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ABSTRACT

This study selects multiple indicators of Web Analytics to measure the volume and quality of traffic, and collects the time series data of a certain brand's sales on JD.com from October 27, 2014 to June 30, 2015, using the Structural Time Series Model to analyze the effect of attracting traffic of five large-scale online promotion activities during this period. The results for the case study show that: large-scale online promotion activities have a significant positive effect on total page traffic, but the difference is showed on the quality effect of the page traffic; different activities affect the volume of unpaid traffic differently, while effects on traffic quality are not significant. This analysis may benefit e-commerce sites to develop a better strategy to carry out similar promotion activities.

Keywords: Online promotion, website traffic, web analytics, structural time series model, JD.com.

INTRODUCTION

Nowadays, promotion activity is one of the crucial methods to attract consumers' attention during the online shopping. Numerous Chinese e-commerce websites such as Tmall.com, Taobao.com and JD.com, developed "Double 11", "618" and other online promotion activities to achieve better sales and greater influence. Price promotion occupies a large share of the marketing budget, and it has also been proved to be the most effective approach to obtain consumers and increase sales [11] [19] [31]. For instance, "Double 11" of Tmall.com in 2015 involved 232 countries and regions, and the transaction amount reached 14.3 billion dollars, refreshing the world record on turnover of single e-commerce platform in single day again [2].

Comparing with the brick-and-mortar stores, it is obviously easier for e-commerce websites to collect large amounts of detailed data on visitor traffic and activities on websites by today's online technology [16]. Web analytics is the measurement, collection, analysis and reporting of web data for purposes of understanding and optimizing web usage [5]. Using Web Analytics can acquire and record key indicators of website, such as page views, unique visitors, referrers, bounce rate and so on. These indicators can effectively reflect the volume and quality of traffic [41]. The main purpose of our paper is carrying out quantitative research on website traffic by these metrics to measure the effect of large online promotion activities.

Online advertising has become the first choice of e-commerce website owing to its diverse styles, low cost, direct access using hyperlink, and easily available data, compared with traditional advertising [13]. E-commerce sites make use of online advertising to increase the exposure of activities and the accessibility of activities' pages during the campaign period, which can bring more traffic. Generally, traffic forms include two types: paid and unpaid traffic. Paid traffic refers to the traffic which activities' page was directly arrived through the network advertising. The traffic from other channels are all defined as unpaid traffic. Promotion activities ordinarily have direct impacts on the paid traffic.

As China's largest ecommerce platform by revenue, JD.com accounts for 58.3% of the market share of Chinese self-run B2C platform transaction size at 2015's second quarter [24]. At different times of the year, JD.com launches large-scale promotion activities. Crest is a brand of personal care belonging to P&G, which is the FMGC industry giant. Fast moving consumer goods have the characteristics of short consumption cycle, high purchase frequency and low brand loyalty, therefore it needs to carry out vast promotion activities [15]. The research object of this paper is the Crest brand page at JD.com, including 136 kinds of goods of the Crest.

In our research, the case of study is Crest, a self-run brand by JD.com. We monitor its pages and then analyze the time series data sample about some key performance indicators of traffic using the Structural Time Series Model. The analysis aims at two aspects: first, the effect on total traffic by large promotion activities; second, the indirect effect on unpaid traffic by large promotion activities. Through this study, we evaluate the effectiveness of online promotion activities, and then explore and summarize its effect further, which can provide the instruction for the similar large-scale promotion activities in the future.

Our research has threefold contributions: first, in the field of online marketing, pervious research attention has focused on consumer behavior [42], promotion form [7] [34] and so on, while this paper analyze effect of attracting traffic from the perspective of promotion activities, which can enlighten enterprises' marketing more directly; second, former researches retrieved data mainly by the questionnaire survey method and the experimental method, while the data using in this paper come from the real web's operation environment, which is more authentic; third, the analysis results show that the Structure Time Series Model can estimate the effect on attracting traffic by promotion activities, providing an effective method for the next related research.

