

The Effects of Bid-Pulsing on Keyword Performance in Search Engines

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Abstract:

The objective of this study is to empirically examine whether and how the bid-pulsing affects keyword auction performance in search engine advertising. In keyword auctions, advertisers can choose a set-to-forget fixed bidding amount (fixed-bidding), or they can change the bid value based on certain type of rules (pulse-bidding). A keyword auction dataset from Yahoo! reveals that around 60% of advertisers frequently changed their bid value for a particular keyword category; moreover, such pulse-bidding behavior is observed throughout the entire time course for some companies. Both cross-sectional and longitudinal analyses on this dataset demonstrate that when a company pulses its bid values, the ranking, the number of exposures, and the number of clicks of the target ad listing will all benefit; in addition, the average bid price will be lower. The results are consistent across four keyword categories. Among the three keyword categories that are in ascending order of level of competitiveness, the magnitude of the bid-pulsing effect also increases. The study extends search engine advertising literature by providing empirical evidence of pulse-bidding strategy under the generalized second price (GSP) auction and by exploring the consequence of such strategy. Managerially, our results suggest that while keeping all other costs and the bidding environment the same, increasing the frequency and scale of bid pulsing will improve keyword performance; this is especially the case when bidding on a highly competitive keyword category.

Keywords: Search Engine Advertising, Bid-Pulsing Strategy, Generalized Second Price (GSP), Competition, Keyword Performance

Introduction

Search engine marketing has been deeply embedded in marketers' advertising strategies since its introduction in 1996. It is a form of internet marketing that promotes and increases the visibility of businesses on search engine result pages, through *search engine optimization* (e.g., improving website structure, increasing inbound links), and through *search engine advertising* (e.g., paid ad placement). SEMPO ([28]) estimates that the search engine marketing industry will reach \$26.8 billion by the end of 2013, having grown by 554% from \$4.1 billion in 2004. The major players in the industry are Google (market share 65.09% in Aug 2011), Yahoo! (15.89%), Bing (13.10%), and others (Ask.com, AOL, etc., make up 5.92% of the market) [4].

In *search engine advertising*, the advertiser specifies a target query (one or more keywords), a certain advertisement, and a bid value for the keyword(s) (i.e., maximum willingness to pay for a click) while competing against other advertisers. When a consumer enters that query in a search box, a keyword auction begins. The search engine will then display the list of the paid advertisement links based on the relevant bid price, ad contents, and the quality scores of the landing pages. Every time a consumer clicks on a sponsored link, the corresponding advertiser's account is billed. Advertisers determine the bid value based on a number of factors, such as keyword performance (the number of exposures, the rankings, and the number of clicks the ad link receives), conversion rate, the revenue generated by clicks, and the resources and effort to manage the bidding process. They can adopt a *fixed-bidding strategy*, under which a predefined bid value for keyword(s) is specified and kept consistent over time; or a *pulse-bidding strategy*, under which the bid value is adjusted to optimize performance whenever necessary. In search engines like Yahoo! and Google, the performance of the keywords is available in almost real-time. Advertisers can choose the frequency and the amount

to change the bid value based on the feedback from the search engine. Other variables, such as keyword choice, ad content, and landing page design can also be adjusted to optimize the performance of following auctions. When a consumer enters the next search query, another round of keyword auction begins. Since reading in English begins in the upper left-hand corner and proceeds from left to right in a top-to-bottom fashion (e.g., [23]), ads displayed at the top (higher ranked ads) are more likely to be exposed to consumers and believed to be more credible. Typically, these ads tend to have higher click-through rates. Another performance measure closely tied to the click probability is impression, or the number of times an ad is displayed on search engine result page. Exposure to an ad link “reminds customers of the existence of their company” ([5] p.7), and is likely to increase the click-through rate of an ad in the future ([6]). Hence, a higher position on search result page, more exposure, and more clicks are always desirable for advertisers.

Previous studies have examined the bidding strategies under the two most common keyword auction formats: the Generalized First Price (GFP) and the Generalized Second Price (GSP) auctions. In both formats, the advertiser with the highest bid is likely to receive the highest rank and most exposures (which in general will lead to higher click-through rate). The only difference is the cost of each click. In the GFP auction, the advertiser will pay the price he bid; while in the GSP auction, the advertiser will pay the price of the next highest bid. The GFP auction is naturally unstable ([10], [11]), featuring a “sawtooth” pattern of bid value (See Appendix for an illustration).

Theoretically, under the simplified GSP condition – only one slot for one keyword, full information, and static condition, a locally envy-free equilibrium exists ([11]). In equilibrium, each bidder pays his Vickrey price and receives the slots he would have under the efficient

allocation, no bidder has a unilateral incentive to change his bid ([22], [32]). In other words, *fixed-bidding* at Vickrey price might be ideal in this situation. In practice, however, the GSP auction can be much more complex. There are multiple ad slots on a search engine results page, and *fixed-bidding* at Vickrey price is no longer the best strategy. Indeed, our data collected under the GSP format indicate that instead of keeping the bid value consistent, around 60% of advertisers change their bid value over time. Moreover, such *pulse-bidding* behavior is observed throughout the entire data period, rather than being concentrating in the earlier stage and stabilizing afterwards as predicted by learning curve. Various drivers of such dynamic bidding have been discussed in the literature: for instance, the previous ad's rank and click-through rate, the search engine's evaluation of the site, and competitors' bidding behavior will all contribute to bid value variations. Researchers have also theoretically explored dynamic bid pricing strategy to optimize the budget allocation across time and across keywords.

Given the quickly expanding analytical and empirical work on search engine advertising, one question remained unanswered: what is the consequence of pulse-bidding strategy in the GSP keyword auction? This study intends to fill the gap by empirically investigating whether and how bid-pulsing affects keyword auction performance in search engine advertising. With cross-sectional and longitudinal analyses on publicly available Yahoo! Search advertising data ([1]), we address the following questions of interest to search engine advertisers: does keyword performance differ between the advertisers who adopt a pulse-bidding strategy and those who adopt a fixed-bidding strategy? How does pulsing the bid price influence the rank, impressions, and clicks of an ad? Is the effect of pulse-bidding different across keyword categories? Which type of keyword is suitable for frequent pulsing and (or) large scale bid value change, and which type is not? These questions are of great importance to both researchers and practitioners. Note

that our study empirically measures the differences between the fixed-bidding strategy and the pulse-bidding strategy in terms of their influences on the performance measures. It does not attempt to propose the optimal keyword bidding strategy or map out the actual underlying bidding rules that the advertisers followed due to the data constraints. Rather, this study is more of a descriptive nature than a normative nature.

The paper is organized as follows. First, we review the literature regarding the auction format and corresponding bidding strategies, academic and industrial perspectives of fixed- and pulse-bidding strategies, and models of bidding behavior in search engine advertising. We then describe the dataset, and present the models and results. We finish with the discussions of managerial implications and future research avenues.

