Online Keyword Based Advertising: Impact of Ad Impressions on Own-Channel and Cross-Channel Click-Through Rates

Ram Gopal, Xinxin Li, Ramesh Sankaranarayanan

University of Connecticut, School of Business

{ram.gopal,xli,rsankaran}@business.uconn.edu

Abstract: Keyword-based ads are becoming the dominant form of advertising online as they enable customization and tailoring of messages relevant to potential consumers. Two prominent channels within this sphere are the search network and the content network. We empirically examine the interaction between these two channels. Our results indicate significant cannibalization across the two channels, as well as significant diminishing returns to impressions within each channel. This suggests that under certain conditions, both channels may need to be used to optimize returns to advertising, both for advertisers and service providers such as Google. Our game theoretic analysis reveals that for intermediate budget values, it is optimal to use both channels, whereas for very low (very high) budget values, it is optimal to use only the content (search) channel. Further, as budget increases, the advertiser should offer more for ads displayed on the search network to optimally incentivize the service provider.

Keywords: online keyword-based advertising, channel cannibalization

1. Introduction

Online advertising is becoming increasingly prominent. According to eMarketer, a leading online market research company, an estimated $23 billion was spent on online advertising of various forms in 2008, of which about $10 billion was spent on keyword based ads (primarily through search engines). Several different formats of online advertising have been tried out, including keyword-based ads (with a 2008 market share of 45%, according to eMarketer), banner ads (20%), classifieds (13%), rich media (8%), video ads (2%), and email based ads (2%). Google is estimated to control about 70% of the online advertising market, according to Browser Media, a UK-based Search Engine Marketing agency. Clearly, keyword-based advertising has come to dominate this landscape. Within keyword-based advertising, two distinct channels have emerged – search channel and content channel.

Ads in the search channel are displayed alongside search results, in response to the search keywords entered by the user. Ads in the content channel are displayed on a page containing content that is relevant to ads. The decision to show an ad on a content page is determined by the relevance of the ad to the content on the page. Search based advertising can be viewed as the more “active” of the two channels, because the user enters specific keywords that they are searching for information about. However, the philosophy behind both channels is the same – the focus is on trying to serve relevant ads based on an accurate determination of the user’s interest, either through keywords that the user enters (in the case of search channel), or through the nature of the content-website the user visits (in the case of content channel).

There are two main reasons why keyword-based ads have come to dominate online advertising – better targeting of customers and better measurability. First, service providers such as Google are successful at targeting such ads at the right audience at the right time, and in aligning users' interests with relevant ads. Second, the business model for keyword-based ads marks a radical departure from previous ad-business models, in that advertisers pay only when a user clicks on an ad (at a cost per click (CPC) that is set by the advertiser), instead of merely when an ad impression is served. An advertisement's main purpose is to bring a product or service to the attention of a potential customer. A user's clicking of an ad impression is a better indicator that this purpose is served, compared to the mere serving of an ad impression.

Google is the dominant company in keyword-based advertising, with 70% of all revenue. Almost 100% of Google's revenue is derived from keyword-based advertising (as per Google's annual report). Google serves keyword-based ads through both search and content channels. Google's data on search keyword based advertising has spawned an active stream of prior research that has looked at a variety of questions pertaining to bidding strategies, pricing of keyword slots, role of ad rank on conversions, and so on, but within the context of the search channel. Our research draws upon a Google ad-dataset that includes search as well as content channels, and focuses on the interaction effects between the search and content channels. This aspect has not been studied hitherto.

Since advertisers have a choice of displaying their ads over Google's search network and/or content network, this raises several questions for advertisers and service providers – do ads shown on one network affect the likelihood of similar ads being clicked on the other network, and if they do, should ads be shown over both networks, or over one network only? In addition, if both networks are chosen, how should the ad budget and impressions be optimally allocated between the two networks? This question is complicated by the fact that both channels are owned by the same firm (i.e. Google). These will be the main research questions studied in this paper.

We explore these questions by first formulating an empirical model to examine the interaction effects between the two networks. Our results suggest the presence of significant cross-channel cannibalization: with an increase in the number of impression on either channel, the click-through rate for the other channel decreases. While this result would imply that the advertiser and service provider should stick with one channel to display ads, this decision is complicated by our further finding on the presence of decreasing returns to impressions within-channel: with an increase in the number of impressions on either channel, the click-through rate for that channel decreases as well. Given the presence of both effects, how channels should be utilized optimally becomes a non-trivial question. We explore this optimal channel utilization problem by formulating a two-stage game theoretic model of interaction between the advertiser and service provider (such as Google). The game theoretic model also provides further managerial insights into the factors that affect the optimal allocation of ad dollars between the two channels. We find that when ad budget is very low (very high), it is better to use only the content (search) channel, but it is optimal to utilize both channels otherwise. Further, we find that when the ad budget increases, in order to properly incentivize the service provider, the advertiser should increase the cost-per-click for search, but not for content. Our research results will be of interest to online advertisers, as it will inform their ad placement choices and help them optimize their advertising dollars over multiple online channels.

The rest of this paper is organized as follows. Section 2 discusses the existing literature. Section 3 lays out the empirical analysis. Section 4 presents the game theoretic model with numerical analysis and results. Section 5 presents the conclusions and discussion.

2. Literature

Keyword based advertising is receiving increasing attention from academic researchers. Prior research on online keyword-based ads has examined this phenomenon from the perspectives of advertisers, service providers (such as Google), and consumers, exploring a range of questions pertaining to keyword auctions, improving rank allocation, impact of rank on clicking behavior, and adverse selection. Research in this area can be classified into various streams, based on the nature of problem being analyzed, which include (i) attempts to understand the optimal behavior of the service provider (such as Google or Yahoo) - e.g. by modeling keyword auction equilibria [16]; (ii) needs of the search intermediary - e.g. improved rank allocation mechanisms ([7], [17]); (iii) needs of advertisers – e.g. profitability of ad display rank [9]; (iv) behavior of advertisers, and implications for consumers who click on keyword based ads – e.g. quality uncertainty and adverse selection in performance based search advertising (use of cost per click) [1]; and (v) interaction effects between different aspects of keyword based search, with implications for advertisers – e.g. the relationship between what consumers search for and what they ultimately buy [10]. Our work is related to this stream of research on online keyword-based advertising. The novelty of our work lies in its focus on the impact of impressions on the click-through rates, both within and across advertising channels, which has not been examined in the prior studies mentioned above.

