Report

Group 6

3/21/2017

Introduction

Fast-food companies spent approximately $4.6B on media advertizing in 2012 (Nielson, cited in Yale 2014), an 8% increase from 2009. The reason for this substantial spend is clear: advertizing has a measurable and lasting effect on sales, and brand awareness, (Little, 1979). In 2012, the top 25 most popular fast-food companies in the US directed an average of 90% of their advertizing spend to TV (Nielson, cited in Yale 2014). The remaining expenditures were distributed between less popular media such as radio, internet, and print. With such huge sums of money being invested in advertizing, it is no wonder that marketing managers carefully study where to direct their money to guarantee maximum return on investment. As one can imagine, this is no simple task. For example, within TV media alone, marketing managers can choose from hundreds of format (length of ad), air time, and channel combinations.

Given the large amount of adverstizing investment, it is no surpise that the research community has spent a lot of time and effort on gaining a deeper understanding of the field. Generally, the methods for evaluating the impact of advertising can be grouped into two approaches: laboratory studies and empirical studies (Tellis, 2007). Whereas laboratory studies usually focus on the behavioral paradigm, empirical studies focus on the modeling paradigm. Therefore, there exists numerous models that capture both the dynamic and diminishing returns of advertizing, as well as varying effects of different media, content, and times of release.

The aim of this report is to provide support in the decision process of marketing managers in the fast-food market. More specifically, the report focuses on the Italian fast-food market. Similar to the US market, companies in the Italian market make heavy use TV advertizing. As such, the report focuses on understanding the effects different TV advertizing formats and air time combinations. In order to analyze these effects, past responses to various levels of investments within different format and air time combinations are analyzed using econometric techniques. Instead of using sales as the response variable, the report decomposes sales into visits and spend per visit and uses these as repsonse variables. The subsequent sections describe the models, the data and transformations performed, the results, and concludes with relevent findings and recommendations.

Model

The model used in the analysis captures the following effects sales:

- current
- carryover
- diminishing returns
- media
- air time
- seasonality
- trend

The current and carryover effects of advertizing are captured in the adstock variable. The adstock variable is calculated as follows:

$$A_t = \alpha A_{t-1} + Adv_t$$

In this formula, A_t and A_{t-1} are the adstock of time t and t-1 respectively. Adv_t represents the level of investment at time t. The parameter $_alpha$ is between 0 and 1 and represents the memory of the system. Values closer to 1 indicate longer lagged effect of advertizing on sales. The adstock transformation has the advantage of summarzing both current and carryover effects of advertizing thereby reducing the complexity of the model. The adstock variable is treated as a normal variable. As such, the log transform is used on the adstock in order to capture the diminishing returns of advertizing investment on sales. Both transformations are performed on all the media types available in the data in order to better isolate the effect of the media of interest (TV).

In addition to modeling the effects of different media types and air time combinations, the model controls for seasonal aspects by including variables for weekday, month of the year, and holidays. The model also includes a trend to capture any increases in average sales.

The final model looks as follows:

