Incremental Clicks Impact Of Search Advertising

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Abstract

In this research we examine how the number of organic clicks change when search ads are present and when search ad campaigns are turned off. We then develop a statistical model to estimate the fraction of total clicks that can be attributed to search advertising. A meta-analysis of several hundred of these studies reveals that over 89% of the ads clicks are incremental, in the sense that the visits to the advertiser's site would not have occurred without the ad campaigns.

1 Introduction

In recent years, as advertisers have sought to expand their media reach online, search advertising has become increasingly popular. US online advertising spend reached $26 billion in 2010, with search advertising making up 46% of the market. Total US online spend is projected to reached $42 billion by 2013 [1]. There are several advantages search advertising has over traditional media advertising. One involves access to direct metrics of impact, such as the number of clicks achieved. Another is search advertising allows advertisers to pay only when a user clicks on an ad. And yet another is that since the ads are triggered by search terms, they tend to be highly relevant to the user.

However, measuring the number of ad clicks alone does not provide information on the incrementality of search advertising. That is, the question "how many of the clicks are incremental to clicks that would have occurred on natural search results in the absence of paid ad results?" is not answered. Advertisers that pause their search advertising campaigns sometimes cite concerns about how much of the traffic to the sites is truly incremental to clicks on natural search results.

The incrementality is dependent on factors such as the organic search result ranking and how similar the paid and organic listings are to each other. By measuring the incremental click impact from search advertising, the advertiser is able to make more informed decisions regarding their advertising spend.

2 Methodology

In order to determine the incremental clicks related to search advertising, we quantify the impact pausing search ad spend has on total clicks. Indirect navigation to the advertiser site is not considered. Each study produces an estimate of the incremental clicks attributed to search advertising for an advertiser. To make comparison across multiple studies easier, we express the incremental clicks as a percentage of the change in paid clicks. This metric is labeled "Incremental Ad Clicks", or "IAC" for short.

IAC represents the percentage of paid clicks that are not made up for by organic clicks when ads are paused. Conversely, when the campaign is restarted, the IAC represents the fraction of paid clicks that are incremental. Since we do not assume a positive interaction between paid and organic search in our analysis, the IAC estimate is bounded at 100%. For example consider the following scenario:

(A) An advertiser spends $1,000 a month and receives 400 organic and 300 paid clicks a month.

(B) Subsequently, they cut their ad spend to $0 and find there are 500 organic clicks a month and 0 paid clicks a month.

Under (A), there are 200 incremental clicks, thereby giving an IAC of (700-500)/(300-0) = 66.7%.

In the above example, we do not consider external factors which could also affect the organic clicks before and after the spend change. To control for this, we employ the statistical model described below.

This estimate of 200 incremental click (IAC) depends on factors leading to the ad spend drop and the state of the account and competitive environment around the time of the spend change. Although the estimate of the IAC should always be considered in the context of the changes preceding the ad spend pause, a meta-analysis of all the Search Ad Pause studies provides insight into the average IAC from search advertising.

2.1 Implementation Details

The studies are implemented via an automated pipeline which runs on a daily basis. The pipeline first attempts to identify a change point. In this case, the change point is the date on which the spend pause began. Also identified are a pre-period (a relatively stable period prior to the spend change), and a post-period (a relatively stable period after the spend change).

If the daily spend in the post-period declines by more than 95% from the daily spend in the pre-period, the companies are labeled as "paused". An analysis is run for each company identified as having paused. The results are compared against validation checks on data integrity and model quality. Validation checks are used to ensure confidence in the statistical model and the models predictions. Around 55% of all studies pass the validation flags. Only studies passing the validation flags are included in this meta-analysis.

2.2 Statistical Model

To determine incremental clicks from search advertising, we need to know the paid and organic clicks at different spend levels over the same time period. Since there can only be one spend level at any given time, we build a statistical model to predict the clicks in the post-period for any given level of spend.

We denote the high and low spend levels as S_H and S_L respectively, in the pre-period and post-period. In the post-period when the spend level was low, we identify paid clicks as P_L and total clicks as T_L. In the same post-period, if the spend level were S_H, and clicks P_H and T_H were observed, the incremental clicks would be $T_H - T_L$. The IAC would then be

$$\text{IAC} = \frac{T_H - T_L}{P_H - P_L} \tag{1}$$

However, since P_H and T_H can not be observed in the post-period, we substitute with model-generated predictions $\hat{P}_H$ and $\hat{T}_H$. To reduce the variance of the predicted IAC, we also substitute T_L and P_L with $\hat{T}_L$ and $\hat{P}_L$, predicted by the same statistical model. The estimated IAC is

$$\widehat{\text{IAC}} = \frac{\hat{T}_H - \hat{T}_L}{\hat{P}_H - \hat{P}_L} \tag{2}$$

