GAM in Marketing Mix Modeling: Revisited
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ABSTRACT

Marketers have always struggled to accurately determine the lagged effects of marketing. Correctly estimating marketing contributions is another important challenge faced by marketing professionals. In an earlier paper, we showed that a generalized additive model (using PROC GAM) accurately estimates the lagged effects of advertising efforts in simulated models with one independent variable. In this paper we take this research a step further, and perform simulations with additional independent variables to examine whether GAM is still able to accurately estimate lagged effects. We also look at the calculation of marketing contributions to determine the accuracy of those estimates. This will allow the end user to determine if the promising results obtained earlier will carry over in real world applications.

INTRODUCTION

The lagged effects of advertising have always challenged marketing researchers and this topic has received a great deal of attention in the marketing literature. Most of the literature has focused on different methods of estimation of advertising lags. Since using several lagged advertising terms in the model equation can lead to problems of multicollinearity and loss of degrees of freedom, researchers have tried to come up with alternate ways of handling advertising lags. For instance the Koyck model (or geometric model) proposed by Koyck (1954) estimates lagged effects by assuming that advertising effect is geometrically decreasing over time. Lambin (1972) uses a combination of direct lags and geometric lags to relate sales to advertising of gasoline based on quarterly data. Similar approaches are used by Montgomery and Silk (1972) and Doyle and Saunders (1985). The Pascal lag structure proposed and applied by Solow (1960) assumes that advertising lags follow a Pascal distribution (also called a negative binomial distribution). A more flexible method of estimating the effect of advertising lags was postulated by Almon. She suggested a method in which the coefficients of the lagged values of the independent variables are assumed to lie on a polynomial curve.

While much of the literature has been devoted to various ways of handling the lags, there have been very few papers that have looked at how an incorrect model specification can affect the estimation of advertising carryover effects. In an earlier paper we pointed out that incorrect model specification can lead to errors in the estimation of advertising lags. We proposed that there are two ways in which incorrect specifications creep into the models in practice. First, when it comes to estimations of dynamic lags, assumptions are made about the relationships between the parameter estimates of the lagged independent variables. For instance, in the geometric lag model, the parameters of the lagged variables are assumed to be geometrically declining over time. Similarly, in the Pascal model, the coefficients of the lagged terms are assumed to follow a negative binomial distribution. The very popular Polynomial distributed lagged model (Proc PDLREG) also assumes that the lag coefficients lie on a polynomial curve. Since in reality, the coefficients of the lagged terms may not be related in any of the above ways, a model fitted under any of those assumptions may be mis-specified. The second factor that complicates matters is that, often, the relationship between the dependent and independent variable may be nonlinear. Therefore, in order to simplify the estimation process, assumptions are often made about the relationships between the dependent and independent variables. For instance, when we know the relationship between the dependent and independent variable is non-linear we may use a specific functional form (such as logarithmic or square root or reciprocal) to model that relationship. [For more details about the types of functional forms that are usually used, please refer to the NESUG 2010 paper by the same author].

However, rarely in the real world does the relationship between sales and advertising follow a specific mathematical functional form. Moreover, predictor variables usually do not show much variation in the sample. Therefore we may only observe values of advertising within a small range. Sometimes with only small variations in the sample, several models can be a good fit for the data.

Since real world data is unlikely to adhere to a specific functional form, using any particular function to model the data may lead to misspecification problems.

In previous papers we have used simulation methods to look at the role of model specification in the estimation of advertising lags. We found that when the true model is different from the model that is specified, incorrect advertising lags will often show up as significant in the model. We found that two kinds of errors can occur when an in-
correct model specification is used. The first type of error is one where some of the lags that are actually significant show up as insignificant in the model. The second type of error occurs when far out irrelevant lags are picked out as significant by the model.

In an earlier paper (NESUG 2010), we compared generalized additive models (using Proc GAM) to regression models (using Proc REG) and found that the generalized additive model is able to determine with a great degree of accuracy the approximate number of periods for which advertising has an effect. In this paper, since we used Proc REG, no restrictions were imposed on the coefficients of the model and the sole reason for inaccurate estimation of lags was mis-specification of the functional forms in the models.

