Intertemporal Effects of Online Advertising Channels on Customers

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Abstract

Advertisement is an attractive means of achieving organizational goals, such as increasing sale, revenues or profits. Previous researchers unanimously agree regarding the effectiveness of advertisement; however, there is a difference of opinion among scholars as to which channels and online sources of advertisement are the most productive. This study investigates additional information about advertising effects that may help business organizations and policy institutions. This study attempts to answer two important questions: 1) Is the long-term effect different from the short-term effect of online advertising? 2) Do the different channels of advertisement have synonymous effects on their corresponding targeted clients? The study uses daily base data on a book-selling company over the course of one year (365 daily observations). The study uses a number of time-series tests to investigate the stationarity of the data. The study then subsequently uses the Pearson correlation test and generalized least-square technique to estimate the short-term, long-term, and carryover effects of various channels of online advertising. The study shows that coupon loyalty advertising is more effective with respect to cumulative effects such as long- and short-term effects. The findings reveal that there is a difference between short- and long-term effects; however, both effects have the same signs and thus follow the same direction. The study also reveals that there is difference between the effects of various advertising channels on the volume of sales and as well as between their carryover effects. System engine marketing has the longest effect (6.7 days), followed by BA and CLA.

Keywords: Advertising, E- Marketing, Customers, Intertemporal Effect

1. Introduction

Advertisement effects are of great importance for stakeholders. Advertising helps organizations significantly in realizing their objectives, such as by helping consumers in purchasing decisions regarding what product to purchase based on the features of the product. It also helps producers to optimally achieve organizational goals, such as increases in sales and revenue. Finally, it also helps policy-making institutions to intervene to effectively regulate the market to achieve optimal policy agendas (McDonald & Cranor, 2010). Numerous studies have identified the benefits of advertising, its suitability in different circumstances, the selection of media and its time-variant effects (McDonald & Cranor, 2010; Shamdasani, Stanaland, & Tan, 2001; Vakratsas & Ma, 2005). Traditional media sources such as television, radio and print media (e.g., newspapers) have significant short- and long-term impacts on customers (Vakratsas & Ma, 2005). The commercial use of the Internet has also brought a revolution in the fields of marketing and advertising. Marketing has now become a buzzword in communication technology and thus attracts the attention of all major stakeholders. The advancement of the telecommunications sector has introduced new concepts, such as e-marketing, and new models and channels of advertisement, such as the use of social media for business organizations (Kim & McMillan, 2008). However, this advancement has posed some serious challenges to stakeholders as well. For example, it has put business organizations into unnecessary advertisement competition, which is unlikely to ever come to an end. Eventfully, the advertising cost is shifted to the customers, thus increasing their cost burden (Woodside, Randolph III, & MacDonald, 1997).

This paper aims to identify the effectiveness of online advertisement in terms of both immediate increases in sales and long-term benefits.

Though numerous studies have been conducted to investigate the effectiveness of online advertisement, very few studies have been able to differentiate between its long- and short-term effects (Breuer & Brettel, 2012). The present study aims to fill this research gap and to open new horizons for academic researchers and policy organizations by investigating the effects of online advertising in terms of timeframe (i.e., short vs. long term). This study will reveal additional information about advertising effects, which may help business organizations and policy institutions in designing optimal policy agendas.

2. A Brief Introduction to Online Advertisements Channels

There is no single form of advertisement. Different forms of advertisement and advertisement channels have been used for different target groups, based on the suitability and availability of sources to the targeted customers (Karaoguz & Bennett, 2004). Banner advertising is a common type of online advertising in which banners are positioned on a third-party website; customers can click the banners to access the advertised website. The frequency of visits to the main site via clicks through the banner is considered as the effectiveness of the banner (Shen, 2002; Sherman & Deighton, 2001). Coupon Loyalty Advertising (CLA) is another kind of advertisement, the primary objective of which is to attract customers for future purchase by offering rewards contingent upon the customers' future purchases (Klayh, 1998; Smith & Potter, 2010). Search Engine Marketing (SEM) is most common and powerful online advertisement source; it accounts for about 90 percent daily use of customers through powerful search engines like Google and Yahoo (Brettel & Spilker-Attig, 2010).

3. Materials and Methods

The data for this study were taken from a leading online platform about new and used books. The sample consists of daily observations over a one-year time period (i.e., 365 observations). Information about different kinds of online advertisement was recorded for each advertisement channel. The following information was gathered from the company regarding the various channels of advertisement.

Table-1: Various Channels of Advertisement, Cost and Number of Visits

Type of advertisement	Minimum expenses per day ($)	Maximum expenses per day ($)	Average visits of customers (daily)
Banner	100	1000	3200
CLA	150	1450	642
SEM	500	6500	7500

The data provide daily aggregate level statistics on the advertising expenses per ad channel. The sales comprise more than 2.5 million purchases from over 1.2 million customers and 20 million website visits, aggregated on a daily basis. The company expenditure on advertisement during the study period was about USD 1.5 million.

