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Marketing Mix Modeling: Techniques and Challenges

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ABSTRACT

Marketing Mix Modeling refers to the analytical and statistical methods used to quantify the effects of various media and marketing efforts on a product's performance. These methodologies help marketing executives comprehend and distinguish the effects of their marketing efforts from other factors that affect sales. Marketing Mix Models can help managers optimize their media budgets and allocate scarce resources into the most profitable marketing and media channels.
This paper provides a brief overview of the methodologies most frequently used in marketing mix modeling and the challenges faced by marketing practitioners.

INTRODUCTION

Corporations spend billions of dollars on media advertising every year. According to data released by TNS, total advertising expenditures in 2006 amounted to $149.6 billion , an increase of 4.1% as compared to 2005. The 2007 advertising market slowed down somewhat due to pessimism about general economic conditions; in spite of that, advertising expenditures in 2007 amounted to $148.99 billion, up 0.2% compared to 2006.

Large media expenditures have traditionally been undertaken by individual corporations in the hope that it will promote sales of the product, build brand image and equity. Not very long ago, marketing was looked upon as more an art than a science and marketing expenditures were justified as a necessary cost of doing business. The trend of the dot com start ups through the 1990s was to use their venture capital to spend profusely on marketing in the hope that these extravagant marketing expenditures would somehow lead to large profits for their firm. With the collapse of the stock market in the early 2000s however, corporations have increasingly become more cautious and operate more efficiently. While overall marketing expenditures have continued to increase, marketing is now looked upon as a planned investment rather than an indispensable cost of business and returns are expected from marketing expenditures just as for any other investment. Hence, there is now greater scrutiny of marketing expenditures and greater demand for accountability within the corporate framework. Marketing practitioners are therefore faced with the task of proving the effectiveness of their marketing efforts to their corporate counterparts. As marketing executives have discovered, this can be a very daunting task indeed. Although marketing expenditures are often a very large part of an organization's budget, they still remain the least understood component of an organization's overall budget. First of, not all advertising efforts are fruitful and achieve the desired objective of enhancing profitability and brand equity. Secondly, even when a campaign is successful, its contribution is difficult to isolate from the several other factors affecting sales. Marketing executives therefore find it very difficult to communicate the efficacy of their advertising to their financial partners. As a consequence marketing expenditures are often viewed with a great deal of skepticism. It is not surprising therefore, that when earnings are low, marketing budget is usually the first to be cut. This however, might be detrimental for the company itself since marketing is supposed to promote the product and generate sales and without this investment future sales and profits may decrease. If marketing expenditures are not providing an adequate return, altering or redirecting them to more fruitful channels may be more productive than eliminating them altogether. Therefore, to justify their marketing expenditures to their corporate counterparts, marketing planners have sought the help of statisticians and econometricians to help them understand exactly how advertising affects the brands sales. The statistical and analytical methods that are used to quantify the effects of marketing on a product's performance are collectively known as "Marketing Mix Modeling". Some of the questions that marketing mix models address are: "How much money should be spent on marketing/advertising overall so as to maximize my profit?" "How should the total advertising budget be allocated among the various media activities?"   "What are the best communication channels for my brands?" This paper explores some of the methodologies that are used by practitioners of marketing mix modeling and the challenges they face.

The paper is divided into sections as follows. In the next section of the paper we outline the challenges that marketing mix modelers face. We include wherever possible, steps that can be taken to overcome these challenges or at least somewhat thwart them. In the following section we go over various methodologies that are used by marketing mix practitioners and outline the conditions under which each method can be used. The paper ends with a brief conclusion which provides an overview of the main points put forward in this paper.

CHALLENGES FACED

Below, we outline some of the challenges faced by the marketing mix modeling industry. Many of the points raised below are common difficulties that are faced by all statisticians performing modeling and analysis with data, whereas others are issues unique to the marketing mix modeling field. As we go over each of these problem areas, we try whenever possible to make recommendations about ways in which some of these issue can be resolved.

