medium
		Brand D Small
		Brand D Medium
		Brand E Large
		Brand F Small
		Brand F Medium
		Brand G Medium

Table 2
Model Inputs—Additional Measures

Promotions	*Others*
Pack Price Promotion	Theme Advertising
Pack Value Promotion	Promotional Advertising
Extra Pack Promotion	Seasonality
Competitor Promotions	Distribution
	Launch of New Variant

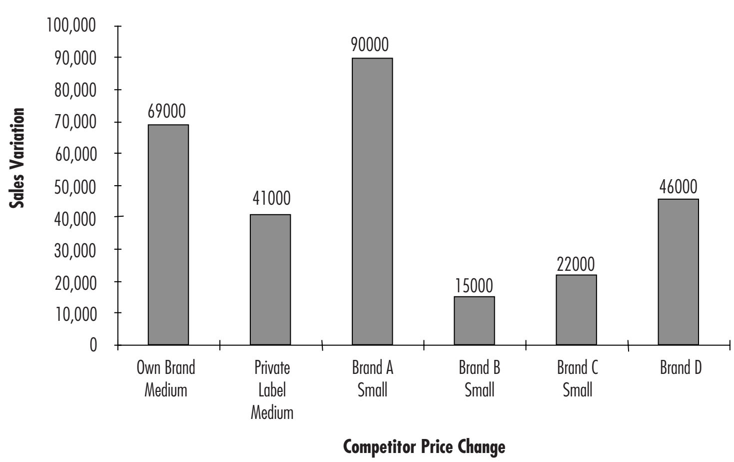
elasticities, the overall elasticities become much stronger for the larger pack sizes.

We also note that price elasticities appear to be considerably greater than those reported two years earlier. Is this evidence to suggest the brand is losing equity and becoming considerably more price sensitive in a relatively short time period? This would have been a disturbing conclusion for the client. Fortunately, this was not the case. The elasticities are no longer comparable because of the change in approach from relative to straight price. The new elasticities are for the individual packs and include the elasticity among brands and within-brand (cannibalization). The original model elasticity was based on competitor brands only. We were able to show that for the new model, the overall elasticity *with other brands* is –2.2, almost identical to what we reported two years earlier using the original formulation.

Third, the multistage modeling approach enabled detailed findings to be identified on the competitor brands and their pack sizes through the development of a competitor index. The competitor index disentangles the contribution of price changes on a set of competitor brands and is obtained from the second phase of the multistage approach.

Figure 7 shows the maximum variation on the sales of the small pack, caused by changes in the six key competitor prices in any one week. For example, changes in price of Competitor Brand A's small size had the largest impact on the sales of the client's small pack brand (up to 90,000 sales units). The next largest variation was due to the client's own medium pack size. This is the cannibalization effect and should be understood and controlled wherever possible. The competitor indices were later validated by other sources of data and research conducted by the client.

Figure 7
Maximum Impact of Competitor Price Changes on Sales of the Modeled Brand



Spreadsheets can now be provided to help the client generate "what-if" scenarios, understand the implications of changes made to the brand's price, and appreciate the likely impact of competitor price changes. A simple hypothetical example shows the estimated impact on sales of the small pack should five key competitors reduce their price by 5% at the same time (Table 3). This (unlikely) action would result in a volume loss of 3.67%. The models could now be used to deduce the impact of temporary price changes and promotions on individual pack sizes.

If the client reduces the price of the small pack, 97% of the extra sales gained will be taken from competitor branded products of similar pack sizes. This is clearly desirable. The small pack size is not competing with the private label. However, when promoting the medium pack, almost all sales will be generated from those consumers switching from the brand's own small pack (predominantly) and the large pack. The overall sales generated through the medium pack promotion are canceled through the loss in sales of the small and larger packs.

When promoting the large pack, just 15% of sales are taken from competitor brands. The majority of incremental sales are still from existing consumers switching from the medium and extra large packs. In contrast, when the extra large pack is promoted, approximately 55% of sales are taken from competitor brands (mainly private label).

Therefore, if the client wishes to optimize incremental sales for the brand and take sales away from competitor brands, the focus should be on promoting the small packs. If the client wishes to protect the brand market share from the private label, the focus should be on promoting the extra large pack sizes.

Table 3
Price Elasticity Spreadsheet

Price	*Before*	*After*	*% Change*	*Volume*
Own Brand Medium	1.68	1.68	—	—
Private Label Medium	1.02	0.97	–5	–0.07
Brand A Small	0.90	0.86	–5	–0.18
Brand B Small	0.88	0.84	–5	–0.04
Own Brand Small	1.05	1.05	—	—
Brand C Small	0.99	0.94	–5	–0.07
Brand D	1.41	1.34	–5	–0.04
			Sum Units (100,000's)	–0.40
			Percentage	–3.67

This case history is a good illustration of how the basic concepts can be applied to developed models that meet a client's specific requirements and were certainly actionable. For the practitioner, this analysis shows differences in price elasticities and potential pitfalls when interpreting models. It would have been very easy for a modeler to misinterpret the results of the new pack size elasticities, particularly when making a comparison with previous results. This could have resulted in misguided marketing decisions being made.

TELEVISION ADVERTISING

How Can We Build Television Advertising into a Model?

We begin by considering the common unit of currency for television advertising: a gross rating point (GRP). In its simplest form, 100 GRPs could represent 100% of the target audience having seen the ad once, or 50% having seen it on two occasions, or any other combination. However, straight GRPs rarely produce significant and/or meaningful results. This is because we invariably find that advertising has a carry-over effect beyond the time the advertising has finished. We therefore adopt an approach discussed in detail by Broadbent (1997). The GRPs are converted into advertising stocks, or adstocks, by carrying over a certain proportion of GRPs each week.

Many practitioners have adopted this approach (or slight variations). The following recursive formula can be used on most occasions:

$$\text{Adstock}_n = (\text{Adstock}_{n-1} \times \text{retention factor}) + \text{GRP}_n.$$

An example is provided for a short flight of advertising with a 90% carry-over effect (retention) or, alternatively, a 10% decay (Table 4). We use the adstocks for the purpose of modeling, not the GRPs.

The modeler should determine the appropriate retention level. This is effectively an iterative process and is usually established after generating many models (often hundreds). Where detectable, advertising variations can vary from as little as 50% to as large as 99%.