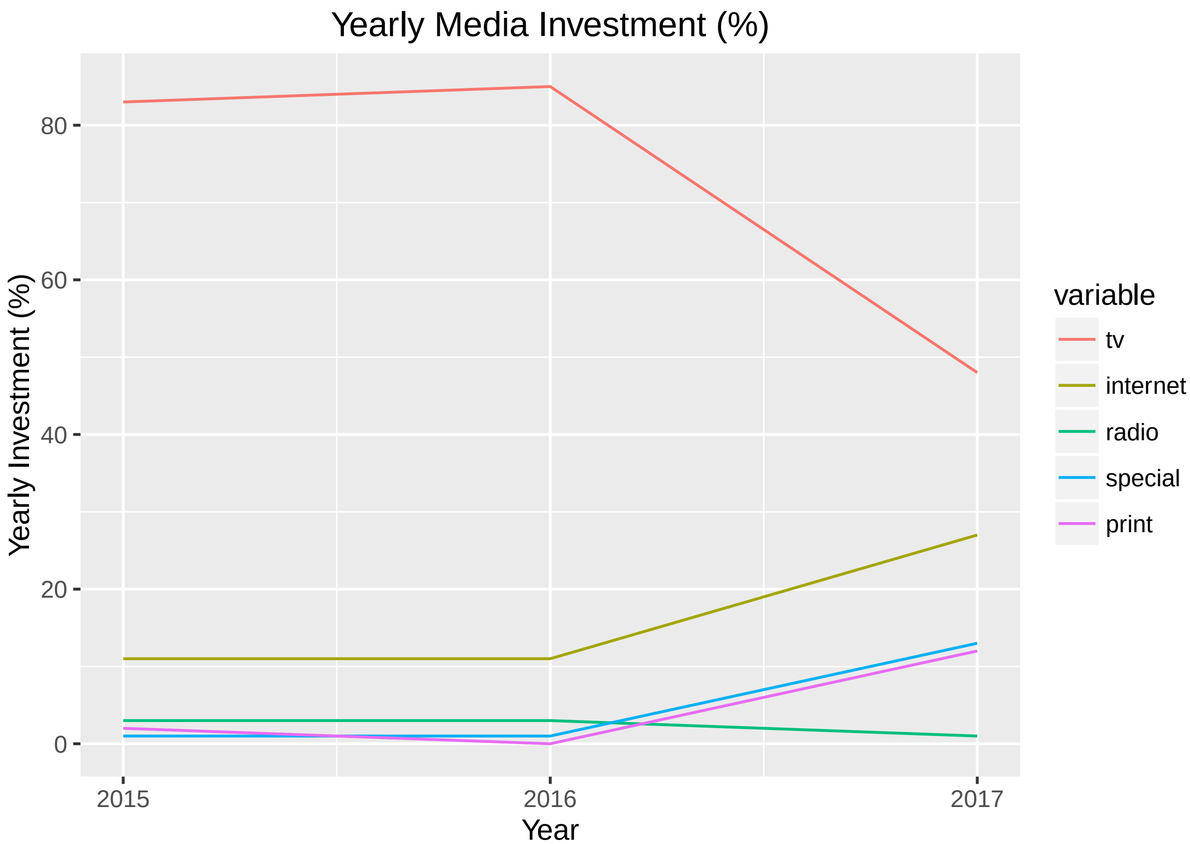
$$S_t = \delta + \beta_A log(A) + \beta_D D + T_t + \epsilon_t$$

where

δ_t = a constant to be estimated,
$log(A)$ = a matrix of adstock variables for different media, formats, and air times (for TV only),
D = a matrix of factor variables for weekday, month of the year, and holidays, T_t = a trend variable,
β_i = a vector of coefficients to be estimated,
ϵ_t = a vector of error terms initially assumed to be IID normal.

Data

The data used in this study are from an Italian restaurant chain which consists of daily sales and visits of each store and the detailed campaign schedules and investments for 5 different medias in restaurant chain-level. Data showed that during 2015 and 2016, TV campaign accounted for more than 80% of the total campaigns investments. This figure had dropped significantly in 2017 to only 47%, leaving the remaining investment budget to increase investment proportion of all other media except radio.



In our study, analysis would only consider stores that opened during the whole period of the data. By doing this, there would be constant number of stores opened from 15 May 2015 until 12 March 2017. Consequently, stores that did not open in the whole period would be removed. After filtering the stores, sales and store visits (indicated by receipts count) data would be aggregated by date, resulting a total sales and visits of the entire restaurant chain for each date.

Campaign data, on the other hand, had been in a chain-level data format but had to be aggregated by media type - TV, radio, internet, print, or other special type of campaign - to identify the amount of investment for a particular media type in each day. For print campaign, whose ads were issued in either weekly or monthly magazine, the investment cost was distributed evenly over the duration of the campaign by dividing investment cost by the length of the campaign (7 for weekly or 30 for monthly). After aggregating the data, it can be seen that some of investment cost for TV were zero but the GRP (gross rating points) indicated a positive value. In order to deal with these 'gift' campaigns, costs were recalculated using regression using GRP as the control variable. For other media types, investment cost for 'gift' campaigns were replaced using the average investment cost for that particular media.

