Source engine marketing: A preliminary empirical analysis of web search data

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ABSTRACT

The purpose of this paper is to empirically investigate a website performance and its marketing efficiency. A replica website was created harvesting public profiles from fallen social network, MySpace. The data are used to empirically investigate not only the traffic impact on the website but may be more significantly the effectiveness of the website traffic source. The value of which can provide a benchmark to empirically evaluate other websites and ultimately assist marketing online efficiency. A series of regressions are specified to measure website efficiency. To forecast and analyse the size of the errors of the model and questions of volatility of the data, the Autoregessive Moving Average model is used. Return visits, a measure for retention efficiency, generates a greater number of times a page is viewed compared to new visits. Direct traffic has positive effectiveness at making the target audience aware of the website. Referral traffic reveals the least impact on bounce rate showing a higher contact efficiency than direct or search traffic. Ultimately the results from this research can be used to make marketing adjustments needed towards website optimization and future marketing efficiency.

Keywords: Autoregressive moving average, Google Analytics, online marketing, website efficiency

INTRODUCTION

Within the world of e-commerce a prime strategy for all businesses is to promote website visitors and convert those visitors into paying and returning customers. The efficacy of website performance is of paramount importance for future business. The objective of this research is therefore to explore the performance and marketing efficiency of a website using data from Google Analytics. As the rapid growth of websites and users continues, more information in the form of data metrics is being automatically collected by web analytics software. It is now possible to utilize web analytics tracking technology to collect, measure, analyse and report large amounts of detailed online data of visitors' traffic and activities on websites. Reporting services are offered through various companies including Google, Alexa Internet, Compete.com., Comscore, Hitwise, Microsoft and Yahoo. The measurement of website traffic exposure provides a valuable source of customer-centric information of the popularity of a site. Based on a replica of Mark Zuckerberg's (founder of Facebook) Facemash website, the Australian domain Facemash.com.au was purchased and a replica website was created harvesting public profiles from fallen social network, MySpace. This Front Facing Website: http://www.facemash.com.au is an online marketing strategy. The objective was simply to access its Google Ranking and implement an empirical model to measure marketing efficiency. To the author's surprise, the overall perceived success of the website was unexpected!

Figure 1 (appendix) shows the Google Analytics traffic overview between November 2010 and October 2011. The site received an average of 171,198 Page Views (136,816 unique page views) per month. These unique time-series data metrics, derived from a purposely constructed website is used to empirically investigate not only the traffic impact on the website but may be more significantly the effectiveness of the website traffic sources. The value of which can ultimately assist marketing efficiency. Benefits of online marketing have been well researched and documented: better quality customer service (Owens, 2000), increased number of customers (Daniel 2000); increased revenue, Auger and Gallaugher (2001); ability to reach a wider market (Gallaugher, 2001); cost reductions, and Owens (2000); Franco and Klien (1999). See Shah and Bokhari, (2002) for further discussions. It is against this backdrop that a series of research questions emerge concerning marketing efficiency via the website usage. To what extent do changes in new visits and return visits to the website impact the number of times a page is viewed? What impact, if any, do changes in unique and returning visits have on pages per view? Which particular source of traffic generates greater return visits? Finally to what extent do the different sources of traffic have on retention efficiency? The following section provides a literature review. Section three describes the data and methodologies used in this study. Section four describes the analysis and results. Finally, section five provides discussion and concluding observations.

BRIEF LITERATURE REVIEW

Web tracking, also known as web log analysis, web logging, and web log file analysis seems to be very popular in information seeking studies (Hsieh-Yee, 2001; Fourie, 2002; Jansen and Pooch, 2001; Pharo and Jarvelin, 2004). Fourie and Bothma, (2007) provide an excellent background overview of web tracking and explain the criteria for researchers working on web usage. With regard to research methodologies, Steyaert (2004) uses five marketing indicators: consumer awareness, popularity, contact efficiency, conversion, and retention to assess six electronic government services programs' performances. Her results support the use and importance of marketing framework in organizing and evaluating websites. Fang (2007) and Bhatnager (2009) use Google Analytics to evaluate and develop a library website utilizing the ordinary reports from Google Analytics without developing specific metrics. Plaza (2008) extends the research to time series data using Google Analytics to provide web metrics of her website http://www.scholars-on-bilbao.info. A site which disseminates Research and Development results in the field of Art-related Humanities and Social Sciences' scientific production. Her methodology analyses the effectiveness of visits depending on their traffic source: direct visits, referring site entries and engine visits. Her results conclude that priority for website designers should be to promote the number of direct visits, then improve the website's search engines' visibility, and lastly employ more time in link-building.