Literature Review

Background: Keyword Auction Format

Search engines have used the generalized first price auction (GFP) and the generalized second price auction (GSP) as keyword auction formats. In this section, we first introduce these two auction formats, then discuss the corresponding bidding strategies, and finally point out the gap in this stream of literature.

The GFP keyword auction format was originally adopted by GoTo (1998, later Overture, now Yahoo! and Bing). In this format, if ad i with bid value b_i is clicked, advertiser i is charged the bid value b_i . In a static setting, the GFP auction has a pure strategy Bayes-Nash symmetric equilibrium ([22]). In a dynamic setting such as keyword auctions, however, the lack of pure strategy full-information equilibrium encourages bidders to constantly change bid value from one period to the next. For example, assume two advertisers (A and B) bid for the same keyword

under the GFP format. Advertiser A has the evaluation of the keyword at \$1, and B has the evaluation at \$1.5. The best strategy for them is to start at their lowest bid (say \$.50), and then continue to outbid each other until the bid price reaches \$1. At this point, A will stop increasing the bid, and B could bid at \$1.01 and win the auction. Therefore, we typically see a “sawtooth” pattern (see Appendix for an illustration), or pulse-bidding behavior under this auction format. The GFP auction structure is naturally unstable, and bidders change their bid value frequently within a large range ([10], [11]). Edelman et al. ([11]) concluded that the GFP format encourages “inefficient investment, causing volatile prices and allocative inefficiencies”.

Yahoo! switched from GFP to GSP format in June 2002, and now the GSP auction is widely adopted by major search engines. In the GSP auction, if ad i with bid value b_i is clicked, rather than paying the bid value b_i (as in the GFP) advertiser i pays an amount equal to the next highest bid b_j (sometime plus a minimum increment, typically \$0.01). Essentially, the ad of the highest bidder is listed in the first slot, but the price paid for a click is the second highest bid. Similarly, the ad for the second-highest bidder will be listed in the second slot, and the price paid for a click is the third-highest bid ([5], [10], [11]).

The GSP auction is a generalized form of standard second-price auction, which coincides with the Vickrey-Clarke-Groves (VCG) auction ([11]). The VCG auction is *incentive compatible*, i.e., the optimal strategy for a bidder is to bid their true valuation. It ensures that the bidder who values the item most will win the auction. Bidders change their bid value less frequently, and the range of the bid value is smaller than that in the GFP format. GSP generalizes the standard second price auction by allowing for repeated bidding and multiple ad slots. In an infinitely repeated game where bidders change bid price frequently and gradually learn the values of others, an extremely large set of equilibria exist ([11]). Thus, to obtain a theoretical solution, Edelman et

al. ([11]) focused instead on a “one-shot, simultaneous move, complete information game” while considering the dynamic nature of the auction. They derived a restricted ex-poste equilibrium known as locally envy-free equilibrium ([11]), or symmetric Nash equilibrium ([31]). In that equilibrium, each bidder pays the Vickrey price and receives the slots he would have under efficient allocation, no bidder has a unilateral incentive to change his bid (*fixed-bidding*). However, it is much more complex in practice: there are multiple advertising slots on search result page, and search engines prevent advertisers from learning the bid value of competitors and colluding with each other through complex algorithms. Fixed-bidding at Vickrey price is not an optimal strategy. Indeed, empirical analyses indicate that bid price in the GSP keyword auction is not stable: for instance, Yuan ([35]) found that advertisers actually change their bid 19% more often under the GSP than under the GFP format. Edelman et.al [11] concluded that there is no equilibrium in dominant strategy in GSP auctions adopted by most search engines.

Given the inconsistencies between the theory and practice, it is important to examine empirically how advertisers bid under the GSP format, and whether fixed-bidding and pulse-bidding affect keyword performance differently. We observe that six out of ten advertisers frequently change their bid value in our data. Bid-pulsing behavior varies widely across firms, with some companies limiting their bid pulsing within a specific period, while others change the bid throughout the entire data period. The magnitude of pulsing also differs radically. Does pulse bidding lead to better keyword performance than fixed bidding under the GSP format? What is the impact of large scale bid pulsing on ad’s rank, impression, and click through rate? Will the effect of pulsing differ across keyword categories? In this study, we attend to the consequence of pulsing in the GSP keyword auction, which has been rarely studied in the literature, yet is of critical importance for marketing managers.

Fixed-Bidding Strategy and Pulse-Bidding Strategy

In keyword auctions, advertisers can choose to adopt a *fixed-bidding* or a *pulse-bidding* strategy. Under the *fixed-bidding strategy*, advertisers specify a predefined bid price (maximum willingness to pay) for keyword(s) and keep it consistent over time. Search engine websites also allow advertisers to set a maximum spending limit, after which the advertiser's account will be paused. Alternatively, advertisers can adopt a *pulse-bidding strategy* and change their bidding amount frequently. For instance, advertisers can adapt their bid value according to rank changes (position-based bidding); a conditional statement (rule-based bidding; e.g., if there are less than five impressions, increase bid by \$2.00); click-through probabilities (probability-based bidding), or the ROI (portfolio-based bidding, where the bid value is set according to the click-to-cost of each combination of keywords).

Pulse-bidding strategy is more performance oriented and enables effective budget allocation; hence, it is widely adopted in practice. Researchers have emphasized the importance of adopting a dynamic perspective of keyword auction, because one important feature of keyword auction is the real time realization of keyword performance. Zhang and Feng ([37]) proved that in a two-player competition game, the dynamic aspect of keyword auctions results in an equilibrium bidding strategy, which is characterized by the cyclical pattern of bid value, rather than converges to a static equilibrium. Feng and Zhang ([13]) called such price dispersion (randomized bid price) the “reactive price dispersion”, because the firm is reacting to the other's bid price in keyword auction. Maillé et al. ([24]) shared a similar opinion by proposing that a natural approach for bidding is to “use past (performance) as a prediction for the future.” The greedy bidding strategy, which adjusts bid price for next round to maximize utility while assuming all other bidders remain the same, works well. Researchers also theoretically explored

the bidding strategy from the budget optimization perspective. Budget constraints in a keyword auction include the daily budget set for campaigns and the budget allocation across keywords. Dynamic adjustment of bid price is essential in achieving budget allocation efficiency. Kitts and Leblanc ([20]) proposed a bid allocation plan in which the bid price is adjusted to maximize total profit while not exceeding the budget during the planning horizon. Such future look-ahead bid price allocation quadrupled the clicks for the same expenditure in a keyword auction experiment. The reason for the improved performance is that pulse-bidding “enables it (the company) to hold back cash for more desirable times of the day” (p.199, [20]). Feldman et al ([12]) explored in a similar vein. They proved that two-bid uniform strategy (advertisers randomize the bid price between bid value $b1$ and bid value $b2$ on all keywords until budget is exhausted) is able to optimize the overall ad’s clicks. This dynamic bidding strategy is simple, robust, less reliant on information, and thus desirable in practice. Zhang et al. ([36]) concluded that because the sponsored search market usually changes rapidly, the bid price and daily budget should be adjusted “in a timely manner according to market dynamics”. The dynamic dual adjustment of bid price and daily budget could help advertisers “avoid wasting money on early ineffective clicks and seize better advertising opportunities in the future” (p.105, [36]). Some industrial reports also share the similar perspective, as Mou ([25]) stated, to avoid losing audience with low bid and hurt ROI with high bid price, the best practice is to “adjust bid price from the mid-point in the recommended bid range” based on performance.