This certainly has implications for the purpose of media planning. An ad with a 60% retention has a very short carry-over effect. An advertising weight of 100 GRPs in week 1 will have less than half its original effect by the end of the third week. This implies that the campaign only has an impact on sales at the time of the advertising and very shortly afterward. The ad must be constantly on air to retain a sales effect. In contrast, an ad with a 90% retention will still have approximately half its original sales effect by the end of the eighth week and a small sales effect for up to six months. The ad does not need to be constantly on air to maintain a sales effect.

Table 4
Calculating Adstocks with a 90% Retention

Week	*GRPs*	*Carry Over*	*Adstocks*
0	0	0	0
1	100	0	100
2	0	90	90
3	100	81	181
4	0	163	163
5	0	147	147
6	0	132	132

We are sometimes able to detect campaigns with higher levels of retention, which implies sales contributions both in the shorter and longer term. For example, a 98% retention will have half its original impact eight months after the campaign and still have a small sales impact up to two years later.

Various factors can influence the rate of retention, including product category, purchase cycle, promotional/theme-based advertising, and the quality and levels of awareness achieved by the ads.

Short-Term Advertising Contributions

We initially focus on those campaigns with sales contributions over a shorter time period only (those with a 90% retention or lower) and make a brief comparison between the additive and multiplicative formulations.

Additive

We express the advertising contribution in terms of sales generated per GRP. This is easily calculated from the model coefficient, though dependent on the retention factor used in calculating the adstocks. The adstocks form a geometric series given by

$$S_\infty = 1/(1 - \text{retention factor}).$$

The return per GRP is given by

$$\text{Return per GRP} = S_{\infty} \times \text{modeled adstock}_{\text{coeff}}.$$

To illustrate, if we have a 90% retention factor and a model coefficient of 50, the sales return per GRP is 500. However, if we have an 80% retention factor and a model coefficient of 50, the sales return per GRP is 250.

Multiplicative

The advertising impact can be deduced directly from the model coefficients. The results are expressed in terms of a percentage increase in sales given a percentage increase in advertising weight. For example, a 1% increase in advertising weight will generate an additional 0.12% increase in sales.

Both models are useful for the brand manager in assessing the advertising effect, but there can be limitations. The very nature of the additive model can lead to misinterpretation. Suppose we estimate the advertising contribution to be 500 sales per GRP. This implies that we achieve 5000 sales with 10 GRPs, 50,000 sales with 100 GRPs, and so forth. This is unlikely, as the return on sales will be influenced by diminishing returns as the advertising weight increases. This does not invalidate the model; we just need to express caution when interpreting and presenting the results.

The multiplicative model allows for diminishing returns but is conceptually more difficult to interpret. We can convert this percentage contribution back to total sales contribution, but this is less practical. And what do we mean by a 1% increase in advertising? Is this 1% of the total campaign or last week's advertising? This provides little guidance on how future advertising spending should be allocated on a week-by-week basis.

Advertising Response Curves

One approach to improve the actionability of the model is to adapt the additive formulation. Rather than assuming a linear relationship between advertising weight and sales, we use NLR to generate advertising response curves.

Nonlinear regression is certainly more computationally demanding and challenging for the modeler who must address common difficulties, including

- ❏ *Overparameterised models* where the asymptotic correlation of the parameter estimates show very large positive or negative values for the correlation coefficients.
- ❏ *Estimating starting values* need to be provided to calibrate the model. Poor starting values can result in a local rather than global solution, nonconvergence, or a physically impossible solution. Many approaches are available to estimate starting

values. Perhaps the simplest is to use the results from an initial additive model.

- *Computational problems* as we look to produce models that require exponentiation. This may cause an overflow (a number that is too large for the computer to handle) or underflow (a number that is too small for the computer to handle). We therefore may need to transform the appropriate measure(s) to overcome this difficulty.

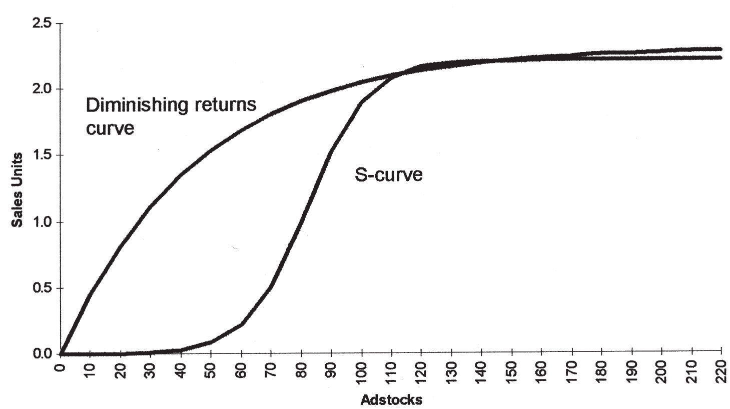
We can facilitate the modeling process by using a sequential quadratic programming algorithm. This allows the modeler to impose sign constraints for the values of the measures in the model. A good introduction to NLR is provided in the SPSS (1998) *Regression Models Manual*.

Although NLR provides more work for the modeler, when we are able to overcome the difficulties associated with the technique, we generally find that the application improves the overall fit of the model and provides more actionable data and detail for media planning. This is important!

The concave diminishing response curve is often found to define a relationship between sales response and increased advertising weight (Figure 8). This can be given by

$$\text{Sales} = \text{Asymptote} \times (1 - \exp^{[-\text{Gradient} \times \text{Adstock}]}).$$

Figure 8
Relationship Between Sales and Adstock Levels



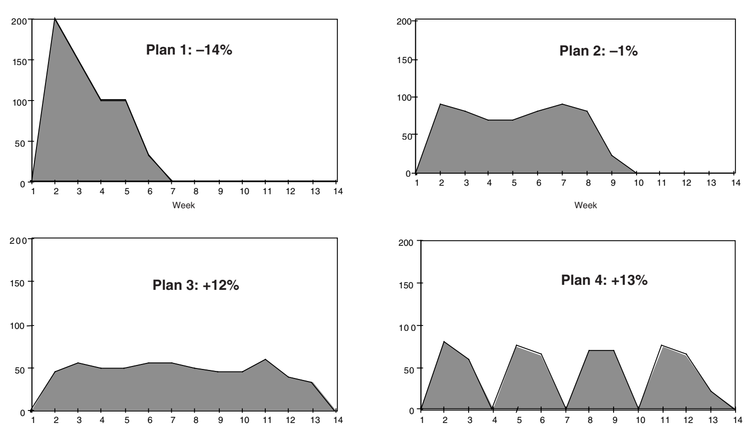
The asymptote is conceptually the maximum number of sales achievable in any one week through television advertising.