In the advertising literature, our work is most directly related to previous studies on media planning, and the optimal allocation of an ad budget among competing conventional media outlets. In one of the earliest papers in this area, [12] proposes a media model that will help advertisers make media decisions more effectively. Other work has considered the role of competing advertisers [13], the role of repetition (involving multiple media) on advertising effectiveness [14], and the possibility of collateral damage from advertising campaigns [4], wherein the ad message leaks to an "activist" audience for whom the ad was not targeted, resulting in damage to the brand. [8] studies the optimal allocation of an ad budget over a set of interacting market segments over multiple periods. Our research is similarly concerned with optimal allocation of advertising budgets, with a focus on *online* keyword based advertising channels – especially search and content channels.

Our work is relevant to the more general marketing literature on advertising as well. Recent work on online marketing has focused on a number of related issues. [3] models consumers' proclivity to click on banner ads. [15] studies the role of third party websites such as Edmunds.com that provide free information on competing products, and the implications for the vendors' product sales. More recently, [5] proposes a method to optimally select online media channels and the advertising impressions to be displayed from the chosen media. However, their work focuses on banner ads rather than keyword-based ads, and on traditional measures of advertising effectiveness such as reach, frequency and effective frequency as applied to impressions rather than clickthroughs. [6] develops and applies a multivariate generalization of a negative binomial distribution to page views across multiple websites, to predict the audience for internet ad campaigns. But none of this prior work has examined the impact of ad impressions on the within-channel and cross-channel information seeking behavior (i.e., clicks) of consumers, which is the focus of our study. Addressing the information seeking behavior of consumers is difficult or impossible in a conventional advertising setting, due to the absence of a reliable means of tracking information-seeking behavior by consumers. Our online ads dataset makes this analysis possible.

3. Empirical analysis

(a) Data Description

We obtained data from eight different Google Adwords accounts (for eight separate companies, including a mix of for-profit and non-profit organizations), over one month period. Each account can have one or more ad campaigns, and each campaign can contain one or more ad groups. We have in total 18 ad groups. A given ad group can serve several similar ads that can be posted to both search and content channels. For each ad group, the following information is available on a daily basis: the number of impressions (the number of times the ads were displayed) on search channel and content channel respectively, the number of clicks on the ads (from which the click through rate, or CTR, can be obtained) on the two channels respectively, the total cost incurred by the advertiser for all clicks of the ads for the day (from which the cost per click, CPC, can be obtained) on the two channels respectively, and the average rank of the ads (the average position in the sponsored ad list – the lower the rank is, the higher the position is) on the search channel. Table 1 presents the description of the variables used in this study and their descriptive statistics, and Table 2 presents their pairwise correlation matrix. In all variables, the subscript “i" represents ad group, the subscript “t” stands for time, the superscript “s” stands for search channel, whereas the superscript “c” stands for content channel.

[Insert Table 1 Here]

[Insert Table 2 Here]

Overall, we have 379 observations in the dataset. This corresponds to observations of 18 ad groups over 31 days with some ad groups not posting ads on any channel for certain days. If an ad group posts ads on only one channel for a day, it is still counted as one observation for which we assign value zero to the number of impressions on the other channel. CPC_{it}^{S} and CPC_{it}^{C} – cost per click on the search channel and content channel respectively – have fewer observations, because cost per click information is not available when there are no clicks, which happens for 179 observations in search channel and 270 observations in content channel. Click through rate information is available when there are no clicks but is not available when the number of impressions is zero. This explains why $\mathrm{CTR}_{\mathrm{it}}^{\mathrm{C}}$ has fewer observations – in 198 observations, the number of impressions on the content channel is zero.

Paired t tests suggest that $\mathrm{CPC}_{\mathrm{it}}^{\mathrm{S}}$ is slightly greater than $\mathrm{CPC}_{\mathrm{it}}^{\mathrm{C}}$; $\mathrm{CTR}_{\mathrm{it}}^{\mathrm{S}}$ is significantly less than $\mathrm{CTR}_{\mathrm{it}}^{\mathrm{C}}$; and $\mathrm{Impression}_{\mathrm{it}}^{\mathrm{S}}$ is not statistically different from $\mathrm{Impression}_{\mathrm{it}}^{\mathrm{C}}$. Accordingly, in our dataset, content channel seems to have a significantly higher click through rate. In the next two sections, we further examine the impact of cross-channel and within-channel impressions on consumers' clicking propensity (i.e., click through rate). Since all companies that participated in the exercise were very small companies and were not very tech savvy to track consumer conversion behavior, we unfortunately do not have consumer conversion data. Therefore, consumers' clicking behavior will be the main focus of this study.

(b) Regression Model

To examine the nature of channel interaction and within-channel effects, we allow CTR of either channel to be affected by both the number of impressions on its own channel (to capture within-channel effects) and the number of impressions on the other channel (to capture cross-channel effects). To be consistent with previous literature (e.g. [9]), we also allow CTR on the search channel to be affected by the position of the ad (Rank). Since CTR is between 0 and 1, it is modeled as a nonlinear function in models (1) and (2), where the lagged dependent variable is added in each regression to account for unobserved heterogeneity across different ad groups (since the likelihood of these ads being clicked can be inherently different).

$$\mathrm{CTR}_{it}^{S} = \frac{\exp\left(a_0 + a_1 \mathrm{Rank}_{it}^{S} + a_2 \mathrm{Impression}_{it}^{C} + a_3 \mathrm{Impression}_{it}^{S} + a_4 \mathrm{CTR}_{it-1}^{S}\right)}{1 + \exp\left(a_0 + a_1 \mathrm{Rank}_{it}^{S} + a_2 \mathrm{Impression}_{it}^{C} + a_3 \mathrm{Impression}_{it}^{S} + a_4 \mathrm{CTR}_{it-1}^{S}\right)} + e_{it} \qquad (1)$$

$$\mathrm{CTR}_{it}^{C} = \frac{\exp\left(b_0 + b_2 \mathrm{Impression}_{it}^{C} + b_3 \mathrm{Impression}_{it}^{S} + b_4 \mathrm{CTR}_{it-1}^{C}\right)}{1 + \exp\left(b_0 + b_2 \mathrm{Impression}_{it}^{C} + b_3 \mathrm{Impression}_{it}^{S} + b_4 \mathrm{CTR}_{it-1}^{C}\right)} + \delta_{it} \qquad (2)$$

In models (1) and (2), a_2 and b_3 capture the cross-channel effects, and a_3 and b_2 capture the within-channel effects. If a_2 and b_3 are negative (positive), then impressions on one channel will cannibalize (reinforce) clicks on the other channel. If a_3 and b_2 are negative (positive), then increasing impressions in one channel will be likely to decrease (increase) its own CTR, suggesting within-channel decreasing (increasing) returns to impressions.