Despite the potential benefit it brings, pulse-bidding strategy requires intensive data support, and may incur a substantial amount of managing cost in practice ([30]). These challenges apply to all types of pulse-bidding strategies, including rule-based, portfolio-based, and position-based pulsing strategies. For instance, a *rule-based strategy* is logically straight

forward, but setting a well-functioned rule, especially for a large number of keywords, can be hard and tedious ([20]). A *portfolio-based strategy* helps with effective spending of the bidding money, yet it requires “large amount of historical data, and may take long time to learn the market conditions” (p.11, [21]). A *position-based bidding* is effective in maintaining the optimal ranking for the brand, yet the optimal ranking is unknown or it is subject to change. Manually monitoring and controlling the proper bid value for each bidding activity is unrealistic for a company with a large number of keywords to manage. To effectively apply pulse-bidding strategy, advertisers need to develop a complex system for efficient data collection, analyzing, and integration, which requires large investment from the company ([30]). Developing the algorithm for the optimal pulse-bidding value based on such expansive, intricate and dynamic keyword performance metrics, is a non-trivial task ([30], [33]).

The other bidding strategy, the *fixed-bidding strategy*, is observed in some keyword auction practices, even though academic researchers clearly emphasize the importance of dynamic adjustment of bid price. Such “set-and-forget” strategy requires much less time and effort to manage the bidding process compared to the pulse-bidding strategy. It is particularly attractive to novice advertisers who have little or no experience with search engine advertising, those who have smaller number of keywords, or those “with little or no capacity (or desire) to measure the effectiveness of the paid search efforts” ([30], p.5). Another advantage of fixed-bidding strategy is the ability to better control the spending on search engine advertising. By setting a fixed daily budget, advertisers could avoid unexpected excessive expenditures due to the sudden surge in keyword search ([8]). On the other hand, the disadvantage of such bidding strategy is obvious: fix-bidding strategy ignores the feedback of the keyword performance and budget allocation, and rarely has a good return on investment ([30]).

Besides the performance emphasis, budget allocation, and management cost, several other factors also affect advertisers' decision on bidding strategies. For instance, if the target company adopts a fixed-bidding strategy while the competitor adjusts the bid value very often, the ad's visibility of the target company will be easily surpassed on search engines. Under such a situation, the target company might consider pulse-bidding strategy ([30]). The company's campaign goal also plays a role. For instance, a branded (specialized) search (such as keyword "ABC Coffee Maker") is less competitive compared to a generic search (such as keyword "Coffee Maker"). If the company's campaign goal is to maintain the ad's rank for branded search, it is not advisable to put in significant amount of time, money, and effort to constantly changing the bid value ([2], [30]).

Therefore, to derive the optimal keyword bidding strategy, one needs information on bid price, auction performance, budget, management cost, campaign goal, and its competitors' bidding rules. As Jansen and Mullen ([15]) pointed out, "an optimal strategy for one keyword market may not be the optimal strategy for another" (p.127). Yet except for bid value and keyword performance, other information often remains as a trade secret and unknown. We acknowledge the importance of such information for developing the best bidding strategies. Hence, rather than suggesting the superior bidding strategies or probing into the underlying pulse-bidding rules, the objective of this paper is to provide an empirical examination of the consequence of the two bidding strategies, given the available bid price and keyword performance information.

Bidding strategies in Search Engine Advertising and Modeling Approaches

In this section, we selectively review some analytic and empirical work in the bidding strategy in search engine advertising.

Since the discussion on GSP by Edelman et al. ([10], [11]) and Varian ([31]), the collection of analytical work on keyword auctions is rapidly expanding. Sen ([29]) studied the optimal investment decision among search engine optimization and paid placement. Athey and Ellison ([3]) studied effect of inter-advertiser competition on advertisers' bids. Kempe and Mahdian ([19]) used a cascade model to explore the externalities in sponsored ads. Chen et al. ([7]) focused on advertising space's distribution among bidding advertisers. More recently, Katona and Sarvary ([18]) developed a dynamic model to capture the impact of previous ad's position on current bidding strategy. They found that advertisers' bidding behavior is strongly affected by the interaction between search results in organic and sponsored sections, as well as the inherent differences in the websites' attractiveness. Zhu and Wilbur ([38]) examined equilibrium strategies in hybrid advertising auctions, i.e., bidding on a pay-per-impression versus a pay-per-click basis. They proposed that a hybrid payment scheme would improve publishers' revenue and achieve socially optimal allocation of advertisers to slots. Jerath et al. ([17]) analyzed the bidding strategies of vertically differentiated firms and found the "position paradox": under a pay-per-impression mechanism, the superior firm will be better off by bidding for a lower position compared to an inferior firm.

Our research adds to the growing body of empirical literature on bidding strategies in search engine advertising. Various datasets and models have been used to examine the keyword bidding strategy. For example, Jansen, Sobel, and Zhang ([16]) investigated the keyword performance and the use of brand terms, and found that matching brand terms in key phrases and ads will significantly improve the effectiveness and efficiency of keyword advertising. Ghose and Yang ([14]) applied simultaneous equations to model the impact of keyword characteristics, position of the advertisement, and the landing page's quality score on advertisers' bid price,

consumers' search and purchase behavior, and the search engine's ranking decision. Rutz and Bucklin ([26]) proposed a dynamic linear model to capture the potential spillover from generic to branded paid search. With complete information of consumer search and clicking, advertiser bidding, and search engine information such as keyword pricing and website design, Yao and Mela ([33]) applied a structure model to capture the relationships among three parties. In their dynamic model, the search engine uses the previous ad's performance to rank the current ad, advertisers gauge consumers' clicking behavior to determine the keyword bid value, and consumers rely on the ad's ranking in their click decisions. Other aspects of search engine marketing, such as search queries ([34]) and click-fraud ([9]), have also been examined in the literature. Most empirical studies on search engine advertising focus on the determinants of dynamic bidding. For example, previous positions, click-through rate, the search engine's evaluation of the site, and competitors are all taken as factors that drive dynamic bidding (e.g., [18], [26], [27], [33]). However, the consequence of the pulse-bidding strategy awaits further investigation. Our research intends to fill this gap by focusing on whether and how bid-pulsing affects keyword auction performance in search engine advertising.