NO STANDARDS OF MEASUREMENT

One of the greatest challenges that the industry faces is the lack of consensus about how the effectiveness of marketing should be measured. Since how well a campaign works depends on so many different factors including the product and the company, it is difficult to quantify how much the campaign itself adds to the bottom line. Moreover, marketing has effects in the short term (incremental sales), in the longer term (repeat purchases) as well as in the very long term (real options such as brand identities) (Stewart, 2008). While it may be possible to identify and measure the short term incremental sales due to a marketing campaign, it is more difficult to estimate the repeat purchases arising from that campaign and virtually impossible to figure out the real options that result from it.

Most marketing practitioners use a measure called ROMI (Return on Marketing Investment) to measure the returns of marketing investment. ROMI is defined as: ROMI = incremental dollar sales from marketing investment/ dollars spent on the marketing investment. Another measure that is often used is Effectiveness = incremental dollar sales from the marketing investment / marketing impressions. It is the incremental dollar sales from the marketing investment, which appears in both the above measures, that may vary depending on the model and carryover effects estimated. In other words, the measure of ROMI and Effectiveness depends on the modeler's estimate of the effect of the campaign which can vary greatly depending on the methods used to calculate lead and lagged effects and isolate the effects of the campaign from other factors affecting sales. In practice, most measures of ROMI and Effectiveness only take into account the short term gains from marketing which means that marketing returns are often underestimated. This can lead to underinvestment in media spending which in turn may have detrimental effects on long term profitability and brand equity.

LACK OF TRANSPARENCY

In the absence of any standard method of measuring the effects of marketing, each individual firm develops its own internal standard for the metrics and methodology that they adopt. What is more, most of these firms make their individual methods "proprietary" and unavailable to its competitors and often also to the very clients that they serve. This implies that the methodology that they use is like a "black box" and they provide predictions on their clients' marketing campaigns without any explanation as to how they came about those predictions. As Bucklin and Gupta (1999) mentioned, "Today, it is possible to engage the services of three different "black box" consultant groups, give them all the same data, and receive in return three completely different predictions. However, it is difficult to trust the soundness of these predictions. Without knowledge about the internal processes which they use to arrive at these conclusions, one cannot be sure about the quality of these estimates. Without any requirement of transparency, it is impossible to distinguish between a low quality consultant who comes to his conclusions by fudging over the modeling process and a high quality practitioner who goes the extra mile to tighten all the loose ends in his statistical models.

LACK OF GOOD DATA

Using statistical and data mining methods to measure the effectiveness of marketing campaigns is a relatively recent phenomenon. Only in the last few years have corporations developed an interest in measuring the activities of their communication departments. A large number of firms are now beginning to realize the benefits of the modeling methods in accounting for their marketing functions. As with all new fields, these firms realize only when they begin the modeling process, that they may not have data for several of the important marketing variables that have affected their sales in the past. An example is an automobile manufacturer who may have data on its past media expenditures and large campaigns but have no information about the local newspaper and TV ads by individual dealers or local promotions offered by these dealers, all of which drives a great deal of traffic to their products. Building the tools and processes for the collection of such data is a difficult and time consuming process and it may be years before this information is tracked and collected to a standard required for analysis. However, without that data it is hard to draw any conclusions about the effectiveness of their past campaigns. Not having the data on so many of these important variables renders it very difficult if not impossible to account for the effect of these and other media variables on their housing sales. If variables are omitted, that could lead to misspecification of the model and bias in the estimates.

Apart from missing variables, the quality of the data that is available may also be suspect. Errors in variables have always plagued all research in the social sciences and media research is no exception. Measurement problems can arise from (Hansens et al.): 1) Problems of definition: There are certain variables such as attitudes, goodwill etc which are unobservable and for which no well-defined meanings and measurements exist; (2) Problems of operationalization : Sometimes a data series has to be modified to make it operational. For e.g.: data stretching

techniques may be used to convert quarterly data into the desired weekly series or missing imputation techniques may be used when some observations are missing on a variable; (3) Mechanical errors : Errors of transcription and other mechanical mistakes.

Missing variables and measurement errors introduce bias in the estimated coefficients and care should be taken to minimize these kinds of errors. If the true variable cannot be measured, it may be possible to use a related variable in its place. Such a variable is called a Proxy variable. In general, the use of even a poor proxy variable is better than omission of unobservable variables.

