# Association for Information Systems

# AIS Electronic Library (AISeL)

WHICEB 2022 Proceedings

Wuhan International Conference on e-Business

Summer 7-26-2022

# Research on the Evaluation of Multi-channel Online Advertising Combination Effects Based on Channel Click Path

Li Li

School of Economics and Management, Nanjing University of Science and Technology, NanJing, 210094, China, lily691111@126.com

## **Bingkun Cao**

School of Economics and Management, Nanjing University of Science and Technology, NanJing, 210094, China

## Zhenyi Yang

School of Economics and Management, Nanjing University of Science and Technology, NanJing, 210094, China

Follow this and additional works at: https://aisel.aisnet.org/whiceb2022

## **Recommended Citation**

Li, Li; Cao, Bingkun; and Yang, Zhenyi, "Research on the Evaluation of Multi-channel Online Advertising Combination Effects Based on Channel Click Path" (2022). *WHICEB 2022 Proceedings*. 53. https://aisel.aisnet.org/whiceb2022/53

This material is brought to you by the Wuhan International Conference on e-Business at AIS Electronic Library (AISeL). It has been accepted for inclusion in WHICEB 2022 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

#### Short Research Paper

# **Research on the Evaluation of Multi-channel Online Advertising**

# **Combination Effects Based on Channel Click Path**

Li Li<sup>1\*</sup>, Bingkun Cao<sup>1</sup>, Zhenyi Yang<sup>1</sup>

<sup>1</sup>School of Economics and Management, Nanjing University of Science and Technology, NanJing, 210094, China

Abstract: The rapid development of the Internet, mobile and social media has brought a large number of new online advertising and marketing channels to e-commerce enterprises. In order to explore the combinatorial effect of multi-channel online advertising, according to the choice set theory, this paper proposes related research hypotheses based on the classified combination effects of online advertising channels, and then constructs the COX model, extracts relevant variables based on the channel data of individual users from an e-commerce company. Perform regression analysis on the model to obtain the combination effects of the specific advertising channel click order. The results show that the combination of advertising channels to Customer-initiated channels will have a positive combination effect on purchases, while the combination of advertising channels from brand search to generic search will have a negative combination effect on purchases.

Keywords: Multi-channel online advertising, Advertising combination effect, COX model, Click path data

### 1. INTRODUCTION

With the rapid development of the online advertising market, companies have to think about how to take advantage of the diversified development of the online advertising channels, make full use of the combination effects of multi-channel online advertising to influence consumer's purchasing decisions, and give play to the " combined force" of different advertising channels <sup>[1]</sup>. However, the diversity of online advertising channels makes it difficult for companies to effectively evaluate the combination effects when using different advertising channels, and it is difficult to support the multi-channel selection of online advertising with effective empirical results.

According to different advertising triggers, online advertising channels can be divided into two types: Customer-initiated Channels (CICs) and Firm-initiated Channels (FICs). Companies often use these two types of channels to publish multi-channel online advertising <sup>[2]</sup>. Under the background of multi-channel online advertising, users may not only contact the online advertising channel once before purchasing, and these channels will affect consumers together rather than independently. Therefore, the combination effects needs to be considered when studying the effectiveness of multi-channel online advertising <sup>[3]</sup>. The combination effect here is shown as the combined effect of online advertising reaching users in a certain order from multiple channels, which may have an impact on the purchase tendency of the advertising audience <sup>[4]</sup>. Although many researchers have confirmed the existence of advertising combination effects through different studies, few studies have evaluated combination effects based on user channel click path data. In addition, the type of online advertising channels and the click order of specific channels may have an impact on the purchase intention <sup>[5]</sup>. Therefore, in order to better understand the preferences and decision-making changes in the process of transfer between different channels under the multichannel online advertising environment, it is worth exploring the combination effects of multi-channel online advertising based on the channel click path data of customers.

Therefore, in view of the measurement of the combination effects of advertising channels, this paper explores the multi-channel online advertising portfolio effect from the perspective of customer online purchase click path,

<sup>\*</sup> Corresponding author. Email: lily691111@126.com(Li Li), njust\_cbk@163.com(Bingkun Cao)

and explores the impact of different channel click sequence combinations on customer purchase trends from the individual level. This paper aims to supplement the research on the combination effects of multi-channel online advertising to help researchers and corporate marketers better evaluate the combination effects of different channel orders.