Data and Descriptive Analyses

We obtained publicly available keyword auction data from Yahoo! (*Search Marketing Advertiser Bid-Impression-Click data on Competing Keywords*, [1]). The data record 16,268 advertisers' 77,850,272 daily bidding activities, spanning four months in 2008, and across six

keyword categories¹. The variables include anonymized advertiser IDs, anonymized keyword(s), bid value for a particular keyword², rank, number of impressions and clicks.

Advertisers may choose to bid on multiple keyword categories at one auction, and the bid price will differ correspondingly. Such price change is due to the variation in keyword categories, rather than pulsing-bidding that we are interested in. Therefore, to avoid complication, we only keep the auctions that focus on a single keyword category. Among all the six keyword categories we obtained, four of them have much larger number of advertisers (A: 4617, B: 4501, C: 5675, and D: 3135) compared to the other two (E: 142 and F: 229). To have meaningful comparisons across categories, we choose the first four categories A, B, C and D, to assess the impact of bid pulsing on keyword performance. The descriptive statistics of these four categories are presented in Table 1.

For each keyword category, we summarize the bidding decisions in the upper panel and the keyword performances (rank, impression and click) in the lower panel. We find that: (1) the numbers of advertisers in these keyword categories varies from 3125 (in category D) to 5675 (in category B). (2) The daily bid value also differs greatly from \$537.3 (in category D) to \$1332 (in category A). (3) Category A receives the most number of bids on average from each advertiser (4736), while category D receives the least number of bids from each advertiser (2328). (4) Finally, the number of advertisers bidding on each keyword also varies across categories (from 2.16 in category C to 2.94 in category A). As shown in the lower panel of each table, the average impressions differ radically across the four keyword categories, with much higher exposure for category A (13.08) than that for the other three keyword categories (B: 8.14; C: 5.14; D: 7.76).

¹ These keyword categories are defined by the data provider, and no detailed information regarding these categories, such as how each category is defined or the identity of the keyword, could be obtained.

² The bid value is aggregated with a granularity of a day. The numbers refer to the total bid value for a keyword by an advertiser (possibly across multiple auctions) within a day.

Similar pattern holds for clicks (A: 0.08; B: 0.06; C: 0.05; D: 0.07). The average ranks also vary across categories (A: 6.66, B: 7.93, C: 5.62, D: 5.69). The rank, impression and click all fluctuate substantially for all four categories. The descriptive statistics of bidding behavior and keyword performance in Table 1 suggest that the four keyword categories are significantly different from each other.

---INSERT TABLE 1 HERE---

To illustrate bid-pulsing behavior and the corresponding keyword performance, we randomly select three companies and plot their bid value for the same keyword category over time (Figure 1). These three advertisers bid for the same keyword category 117, 409, and 8,693 times, respectively. The number of auction activities, the number of changes in the bid values, and the changes in the bid value vary significantly across advertisers. Some advertisers pulsed more often and pulsed at larger scale in the earlier or later period, while others spread their pulsing behavior across the entire data period. Figure 2 plots the rank, impressions, and clicks of the search engine ads over time for three companies. It is clear that all these measurements fluctuate substantially over time.

---INSERT FIGURES 1 and 2 HERE---

To obtain a detailed understanding at different levels, we generate two datasets for each keyword category. The first dataset, the *longitudinal dataset*, keeps the entire bidding activities for each advertiser during the observed period. In this dataset, each line of observation represents a summary of the keyword auctions on a particular keyword by an advertiser in one day. The longitudinal data for category A, B, C, and D record over 21 million, 16 million, 19 million, and 7 million auction activities respectively. The second dataset, *cross-sectional dataset*, averages the bidding behavior and keyword auction performance over the observed period for each

advertiser and keyword. In this dataset, each line of observation represents an advertiser-keyword combination.

We generate some variables to capture the pulsing behavior in each dataset. In the *longitudinal dataset*, the first variable created is *Pulsing Dummy*, indicating whether there is a change in the bid value for a specific keyword within the keyword category. *Pulsing Dummy* takes the value one if bid value for a keyword at time t is different from that in time $t - 1$, zero otherwise. The second variable created is the percentage of bid value change (or *Pulsing Strength*), reflecting the magnitude of the change in the bid value from time $t - 1$ to time t , normalized by the average bid value for the same keyword. Specifically, it is calculated as the ratio of the change in the bid value for a keyword from $t - 1$ to t , relative to the average bid value for the same keyword:

$$Pulsing\ Strength = \frac{BidValue_t - BidValue_{t-1}}{\frac{1}{T} \sum_{t=1}^T BidValue_t}.$$

Similarly, In the *cross-sectional dataset*, we calculate the *Pulsing Intensity*, which is the percentage of times an advertiser changes its bid for the same keyword category; and *Pulsing Variation*, which is the average of the absolute value of *Pulsing Strength* over time. Specifically,

$$Pulsing\ Variation = \frac{1}{T} \sum_{t=2}^{t=T} \frac{abs(BidValue_t - BidValue_{t-1})}{\frac{1}{T} \sum_{t=1}^T BidValue_t}$$

A metric evaluating the performance fluctuation (impressions, rank, and clicks) for each advertiser-keyword is also added. We label it as *Performance Fluctuation*, which is the average of absolute changes in keyword performance from time $t - 1$ to time t :

$$(Performance\ Fluctuation = \frac{1}{T} \sum_{t=2}^T abs(Performance_t - Performance_{t-1})).$$

Analyses

In this section, we examine the impact of bid-pulsing on keyword performance at two levels. First, using the cross-sectional data, we study the differences in keyword performance between the fixed-bidding strategy and the pulse-bidding strategy. Then we take a time-series perspective by applying a mixed two-stage-least square approach to the longitudinal data to study the impact of pulse-bidding on current keyword auction performance.

Search engine websites have developed complex algorithms to determine an ad's rank and impressions. The major components of this decision are keyword(s)' bid value, ad design, and the quality the landing page. However, the algorithm itself is a business secret and remains unknown to advertisers and researchers. Additionally, search engines may adjust their algorithms randomly when conducting experiments. The random features of these experiments are expected not to change the basic algorithm dramatically. By leveraging statistical tools to analyze a large set of auction data, our study provides an empirical examination of the impact of bidding strategy, even with the unknown algorithm and random search engines experiments.

