Strategic Bidder Behavior in Sponsored Search Auctions

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Abstract

We examine prior and current sponsored search auctions and find evidence of strategic bidder behavior. Between June 15, 2002, and June 14, 2003, we estimate that Overture's revenue from sponsored search could have been substantially higher if it had been able to prevent this strategic behavior. We also show that advertisers' strategic behavior has not disappeared over time; rather, such behavior remains present on both Google and Overture. We conclude by discussing alternative auction designs that could reduce this strategic behavior and raise search engines' revenue, as well as increase the overall efficiency of the market.

Keywords: auction design, mechanism design, efficiency, revenue maximization.

1 Introduction

Search engines have considerable flexibility in designing systems to allocate their sponsored links. Modern information systems make it easy to receive information from advertisers about their desired ad placements and other goals, as well as to provide feedback about outcomes. But how exactly should search engines structure these sales?

Auctions are a natural choice. They relieve sellers of explicitly assigning a valuation to each item to be sold; instead, the market structure naturally assigns a valuation [7]. This benefit is surely substantial in the context of thousands of search keywords, each independently valued by different would-be advertisers. Furthermore, auctions generally assure that each available item is sold—also an important benefit, since search advertising inventory is perishable, disappearing instantly if no advertisement is available to fill a placement spot.

Hence, it is not surprising that most search engines choose to auction off their sponsored link advertisements. But even after choosing an auction over alternative sales channels, important decisions remain to be made. How much information should advertisers receive about other advertisers' bids? In what order should bids be shown in search results? What relationship should there be

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between an advertiser's bid and the amount the advertiser is actually charged? More broadly, how should these auctions be designed?

While it is clear that differently designed auctions will have different properties, it is not immediately obvious that these differences are important enough for market designers to worry about. After all, if there are many bidders who compete for the same keywords, prices might be expected to be close to efficient, and revenue might be close to the highest possible level. In this paper, we show that this is not necessarily the case, and that auction design is a first-order question in these markets. More specifically, we estimate that during the period for which we have bidding data, an alternative design would have increased the revenues of a major search engine by more than 14%. If the rate of losses is the same today (which, of course, we cannot be certain about), our results imply that the search engine can raise its revenues by more than $400 million per year.[1]

We emphasize search engine revenue conditional on users staying at search engines, and search engines remaining otherwise the same. We bracket the important issues raised in [1] and [8] as to a tradeoff between advertisement inclusion and a notion of quality (i.e., user satisfaction); this tradeoff should not be altered by the change from one auction structure to another. We also put aside the relationship between relevance and advertiser valuations, as raised in [5]. Instead, we take advertiser valuations as given, conditional on other search engine characteristics (i.e., overall quality, user demographics, etc.), which we take to be unchanged across our counterfactuals.

The remainder of this article proceeds in three parts. In Section 2, we explain why auction design matters to such a large extent, and we estimate revenue losses based on historical bidding data. In Section 3, we present an analysis of current advertisement data, suggesting that strategic bidding behavior and opportunities for revenue improvements have not disappeared. In Section 4, we present a specific improvement—the use of Vickrey auctions to induce truthful bidding and discourage strategic behavior. In Section 5, we conclude by discussing potential design improvements.

2 Strategic Behavior: Historical Evidence from Bidding Data and Estimates of Revenue Losses

In this section, we present evidence of strategic behavior of bidders using Overture's paid placement auctions between June 2002 and June 2003.[2] During this period, Overture generally operated a first-price auction. That is, when a user clicked on an advertiser's link, the advertiser paid Overture the amount of his bid.

This first-price auction structure is naturally unstable, in the sense that if bids can be adjusted frequently, bidders will not state their true valuations, and will keep changing their bids in response to other bidders' behavior. For example, in a keyword market with two advertisers, suppose a click is worth $0.60 to the first advertiser and $0.80 to the second. If the first advertiser bids $0.60, the second will bid $0.61, thereby claiming the first spot.[3] Then, the first bidder is likely to lower

[1] This number is based on the search engine's latest revenue estimates.