Because in models (1) and (2), the independent variables $\mathrm{Rank}_t^S, \mathrm{Impression}_t^C$ and $\mathrm{Impression}_t^S$ are determined by the service provider (Google) who may take into account consumers' clicking behavior when making these decisions, these variables can potentially be endogenous. Thus to appropriately identify models (1) and (2) empirically, we further model the service provider's decisions on rank and impressions explicitly.

Service provider's decision on assigning ranks to a sponsored ad is usually made through a keyword ad auction, in which advertisers bid by submitting the maximum CPC they agree to pay. The service provider maximizes its ad revenue by taking into account both the CPC bids and the likelihood of different ads being clicked ([16], [2]), while the latter part can be estimated using the CTR that is most recently observed. Therefore, consistent with previous literature (e.g. [9]), we use both CPC and the one period lagged value of CTR to model rank in model (3) where the lagged dependent variable is again added to control for heterogeneity across ad groups. In a similar manner, we model impressions on the two channels as the functions of the CPC bids and the one period lagged value of CTRs on the two channels respectively in models (4) and (5).

$$\ln\left(\mathrm{Rank}_{it}^S\right) = f_0 + f_1 \mathrm{CPC}_{it}^S + f_2 \mathrm{CTR}_{it-1}^S + f_3 \ln\left(\mathrm{Rank}_{it-1}^S\right) + u_{it} \quad (3)$$

$$\ln\left(\mathrm{Impression}_{it}^S\right) = h_0 + h_1 \mathrm{CPC}_{it}^S + h_2 \mathrm{CTR}_{it-1}^S + h_3 \ln\left(\mathrm{Impression}_{it-1}^S\right) + v_{it} \quad (4)$$

$$\ln\left(\mathrm{Impression}_{it}^C\right) = g_0 + g_1 \mathrm{CPC}_{it}^C + g_2 \mathrm{CTR}_{it-1}^C + g_3 \ln\left(\mathrm{Impression}_{it-1}^C\right) + \omega_{it} \quad (5)$$

In models (3), (4) and (5), the service provider makes decisions by taking into account the advertiser's choices of CPC bids on both channels.[1] [9] suggests that the advertiser chooses a keyword's CPC based on the keyword's past performance – specifically, the rank of the same keyword in previous period. Accordingly, we model CPCs in both channels as functions of lagged rank in models (6) and (7) where the lagged dependent variable is again added to control for heterogeneity across ad groups.

$$\ln\left(\mathrm{CPC}_{it}^{S}\right) = c_0 + c_1 \mathrm{Rank}_{it-1}^{S} + c_1 \ln\left(\mathrm{CPC}_{it-1}^{S}\right) + \varepsilon_{it} \tag{6}$$

$$\ln\left(\mathrm{CPC}_{it}^{C}\right) = d_0 + d_1 \mathrm{Rank}_{it-1}^{S} + d_2 \ln\left(\mathrm{CPC}_{it-1}^{C}\right) + \varphi_{it} \tag{7}$$

(c) Empirical Results

By modeling consumers' clicking behavior and both the service provider's and the advertiser's decisions explicitly, we can now see that (1) – (7) closely resembles the triangular system in standard econometrics [11]. Specifically, since Rank_{it-1}^{S}, CPC_{it-1}^{S} and CPC_{it-1}^{C} are given in period t, CPC_{it}^{S} and CPC_{it}^{C} can be considered as exogenously determined. They in turn affect Rank_{it}^{S}, $\mathrm{Impression}_{it}^{S}$ and $\mathrm{Impression}_{it}^{C}$, which then further affect CTR_{it}^{S} and CTR_{it}^{C}. Therefore, models (1) – (7) can be treated as non-simultaneous, and can be estimated independently or using seemingly unrelated regression (SUR) if error terms of models (1) – (7) are correlated. In this case, since there are no cross-model constraints and SUR estimates only have potential to improve efficiency but not consistency, OLS estimates can be considered more conservative. In addition, SUR estimates of (1) - (7) can utilize only the 37 observations that are common to all seven models, leaving out all the other observations, potentially affecting the consistency of

[1] Since we do not have data on actual bids, we use the cost per click that is actually incurred as the proxy. This proxy is also used in previous literature (e.g. [9]).

the results. Therefore, we first report the result of standard OLS regression for each model separately in Table 3. Cluster robust standard errors are used to control for potential serial correlation within ad group and heteroskedasticity. We use lagged dependent variables to control for unobserved heterogeneity across different ad groups instead of ad group fixed effects given the unbalanced and short panel of data. In addition, lagged dependent variables can control for unobserved heterogeneity that may change over time. According to Table 2, only CPC_{it}^{S} and CPC_{it}^{C} are highly correlated, which do not appear in the same regression, and so multicollinearity is not an issue here.

[Insert Table 3 Here]

Since our main focus in this study is on the impacts of cross-channel and within-channel impressions on consumers' clicking propensity (CTR), we will focus our discussion on models (1) and (2). The results of these two models in Table 3 suggest the following three main findings.

First, the impact of $\mathrm{Impression}_{it}^{C}$ on CTR_{it}^{S} and the impact of $\mathrm{Impression}_{it}^{S}$ on CTR_{it}^{C} are both negative, suggesting channel cannibalization effects between Google search channel and content channel.

Second, the impact of $\mathrm{Impression}_{it}^{S}$ on CTR_{it}^{S} and the impact of $\mathrm{Impression}_{it}^{C}$ on CTR_{it}^{C} are both negative. This suggests that CTR in each channel decreases as the number of impressions on its own channel increases.

Third, the negative impact of $\mathrm{Impression}_{\mathrm{it}}^{\mathrm{C}}$ on $\mathrm{CTR}_{\mathrm{it}}^{\mathrm{C}}$ is significantly higher than the two cannibalization effects as well as the negative impact of $\mathrm{Impression}_{\mathrm{it}}^{\mathrm{S}}$ on $\mathrm{CTR}_{\mathrm{it}}^{\mathrm{S}}$.