3.1 Methodology

This study uses different statistical and econometric tools to assess intertemporal effects of advertising on different customers. Because the study uses daily data, a time-series approach is used to investigate the relationship between variables of interest. As per general rules of time-series data, prior to the analysis we must test the stationarity of the data and the properties of time series; otherwise, the result will be spurious (Gujarati, 1995). This study uses the Augmented Dickey-Fuller test to identify the stationarity of the variables.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t, \quad \textbf{(1)}$$

Where α is a constant, β is the coefficient on a time trend and *p* is the lag order of the autoregressive process. Optimal lags have been selected on the basis of Schwarz's Information Criterion (SIC) and Akaike's Information Criterion (AIC). For estimating the long-term relationship among the variables, the same order of integration of the variables is important. If variables of interest are integrated in the same order, such that one (I(1)) or (I (2)), then we can apply some econometric test to get further results (Gujarati, 1995).

After applying a stationarity test (ADF), a Pearson correlation test was used to identify the strength and direction of relationship among different advertising channels such as Banner, CLA and SEM.

$$r = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{\sqrt{[n\Sigma x^2 - (\Sigma x)^2][n\Sigma y^2 - (\Sigma y)^2]}} \quad (2)$$

Where r is the correlation coefficient representing the strength and direction of relationship. $-1<r<+1$ where -1 indicates a negative perfect correlation while +1 indicates perfect positive correlation.

Our method of aggregation of data is based on of that of Srinivasan and Weir (1988). For example an advertising channel such as banner advertising has been aggregated as per equation 3:

$$S_t = a + bAdv_t^* + e_t, \quad (3)$$

$$BA_1^* = BA_1$$

$$BA_2^* = [(1-\lambda_{BA})BA_2 + \lambda_{BA}BA_1^*]$$

$$BA_3^* = [(1-\lambda_{BA})BA_3 + \lambda_{BA}BA_2^*]$$

$$BA_t^* = [(1-\lambda_{BA})BA_t + \lambda_{BA}BA_{t-1}^*] \quad (4)$$

S_t = Sale at time period t
λ = Carryover effect
Adv_t = Online advertising for a channel such as banners on day t
Adv_t^* = Advertising stock at time t

The carryover effect refers to the percentage of the advertising effect that carries over from time period t to time period 1 (Breuer & Brettel, 2012). The value of λ is arbitrary selected and continues to change until the minimum residual score are observed. The short-term effect of advertising is estimated under a multiple linear regression model by incorporating advertising stock into the model, while the long-term effects of advertising are estimated using (b/1−λ**), which is an estimate of the size of the total cumulative effect.

The following multiple linear regression model has been suggested to investigate the effect of advertising:

$$St = \alpha + \beta BAt + \pi CLAt + \omega SEMt + \mu t \quad \textbf{(5)}$$

Where BA is banner advertisement, CLA is coupon loyalty advertisement, SEM is search engine marketing and S_t is sale value at time period t. Where t is subscript represents the time period. μ_t is stochastic error term used to incorporate random changes into the model.

3.2 Estimation of Results

The analysis of data has been presented in this section to estimate the correlation among the various types of advertising channels and their directions. Before proceeding to test any relationship, we have tested the stationarity of the data. The result of ADF reveals that all data is stationary and integrated of order one with and without trend. The following Table-2 reports the correlation results.

Table-2: Correlation Coefficient Results

Variables	Banner	CLA	SEM
Banner	1	0.570*	0.152
CLA	0.570*	1	0.548*
SEM	0.152	0.548*	1

*Significant at 5%

Table-2 reveals a positive correlation among all kinds of online advertising with different levels of intensity. Banner and CLA show a positive and statistically significant relationship, while banner and SEM show a positive but statistically insignificant relationship. The following Table-3 shows estimates of the multiple linear regression model (equation 5).

Table-4: Short- and Long-term Estimates of Sale

Parameters	Short-term effect	Long-term effect	Significance	90% days interval	Tolerance	VIF
α	-1345					
β	2.47	3.85	**	1.65	.679	1.472
π	3.46	3.65		0.72	.780	1.282
ω	0.15	0.53	**	6.7	.316	3.163
R^2 = 0.84 DW = 1.94						

****significant at 1%**

Table-4 shows the λ-values of system engine marketing correspond to a 90% duration interval of 6.7 days. In other words, 90% of the cumulative effect of a unit impulse of SEM advertising takes place within 6.7 days. It shows that the carryover effects of CLA and BA are smaller than those of SEM. The short-term effect of the regression model can be interpreted to mean that, if BA, CLA and SEM increase by one corresponding unit, then, on average, sales volume will increase by 2.47, 3.46 and 0.15 units, respectively, keeping the effect of all other variables constant. A similar interpretation is useful for the long-term parameters of the model. Like the short-term results, BA, CLA and SEM have positive signs and thus have a positive effect on sales volume. SEM has a higher carryover effect than that of the other two sources of online advertising (CLA, BA). The findings show that current studies tend to ignore the long-term effects of advertising, assuming the same λ value to assign equal weights to all different channels of advertisement. From these results, it appears that assigning equal weight to all channels of advertisement is perhaps not a good idea, as the channels have a long-term effect in addition to the short-term effect.