DIFFICULTY MEASURING ADVERTISING CONTENT

The content and creativity of an ad is an important determinant of the effectiveness of advertising. However, it is very difficult to measure the content or creative qualities of a particular advertisement and compare it to any other ad. Marketing mix modelers usually use marketing expenditures or gross rating points or impressions to measure advertisement. However, two advertisements with the same gross rating points or impressions may have completely different responsiveness based on the emotional appeal or creative genius of the ad.

MULTICOLLINEARITY

Several marketing and media efforts often take place at the same time (e.g.: coupons may coincide with Magazine and TV ads). This causes collinearity which means that the independent variables are strongly related to each other. In this case the influence of one variable may be difficult to separate from that of another and we may end up getting only a joint effect for two or more media variables that are extremely correlated. Other difficulties arise from the common practice of the various different media efforts coinciding with seasonal peaks making it more difficult to separate the effects of seasonality from those of marketing. Care should be taken to check and correct for multicollinearity by taking one or more of the followed steps : (1) Delete some predictors that are correlated to others (PROC VARCLUS) ; (2) Combine correlated variables by constructing composite indexes using principal component analysis (PROC PRINCOMP); (3) Apply other estimation methods specifically developed for cases with severe multicollinearity (e.g.: ridge regression).

DYNAMIC EFFECTS (ADVERTISING LEADS AND LAGS & WEARIN / WEAROUT

One of the factors that greatly complicate the analysis of marketing effects is the carryover effects of advertising. Sometimes advertising may affect sales not only in the current period but also in future periods. These lagged effects can be due to several reasons including (1) viewing delay: a particular customer may view the ad a few days after it first appears, (2) customer inertia: the time lag between the customer seeing the ad and actually going to the store to purchase the product, (3) repeat purchases: customer may make repeat purchases for a few periods after the initial stimulus. These lags are an important reason for *advertising wearin* which typically occurs at the start of a campaign. *Advertising wearin* is the phenomenon due to which advertising responsiveness does not kick off until a few weeks have past after the start of the campaign. It occurs because repetition of the campaign in subsequent periods enables more people to see the ad, talk about it, think about it and respond to it than in the first week of the campaign (Tellis, 2006).

These lagged effects of advertising have to be taken into account in the marketing model and can result in a large number of additional independent variables in the model. Moreover these carryover advertising variables are usually highly correlated to the original variable, thus adding to the collinearity in the model.

Also, determining the number of periods of lags to include in the model proves to be quite challenging. Research has shown that the estimated duration of the lag often varies with the periodicity of the data. In other words, the number of significant lags when we have weekly data may turn out to be completely different from that when the data is monthly or yearly. This data interval bias has been shown in several studies including some studies where the same dataset has been used with different periodicity (Leeflang and Reuyl, 1985) and has shown such a bias.

Advertising wearout where the effectiveness of an ad diminishes with overexposure to the advertisement also has to be accounted for in marketing mix models and accurate information about the point of diminishing returns is greatly valued by commercial companies. However, the limited range of variation of advertising that occurs in practice implies that data is only available for a small range of predictor values. Thus within the available sample, the predictor variables may not show much variation and several models can provide a good fit (Leeflang et al., 2000) However, with some of those models, forecast accuracy may decrease as we move away from the range of predictor values. The lack of data outside this limited range, renders it difficult to make accurate predictions about extremely high values of advertising and the point of diminishing returns.

NON LINEAR FUNCTIONAL FORMS

Practitioners in media modeling world often use complicated non linear functional forms to estimate media response curves. For instance, a common approach is to assume that the media response curve is S shaped, i.e. has an initial convex and subsequently a concave section. The driving force behind this is the existence of the so called "threshold effects" of advertising, i.e. the phenomena that marketing efforts are not effective until they exceed a certain minimum level (Hanssens et al. 2001, p. 113). Most managers and practitioners agree that advertising

threshold effects exist so that there are levels of advertising below which there is essentially no sales response (Corkindale and Newall, 1978; Ambler, 1996). This has led to the use of a non linear S shaped media response curve by practitioners. Apart from threshold effects, there are a large variety of different factors to take into account including various types of media, advertising lags and multiple brands / markets / stores, all of which increase the complexity in the relationship between advertising and sales often leading to the use of complicated functional forms to get a good fit.