We now have an advertising response curve, but how do we use it? The client wanted to optimize sales from the advertising campaign. We were therefore provided with four alternative media plans, each of which had the same total media spending. We ran the plans through spreadsheets that contained the advertising response curve. The shaded areas show the weekly GRPs on the vertical axis (Figure 9). The benchmark is the original plan proposed prior to the modeling work (which also has the same weight).

The first plan is the most *inefficient*. We would expect a 14% reduction in *advertising-related* sales if this flight was executed. There is little to choose between the continuous flighting with lower advertising weights and the drip campaigns (Plans 3 and 4, respectively). Gains of up to 13% of advertising-related sales with the *same media spending* can be expected. This is significant.

There are four observations to be made at this stage. First, other advertising response curves can be considered. For example, many practitioners believe that the S-shaped response curve is more appropriate, though the implications of the two curves differ. To illustrate, for this campaign, we produced two separate models, one with the diminishing

Figure 9
Estimated Sales Return from Four New Media Plans, Shown as Percentage Increase/Decrease of Original Plan



returns curve and the other with the S-curve (Figure 8). The S-curve only has a small sales effect until a threshold of 60 adstocks is achieved, and then we see a sharp increase in the rate of sales from 60 to 110 adstocks. In contrast, the diminishing returns curve generates a strong sales response with the first 60 adstocks.

Second, we are currently covering the short-term response. There may be merits in exceeding these optimum levels in the longer term that outweigh short-term efficiencies.

Third, we must always remember to assess the media plans in terms of the campaign objectives. For a seasonal, promotional campaign or new product launch, the burst strategy may be the more appropriate.

Fourth, the shape of our advertising response curve and the potential gains from media laydown will largely be influenced by the quality of the ad, or creative. We now consider this particular concept in greater detail.

Television Advertising Campaigns and the Quality of the Creative

The Millward Brown company has been specializing in advertising and communication effectiveness for more than 20 years. We see strong variations in the quality of the creative in terms of persuasion and the ability of the brand to build brand awareness. For example, some advertising is highly persuasive, may coincide with a promotion, or may successfully generate short-term sales but then fail to generate repeat sales or sales in the longer term. Other campaigns may focus on building brand equity and qualities of the brand. They tend to be more successful in generating advertising awareness or recall over a longer time period, which will in turn ultimately have a favorable impact on the underlying level of base sales.

Television advertising should therefore *not* be incorporated as a single measure in the model. Wherever possible, we should attempt to split the advertising into campaigns. The quality of campaigns differ so intuitively that we would expect the corresponding sales response to differ.

The gradient of the advertising response curve is largely influenced and correlated with the efficiency of the ad in generating levels of advertising awareness (Dyson 1998). By advertising awareness, we do not mean awareness of the ad but awareness that the *brand* in question has been advertised on television (or other media) recently.

We investigate awareness in this way because it is vital that the ad gets the brand name across. An ad may communicate certain messages very strongly or be highly motivating, but if these memories of the ad are not remembered in the context of the correct brand, the effect will be greatly reduced.

So, although advertising awareness must never be seen as the only measure by which to evaluate an ad, its importance must not be underestimated because it is fundamental to the success of whatever else the ad is trying to do. The importance of advertising awareness can be seen in the way it relates to sales. Hollis (1994) has shown how the *efficiency* with which an ad generates advertising awareness is directly related to the efficiency with which it generates sales (Figure 10).

The Millward Brown company has been modeling advertising awareness using the current model since 1985 (Brown 1986). The model produces an efficiency statistic called the Awareness Index (AI), which, put simply, measures the rise in advertising awareness per 100 GRPs. Referring to Figure 11, an ad with a higher AI is more likely to hit the maximum weekly sales asymptote quicker than an ad with a low AI (low, straighter response curve). The ad does not need to work as hard to generate the same sales response. We typically find that the greater the AI, the greater is the opportunity to generate more sales with the same media spending but a different media laydown.

Advertising Contributions in the Longer Term

This is the most difficult element of the marketing mix to reliably quantify. We briefly introduce a series of approaches for trying to understand the longer-term contribution.

Figure 10
Sales Effects and the Awareness Index

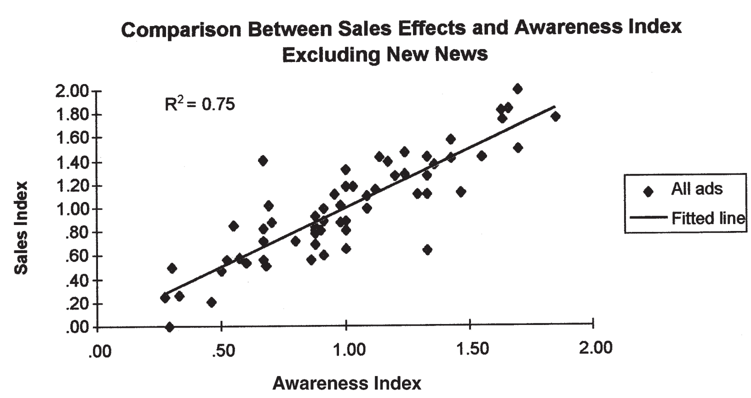
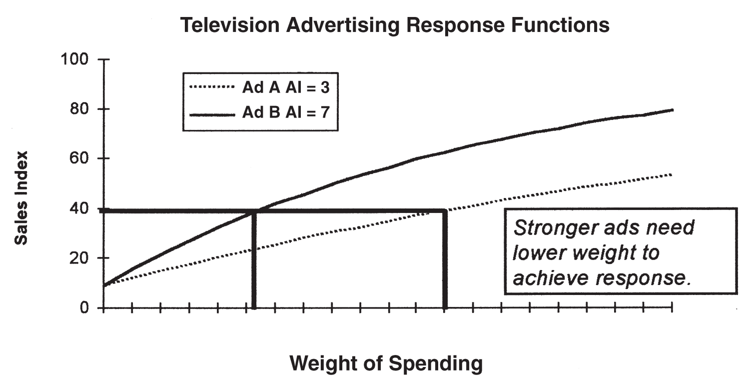


Figure 11
The Power of the Creative on Advertising Response



Regional Variations

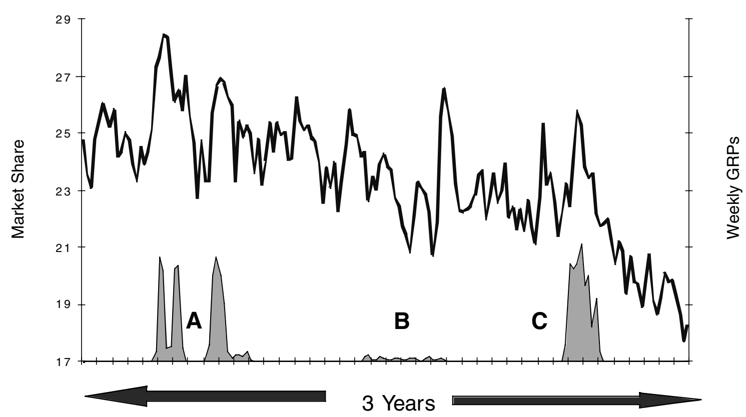
"*Pictures Paint a Thousand Words*". In these days of sophisticated statistical software and complex modeling approaches, the modeler should never forget a key basic principle: Look at your data.