### 2. LITERATURE REVIEW

### 2.1 Research status of the impact of online advertising channel order on purchase

In order to understand the internal mechanism of advertising combination effects, we need to pay attention to the impact of the order of customers' contact with online advertising channels on their purchase. From the perspective of the order in which consumers contact advertising channels, when consumers are exposed to a variety of advertisements at the same time(such as browsing the web while looking at mobile phones) will make the advertisements exposed at the same time, resulting in a parallel combination effect. When consumers successively use a variety of online advertising channels, resulting in the sequential combination effect <sup>[6]</sup>.

In the study of the combination effects of channel order in traditional advertising, Stolyaroa <sup>[7]</sup> conducted an exploratory analysis on the marketing efficiency and synergy of multi-channel advertising, found that there was a combination effects in certain specific channel combinations. Under the exposure order of "print advertising-negative word-of-mouth", print advertising would reduce the cognitive impact on negative word-of-mouth. Micu <sup>[8]</sup> examined the relationship between the 4 product promotion methods in marketing and analyzed the experimental data with MANCOVA. The results show that for non-technical products, advertising before publicity would effectively improve the customer's attitude towards the brand, while publicity before advertising is more effective for technical products. Micu <sup>[9]</sup> later designed a mixed experiment of 4(4 experimental conditions) ×4 (4 product categories) for further analysis and found that the news-advertising exposure sequence was more effective in improving users' attitudes towards the brand. Loda <sup>[10]</sup> conducted an experiment on a sample of students from a university in the United States and also found that the exposure order of publicity-advertisements would affect the purchase intention of potential customers and promote marketing effect.

In the study of the combination effects of channel order in online advertising, Micu<sup>[11]</sup> randomly divided the recruited participants into 3 groups for a control test, each receiving a different advertising exposure order. It was found that only the exposure sequence of news-advertisement can produce a combination effect on brand attitude. Based on the behavior path data before individual purchase, Danaher et al. <sup>[12]</sup> established the Probit model to evaluate the sequence combination effects of online advertising channels, found that 7 of the 10 advertising channels studied had significant impact on consumer purchase. Klapdor <sup>[13]</sup> used a nested logistic regression model to evaluate the combination effects of the exposure sequence between information network advertising and navigation network advertising by analyzing personal clickstream data. The research found that when users first contacted information network advertising and then the navigation network advertising, the user's purchase conversion rate is higher.

In summary, the research on the combination effects of multi-channel advertising mostly focuses on the traditional channel combination effects, and lacks the research on the combination effects of online advertising channels. In addition, most researches only focus on a limited number of channels, most of the data are obtained from traditional questionnaires or experimental analysis, rather than the real data of companies. Therefore, the evaluation results of channel combination effects in previous studies may be biased.

# 2.2 Research status of the influence of advertising and channel characteristics on the combination effect of multi-channel online advertising

From the perspective of product type, in the formation process of multi-channel advertising combination effect, experience-based products do not require the order of user contact channels, while search-based products need a specific channel contact order <sup>[14]</sup>. From the perspective of advertising exposure time and exposure

sequence, the exposure time of the combination of print advertising and online advertising will have a certain role in promoting the advertising combination effect <sup>[15]</sup>. In addition, in the process of marketing, allowing users contact publicity first and then advertising will achieve better marketing results <sup>[8]</sup>. From the perspective of advertising forms, differentiated advertising forms can strengthen the cognition and attitude of the audience, and then promote the generation of advertising combination effect <sup>[16]</sup>. From the perspective of advertising channel characteristics, Firm-initiate channels, such as e-mail, SMS, etc., and consumers passively accept the messages pushed by them. The Customer initiated channels, such as search engines, price comparison websites, etc., are initiated by customers <sup>[17]</sup>. Since the CICs is based on the customer's own query and is more in line with the customer's interest, its response rate is also higher.

From the above research, different advertising characteristics and channel characteristics will affect the combination effect of online advertising. In addition, this study should also consider the individual heterogeneity of the audience as a control variable in order to better study the combination effect of multi-channel online advertising.

## 3. CONSTRUCTION OF MULTI-CHANNEL COMBINATION EFFECTS EVALUATION MODEL BASED ON CHANNEL CLICK PATH

### 3.1 Hypothesis

This paper analyzes the multi-channel combination effects of all the online advertising channels used by a company. Specifically, it includes 5 channels from CICs: direct type-in, brand paid search, brand organic search, generic paid search, generic organic search, as well as 4 channels from FICs: SMS, E-mail, WeChat, referral link.