[2] Overture was acquired by Yahoo! in the second half of 2003, after the end of our sample.

[3] Assuming, of course, that the top spot is more desirable than the second spot.

his bid to the minimum bid (say, \$0.05), reducing his costs while still preserving his number two position, apparently the best position he can obtain given the other advertiser's high bid. But then the second advertiser will lower his bid, e.g., to \$0.06, and the advertisers will raise each other in pennies until the second advertiser again outbids the first advertiser's valuation (e.g., with a bid of \$0.61), and the first advertiser again drops back to the minimum bid. Under these assumptions, their cycling will continue indefinitely.

Moreover, some Overture advertisers apparently used an "autobid" system, whereby an Overture software system automatically adjusted an advertiser's bid to achieve desired placement and to avoid overbidding. Advertisers began by telling the autobidder their maximum willingness to pay for a click, for a given keyword. The autobidder then automatically raised the advertiser's bid in \$0.01 increments to obtain the highest possible position given the advertiser's willingness to pay. The autobidder recognized opportunities to lower the advertiser's bid without losses in rankings. For example, if a bidder was paying \$0.80 per click for the first place, while the next highest bidder was paying \$0.60, the autobidder would recognize that the first bidder could lower his bid to \$0.61 while remaining in the first place.

Overture's (and, possibly, outside software developers') autobidders exacerbated the instability of first-price auctions.[4] When two or more advertisers activated autobidders, their bids tended to form a distinctive "sawtooth" pattern of gradual rises in price followed by sudden drops. Figure 1(a) shows an example of such behavior. The figure presents the top bids, in dollars, for a specific keyword ($phrase\_id = 24$ in our sample), every 15 minutes from 12:15 AM to 2:15 PM on July 18, 2002. As indicated at point A, bidding starts with both advertisers below their maximum bids. The first advertiser's autobidder recognizes an opportunity to obtain the first listing position by raising the second bidder's bid by \$0.01, and the first advertiser's autobidder does so. But then the second advertiser's autobidder sees that it has been outbid, and raises its bid in turn. This process continues until the bids reach one advertiser's maximum bid (say, the first advertiser's maximum), as shown at B. The first advertiser's autobidder can no longer increase its bid to obtain the first place, so it instead looks to avoid overspending, which it does by lowering its bid to \$0.01 more than the third-place bidder, yielding the bid at C. But then the second advertiser sees that it can still obtain first place by bidding \$0.01 more than the first advertiser's newly-lowered bid. Bidding therefore begins to increase, yielding more and more "teeth" in the sawtooth pattern. Figure 1(b) shows the continuation of this pattern, for one week. Of course, there are occasional deviations from the simple pattern, as well as time differences between some subsequent peaks, but the general pattern is clearly present. In fact, this pattern is ubiquitous in the 2002-2003 Overture data, and it is present for most keywords and most time periods.

Clearly, this sawtooth pattern reduces market efficiency: the bidder who values the first spot the most spends only half the time at the top, and even less if there are more than two bidders competing for the top spot. Moreover, our analysis also indicates that this bidding pattern substantially

[4]Cycling is a particularly natural strategy in repeated first-price auctions, and as described below we actually observe it in this context. But it bears mention that cycling can occur in second-price auctions also. Cycling has also been reported in other contexts, e.g., retail gasoline markets [6].

reduced Overture's revenue. We first present a brief theoretical example and then turn to empirical evidence.

2.1 Revenue Losses: Theoretical Example

Under very strong assumptions, sawtooth bidding can be revenue equivalent to an alternative "second price" auction, in which each advertiser pays the next-highest advertiser's bid. Consider the case of a two-advertiser auction, in which the advertisers have valuations V_a and V_b for a click, $V_a \geq V_b$, the minimum payment is ϵ, and, crucially, the first and second ads are equally likely to be clicked.[5] Under Overture's first-price bidding structure, prices increase in stair-steps from ϵ to V_b. Assuming that prices, on average, spend equal time at each step, the expected revenue conditional on a click is equal to $\frac{V_b+\epsilon}{2}$.

