Time series models for advertising tracking data

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In this paper, we summarize a conceptual framework that describes the possible effects advertising can have on such marketing metrics as awareness, image, consideration, and brand choice. We show that these effects can be measured with the right marketing research data and the appropriate analytical tools. We outline the industry standard — regression coupled with the ad-stock approach. This approach makes assumptions that can be incorrect and lead to a convoluted way of analysing the data. As alternatives to the ad-stock approach, we propose three econometric time-series models that require fewer assumptions — the geometric lag model, the error-correction model, and the polynomial distributed lag model. We compare these models and recommend a modeling strategy based on the relative strengths and weaknesses of the various approaches.

Introduction

Although companies often spend more on advertising than they make in their net after-tax profits, they do not know whether these investments pay off. A look at the literature reveals our incomplete knowledge about what advertising really does in the marketplace, although some companies, such as Millward Brown, have extensive knowledge about how advertising works, especially in the markets where their clients operate.

Without knowing what the return is on advertising expenditures, it is difficult for a company to appropriately allocate budget dollars to it. Given the size of the advertising business and the fact that many companies drastically scaled back their expenditures in 2001, the industry must be able to demonstrate the results of advertising expenditures, both qualitatively and quantitatively. Once this is accomplished, one can determine whether a company or brand is over-spending or under-spending and whether media allocations are fully leveraging the advertising budget.

In this paper we discuss possible advertising effects, specific marketing research data requirements, and a variety of econometric time-series models that can be used to identify potential advertising effects. We compare these econometric approahces with the current industry standard: standard regression coupled with the ad-stock approach. We demonstrate that the more advanced econometric time-series models can give additional insights into the effects of advertising. We illustrate how we can determine the efficiency of advertising expenditures, using a hypothetical example based on empirical analyses we have done in various categories. We also show how this same information can be used to improve tactical and strategic decisions.

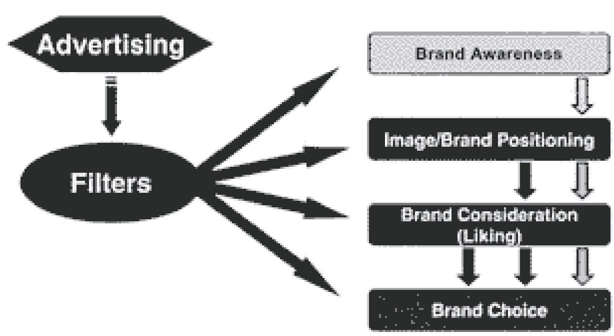
Possible advertising effects

Understanding how advertising affects consumers involves an understanding of:

- how advertising leads to brand awareness, brand image, brand consideration, brand choice, and sales;
- if and how the effects of advertising are spread out over time;
- how efficient different media (e.g., TV vs. print advertising) are and how their interaction may lead to synergy effects; and
- the role and impact of competitive advertising.

Based on a literature review of over 250 journal articles and books, Vakratsas and Ambler (1999) proposed a basic process by which advertising leads to brand choice and sales. Our framework (Exhibit 1) is similar to that of theirs, but we use awareness instead of cognition; image and brand positioning (which contains both affective and cognitive elements; see Vriens & ter Hodstede 2000) instead of affect; and brand choice instead of consumer behaviour.

