Short-Term Effects of Fics and Cics Advertisements -Purchase Funnel Model Perspective

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Abstract. Based on various types of data such as clickstreams in e-commerce websites, this paper develops an evaluation model on the short-term effects of online advertisement of firm-initiated contacts (FICs) and customer-initiated contacts (CICs). The results show, it is found that the short-term effect of CICs brand ads is the largest (the short-term effect of brand paid search ads is the strongest), followed by CICs generic ads, and FICs ads has the weakest effect on instant consumption promotion.

Keywords: Multi-channel Online advertisements, Short-term Effects, Purchase Funnel Model, SVAR Model.

1. Introduction

In order to increase the number of online views and improve brand awareness, e-commerce enterprises can choose a variety of channels to publish online ads. One is firm-initiated contacts (FICs) online ads, which are generally released initialy by online marketing enterprises, such as various types of display advertisements on mobile and web terminals, SMS ads, WeChat ads, and EMA ads. One is customer-initiated contacts (CICs) online ads, which is generally triggered by user behavior, search behavior and even the location, such as personalized recommendation display ads, paid search ads, fence ads based on user location, etc.

Different types of online advertisement may have different effects, such as SMS ads will attract more mobile customers. Advertisement effect is mostly measured as short-term effect, which refers to the impact of the same kind of advertisement on consumer purchase behavior in a short time after the display. There is evidence that after users click on an online advertisement, they usually need to experience multiple purchase funnel stages before purchasing [1], including user advertising click, access and purchase stages, which have different impacts on the possibility of purchase [2]. This paper evaluates the short-term effects of different types of online ads in different channels based on the purchase funnel stage, in order to help enterprise managers better carry out advertising strategies.

2. Literature Review

In practice, online advertising providers usually analyze the short-term instant effect of online advertisement through the click rate and purchase conversion rate of online advertisement on the day. Zhang et al used artificial neural network algorithm to model the user's click behavior of paid search ads, and found that the length of keywords in paid search ads and the content of advertisement itself have a great influence on user click ads [3]. Moe et al use the clickstream data of user ads to predict the user purchase conversion rate according to the user's historical visits and purchase records to evaluate the short-term effect of online ads [4]. Montgomery et al used the dynamic multinomial Probit model to empirically verify the clickstream data of an online bookstore and predict the purchase conversion rate [5].

Therefore, we find that most of the current research on user purchase funnel focuses on the specific funnel stage, and it is difficult to comprehensively evaluate the online advertising effect on the process of user purchase decision. Based on this, this paper will be based on various types of online advertising data combined with user purchase decision-making process of each funnel stage to comprehensively evaluate the effect of online advertisement.

3. Research hypothesis and design

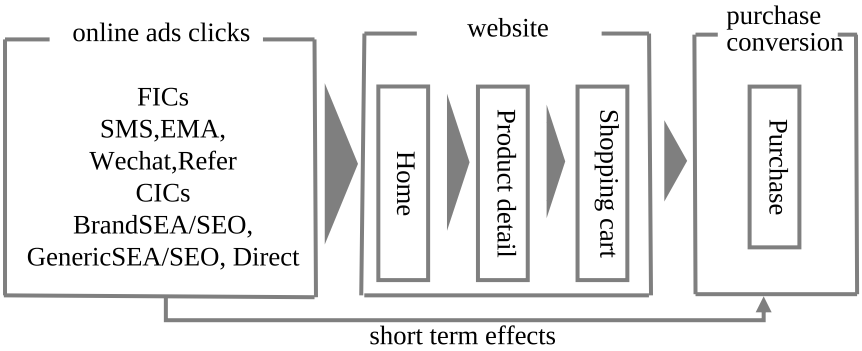

Figure 1. Purchase funnel model of multi-channel online

It is not a one-step process for a user to form clicking on a certain online advertisement to making a purchase decision. It has to go through multiple stages of the funnel generally. Therefore, this study disassembles each stage of the user's purchase decision-making process to form a multi-channel online advertising effect. The purchase funnel model, as Figure 1.

3.1 Research hypothesis

According to different advertising channels for users to enter the purchase process, this paper can divide them into firm-initiated contacts (FICs) and customer-initiated contacts (CICs). FICs are advertising channels for enterprises to push, including SMS ads, EMS ads, WeChat ads and refer ads, focusing on pushing messages to consumers. On the contrary, CICs is triggered by customer behavior, including direct ads, brand paid search ads, brand natural search ads, generic paid search ads, generic natural search ads, now has shown great potential, and has become an important part of the company's marketing. Because CICs is based on customers' own interests and queries, it is considered to be less interference marketing channels than FICs. Hence, customer response to CICs is much higher than traditional FICs. Based on this, this paper puts forward the hypothesis:

Hypothesis 1: CICs ads has a stronger effect on purchase than FICs ads.

In addition, current studies shows that product brand awareness will affect consumers' purchasing decisions, so the strength of advertising effect may be related to product brand [6]. Based on this, this paper puts forward the hypothesis:

Hypothesis 2: CICs brand ads has higher effect than CICs generic ads.

Based on the above hypotheses and the purchase funnel model, the relevant variables are selected. Among them, the advertisements of CICs and FICs are measured by the number of clicks per day, and the customer access phase is measured by the number of visits per day of Homepage, detail and cart. The result variable is measured by the number of purchases per day.