RESEARCH DESIGN

Traffic Metrics

Website traffic data are usually collected by professional web analytics tools, such as Google Analytics and Baidu Statistics. Google Analytics is a free web service with powerful capabilities about websites' traffic. It has been extensively used in various research fields, e.g. tourism websites [38], library websites [3] [14] [40], food composition websites [35] and medical websites [6] [27]. Baidu Statistics has been used in the field of education website research [28].

Several scholars have proposed different metrics about analysis of website traffic in their research based on Google Analytics. Hasan et al. [23] selected 13 metrics to evaluate the usability of e-commerce websites from six aspects, e.g. navigation, internal search and architecture. Plaza [36] proposed a performance measurement of websites and four traffic indicators related. Plaza et al. [38] optimized the metrics in Plaza [36] and used them to assess a tourism website. Considering the situation of our research object, the volume and the quality of traffic are characterised here by metrics referred to Hasan et al. [23] and Plaza et al. [38], which consist of five key performance indicators (KPIs):

Metrics measuring the volume of traffic

page views: the total number of page visits in a specified period.

unique visitors: the total number of visitors reaching the pages in a specified period. Each visitor is identified and distinguished by unique cookies generated in their browsers.

Metrics measuring the quality of traffic

time of the visit: the average duration of page views measured in seconds.

bounce rate: the percentage of visits in which the visitor closes the page or browser directly instead of interacting with the page.

Order conversion rate: the percentage of visits that result in an order.

Generally, high quality traffic represents longer time of the visit, lower bounce rate and higher order conversion rate. Abbreviated name of these KPIs are shown in Table I.

Table I. Abbreviation of KPIs

Abbreviation	PV	UV	ToV	BR	OCR
KPI	page views	unique visitors	time of the visit	bounce rate	order conversion rate

Structural Time Series Model

Moral et al. [32] pointed out the elements which are common in economic time series, such as trend, seasonality and holiday effects. These factors should be considered simultaneously in our model, though the model focuses on the effectiveness of large online promotion activities. In order to capture and reflect the influences of these unobservable components, we apply a framework of univariate time series known as Structural Time Series Model (STSM) [20].

STSM generally indicates economic indicators using factors of trend, seasonality, cycle and irregularity, based on structure characteristics of time series [12] [20] [21]. This model has at least two advantages over other time series models, such as Autoregressive Integrated Moving Average Model (ARIMA). First, the model breaks through the limitations that traditional Box-Jenkins method is only able to be applied to stationary time series, prompting more extensive research and application of non-stationary time series. Second, the components of time series can be direct interpreted in the model [8] [22]. Since the components decomposed from time series of economic indicators are unobservable in STSM, traditional regression analysis methods cannot solve the model. State space form is used here to represent STSM in statistic treatment. Apart from utilizing state vectors to represent unobservable components, state space model also provides methods for optimal estimation, smoothing and forecasting using the recursive algorithm named Kalman Filter. Meanwhile, the model can deal with explanatory variables, structural breaks, interventions, outliers, and missing observations.

The basic framework of STSM is very flexible, so that complex patterns in the data can be captured using a relatively parsimonious model. STSM can also naturally combine the estimation of a series of components and the effects of explanatory variables. The general structure of our estimated model is built as follows:

(1)

where , , and are components of trend, cycle, seasonality and irregularity, respectively; C represents the effectiveness of large online promotion activities; H is the component of holiday effects (such as Christmas, Chinese New Year and other holidays).

DATA COLLECTION AND MODEL MODIFICATION

Descriptive Statistics

Like Google Analytics, JSHOP's traffic statistics module of JD.com can collect data from specified pages at different time granularity, such as monthly data, weekly data and daily data. The data are composed of aggregated data of pages and particular traffic source data: aggregated data of pages include collective data of each metric in unit time, and the data of metrics in unit time from different source URLs are collected in particular traffic source data. According to the source URLs, traffic is divided into two categories: traffic from Internet advertising, which is called paid traffic (or sponsored traffic), and traffic from other channels named unpaid traffic (or organic traffic), and mainly are direct visits by entering URL at browsers or clicking the link in Favorites. Considering the continuity for monitoring web pages and uncertainty of promotion activity duration, we collect daily traffic data. The data for analysis runs from 27 October 2014 to 30 June 2015, which makes a total of 247 daily observations about pages of Crest on JD.com. In this period, Crest participated in 5 large online promotion activities, which are detailedly showed in Table II.