To illustrate, we overlay the volume share of a seasonal packaged goods brand over a three-year period with the television advertising weight (Figure 12). Historically, the brand had generated strong levels of advertising awareness, with the in-market AIs being considerably higher than the category norm. During the second year of the modeling period (B), the client decided to switch the television advertising spending to other forms of media, with the exception of just one television region (hence the low advertising weights shown in Figure 12).

We clearly see the gradual decline in the national share of the brand. Following the 18-month advertising hiatus, the brand reverted to national television advertising (C). However, the new creative was weaker and less visible, and the momentum of the decline continued.

A simple comparison of market share was made between the television region retaining support and the rest of the country over the three discrete years (Figure 13). The equity of the brand in the supported region appears to have been maintained during the last two years of the modeling period. Sales were certainly more buoyant than in the rest of the country, whereas traditionally, they had been lower.

Figure 12
Market Share and Advertising Weight



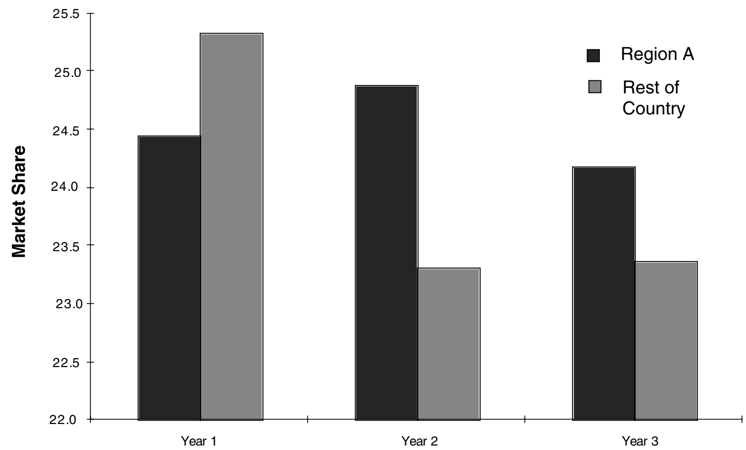
We therefore have evidence to suggest the difference could be attributable to the long-term impact of cutting the television budget in the rest of the country. This is nothing more than exploratory and is not statistically conclusive. However, it does make intuitive sense because there was no substantial variation in distribution, change in price relative to competitors' during this period, or other changes in the market. Something must have caused the difference. These observations were also supported by the in-market tracking study.

Underlying Trends. Trend variables can be incorporated to detect slow movements in the sales we have been unable to account for within the model. These are often used when the quality of the model inputs are inadequate or the movements are too difficult or slow moving to measure.

The longer-term contribution of advertising is often associated with these trends. Models can be produced at the market or regional level. We can then overlay the gradients of the underlying trend with the weight of television advertising support in those regions.

Accepting that this is a crude approach and again statistically inconclusive, we have seen many cases in which the underlying base level of sales is stronger in the regions retaining a greater television advertising support. (We do need to express caution with the use of trend variables because they can exacerbate difficulties with collinearity.)

Figure 13
Comparison of Annual Market Share: Supported Region Versus Rest of Country

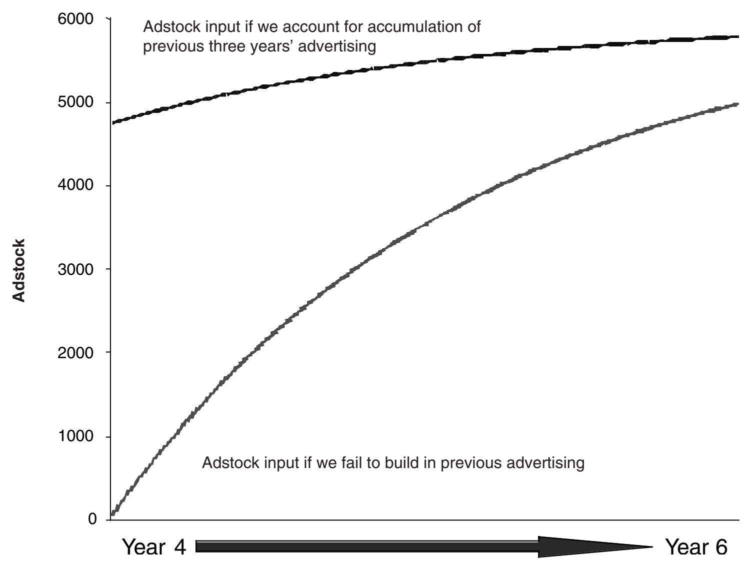


Adstocks with High Retention Rates

We attempt to build two components into the model. The first will represent the short-term sales response from television advertising; the second will represent the longer-term contribution. This approach is almost impossible with highly aggregated data because of the collinearity with short- and long-term adstocks, the number of data points we have to work with, and inadequate variation in the model inputs. However, the concepts can be successfully applied if we have detailed regional sales data.

When adopting this approach, a considerable pitfall must be avoided. The long-term advertising component must be calibrated with the carry-over effect from a significant period prior to the start of modeling period. Consider the following hypothetical example: A new brand is launched, and we have 60 GRPs per week for three years. We are to begin modeling at the beginning of year 4, and a support of 60 GRPs per week is retained for the next three years. If we use a long-term retention rate of 99%, the top line represents the true model input starting from just under 5000 adstocks, slowly increasing, and tending toward 6000 adstocks (Figure 14).

Figure 14
Long-Term Advertising: Calibrate from Previous Advertising Weight



If we do not account for the advertising history, then we could inadvertently build in the lower function to represent the longer-term advertising contribution. This is clearly wrong and is nothing more than a steep trend curve starting from zero and quickly rising to high levels of adstocks. The inclusion of this term could lead to erroneous conclusions and misattribution, particularly if some other activity is happening in the market at the same time (new variant, increase in distribution, and so on).

