Evaluating Media Advertising at Victoria's Secret Stores

by

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This report proposes a method of evaluating advertising programs at Victoria's Secret Stores (VSS) The methodology was developed through a collaborative effort between Ohio State faculty and members of the marketing and finance departments at VSS. The analysis described below is based on one advertising campaign (underwear) which ran during the summer of 1996 in six test cities. Because the results pertain to just one test, the proposed methodology should be viewed as a preliminary proposal pending further verification.

<u>The Underwear Campaign</u>

Figure 1 displays a time series plot of weekly sales per store for three of the six test cities (Boston, Miami and Minneapolis) beginning June, 1996 through November 1996. Also plotted are sales figures for the balance of stores which did not receive the advertisement. The rectangles in the figures correspond to the actual periods in which the advertisements were aired. Figure 2 displays a similar graph for the other three tests cities (Washington, Chicago and Dallas). The two figures differ in the timing and duration of the advertisement (note differences in the third rectangle). Hence, the analysis was performed separately for the two groups of cities.

<u>Dealing with Seasonal Fluctuations</u>

A striking feature in both figure 1 and 2 is the marked seasonality present in the data. For both test and non-test cities, sales dipped between 6/22/96 and 7/6/96, then rose and later fell again during the month of September. This systematic variation of the data is due to marketing activities and other factors not part of this analysis. These seasonal effects lead to sales figures during the advertising period which are actually lower than sales prior to the campaign. The proper analysis of advertising effects must remove the potentially confounding effect of these seasonal effects.

To this end, consider a multiplicative model in which sales per store are determined by (1) a baseline of sales; (2) seasonal effects; and (3) advertising effects which serves to lift sales from the baseline:

$$\text{Sales per Store} = \text{Baseline} \times \text{Seasonal Factor} \times \text{Advertising Effect} \tag{1}$$

For cities which do not receive any media advertising the model would be:

$$\text{Sales per Store} = \text{Baseline} \times \text{Seasonal Factor} \tag{2}$$

Note that we view the base level of sales to be different across stores and cities, but assume that the seasonal factor is the same. This later assumption is supported by the data (figures 1 and 2) since the sales per store in the test and balance cities closely track each other and are highly correlated. Dividing (1) by (2) leads to an estimation equation free of seasonal fluctuations:

$$\text{Ratio of Sales} = \text{Ratio of Baselines} \times \text{Advertising Effect} \tag{3}$$

Further, this multplicative model is equivalent to an additive model:

$$\text{Ratio of Sales} = \beta_0 + \beta_1 \text{Adv} \tag{4}$$

where β_0 is measured from the data and reflects the ratio of baseline sales in test stores to the balance, β_1 is the lift in sales due to an advertisements (relative to average weekly sales in the balance of stores), and Adv is a variable equal to one during the periods of advertising and zero elsewhere. We propose use of equation (4) to begin our analysis of the underwear advertising campaign.

This approach to dealing with seasonal sales variations is different from the approach currently employed by VSS. The current approach first identifies a set of control stores not exposed to the advertisements, and then includes the sales from these stores as a covariate in the analysis. Control stores are identified by high correlation between their sales and the sales of the test stores. Problems with this approach include: (1) high correlations are primarily driven by sales spikes around particular holidays, and not necessarily all of the periods under study. Hence two cities may have highly correlated sales patterns because of a few important sales days and not because of a close pattern overall; and (2) the inclusion of the sales in the control city as a covariate does not properly "control" for seasonal effects because these sales data are influenced by other random disturbances. The effect of these disturbances is to downwardly bias the estimated effects. We therefore believe the proposed procedure for removing the effects of seasonal fluctuations is better because it does not require the identification of control cities and is not subject to the influence of these other disturbances.

Analysis of the Transformed Data

Figures 3 and 4 provide time series plots of the ratio of sales per store (test/balance). Analysis of this data reveals the existence of a carryover effect of advertising not captured by equation (4). Equation (4) assumes the effect of advertising ceases immediately after the advertising period when Adv takes on values of zero. A study of the carryover effect using a techniques known as Time Series Analysis leads to a different model specification which supports a carryover effect (see Box and Jenkins 1976, Time Series Analysis: Forecasting and Control, Holden-Day, and Box and Tiao, 1975, *Journal of the American Statistical Association* p.70-79):

$$\text{Ratio of Sales}_t = \beta_0 + \beta_1 \text{Adv}_t + \beta_2 (\text{Ratio of Sales})_{t-1} \tag{5}$$

where "t" refers to the current period and "t-1" to the previous period. To understand the ability of equation (5) to represent carryover, consider the effect of an advertising "pulse" in period t. "Ratio of Sales_t" is increased by β_1 units. Then, in time t+1, Ratio of Sales_{t+1} is increased because Ratio of Sales_t was higher β_1 units due to the advertisement. This results in a lift to sales of $\beta_1 \times \beta_2$ units. Then in time t+2 there also exists carryover because Sales_{t+1} was above average due to the advertising pulse, and so on. The total effect is equal to:

Period	Effect of Advertising	
t (advertising pulse)	β_1	(immediate effect)
t+1	$\beta_1 \times \beta_2$	(carryover)
t+2	$\beta_1 \times \beta_2 \times \beta_2$	(carryover)
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.	.	.
t+k	$\beta_1 \times \beta_2^k$	(carryover)

Total Effect of Advertising: $\beta_1/(1-\beta_2)$

The Effect of Advertising

The result of applying equation (5) to the underwear campaign data in figures (3) and (4) produced the following coefficient estimates:

Boston, Miami and Minneapolis: $\beta_1 = .044$; $\beta_2 = .537$; $\beta_1/(1-\beta_2) = .095$

Washington, Chicago and Dallas: $\beta_1 = .059$; $\beta_2 = .490$; $\beta_1/(1-\beta_2) = .112$

The results indicate that one week of media advertising resulted in a **9.5%** lift in sales in Boston, Miami and Minneapolis, and a **11.2%** lift in sales in Washington, Chicago and Dallas. These percentages are relative to the base level of sales in the balance of store. Furthermore, the effect is additive in that it is achieved for each week the advertisement is aired.

Conclusion

The proposed methodology has a number of distinct advantages relative to alternative approaches: (1) it eliminates seasonal variation (see figures 1 and 2) and hence the need to match test cities with non-test cities; (2) the carryover effect of the advertising is measured and included in the determination of the lift to sales; (3) the methodology can be implemented using standard software packages such as Microsoft Excel if the correct sales model is similar to equation (5). This later point is dependent on the nature of the data and must be verified with the further analysis of other advertising campaigns.