WHITEPAPER

Quantifying the Impact of Advertising on Business Results

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Introduction

Understanding and quantifying the benefits of advertising is a problem as old as advertising itself. The problem stems from the many purposes advertising serves: building awareness of products, creating brand equity, and generating sales. Many of these aims are not easily measured or related to the advertising that may have affected them. Moreover, today’s marketers have to deal with several other important developments that have either made measurement more difficult or added pressure to getting it done.

First, there has been an explosion in the media mix from the traditional standbys of television, radio, and print into a broader spectrum of both offline and online options, with the Internet clearly being the most visible example of this change. To exacerbate matters, the choices within each medium have also expanded, in an attempt to reach more targeted audiences. Television, for example, has burgeoned from three primary networks to literally dozens of mainstream cable channels, all capable of reaching large audiences with brand messages or product promotions. Hundreds of new magazines now serve as many special interest groups, while Web advertising presses the edge of one-to-one marketing. Furthermore, more and more companies are using integrated, multi-media strategies to reach their desired audiences, layering broadcast advertising over direct response campaigns or combining online with offline campaigns. All of this is making it appreciably harder to separate out the individual influences of each advertising effort.

Second, most companies are no longer satisfied relying solely on traditional methods of measuring advertising effectiveness, namely awareness surveys and tracking studies, and want more precise and concrete evidence that their marketing investments are paying off. It is one thing to know how memorable an ad might be or how potential customers feel about a company or its products, but it is quite another to quantify the sales and profitability impact that advertising might produce. The difficulty is that measuring these effects may involve tracing advertising’s stimulus through a protracted behavioral chain of events that eventually may culminate in a sale long after the advertising has been delivered.

Third, companies today are, for the most part, in a more competitive and faster-paced environment than ever before, accelerating the need to understand the consequences of their marketing efforts. Time is truly of the essence. Marketers simply do not have the luxury any more to assess in retrospect how a set of campaigns performed or to rest on prior laurels. The marketplace is moving so rapidly that current information regarding what's working and what's not has greatly appreciated in value. The need to know is more immediate because critical decisions affecting a company's performance are a constant dilemma.

This paper describes a methodology for measuring the effectiveness of cross-media advertising, delving into the many factors that must be considered and accounted for.

An Approach to Evaluating the Effectiveness of Advertising

While advertising may have several objectives, ultimately marketing and business executives want to know, “How has advertising contributed to sales’1, and ultimately to the company’s bottom line?” Since consumers rarely tell us what made them purchase a product, we have no choice but to intuit this by other means.

1 For simplicity, in this paper we have used the term “sales” to represent the primary result of advertising that we want to measure. Our mass media analysis methodology can be applied to any key business metric.
Quantifying the Impact of Advertising on Business Results

The first thing to recognize is that advertising is only one of many marketing elements that affect sales. (For a review of the literature on advertising effects, readers are referred to Vakratsas and Ambler, 1996.) Other elements include pricing, promotional offers, product attributes, and reactions by competitors (see Lilien, Kotler, and Moorthy, 1992). In addition, external factors, such as macroeconomic trends and seasonality, are likely to affect response in the market. Consequently, the response to advertising can best be evaluated by techniques that allow researchers to account for the mix of marketing and other external variables.

Econometric techniques, especially time series regression, provide a well-structured means of evaluating the impact of advertising on sales by isolating key explanatory variables and holding constant certain variables that may mask the effects of advertising (see Tellis, Chandy, and Thaivanich, 2000). Using these techniques, it is possible to construct a model that relates how sales respond to changes in advertising and other marketing variables. In fact, the sales response function of the model quantifies the marginal impacts caused by changes in advertising investments or other explanatory variables.

Because modeling is built upon strong statistical foundations, and therefore can be understood and evaluated according to the confidence level of the statistics, we favor a modeling approach to measure the effectiveness of cross-media advertising. But, as will be discussed, we also recommend that marketing decision makers use additional information in deciding how much advertising to do and what the mix should be. In fact, we posit that the ideal way to manage marketing performance involves both statistically robust analytics, enabled and enhanced by automated technology, and marketing consulting expertise. This approach increases the likelihood of success because measuring advertising effectiveness is not an exact science, there are significant risks associated with many decisions, and the future is uncertain.
Quantifying the Impact of Advertising on Business Results

Basic Modeling Requirements

Any model that measures the impacts of marketing activities includes a dependent variable (in our case, sales) and a number of explanatory variables. These explanatory variables include both advertising and non-advertising variables. For example, Equation 1 below illustrates that a company’s sales may be a function of the robustness of the industry, seasonality, product attributes and prices, and a host of advertising investments.