To corroborate our analysis, we also report the result of SUR regression in Table 4 which controls for potential correlations among error terms of models (1) – (7). All the three findings are supported. Although in Table 3, the impact of $\mathrm{Impression}_{\mathrm{it}}^{\mathrm{S}}$ on $\mathrm{CTR}_{\mathrm{it}}^{\mathrm{S}}$ is not significant and the impact of $\mathrm{Impression}_{\mathrm{it}}^{\mathrm{C}}$ on $\mathrm{CTR}_{\mathrm{it}}^{\mathrm{S}}$ is significant at only 10% level, in our corroboration analysis in Table 4, after controlling for correlations among error terms of models (1) – (7), they are both significant at the conventional 5% level.

[Insert Table 4 Here]

These three findings together suggest that increasing the number of impressions on one channel is likely to be associated with lower CTRs on both channels. In addition, for an ad that appears on content channel, an additional impression on its own channel (i.e. a content page) has a bigger negative impact on CTR compared to an additional impression on the other channel (i.e. a search page).

Other than the main results which are new to the literature, the other results are consistent with those in previous literature (e.g. [9]). As shown in model (1), ads placed in lower ranks (i.e. higher positions in the sponsored ads list) have a higher probability of getting clicked (i.e. higher CTR). As shown in model (3), the service provider (Google) places ads that have high CPC and good past performance in lower ranks (i.e., higher positions in the sponsored ads list). Models (6) and (7) suggest a negative relationship between CPC and lagged rank, suggesting that the advertisers may not be necessarily bidding optimally. This finding, which also appeared in [9], especially makes sense for our data given the small size of the advertising companies and the short length of the observation periods. Models (4) and (5) in Table 4, after controlling for correlations among error terms of seven models, suggest that Google's decision on Impressions are not significantly affected by CPC and past performance (lagged CTR) except on content channel where the number of impressions posted positively relates to CPC.

4. Optimization of channel utilization from a game theoretic perspective

We now focus on the implications of the empirical findings. Empirically, we find that increasing the number of impressions on one channel is associated with lower click-through rates on both channels. We explore how this affects the optimal policies of the ad service provider (such as Google) and the advertiser. Should they rely on just one channel, or should they mix both channels?

To answer this question, we use the empirical framework to formulate a game theoretic model of interaction between the service provider and advertiser. For any day (t), in a two stage model (see Figure 1), the advertiser moves in the first stage to select the cost per click for the search network (CPC_t^S) and the content network (CPC_t^C) given the budget ($Budget_t$) to maximize her expected number of clicks for an ad. In the second stage, given the advertiser's budget and choice of CPCs, the service provider maximizes her profit by choosing the optimal number of impressions of the ad on the search and content network, subject to the budget constraint. This results in a certain number of clicks on each network, which yields a monetary payoff to the service provider. The advertiser incurs the associated cost of the clicks, and enjoys the resulting utility from web-page visits. In our paper, the advertiser's objective is to maximize the expected number of clicks for a given budget. Therefore, for a given budget, we compute the optimum number of impressions for each allocation of CPCs for search and content network from the service provider's perspective, and then choose the CPC allocation that maximizes the number of clicks from the advertiser's perspective. Since there is only one advertiser in this game theoretic analysis, subscript "i" is omitted in all variables in this section.

[Insert Figure 1 Here]

We solve this game theoretic model by backward induction. In the second stage, the advertiser's choices of CPC_t^S and CPC_t^S are given to the service provider. They affect the rank of the ad, as per equation (3) of the regression model:

$$\ln(Rank_t^S) = f_0 + f_1 CPC_t^S + f_2 CTR_{t-1}^S + f_3 \ln(Rank_{t-1}^S).$$

The service provider chooses the number of impressions on the two channels ($Impression_t^S$ and $Impression_t^C$). $Rank_t^S$,$Impression_t^S$ and $Impression_t^C$ together affect the click through rates on the two channels (CTR_t^S and CTR_t^C) as per equation (1) and (2) from the regression model:

$$CTR_t^S = \frac{\exp\left(a_0 + a_1 Rank_t^S + a_2 Impression_t^C + a_3 Impression_t^S + a_4 CTR_{t-1}^S\right)}{1+\exp\left(a_0 + a_1 Rank_t^S + a_2 Impression_t^C + a_3 Impression_t^S + a_4 CTR_{t-1}^S\right)},$$

$$CTR_t^C = \frac{\exp\left(b_0 + b_2 Impression_t^C + b_3 Impression_t^S + b_4 CTR_{t-1}^C\right)}{1+\exp\left(b_0 + b_2 Impression_t^C + b_3 Impression_t^S + b_4 CTR_{t-1}^C\right)}.$$

The coefficients in the three equations above are taken from table 3 and the average values from table 1 are used for previous period's click through rates CTR_{t-1}^S and CTR_{t-1}^C and previous period's rank $Rank_{t-1}^S$. and other In our empirical analysis, these lagged values are added to control for unobserved heterogeneity across ads. They convey the same meaning here and capture whether the ad is in nature likely to have low rank and/or high click through rate. In our numerical analysis, we also vary the values assigned to these lagged variables to check the robustness of our results. Overall, according to the three equations above, CTR_t^S and CTR_t^C are simply functions of CPC_t^S, $Impression_t^S$, $Impression_t^C$ and other constants.

For impressions, we ascribe a "Cost Per Impression" for search (CPI^S) and content (CPI^C) – a small cost incurred by the service provider for the display of each impression, in order to capture the opportunity cost to the service provider. (Please note that we do not have CPI information, as that is the search engine's proprietary information.)

The profit function of the service provider from the search and content networks is therefore given by the expression

$$\min\{Budget_t, (CTR_t^S * Impression_t^S * CPC_t^S + CTR_t^C * Impression_t^C * CPC_t^C)\} - (CPI^S * Impression_t^S + CPI^C * Impression_t^C).$$

Once the advertiser's choices of CPC_t^S and CPC_t^S are given, the above profit function is basically a function of $Impression_t^S$ and $Impression_t^C$ and other given constants. Therefore, the service provider maximizes the above profit function by selecting the number of impressions on the two channels for each given budget and CPC allocation:

$$\max_{(Impression_t^S, Impression_t^C)}[\min\{Budget_t, (CTR_t^S * Impression_t^S * CPC_t^S + CTR_t^C * Impression_t^C * CPC_t^C)\} - (CPI^S * Impression_t^S + CPI^C * Impression_t^C)].$$