In another paper (NESUG 2011), we compared generalized additive models (using Proc GAM) to Polynomial Distributed Lagged Models (using Proc PDLREG) and once again found GAM to be more accurate in estimating the lagged effects of marketing. Since Polynomial distributed lagged models were fitted in these cases, restrictions on coefficients as well as incorrect functional form were both responsible for the inaccurate estimation of lags.

Our analysis in both those paper, however, was limited to the scenario when there was only one independent variable with lagged effects in the model. In this paper, we take this research a step forward and assume that there are two independent variables in the model. Both variables are assumed to have dynamic effects on the dependent variable, sales.

**MARKETING CONTRIBUTIONS**

We would like to introduce the reader to the concept of marketing contributions. Sales of any product is driven by a variety of different factors such as brand equity, seasonality, advertising campaigns, competitor effects, government regulations, economic growth as well as several other factors. The objective of a marketing mix modeling exercise is to separate out the effects of advertising campaigns from all these variety of factors that affect sales and identify the sales impact of each campaign. The contribution of a media variable towards the sales of a product is defined as the ratio of the incremental sales resulting from advertising in that media to the total sales of the product. To illustrate with the help of an example, suppose that the total sales of the product in week j can be represented by S(j). However, only m(j) of those sales can be attributed to the media variable M and the remainder is a result of other factors. Then the contribution of the media variable M is defined as the ratio: m(j)/S(j). In other words, if 2% of the total sales is a result of advertising in a certain media (say TV) then the contribution of TV advertising towards sales is 2%. Understanding the contributions of the different media variables is important to the media planner as it enables future planning of media investments in those channels that contribute most to sales relative to cost and maximizes profitability.

In this paper, we look at estimation of advertising contributions and using several simulations we investigate how well generalized additive models estimate the contributions of the different media as compared to the other models.

**FUNCTIONAL FORMS USED IN THE PAPER**

The general consensus about the relationship between sales and marketing is that sales response curve to advertising is non-linear. For instance, practitioners in the media world often assume that the media response function is S-shaped, i.e. has an initial convex and subsequently a concave section. Figure 1 shows a typical S shaped sales response curve. The reason for this non-linear relationship is two-fold. First, it is well known that at very low levels of advertising there is very little or almost no sales impact (Corkindale and Newall, 1978 ; Ambler, 1996). This is called threshold effects, i.e. the phenomena that marketing efforts are not effective until they exceed a certain minimum level (Hanssens et al. 2001, p. 113). As advertising increases beyond the threshold levels we observe a positive sales impact and we may observe increasing returns to scale which means that the proportional increase in sales is greater than the proportional increase in advertising. Eventually however, at very high levels of advertising we observe saturation effects of advertising. This causes diminishing returns to scale which means that the proportional increase in sales response is less than the proportional increase in advertising. Therefore the advertising response curve has a concave section at high levels of advertising. This has led various researchers to recognize an S shaped advertising response curve.

Most of the time however, media variables do not show much variation within the data available. Years of experience enable marketing managers to more or less optimize their media levels and we may only observe advertising levels that vary within a small range (say AB) in the figure.
Since data for the entire range is often not available marketing researchers use non-linear functional forms such as logarithmic, square root, reciprocal etc to model the relationship between sales and advertising. The advantage of these non-linear functions is that they result in concave response functions which agree with the assumption of diminishing returns to scale. For more details about the types of functional forms that are usually used, please refer to the NESUG 2010 paper by the same author.

In this paper we use three different types of functional forms to represent the true relationship between sales and advertising. The first function assumes that sales is a logarithmic function of advertising as shown in equation (1a).

\[ S_t = \alpha + \beta \log(a_t) + \gamma \log(b_t) \quad \beta, \gamma > 0 \]  

where “a” and “b” are two different media variables (for instance “a” might refer to TV advertising and “b” can refer to magazine advertising).

The second function assumes that incremental sales is proportional to the square root of advertising as shown in equation (1b).

\[ S_t = \alpha + \beta \sqrt{a_t} + \gamma \sqrt{b_t} \quad \beta, \gamma > 0 \]  

Both equations (1a) and (1b) imply that the relationship between sales and advertising is concave so that there is diminishing returns to scale in advertising.