Table II. Details of large promotion activities

	Activity 1	Activity 2	Activity 3	Activity 4	Activity 5
Name	Double 11	Double 12	New Year's shopping festival	Butterfly festival	618
Start time	2014.11.1	2014.12.8	2015.1.19	2015.3.1	2015.6.1
End time	2014.11.12	2014.12.14	2015.2.23	2015.3.13	2015.6.19
Duration	12	7	36	13	19
Merchandise categories involved	all categories	all categories	all categories	mainly personal care products	all categories

Table III shows the mean values of the five key performance indicators (KPIs) for two subsamples, depending on whether or not the day was involved in the period of large promotion activities. The figures reflect that all 5 KPIs have better performance during the period of campaigns: more page views per day means more visits on pages in campaign period; bounce rate decreased from 78.77% to 68.77%, which illustrates that larger rate of visits have interactions with the pages during the activities' time; and order conversion rate, the metric which is more important to e-commerce websites, grew nearly by one time.

Table III. Mean values per source

	PV	UV	ToV (s)	BR (%)	OCR (%)
Campaign period (87 observations)					
Total traffic	49269	31666	127.984	68.766	0.825
Organic	26164	15514	137.706	72.054	0.038
Paid	23105	16152	120.574	53.266	3.031
Out of campaign (160 observations)					
Total traffic	13953	10977	111.881	78.766	0.363
Organic	6763	5242	112.678	84.298	0.026
Paid	7190	5735	111.442	63.520	1.167

Figure 1 shows the evolution over time the indicator of page views for total traffic and unpaid traffic. The figure intuitively shows that the promotion activities increase the volume of traffic, but behavior differ from one activity to another. Finally, it should be pointed out that we lost data between 1 and 9 April 2015 because of system failure, as can be seen in the figure.

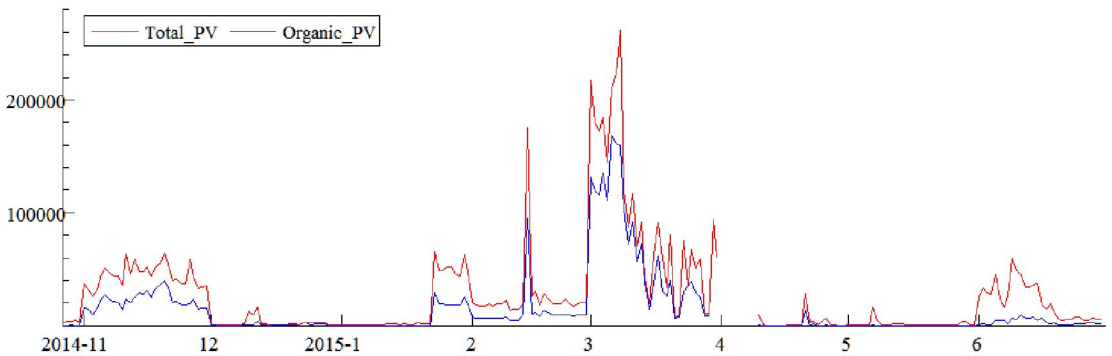

Figure 1. Page views

Model Modification

With the purpose of providing a user-friendly environment for analyzing, modelling, and forecasting of STSM, Koopman et al. [33] developed STAMP (Structural Time Series Analyser, Modeller and Predictor) package. This modelling approach has proved useful in many contexts, including the field of tourism economy [17] [18] [32] and energy economy [1] [25]. The version we applied here is STAMP 8.2.

The factor of cycle will be ignored in our model since the time span of sample is less than a year. Therefore, the model should include: the factor of large promotion activities, trend, seasonality, holiday effects and irregularity. The specification of the different elements of model is explained below.

First, the five large campaigns staged during the sample period are included in the model by means of five dummy variables C1, C2, C3, C4 and C5. Each of these variables is set to 1 for the observations related to the corresponding campaign and 0 otherwise.