Working backward, in the first stage of the game, the total number of clicks that the advertiser expects to get from both channels is

$$CTR_t^S * Impression_t^S + CTR_t^C * Impression_t^C,$$

where $Impression_t^S$ and $Impression_t^C$ will be chosen by the service provider based on the budget and the advertiser's choices of CPC_t^S and CPC_t^S, whereas CTR_t^S and CTR_t^C are functions of CPC_t^S, $Impression_t^S$ and $Impression_t^C$. Thus, the advertiser chooses (for a given budget constraint) the cost per click values that will motivate the service provider to maximize the number of clicks on search and content network:

$$\max_{(CPC_t^S, CPC_t^C)}[CTR_t^S * Impression_t^S + CTR_t^C * Impression_t^C].$$

(a) Numerical analysis

To illustrate the interaction between the advertiser and service provider, suppose the advertiser's budget is $1 for a day, and she chooses a cost per click for search (CPC_t^S) of 30 cents, and 20 cents for content (CPC_t^C). The service provider works within these constraints and determines her optimal number of impressions, which turns out to be 187 impressions on the search network, and 7 impressions on the content network. That results in on average about 0.7 clicks on the search network, and 3.7 clicks on the content network. That yields revenue of 95 cents to the service provider, and a maximum profit of 75 cents (after accounting for the cost of impressions, assumed to be 0.1 cents for the search network, and 0.2 cents for the content network).

Now, from the advertiser's perspective, for the given budget of $1, we compute the number of clicks obtained for all possible combinations of CPC_t^S and CPC_t^C. The advertiser should choose the (CPC_t^S, CPC_t^C) combination that yields the maximum number of clicks across both networks putting together, which turns out to be (40 cents, 10 cents).

Thus, in this particular example, optimally the advertiser should select the combination of CPC as (40 cents, 10 cents) and the service provider will select the number of impressions to be 433 impressions on the search network and 7 impressions on the content network. The expected number of clicks from both networks will be about 5.17.

In our numerical analysis, we vary the advertiser's budget and for each budget value, we consider all possible values of CPC_t^S and CPC_t^C starting from 10 cents in increments of 10 cents to derive the optimal solutions. We also vary different parameters in the model, such as budget, CPIs, and lagged variables, to examine the pattern of optimal ad allocation across channels.

(b) Results

We find that when both parties behave optimally, ads are displayed only on the content channel when the budget is small, but for higher budget values, both channels are utilized (see Figure 2). Increasingly more impressions will be placed on the search channel while the number of impressions on the content channel is weakly decreasing. Following this trend shown in Figure 2 (verified also by further simulations), we also find that for extremely high budget values, ads may be displayed only on the search channel. These results arise because the content network features a high payoff for a small number of impressions; however this is quickly followed by significantly high diminishing returns to impressions. Thus, for low budget campaigns, it may be optimal to use only the content channel. But to get a large number of clicks for a high budget, it is optimal to rely more on the search channel. As the number of impressions on the search channel increases continuously, however, the cross-channel cannibalization effect will reduce the effectiveness of the content channel, eventually to the point where the effectiveness of content channel is so low that it may not be utilized at all for extremely high budgets. This answers a key question raised by the empirical analysis – the presence of cannibalization across channels does not imply that only one channel should be used under all conditions.

[Insert Figure 2 Here]

By further examining the tension between the two parties, we find that as budget increases, to induce the service provider to display ads on both channels, the advertiser has to increase its cost per click value constantly for the search channel to achieve more clicks, but not necessarily for the content channel (see Figure 3). This follows because of two reasons. First, the relatively lower click through rates on the search network imply that to get the same number of clicks, the service provider needs to display more impressions on the search channel than on the content channel. This is costly to the service provider, who in turn requires higher reimbursement (i.e, higher CPC). Second, the significant high diminishing returns to impressions on the content channel suggest that once the first few clicks are achieved on the content channel, its click through rates can become so low that it is not cost effective for the advertiser to increase CPC significantly to get more clicks from that channel.

[Insert Figure 3 Here]

These results are robust whether the cost per impression is higher for search network or for content network as long as they are not so high that any impression on either channel is cost prohibitive for the service provider. These results are also robust to different values of lagged CTRs and lagged rank, which, as we discussed before, capture the unobserved characteristic of the ads.

The optimal number of clicks increases with budget, but tends to display diminishing returns (see Figure 4). This can be explained by the cross-channel cannibalization effects and within-channel diminishing returns to impressions. This diminishing return of clicks to budget is especially evident for ads that in nature are less likely to be clicked on the search channel, for example, the ones with higher lagged rank (lower position in the sponsored ads list on the search channel) or lower lagged CTR on the search channel (see Figure 4). For these ads, since the effectiveness of search ads is low, this results in a greater impact of content ads, which however suffer from very high diminishing returns. In addition, our earlier results suggest a greater reliance on search based advertising as budget increases. This further explains why we observe that the number of clicks flattens out for higher budgets especially for ads that are in nature less likely to be clicked on the search channel (i.e. with lower lagged rank and CTR on search channel).

[Insert Figure 4 Here]

In contrast, how likely an ad inherently is clicked on the content network (as measured by lagged click through rate on the content network) does not have a commensurate effect on the number of clicks obtained for various budget values (see Figure 5). This reflects the fact that for higher budget values, there is a greater reliance on search rather than content network, so that an inherent lower likelihood to be clicked on the content network does not have much impact on the number of clicks for higher budgets.

[Insert Figure 5 Here]

While our results are robust to the cost per impression values on the two channels, we also find that the advertiser gets a better payoff for her spending when the cost per impression is lower for search, compared to content (see Figure 6). This is interesting since posting impressions incur costs only to the service provider, not to the advertiser. This result is driven by our earlier result that a higher budget demanding a higher number of clicks will require significantly more ads on search channel. If cost per impression is higher on search, fewer impressions can be displayed for a given budget, which results in fewer clicks for the advertiser.

[Insert Figure 6 Here]

5. Conclusion and Discussion

To conclude, in this paper we present an analysis of interaction between ad impressions and within-channel and cross-channel click-through behavior in online keyword-based advertisements over search and content networks. This is novel in the context of research on online keyword advertising, where previous work has focused on other issues such as optimal rank-allocation of search ads and the impact of rank on ad performance. Additionally, our work is novel in the context of work on advertising in general that is related to multiple media planning, as we explore the role of ad impressions in influencing the information-seeking behavior of consumers across multiple channels. The availability of click-through data, which was hitherto not available in conventional media settings, makes it possible to conduct this analysis.