Cross-Sectional Data Analyses

Fixed-Bidding Group vs. Pulse-Bidding Group

We start the analyses by comparing fixed- and pulse-bidding strategies based on cross-sectional data. Bidding activities for each keyword category are divided into two groups: the *fixed-bidding group* contains the bidding activities of the advertisers who never changed their bid value during the data period, and the *pulse-bidding group* includes the bidding activities of the advertisers who changed their bid value at least once during the data period³. The comparison of

³ The pulse-bidding defined here includes the situation where the advertiser kept its bid value the same for some bidding activities and changed it for some other bidding activities. We did not find any advertiser that changed its bid value for all bidding activities (the "pure" pulse-bidding strategy).

various keyword performance metrics is presented in Table 2. When bidding for keyword category A, 1890 advertisers adopted a fixed-bidding strategy (40.9%), and the remaining 2727 advertisers adopted the pulse-bidding strategy (59.1%). The split between fixed-bidding and pulse-bidding group are very similar in category B (45.3% vs. 54.7%), C (42.3% vs. 57.7%), and D (40.5% vs. 59.5%). Furthermore, in category A, the average bid for the fixed-bidding group is significantly higher than that in the other one (2153.20 vs. 763.64; $p = .026$). The same can be said for all other three keyword categories (B: 754.8 vs. 632.3; C: 954.6 vs. 695.6; D: 577.2 vs. 510.08). A preliminary conclusion here is that pulse-bidding may help lower the average bid value or the cost of advertising on search engines.

---INSERT TABLE 2 HERE ---

Interestingly, even with a lower average bid value, the pulse-bidding group usually has better rank than the fixed-bidding group (the difference are 0.53, 1.13, 0.1, and 0.46 respectively for category A, B, C, and D). By varying bid value, the ad also achieves more impressions and clicks. Specifically, the number of exposures an ad receives in pulse-bidding group is on average 2.87 higher than that in fixed-bidding group; and the number of clicks in pulse-bidding group is on average 3.25 higher than that in fixed-bidding group. Note that the fluctuations in rank, impressions, and clicks are not eliminated in the fixed-bidding group. Even if the advertiser keeps its bid value consistent, the keyword performance cannot be guaranteed to stay stable due to competitors' dynamic bidding strategies and undisclosed search engine manipulation (for example, a controlled experiment).

Regression Analyses with Pulsing Intensity and Pulsing Variation

The above cross-sectional analyses draw our attention to the effect of pulsing on keyword performance. Does higher pulsing frequency leads to better rank, impressions and clicks? Is

larger pulsing variation beneficial to keyword performance? How does the sensitivity of keyword performance to pulsing vary by keyword categories? Figure 3a and 3b plot the histograms of the *Pulse Intensities* and *Pulsing Variations* for pulse-bidding group across four keyword categories. These plots demonstrate that the *Pulse Intensities* and *Pulsing Variations* vary significantly across advertisers within keyword categories.

--- INSERT FIGURE 3a and 3b HERE ---

In this subsection, we examine the impact of *Pulse Intensities* and *Pulsing Variations* on keyword performance through regression analyses. These two variables are highly correlated in all keyword categories (*correlation*: A: .753; B: .742; C: .696; D: .733). Therefore, instead of estimating one regression with both variables, we estimate two sets of regressions for each keyword category. In the first set of regressions, we use *Pulse Intensities* as the independent variable, and the values and the fluctuations of average rank, impressions, and clicks as the dependent variables. The average bid value of each keyword is included as a control variable. In the second set of regressions, we replace *Pulse Intensities* with *Pulsing Variations*. We apply these regressions to the advertisers who adopt the pulse-bidding strategy. Specifically:

The first set of regressions:

$$\begin{aligned}
 Rank &= \beta_0^R + \beta_1^R AvgBidValue + \beta_2^R Pul \sin gIntensity \\
 Im\ pression &= \beta_0^I + \beta_1^I AvgBidValue + \beta_2^I Pul \sin gIntensity \\
 Click &= \beta_0^C + \beta_1^C AvgBidValue + \beta_2^C Pul \sin gIntensity \\
 RankFluctuation &= \beta_0^{RF} + \beta_1^{RF} AvgBidValue + \beta_2^{RF} Pul \sin gIntensity \\
 Im\ pressionFluctuation &= \beta_0^{IF} + \beta_1^{IF} AvgBidValue + \beta_2^{IF} Pul \sin gIntensity \\
 ClickFluctuation &= \beta_0^{CF} + \beta_1^{CF} AvgBidValue + \beta_2^{CF} Pul \sin gIntensity
 \end{aligned} \tag{1}$$

The second set of regressions:

$$\begin{aligned}
Rank &= \gamma_0^R + \gamma_1^R AvgBidValue + \gamma_2^R Pul\ sin\ gVariation \\
Im\ pression &= \gamma_0^I + \gamma_1^I AvgBidValue + \gamma_2^I Pul\ sin\ gVariation \\
Click &= \gamma_0^C + \gamma_1^C AvgBidValue + \gamma_2^C Pul\ sin\ gVariation \\
RankFluctuation &= \gamma_0^{RF} + \gamma_1^{RF} AvgBidValue + \gamma_2^{RF} Pul\ sin\ gVariation \\
Im\ pressionFluctuation &= \gamma_0^{IF} + \gamma_1^{IF} AvgBidValue + \gamma_2^{IF} Pul\ sin\ gVariation \\
ClickFluctuation &= \gamma_0^{CF} + \gamma_1^{CF} AvgBidValue + \gamma_2^{CF} Pul\ sin\ gVariation
\end{aligned} \tag{2}$$

The model results are presented in Tables 3a and 3b. The auctions with higher pulsing intensities tend to have significantly better ranking after controlling for average bid value (A: $\beta = -1.255^4$, $p < .000$; B: $\beta = -1.167$, $p < .000$; C: $\beta = -.273$, $p = .065$). A similar pattern is observed in impressions and clicks for four keyword categories (Impressions, A: $\beta = 11.967$, $p = .007$; B: $\beta = 5.137$, $p < .000$; D: $\beta = 4.562$, $p = .010$; Clicks, A: $\beta = .105$, $p < .000$; B: $\beta = .090$, $p < .000$; C: $\beta = .051$, $p < .000$; D: $\beta = .083$, $p < .000$). For instance, one unit increase in the pulsing intensity will lead to almost 12 units improvement in the ad's impressions, and an 10.5% improvement in the ad's click probability for keyword category A. The effect of pulsing intensity is much higher in category A than that in the other three categories. In particular, the impact of pulsing intensity on impressions in category A is almost three times greater than that in category D, and the impact on rank in category A is more than four times as that that in category C. *Pulsing Variation* exerts similar influence on the ad's rank, impression, and click. For instance, the effect of *Pulsing Variation* on impression in Category A is 18.703 ($p = .007$), followed by that in Category B, 9.048 ($p < .000$), and Category D, 8.750 ($p = .001$). The average impact of *Pulsing Variation* on ad's ranking is -1.227. The click probably is also significantly affected by the scale of bid value change, in general, the greater the pulse variance, the higher the click-through rate

⁴ The rank variable is set up in a way that the larger the number, the lower the rank.