Trend component usually explains the track of long-term development. In our research, it relies on a stochastic formulation that allows the level, , and the slope, , of the trend to vary slowly over time with the changes observed in the data:

(2)

where and are mutually independent Gaussian white noise disturbances with zero mean and variances and , respectively. The changes related to long-term and medium-term factors that influence the website's evolution, such as popularity, economic situation, etc., are captured by this local linear trend. It is a local approximation to a linear trend; it will collapses to the deterministic global linear trend when ==0, in fact.

We express the seasonal fluctuations using daily dummy variables alone since the time of our sample doesn't involve all 12 months. Daily dummies from Tuesday to Sunday are defined as D2, D3, …, D7 = 1 for corresponding observations and 0 otherwise.

Holiday effects considered traditional Chinese festivals, traditional Western festivals and other holidays. The following dummy variables were therefore constructed: =1 for Chinese New Year and Dragon Boat Festival and 0 otherwise; =1 for Christmas and Valentine's Day, two western festivals which are very popular in China nowadays, and 0 otherwise; =1 for New Year's Day, Women's Day, Labor Day and Children's Day and 0 otherwise.

More volatility has been showed by daily data than weekly data and monthly data. Meanwhile, daily data present data irregularities such as outliers. In addition, there are no data collected from 1 to 9 April 2015, when the statistical system suffered some breakdowns, so some observations can be considered as missing. We use the automatic identification and estimation procedures implemented in STAMP package to handle the outliers and missing data.

After the modifications of components above, the STSM for the website traffic metrics is the following, assuming that the functional form is linear or log-linear:

(3)

where is the logarithm in three of the indicators considered (PV, UV and ToV) and raw data for the other two (BR and OCR), follows model (2) and , the irregular component that captures all the short-term shocks in the series, is a white noise with zero mean value and variance which is not correlated with and . The regression coefficients , , , , , the variances of the unobserved components and , and of the irregular term are unknown parameters to be estimated. Model (3) can be interpreted as a generalization of the classical general linear regression model. This model will collapse to a standard regression model with a linear deterministic time trend when ==0.

, the coefficients control the influence of each promotion activity on the metrics, are the focal points in our research. Generally, a positive effect of campaign implies that the coefficient is negative for the bounce rate and positive for the other four indicators. The behavior of the indicator is not affected by campaign i if the value =0. The coefficients 、 and indicate the effects of different kinds of holidays to those KPIs.

RESULT ANALYSIS

In this chapter, the effectiveness of each large online promotion activity is analyzed in two aspects below, and there are some discussion and implication after the analysis.

The Effectiveness of Campaigns on Total Page Traffic

Model (3) is estimated for all five indicators of total page traffic and the results are showed in Table IV. is not present in the table for its static 0 value. The values of test statistics reflect that all situations have passed diagnostic tests.

PV and UV are the metrics directly representing the volume of traffic. The first two rows of Table IV show the estimation and test results when the endogenous variables are ln(PV) and ln(UV) respectively. The impact of the five activities on traffic volume is seen to be positive and statistically significant, while the effect size differs from one activity to another apparently: Activity 5 (“618”) performed best and Activity 2 (“Double 12”) performed worst at the aspect of attracting traffic, demonstrated by the coefficients of Ci.

Other factors also have some impacts on traffic volume that can be found in Table IV. For instance, PV and UV increase significantly on Thursday and Friday. As far as holiday effects are concerned, traffic mounts up obviously during Christmas and Valentine’s Day, the two well-known Western festivals in China. However, Chinese traditional festivals and other holidays selected have no strong, significant impact on these metrics.

The estimates of the variances of the stochastic components are constant 0, showing that the slope of trend component is constant over time, so the trend of the model follows a random walk plus drift process. The irregular component is the biggest source of variability.