Calculation of Adstock Variables

The adstock variables for each media and format (and air time for TV) are calculated using the formula described above. The optimal α is calculated using a grid search algorithm. For each α (between 0 and 1 in 0.01 increments), the calculated adstock is used in the model (which model? simplified version of final?). The α that produces the adstock that returns the lowest root mean squared error (RMSE) is kept for the final model. The values of the optimal α can be seen in Table 2.

TV, internet, and radio have an optimal α of over 0.90. This indicates that these media have a long lasting effect which extends several periods over the original exposure.

Table 1: Summary of Media Investment

	media	alpha
1	TV	0.96
2	Internet	0.94
3	Print	0.78
4	Radio	0.94
5	Special	0.86

Results

- elasticities and so on (short and long term)

Findings and Concluding Discussion

Based on the results of our regression models, we recommend that the client alter its advertising models to better spend its marketing budget. The client can improve its marketing via two components: increasing the number of customers in its stores or increasing each customer's transaction amount.

With respect to increasing store volume, they should increase spend on 45 second advertisements during the daytime, 15 second adverts in the morning, and 20 seconds during primetime. Conversely, advertising for 45 seconds at night and during primetime actually decreases visitors.

With respect to increasing transaction amount, the client should increase spending on 45 second advertisements during the day, 15 second adverts in the morning, and 20 second primetime ads. These match their best three formats for store volume. Therefore, the client should focus on these categories. As with visits, 45 second ads at night decrease sales per visit, so such ads should be avoided.

Overall, we recommend the client follow two key principles regarding their advertising. The first is that the best TV advertising format depends heavily on the time of day it is aired. Second, many of their advertising formats are largely insignificant and increase neither visits nor sales per visit. Such spend appears wasteful and should be more closely examined.

Appendix

Table 2: Summary of Media Investment

	media_grouped	year	investment	n	max	min	average.inv
1	internet	2,015	2,553,505	3,515	40,000	16	726
2	internet	2,016	2,365,211	2,042	50,000	3	1,158
3	internet	2,017	1,274,119	1,695	23,084	45	752
4	print	2,015	408,865	107	34,000	850	3,821
5	print	2,016	68,171	11	17,001	1,700	6,197
6	radio	2,015	573,951	1,060	43,250	45	541
7	radio	2,016	553,019	2,617	1,768	23	211
8	radio	2,017	33,073	174	500	57	190
9	special	2,015	310,101	177	80,000	450	1,752
10	special	2,016	232,613	25	32,000	556	9,305
11	special	2,017	634,460	38	20,000	2,500	16,696
12	tv	2,015	18,546,503	97,290	46,861	0	191
13	tv	2,016	18,129,782	101,352	38,387	0	179
14	tv	2,017	2,290,379	15,232	42,840	0	150

Works Cited

Little, J. (1979) Aggregate Advertising Models: The State of the Art. *Operations Research* 27(4), 629-667.

Tellis, G. (2004) *Effective Advertising: Understanding When, How and Why Advertising Works.* Thousand Oaks CA, SAGE Publications.

Yale Rudd Center for Food Policy & Obesity. (2012) *Fast Food Marketing Ranking Tables.* Available from: http://www.fastfoodmarketing.org/media/FastFoodFACTS_MarketingRankings.pdf

Advertizing has a dynamic effect on sales. For example, the actual purchase of a good (or service) is often done several days after the original exposure to advertizing. Reasons for this vary but include the inability to purchase directly (depending on the product or service) or the transfer of the advertizing message to another consumer. In addition to being dynamic, the effect of advertizing on sales is likely to be non-linear. For example, the effect 200 units of advertizing investment is likely less than half of the effect of 100 units of advertizing investment over the same period. In additionAs such, a simple linear model cannot be used to accurately estimate the effect of advertizing on sales.