Now consider a second-price auction. If each advertiser bids its valuation, the bids will be V_a and V_b. Advertiser a will be chosen to be first, and advertiser b will be second. Their payments will be V_b (the second advertiser's bid) and ϵ (the minimum payment). Since, by assumption, both ads have equal clickthrough rates, expected search engine revenue conditional on a click will be $\frac{V_b+\epsilon}{2}$, just as above.

Of course, the assumption of equal click-through rates for the two spots is unrealistic [2]. Relaxing this assumption would lead to the revenue inferiority of the first-price bidding structure: if the first advertisement is more likely to be clicked, revenue in the counterfactual second-price auction strictly increases (by placing more than .5 weight on V_b, and less than .5 weight on ϵ). Moreover, the addition of more bidders also makes second-price auctions further dominate first-price auctions under reasonable assumptions on bidder valuations. We will now present our estimates of these revenue losses in the actual bidding data.

2.2 Revenue Losses: Empirical Results

We received from Yahoo! a dataset reporting times and amounts of all bids in 1000 top Overture markets, along with unique identifiers for bidders and keywords, between June 15, 2002, and June 14, 2003.[6] Using this sample, we compared Overture's actual revenue from its first-price auctions during this period with the counterfactual revenue from auctions under a second-price auction regime.

In order to form counterfactuals of second-price revenue, we need a way to deduce advertisers' valuations from their observed bids in Overture's first-price auction. We take as our starting point the assumption that advertisers never bid above their valuation. Therefore, when we observe an advertiser's maximum first-price bid, that is a lower bound for its valuation and for its bids under a second-price regime.

[5] For the purposes of this example, we put aside the question of why advertisers would prefer the first position if both positions have equal click-through rates.

[6] All unique identifiers are arbitrary, giving us no individually-identifiable information about specific market participants and keywords.

In backing out advertiser valuations from observed bids, we face a tradeoff. On one hand, we want to take valuations over a long period in order to make sure we catch the "peak" of a bidder's sawtooth cycle. On the other hand, advertisers' valuations may change over time, and so we hesitate to take maxima over unduly long periods. As a compromise, we take maxima over one-week periods. In particular, we take each bidder's valuation for a given week to be its maximum bid during that week, in the actual first-price auctions we observe.

We assume that advertisers will bid their valuations in a second-price auction.[7] Since we do not have data on individual clicks, we also assume that click-through rates are the same for all bidders on a given keyword, and that they decline, from the top spot to the bottom of a page, at the same rate for all keywords. We get data on the rate of decline, by position, from [2]. An ad ranked second is 77.7% as likely to be clicked as an ad ranked first for the same keyword. An ad ranked tenth is 7.8% as likely to be clicked. We assume that ads ranked below tenth do not get clicked.

Once we make these assumptions, for each keyword, we estimate the ratio of the revenue to Overture under the counterfactual second-price auction[8] to the revenue under the actual mechanism. Note that while the revenues themselves are not identified (since we do not know the numbers of impressions and the actual click-through rates), the ratios of counterfactual revenues to actual revenues *are* identified, because the numbers of impressions and CTRs cancel out.