Our empirical analysis finds that ad impressions on the search network are associated with a decrease in click-through rates on the content network, and vice-versa. We also find evidence of a within-channel effect, wherein an increase in ad impressions on the search (or content) network is associated with a decrease in click-through rates on the same search (or content) network. We use the empirical results to formulate a model of the strategic interaction between the advertiser and service provider in the form of a two-period game, wherein the advertiser chooses the cost per click values given budget in the first period to maximize her expected number of clicks, and the service provider chooses the number of impressions given the advertiser's choice of CPC values to maximize her click-driven profit. A numerical analysis of this model reveals that to get the initial few clicks, the advertiser will choose cost per click values to motivate the service provider to post the ads on the content channel first. As budget increases, the advertiser will motivate the service provider to increasingly post more impressions on the search channel and eventually maybe to utilize the search channel solely if budget is extremely high. In this process, to motivate the service provider, the advertiser needs to increase cost per click for search channel constantly as budget increases, but not necessarily for the content channel.

Our results also have implications for the ROI (return on investment) of the advertiser. When budget size increases, the number of clicks can be expected to increase but with a decreasing rate of return. However, this decreasing return is especially sensitive to an ad's inherent likelihood of being clicked on the search channel, but not to that likelihood on the content channel. Finally, when the cost per impression (for the service provider) is lower for showing impressions on the search network, compared to the content network, that results in a better payoff for the advertiser in the form of more clicks at higher budgets. These results have important implications for managers in companies that seek to harness the power of online keyword-based advertising, as well as for firms (such as Google) that seek to optimize their returns from keyword-based ads.

Ours is early work in this growing area, but we are mainly constrained by lack of data. For instance, we do not know the actual costs per impression incurred by Google or other comparable service providers. Further, we do not know the extent of actual overlap between consumers who view ads on the search and content networks. Our data is for eight small companies over a one month period. Having data on more companies from a more diverse pool over a longer time period could be helpful. As a result, the generalization of our results to companies with higher budgets can be explored in future work.

Tables

Table 1 Descriptive Statistics

Variable	Description	Number of Observations	Mean	Standard Deviation	Min	Max
CPC_{it}^{C}	Average cost per click on content channel on day t for ad group i	109	0.62	0.55	0.18	3.99
CTR_{it}^{C}	Click through rate on content channel on day t for ad group i	181	0.08	0.24	0	1
$Impression_{it}^{C}$	Number of impressions on content channel on day t for ad group i	379	4344.19	30091.29	0	462707
$Rank_{it}^{S}$	Average rank on search channel on day t for ad group i	379	5.18	5.37	1.1	90
CPC_{it}^{S}	Average cost per click on search channel on day t for ad group i	200	0.72	1.04	0.05	10
CTR_{it}^{S}	Click through rate on search channel on day t for ad group i	379	3.07e-2	0.01	0	0.07
$Impression_{it}^{S}$	Number of impressions on search channel on day t for ad group i	379	2692.13	5913.89	1	51442

Table 2 Pairwise Correlation Matrix

	CTR_{it}^{S}	CPC_{it}^{S}	$Impression_{it}^{S}$	$Rank_{it}^{S}$	CTR_{it}^{C}	CPC_{it}^{C}	$Impression_{it}^{C}$
CTR_{it}^{S}	1						
CPC_{it}^{S}	0.07	1					
$Impression_{it}^{S}$	-0.13	0.04	1				
$Rank_{it}^{S}$	-0.14	-0.24	-0.11	1			
CTR_{it}^{C}	0.32	-0.09	-0.10	-0.03	1		
CPC_{it}^{C}	0.04	0.93	0.12	-0.38	-0.08	1	
$Impression_{it}^{C}$	-0.06	0.07	0.45	-0.06	-0.07	0.09	1

Table 3 OLS estimates of models (1) – (7)

Dependent Variable	(1) CTR_{it}^{S}	(2) CTR_{it}^{C}	(3) $\ln(Rank_{it}^{S})$	(4) $\ln(Impression_{it}^{S})$	(5) $\ln(Impression_{it}^{C})$	(6) $\ln(CPC_{it}^{S})$	(7) $\ln(CPC_{it}^{C})$
CPC_{it}^{S}			-0.06**	-0.15			
			(0.02)	(0.16)			
CPC_{it}^{C}					0.16		
					(0.22)		
$Rank_{it-1}^{S}$	-0.46**					0.02	-0.09**
	(0.18)					(0.05)	(0.04)
$Impression_{it}^{S}$	-1.07e-4	-3.15e-4**					
	(7.19e-5)	(1.39e-4)					
$Impression_{it}^{C}$	-2.09e-3*	-0.32***					
	(1.12e-3)	(0.11)					
CTR_{t-1}^{S}	26.87***		-6.72**	-29.74*			
	(9.12)		(3.15)	(16.11)			
CTR_{it-1}^{C}		2.43***			1.22		
		(0.61)			(1.40)		
$\ln(Rank_{it-1}^{S})$			0.51***				
			(0.09)				
$\ln(Impression_{it-1}^{S})$				0.43***			
				(0.11)			
$\ln(Impression_{it-1}^{C})$					0.77***		
					(0.19)		
$\ln(CPC_{it-1}^{S})$						1.05***	
						(0.05)	
$\ln(CPC_{it-1}^{C})$							0.85***
							(0.08)
Constant	-3.60***	2.23**	0.70***	4.50***	1.84	-0.02	0.20
	(0.75)	(1.03)	(0.14)	(0.96)	(1.50)	(0.14)	(0.12)
Observations	358	136	186	186	83	149	59
R-squared	0.421	0.965	0.471	0.342	0.479	0.791	0.791

Cluster Robust Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4. SUR estimates of model (1) – (7)