(A: $\beta = .195, p < .000$; B: $\beta = .183, p < .000$; C: $\beta = .083, p < .000$; D: $\beta = .127, p < .000$). We draw the tentative conclusion that frequent bid pulsing and higher level of pulsing variation are beneficial to keyword performance; this is especially true for category A, which has the highest average bid price and highest number of advertisers in the keyword category.

--- INSERT TABLES 3a and 3b HERE ---

The fluctuation in keyword performance can be attributed to pulse-bidding. Advertisers who pulse frequently and pulse with greater variance in bid value generally have a larger variation in their ads' impressions and rank (Impression: *Pulsing Intensity*: A: $\beta = 24.381, p = .003$; B: $\beta = 7.787, p < .000$; D: $\beta = 9.606, p = .001$; *Pulsing Variation*: A: $\beta = 37.653, p = .003$; B: $\beta = 17.230, p < .000$; D: $\beta = 11.540, p = .008$. Rank: *Pulsing Intensity*: C: $\beta = .506, p < .000$; D: $\beta = .502, p = .002$; *Pulsing Variation*: C: $\beta = .527, p < .000$). It is clear that pulse-bidding is not necessarily suitable for those advertisers who wish to have a more stable ad's ranking and impressions. The click probabilities, in contrast, are much less susceptible to the pulse-bidding (*Pulsing Intensity*: A: $\beta = .207, p < .000$; B: $\beta = .171, p < .000$; C: $\beta = .101, p < .000$; D: $\beta = .159, p < .000$; *Pulsing Variation*: A: $\beta = .178, p = .010$; B: $\beta = .143, p < .000$; D: $\beta = .111, p = .037$). The reason behind such differences might be that the effect of bid value on impression and rank is almost immediate: once consumer inputs the search query, the search engine begins the auction and ranks the ads based on the bid value, ad content, and landing page quality scores. An ad's click decisions, however, resides in consumers' evaluation of the ad. It is affected by the number of previous exposures (impressions) the consumer receives, the "goodwill" stock of the ad's reputation (the higher the rank, the more credible the ad), and many other exogenous variables, such as quality score of the landing page, and brand awareness. Therefore, the

fluctuation in ad's click probability is much less influenced by pulsing compared to the other two performance metrics.

The cross-sectional analyses generate useful insights for search engine advertisers. To achieve a high level of ad's rank, exposure, and click propensity, a common approach is to increase the keyword bid value. Our results show that alternatively, advertiser can pulse the bid value to achieve a similar goal. For instance, to reach 100 ad impressions for category A, the advertiser can save 9.86% in bid price by pulsing the bid price at 80% frequency. Even for category D, which has the smallest impact from pulse frequency, the advertiser could save 3.89% in average bid value by pulsing the bid value at 80%. From a cross-sectional perspective, pulse-bidding not only saves money; it leads to improved keyword performance, especially in ad's impression and click.

Longitudinal Data Analyses

The above cross-sectional analyses demonstrate the significant impact of pulsing on the keyword performance and its fluctuation. The identification of the model relies on the cross-sectional (across advertisers) features in the data. Next, we examine whether the pattern still hold in the *longitudinal data* when incorporating the time dimension. Specifically, we look at how time-to-time changes in bid value affect the keyword performance.

In this set of analysis, the dependent variables are the values of three performance metrics, i.e., rank, impression and click, as well as their changes between time $t - 1$ and time t ($Performance\ Change_t = Performance_t - Performance_{t-1}$). The predictors are *Pulsing Dummy* and *Pulsing Strength* (defined on p.17). *Bid Value* at time t is incorporated as a control variable. As mentioned previously, some companies may use previous keyword performance feedback in their bidding strategies; therefore, *Bid Value*, *Pulsing Dummy*, and *Pulsing Strength* are treated

as endogenous variables. Specifically, we use keyword auction performance at time $t-1$ as instrumental variables. To accommodate unobserved heterogeneity among advertisers and the specific keyword they bid on, we allow parameters γ_{ji} to vary across advertiser-keyword groups ($i = 1: N$ advertiser-keyword groups; $j = \{0,1,2,3\}$, which indexes for different parameters in each model). γ_{ji} is assumed to be i.i.d. across i , following a multivariate normal distribution. The mixed two-stage least square model is specified as the following:

$$\begin{aligned}
Rank_{i,t} &= \gamma_{0i}^R + \gamma_{1i}^R BidValue_{it} + \gamma_{2i}^R Pul \sin gDummy_{it} + \gamma_{3i}^R Pul \sin gStrength_{it} \\
\gamma_{ji}^R &\sim MVN(\bar{\gamma}^R, V^R); j = \{0,1,2,3\}; i = 1: N \text{ advertiser - keyword groups} \\
Impression_{i,t} &= \gamma_{0i}^I + \gamma_{1i}^I BidValue_{it} + \gamma_{2i}^I Pul \sin gDummy_{it} + \gamma_{3i}^I Pul \sin gStrength_{it} \\
\gamma_{ji}^I &\sim MVN(\bar{\gamma}^I, V^I); j = \{0,1,2,3\}; i = 1: N \text{ advertiser - key word groups} \\
Click_{i,t} &= \gamma_{0i}^C + \gamma_{1i}^C BidValue_{it} + \gamma_{2i}^C Pul \sin gDummy_{it} + \gamma_{3i}^C Pul \sin gStrength_{it} \\
\gamma_{ji}^C &\sim MVN(\bar{\gamma}^C, V^C); j = \{0,1,2,3\}; i = 1: N \text{ advertiser - keyword groups} \\
RankChange_{i,t} &= \gamma_{0i}^{RC} + \gamma_{1i}^{RC} BidValue_{it} + \gamma_{2i}^{RC} Pul \sin gDummy_{it} + \gamma_{3i}^{RC} Pul \sin gStrength_{it} \\
\gamma_{ji}^{RC} &\sim MVN(\bar{\gamma}^{RC}, V^{RC}); j = \{0,1,2,3\}; i = 1: N \text{ advertiser - key word groups} \\
ImpressionChange_{i,t} &= \gamma_{0i}^{IC} + \gamma_{1i}^{IC} BidValue_{it} + \gamma_{2i}^{IC} Pul \sin gDummy_{it} + \gamma_{3i}^{IC} Pul \sin gStrength_{it} \\
\gamma_{ji}^{IC} &\sim MVN(\bar{\gamma}^{IC}, V^{IC}); j = \{0,1,2,3\}; i = 1: N \text{ advertiser - key word groups} \\
ClickChange_{i,t} &= \gamma_{0i}^{CC} + \gamma_{1i}^{CC} BidValue_{it} + \gamma_{2i}^{CC} Pul \sin gDummy_{it} + \gamma_{3i}^{CC} Pul \sin gStrength_{it} \\
\gamma_{ji}^{CC} &\sim MVN(\bar{\gamma}^{CC}, V^{CC}); j = \{0,1,2,3\}; i = 1: N \text{ advertiser - key word groups}
\end{aligned} \tag{3}$$