MacFarlane, (2007) investigates the value of web information for the practitioner. This paper argues that the use of diagnostic measures is essential in web search, as precision measures on their own do not allow a searcher to understand why search results differ between search engines. Mansourian (2008) explores web-based research into two categories: technical orientated and user orientated. He defines the users as an influential element in the success of web based services and explains the link between users' characteristics and search results. He further introduces a new conceptual measure called "web search efficacy" to evaluate the performance of searches mainly based on users' perceptions. The analysis of the dataset led to the identification of five categories of influential factors: searcher's performance, search tool's performance, search strategy, search topic, and search situation.

Plaza (2009) further uses Google Analytics data to monitor web traffic of a particular website. Using a time series analysis she investigates the web traffic source effectiveness with the data. She identifies that web site direct visits are the most effective visits which stay longer on site, followed by search engine visits and then link entry visits. Return visits are the main engine for creating session length. Watson, Berton, Pitt and Zinkhan (2000) develop a marketing website frame work which identifies five stages: awareness efficiency, identified by the proxy direct traffic i.e. people who are aware of the website and directly type the address into the browse; attraction/popularity efficiency identified by a person who is aware that a certain brand has a website, but never visited (search traffic and referral traffic are the proxies); and contact efficiency, measured by the number of page views and pages per visit are the proxies. These proxies identify the conversion of a "hit" to a "visit". Closure efficiency identifies average time on site; retention efficiency is identified by returning visitors and finally overall efficiency identifies the maximum total of all efficiencies. How do visitors discover the site? What are their initial intentions to visit the site? What determines their duration on line? What makes them purchase and finally what makes them return are the many questions that this particular framework attempts to answer. Previous internet marketing studies have looked at the most effective means of advertising in generating actual web visits. Bellizzi (2000) found that traditional advertising methods are very effective in generating both interested consumer leads and website visitors. The authors concluded that it would be a mistake for online businesses to rely completely on online advertising to create awareness and site visitation. Other researchers have examined how the changing technology of the internet will affect brand-building. Adamic and Huberman (2000) found that branding was highly significant on the web since a few sites dominated hundreds of others in the quest for internet traffic. Ilfeld and Winer (2002) empirically determined the factors that drive traffic and brand equity in the internet space. They concluded that advertising spending for websites should be on awareness and traffic-building and not on brand building. The aim of this paper is to empirically explore further, the performance and marketing efficiency of a website effectiveness using web traffic data source.

METHODOLOGY AND DATA

Data of web traffic for Front Facing Website: http://www.facemash.com.au. are collected from Google Analytics implemented in-page scripts from 5th October 2010 to 5th November 2011 inclusive. The data are formulated into categories of efficiency following Watson *et al.* (2000). The daily data are transformed into weekly data series following the failure of the initial Jarque-Bera normality tests. Table 1 (appendix) shows the descriptive statistics of the 47 weekly observations including the Jarque-Bera tests. A small probability value leads to the rejection of the null hypothesis of a normal distribution. A lower standard deviation of each data compared to the mean generally reflects less volatility.

The awareness efficiency of the website is identified by the variable direct traffic. It refers to the effectiveness at making the target audience aware of the website. Direct traffic represents visitors who are aware of the website and directly type the address into their browser address bar. The variables search traffic and referral traffic indicate popularity efficiency. Search traffic is traffic which has been organically generated from search engines. Organically meaning not paid advertising. A website which ranks well on search engine is said to have strong Search Engine Optimisation (SEO) and as such will rank well for common search terms related to the website. Graph 1 (appendix) illustrates a very strong increase in the volume of search traffic over the observed period, though less dynamic increases in direct and referral traffic. Referral traffic is related to the Search Engine Marketing (SEM) ideology of linking a website to as many websites as possible. Whilst, this has been negatively implemented through link farms it is meant to encourage reciprocal links to associations, other websites, forums, directories and social networks of similar topics. In much the same way that academic papers include citations to good research on a similar topic. Referral traffic is what allows the internet to work as an information source (the way that it does). Referral traffic is traffic from a website which has your URL on it. This may be place by the webmaster or it may be someone suggesting the website in a forum.