The statistical model for paid and organic clicks utilizes the search ad spend and organic impressions as predictors. First, let

O – Organic clicks
P – Paid clicks
T – Total clicks (paid plus organic)
I – Organic search impression
S – Spend on paid search

We use the following Bayesian model:

$$\begin{aligned} O &= (I + \alpha_1)(\kappa_1 + (\kappa_2 - \kappa_1)e^{-\beta_1 S/I}), \\ P &= \beta_0(I + \alpha_2)(1 - e^{-\beta_2 S/I}), \\ T &= O + P. \end{aligned}$$

The constraints for the parameters are

$$\alpha_1, \alpha_2 > 0, \quad \beta_0, \beta_1, \beta_2 > 0, \quad 0 < \kappa_1 < \kappa_2 < 1.$$

Flat uninformative priors are used for the parameters. We also assume concavity for the marginal CPC, which is defined as $\frac{\partial T}{\partial S}$. This assumption introduces an additional constraint

$$1 < \frac{\beta_1}{\beta_2} < \sqrt{\frac{\beta_0}{\kappa_2 - \kappa_1}}.$$

Gibbs sampling [2] and Slice sampling [3] are used to infer the posterior distribution of the model parameters, and to make predictions for the paid and organic click volumes. We ensure the model fits the observed data by setting stringent thresholds for adjusted r-squared, residual auto-correlation (Durbin-Watson statistic [4]) and Markov Chain Monte Carlo (MCMC) convergence (Gelman-Rubin statistic [5]). Additionally, we impose several minimum constraints on click volume and percentage of paid clicks among total clicks, to ensure there is adequate data for the model.

3 Meta-Analysis Results

The meta-analysis is based on 446 valid studies conducted between October, 2010 to March, 2011. Table 1 summarizes the study count for four countries by the month the study was produced.

Date	DE	FR	GB	US
10/2010	2	3	4	11
11/2010	6	2	0	9
12/2010	14	3	1	63
01/2011	22	19	16	110
02/2011	9	7	8	65
03/2011	5	2	5	60
Total	58	36	34	318

Table 1: Count Of Search Ad Pause Studies

In January 2011, we saw an increase in the number of companies that paused their search advertising. This increase may correspond to advertisers revisiting their ad spend budgets for the year. Figure 1 is a histogram plot of the IAC across all 446 studies. The average IAC across all studies is 91%, with the median rate at 95%. The average IAC weighted by the volume of paid clicks in each study is 89%. More than 64% of the studies had an IAC value greater 90 with only a few studies showing a low IAC value.

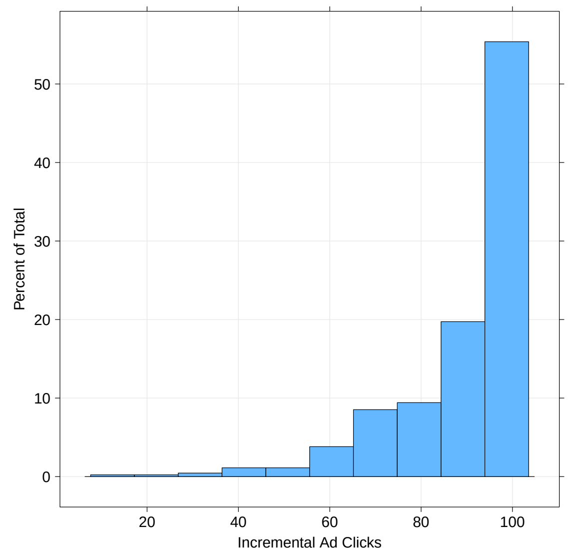

Figure 1: Histogram of Incremental Ad Clicks

A low value for IAC may occur when the paid and organic results are both similar and in close proximity to each other on the search results page. This increases the likelihood of a user clicking on an organic result as opposed to a paid result. Close proximity occurs when the ranking of the organic result is high, placing it near the paid results. Organic results triggered by branded search terms tend to have a higher ranking on average and this may lead to a low IAC value. However, a low IAC value is not necessarily a deterrent to investing in search advertising. Section 4 discusses in more detail when it would be worthwhile to make such an investment.

3.1 IAC Statistics by Country and Vertical

We now consider IAC statistics by country, industry vertical and daily spend level. Table 2 includes both the mean and median IAC for each country.

Country	N	Mean	Sd	Median
Germany (DE)	58	87%	16%	94%
France (FR)	36	88%	10%	88%
United Kingdom (GB)	34	90%	14%	96%
United States (US)	318	90%	14%	95%

Table 2: IAC Statistics by Country

Table 3 summarize the IAC statistics by industry vertical. We have omitted industry verticals with less than 20 studies from the table and boxplot.