Table 1 presents the summary statistics of these ratios for all 1000 keywords. For the median keyword, the ratio is equal to 1.17, i.e., using an alternative design would have generated 17% higher revenues. From the 10th percentile to the 90th percentile, the ratio varies from 1.02 to 1.48; in fact, for more than 89% of the keywords (all but 105), the ratio is greater than 1, and so Overture's revenue would have been higher under the alternative design. To aggregate the ratios for individual keyword markets up to a total change in revenue, we need to know the contribution of each keyword market to Overture's total revenues. Since we do not have this data, we use two different assumptions: all keyword markets contribute the same revenue to the search engine ("average ratio by keyword"), and all keywords have the same numbers of search requests and the same average click-through rates ("average ratio by click"). Fortunately, these numbers are relatively close (1.21 and 1.14). We therefore conclude that if Overture had switched from its first-price auction regime to the second-price structure, during the period covered in our data, its revenues would have increased by more than 14%. We think the true increase would have been larger—perhaps substantially larger—because markets have become more dense (with more participants) and because our method of deducing valuations from bids yields only a lower bound on valuations.

[7]In a single-unit setting, this is a dominant-strategy equilibrium [7]. There is, however, a caveat: with multiple objects, this is no longer true. We discuss this point in more detail in Section 5.

[8]When computing Overture revenue, we bear in mind the canonical advertisement pricing policy: An advertiser is charged $0.01 more than the bid of the next-highest advertiser, or $0.05 if the advertiser is the lowest bidder for a given keyword.

3 Strategic Behavior: Current Evidence from Ranking Data

In the previous section, we presented evidence of strategic bidder behavior and corresponding revenue losses in the data from one search engine, covering the period from June 2002 to June 2003. Since that was a relatively early period for sponsored search auctions, one might wonder whether our results are peculiar to that early period—whether markets have subsequently stabilized and strategic behavior has disappeared. In this section, we show the contrary: on both large search engines, Google and Yahoo!, strategic behavior still seems to be widespread.

Since we do not have current bidding data for either of the two largest search engines, we rely on publicly available information—the outcomes of the auctions, i.e., the rankings of advertisers displayed by the engines for various keywords. We have collected these rankings for ten keywords and phrases ("air travel", "antivirus", "arthritis", "business card", "car rent", "contact lenses", "credit", "mesothelioma", "singles", "travel agent"), once approximately every 7 minutes, from March 23, 2005, until April 4, 2005, from the main search pages at both Google and Yahoo!.

To assess stability of each keyword market, we look at how often bidders' rankings change. For each keyword, each search engine, and each search engine, we identified the highest-ranked website. We then looked at "streaks"—periods in the data when the highest-ranked website remained unchanged.[9] If advertisers' bids equal their true valuations of clicks, then rankings should change rarely, i.e., only when economic fundamentals change, and so streaks should be relatively long. However, if bidders track each other's behavior and adjust their own bids accordingly, then we should see frequent changes in rankings, corresponding to frequent changes in bids; streaks would therefore tend to be short.

Table 2 presents the medians of streak lengths, in minutes, for the ten keywords and two search engines that we looked at. Several characteristics should be noted. First, over all keywords, the median length of a streak is 14 minutes at each of the search engines. This is a very short time interval, and it is hard to believe that economic fundamentals change so often, even if they depend on the time of the day and on the day of the week. Moreover, since we capture rankings only at discrete time intervals, we miss any changes that occurred between our requests, and so the true streak lengths are likely to be even shorter.

Second, streak lengths vary dramatically by keyword and search engine, with no clear pattern. Many keywords on both search engines (but especially on Google) have very short median streak lengths: 14 and 21 minutes. On the other hand, some keywords have very long streaks, and one, "car rent" had the same top bidder on Yahoo! throughout our sample![10] However, the highest-ranked bidder for the same keyword on Google changed very often. For "contact lenses," Google and Yahoo! traded roles: streaks on Yahoo! were very short, while on Google they were comparatively very long—the median streak was longer than one day.

[9]Of course, since our requests had 7-minute gaps, it is possible that there were changes between the requests that we do not capture. However, this would imply that our estimates are biased upward, and would therefore only strengthen our conclusions.

[10]This bidder was Travelocity.

It is also instructive to look at particular examples of keywords with low streak lengths. Tables 3 and 4 present typical examples of advertisers competing for the top spot and constantly replacing each other there. Table 3 shows a sequence of top ads for keyword "mesothelioma" on Yahoo! and Table 4 presents such sequence for keyword "arthritis" on Google. Each line in the tables gives the URL associated with the top ad, the time stamp of the beginning of the streak with this ad at the top, and the length of the streak.