Dependent Variable	(1) CTR_{it}^{S}	(2) CTR_{it}^{C}	(3) $\ln(Rank_{it}^{S})$	(4) $\ln(Impression_{it}^{S})$	(5) $\ln(Impression_{it}^{C})$	(6) $\ln(CPC_{it}^{S})$	(7) $\ln(CPC_{it}^{C})$
CPC_{it}^{S}			-0.03*	0.10			
			(0.02)	(0.10)			
CPC_{it}^{C}					0.50**		
					(0.21)		
$Rank_{it-1}^{S}$	-0.32*					-0.10	-0.09**
	(0.17)					(0.10)	(0.03)
$Impression_{it}^{S}$	-3.64e-4***	-3.87e-4***					
	(1.04e-4)	(1.21e-4)					
$Impression_{it}^{C}$	-8.28e-5**	-0.03***					
	(3.67e-5)	(0.01)					
CTR_{t-1}^{S}	13.05		-14.39**	38.41			
	(18.05)		(6.06)	(54.49)			
CTR_{it-1}^{C}		-0.69			2.11		
		(0.68)			(1.67)		
$\ln(Rank_{it-1}^{S})$			0.71***				
			(0.05)				
$\ln(Impression_{it-1}^{S})$				0.64***			
				(0.13)			
$\ln(Impression_{it-1}^{C})$					0.76***		
					(0.16)		
$\ln(CPC_{it-1}^{S})$						0.80***	
						(0.11)	
$\ln(CPC_{it-1}^{C})$							0.86***
							(0.07)
Constant	-3.78***	2.02**	0.38***	2.96**	1.58	0.28	0.19
	(0.63)	(0.85)	(0.07)	(1.17)	(1.41)	(0.29)	(0.15)
Observations	37	37	37	37	37	37	37
R-squared	0.811	0.970	0.819	0.372	0.427	0.757	0.820

Robust Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Figures

Figure 1 Time line of the two-stage game-theoretical model

Figure 2 Optimal numbers of impressions on the two channels for different budgets

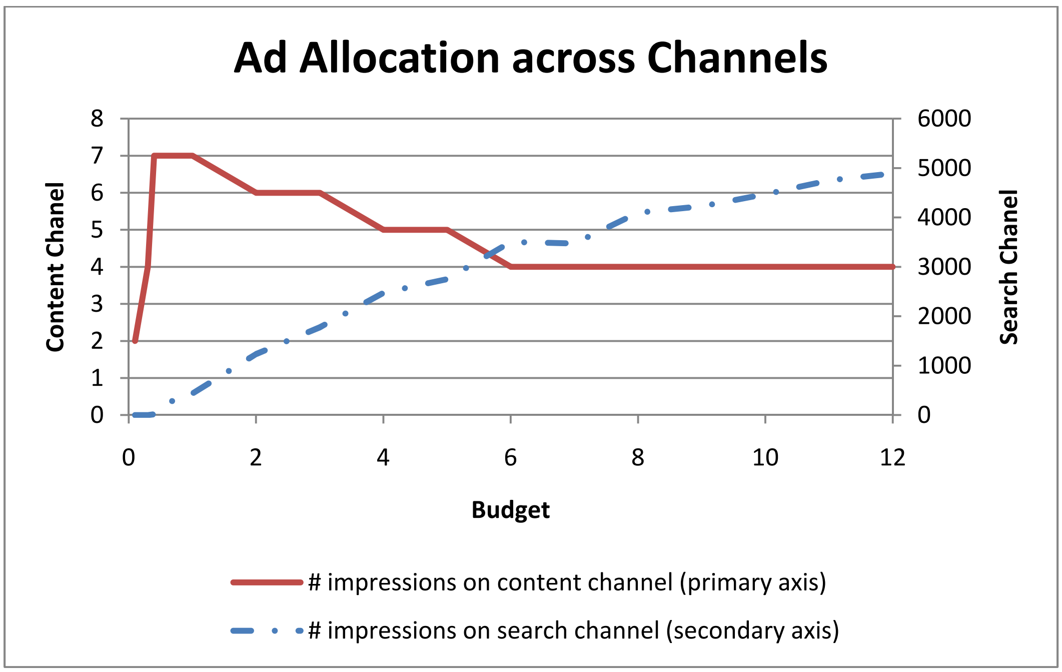


Figure 3 Optimal cost per click values for the two channels for different budgets

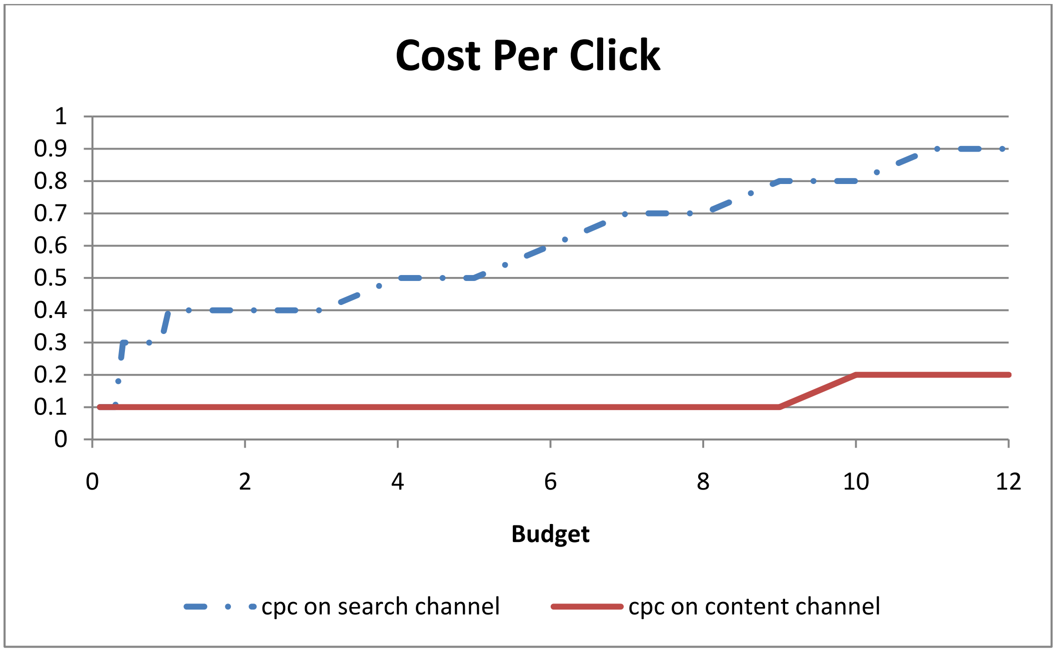
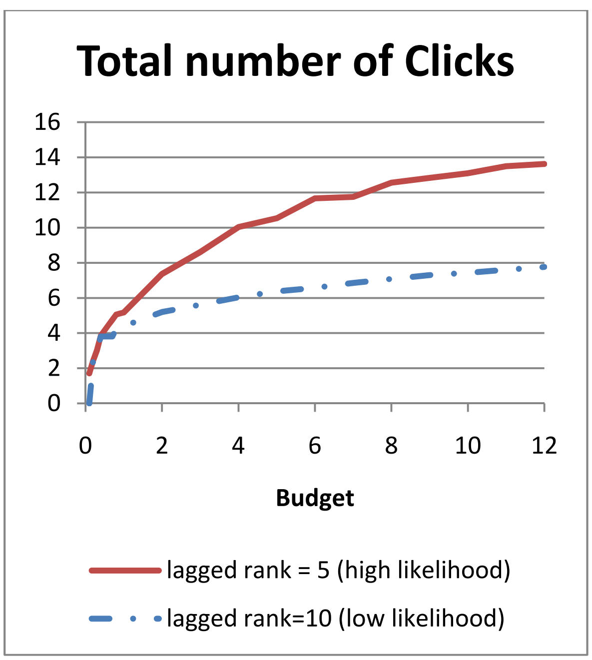