Exhibit 1
Possible advertising effects: The basic process



Advertising dollars are spent to generate specific advertising messages, PR copy, or promotional activities. For example, for a manufacturer of desktop PCs we might distinguish between spending on television advertising, radio advertising, newspaper advertising, and vertical trade advertising. All this activity reaches some consumers at some point, and they will or will not pay attention and process these messages. This then may lead to a number of advertising effects. Three types of effects are possible: cognitive, affective, and behavioural. Examples of effects are brand awareness (cognitive), brand positioning (cognitive, affective), consideration or liking (affective), and brand choice (behavioural). The extent to which consumers who are exposed to advertising will go through these stages depends on their ability and motivation to process the information and messages offered to them (Petty, *et al.* 1985). Awareness is a necessary condition for advertising effectiveness. For example, when consumers who are unfamiliar with a product category have to choose between a well-known brand and an unknown brand, they are more likely to choose the well-known brand (Hoyer & Brown 1990). Whether behaviour such as brand choice and purchasing is preceded by brand positioning and brand consideration depends on the context. For example, in a low-involvement, low-risk category, it is not uncommon for purchase to precede any affective response. In situations where involvement and risk are higher, brand differentiation and consideration precede purchase. It is beyond the scope of this article to discuss how the context can affect the order of the various effects. We refer to the article of Vakratsas and Ambler (1999) for additional details.

How advertising affects consumers may also depend on whether the impact of advertising on the various metrics (e.g., awareness, consideration, purchase) is spread out over time. Different media have a different short-term effect; therefore, it may be possible that they will have different long-term effects (Doyle & Saunders 1990; Berkowitz, *et al.* 2001). Advertising researchers generally assume that a specific advertisement that appears this week will have an effect not only this week but also next week, and its effect will gradually decrease over the following weeks. For example, Buzzell and Baker (1972) cited one case of an advertising budget being cut by 40%: sales were not affected in the first month after the cut, but decreased during the second and third month after it. At Millward Brown, we have observed that our standard measure of ad awareness decays at 10% a week. Image and brand positioning (repositioning) effects may take longer to change as a result of an advertising campaign than changes in brand awareness or sales.

Time-delayed effects of advertising, or carry-over effects, may vary in type and duration across brands and product categories. Several types of time-delayed effects are possible. The effect of advertising can increase initially and then flatten out before it starts gradually decreasing. Or the ad can have its biggest impact shortly after it comes out and then immediately decrease in impact. The duration, defined as the period in which the ad has some effect, and the total effect (summed up across time periods) can vary widely. It some cases the long-term effect of advertising can dramatically outweigh its short-term effect. In one case, Millward Brown identified a long-term advertising effect that dominated the short-term effect by nine to one. Taking the long-term effects of advertising into account can make the difference between having a positive return on advertising investment and not. The question we need to answer is: What is the time span across which advertising works and how exactly is its effect spread out over time? The answer is bound to be context specific, depending on such factors as how well known the brand is and the effectiveness of the ad. Answering this question has implications for when and how much to advertise.

How advertising affects consumers also involves the role of media. Different media, such as television, radio, and magazines, are used and consumed differently. Therefore, not only may they have a different overall impact, but also it is likely that their effects over time differ. For example, the impact of a television ad may be large in the period in which it appears but may quickly fade over the subsequent periods; whereas a magazine ad may have a lower initial impact, but show a sustained impact over a number of periods because the magazine can be read over time, picked up again, and used by other people.

Competitor advertising spending affects consumers, too. If the advertising spending of any direct competitor increases or decreases significantly in relation to a firm's own advertising, this may substantially alter its effectiveness. Aaker and Carman (1982) cite an example involving two brands. The advertising of brand 1 had a positive effect on its own sales but had no effect on the sales of brand 2. The advertising of the brand 2 had a negative significant effect on the sales of brand 1 but had no positive effect on its own sales.

Marketing research data requirements

There has been much empirical modeling relating advertising expenditures to sales. It is beyond the scope of this paper to review previous studies. To study the full scope and impact of advertising expenditures we need data not only on sales (or some other behavioral measure) but we also need data on awareness, image and consideration. We use the Millward Brown IntelliQuest IntelliTrack database. We collected data on a number of technology products over the past 10 years on an on-going daily basis and reported monthly. We conducted about 500 interviews a month on a continuous basis with Technology Influencers on: brand awareness; perception on brand imagery attributes; brand consideration; and brand choice.