Graph 2 (appendix) clearly shows a positive increase in total visits to the website over time, dominated by new visits. A high number of new (unique) visitors would indicate strong visitor 'recruitment'. Return visits show a positive increase, albeit much subdued compared to unique visits. Unique visits are new visitors to the site and can interpret the overall efficiency of the site, as can the variable total visitors. The variable pageviews is a calculation of how many times a page is viewed. A page view (impression) is a request by a visitor to load a single file (HTML page) form the web server. On a typical website a 'page' request would result from a visitor clicking on a link or navigating to another page. Every time a user refreshes their browser, navigates to another page or in the case of Facemash.com.au 'casts a vote', they are requesting a page refresh and this is counted as a page Impression. Page views acts as a proxy for contact efficiency of the website. Returning visits can be directly related to the loyalty of visitors and the retention efficiency of a website. Loyal visitors are frequently highly engaged with a website and also indicate positive visitor retention. A returning visitor could be defined as a user who has been to your website previously.

Graph 3 (appendix) shows a positive relationship between return visits and page views. This illustrates a positive engagement and visitor retention to the site. Bounce rate identifies closure rate. Retention efficiency shows customer loyalty based on repeat visits. Many first time visitors will only stay for a few seconds before hitting the "back" button or closing the browser. There are a number of reasons why it may be difficult to keep the visitors attention: slow loading, uninterested in content, aesthetically unpleasing, or simply didn't have time to make it through the site. Graph 4 (appendix) shows an increasing rate of change in bounce rate compared to return visits.

Table 2 (appendix) reports 71 per cent of Facemash.com.com.au total visitors land on the homepage and 69.49 per cent of users also leave from homepage. This reflects the way in which the website is created (programmed). In order for users to browser multiple profile images (and vote) they do not need to navigate to multiple pages (passed the homepage). Each time they vote the homepage refreshes and the new profile pictures are shown. This is reflected in the 'average time on page' ~ two minutes, and the 'Frequency and Recency' shown in Table 2 (appendix). Of the total visitors who visited the site, only once (15,130) there were more than one pageviews (24,926). This increases the user visits the site, more than once. For this reason, it can be concluded that the 'site' is 'successful' despite having a high bounce rate. The bounce rate could be considered in respect to this type of site, as a statistical anomaly.

The forecasting of time series data requires important testing and subsequent equation specification modeling. The conceptual framework of this analysis follows two important steps: initial analysis of the raw data collected from Google Analytics and the specification of the equations to be used. Using Eviews7 software data the statistical Jarque-Bera normality tests are performed to ensure the data are appropriate for the following time series regressions.

To determine how much one variable will change in response to a change in some other variable, a series of regressions are specified. To forecast and analyse the size of the errors of the model and questions of volatility of the data, the Autoregessive Moving Average (ARMA) model is used. The basic version of the ordinary least squares (OLS) model assumes that the expected value of all error terms, when squared, is the same at any given point. This assumption is called homoskedasticity, and it is this assumption that is the focus of the ARMA model. Data in which the variances of the error terms are not equal, and when the error terms may reasonably be expected to be larger for some points or ranges of the data than for others, are said to suffer from heteroskedasticity. The standard warning is that in the presence of heteroskedasticity, the regression coefficients for ordinary least squares (OLS) are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision. Instead of considering this a problem to be corrected, ARMA treat heteroskedasticity as a variance to be modeled and the deficiencies of least squares corrected (Engle 2001:157). Further a common finding in time series regressions is that the residuals are correlated with their own lagged values. This serial correlation violates the standard assumption of regression theory that disturbances are not correlated with other disturbance. The primary problems associated with serial correlation are that OLS is no longer efficient among linear estimations. Furthermore, since prior residuals help to predict current residuals, information to form a better prediction of the dependent variable can be adopted. Standard errors computed using OLS formula are not correct, and are generally understated. Finally, if there are lagged dependent variables on the right hand side, OLS estimates are biased and inconsistent (Eviews, Guidebook II 2011:85).