Endogenous Equations:

$$\begin{aligned}
BidValue_{it} &= \alpha_{10} + \alpha_{11} Rank_{i,t-1} + \alpha_{12} Impression_{i,t-1} + \alpha_{13} Click_{i,t-1} \\
PulseDummy_{it} &= \text{probit}(\alpha_{20} + \alpha_{21} Rank_{i,t-1} + \alpha_{22} Impression_{i,t-1} + \alpha_{23} Click_{i,t-1}) \\
\% BidChang_{it} &= \alpha_{30} + \alpha_{31} Rank_{i,t-1} + \alpha_{32} Impression_{i,t-1} + \alpha_{33} Click_{i,t-1}
\end{aligned} \tag{4}$$

Table 4 presents the estimation results. The first three sections are associated with the performance measures (rank, impression and click), and the next three sections are associated with the changes in these performance measures. We find that a higher bid value will lead to

better ranking, more impressions and higher click probability. The effects are statistically significant for all four categories.

More importantly, pulse-bidding has a statistically significant influence on keyword performance. This is a pattern consistent across four keyword categories, after controlling for bid value and considering advertiser-keyword heterogeneity. When an advertiser pulses the bid, the rank of the ad, the number of impressions it receives, and the click probability will all improve. For example, an ad will be ranked on average 10% higher when the advertiser pulses the bid (*Pulsing Dummy*: A: $\beta = -.169, p < .000$; B: $\beta = -.094, p < .000$; C: $\beta = -.073, p < .000$; D: $\beta = -.065, p < .000$). The magnitude of the change in bid value in relative to the average bid value also positively influences ad's position on search engine result page (*Pulsing Strength*: A: $\beta = -.021, p < .000$; B: $\beta = -.012, p < .000$; C: $\beta = -.014, p < .000$). Both *Pulsing Dummy* and *Pulsing Strength* exert positive impacts on click-through rates (the average parameter values across four keyword categories: .064 and .024, respectively). In addition, pulse-bidding increases the number of exposures an ad receives, reflected by the positive estimates of *Pulsing Dummy* (A: $\beta = 8.391, p < .000$; B: $\beta = 5.175, p < .000$; C: $\beta = 5.993, p < .000$), and *Pulsing Strength* on impressions (A: $\beta = 6.653, p < .000$; B: $\beta = 3.414, p < .000$; C: $\beta = 1.492, p < .000$; D: $\beta = .050, p < .000$). If the advertiser changes the bid value relative to the average bid price by 1%, the exposure of an ad in category A will improve by more than 6%, and that of category B will improve by more than 3%. The pulse-bidding behavior itself (*Pulsing Dummy*) will additionally increase the impressions by over eight-fold in category A and five-fold in category B. This is in stark contrast with the effect of bid value: increasing bid price by one unit only leads to a 1.5% change in exposure in the category A and 0.8% in category B.

Pulsing strategy not only affects the keyword performance, it also influences the scale and the direction of the changes. For instance, if the advertiser changes the bid value for category A at time t , the level of improvement in rank will be strengthened by 1.3%. The same can be said for category B (.07%) and C (1.2%). Similarly, pulsing the bid value enhances the improvement in impressions by 5.558 units and in clicks by 3.9% for the category A. The numbers for B are 3.384 units and 2.6%, and for C are 3.692 units and 1.7%. Note that such effects are in addition to the effect of keyword bid value that has been controlled for. The changes in keyword performance metrics are consistent with the direction of the changes in bid value at each time point, and again the effect is much stronger in category A than the other keyword categories. The greater the increase in the relative bid value (*Pulsing Strength*), the larger the level of improvement in the rank, impression, and click will be (the average parameter values across four keyword categories: rank: .011; impression: 5.838; click: .051; all parameters are significant).

The consistent patterns across the four keyword categories demonstrate the robustness of our proposition that pulse-bidding will lead to improved keyword auction performance. Taking a closer look, the magnitude of the effect of bid pulsing differ radically across four categories: all three keyword performance metrics – rank, impression, and click, are much less sensitive to the *Pulsing Dummy* and *Pulsing Strength* in category D compared to its counterparts. Actually, the effect of bid pulsing is in descending order among category A, B, and D. For instance, the adoption of a pulsing strategy (*Pulsing Dummy*) improves the click probability by about 8.6% in the category A, about 1.2 times the influenced enjoyed in category B, and 1.5 times in category D. The effect of *Pulsing Strength* on ad's rank for category A is about 1.75 times of that in category B, and 10.5 times of that in category D. The difference in the effect of *Pulsing Strength*

on ad's impressions is even more striking: the effect for category A is more than 133 times of that in category D.

Interestingly, these three keyword categories, i.e., A, B, and D, are in descending order in the average bid value for the keyword category (\$1332 vs. \$699.3 vs. \$537.3 per day), the number of competitors the keyword category (4617 vs. 4501 vs. 3135), and the average number of bidders per keyword within the category (2.94 vs. 2.48 vs. 2.47). Other measures, such as the number of auctions recorded, bidding frequency, and pulse-bidding scale, are comparable among the three (see Table 1). Since the advertisers bidding for the same keyword and keyword categories are considered to be competitors, and the average bid value indicates the popularity of the keyword, we could use these three measures to gauge the level of competitiveness⁵. Hence, category A should be a *high-competition keyword category*, B should be a *medium-competition keyword category*, and D should be a *low-competition keyword category*. The benefit of bid pulsing increase as the level of competitiveness rises: for an keyword auction in a highly competitive keyword category, pulsing the bid will results in a much larger positive impact on the ad's rank, exposure, and click-through, and a much lower average bid value, compared to that in less competitive ones. In summary, pulsing is useful in improving keyword auction performance, especially for keywords with higher level of competition. This proposition holds in both longitudinal analyses and cross-section analyses.

--- INSERT TABLE 4 HERE ---

All three keyword metrics – rank, impression and click – improve with pulse-bidding even after controlling for bid value. Keeping the bid value constant at a high level does lead to better keyword performance, yet such performance comes at a high cost. Alternatively,

⁵ Other information might also be useful to gauge the level of competitiveness, yet due to the anonymity of the data, we do not have detailed information about the advertisers and the keyword categories.

advertiser could leverage pulse-bidding to achieve similar, or even better, keyword performance at lower cost. For example, the advertiser can spend \$5963.93 to achieve 100 impressions for category A; or, it could lower the bid value to \$5400.09⁶ (9.45% saving) and reach the same level of exposure. Similarly, advertiser in category D could save \$13585 (.58%) by pulsing the bid value if the goal is to reach 100 ad clicks. In a simplified situation where the only cost is bid price and all other factors (e.g., cost and effort to manage the pulse-bidding, learning cost, etc.) are kept constant, pulse-bidding suggests a better performance-to-cost ratio compared to the fixed-bidding strategy in our empirical analyses. Therefore, in addition to bid value, pulse-bidding frequency and pulse-bidding scale should also be taken into account when developing keyword auction strategies. Moreover, advertisers should gauge the intensity of the keyword auction competition. Our empirical analyses suggest that the higher the competition intensity, the more frequent advertisers should pulse bid value, and the larger the bid value pulsing range should be. In a less competitive keyword category, pulsing may not bring as much improvement in keyword performance metrics.