Figure 4 Total numbers of clicks under optimal ad allocation for ads with different likelihood of being clicked on the search channel



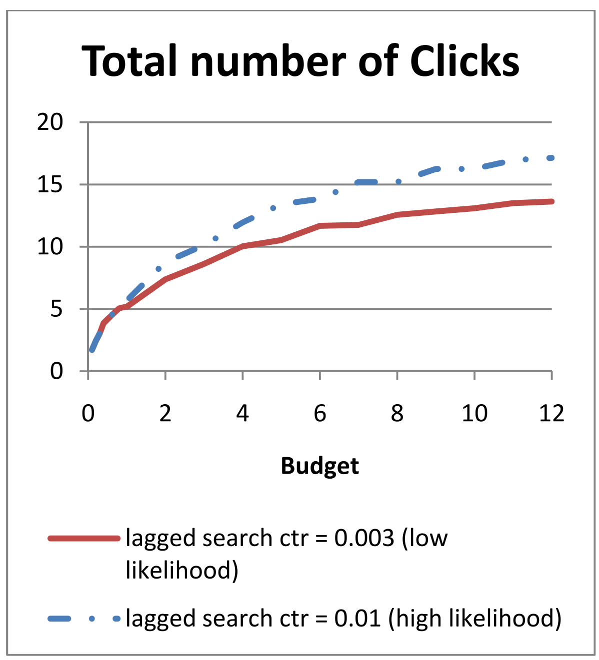


Figure 5 Total numbers of clicks under optimal ad allocation for ads with different likelihood of being clicked on the content channel

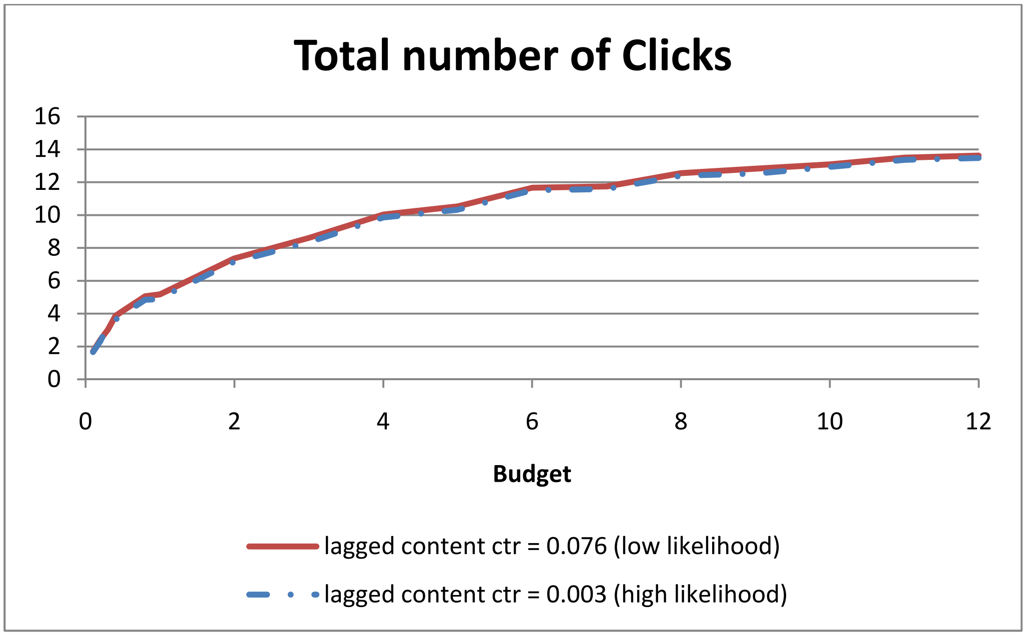
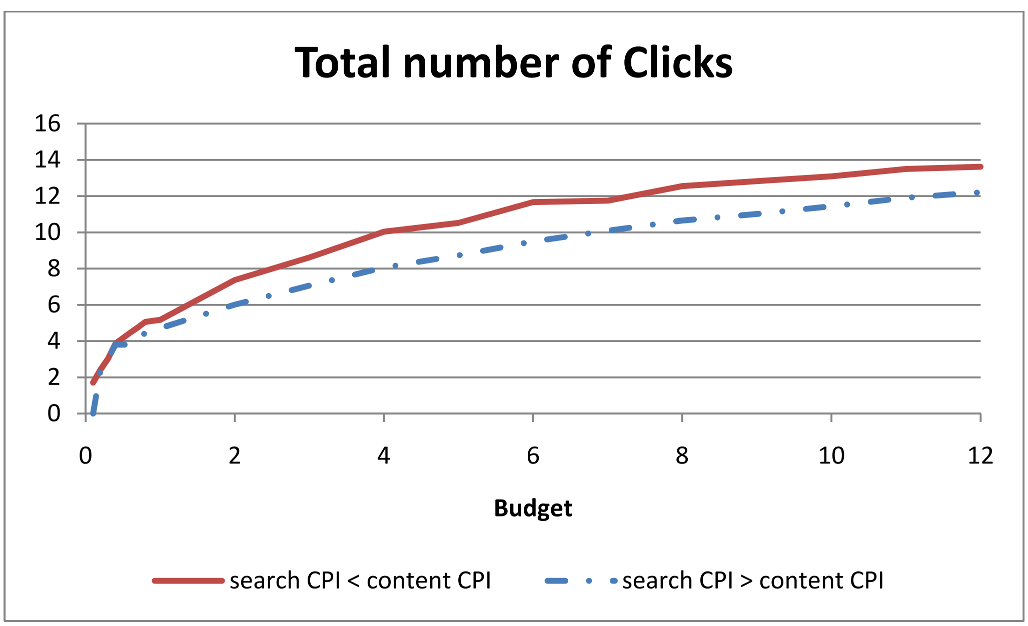


Figure 6 Total numbers of clicks under optimal ad allocation for different costs of impressions (CPI)



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