For our analyses, we used a data set that covered a period of three years, yielding 36 data points. We had five brands within a technology category. In addition, we analysed data from numerous proprietary studies that are similar in format in fast-moving consumer goods categories (e.g., soup, coffee) and financial services. The structure of this type of tracking data is shown in Exhibit 2. The bottom part shows how we roll this data up for dynamic modeling. From a third party, we also have available advertising expenditures for four media: TV, vertical trade, magazines, and newspapers. For each of the five brands, we obtained monthly advertising expenditure data (in some cases we have actual dollar amounts, in other cases we have monthly GRP data). Exhibit 2 shows awareness, consideration and brand choice expressed as percentage aware, percentage brand consideration, and percentage purchasing a brand.

Time series models

Exhibit 1 shows conceptually the process of how advertising works:

1. Brand awareness is a function of advertising expenditures.
2. Image is a function of advertising expenditures and brand awareness.
3. Brand consideration is a function of advertising expenditures, brand awareness, and brand image.
4. Brand choice is a function of advertising expenditures, brand awareness, brand image, and brand consideration.

In addition to this basic structure, the model has a time component. Advertising at a given time period t can have an effect in that same time period t, plus potentially an effect in time periods t+1, t+2, and so on. This leads to the following basic equations:

$$\text{Brand}-\text{Awareness} = \boldsymbol{f}(\text{Expenditures}_L)$$
$$\text{Brand}-\text{Image} = \boldsymbol{f}(\text{Expenditures}_L, \text{Awareness}_L)$$
$$\text{Brand}-\text{Consideration} = \boldsymbol{f}(\text{Expenditures}_L, \text{Awareness}_L, \text{Image}_L)$$
$$\text{Brand}-\text{Choice} = \boldsymbol{f}(\text{Expenditures}_L, \text{Awareness}_L, \text{Image}_L, \text{Consideration}_L)$$

The first equation states that brand awareness is a function of advertising expenditures (E). The subscript L refers to the fact that an expenditure at a certain time period, let's say month 1, can have an impact upon awareness in that same month 1, but may also have some impact upon awareness in months 2, 3, and so on. The second equation states that brand image is a function of advertising expenditures (E) and brand awareness (A). The L again refers to

Exhibit 2
Organizing data for dynamic modeling

Original data at the individual respondent level

Month 1	unaided awareness for brand x	unaided awareness for brand y	consider brand x	consider brand y	purchase brand x	purchase brand y
Respondent						
1	1	0	0	0	0	0
2	0	1	1	0	0	0
3	0	1	1	0	0	0
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
100	1	0	0	0	1	0
Roll-up:	**40%**	**20%**	**20%**	**10%**	**20%**	**15%**
Month 2						
Respondent						
101	1	0	0	0	0	0
102	0	0	0	0	0	0
103	0	0	0	0	1	0
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
200	1	0	1	1	1	0
Roll-up:	34%	22%	22%	9%	22%	28%

Transformed data: Individual data are aggregated to the brand and market level

	unaided awareness for brand x	unaided awareness for brand y	consider brand x	consider brand y	purchase brand x	purchase brand y
Month 1	40%	20%	20%	16%	20%	15%
Month 2	34%	22%	22%	9%	22%	28%
Month 3	28%	42%	18%	22%	21%	11%
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
Month 36	**27.00%**	**44.00%**	**11.00%**	**22.00%**	**20.00%**	**9.00%**

the fact that effects may spread out over time. The third equation states that brand consideration (i.e., not purchase) is a function of advertising expenditures, brand awareness, and brand image. The fourth equation states that brand choice is a function of advertising expenditures, brand awareness, brand image, and brand consideration, with L again denoting the time component.

A key element of this model is that the total effect of advertising expenditures is a sum of both its direct and indirect effects at the various time periods. For example, advertising will have a direct effect on brand choice and, through impacting awareness and brand consideration, will have an indirect effect upon brand choice. We also note that advertising expenditures can be defined in the model in several ways: we can take the absolute expenditure for each firm in the equations, the firm's expenditure relative to the category expenditure, the firm's expenditure relative to the closest competitor, and so on. We can extend the model by allowing the effects to be brand specific and/or to allow different media to have different short- and long-term effects.