EQ1: \[ \text{Sales} = f(\text{Market Trends, Seasonality, Own Prices, Competitors’ Prices, Product Attributes, Promotions, and Advertising}) \]

Where: Advertising includes variables for each media type to separate the effects of TV, Radio, Print, Direct Mail, Online Banners, and Outdoor advertising.

The non-advertising variables capture the effects on sales when there is no advertising and constitute a baseline. The baseline level of sales is not necessarily constant, varying with factors such as seasonality, changes in price, and actions by competitors in the market, but reflects the fact that response does not fall to zero when marketing efforts are shut off. The advertising variables then capture the effect on response due to variations in the level of advertising investment. In theory, it is possible to estimate the advertising effects at highly detailed levels, even by creative element, but in most cases data limitations will restrict the model to estimating the effects of advertising by media type (i.e., television, print, radio, and so forth).

Estimating a model to measure incremental sales resulting from advertising investments must confront four key issues:

1. It is necessary to specify which variables affect the response in a cause-effect relationship.
2. Given an understanding of which variables are likely to influence that response, it is important to consider how they affect it — whether an increase in the level of advertising investment is at a point where it is likely to result in increasing, constant, or diminishing returns.
3. The duration of advertising; that is, how past advertising affects current response is also a key consideration.
4. Finally, advertising campaigns typically run ads in several media concurrently, and it is essential that any model be able to capture these interaction effects.\(^2\)

Model Specification and Data Requirements

\(^2\)The term “interaction effects” in this paper refers to its statistical meaning in capturing the joint effects of two or more variables, say TV and print advertising, and does not refer to on-line activities.
Quantifying the Impact of Advertising on Business Results

A major challenge in estimating the sales response function is to recognize all the variables that may affect sales and to find the data to account for their effects. The objective is to determine if each media type being used can be identified as a key explanatory variable in the model. Advertising investments are typically measured in terms of dollars spent or impressions or GRPs delivered, and are usually available from ad agencies on a weekly basis. Advertising agency buyers devise plans that estimate impressions, but actual, realized impressions may deviate significantly from planned impressions due to cancellations and changes in schedule. Thus, it is critical to estimate the model based on actual, delivered impressions not estimates contained in plans.

In addition to advertising, changes in market trends, promotional pricing, product attributes, seasonal effects, marketing actions by competitors, and other factors are likely to affect response in the short run. Data for these explanatory variables can usually be obtained from a variety of sources and added to the model. Over the long run standard determinants of demand and supply, including changes in population, income, tastes, numbers of competitors, and technology, are likely to affect sales of most products and services. Many different economic indicators are available from government and private sources and are often used as significant variables in these models.

Given weekly data for response and explanatory variables, how many weekly observations are required to estimate a model? There is no simple answer to this question, since it depends on how many explanatory variables need to be included in the model. Typically, we like to have at least a year of weekly data, or about 50 observations, to estimate a model that includes a number of both advertising and non-advertising impacts. Clearly, more data usually results in more reliable estimates, and two or more years of data are preferable in order to understand seasonal and other repetitive effects.

Shape of the Sales Response Function

Researchers have tested a variety of theories about the shape of the sales response function. There seems to have emerged a consensus that, as advertising reaches high levels, its effectiveness declines, i.e., it results in diminishing returns (see Aaker and Carman, 1982, Simon and Arndt, 1980). And, in fact, many researchers postulate that very high levels of advertising result in saturation where there is no effect, or even a negative effect, on sales. At lower levels some empirical evidence suggests an advertising threshold below which advertising has no effect (see Eastlack and Rao, 1986; Rao and Miller, 1975). Between these extremes the response curve may exhibit a region of increasing returns to scale. For these reasons, most of the studies of advertising effectiveness have specified either concave or S-curve models (see Lilien, Kotler, and Moorthy, 1992).

Why is this important? It is important to consider the nature of the sales response function because of its implications on decisions regarding the optimal level of advertising, as well as the optimal mix. Essentially, marketers should realize that they might need to spend a certain minimum amount on advertising before seeing any significant effects on their business. Likewise, after some point, additional spending might produce little or no benefit.
Shifting spending from one media type to another will have multiple impacts and saturation effects may limit additional investments in any one media regardless of currently how good its ROI might appear relative to other media’s.

**Advertising Carryover and Wear-out**

Another important consideration in quantifying the effect of advertising is measuring its persistence over time. Advertising media deliver impressions at a point in time, and psychological measurements of retention demonstrate attrition or decay of the advertising message over time. Consequently, models of the sales response function must capture the duration of this carryover and the subsequent rate of wear-out or decay. This entails estimating the effects of recent advertising on current sales - what is known as the lag structure.