Table IV. Estimation results for KPIs of total page traffic

	ln(PV)	**ln(UV)**	**ln(ToV)**	**BR**	**OCR**
	1.5076**	1.5660**	0.0327	0.4058***	-0.0450**
	(0.6078)	(0.6044)	(0.1654)	(0.0884)	(0.0189)
	1.0267*	1.0530*	0.2285	0.1055	-0.0166
	(0.5985)	(0.5952)	(0.1909)	(0.0870)	(0.0162)
	1.2404**	1.2286**	-0.1615	0.0230	0.0012
	(0.6069)	(0.6035)	(0.1661)	(0.0885)	(0.0189)
	1.4627**	1.1360*	0.2711*	-0.1813**	0.0105*
	(0.6066)	(0.6032)	(0.1617)	(0.0884)	(0.0164)
	2.2374***	2.1223***	-0.0194	-0.1819**	0.0337**
	(0.6253)	(0.6215)	(0.1655)	(0.0917)	(0.0170)
	0.2162	0.2426*	-0.0482	0.0313	0.0020
	(0.1404)	(0.1400)	(0.0743)	(0.0200)	(0.0037)
	0.2606	0.2925*	-0.0270	0.0222	0.0048
	(0.1723)	(0.1713)	(0.0747)	(0.0260)	(0.0048)
	0.3509*	0.3905**	-0.0042	0.0053	0.0047
	(0.1877)	(0.1864)	(0.0761)	(0.0286)	(0.0053)
	0.4820**	0.5284***	0.0076	0.0282	0.0027
	(0.1873)	(0.1860)	(0.0762)	(0.0286)	(0.0053)
	0.1207	0.1366	-0.1218*	0.1019***	0.0043
	(0.1724)	(0.1713)	(0.0750)	(0.0261)	(0.0049)
	0.0619	0.0816	0.0299	0.1049***	0.0001
	(0.1418)	(0.1415)	(0.0744)	(0.0208)	(0.0039)
	0.8820**	0.8658**	-0.3671**	-0.0514	-0.0038
	(0.4400)	(0.4386)	(0.1774)	(0.0620)	(0.0116)
	0.0738	0.0854	-0.0663	0.0151	0.0042
	(0.4271)	(0.4248)	(0.1383)	(0.0620)	(0.0115)
	0.3960	0.3435	-0.2780**	-0.0558	0.0066
	(0.3207)	(0.3196)	(0.1299)	(0.0455)	(0.0085)
	0.5658	0.5498	0.0074	0.0151	0.0005
	0.0853	0.0907	0.0863	0.0002	7.08E-6
Diagnostics					
r(1)	0.0528	0.0565	0.0549	-0.0388	0.0568
Q(15)	16.000	16.175	12.491	15.980	13.338
H(72)	1.0237	0.9904	1.4855	1.0104	0.6200
	0.4422	0.4370	0.7122	0.6755	0.6280

Notes: Numbers reported in parentheses are standard errors; *, ** and *** respectively denote significant at the 10%, 5% and 1% level; r(1) is the first-order autocorrelation coefficient of the one-step-ahead prediction errors; Q(15) is the Box-Ljung statistic distributed as chi-square(15); H(72) is a test for heteroscedasticity, distributed as F(72,72) based on a two-tailed test [10]; is a modified coefficient of determination where the actual observations have been replaced by their first differences.

The estimates and test results are showed in the last three rows of Table IV when are ln(ToV), BR and OCR respectively. According to the results, evident differences can be identified among these three indicators representing the effect of large promotion activities on traffic quality: For BR and OCR, Activity 4(“Butterfly Festival”) and Activity 5(“618”) bring better quality traffic with lower BR and higher OCR, but the situation of Activity 1(“Double 11”) is opposite; For ToV, there is no significant effect by the indicator.

Considering the estimation results of all metrics, we evaluate all five activities as follows: Activity 4("Butterfly Festival") and Activity 5("618") are the best two online promotion activities on the effect of attracting traffic since the two activities significantly promote the volume and quality of total page traffic. Activity 1("Double 11") also attract considerable volume of traffic. However, the lack of retention and conversion has negative impact on traffic quality, making the effect of activity discount. Activity 2("Double 12") and Activity 3("New Year's Shopping Festival") significantly increase traffic volume, but has no strong effect on traffic quality.

The Effectiveness of Campaigns on Unpaid Traffic

As revealed in Table III, plentiful paid traffic has been brought to the pages in the period of the campaigns by the means of online advertising. Meanwhile, the metrics' daily average values of unpaid traffic are promoted. Some researches has focused on the relationship between paid and organic search traffic: Yang and Ghose [43] found positive interdependence between these two kinds of traffic after analyzing six months' weekly data of a large retail store's website; and Rutz et al. [39] analyzed daily traffic data during May to September 2006 from a commercial website in the field of automotive industry and realized that paid search traffic has significant effect on unpaid traffic.