To ensure stationarity an Augmented Dickey-Fuller Test is used. If the variables have a unit root they are transformed to stationary by Difference-Stationary Process. If the all the variables do not meet these properties, a series of Autoregressive Moving Average (ARMA) model regressions are created to test the hypotheses. All residuals are tested by the Breusch-Godfrey serial correlation LM test, Breusch-Pagan- Godfrey Test, and the Jarque-Bera Statistic for serial- or auto-correlation, homoscedastcity and normal distribution respectively.

ANALYSIS AND RESULTS

Invalid regressions can arise if the time series data are not stationary. Hence the Dickey-Fuller stationarity (unit root) tests are calculated for each of the variables. Results in Table 3 (appendix) display almost all variables are stationary. In view of these properties, this paper employs the Autoregressive Moving Average (ARMA) models to test the following hypotheses. The use of regression analysis provides an opportunity to determine the extent a change of one independent variable has on the change of a dependent variable over time. The first regression analyses to what extent changes in new visits and return visits to the website impact on the number of times a page is viewed? Table 4 (appendix) reports the ARMA results as well as the ARMA structure tests and residual diagnostics tests..

The reported inverted AR MA roots 0.66 and 0.54 are less than one and therefore indicate a stationary ARMA model, i.e. the means the process is invertible and allows for the interpretation of the results. For every new visit, there is a 1.4 increase in page views generated, and for every return visit, 6.2 page views are generated. This suggests return visitors are generating a greater number of times a page is viewed compared to new visits. This may be interpreted that they like what they see the first time and overall efficiency is effective. Changing the dependent variable to pages per visit, the regression results reported on Table 5 (appendix) show a negligible impact of new visits and return visits on pages per view. This may further suggest that the penetration of the viewer is shallow, with little interest to search further.

The next regression tests the impact of which particular traffic source generates greater return visits. Table 6 (appendix) shows that only direct traffic shows some positive effectiveness at making the target audience aware of the website. The coefficients of search traffic and referral traffic conclude negligible popularity efficiency. It could be that the bounce visits may distort the accuracy of the interpretation the above results. Retention efficiency shows customer loyalty based on repeat visits. Many first time visitors may only stay a few seconds. The impact of traffic source on bounce rate can illustrate the extent of closure efficiency. The effectiveness of each source of traffic on bounce rate shows on Table 7 (appendix) that referral traffic had the least impact on bounce rate showing higher contact efficiency.

DISCUSSION AND CONCLUDING OBSERVATIONS

Four very important questions relating to website marketing efficiency are tested. The first result identifies and shows that return visits (a sign for retention efficiency) to this website generates a greater number of times a page is viewed (a proxy for contact efficiency) compared to new visits. Considering the content of the website, this may reveal the interest of individuals who initially posted themselves on the site to return to the same page to monitor their popularity. The second question tested contact efficiency. It tested the effectiveness of new visits and return visits on the number of pages per view. Results show little impact of any specific source of traffic on pages per view. The next question asks which particular source of traffic generates greater return visits. The object is to test popularity efficiency. Results show that direct traffic had some positive effectiveness at making the target audience aware of the website. The coefficients of search traffic and referral traffic conclude negligible popularity efficiency. Finally retention efficiency was tested by regressing bounce rate against different sources of traffic to test what extent different sources of traffic have on retention efficiency? Referral traffic reveals the least impact on bounce rate showing a higher contact efficiency than direct or search traffic.

This preliminary research provides a benchmark for future more extensive and larger empirical studies to measure the performance efficiency of other websites. Policy implications are apparent. Any model which provides a framework to identify the efficiency of website performance can provide valuable information for future effectiveness of online marketing, and ultimately business optimization.