For simplicity in both the above equations we assume that the functional form is the same for both types of media. In other words in equation (1a) we assume that sales is related to both TV and magazine through a logarithmic function and in equation (1b) we assume that sales is related to both the media variables through a square root function. In reality this need not necessarily be true and the relationship between sales and TV advertising may be completely different from that between sales and magazine advertising.

The next functional form that we use relaxes this assumption and assumes two different functions for the two media variables. Also in order to allow for threshold effects of advertising as well as diminishing returns to scale, we
decided to choose functions which result in S shaped sales response curves. Two popular and commonly used functions (exponential and Gompertz) were chosen to represent the S shaped sales response to the two media variables. Sales is assumed to be an exponential function of the media variable, “a” and it is related to media variable “b” by a Gompertz function as shown in equations (1c) and (1d).

\[ S_t = \alpha + \beta f(a_t) + \gamma g(b_t) \quad \beta, \gamma > 0 \quad \text{..................................................}(1c) \]

where \( f(a_t) = \exp(1 - \lambda \cdot (a_t + 1)) \) and \( g(b_t) = \theta^\gamma (\eta^\gamma b_t) \) \quad \text{..................................................}(1d) \]

where \( \lambda, \theta, \) and \( \eta \) are parameters.

**SIMULATION METHOD**

We use a dataset that contains media impressions for TV and magazines. The data are simulated to be as close to real world data as possible. In our earlier paper we had assumed that sales is affected by only one media variable. We extend that research in this paper by assuming that there are two media variables, TV and magazine, that affect sales. We assume that carryover effects exist so that the media variables influence sales not only in the period in which it is aired but also in future periods. Therefore sales in any period is determined by the value of each media variable in that period as well as lagged values of each media variable. In this paper we assume that there are 3 significant lags of TV and 5 significant lags of magazine so that in the true model, sales in the current period is affected by the TV advertising in the current and 3 preceding periods and by magazine advertising in the current and 5 previous periods. The way we conduct our experiment is as follows. We postulate the true relationship between sales and the media variables by specifying the model and the values of the parameters.

Next we use Monte Carlo simulation methods to try to fit several different models (including the true model) to estimate the relationship between sales and the current and lagged media variables and see which lags come up as significant in the model. For example, suppose we assume that the true relationship between sales and the media variables TV and Magazine can be represented by a semi-log model as follows:

\[ S_t = \alpha + \beta_1 \log(T_t) + \beta_2 \log(T_{t-1}) + \beta_3 \log(T_{t-2}) + \beta_4 \log(T_{t-3}) + \beta_5 \log(T_{t-4}) + \beta_6 \log(T_{t-5}) + \lambda_1 \log(M_t) + \lambda_2 \log(M_{t-1}) + \lambda_3 \log(M_{t-2}) + \lambda_4 \log(M_{t-3}) + \lambda_5 \log(M_{t-4}) + \lambda_6 \log(M_{t-5}) \]

\[ + \epsilon_t \]  

where \( T \) represents TV advertising and \( M \) represents magazine advertising. Using the current and lagged values of the media variables that we have in our dataset, and a randomly chosen set of parameters \( (\beta, \lambda) \), we calculate the value of sales using equation (2). This is assumed to be the true relationship between sales and the media variables, TV and magazine.

Taking this as the true model, we will next try to simulate a bunch of data sets each with a different random scatter. In order to do this we first create a new variable stream (called \( \delta \), say) the values of which are chosen from the standard normal distribution with replacement. We next add this new variable, \( \delta \) to our dependent variable, sales to create a new sales variable (New_St).

\[ \text{New}_t \text{_St} = \alpha + \beta_1 \log(T_t) + \beta_2 \log(T_{t-1}) + \beta_3 \log(T_{t-2}) + \beta_4 \log(T_{t-3}) + \beta_5 \log(T_{t-4}) + \beta_6 \log(T_{t-5}) + \lambda_1 \log(M_t) + \lambda_2 \log(M_{t-1}) + \lambda_3 \log(M_{t-2}) + \lambda_4 \log(M_{t-3}) + \lambda_5 \log(M_{t-4}) + \lambda_6 \log(M_{t-5}) + \delta_t \]  

where \( \delta \sim N(0,1) \). This new sales variable, New_St, is used to run a regression model using the true (semi-logarithmic) specification and that exercise helps us obtain an estimate of the standard deviation of the residuals, S(yx). This gives us an estimate of the variance in sales that we can observe when the true relationship is given by equation (2).