Unfortunately, we do not currently know the bids corresponding to these ads, and so we cannot be certain that these observations correspond to the bidding cycles that we described in Section 2. (For example, perhaps some reordering at Google reflects fluctuations in click-through rate.) However, our observations suggest that it is likely that bidders are engaged in strategic behavior. Note that in Table 3, both bidders respond quickly—here too, probably even more quickly than our discrete data indicates. In contrast, in Table 4, only one bidder responds very quickly (perhaps almost instantly), while the other bidder takes a long time to respond. It is likely that the first bidder uses a fast robot to update his bids, while the second bidder either uses a slow robot or updates the bids manually. In both cases, it is hard to justify the observations by the constantly changing economic fundamentals, while the hypothesis of strategic behavior similar to that observed in Section 2 seems highly plausible.

4 Allocation and Revenue Effects of Vickrey Auctions

The preceding sections demonstrate that strategic behavior in sponsored search auctions can lead to substantial foregone revenues to the search engines. We have also shown evidence suggesting that strategic behavior remains present on two largest search engines, Yahoo! and Google, even though they use different auction mechanisms.

A natural question, therefore, is whether there exists an incentive-compatible auction in which it is optimal for each bidder to submit his true valuation. Note that a simple second-price auction, like the one we used to estimate counterfactual revenues or the one used by Google, is not necessarily incentive compatible: a bidder may prefer to submit a lower valuation if he can get a reasonably good spot at a very low price, rather than submit his true valuation to get the top spot, but in the process pay a high price. Moreover, the question is complicated by the fact that click-through rates may differ by both the advertiser and the position.

Fortunately, the standard Vickrey-Clarke-Groves mechanism works in this setting, at least in theory.[11] However, it is more subtle than in the standard single-object case (where it is equivalent to the second-price auction), and it should be implemented carefully. The basic idea of the VCG mechanism is to maximize social welfare (given reported valuations), and to charge each player the negative externality he imposes on others. In the sponsored search setting, assuming that advertisers' valuations of clicks do not vary much by position (which is indeed the case, at least on average [3]), a search engine should ask for each bidder's valuation of a click. It should then, based

[11] See [4] for a detailed theoretical analysis.

on each advertiser's historical click-through rates in each position, compute the allocation of ads to maximize expected welfare; then, for each bidder, compute the maximum welfare without that bidder, and charge the bidder the difference between the two numbers, divided by the expected number of clicks. By the standard VCG argument, this auction is incentive compatible, and it is also efficient. Note that it is different from both Yahoo!'s mechanism, which does not even take CTRs into account, and Google's mechanism, which does not take CTRs by position into account and also charges fees that are not equal to VCG payments.

Table 5 presents the estimated ratios of counterfactual VCG revenues to the actual revenues, using Overture's 2002-2003 bid data and valuation estimates as described above. On the whole, VCG yields lower revenue than Yahoo's actual 2002-2003 auction rules, with mean and median revenue ratios (VCG revenue compared to actual revenue) of 0.66 and 0.68, respectively. However, restricting analysis to "popular" keywords (where the average number of bidders was greater than or equal to 10), the average and median revenue ratios were 1.07 and 1.06. Note, however, that these are lower bounds on the true values, since our estimates of bidder valuations were lower bounds. Also, today most keywords (especially high-value keywords) have many bidders. For these reasons, we believe VCG may not actually yield the decreases suggested by the second column of Table 5.

5 Conclusions

Our theoretical and empirical analyses suggest that strategic behavior is serious, widespread, and costly. But as the prior suggestion explains, a switch to VCG auctions could stabilize auction outcomes with neutral or even positive effects on revenue.