In estimating the relationships that are represented in the general equations, we note two considerations. First, we must consider whether to model the system simultaneously or model each equation separately. The four components of our model show that its amounts to a recursive system: there are no equations where variables appear both on the left side and at the right side at the same time. Otherwise, we would have a simultaneous equation model and need corresponding parameter estimation routines. It is well known that neglecting simultaneity, if there is any, leads to inappropriate parameter estimates. Second, we need to know how to identify the potential time-distributed or long-term effects. Modeling alternatives range from "relatively simple models with fairly strong assumptions about what advertising does" to "more complicated models where I can relax some of the strong assumptions". We discuss the alternatives below.

The data as shown in Exhibit 2 can be analysed in a number of ways. Practitioners often use simple regression; however, this will not allow one to understand the time-distributed nature of advertising effects and may, because of the presence of serial correlation, lead to biased parameters (Kyle 1978). A second class of approaches aims at explicitly understanding the time-distributed nature of advertising effects. Time-distributed effects are called lag structures. Approaches that can be used here include:

- simple regression with ad-stock modeling (ASM);
- the geometric lag, or Koyck model (GLM);
- the error correction model (ECM); and
- polynomial distributed lag modeling (PDLM).

Ad-stock modeling (ASM)

ASM involves three steps. First, ad-stocks have to be calculated. In Exhibit 3, we show an example of the concept of ad-stock. We assume that in Week 1, a company spends 100 GRP. If we assume a retention rate of 90% (upper half of the exhibit), this implies that in Week 2, we still have 90% of the original 100 GRP, being 90 GRP "in stock". In Week 3, we have 81 GRP (90% of 90 GRP), and so on. In a five-week period, Weeks 2, 3, 4, and 5 all would accumulate some ad-stock. We end up with GRP numbers that are a combination of the actual GRP spend during a particular week, plus the ad-stocked amounts: the result being the number in the last column. Second, the regression equation has to be estimated. Usually, weekly sales are related to weekly ad-stocked GRPs. To avoid misspecification, the regression equation may also include weekly distribution numbers, pricing variables, and promotional variables. From this regression equation, we obtain a coefficient for "advertising". Let's say that the coefficient is 5 (and statistically significant). This means that for each ad-stock GRP, our sales increase by 5 units. Hence our total campaign is 1215 (100+190+271+344+310) GRPs. This resulted in 6075 (5×1215) sales units. However, the actual amount of GRPs was 400; hence, the advertising effectiveness is 15.2 (6075/400) sales units per real GRP. Third, steps 1 and 2 are replicated for different retention rates. It is common to estimate several regression equations using different retention rates, e.g. 60%, 70%, 80%, 90%, and then 91%, 92%,...,99%. Based on fit of the model and a qualitative assessment of how reasonable and logically the results look a decision is made for the best-fitting retention or decay rate.

Exhibit 3
An example of ad-stock calculations

Weeks	Actual GRPs	Adstock Week 1	Adstock Week 2	Adstock Week 3	Adstock Week 4	Adstock Week 5	Total GRPs
Week 1	100	0	0	0	0	0	100
Week 2	100	90	0	0	0	0	190
Week 3	100	81	90	0	0	0	271
Week 4	100	72.9	81	90	0	0	343.9
Week 5	0	65.61	72.9	81	90	0	309.51

The model assumes that the effects of advertising decays over time. The analyst does not know the real decay rate and, therefore, in practical situations, has to assume a number of different decay rates, compute the corresponding regression equation, and assess their fit. The ad-stock approach has a number of disadvantages.

- Assuming a decay rate for advertising is speculative.
- This approach is cumbersome from a practical perspective. If data are available on several media and for several competitors, this approach involves a convoluted way to assess advertising efficiency.
- Sometimes the effect of the advertising increases over two or three periods before it starts decaying. This would not be picked up by the ad-stock approach.