DISENTANGLING THE IMPACT OF TELEVISION AND PRINT

Collinearity is a common and major problem when conducting marketing mix analysis. Many marketing activities are timed to coincide, and trying to reliably disentangle the true contribution of the different elements of the marketing mix can be a real challenge.

For example, television and print campaigns often occur at the same time, particularly in nonpackaged goods. We usually apply the adstock concept for magazine and newspaper spending but with shorter retention levels because the response to print tends to be more immediate. There are also issues with lagging magazine spending, though this point is beyond the scope of this chapter.

In such cases, conventional general linear modeling methods allow us to quantify the impact of the *advertising campaign* but not necessarily the individual contribution of print and television. The usual methods of least squares can produce estimates that are unstable and have large variances. One possible consequence of this is to have regression coefficients with the wrong sign.

Ridge regression (Hoerl and Kennard 1970) is one tool available to help overcome these difficulties. This is a form of bias estimation that attempts to stabilize the parameter estimates by trading off unbiasedness in estimation for variance reduction. Instead of solving the usual least squares equation

$$b = (X'X)^{-1}X'Y,$$

we solve

$$b(\text{ridge}) = (X'X + kI)^{-1}X'Y.$$

The biasing constant k should be small. As k increases, the bias in the parameter estimates increases and variances decrease. The residual sum of squares for the regression also increases with increasing k, so R^2 decreases. A value of k should be selected so that the decrease in variation is greater than the increase in bias (for further detail, see Montgomery and Peck 1982).

A common method for determining the value of k is called the ridge trace, suggested by Hoerl and Kennard (1970). The ridge trace plots the ridge regression coefficient estimates for alternative values of k.

An example from financial services shows the ridge trace for a series of modeled parameters incorporated into a model to predict the sales of a new product. The majority of the modeled parameters quickly stabilize around $k = 0.3$ (Figure 15).

Focusing on television and press, we observe the change in the sign of the press coefficient (Table 5). The parameter estimates are both highly significant when $k = 0.3$.

A good macro for running ridge regression is available in SPSS, with a more detailed description of the approach (see the SPSS Advanced Statistics 6.1 Manual, Appendix A). A further example of a ridge regression application is provided in the next section.

Figure 15
Ridge Trace—Financial Services Product

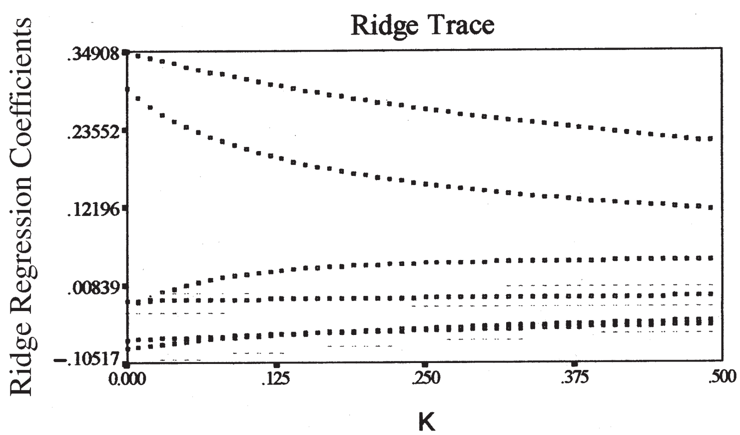


Table 5
Financial Services: Impact of Increasing Biasing Adstock on Model Estimates for Television and Print

	Coefficients		
K	*Television*	*Press*	*Adjusted R^2*
0 (television only)		Excluded from model	
0	0.93*	−2.0*	0.92
0.1	1.54**	0.3	0.91
0.2	0.82	0.9*	0.90
0.3	0.70**	1.1**	0.88
0.4	0.64**	1.3**	0.87
0.5	0.62**	1.4**	0.85

*5% significance level.
**0.1% significance level.

QUANTIFYING MARKETING ROI: A CASE HISTORY

We have discussed several issues, considerations, and concepts the practitioner must consider when conducting a marketing mix analysis. We now share extracts from a detailed case history that has been selected not for its statistical complexity but because it shows how the modeling tools can be adapted to answer one of the most frequently asked questions in marketing: "What is my return on investment?"

In addition, the case history expands on many of the concepts we have introduced in this chapter and shows how the sales effectiveness can be easily underestimated or misinterpreted if we do not consider all aspects of the available data.

Modeling Measures

Although this was our first venture into the modeled product field, the objectives for the client were almost identical to any other nonpackaged goods (and packaged goods client):

- ❑ The contribution of marketing activity to sales with the particular focus on media spending,
- ❑ The short- and long-term impact of the marketing activity,
- ❑ Optimizing media spending, and
- ❑ What would happen if we stop advertising?

The second part of the modeling period coincides with the client's first significant media campaign for the brand. The initial focus was on new sales, namely, those buying the product or service for the first time.

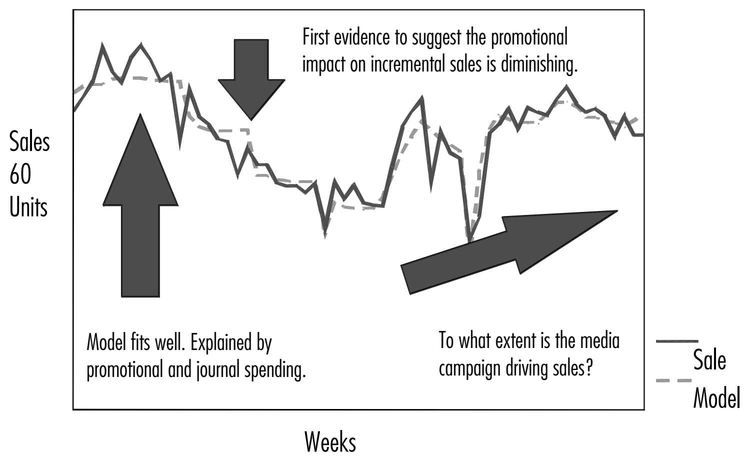
We were able to build a good model of sales that incorporated the new media campaign (dominated by television and print ads), journal spending to target the business professional, promotional activity, and seasonality. We also attempted to build in Internet activity, which visually correlated with sales. However, the relevant Internet inquiry data were unavailable on a continuous basis, so this measure was excluded from the model.

The sales and model prediction for the last 60 weeks of the modeling period are presented (Figure 16). The sales units have been standardized to hide the identity of the client.