Next we use Monte Carlo simulations to determine other plausible values that the dependent variable can take assuming that the true relationship is (2). These are the values of sales that may be observed in practice when the true sales stream is \( S_t \) in equation (2). To obtain these possible values for the sales stream, we proceed as follows. To each ideal point we add random scatter drawn from a Gaussian distribution with a mean of 0 and SD equal to the value of S(yx) reported from the linear regression of our experimental data. This gives us the probable values that the sales stream can take when the true values is given by equation (2). We repeat this step 10 times to obtain 10 different data sets each containing different sales streams. With each dataset and each new sales stream we try to fit the simulated data using different model specifications including the true model specification. For instance since the true model specification is semi-log the simulated data set is fitted using a semi-log model, a reciprocal model, a square root model as well as the generalized additive model.
In the above example, we used the semi-logarithmic model to obtain the ideal data set and then tried to fit other types of models to the simulated data that we derived from this ideal data. We repeat this exercise outlined in the previous paragraph for other types of models as well. More specifically, apart from the semi-log model, the above simulations are also performed using the square root model in equation (1b) and the general model in equation (1c) as the ideal models. Therefore, in the second phase of the experiment we use the square root model as the true relationship between sales and advertising and then try to derive a bunch of simulated data sets from this ideal data set. Next these simulated data sets are fitted using the reciprocal model, the semi-log model, a square root model as well as the generalized additive model. In the third phase of the experiment, we assume that the true relationship between sales and advertising is represented by equation (1c). All of the above steps are then repeated assuming that this general model is the true model.

Notice that to obtain the ideal relationship between sales and media variables (and their lagged values) as shown in equation (2) we need to come up with values for the parameters (β, λ). This parameter combination is chosen randomly (with certain restrictions) in order to make sure that the choice of parameters does not influence any of the results. In fact, for each model type, 1000 different parameter combinations are used to obtain the dependent variable and create 1000 ideal data sets. Therefore for each model type, the method of simulating 10 datasets outlined in the previous paragraph was repeated for each of the 1000 different parameter combinations.

Therefore, a total of 30000 model simulations were run with 10 simulations for each of 3 model types and 1000 parameter combinations.

INTRODUCTION TO THE GAM PROCEDURE:

The GAM procedure fits generalized additive models as those models are defined by Hastie and Tibshirani (1990). The procedure is based on nonparametric regression and smoothing techniques which relaxes the assumption of linearity and enables us to uncover structure in the relationship between the independent variables and the dependent variable that might otherwise be missed. Multiple lag terms and /or other covariates can be entered into the model by using additional spline functions in the syntax as shown below. If multiple lag terms are entered into the model, the number of lag terms that remain significant can be used to understand the duration of the lags.

The following statements invoke the GAM procedure.

```
proc gam data=diabetes;
model y = spline(x) spline(lag1x) spline(lag2x)..... spline(lagix);
run;
```

where y is the dependent variable and x is the independent variable. Lagix represents the ith lag of x.

In our paper, the GAM procedure was invoked using the following code:

```
proc GAM data=test;
model sales = spline(T) spline(lag1T) spline(lag2T) spline(lag3T) spline(lag4T) spline(lag5T) spline(lag6T) spline(lag7T) spline(lag8T) spline(lag9T) spline(lag10T) spline(M) spline(lag1M) spline(lag2M) spline(lag3M) spline(lag4M) spline(lag5M) spline(lag6M) spline(lag7M) spline(lag8M) spline(lag9M) spline(lag10M) / dist = normal;
ods output Anodev = Anodev_out
run;
```

where lagiT represents the ith lag of TV and lagiM represents the ith lag of magazine.