In order to analyze the transfer of choice among multiple channels, this paper forms several inferences about channel combination effects based on selection set theory. Before making a purchase decision, if a customer first visits the e-commerce website through FICs and then uses the CICs to visit the e-commerce website, this situation may mean that the customer has a certain interest after contacting the firm-initiated advertising and starts to actively search for new information to narrow down their selection set. Therefore, the transfer from FICs to CICs may indicate the enhancement of user's willingness to buy. Similarly, expanding Rutz and Bucklin's <sup>[18]</sup> view that generic search advertising can improve people's understanding of relevant brand information, switching from generic customer-initiated channel to brand customer- initiated channel may mean that the customer has included the company's product in the consideration and is looking for more detailed information. If the customer switches from a branded CICs to a general-purpose CICs, it may indicate that the customer is looking for alternatives to this product, which indicates that the purchase probability is reduced.

Accordingly, the following hypotheses are proposed in this paper:

H1a: Combination order of "FICs-CICs" will have a positive combination effect on purchasing;

H1b: Combination order of "CICs-FICs" will have a negative combination effect on purchasing;

H2a: In the CICs, the combination order of "generic search-brand search" will have a positive combination effect on purchasing;

H2b: In the CICs, the combination order of "brand search-generic search" will have a negative combination effect on purchasing.

#### **3.2** Variable descriptions

Through the review of previous studies, it is found that questionnaires or experiments are mostly used in the research on the effects of online advertising, while the empirical research is more objective in this paper using the actual business data of enterprises. Since the channels to be analyzed are keyword/link advertising marketing channels, this study used the number of user clicks on 9 types of online advertising channels as explanatory variables, whether to complete the purchase translates into the explanatory variable.

In addition, the historical behavior of customers as well as individual heterogeneity differences also affect

Туре	Level-one variable	Level-two variable	Description				
Explanatory	CICBrand	BrandSEA	Current clicks of brand paid search ads				
		BrandSEO	Current number of brand organic searches				
		Direct	Current number of direct visits				
	CICGeneric	GenericSEA	Current clicks of general paid search ads				
		GenericSEO	Current number of universal organic searches				
	FIC	SMS	Current clicks of SMS ads				
		EMA	Current clicks of E-mail ads				
		Wechat	Current clicks of E-mail ads				
		Referer	Current clicks of referral ads				
variables		PastBrandSEA	Past clicks of brand paid search ads				
	PastCICBrand	PastBrandSEO	Past number of brand organic searches				
		PastDirect	Past number of direct visits				
	PastCICGeneric	PastGenericSEA	Past clicks of general paid search ads				
		PastGenericSEO	Past number of universal organic searches				
	Past FIC	PastSMS	Past clicks of SMS ads				
		PastEMA	Past clicks of E-mail ads				
		PastWechat	Past clicks of E-mail ads				
		PastReferer	Past clicks of referral ads				
	PastPurchase		Whether the customer has purchased in the past				
	PastCollect		Whether the customer has collected in the past				
Control variables	PastShare		Whether the customer has shared in the past				
	Gender		Client gender 0-woman; 0-man				
	Age		Customer's age				
Explained variable	Convert		Whether the customer finally purchases or not				

the final purchase. Therefore, some control variables are also added to the model, which are shown in Table 1. Table 1. Variable

### 3.3 Cox Model Construction

Through communication with partner companies, we find that advertisers usually use cookies with a 30-day life cycle, so 30 days are selected as the observation period to obtain complete and effective customer channel path data. In addition, customer's channel click behavior is continuous, the model also needs to reflect the timing and order of channel clicks. In view of the above data characteristics, the Proportional Hazards Model (Cox model) was chosen to model the data. The Cox model provides a way to process right-merge data and assume proportional hazards, which can introduce explanatory variables that change over time if this assumption is not met. The Cox model with time-varying covariates also provides an effective way to represent the online advertising channel click order and interaction impact during the customer journey <sup>[19]</sup>, which is widely used in online marketing research. Therefore, this paper uses the Cox model with time-varying covariates to evaluate the combination effects. The Cox model in this paper is constructed based on the channel click path and purchase journey of individual customers. The multi-channel click order data and purchase behavior data of individual customers in their purchase journey are counted by day <sup>[20]</sup>, and the dependent variable is the time of customer purchase event.