Industry Vertical	N	Mean	Sd	Median
Classifieds & Local	62	94%	9%	97%
Retail	59	87%	18%	94%
Finance	41	88%	16%	95%
Healthcare	38	93%	11%	98%
Technology	28	90%	14%	96%
Consumer Packaged Goods	26	88%	14%	94%
Automotive	24	88%	13%	94%
Business & Industrial Markets	24	93%	8%	96%
Food & Beverages	24	89%	15%	95%

Table 3: IAC Statistics by Industry Vertical

Figure 2 is a histogram plot of the daily search ad spend in the pre-period on a log10 scale. For confidentiality reasons, the numbers on the x-axes have not been included.

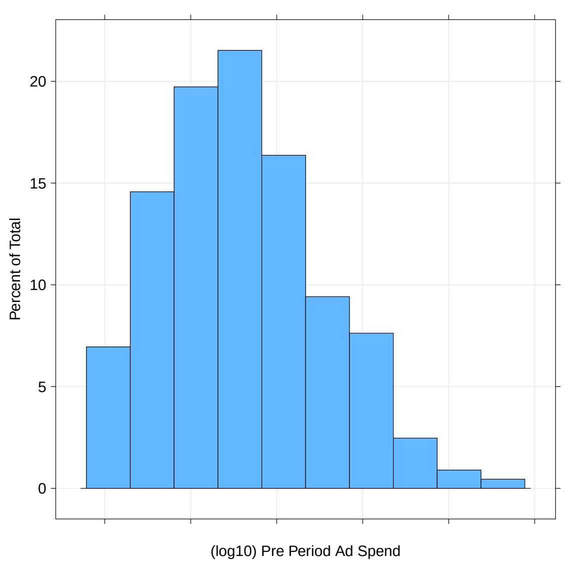

Figure 2: Histogram plot of daily pre-period search ad spend

Table 4 summarizes the IAC by the pre-period daily spend level. The studies were split into four quartiles according to their pre-period daily spend level.

Spend level	N	Mean	Sd	Median
1st Quartile	112	88%	15%	94%
2nd Quartile	111	92%	10%	96%
3rd Quartile	111	88%	15%	95%
4th Quartile	112	88%	15%	94%

Table 4: IAC Statistics by Spend Level

4 When Is Search Advertising Worthwhile?

As noted earlier, a low IAC value does not necessarily suggest a pause in search advertising is in order. In fact, for many advertisers with a low IAC, it is still profitable to invest in search advertising. To evaluate the economic benefits of search advertising, an advertiser must run a calculation incorporating their individual IAC, conversion rates, and conversion revenue. The below equation can help determine whether search advertising is worthwhile on a case by case basis.

Let v be the value of a paid click to the advertiser, c be the cost of a paid click and rv be the value of an organic click, where r is a multiplier indicating the relative value of an organic click to a paid click. Let $\hat{O}_H$ and $\hat{O}_L$ be the predicted organic clicks at the high and low level of spend, respectively. If the profit from paid clicks plus organic clicks exceeds the value of the organic clicks alone, it is profitable to buy search ads.

$$(v-c)\hat{P}_H + rv\hat{O}_H > (v-c)\hat{P}_L + rv\hat{O}_L$$

Re-arranging this expression gives the following inequality

$$\frac{v-c}{v} > r(1-\widehat{\mathrm{IAC}})$$

where $\widehat{\mathrm{IAC}}$ is defined in (2). The left-hand side is the profit margin on clicks. The right-hand side is the relative value of organic clicks times the *displacement percentage* which is one minus the IAC. Advertisers are more likely to advertise when

1. the profit margin on clicks is high,

2. the replacement factor is low, and

3. the relative value (r) of organic clicks is low.

5 Concluding Remarks

We have examined those accounts which have exhibited a spend pause and for which our models produce valid results. The meta-analysis is not representative of all the possible factors which could drive ad spend decline. However, given the large volume of studies produced, across multiple countries and industry verticals, our analysis does provide a reasonable cross section of expected IAC. It is also reasonable to assume that seasonality could play a part in the IAC that we estimate. As of yet, we have not accumulated enough studies over a long enough time period to determine the impact of seasonality on IAC.

A more rigorous approach to determining IAC would be to conduct a randomized experiment. A test group would be exposed to the pull back in paid search ads while search spend would be held constant in a control group. A comparison of the paid and organic click volumes in the two groups would then yield an IAC estimate. However, many advertisers are adverse to conducting such experiments due to the setup costs involved and the potential revenue impact from having a hold-out group. In the case of spend pauses, advertisers presumably believe the benefit of pausing their spend outweighs lost revenue.

Ultimately, advertisers are interested in how much income can be attributed to their search advertising campaigns. Our analysis does not include an estimate for incremental conversions. Other factors such as the ranking of the organic search result or the strength of brand awareness of the search term could influence the IAC estimate. Being able to track these factors for each study will allow us to better understand their influence on the IAC estimate.

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