In this section, model (3) is used to evaluate performance of the five campaigns affecting volume and quality of unpaid traffic. Table V shows estimation and test results of each coefficient in model (3) for the five KPIs. Trend component here also follows a random walk plus drift process owing to the constant slope over time. The model passes diagnostic test explicitly relying on the test result.

Table V. Estimation results for KPIs of unpaid traffic

	ln(PV)	**ln(UV)**	**ln(ToV)**	**BR**	**OCR**
	2.7860***	2.8812***	0.2007	0.3526***	-0.0222*
	(0.6716)	(0.6685)	(0.2987)	(0.0916)	(0.0125)
	0.8410	0.8609	0.0642	-0.0060	0.0106
	(0.6617)	(0.6587)	(0.3272)	(0.0903)	(0.0118)
	0.7606	0.8015	0.2079	-0.0746	0.0295**
	(0.6893)	(0.6686)	(0.3044)	(0.0919)	(0.0124)
	1.7393**	1.4892**	0.2819	-0.1442	0.0016
	(0.6697)	(0.6667)	(0.2957)	(0.0912)	(0.0118)
	2.0975***	2.1403***	0.6651**	-0.1501*	0.0008
	(0.6880)	(0.6850)	(0.2914)	(0.0933)	(0.0120)
	0.2267	0.2606	0.0177	0.0170	0.0028
	(0.1652)	(0.1648)	(0.1338)	(0.0246)	(0.0041)
	0.2025	0.2186	0.1569	0.0094	0.0036
	(0.1921)	(0.1924)	(0.1375)	(0.0274)	(0.0042)
	0.3319	0.3699*	0.0639	0.0189	0.0099**
	(0.2067)	(0.2070)	(0.1411)	(0.0290)	(0.0044)
	0.5260**	0.5447***	0.1468	0.0357	0.0010
	(0.2049)	(0.2052)	(0.1365)	(0.0293)	(0.0043)
	0.4588**	0.4527**	-0.1842	0.1156***	0.0037
	(0.1922)	(0.1926)	(0.1368)	(0.0275)	(0.0042)
	0.3571**	0.3533**	-0.0876	0.0869***	-0.0028
	(0.1649)	(0.1660)	(0.1354)	(0.0248)	(0.0041)
	1.4154***	1.2527**	0.2100	0.0248	-0.0041
	(0.5291)	(0.5402)	(0.3254)	(0.0748)	(0.0109)
	-0.0994	-0.1125	-0.2568	0.0704	-0.0040
	(0.4743)	(0.4721)	(0.2507)	(0.0655)	(0.0090)
	0.1371	0.1392	-0.1995	-0.0593	0.0031
	(0.3631)	(0.3612)	(0.3901)	(0.0517)	(0.0077)
	0.5728	0.5706	0.0229	0.0082	7.39E-5
	0.1915	0.1872	0.2903	0.0060	0.0002
Diagnostics					
r(1)	-0.0117	0.0006	0.0111	0.0110	-0.0320
Q(15)	8.8100	8.4678	16.172	17.167	17.169
H(72)	1.1780	1.1844	1.2316	1.2863	0.5852
	0.4808	0.5089	0.6939	0.5431	0.7311

Notes: Numbers reported in parentheses are standard errors; *, ** and *** respectively denote significant at the 10%, 5% and 1% level; r(1) is the first-order autocorrelation coefficient of the one-step-ahead prediction errors; Q(15) is the Box-Ljung statistic distributed as chi-square(15); H(72) is a test for heteroscedasticity, distributed as F(72,72) based on a two-tailed test[10]; is a modified coefficient of determination where the actual observations have been replaced by their first differences.

It can be concluded that different campaigns have discrepant effects on unpaid traffic. For the two metrics reflecting traffic volume (PV and UV), “Double 11”, “Butterfly Festival” and “618” have significant positive effect on unpaid traffic, but other two campaigns do not show the effect significantly. As for the three indicators reflecting quality of traffic (ToV, BR and OCR), data in Table V reveal that a majority of coefficient estimations don’t arrive significance level. Only a few coefficients are significant, showing that “618” promoted unpaid traffic quality while “Double 11” did the opposite. Meanwhile, OCR increased in the period of “New Year’s Shopping Festival”. In addition, unpaid traffic had significant growth at weekends and Western holidays.