Further details about the ad-stock approach can be found in Broadbent (1997) and Broadbent and Fry (1995).

Geometric lag model (GLM)

The GLM (Koyck 1954) does not assume a specific decay pattern but assumes that advertising has a maximum contemporaneous effect fading away at a regular (exponential) rate. The GLM assumes that the influence of X t – s declines proportionally (geometrically) over time, where s is the length of the lag. The general formula is shown in the equation below.

$$(1)\quad Y_t = \alpha + \beta(X_t + \lambda X_{t-1} + \lambda^2 X_{t-2} + ...) + \varepsilon_t$$

Where Y is the dependent variable, for example sales, and where the Xs represent advertising expenditures in various time periods. To understand λ, for example, consider λ = .50. The equation above then becomes:

$$(2)\quad Y_t = \alpha + \beta(X_t + 0.5X_{t-1} + 0.25X_{t-2} + ...) + \varepsilon_t$$

This model has infinite independent variables; to correct for this, take:

$$(3)\quad \lambda Y_{t-1} = \lambda\alpha + \beta(\lambda^1 X_{t-1} + \lambda^2 X_{t-2} + \lambda^3 X_{t-3} + ...) + \varepsilon_t$$

Subtracting equation (3) from (1):
(4)

$$Y_t - \lambda Y_{t-1} = (\alpha - \lambda\alpha) + \beta(\lambda^1 X_{t-1} + \lambda^2 X_{t-2} + \lambda^3 X_{t-3} + ...) - \beta(\lambda^1 X_{t-1} + \lambda^2 X_{t-2} + \lambda^3 X_{t-3} + ...) + (\varepsilon_t - \lambda\varepsilon_{t-1})$$

The common terms cancel, and the last lag on X t – s approaches zero. Rearranging this equation gives:

$$(5)\quad Y_t = (\alpha - \lambda\alpha) + \beta X_t + \lambda Y_{t-1} + (\varepsilon_t - \lambda\varepsilon_{t-1})$$

This is the equation that needs to be estimated.

Compared to the ad-stock approach, the GLM is more flexible because it does not immediately assume the rate of decay. However, its assumption of a monotonic rate of decay may not be realistic in all situations. Statistical analysis (i.e., testing) of the model is somewhat cumbersome (Franses 2002).

Error correction model (ECM)

ECMs are popular for trying to capture (especially) long-term dynamics. The ECM equation includes one or more error correction terms that mathematically adjust to account for a long-term equilibrium. That is, it implies the existence of some adjustment process that prevents the errors from continually increasing: "The error correction model integrates the long-run equilibrium analysis and short-run dynamic adjustment by including in the short-term dynamic model a measure of how much out of equilibrium or target the variables are in the last period. It relates changes in Y_t, $Y\Delta_t$, to last period's error, $Y^*_{t-1} - Y_{t-1}$, where Y^*_t denotes a target or equilibrium value."

As a simple example (derived from Kennedy 1998:267), consider the relationship:

$$(6)\quad Y_t = \alpha + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 Y_{t-1} + \varepsilon_t$$

Assume that Y is some dependent variable (sales) and the Xs represent advertising expenditures. The y and x are measured in logarithms and theory suggests in the long run they grow at a constant rate, that is, $y - \gamma x$ is assumed constant. We can write this as:

$$(7)\quad Y_t - Y_{t-1} = \gamma_0 + \gamma_1(X_t - X_{t-1}) + \gamma_2(Y_{t-1} - \gamma X_{t-1}) + \varepsilon_t$$

The γ parameters are functions of the α, and β parameters in (6). This is the ECM equation with the last term the error correction that is assumed to reflect disequilibrium responses and that $\gamma_1 \Delta X_t$ is assumed to reflect short-run responses. Thus, if Y grows too fast, the error correction term increases and since the coefficient is negative, ($\beta_3 < 1$) ΔY_t is reduced, correcting this error.