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APPENDIX

Figure 1 Traffic Sources Overview (Daily) New Interface

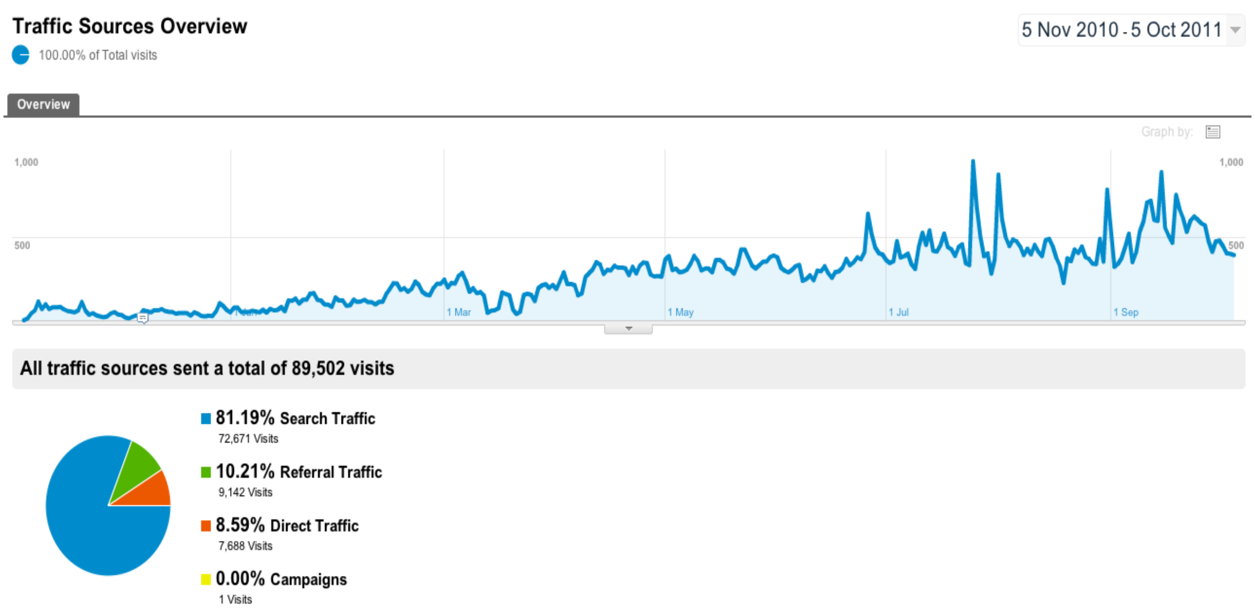


Table 1 Descriptive statistics of weekly data.

	Direct Traffic (DT)	Referral Traffic (RF)	Search Traffic (ST)	Page Views (PV)	Bounce Rate % (BR)	Return Visits (RV)	Unique Visits (UV)	Total Visits (TV)
Mean	161.40	191.25	1506.57	3582.57	67.38	133.36	1725.87	1859.25
Median	171.00	188.00	1685.00	3748.00	67.28	129.00	1883.00	2003.00
Maximum	283.00	336.00	4140.00	8144.00	77.82	274.00	4402.00	4667.00
Minimum	51.00	89.00	50.00	374.00	52.53	21.00	173.00	213.00
Std. Dev.	61.86	58.87	1115.57	2147.38	4.67	76.44	1134.18	1205.20
Skewness	0.147	0.385	0.274	0.157	-0.368	0.224	0.293	0.274
Kurtosis	2.147	2.480	2.105	1.869	4.455	1.833	2.104	2.063
Jarque-Bera	1.59	1.69	2.15	2.69	3.21	3.05	2.24	2.30
Probability	0.45	0.42	0.33	0.25	0.17	0.21	0.32	0.31
Obs.	47	47	47	47	47	47	47	47

Table 2 Frequency and recency statistics

No.of visits	1	2	3	4	5	6	7	8	9-14	15-25	26-50
Visits	15,130	677	115	45	26	21	13	15	34	31	25
Pageviews	24,926	1,638	244	89	42	23	17	11	59	44	50

Table 3 Augmented Dickey-Fuller Unit Root Tests:

	Direct Traffic (DT)	Referral Traffic (RF)	Search Traffic (ST)	Page Views (PV)	Bounce Rate (BR)	Return Visits (RV)	Unique Visits (UV)	Total Visits (TV)
Test Statistic	-2.34	-2.27	-1.87	-2.16	-3.43	-1.92	-1.97	1.97
10 per cent Critical Value	-2.60	-2.60	-2.60	-2.60	-2.60	-2.60	-2.60	-2.60

Table 4 Regression results for the impact of a change in unique and returning visits have on the number of times a page is viewed

Dependent Variable: PV
Included observations: 46 after adjustments
Convergence achieved after 19 iterations
MA Backcast: 11/12/2010

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	265.9527	139.0321	1.912887	0.0628
UV	1.449610	0.100033	14.49134	0.0000
RV	6.271570	1.415858	4.429518	0.0001
AR(1)	0.660646	0.369325	1.788792	0.0810
MA(1)	-0.537882	0.423998	-1.268594	0.2117

R-squared	0.885195	Mean dependent var	3641.609
Adjusted R-squared	0.883750	S.D. dependent var	2132.200
S.E. of regression	271.8016	Akaike info criterion	14.15034
Sum squared resid	3028921.	Schwarz criterion	14.34911
Log likelihood	-320.4579	Hannan-Quinn criter.	14.22480
F-statistic	682.0658	Durbin-Watson stat	2.066240
Prob(F-statistic)	0.000000		
Inverted AR Roots	.66		
Inverted MA Roots	.54		
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.589558	Prob. F(2,39)	0.5594
Heteroskedasticity Test: White			
F-statistic	1.618444	Prob. F(20,25)	0.1266
Jacque-Bera Normality test	1.4	Prob.	0.0901

Table 5 Regression results for the impact of a change in unique and returning visits have on pages per view

Dependent Variable: PPV
Included observations: 46 after adjustments
Convergence achieved after 14 iterations
MA Backcast: 11/12/2010

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.88613	0.552321	28.76249	0.0000
UV	-0.002147	0.000492	-4.362766	0.0001
RV	0.015487	0.006856	2.258734	0.0293
AR(1)	-0.403211	0.116180	-3.470568	0.0012
MA(1)	0.999813	0.051784	19.30737	0.0000

R-squared	0.71207	Mean dependent var	14.19326
Adjusted R-squared	0.429373	S.D. dependent var	2.250562
S.E. of regression	1.543936	Akaike info criterion	3.808869
Sum squared resid	97.73328	Schwarz criterion	4.007634
Log likelihood	-82.60399	Hannan-Quinn criter.	3.883328
F-statistic	13.65430	Durbin-Watson stat	1.944909
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.40
Inverted MA Roots	-1.00

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.376587	Prob. F(2,39)	0.6887

Heteroskedasticity Test: White

F-statistic	17.22986	Prob. F(19,26)	0.0000
Jacque-Bera Normality test	4.87	Prob.	0.0681

Table 6 Regression results for the impact of a change in traffic source have on return views

Dependent Variable: RV
Included observations: 46 after adjustments
Convergence achieved after 22 iterations
MA Backcast: 11/12/2010

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	22.05990	20.52158	1.074961	0.2888
DT	0.180274	0.142461	1.265432	0.2130
RT	-0.004960	0.127083	-0.039028	0.9691
ST	0.054905	0.009552	5.748154	0.0000
AR(1)	0.474946	0.574162	0.827199	0.4130
MA(1)	-0.281238	0.619443	-0.454018	0.6523
R-squared	0.776055	Mean dependent var		134.9130
Adjusted R-squared	0.760562	S.D. dependent var		76.53375
S.E. of regression	28.57873	Akaike info criterion		9.664310
Sum squared resid	32669.76	Schwarz criterion		9.902829
Log likelihood	-216.2791	Hannan-Quinn criter.		9.753661
F-statistic	56.54498	Durbin-Watson stat		1.954481
Prob(F-statistic)	0.000000			
Inverted AR Roots	.47			
Inverted MA Roots	.28			
Heteroskedasticity Test: White				
F-statistic	3.518595	Prob. F(26,19)		0.0032
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.016990	Prob. F(2,38)		0.9832
Jacque-Bera Normality test	0.63	Prob.		0.0427

Table 7 Regression results for the impact of a change in traffic source have on bounce rates