It is important to note that search engines are not the only parties who would benefit from improvements in mechanism design. For one, under unstable mechanisms, the bidders who value top spots the most spend only a fraction of time there. Second, behaving strategically requires substantial investments: time, effort, bidding tools and software, consultant fees, etc. These costs seem to be substantial based on the numerous message boards discussing bidding strategies as well as the various companies developing expensive bidding software with built-in tools for strategic behavior. Finally, if an advertiser's willingness to pay for a click is generally positively correlated with the relevance of the advertiser's website, then users also suffer from suboptimal content.

Beyond VCG, there may be alternative ways to reduce the problem of strategic behavior. For example, search engines might allow advertisers to update their bids only a few times a day. But such an approach is unlikely to eliminate strategic behavior completely. It might also have negative side effects—preventing advertisers from quickly responding to changes in economic fundamentals, or even facilitating collusion.

Of course, changing overnight from the current mechanisms to the efficient one would be too risky for the search engines. After all, advertisers have developed extensive institutional knowledge about the current design. However, given the magnitudes of revenue losses, as well as the costs to bidders and efficiency losses to search engine users, it would be worthwhile to experiment with alternative designs in small segments of sponsored search markets. Perhaps experimentation could begin with a number of keywords related to one specific geographical area, or a field with particularly savvy bidders. Useful insights can also be gained by analyzing richer data sets than what we have considered here, including position-specific click-through rates, conversion ratios, and changing bidding patterns over time.

Progress will most likely be achieved through a combination of auction-theoretical analysis, empirical work, and experimentation, which, in addition to being important, makes sponsored search an exciting field for future research.

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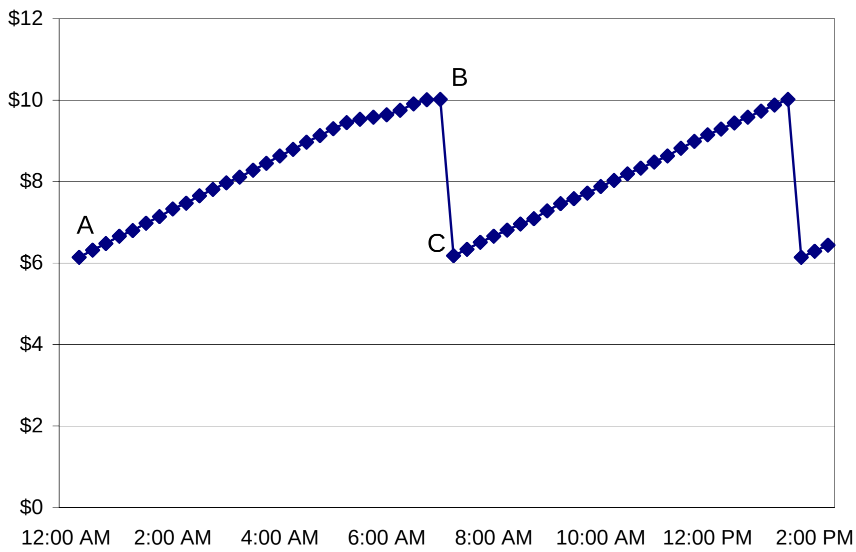
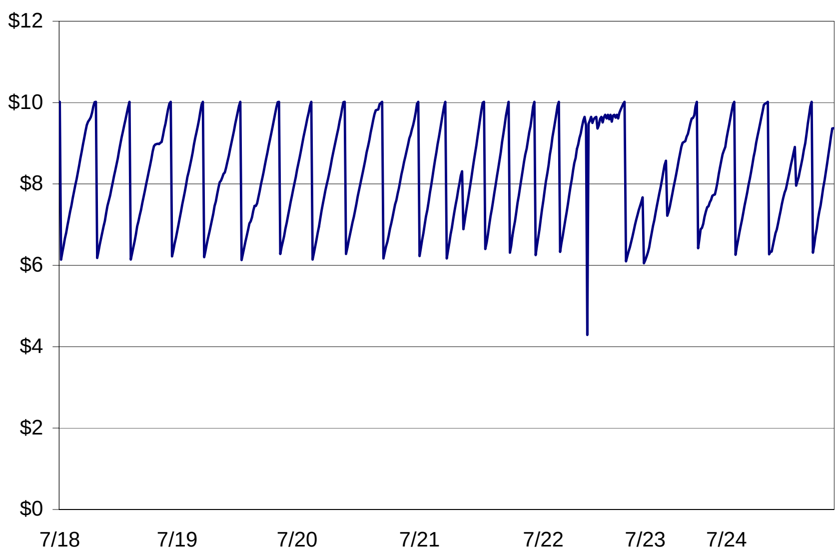