The value of R^2 = 0.84, which shows that the model is a good fit. Specifically, it shows that 84% of the total variation in the dependent variable has been explained by the explanatory variables. The highest value of R^2 is one, which shows a completely perfect model. Also, the value of the Durban Watson test is 1.94, which shows that there is not a first-order autocorrelation problem in the model. The subsequent orders of autocorrelation have been tested with an LM test, results of which are reported in Appendix-1.

The validity of the results has been checked and cross-checked using different econometric techniques. Multicollinearity has been detected through Variance Inflating Factor (VIF) and tolerance and has been reported in Table-4. VIF and tolerance are based on the proportion of variance. This is a measure of one independent variable's collinearity with the other independent variable(s) in the analysis and is connected directly to the variance of the regression coefficient associated with this independent variable. A VIF indicates how much the variance has been inflated by the lack of independence (Brien, 2007). As a rule of thumb, when the value of VIF is greater than 10 or the value of tolerance is less than 0.10, this will indicate severe multicollinearity (Gujarati, 1995; Kleinbaum, Kupper, Nizam, & Rosenberg, 2013). Based on these rules, the independent variables reported in Table 4.17 are free from the problem of severe multicollinearity.

To detect heteroskedasticity, Breusch and Pagan (1979) and White (1980) tests have been used. Based on these tests, the null hypothesis that there is no heteroskedasticity cannot be rejected based on F-statistics probability values (Breusch and Pagan test p-value 0.486, White test 0.91).[1]

[1] For detailed results on heteroskedasticity, see Appendix-1.

4. Conclusion and Policy Implications

This study attempts to identify the effectiveness of online advertisement in terms of immediate increase in sales as well as long-term benefits. Though numerous studies have been conducted to investigate the effectiveness of online advertisement, very few studies have been able to differentiate between the long- and short-term effects. This gap has attracted the attention for this study, to know, how decomposition of online advertising channels' effect into timeframe such as short and long run, can open new horizons for academic researchers and policy organizations. This study reveals important additional information about advertising effects which may help the business organizations and policy institutions while designing optimal policy agenda. The study shows that coupon loyalty advertising is more effective with respect to cumulative effects such as long- and short-term effects. The study reveals that there is a difference between short- and long-term effects; however, both have the same sign and thus follow the same direction. The study also reveals that there is difference between the effects of various advertising channels in terms of both volume of sales and carryover effect. System engine marketing has the longest effect (6-7 days), followed by BA and CLA.

Based on the findings regarding different advertisement channels' effects, this study suggests that CLA should be used for effective short-term advertisement, while BA should be used for effective long-term advertisement results. The study further suggests that business organizations should not rely on only one kind of advertising channel, as the effects of different channels are not identical.

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APPENDIX-1

Breusch-Godfrey Serial Correlation LM Test

F-statistic	1.162819	Prob. F (2,18)		0.3350
Obs*R-squared	3.318150	Prob. Chi-Square (2)		0.1903
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002600	0.594512	-0.004374	0.9966
BA	0.007865	0.053141	0.148005	0.8840
CLA	0.184195	0.422132	0.436345	0.6678
EMS	-0.013224	0.057564	-0.229724	0.8209
RESID (-1)	-0.143071	0.271729	-0.526520	0.6050
RESID (-2)	-0.387854	0.258177	-1.502280	0.1504
R-squared	0.754419	Mean dependent var.		-7.03E-17
Adjusted R-squared	0.377570	S.D. dependent var.		0.196553
S.E. of regression	0.230694	Akaike info criterion		0.186245
Sum squared resid.	0.957952	Schwarz criterion		0.704874
Log likelihood	8.299454	Hannan-Quinn criter.		0.348673
F-statistic	0.232564	Durbin-Watson stat.		1.970171
Prob. (F-statistic)	0.988573			

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.970102	Prob. F (8,20)		0.4860
Obs*R-squared	8.107242	Prob. Chi-Square (8)		0.4231
Scaled explained SS	3.962324	Prob. Chi-Square (8)		0.8605
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.036455	0.133753	-0.272553	0.7880
BA	0.004171	0.011899	0.350535	0.7296
CLA	-0.126649	0.094212	-1.344291	0.1939
SEM	0.004809	0.013405	0.358773	0.7235
R-squared	0.879560	Mean dependent var.		0.037301
Adjusted R-squared	0.078616	S.D. dependent var.		0.054420
S.E. of regression	0.054654	Akaike info criterion		-2.726463
Sum squared resid.	0.059741	Schwarz criterion		-2.302130
Log likelihood	48.53371	Hannan-Quinn criter.		-2.593567
F-statistic	0.970102	Durbin-Watson stat.		2.148204
Prob. (F-statistic)	0.485952			