An advantage of ECM is its simplicity of interpretation and ease of estimation. Furthermore, it can easily be extended to multiple equations.

Polynomial distributed lag model (PDLM)

The PDLM estimates the duration of the various effects. It allows us to estimate the size of each of the effects at each subsequent period. That is, the model estimates how long advertising effects last as well as what its impact is in each period. PDLM assumes that the lag weights can be specified by a continuous function, approximated by a polynomial of appropriate degree. (The degree of the polynomial should be less than the number of terms in the distributed lag minus one, or there will be no decrease in the number of lag-estimated coefficients. Also, the number of observations must be at least the degree of the polynomial.) That is, the data define the specification.

A PDLM needs to have the degree of the polynomial specified and the length of the lag. That is, assume:

$$Y_t = \alpha + \beta(w_0 X_t + w_1 X_{t-1} + \ldots + w_m X_{t-m}) + \varepsilon_i$$

where w are the weights and x are the lags. For example, suppose the degree of the polynomial is 4. To make each of the weights w lie along a fourth-degree polynomial, the specification is $w_i = \lambda_0 + \lambda_1 i + \lambda_2 i^2 + \lambda_3 i^3 + \lambda_4 i^4$ where i goes from 0 to m. The polynomial lag model is then:

$$\begin{aligned}(8)\quad Y_t = \alpha + \beta[&\lambda_0 x_t + (\lambda_0 + \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4)X_{t-1} + \\ &(\lambda_0 + \lambda_1 2 + \lambda_2 2^2 + \lambda_3 2^3 + \lambda_4 2^4)X_{t-2} + \\ &(\lambda_0 + \lambda_1 3 + \lambda_2 3^2 + \lambda_3 3^3 + \lambda_4 3^4)X_{t-3} + \\ &(\lambda_0 + \lambda_1 4 + \lambda_2 4^2 + \lambda_3 4^3 + \lambda_4 4^4)X_{t-4}] + \varepsilon_i\end{aligned}$$

The output of this model will have an estimated coefficient for each lag for each degree of the polynomial. The advantage of PDLM is that the data allow the estimated coefficients for the degree of the polynomial and the lengths of the lags. Typically a very small value of each is necessary. The model can be estimated with OLS and only those polynomial degrees and lag lengths that are significant need be kept in the model. The disadvantage of PDLM is its complexity, especially if more than one independent variable is estimated via PDLM.

Exhibit 4 shows the hypothetical results of the recursive equations above with a PDLM specification. Although the specific numbers are hypothetical, they are based on several dynamic analyses that we have performed in both fast-moving consumer goods industries and technology (business-to-business) industries. Advertising expenditures are measured in GRP. In the example, we have significant advertising effects in three or four periods (i.e., months or weeks). The first effect occurs in the period where the advertising has appeared. We call this period L_0. There are three subsequent periods. These are L_1, L_2, and L_3. So, if the unit of measurement were at the month-level, then L_0 would be the month in which the advertisement first appeared, L_1 would be the first month after the advertisement first appeared, and so on.