INSTABILITY OF COEFFICIENTS
High degree of multicollinearity, omitted variables and measurement errors all contribute to instabilities in the coefficients of market response models. This means that the coefficient of a media variable may change as more time periods of data becomes available. While structural changes (such as changes in the creative, flighting etc of the media) may cause coefficients to change from one period to the next, any such structural changes can be taken care of by formulating the model to have different coefficients for the separate time periods and one would expect the past periods' coefficients to remain unchanged even with additional data. Unfortunately, data and modeling flaws often do lead to changes in these coefficients and a common practice is to artificially "fix" the coefficient to its past value and move forward with the additional data. Care should be taken before the start of the project about the factors that may lead to non-robust estimates and try to minimize those deficiencies in the model. Bootstrapping and other methods may also be used to get more robust estimates.

INTERACTION EFFECTS
Since combinations of marketing activities often work better than individual campaigns, it is important to check for significant interactions among the various marketing variables. Classification and decision trees methods or chaid can be used to test for interaction effects between the numerous variables and the significance of those variables should be examined by entering them into the model.

MODELING METHODS

Marketing efforts may include all sorts of media and promotional activities such as TV, radio and print advertising as well as price discounts, coupons, FSI etc. Obviously, a complex mix of own actions, competitive actions and regulatory and market events affect a product's performance and the challenge lies in correctly separating the effects of marketing activities from all the other components. Various methods have been adopted by marketing mix practitioners to isolate the effects of marketing. Most often availability of appropriate data is the greatest challenge faced by market researchers. It is no surprise therefore that exact models / methodologies used frequently depend on the data obtainable. In this section of the paper we outline the different types of models that are most often used by marketing mix modelers. We also highlight the main variations in modeling methodologies that arise from differences in available data.

We identify several important characteristics of datasets that can lead to different modeling techniques. Model specification can vary depending on the following factors that distinguish one dataset from another

- Aggregated data vs. Disaggregated data
- Point of success: Sales / market share / equity / other?
- Observed variables vs. Latent variables

AGGREGATED DATA
This type of data is the easiest to obtain and is often used. A typical example is National Sales Data across various time periods (e.g. by week). Regression methods (PROC REG) or time series regression methods (PROC AUTOREG) are most frequently used with this type of data. With reference to the above example, National sales of the brand is used as a dependent variable while Marketing and media activities, seasonality and holiday dummies and other relevant variables are used as independent / explanatory variables. Coefficient of each media variable multiplied by the variable itself is assumed to be the contribution of that variable. Contribution for a year is defined as the incremental sales that resulted that year due to the media in question. For linear models, coefficient of the variable multiplied by the variable stream itself is taken to be the contribution of that variable. Complicated transformations of dependent and independent variables may require other back calculation steps to obtain the contribution.

To estimate the returns from media investment during a given period, the contribution for that period is usually adjusted for lead and lagged effects thereby excluding the lagged effects of media spending in earlier periods and taking into account delayed effects (of current spend) in future periods. These returns divided by the dollars spent on that media is the ROMI of that media.

SOMEWHAT DISAGGREGATED DATA
Data may be available at a slightly more disaggregated level. This occurs for instance when we are able to obtain

market level or brand level data over a time period. Three approaches can be used to deal with this kind of data:

(1) Data can be pooled and a regression model applied to the pooled data. This method assumes that the effect of marketing activities is the same across markets and ignores any variations between groups.

(2) Fixed Effect Modeling (LSDV Approach) is another technique that can be used to analyze this data. In this method we regress the dependent variable on predictors at the individual level but use as predictors a set of n-1 dummy variables for the n groups to identify the group membership of each individual in the data set. This method allows differences in intercepts of the individual groups and therefore considers variations between groups. However, the slope of each predictor is assumed to be same for all groups. In reality we expect the predictor variables (such as advertising) to have differing effects on the separate groups and so the slope of the predictor variables should change between groups. The regression coefficient for each predictor obtained from the Fixed effects method therefore is the weighted average of the regression coefficients in each of the individual groups.