The model first constructs the risk rate $(h_i(t, X))$  of the customer *i*, which refers to the possibility of customer *i* purchasing on day *t*. The risk rate of customer *i* can be described as a product of 2 quantities, the formula is as follows:

$$h_i(t, X) = h_0(t) \times \exp(\sum_{i=1}^p \beta X_{ij})$$
(1)

 $h_0(t)X_{ij}$  represents the benchmark risk rate, which refers to the possibility of purchase at time t without the influence of other factors(X), is used to capture the time effect,  $X_{ij}$  is a covariate. Considering whether users have purchased in the past is not in line with the proportional risk assumption, this paper should also include the interaction of past purchases with time in the model.

The basic expansion of  $\exp(\sum_{j=1}^{p} \beta X_{ij})$  in formula (1) is shown in formula (2):

$$\exp\left(\sum_{j=1}^{p} \beta X_{ij}\right) = \exp(\beta X_{i1} + \beta X_{i2} + \dots + \beta X_{ij} + \beta PastX_{i1} + \beta PastX_{i2} + \dots + \beta PastX_{ij} + \beta X_{i1} \\ \times PastX_{i1} + \beta X_{i2} \times PastX_{i2} + \dots + \beta X_{ij} \times PastX_{ij} + \beta CICBrand_i \\ \times PastCICBrand_i + \beta CICBrand_i \times PastCICGeneric_i + \beta CICBrand_i \times PastFIC_i \quad (2) \\ + \beta CICGeneric_i \times PastCICBrand_i + \beta CICGeneric_i \times PastCICGeneric_i \\ + \beta CICGeneric_i \times PastFIC_i + \beta FIC_i \times PastCICBrand_i + \beta FIC_i \\ \times PastCICGeneric_i + \beta PastPurchase_i + \beta PastPurchase_i \times t + \beta PastCollect_i \\ + \beta PastShare_i + \beta Gender_i + \beta Age_i)$$

Where,  $X_{ij}$  represents the number of current clicks of customer *i* to channel *j*,  $PastX_{ij}$  corresponds to the total number of clicks in the same channel in the past. The model also includes the interaction between current channel clicks and past channel clicks. In addition, there are interaction items between channel categories to analyze the combination effects of different channels,  $PastPurchase_i$  capture the past purchase behavior of users, and  $PastCollect_i$  capture the collection behavior of users in the past.

### 4. EMPIRICAL ANALYSIS

### 4.1 Data

The research data comes from an Internet insurance agency company in Nanjing, which mainly includes network log database and business database. This paper uses the company's network log data for a total of 730 days from January 1, 2018 to December 31, 2019, as well as customer registration, sharing, collection and purchase data. After data cleaning, data table association, user access channel identification and session division of the original data, the basic data set of this research is obtained, and the data is further sorted and extracted according to the research needs of this experiment. The data set covers the channel click path data of 303,301 customers, based on which the data and are collated for subsequent analysis.

### 4.2 Empirical results and analysis

Relevant statistical software was used for COX regression calculation, and the final results are as shown in the table.

Classify	Variable	Risk rate	Coefficient	95% confidence interval			
CIC Brand	BrandSEA	1.376621	.3196322	[1.349119,1.404685]			
	BrandSEO	1.232537	.2090745	[1.197678,1.26841]			
	Direct	1.056594	.0550505	[1.052907,1.060294]			
	GenericSEA	1.301444	.2634744	[1.25575,1.348801]			
CIC Generic	GenericSEO	1.329769	.2850054	[1.30741,1.35251]			
FIC	SMS	.9470766	0543753	[.8908946,1.006802]			