Dependent Variable: BR
Included observations: 46 after adjustments
Convergence achieved after 25 iterations
MA Backcast: 11/12/2010

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.620581	0.016738	37.07521	0.0000
DT	8.23E-05	0.000120	0.685399	0.4970
RT	-9.45E-05	9.93E-05	-0.951695	0.3470
ST	3.00E-05	8.84E-06	3.398622	0.0015
AR(1)	0.677836	0.076558	8.853926	0.0000
MA(1)	-0.999926	0.119406	-8.374199	0.0000

R-squared	0.598175	Mean dependent var	0.673489
Adjusted R-squared	0.547947	S.D. dependent var	0.047176
S.E. of regression	0.031719	Akaike info criterion	-3.942701
Sum squared resid	0.040244	Schwarz criterion	-3.704183
Log likelihood	96.68213	Hannan-Quinn criter.	-3.853351
F-statistic	11.90919	Durbin-Watson stat	1.466218
Prob(F-statistic)	0.000000		

Inverted AR Roots	.68
Inverted MA Roots	1.00

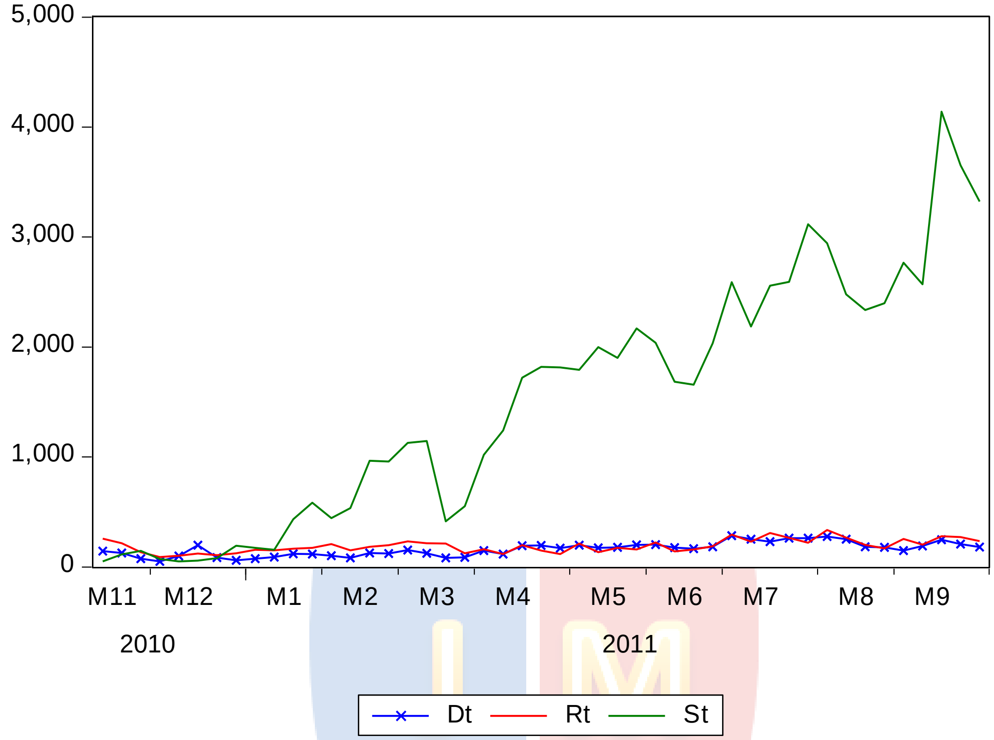
Heteroskedasticity Test: White

F-statistic	16.04948	Prob. F(23,22)	0.0000

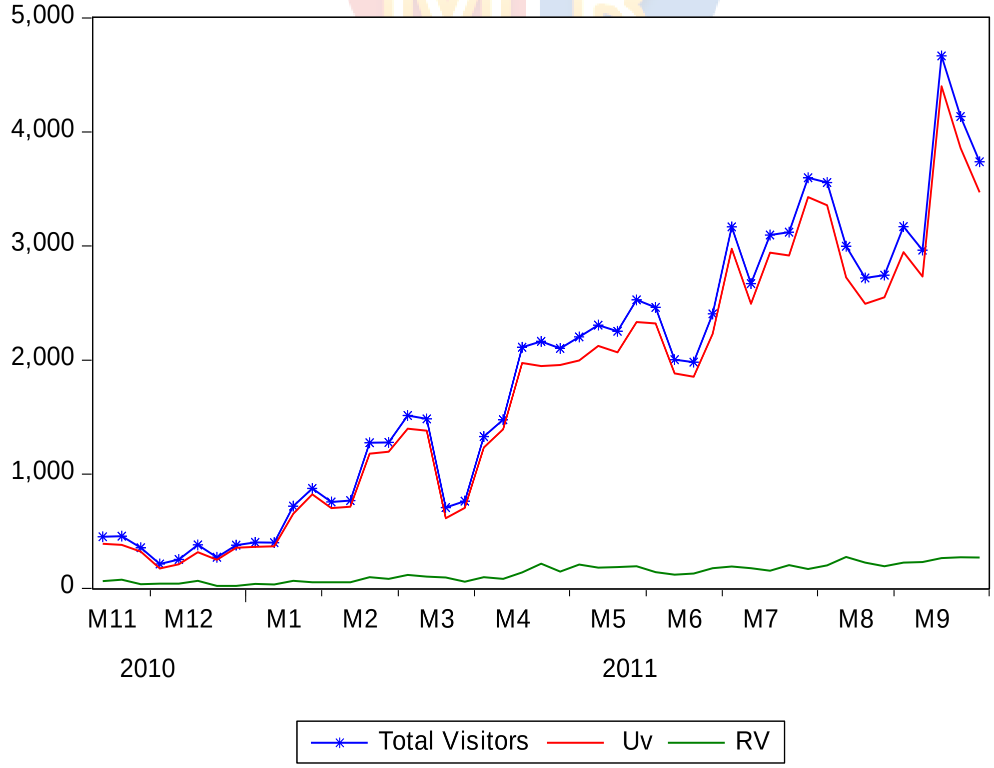
Breusch-Godfrey Serial Correlation LM Test:

F-statistic	3.624612	Prob. F(2,38)	0.0362
Jacque-Bera Normality test	1.2130	Prob.	0.5430

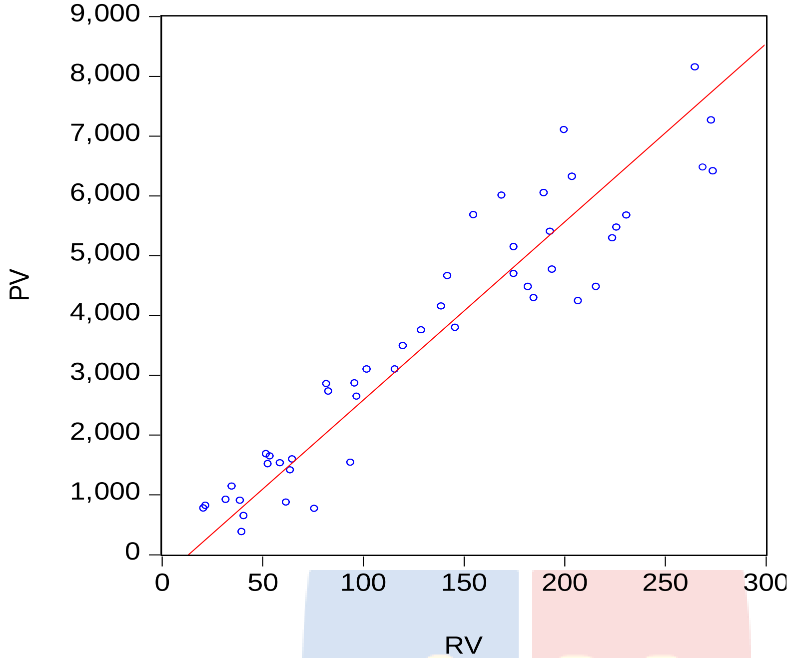
Graph 1 Direct traffic, return traffic and search traffic



Graph 2 Weekly data of Total visits, Unique visits(Uv) and Return visits (RV).



Graph 3 Return visits and page views



Graph 4 Bounce rate and return visits