(a) 14 hours



(b) 1 week

Figure 1: "Sawtooth" bidding pattern

Table 1: Distribution of Counterfactual-to-Actual Revenue Ratios by Keyword

Statistic	Value
10th percentile	0.99
25th percentile	1.10
Median	1.17
75th percentile	1.28
90th percentile	1.47
Average ratio (by keyword)	1.21
Average ratio (by click)	1.14

Table 2: Median Streak Lengths (minutes)

Keyword	Google	Yahoo!
"air travel"	14	999
"antivirus"	14	14
"arthritis"	14	186
"business card"	21	5200
"car rent"	14	17049
"contact lenses"	1979	21
"credit"	14	91
"mesothelioma"	14	14
"singles"	98	314
"travel agent"	1286	364
All Keywords	14	14

Table 3: Keyword "Mesothelioma" on Yahoo!

Top Ad	Beginning	Length
www.mesotheliomaoptions.com	3/25 15:33	7
www.mesotheliomaweb.org	3/25 15:40	14
www.mesotheliomaoptions.com	3/25 15:54	21
www.mesotheliomaweb.org	3/25 16:15	21
www.mesotheliomaoptions.com	3/25 16:36	7
www.mesotheliomaweb.org	3/25 16:43	7
www.mesotheliomaoptions.com	3/25 16:50	7
www.mesotheliomaweb.org	3/25 16:57	7
www.mesotheliomaoptions.com	3/25 17:04	21
www.mesotheliomaweb.org	3/25 17:25	7
www.mesotheliomaoptions.com	3/25 17:32	21
www.mesotheliomaweb.org	3/25 17:53	7
www.mesotheliomaoptions.com	3/25 18:00	7
www.mesotheliomaweb.org	3/25 18:07	14
www.mesotheliomaoptions.com	3/25 18:21	14

Table 4: Keyword "Arthritis" on Google

Top Ad	Beginning	Length
www.StudyForKneePain.com	4/2 9:15	845
www.kaiserpermanente.org	4/2 23:20	7
www.StudyForKneePain.com	4/2 23:27	322
www.kaiserpermanente.org	4/3 4:49	7
www.StudyForKneePain.com	4/3 4:56	238
www.kaiserpermanente.org	4/3 8:54	7
www.StudyForKneePain.com	4/3 9:01	42
www.kaiserpermanente.org	4/3 9:43	7
www.StudyForKneePain.com	4/3 9:50	238
www.kaiserpermanente.org	4/3 13:48	7
www.StudyForKneePain.com	4/3 13:55	14
www.kaiserpermanente.org	4/3 14:09	7
www.StudyForKneePain.com	4/3 14:16	964
www.kaiserpermanente.org	4/4 6:20	7
www.StudyForKneePain.com	4/4 6:27	28

Table 5: Distribution of VCG Counterfactual-to-Actual Revenue Ratios by Keyword

Statistic	Value (all keywords)	Value ("popular" keywords)
10th percentile	0.36	0.95
25th percentile	0.52	1.02
Median	0.68	1.06
75th percentile	0.81	1.12
90th percentile	0.92	1.13
Average ratio (by keyword)	0.66	1.07
Average ratio (by click)	0.76	1.09