Promotional Activity

Promotional activity (Figure 17) and journal spending have a substantial impact on sales, particularly in the earlier stages of the modeling period. However, the impact does not remain constant over time and is

Figure 16
Brand A Model



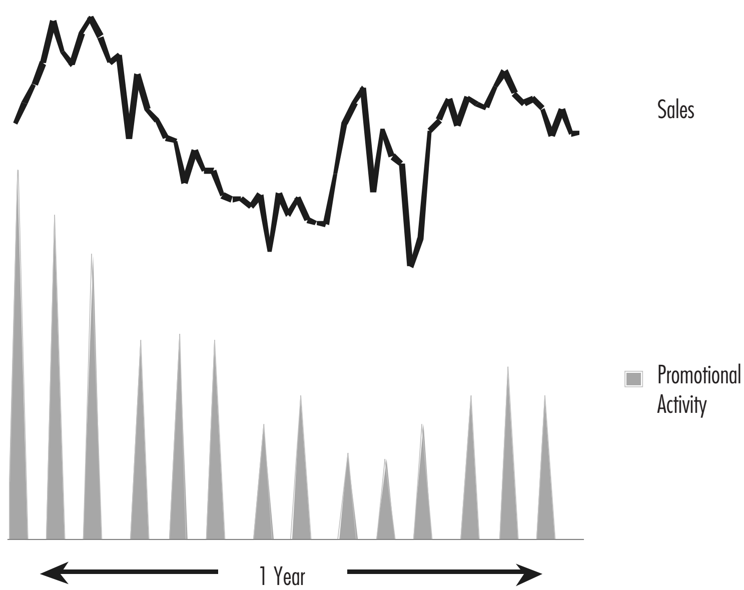
diminishing toward the end of the modeling period. We also observe that as the weight of promotional spending is reduced, sales quickly fall to a base of approximately 30 sales units. This implies that the promotional activity is successfully generating short-term incremental sales but that the impact quickly diminishes and fails to grow base-level sales. This is a finding we typically observe in modeling both packaged and nonpackaged goods.

The quantifiable ratio of sales return to spending across the whole modeling period is approximately 1:1 (every dollar spent has resulted in a dollar return). However, because the dollar-for-dollar contribution is diminishing over the modeling period, future promotional spending is unlikely to generate profitable incremental sales using the current promotional strategy.

Short-Term Incremental Sales Effects for Television Advertising and Print

We overlay the GRPs with sales of the modeled brand (Figure 18). Eyeballing the data, there appears to be a reasonable association with sales. The first flight generates a sharp incremental lift in sales commonly

Figure 17
Monthly Promotional Spending

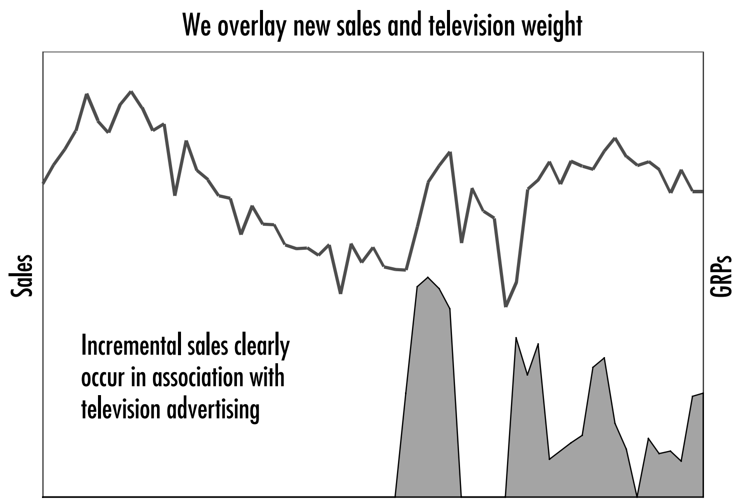


associated with "new news" (Farr 1994), followed by a steadier increase in sales corresponding with subsequent advertising flights.

The impact of television advertising over the modeled period is 123 standardized sales units. Advertising has a carry-over effect beyond the end of the advertising period (see "How Can We Build Television Advertising into a Model?" section). Because there is a reasonable advertising weight at the end of the modeling period, an additional estimate should be made to account for the sales we expect to be generated in subsequent weeks. We were able to use a reliable and validated advertising sales response curve to estimate additional incremental sales of 44 units (making 167 sales units in total).

The additional 44 sales units represent an increase of more than 36% on the advertising contribution initially reported. The level of this return will of course be dependent on many factors, including the quality of the creative (Farr 1994), the rate of decay of the advertising response curve,

Figure 18
Television Advertising Weight and New Sales



and the weight of advertising in the last few weeks of the modeling period. However, in most cases, this effect will be substantial.

When incremental sales are converted into revenue, these 44 units of potentially unreported sales are worth almost an additional $4 million on the ROI for the advertising campaign.

We now consider the impact of the print campaign that coincided with the second, third, and fourth flights of television advertising. Print is certainly successful in generating short-term incremental sales, and like television, there is a diminishing effect continuing into following weeks. However, this continuing effect is considerably shorter for print spending, which implies that print will generate short-term incremental sales at the time of the print campaign but the impact will become minimal only a few weeks after the campaign.

This has been seen in other marketing mix analysis projects, particularly in the U.K. financial services sector. A strong television advertising campaign may generate and build brand awareness, but the supporting print activity is often the mechanism from which the inquiry or sale will be made. Without the television campaign, the response to print considerably diminishes. To date, we have seen few occasions on which the base level of sales has increased through an unsupported print campaign.

Ridge regression was used to disentangle the effects of television and print. The print campaign on its own generated approximately 43 sales units. This is clearly not as strong as for television, but this is not surprising because the weight of television to print spending is approximately 7:1. However, the ratio of sales is only around 4:1 in favor of television. At first sight, the return for the dollar appears to be greater for print.

On the basis of this evidence, should we switch all future media spending to print? The answer is no. We have not yet completed our ROI calculations, and this decision will become apparent as additional factors are considered. We also observe that we could have completed the modeling at this stage. We had a model that was statistically acceptable, produced an ROI for the media, and concluded that print generated more sales than television dollar for dollar and that the media campaign is unprofitable. This would be wrong yet feasible for those who do not understand the advertising mechanisms and potential paybacks. There are many additional factors we need to consider.

