

- Which measures, if any, from a pre-testing system can predict this impact?

The second question has too often been debated by asking which *measure* is the best predictor of sales effectiveness. Our experience shows that this is not the right question. Rather it should be: which *measures* are the best indicators.

Finding advertising effects

The idea of truly validating and calibrating pre-test scores to sales has been an elusive goal for years. The admitted difficulty in identifying and isolating sales effects has led many simply to ignore this link. But how important is it if the ad communicates, is well liked or generates awareness, if it does not move the consumer to experience the product? Feeling good about a brand does not pay the bills! Understanding the link between test results and sales is crucial.

Fortunately, advances in databases and marketing science have changed things. We can now measure the direct contribution of advertising to sales even down to the level of an individual execution. And when we do that, we can tie pre-testing measures directly to these results. This is made possible through the integration of two disciplines: market mix modelling and pre-testing.

Not all market mix models will allow you to do this. But there are two technical advances that are used by our market mix modelling group that allow for this precision.

- The use of additive rather than the more common log-linear models. This means we can look at the contribution of individual variables on an additive basis, rather than the multiplicative terms generated by the log-linear model.

- The use of a pooled regression approach in the modelling. By modelling at this level, we have many more observations and degrees of freedom—that allow us to drill down to the level of the copy.

An example can help. The full results of a model for a US food brand over a three-year period produces an impossibly complex picture (not reported here). There is too much detail to see clearly, so let's just consider some of the drivers for this brand: trade activity, pricing fluctuations for the advertiser and its competitors, coupons, press advertising and TV all contributed. No wonder it has been so hard to find advertising effects.

If we zoom in on one 18-week period, we can turn up the magnification to see the detail (Exhibit 1). Not only does this separate the sales contributions of advertising from other factors; it also lets us see the contribution of various commercials. Note that we can even differentiate between executions when they overlap, as long as there is some variation and separation during the airing schedules for the two ads.

You can see how some ads, particularly commercial D, are clearly contributing more sales than others. But this does not necessarily mean that they are more effective. It may in fact mean that some ads received more media weight than did others. A simple, but effective means of eliminating the weight effect is to look at sales per 100 GRPs. This is done in Exhibit 2 (on a normalised basis) for four of the ads for this brand. (Ads A and B ran simultaneously, so effects cannot be separately identified.)

The power of what has been identified here is obvious.

We can quantify advertising's short-term contribution to sales, revenue, profitability, compared to other brands in the advertiser's portfolio, and so on. We also can (and do) calculate a return on investment, which can be compared to that from other elements of the mix.

It demonstrates the wide range of quality in commercials. The weakest set

of commercials is less than half as effective as the average ad (the results indexed, so that 100 represents the average ad for the brand). These ads generate less than a quarter of the sales per 100 GRPs for the most effective. The marketer's concern about quality is well founded. (Remember this is in-market data. This marketer unfortunately ran these ineffective ads with considerable media weight.)

It sets up a scenario for a unique, thorough validation exercise for test measures.

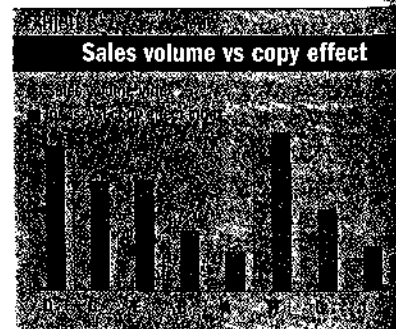
Linking sales and pre-testing data

The data set is very different from what has normally been used to validate pre-testing. Previous validation efforts included measuring whether sales changes when the advertising is run in split-cable copy tests (in the US particularly). But both have their limitations. The market-mix model data provides the promise of more calibrated, comprehensive validation.

It seems that we had just not been looking in the right places when pursuing the elusive goal of validation.

How do we use modelling data to validate pre-testing? By running a series of analyses to see which measures, if any, could consistently predict the direction and the magnitude of the sales effect. The results of this more thorough analysis provide an interesting answer to the recall vs persuasion debate.

Our first analyses simply looked at whether the addition of either recall or persuasion increased our predictive power over simply using a media plan. An example from a series of analyses for a different brand is shown in Exhibit 3. These results were not particularly promising. Recall alone clearly did



Above: The copy effect index.