Exhibit 4
Hypothetical Results of a Dynamic Advertising Effects Model

Type of Effect	Coefficient
The Brand Awareness Equation:	
L_0: Effect of GRP on brand awareness in period where advertising appears	0.0518
L_1: Effect of GRP on brand awareness in the second time period	0.0515
L_2: Effect of GRP on brand awareness in the third time period	0.0509
The Brand Consideration Equations	
Equation 1: Effect of GRP on Brand Consideration	
L_0: Effect of GRP on brand consideration in period where advertising appears	0.0009
L_1: Effect of GRP on brand consideration in the second time period	0.0054
L_2: Effect of GRP on brand consideration in the third time period	0.0149
L_3: Effect of GRP on brand consideration in the fourth time period	0.0101
Equation 2: Effect of Unaided Brand Awareness on Brand Consideration	
L_0: Effect of unaided brand awareness on brand consideration in period where advertising appears	0.000
L_1: Effect of unaided brand awareness on brand consideration in the second time period	0.2903
L_2: Effect of unaided brand awareness on brand consideration in the third time period	0.3677
L_3: Effect of unaided n brand awareness on brand consideration in the fourth time period	0.2321
The Brand Choice Equations	
Equation 1: Effect of GRP on Brand Consideration	
L_0: Effect of GRP on brand consideration in period where advertising appears	0.000
L_1: Effect of GRP on brand consideration in the second time period	0.0970
L_2: Effect of GRP on brand consideration in the third time period	0.0747
L_3: Effect of GRP on brand consideration in the fourth time period	0.0322
Equation 2: Effect of Unaided Awareness on Brand Choice	
L_0: Effect of unaided brand awareness on brand choice in period where advertising appears	0.000
L_1: Effect of unaided brand awareness on brand choice in the second time period	1.6837
L_2: Effect of unaided brand awareness on brand consideration in the third time period	2.2051
L_3: Effect of unaided brand awareness on brand consideration in the fourth time periodL_0	0.5566
Equation 3: Effect of Brand Consideration on Brand Choice	
L_0: Effect of brand consideration on brand choice in period where advertising appears	0.000
L_1: Effect of brand consideration on brand choice in the second time period	1.0247
L_2: Effect of brand consideration on brand choice in the third time period	1.4596
L_3: Effect of brand consideration on brand choice in the fourth time period	1.2967

Exhibit 4 shows some very interesting results (assume we have jointly estimated the three equations):

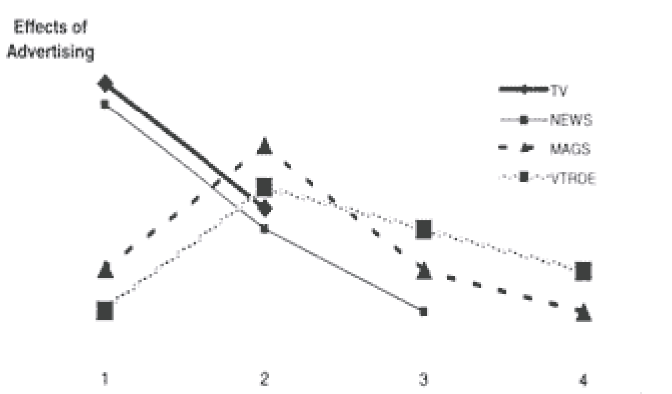
1. The direct effect of advertising expenditure on brand awareness in the period that the advertising appeared is 0.518 (10×0.0518). These coefficients can be interpreted as elasticities. If we increase advertising expenditures with 10%, brand awareness would increase 0.518% as a result of advertising in that period. In Period 2, this effect is 0.0515, and in Period 3 it is 0.0509.

2. The second equation is more complicated. The direct effect of advertising expenditure on brand consideration in the period when the advertising appeared is 0.009. For the total direct effect of advertising expenditures on brand consideration, we add all the lagged effects: 0.009+0.0054+0.0149+0.0101. Note that advertising also indirectly affects brand consideration, mainly through brand awareness. The total effect of GRP on awareness is 1.542.

Hence, PDLM does not assume that advertising has a maximum contemporaneous effect. The PDLM is able to identify a situation where the initial effect is low, then increases and reaches a peak before it decays. The PDLM has two advantages over the previous two models. First, PDLM can estimate the duration of the advertising effects, the number of time periods in which there is a significant advertising effect. Second, PDLM can estimate the shape that these time-distributed effects take, so we do not have to assume *a priori* that effects will always decrease over time. A PDLM can identify a pattern where the initial effect is small, then increases, and after reaching its peak gradually decreases.