There is a strong synergy with print and television, with the interaction being worth an additional 54 units in short-term incremental sales. This is almost a 26% increase in sales associated with the media campaign. Incremental sales would have been generated with a print campaign only or a television campaign only. However, a complementary print/television effect generates a substantial increase on the ROI and should be considered in all ROI calculations for nonpackaged goods brands. This interaction was worth an additional $4.9 million in revenue for the media campaign

This concept can also be extended to other key components of the marketing mix. For example, many clients place significant dollar spending behind mail drops. Clients typically argue that they know the response rate from the mail drop, but they rarely consider the influence of a television advertising campaign on the mail drop response rate.

Mail drops are irrelevant for the brand in this case history. However, we make brief reference to the field of financial services in the United Kingdom. A bank wanted to encourage current customers of its regular checking account to switch to a new form of bank account that offered additional benefits and services but with a monthly fee. Somewhere in the region of 40% of those switching accounts were directly associated with the response to mail drops. The mail drops coincided with a national television campaign primarily aimed at attracting customers who would be new to the bank. A marketing mix analysis was able to demonstrate a 20% increase in the response rate associated with the television interaction, which would clearly be lost or hidden in the client's internal reporting systems. This figure must be credited to the overall ROI for the advertising campaign and, once again, emphasizes the importance of timing in both the media laydown and additional supporting marketing activity.

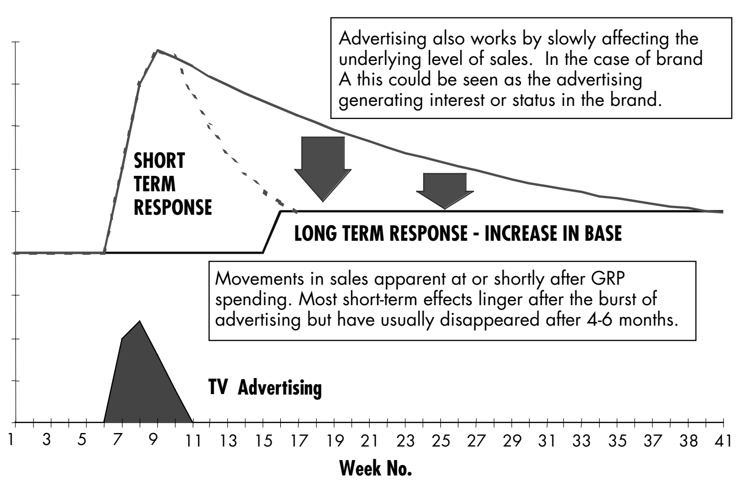
Longer-Term Contribution of Media Spending to Sales

We have focused on the short-term incremental sales associated with the media campaign, but is there also a longer-term contribution of advertising to sales? At this stage, we introduce the base that, in the context of nonpackaged goods and in simplistic terms, is a conceptual level of sales expected over a longer time period should you stop all marketing activity. The base comprises components we are typically unable to build into the model and could include measures such as additional promotional activity when data are not readily available, the longer-term impact of PR, and so on (Figure 19).

The base is not static and can be influenced by an increase/decrease in marketing activity, competitor activity, economic measures, and so on. The base is typically the largest component of sales in a marketing mix analysis and represents more than 60% of sales for the brand in this case history. The modeled product is a relatively new brand, and we would expect the contribution of the base to increase further over time (an 80% contribution not being unusual for an established brand). These are effectively "sales in the bag" or "guaranteed weekly sales," and so what happens to the base is important.

Recent developments in the Millward Brown model formulation enable an estimate of the base component directly associated with the

Figure 19
Shorter- and Longer-Term Advertising Response



longer-term impact of television advertising to be calculated. Typically, a minimum of two to three years of sales data is required, and because we only had access to approximately 18 months of sales data, a caveat must be placed on the following estimates. To compensate, we have the full media history for the brand, so, adapting the same modeling concept, we attempted to generate a projected response to estimate the longer-term contribution. This should be reasonably reliable assuming advertising response does not change in subsequent months.

So what is the value? The short-term incremental sales associated with the media campaign are worth 265 sales units. This is approximately the level of sales required to pay back the cost of the media campaign. The projected longer-term contribution attributable to television is an additional 244 units. The overall impact of the television campaign has practically doubled and is worth an additional $21.9 million on the ROI for the television campaign. If we had just considered the short-term effects of advertising, we might have reached the wrong conclusion about the advertising contribution, which could potentially threaten future media campaigns for the brand

Accepting that this is an estimate at this stage, the findings are supported by other modeling projects conducted by Millward Brown. In some cases, the longer-term effects of advertising can be as much as eight times higher than the short-term effects. Established brands tend to have larger long-term effects, whereas new brands have stronger short-term effects because consumers react to the news value of the launch and may enter the market (Scott and Ward 1997).

Additional Long-Term Contribution to Sales—Repeat Business

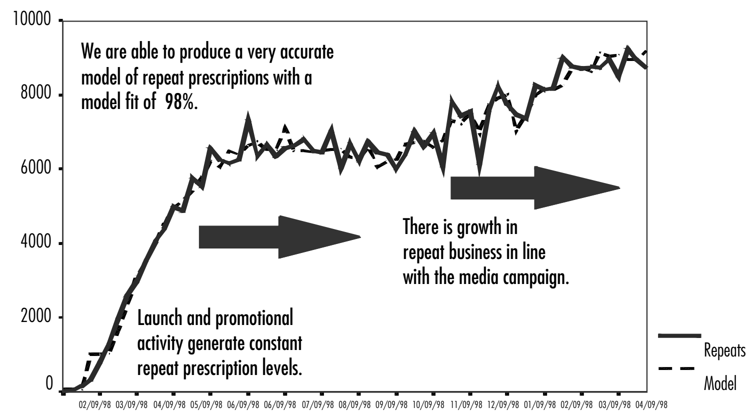
The final component of the ROI calculation is to assess the impact on the ROI of the sales generated through repeat business. Unlike conventional modeling of packaged goods brands, repeat sales at the weekly macro-level were provided. The purchase cycle for the modeled brand is monthly.

A very accurate model explaining almost 98% of sales variation (Figure 20) incorporates a term to represent the first repeat purchase (based on new sales four to five weeks prior) and then subsequent four to five week purchases (based on repeat sales).

The calculation of this indirect contribution to sales can be complex. If the advertising is responsible for the initial sale, then all subsequent repeat sales must be included in the ROI. Without the initial sale, there would be no repeat sale.

The short-term incremental sales associated with the media campaign are approximately 265 sales units. The first repeat sale directly associated with the 265 sales units is approximately 21 units. The probability of second, third, and fourth sales (and so on), given someone purchases the product on a second occasion, is high, and an additional 34 units are generated over the duration (and beyond) of the modeling period.