CALCULATING CONTRIBUTIONS IN THE GENERALIZED ADDITIVE MODEL

The generalized additive model can be represented by the following equation:

\[ S_i = \alpha + \sum_i f_i(x_i) \]  

where the \( f_i \) are arbitrary non-linear functions. A special case of equation (4) is the linear model where
\[ f_i(x_i) = \beta_i x_i \quad \text{.................................(5)} \]

Based on equations (4) and (5), in the linear model, the contribution of \( x_i \) is given by:

Contribution of \( x_i = \beta_i x_i / S_i \quad \text{.................................(6)} \)

Therefore, from equation (6) we observe that in the linear model, the contribution of each input is directly proportional to the input and the contributions of all the inputs taken together add up to 1. In the generalized additive model each input still makes a separate contribution to the response and these can be added up but unlike the linear model, in the generalized additive model, these contributions don’t have to be strictly proportional to the inputs. Also, we need to add certain restrictions to make the contributions identifiable. To see why this is, suppose we start with equation (4) and add constants \( c_1 \) and \( c_2 \) to two functions \( f_1 \) and \( f_2 \) and then subtract \( c_1 + c_2 \) from \( \alpha \), then nothing observable has changed in the model. The model cannot obtain separate estimates for \( c_1 \), \( c_2 \), and \( \alpha \) and instead will obtain an estimate for the term \( \alpha - (c_1 + c_2) \). Therefore, the true contribution of \( x_1 \) (i.e. \( f_1(x_1) + c_1 \)) cannot be determined without imposing some restrictions on the model.

For the purpose of this paper, since we are applying these methods to marketing mix modeling we feel it is reasonable to assume that \( f_1(x_i) = 0 \) when \( x_i = 0 \). In other words, if there is no investment in any particular marketing input then the contribution of that marketing input towards sales is 0. If the firm does not invest in TV advertising then it is unlikely that TV advertising will have an impact on the firm’s incremental sales. We use this assumption both while postulating the true relationships as well as during the estimation process. Using this assumption we are able to obtain accurate estimates of the contributions in several of the simulations.

In SAS, the \( p \) option in the GAM statement can be used to obtain the partial predictions of each independent variable as follows:

```sas
proc GAM data = test;
model Sales = spline(T) spline(lag1T) spline(lag2T) spline(lag3T) spline(lag4T) spline(lag5T)
  spline(lag6T) spline(lag7T) spline(lag8T) spline(lag9T) spline(lag10T) spline(M) spline(lag1M)
  spline(lag2M) spline(lag3M) spline(lag4M) spline(lag5M) spline(lag6M) spline(lag7M) spline(lag8M)
  spline(lag9M) spline(lag10M) / dist = normal;
output out = estimates p;
run;
```

We can obtain the total partial prediction for each independent variable by adding the estimated linear terms to the respective partial prediction. This total partial prediction allows us to explore the shape of the relationship between the dependent and independent variable. However, it does not completely define the relationship and provide the contributions. We adjust this total partial prediction by a constant term in such a manner as to make the total partial prediction equal zero when the original variable is zero. This allows us to obtain the correct contributions for each variable.

**RESULTS**

The tables in this section illustrate the results obtained from the simulation exercises. Recall that we have assumed that TV advertising affects sales in the current and 3 future periods and magazine advertising impacts sales in the current and 5 future periods.

Table 1a shows the results when the true model is semi-logarithmic. When we use the semi-logarithmic model to fit the data, correct lag terms are picked up in almost all of the simulations. In fact, lags 0 through 2 for TV and lags 0 through 5 for Magazine are picked up in 100% of the simulations. Lag3 for TV also shows up in 97% of the simulations. However if the fitted model is reciprocal or square root, either several incorrect lags or far away lags show up as significant in the model. In our simulations, when we tried to use the reciprocal model to fit the data, only 24% of the simulations picked up lag 0 for TV and none of the simulations picked up lags 1 through 3 for TV or lags 0 through 5 for magazine. 100% of the simulations picked up lags 8 through 10 for Magazines. When using
the square root model the results don’t look too bad except for the fact that 100% of the simulations pick up a far away lag (lag 10) of TV as significant. When a generalized additive model is used to fit the data, 100% of the simulations pick up lags 0 through 2 of TV and lags 0 through 5 of Magazine as significant. However, only 62% of the simulations pick up lag 3 of TV as significant and 87% of the simulations also pick up an incorrect lag (lag 6) of Magazine as significant. However, overall the Generalized additive model does well and picks up most of the correct lags and does not pick up any of the far away lags as significant.