(3) Alternatively, hierarchical linear models (HLM) models or mixed models as they are often called (PROC MIXED) may be applied if coefficients are assumed to be different across markets. This method accounts for both within group variation and between group variation. The responsiveness of advertising can be expected to vary between different markets as well as different brands, and the advantage of mixed models is that they inherently account for this feature. These models can also handle data structures that have multiple levels (e.g.: brands within stores within markets). This method also allows parameter estimation of advertising effects in markets with very few observations as well as helps to quantify or differentiate the individual effect of each group from the average effect across all groups. Also, these models are very powerful since all the available information for all groups is used to obtain the coefficients for each subgroup and even observations with missing data are used instead of being deleted.

VERY DISAGGREGATED DATA

Data may be available at a very disaggregated level. E.g. A.C. Nielsen / IRI data where consumer purchases at a store are scanned and entered into a database containing consumer demographics and media information. Limited dependent variable models can be used to analyze this kind of data, e.g. Logit Models, Probit Models (PROC LOGISTIC, PROC CATMOD). In most situations, this level of disaggregated data is not available for all the individuals in the population. Rather data is only available for a sample of individuals who visit certain stores in a specified market. Since the marketing planner is interested in the performance of the overall brand and not only in the specified market, appropriate methods have to be employed to project the brand market shares from the individual level choice probabilities. Several methods can be used to estimate the market shares. Since the level of predictors are unknown outside the sample, one possibility is to assume some appropriate distribution for the predictors and sum the choice probabilities over that distribution to get an estimate of market share. This method leads to computational difficulties when there are a large number of predictors. An alternative method may be to evaluate the choice probability at the average values of all the predictors and use that as an estimate of the brand market share. Another frequently used method is to use the average of the choice probabilities in the sample as an estimator of the brand market share.

POINT OF SUCCESS : MARKET SHARE

Sometimes instead of sales data, only market share data may be available for each brand for each time period. In this case market shares have to be used as the point of success and the responsiveness of each brand's market share to the firm's advertising efforts has to be estimated. Attraction models are most commonly used with this type of data. Attraction models are useful for analysis of competitive structures and cross effects of marketing mix variables can be estimated along with own effects. Since market shares must always lie between 0 and 1, these models must satisfy the constraint that the predicted values must lie in the same range. Moreover, the market shares of all the brands must add up to 1. Attraction models are estimated using Seemingly Unrelated Regression (SURE) methods (PROC SYSLIN).

UNOBSERVABLE/LATENT VARIABLES:

Sometimes behavioral and psychological variables may be included in the model. For instance, advertising may influence brand awareness, brand image, motivation to purchase etc. which in turn may influence product sales. These behavioral / psychological variables are not easily measured and are called unobserved or latent variables. Various measured constructs may be used to measure each latent variable. For instance, to measure brand awareness of the ABC brand in the fabric softener industry, several questions may be asked in a survey such as "Do you recognize ABC brand?", "What does brand ABC sell?" , "What types of fabric softeners are you aware of?" etc. Structural Equation Models (PROC CALIS) can be used when some of the variables are unobserved or latent. These models are especially helpful when several constructs (or indicator variables) are used to measure each latent variable. The indicator variables for each latent variable can be expected to be correlated which might lead to problems when using multiple regression. SEM may also be more useful than regression methods when we expect indirect effects in the model. For instance print advertising may not affect sales directly but may do so indirectly through brand recall. In this case SEM may provide a coefficient for the path between print advertising and brand recall whereas regression methods will not find a significant relationship between sales and print advertising.

CONCLUSION

The use of statistical and analytical methods to understand the effects of marketing activities is a fairly recent phenomenon and this practice is called Marketing Mix Modeling. The paper looks at the various methods used by marketing mix modeling practitioners and the challenges that they face. While a lot of the issues are commonly confronted by all individuals in the data modeling occupation, some of them are idiosyncratic to the marketing mix modeling field. Wherever possible, the paper outlines steps that can be taken to somewhat thwart these difficulties. Since Marketing Mix Modeling is a relatively new field, the data available is often incomplete and/or insufficient; a result of unstructured and relatively primitive methods of data collection. Consequently, the modeling methodologies used and the results obtained are frequently dictated by the availability of appropriate data. The paper highlights the various types of data that may be available and the corresponding modeling approaches that may be used.

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