Figure 20
Repeat Business Model



In addition, there are 27 units of repeat business directly associated with the media campaign. These are people who may have become lapsed users, but the strength of the television campaign in enhancing customers' awareness of the product benefits in the context of competitor activity ensured a continued purchase of the product. If we are to use the same rationale, a further 44 sales units could be obtained from future repeat business (though this is more contentious).

The total number of repeat sales associated with the media campaign is therefore a minimum of 82 sales units. This could arguably be 124 sales units or double that if we were to take into account the conventional longer-term contribution of the media spending.

Being in the fortunate position of having access to repeat sales and new sales enables us to calculate the contribution. In essence, this is a second long-term component of television advertising. The repeat purchases may not be directly associated with the brand memorability of the advertising campaign but more with the experiences of the product or service. However, if the initial purchase was attributable to the advertising campaign, then all repeat purchases should be included in the advertising ROI. If we were modeling a packaged goods brand, the majority of the repeat purchases following an initial purchase directly associated with advertising would be lost in the base and difficult to disentangle.

The impact from repeat business is worth a minimum of $7.3 million on the ROI for the modeled brand (this is a conservative estimate).

This mechanism occurs across all product fields and categories. For example, in a recent project in the U.S. automobile market, advertising accounted for approximately 11% of incremental sales. Given information from other sources of research, a purchase or lease of a particular marque or nameplate has a reasonable likelihood of a repeat purchase or lease of the marque within two to four years. Simple probability theory can be applied to determine the expected repeat business associated with the initial incremental sale from the media campaign.

Summarizing the ROI

Many calculations have been included. Table 6 therefore summarizes the ROI for this media campaign. Results presented are factored sales units.

Had we only accounted for the incremental short-term sales effect of print and television, the presented media contribution would have been less than 200 sales units and the campaign would have been unprofitable. This could have had a detrimental effect on future media campaigns for the brand. The additional revenue from the print and television synergy, long-term contribution of television advertising, and repeat business associated with the media campaign are worth an additional $35 million. The campaign is profitable, with the ratio of dollar return to spending being approximately 1.6 to 1, which is considerable given the weight and cost of the media spending.

Table 6
Contribution of the Media Campaign to Sales

Short-Term Incremental Sales:	*Sales Units*
Television only	167
Print only	43
Television/print interaction	54
Longer-Term Base Sales:	
Television mainly	244
Repeat Sales:	
Campaign	81*
Total	589

*Minimum—more likely to be in the region of 200 units.

Returning to the initial results (see "Short-Term Incremental Sales Effects for Television Advertising and Print" section), the return for dollar spent appeared to be greater for print than television. When adjusting for the additional contributions to the ROI, summarized in Table 1, we find that the sales ratio of television to print is just more than 7 to 1. This is now in line with the respective media spending for the two forms of media. The current strategy appears to work well.

This case history explains in detail the many phases to be considered when identifying the advertising contribution to sales and the extent of the detail we are able to extract from the data. Additional analysis also covered the effect on inquiries, how to optimize the ROI using advertising response curves, and daypart analysis. A full paper was presented and published for the Advertising Research Foundation Week of Workshops in October 1999 (Gascoigne 1999).

OTHER FORMS OF MARKETING ACTIVITY

The main focus of this chapter has been on price and advertising. Many other measures could have been included. To illustrate, we consider *distribution*. A brand with good advertising, competitive price, and a great product is of no benefit if the product is unavailable on the shelf of a grocery store. Many brands may have constant distribution for the duration of the modeling period. There is no variation in the model input, so a distribution term is not required because the contribution will form part of the base sales. If there has been a change in distribution, then this should be incorporated into the model and the subsequent impact on sales should be assessed.

Seasonality is also important because the price, promotional, and advertising elasticities can be affected by the timing of the advertising. There are many approaches for incorporating seasonality, ranging from crude seasonal dummy variables to more sophisticated techniques used in conventional time series (refer to good statistical or econometric textbooks for further detail).

The modeler therefore must use skill and judgment to determine which measures should be incorporated and how they can be incorporated.

SUMMARY AND CONCLUSIONS

Application

Marketing mix analysis can be applied to any brand and in any category providing the client has access to adequate sales and marketing inputs. Many categories have different issues, features, and quirks. Every brand manager believes his or her product category has greater complexity than any other. However, for most projects, the complexity is not in the statistical tools and modeling formulations we employ but in the following:

- ❑ Application of those tools;
- ❑ Collation, handling, and manipulation of the client's data, which often arrive from many different sources;
- ❑ Understanding the client's objectives and issues; and
- ❑ Correct interpretation and application of the model.

Model Complexity

Most marketing mix analysis is conducted using various forms of general linear modeling. Some modeling formulations can be very simple and applied on highly aggregated data. This is reasonable, providing the modeler understands the limitations and scope of the analysis and conveys this to the client. If more detailed data are available, then more complex formulations can be adopted. However, we should never forget that there can be more error or bias in the sales and model inputs we work with, which can negate the extra efforts involved in producing complex solutions.

Adapting the Conventional Modeling Approach

We considered three examples that showed how the conventional modeling approaches can be adapted to meet clients' specific requirements. First, we applied a multistage modeling approach to produce a competitor index, something that would have been impossible to achieve using multiple regression on the available data. Second, we applied a nonlinear model on a linear model formulation to generate advertising response curves. These can then be used to help optimize sales from future advertising spending by controlling weekly advertising weights to ensure we minimize "wasted" spending (diminishing returns). Third, ridge regression was applied to disentangle the effect of two marketing activities (television and print) occurring at the same time. There is no one standard approach for marketing mix analysis.

Address the Business Issues

The case histories we have used show our approach for addressing the clients' business issues. Other practitioners will have their own approaches. This is fine, providing they always refer back to the objectives and make optimum use of the available data.

For example, a client wants to assess the sales impact of a media campaign. We therefore need to ensure all factors are taken into consideration when assessing the impact of the campaign. We must go beyond reporting the incremental short-term sales during the modeled period. We must try and establish the synergy across the different forms of media and other marketing activity, estimate projected sales expected to occur beyond the modeling period from both the short- and long-term advertising components, and attempt to account for the impact of repeat business. We may not always be able to find the effects with statistical reliability, and in such circumstances, we obviously cannot report such an impact. We may occasionally need to place caveats on the results (as with the ROI case history), but providing the model you are working with is statistically acceptable, this is much better than completely ignoring the contribution (the model can also be further validated at a later stage).

Marketing mix analysis is a science—but it's equally an art.

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