Consider this example. If there are four kinds of advertising media (TV, magazines, vertical trade, and newspaper), they would likely have a different time-distributed impact on purchase. These differences are critical to managers. Exhibit 5 shows graphically the lag structures of different vehicles. For example, the effect of TV advertising lasts for only two periods, but its impact is very strong in these two periods. On the other hand, the impact of magazine advertising lasts for four periods with a very small impact in the first period but a larger impact in the second period and a smaller impact in the third period and an even smaller impact in the fourth period until the effect is zero. Newspapers have a strong impact in the first period but its effects fade very quickly.

Exhibit 5
Example of the Impact of Advertising over Time



Modeling in practice

How should we model in practice? First, we need to understand the trade-offs across the modeling alternatives. Since each model makes different assumptions, different numbers of parameters have to be estimated. More parameters usually mean that we have fewer assumptions to make. If an assumption does not reflect reality, our estimates will be biased. However, as the number of parameters goes up, the reliability with which each of these parameters is estimated goes down. It is possible that the curse of low reliability is worse than the curse of biased estimates (Hagerty & Srinivasan 1991). Both bias and error variance (reliability) determine the predictive accuracy of a model. Hence, the model with the most parameters, or the least number of assumptions, is not necessarily the best model to use in practice. To find the best model for the data, we recommend evaluating the results of the various models. To statistically compare the four approaches, we run into a few complications. First, the ECM model has a variable to be explained (e.g., changes in sales) that differs from the three other models. Second, what is fixed in the ASM can get estimated in the other three models. Third, various models have different variables on the right-hand side and so are difficult to compare. Therefore, except for face validity and the statistical significance of parameters, we have to resort to comparing the models on their out-of-sample forecasting performance. There is little empirical evidence that would enable us to make a recommendation for one model over another. Zanias (1993) is the only study we know that demonstrates a better out-of-sample predictive accuracy for the ECM, when it is compared to several distributed lag models.

The main advantage of the ASM is that it is relatively simple to implement and interpret. Its main disadvantage is its assumption about the specific decaying nature of advertising effects. In markets where we have a lot of historical knowledge, this disadvantage can be small. In markets where we have information on multiple brands and multiple media, this system becomes convoluted. The ECM is a very nice alternative to the ASM. It is a parsimonious model, requiring less data than the PDLM, while not having to make the specific assumption about the decaying nature of the advertising effects.

Conclusion

By looking at only the relationship between advertising expenditures and sales, we omit a large part of the effects advertising has on consumers — namely its impact on awareness, positioning/image, and consideration. Our approach provides a more detailed and richer insight into the effects of advertising. Advertising campaigns often have specific objectives, such as increased sales, awareness, or reposition the brand. By looking at our joint modeling results, we can immediately see whether these objectives are being realized. These are a few examples of the implications of our modeling.

• First, if our focus is on increasing sales but all our campaign does is increasing awareness, then clearly we must consider a correction to the campaign.

• Second, if our analyses show that our campaign does increase sales but the optimal level of profits implies more advertising weight, then we should probably increase or decrease spending, depending on the results of the model.

• Third, if we have modeled the different media, it becomes possible to identify which media affect which metrics. This allows us to better allocate our advertising budget across the different media.

• Fourth, if competitive data are available, we can understand how our advertising is affecting the competition and vice versa. We may find that absolute spending levels are less important than relative-to-the-competition advertising levels.

In this article, we have shown the powerful combination of having strong data and powerful econometric time series modeling tools. We have illustrated that, by combining a comprehensive behavioral framework with the required data and econometric models, we can obtain unique insights and knowledge about advertising efficiency. This allows managers to evaluate efficiency of marketing efforts and plan additional marketing actions, depending on when advertising kicks in and when it wears out. The modeling described in this paper is relatively complex. Our model is complex because the problem studied is complex. Effects of advertising typically play out over time and may be nonlinear, and their impact may depend on other elements, such as competition in creating awareness, image, consideration, and ultimately sales. In practical applications, it is important to be aware off and deal with potential methodological issues that may come into play, such as aggregation bias, specification, and identification problems. For an in-depth overview of the many modeling issues we refer to Leeflang, *et al.* (2000).

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