A number of early studies attempted to measure persistence and decay for TV advertising. However, these studies implied very different advertising durations depending on whether they used annual or monthly data. For studies that employed monthly data Clarke (1976) determined that the maximum effect of TV advertising for some brands in some markets extends up to a year, but for more frequently purchased brands it is much less - about two months. Follow-up research on the effects of data aggregation suggests that more research is needed to provide reliable estimates of advertising duration (see Hanssens, Parsons, and Schultz, 1990).

What seems clear is that the effect of advertising persistence differs by media type. The impact of broadcast TV, for example, may persist for weeks or months while the impact of Internet banners is likely to fade quite quickly. For other advertising media, typical maximum durations are probably measured in weeks.
Quantifying the Impact of Advertising on Business Results

Thus, each type of advertising investment is likely to have a different lag structure, and our models of advertising impacts recognize and account for these differences.

Interaction Effects

Advertisers have found that integrated campaigns that combine various media often produce higher sales than single media campaigns (see Edell and Keller, 1999). Thus, any model of sales' response to advertising must be capable of estimating both the effect of each media type operating alone and in conjunction with other media types. Advertisers often refer to lift from running broadcast TV or radio at the same time as direct mail or print. This lift metric captures the interaction effect of combining two or more types of advertising. For example, running TV and magazine advertising concurrently has the potential that respondents receive impressions from both and respond at a higher rate than either ad type running by itself. In fact, many integrated campaigns represent the interaction effects of several different media types, and our impact models recognize this and are capable of handling multiple-dimension, interactive effects.

While modeling the effectiveness of advertising is, as implied above, a difficult and often complex undertaking, we feel that given the large amounts of data that are currently being captured by companies there is a reasonable chance that such an effort will produce useful and valuable information that can advance marketers' capacity to understand what they are getting from their advertising investments and to make better investment decisions.
Quantifying the Impact of Advertising on Business Results

Estimation of the Baseline Impact

As mentioned earlier, the baseline represents the level of response that would occur in the absence of any marketing efforts. To determine the baseline, all the non-advertising variables that might affect the response variable must be identified and accounted for in the model. Typical baseline effects include market seasonality and other market trends along with changes in promotions, product-specific attributes, and competitive response. These non-advertising variables affect sales, some positively and some negatively, but in total comprise a baseline. Note that this baseline is not constant, but will vary with changes in these non-advertising variables.

It should also be pointed out that the presence of a large baseline impact should not necessarily mean that a company is safe to dramatically reduce its advertising investments over the long term. If advertising were reduced this way, the baseline would likely decline as competing brands gained more share of voice.

Estimation of Advertising Impacts

The coefficients for each advertising media type, coupled with the interactive terms, provide the basis for quantifying the impact of advertising on the response variable. As explained above, the advertising effect is likely to vary in duration and persistence by media type because of their different lag structures. Therefore, for each media type, we combine the lagged coefficients to determine the aggregate response effect of that media type during the impact period being analyzed.
Quantifying the Impact of Advertising on Business Results

We then apply these estimated effects in two separate ways:

1. They are used to estimate the impact of past advertising, redistributing the actual total response (in most cases week by week) to capture the effectiveness of all media types, including broadcast media and the interactions between media types.

2. Over a specified time period they are also used to project responses to planned advertising investments, breaking out the impact of each media type and any interactions resulting from integrated advertising campaigns.

Thus, this analysis can be used to ascertain the impacts that prior advertising had on results already experienced (a retrospective analysis), as well as to estimate the likely impacts that current or future advertising may have on future results (a prospective analysis).

Validating Impacts Using Controlled Tests

While modeling is, in our view, a fundamentally sound way to try to discern the impacts of advertising, there may be times when modeling cannot be done or when the modeling output is questionable. In addition, modeling requires a fair amount of historical data, which not every company will have. The company may be relatively new, or may be launching a new business, or simply may not have retained all the historical data in the required granularity needed to estimate a reliable model of advertising effectiveness. Likewise, a modeling approach may suffer when the relationship between advertising investments and business results is not strong enough to generate reliable coefficients with a high degree of statistical confidence. In these instances another methodology can be used to help validate modeling results or to provide preliminary impact factors until the time when more data are gathered and statistical modeling can be performed more reliably.

We recommend supplementing the modeling process with a procedure commonly referred to as a “controlled test.” In this case, advertising variables are isolated in distinct, but relatively comparable control and test areas, and coefficients (the impact factors) are derived from the ratios in performance across these areas. The control and test areas are typically defined by time and place, and an attempt is made to account for inherent biases in the sample populations.