Discussion and Implications

Based on the analysis above, similar large promotion activities can be improved from the following four aspects when designing and carrying out them in the future:

First, the time duration of large promotion activities should be reasonably arranged. Blattberg and Neslin [4] found that most promotion activities are short-term and these campaigns stimulate consumers to buy some certain commodities and services in abundance with a relatively short time. Li et al. [29] studied on promotion activities of a large supermarket in China and found that the longer the price promotion time last, the worse the promotion effect will be. So far, the large online promotions mostly focus on some specific dates, such as "Double 11" (means November 11) and "618"(means June 18), yet e-commerce websites tend to begin these activities earlier before the dates in order to enhance population and influence. Analysis results in Table IV show that Activity 2 ("Double 12") and Activity 3 (“New Year’s Shopping Festival”) performed poor on the effect of traffic volume. This may be caused by its time duration last too short or too long. While Activity 1 ("Double 11"), Activity 4 (“butterfly festival”) and Activity 5 (“618”) whose time duration is about 15 days have achieved good performance, therefore, it can be concluded that the duration of a large online promotion activities within a certain time range can bring a better traffic effect.

Second, businesses should put more marketing resources on their own initiative large-scale promotion activities rather than spending much effort in the competition against opponents. "Double 11" and " Double 12" didn’t work well: the overall quality of traffic decreases although the volume of the traffic increases significantly during “Double 11”; and "Double 12" activity of JD.com are ineffective for attracting traffic. Both of the campaigns are initiated by Alibaba, JD’s most powerful competitor. The JD’s initiative promotion activity “618”, by contrast, brings better effect of traffic regardless of quantity and quality. “Butterfly Festival”, another initiative campaign by JD, performs excellently on attracting traffic as well. What’s more, the initiative promotion can make a close connection between campaigns and businesses, promoting influence and popularity of both.

Third, aiming at different categories of goods, businesses are able to design large promotion activities more specific. The commodities of "Butterfly Festival" mainly involve personal care and beauty. Although the popularity and influence of the campaign are not as great as "Double 11" and "618", the effect of attracting traffic for Crest is favorable, just behind “618”. Chances are that the restricted categories of goods make consumers visit web pages more pertinent, and more likely conduct further operations.

Fourth, e-commerce websites should pay more attention to unpaid traffic brought by promotion activities, and send targeted messages to the consumers involved before the next promotion. The analysis result of 4.2 indicates that large online promotion activities do have effect on unpaid traffic. The reason may be that, on the one hand, consumers visit the pages autonomously during the promotion based on their past shopping experience, since some activities already have enough awareness and influence. On the other hand, businesses usually run marketing and broadcast campaigns taking advantage of various channels. These measures expand the coverage of activity information. Consumers probably obtain information and related links through these channels and then autonomously access activity pages. This part of the traffic shows strong purpose and autonomy to some extent, which means that they may have stronger purchase intention. Businesses should focus on this group of consumers [30].

In addition, we notice that Western festivals have significant positive effect on traffic volume, while other types of festivals present little effect. It indicates that Chinese online consumers may have greater willingness to go shopping at e-commerce websites in western festivals. Therefore, businesses should concentrate on western festivals, especially those popular in China, such as Christmas and Valentine's day, in the design of promotion activities related to festivals.

CONCLUSION

Our study found that large promotion activities: (1) have significant positive impact on total page traffic; (2) show the difference in the impact of total page traffic’s quality, "618" has the best effect, while "Double 11" has the worst; (3) have positive effect on unpaid traffic, although “Double 12” and “New Year’s Shopping Festival” are not significant; (4) nearly have no significant effect on the quality of non-paid traffic expect the negative effect of “Double 11” and the positive effect of “618”.

However, the case study only involves single brand on JD.com. Further studies can research on different e-commerce sites, different types of goods or different brands within the same goods, and consider more direct indicators related to e-commerce websites, which will more directly reflect ROI of promotion activities.

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