We also look at how the models perform in terms of calculating contributions. To do this we look at the total contributions for TV and Magazine over the entire modeling period and see how the estimated contributions differ from the true contributions in absolute terms. Table 1b shows the minimum and maximum absolute percentage difference between estimated and true contributions for each fitted model. When the fitted model is semi-logarithmic, both the minimum and maximum absolute difference in contributions are zero indicating that the estimated contributions are almost exactly equal to the true contributions. When the fitted model is reciprocal the estimated contributions are very different from the true contributions as both the minimum and maximum percentage differences are quite high. When the fitted model is GAM or Square root the estimated contributions are relatively close to the true contributions. GAM in fact performs better than the square root model in estimating the contributions as is also evident from Table 1c which compares the performance of GAM relative to the other models. For each simulation, we compare the absolute percentage difference between estimated and true contributions obtained from each fitted model and the results (when the true model is semi-logarithmic) are shown in Table 1c. The first column heading “GAM <= SLOG” indicates that the absolute percentage difference between estimated and true contributions is lower when the fitted model is GAM than when the fitted model is SEMILOG. The table shows that in 2% of the simulations, the absolute percentage difference in TV contributions is lower when the fitted model is GAM than when the fitted model is SEMILOG. This indicates that GAM performs better than the SEMILOG model in estimating the TV contributions for 2% of the simulations. However, SEMILOG model clearly performs better than GAM in estimating the TV contributions for 98% of the simulations. Also in estimating the Magazine contributions, the performance of the SEMILOG model is better for 100% of the contributions. Compared to the Square root or Reciprocal models however, GAM performs universally better and both TV and Magazine contributions are estimated more accurately using GAM in 100% of the simulations.

The results are very similar when the true model is square root model and will not be repeated here.

We decided to also try out a more general case, where both the TV and Magazine response curves are S shaped. In this case, once again, the GAM came out stronger than any of the other models. Table 2a shows the results when the true model is a combination of exponential and Gompertz curves. When a semi-logarithmic or a square
root model is used to fit the data, only lags 0 through 2 of TV and lag 4 of Magazine are picked up by the models. None of the simulations are able to pick up lag 3 of TV or lags 0, 1, 2 and 5 of Magazine. The reciprocal model completely fails to pick up any of the TV or Magazine variables. However, when a GAM model is used to fit the data, all of the correct lags and none of the incorrect lags are picked up by the model.

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<th>Magazine Lags</th>
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Table 2b shows the minimum and maximum absolute percentage difference in contributions for each fitted model. When the fitted model is square root or reciprocal or semi-logarithmic the estimated contributions are very different from the true contributions as both the minimum and maximum percentage differences are quite high. When the fitted model is GAM however, the estimated contributions are relatively close to the true contributions. In fact in all of the simulations GAM performs universally better than any of the other models and both TV and Magazine contributions are estimated more accurately using GAM in 100% of the simulations.

CONCLUSIONS
In this paper, we look at estimation of marketing contributions as well as dynamic effects of advertising. Since the true relationship between sales and advertising is unknown, marketing researchers often use specific functional forms to model the relationship between sales and advertising. Based on theoretical assumptions (eg. diminishing returns to scale of advertising etc.) about this relationship some of the more popular functional forms used are semi-logarithmic, square root and sometimes reciprocal functions. In an earlier paper, we showed that incorrect model specifications may result in inaccurate estimation of the lagged effects of advertising. Using a simple functional form where sales is a function of only one advertising variable we showed that a generalized additive model (proc GAM in SAS) instead of a specific functional form may help to more accurately identify the significant lags in the model. In this paper we take this research a step further and assume that sales is a function of two media variables. Once again, our results seem to indicate that a Generalized Additive Model allows greater flexibility of the functional form and helps to get more accurate results.

However it is important to note that, throughout this paper, we have used some specific continuous functions to define the true relationship between sales and advertising. In reality, these relationships may not be determined by any continuous functional form and more investigation is needed into how GAM performs in those scenarios. Besides, most of the time, the sales of a product is affected by more than two media variables as well as several other factors such as competitor effects, regulatory effects as well as the performance of the economy. Therefore, further research is needed before we can conclusively say that GAM performs better in every situation.

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