 Table 2. Results of the evaluation of the multi-channel combination effects

Classify	Variable	Risk rate	Coefficient	95% confidence interval
	EMA	1.004699	.0046878	[.945469,1.067639]
	Wechat	1.051958	.0506528	[1.04241,1.061593]
	Referer	1.139831	.1308801	[1.111762,1.168609]
	PastBrandSEA	1.083197	.0799173	[1.076472,1.089965]
CIC Brand (Past)	PastBrandSEO	1.097897	.0933967	[1.080927,1.115134]
(	PastDirect	1.033015	.0324814	[1.03083,1.035204]
CIC Generic	PastGenericSEA	1.032367	.0318545	[1.016479,1.048504]
(Past)	PastGenericSEO	1.151289	.1408821	[1.137925,1.164809]
	PastSMS	1.028429	.0280325	[1.009557,1.047654]
FIC	PastEMA	1.088255	.0845752	[1.067482,1.109431]
(Past)	PastWechat	1.013436	.0133466	[1.007474,1.019433]
	PastReferer	1.090281	.0864352	[1.074558,1.106234]
	Tvc(PastPurchase)	1.033202	.032663	[1.03041,1.036002]
	PastCollect	1.04909	.0479232	[.9973525,1.103512]
Control variables	PastShare	.7789408	2498202	[.7222619,.8400675]
	Age	1.020329	.0201248	[1.019006,1.021653]
	Gender	.7443692	2952181	[.7213648,.7681072]
	CICBrandXPastCICBrand	.9988527	0011479	[.998624,.9990814]
	CICBrandXPastCICGeneric	.9913489	0086887	[.9876881,.9950234]
	CICBrandXPastFIC	1.000438	.0004377	[.9995748,1.001302]
Channal	CICGenericXPastCICBrand	.9913958	0086415	[.9903099,.9924828]
Combination	CICGenericXPastCICGeneric	.9875699	012508	[.9850152,.9901312]
Interaction Terms	CICGenericXPastFIC	1.020031	.0198334	[.9886829,1.052374]
	FICXPastCICBrand	.9917311	0083032	[.9894646,.9940029]
	FICXPastCICGeneric	.9918315	008202	[.9773885,1.006488]
	FICXPastFIC	1.001395	.0013936	[1.00085,1.00194]

(1) As far as the online advertising effect, the current channel effects of brand search and generic search channels in CICs are both positive and significant. In FICs, the current impact of SMS advertising is negative( $\beta$ \_SMS=-0.0543753), but there is a positive lagging impact( $\beta$ \_PastSMS=0. 0280325). The current advertising effects of E-mail ads, WeChat ads and referral ads channels are positive. in terms of the past online advertising channel effect, most channels have a certain lag and positive impact on the purchase probability. Among them, the past brand generic search channel is more prominent for future purchase conversion than other channels. Finally, from the perspective of individual heterogeneity, customers who have purchased and collected in the past are more likely to make purchases in the next time. With the increase of age, customers are more likely to tend to buy insurance products. In terms of gender, men are less likely to buy insurance products than women.

(2) In terms of the combination effects of the same channel, it can be seen from the interaction term coefficient that the past same channel clicks of FICs will promote subsequent purchases ( $\beta$ \_FIC×PastFIC=0.0013936), while the click of CICs have a negative impact on subsequent purchases( $\beta$ \_CICBrand×PastCICBrand=-0.0011479, $\beta$ \_CICGeneric×PastCICGeneric=-0.0012508). If a customer repeats the same search many times in the past, it may indicate that the company's product does not meet his needs,

so the purchase probability may be low. For the FICs, multiple clicks may represent multiple viewings, reflecting customer's interest in them, so the combination effect of the same channel of such advertising channels is positive. Assumption 1a and Assumption 1b are verified.

(3) In terms of cross-channel combination effects, the transformation from FICs to the CICs brings consumers more information, and facilitate the final purchase ( $\beta$ \_CICBrand×PasteFIC=0.0004377) ( $\beta$ \_CICGeneric× PastFIC=0.0198334). Such consumers actively search for more information, which means that they have developed interest and have more in-depth consideration and evaluation of the information obtained from FICs. For such customers, targeted advertising incentives can be given. However, those who move from brand search of CICs to other channels are less likely to purchase ( $\beta$ \_CICGeneric×PasteCICBrand=-0.0086415 ,  $\beta$ \_FIC×PastCICBrand=-0.0083032). This order of channel combination may mean that potential customers are identifying a set of alternatives and products. For such potential customers who may lose, companies can combine telemarketing and better provide them with products that meet their needs in the form of telephone follow-up. Therefore, reject hypothesis 2a, accept hypothesis 2b.

### 5. CONCLUSION

In order to analyze the impact of channel combination on the final purchase in the complete online advertising channel system of companies, this paper analyzes the current and delay effect of different channels by constructing a COX model, and also summarizes the combination effects of specific channel order based on the classification of online advertising channels. The results show that 1) in terms of the same channel combination effects, the FICs has a positive channel combination effect, which will promote future purchases. 2) In terms of cross-channel combination effect, the channel combination order from the FICs to the CICs will have a positive combination effect on the purchase conversion, while the channel combination order from the CICs to the FICs to the FICs will have a negative combination effect on the purchase conversion.