3.2 Model Construction

In order to reveal the dynamic dependence between various advertising marketing channels, website access funnel stage and the number of final purchases, this paper chooses SVAR method to analyze.Construct the following advertising effect model :

$$\left\{\begin{matrix} Advertising_t \\ Homepage_t \\ Detail_t \\ Cart_t \\ Purchase_t \end{matrix}\right\} = A + B_t \left\{\begin{matrix} Advertising_t \\ Homepage_t \\ Detail_t \\ Cart_t \\ Purchase_t \end{matrix}\right\} + e_t \tag{1}$$

Where B_t is the parameter matrix of the short-term effect, indicating the current impact of the unit change of a variable in period t on other variables, which is the embodiment of the immediate effect of online advertisement.

For the parameters in B_t in the above equation, this paper can limit some of these parameters to zero to capture specific relationships. These restrictions convert VAR model to SVAR model.

$$\begin{bmatrix} Advertising_t \\ Homepage_t \\ Detail_t \\ Cart_t \\ Purchase_t \end{bmatrix} = A + \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ \beta_{21}^0 & 0 & \beta_{23}^0 & \beta_{24}^0 & \beta_{25}^0 \\ \beta_{31}^0 & \beta_{32}^0 & 0 & \beta_{34}^0 & \beta_{35}^0 \\ \beta_{41}^0 & \beta_{42}^0 & \beta_{43}^0 & 0 & \beta_{45}^0 \\ \beta_{51}^0 & \beta_{52}^0 & \beta_{53}^0 & \beta_{54}^0 & 0 \end{bmatrix} \begin{bmatrix} Advertising_t \\ Homepage_t \\ Detail_t \\ Cart_t \\ Purchase_t \end{bmatrix} + e_t \tag{2}$$

Limit block 1 in the upper expression means that the change in the funnel phase variable for site access cannot affect its previous funnel phase variable on the same day. Limit block 2 means that consumers typically don't skip a phase in the site access funnel on the same day.

4 Empirical results and analysis

4.1 Data Processing and Feature Extraction

The data of this study are from an Internet insurance e-commerce company. This paper uses the network log data of the company in 2018 and 2019 and the data of customer registration, sharing, collection and purchase, a total of 7,231,956. In this paper, the number of visits and the total purchase characteristics of the nine kinds of online ads are summed up in the day as a unit, and the total purchase amount of each day in two years and the number of visits of the nine kinds of ads are obtained, so as to obtain a single customer's daily advertising click characteristics, purchase funnel stage access characteristics and purchase characteristics data, a total of 220,294.

Table 1. Short-term effects of different types of online advertisement

Classification	Variables	Short-term effects (β_{51})	Standard deviation	P-value	Confidence interval
CICs Brand	BrandSEA	0.271***	0.044	0.000	[0.186, 0.357]
	BrandSEO	0.249***	0.043	0.000	[0.164, 0.334]
	Direct	0.245***	0.034	0.000	[0.178, 0.312]
CICs Generic	GenericSEA	0.187**	0.093	0.044	[0.005,0.368]
	GenericSEO	0.178**	0.072	0.013	[0.037, 0.319]
FICs	SMS	0.102**	0.051	0.045	[0.002, 0.202]
	EMA	0.074*	0.040	0.066	[-.005,0.153]
	Wechat	0.108*	0.062	0.078	[-0.012, 0.230]
	Referer	0.143**	0.065	0.028	[0.016, 0.270]

Advertising represents the number of clicks per user on the advertisement every day. Homepage represents the number of sessions per user visited on the home page every day. Detail represents the number of sessions visited by product details page every day. Cart represents the number of sessions per day that include shopping cart behavior. Purchase represents the number of customer purchases per day.

4.2 Model Evaluation and Analysis

This paper first makes Granger causality test for each model constructed by online advertisement. Granger causality test shows that advertising type variables, three stage characteristics of website funnel access, and the number of purchase conversions are at least caused by another other variable. This result shows that this paper must treat all these variables as endogenous and incorporate them into the model.

Then, the eigenvalue test verifies that the VAR system constructed by each online advertisement is a stable process. Then the SVAR model can be evaluated.

Table 1 integrates the key estimation results of the nine online advertising SVAR models. The B_t parameter matrix in SVAR model reflects the current impact between variables. This paper uses the estimated results of β51 to measure the short-term effect of online advertisement on final purchase. It can be seen from the results in the table that the short-term effect of CICs brand ads is the largest and has strong visibility, followed by the short-term effect of CICs generic ads, which supports hypothesis 2. The short-term effect of FICs ads is the smallest, and the short-term effect of EMA ads is weak. Overall, CICs ads is more effective in facilitating purchases than FICs ads in a short time. It supports hypothesis 1.

5 Conclusions

Based on the purchase funnel model theory, this paper selects advertising variables, website access stage variables and purchase variables as the input variables of the later model, and constructs SVAR model based on the purchase funnel model to analyze which online advertisement is the most effective for purchase. Through the final results, it is found that the short-term effect of CICs brand ads is the largest (the short-term effect of brand paid search ads is the strongest), followed by CICs generic ads, and FICs ads has the weakest effect on instant consumption promotion.

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