For example, after establishing base rates of sales in the control and test areas, a measure of advertising impact is estimated from the observed increases or lifts in performance once the media have been run. Typically, areas are isolated in the following manner: one area is a control population that receives no advertising; other areas have one media running, say, television or direct mail; in other areas combinations of media run interactively, such as direct mail and television, or print and television, or even direct mail, print, and television. The ratios in sales performance in one area over another define the impact coefficients associated with the different media.

Marketers often rely on controlled experiments to gauge how certain media perform either independently or in combination. The approach has its obvious limitations: it requires significant planning and cooperation within the company; biases in the samples generally are not totally eliminated; and the tests must be long enough to determine reliable and stable coefficients. Moreover, the controlled tests may only need to serve as a temporary solution until enough data have been captured to build statistical models or as a validation check if models are already being used.
Quantifying the Impact of Advertising on Business Results

Assessing Advertising Impacts Continuously in Marketing Impact Modeling

Over the years, many attempts have been made to model the effectiveness of advertising, with varying degrees of success. But, as far as we can tell, these efforts have largely been one-time or, at best, sporadic projects designed to answer a specific question at a specific time. We think that, in order to have a meaningful impact on a company's business, managing marketing performance (of which the modeling we are discussing is a key part) needs to be a systematic, ongoing, and iterative process, where improvement occurs continuously over time as a result of more data and greater understanding of responses to advertising. We also believe that the analytic modeling process and output is only part of the solution, recognizing that marketing decision makers typically incorporate other information, including survey research and expert judgment, when making decisions.

It is important to note that this analysis also tracks and measures the interactions and transactions of consumers who may be either identifiable or anonymous, but for which direct attribution is not possible. These responses may have occurred for a number of reasons. They could represent the baseline rate of buying that the company would enjoy in the absence of advertising. They could result from advertising of competitive brands, which may have a halo effect over the entire product category. Or, they could be in the responses of consumers who were indeed affected by the advertising, but whose attribution was just not possible by any tracking mechanism. All these responses are needed to fully assess the aggregate advertising and non-advertising impacts.

Using the econometric modeling techniques discussed earlier, the Marketing Impact Models calculate the advertising impacts by multiplying the independent variables (e.g., advertising spending or impressions) by their respective coefficients, taking into account appropriate time lags and other relevant factors. The output of the analysis shows the impact that each variable or interactive term has had on sales. In effect, the model redistributes the observed sales outcome, including both the attributed and unattributed totals across the media that should be credited with generating them.

The advertising impact models are also used to project the likely results of ongoing or future marketing activities. This capability is a key component of the system because it helps the marketer understand what is likely to result from the money he is spending now or is about to spend - which is far more relevant than looking at past spending. The models enable the marketer to forecast results across all media and, with the advertising impact models, can account for baseline effects and other non-advertising influences.

Managing the Marketing Mix

The ultimate objective of the Marketing Impact Modeling is to provide marketing decision makers with more relevant and timely information to help them manage their marketing mix and improve performance. Historically, this marketing performance management has largely been an exercise in uncertain intuition and 'gut feel' for marketers. It is important to remember that managing the marketing mix will never be simply a quantitative exercise; there are simply too many factors shifting in the marketplace to keep the mix in some optimal balance. Furthermore, each decision-maker brings to the table his own personal attitudes toward advertising, data analysis, and risk. Confronted with the same information, two decision-makers may very well embark on two very different courses of action.
Quantifying the Impact of Advertising on Business Results

Acknowledging this, we suggest this information is made the decision-maker as comfortable as possible that the decisions made are the best at the time and provide the best chance of achieving the marketing goals. The output from Marketing Impact Modeling is likely to be but one piece of information used by the marketer that might also, include market research, staff opinion, advertising agency opinion, and conventional wisdom. However, as a new and powerful form of information this analysis may make the difference between a bad decision and a good one, or a good one and a better one.

Realistically, we will never know the truth about advertising's effectiveness because there is no precise accounting procedure to measure it; even the best approaches produce mere estimates of the true impact of advertising. But, with this form of mass media analysis, we may know a lot about advertising's impact both directionally and in terms of relative magnitude. This is often enough to help companies meet their marketing goals while staying within acceptable advertising cost to sales ratios.

The Benefits of Mass Media Analysis

The benefits of using this Marketing Impact Modeling methodology to help manage a marketing mix will vary from business to business. Clearly, businesses using this service will be of different sizes and forms, and the sales impacts associated with their advertising will inevitably differ. Our experience shows, however, that new information generated on a regular basis will greatly enhance a decision-maker's ability to beneficially adjust the amounts invested in advertising or the mix. For some, this will translate into multi-million dollar benefits; for others, where the benefits are less, it may be a significant advance for them to know, perhaps for the first time, the returns to their advertising and how they might be improved.

References


Quantifying the Impact of Advertising on Business Results


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