The results of this paper provide some ideas for the combination marketing of enterprises. For customers who switch from generic search to brand search channels, companies can push them some preferential information to stimulate them to make faster purchase decisions. For customers who are about to churn from brand search to generic search channels, companies can proactively communicate by phone to understand their needs and redeem them.

In addition, there are some limitations in this study. Due to resource and data limitations, this paper has no control over other variables that may affect the performance of customer's purchase, including other demographic information such as income, family members, location, etc. Future studies could consider controlling the effects of these variables on advertising effects.

### ACKNOWLEDGEMENT

This research was supported by the National Natural Science Foundation of China under Grant 71771122.

### REFERENCES

- Lim J S, Ri S Y, Egan B D, et al. (2015). The cross-platform synergies of digital video advertising: Implications for crossmedia campaigns in television, internet and mobile TV. Computers in Human Behavior, 48: 463–472.
- [2] Li H, Kannan P K. (2014). Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment. Journal of Marketing Research, 51(1): 40-56.
- [3] Assael, Henry. (2011). From silos to synergy. Journal of Advertising Research, 51 (1): 42-58.
- [4] Naik P A, Peters K. (2015). True synergy for real effects: How to control integrated marketing successfully. GfK-Marketing Intelligence Review, 7(1): 34-41.
- [5] Wang ping, Sun Wanling, Fan Xiucheng, et al. (2016). A literature review and outlook on advertising synergy research.

Foreign Economics and Management, 38(11): 14-29 (in Chinese).

- [6] Enoch G, Johnson K. (2010). Cracking the cross-media code: How to use single-source measures to examine media cannibalization and convergence. Journal of Advertising Research, 50(2): 125–136.
- [7] Stolyarova E, Rialp J. (2014). Synergies among advertising channels: An efficiency analysis. Journal of promotion management, 20(2): 200-218.
- [8] Micu A C. (2005). Testing for a synergistic effect between online publicity and advertising in an integrated marketing communications context. Doctoral dissertation. Columbia: University of Missouri.
- [9] Micu A C, Thorson E. (2008). Leveraging news and advertising to introduce new brands on the web. Journal of interactive advertising, 9(1): 14-26.
- [10] Loda, M D. and Barbara C C. (2006). Sequence matters: A more effective way to use advertising and publicity. Journal of Advertising Research, 45 (4): 362- 372.
- [11] Micu A C, Pentina I. (2015). Examining search as opposed to experience goods when investigating synergies of internet news articles and banner ads. Internet research, 25(3): 378-398.
- [12] Danaher P J, Dagger T S. (2013). Comparing the Relative Effectiveness of Advertising Channels: A Case Study of a Multimedia Blitz Campaign. Journal of Marketing Research, 50(4):517-534.
- [13] Klapdor S, Anderl E, Schumann J H. (2015). How to use multichannel behavior to predict online conversions behavior patterns across online channels inform strategies for turning users into paying customers. Journal of Advertising Research, 55(4): 433-442.
- [14] Micu A C, Pentina I. (2015). Examining search as opposed to experience goods when investigating synergies of internet news articles and banner ads. Internet research, 25(3):378-398.
- [15] Wu G, Sandeep B. (2007). The synergy effect of print and web advertising: A field experiment. In American Academy of Advertising. Conference. Proceedings (Online). Lubbock: American Academy of Advertising. 208-213.
- [16] Voorveld H A M, (2015). Valkenburg S M F. The fit factor: The role of fit between ads in understanding cross-media synergy. Journal of Advertising, 44(3):185-195.
- [17] Wiesel T, Pauwels K, Arts J. (2011). Marketing's profit impact: Quantifying online and off-line funnel progression. Marketing Science, 30(4):604-611.
- [18] Rutz, O J., Bucklin, R.E. (2011). From generic to branded: A model of spillover in paid search advertising. Journal of Marketing Research, 48(1): 87-102.
- [19] Hausman J A, Woutersen T. (2014). Estimating a semi-parametric duration model without specifying heterogeneity. Journal of Econometrics, 178:114-131.
- [20] Lambrecht A, Tucker C E. (2013). When does retargeting work? Information specificity in online advertising. Journal of Marketing Research, 50(5): 561-576.