Discussions

In this study, we conducted an empirical investigation of the consequence of pulse-bidding strategy on keyword performance in search engine advertising. The main findings are: (1) advertisers who take the pulse-bidding strategy generally pay a lower bid price, yet achieve better rank, impressions and click-through rate, compared to the advertisers who do not change their bid value. (2) Higher pulsing frequencies and larger, positive bid price change will improve all three keyword performance metrics even after controlling for bid value; (3) The above

⁶ We assume that the *Pulsing Strength* is 1%.

findings are robust across four keyword categories that differ in terms of the number of bidders, bid values, and keyword performance. (4) The magnitude of the pulsing effect varies across four keyword categories, with the strongest impact observed in the most competitive keyword category. As the level of competition drops, the magnitude of the pulsing effect decreases as well.

Our study adds to the growing body of search engine advertising literature by empirically examining the performance of two bidding strategies under the GSP format. Analytical papers of search engine advertising discuss the equilibrium in the GFP and GSP auctions. The standard, full-information, and one-slot static second price auction has equilibrium where the bidders prefer to keep the bid value consistent at Vickrey price. However, existing research argued that the keyword auction in practice, which has multiple ad slots and no-information, does not have equilibrium in dominant strategies. This calls for further examination of bidding strategies under the GSP format. In addition, most extant studies focused on identifying the rationale of dynamic bidding and offering theoretical solutions to the dynamic bidding strategy. Researchers emphasize the importance of adjusting bid price based on keyword auction feedback, and have developed several dynamic bidding strategies theoretically to achieve optimal budget allocation across time, campaigns, and keywords. These bidding strategies include the future look-ahead bid price allocation ([20]), the two-bid uniform strategy ([12]), and the dynamic dual adjustment of bid price and daily budget ([36]). The *consequence* of dynamic bid, however, is rarely examined with real-world keyword auction data. We take both longitudinal and cross-sectional perspectives, and study the effect of bid pulsing on keyword performance using recorded keyword auction activities from a major search engine. Our paper provides empirical evidence that keeping bid value fixed does not benefit the rank, impression and click in the GSP keyword

auction. *Pulse-bidding*, on the other hand, is prevalent under the GSP format, and such bidding strategy significantly improves the keyword performance while lowering the bid price.

Managerial Implications

Managerially, our research offers some key insights regarding the impact of bid pulsing frequencies and strengths, and the difference in such impact across various keyword categories given the current empirical setup. Advertisers in search engines can pursue either a fixed-bidding strategy or a pulse-bidding strategy. Despite the fact that pulse-bidding requires intensive data support and may incur higher management and learning cost, it is more performance oriented and enables efficient budget allocation. Indeed, the results of both cross-sectional and the longitudinal analyses lend strong support to the pulse-bidding strategy. We found that across four keyword categories, the advertisers who pulse their bid always achieved an improved rank, better exposure, and more clicks on the ad. While those who keep their bid value the same over time incur higher cost of advertising and poorer keyword performance. To illustrate, the improvement in rank, impression and click of the pulse-bidding strategy over fixed-bidding strategy are 8.23%, 26.94% and 50%, respectively, for auctions in category A; and 8.49%, 13.39% and 37.5%, respectively, for auctions in category D. Longitudinal analyses demonstrate that in addition to bid value, the bid pulsing behavior itself results in an improvement in the ad performance; and a large, positive change in the bid value can further strengthen the effect on ad's rank, exposure, and clicks. For instance, simply pulsing the bid will increase the number of impressions by more than five units in category C, and one unit positive change in bid value will add extra 1.492 units to the exposure. Therefore, our results suggest that while keeping all other cost (such as the cost of learning dynamic bidding, and the time and resources to manage the bidding process) and the

bidding environment (such as the distribution of fixed- and pulse-bidding advertisers) the same, increasing the frequency and scale of bid pulsing will improve the keyword performance.

Our results suggest that pulse-bidding is able to lower the keyword bid price substantially while achieving the similar level of ad effectiveness in our data. The common approach to achieve a better rank, impression and click is to increase the keyword bid value. However, our study indicates that rather than merely relying on increasing the keyword bid value, advertisers could manipulate pulse-bidding frequency and scale to achieve a similar or even better performance-to-cost ratio. For example, by pulsing-bid price at a high frequency (e.g., 80%), an advertiser could save 9.86% in its average bid value while achieving the same level of ad exposure (100 impressions) for category A. The number demonstrates the additional positive impact of pulse-bidding on keyword performance after controlling for bid cost. Hence, when developing a keyword auction strategy, marketers should consider the level of bid pulsing intensity and bid pulsing range in addition to the bid price.

We also find that the effects of pulse-bidding are much stronger in keyword category A than the other three categories. In fact, the effect of bid pulsing increases as the intensity of keyword competitiveness increases. For example, the influence of pulsing intensity on the impression of an ad's in category A is about 2.3 times that of category B, and 12.7 times that of category D. Note that category A is the most competitive keyword category, and D is the least competitive one in our data. Similarly, the effect of the relative bid value change on an ad's rank for category A is 1.75 times that of category B, and more than 10 times that of category D. It is possible that for a highly competitive keyword category, with limited ad space on the search engine result page yet many competitors (advertisers), the price (bid value) difference between two slots can be much smaller than that in the less competitive keyword category. Therefore, a

small improvement in the bid value leads to large variation in the rank, impressions and clicks, and keyword performance becomes very sensitive to changes in bid value. However, in a less competitive keyword category, the price difference between two slots can be much larger, and a pulse bid that does not pass the threshold is not guaranteed to lead to the significant improvement in the keyword performance. Hence, it is important for advertiser to gauge the level of keyword competitiveness when developing bidding strategies. The average bid value and the number of bidders bidding for the same keyword (category) provide information with respect to the keyword competitiveness. If an advertiser is bidding for a highly competitive keyword, it is advisable to change the bid value more frequently and enlarge the bid price range. Yet for a less competitive keyword category, the return of bid pulsing could be much less.

Nevertheless, we find that about 40% of the advertisers still choose the fixed-bidding strategy in our dataset. It is likely that these advertisers try to avoid the high management cost of keyword auction, such as the cost of collecting and integrating keyword performance, and of developing the complex algorithm to for proper bid value. The budget, the campaign goals, the size of the account, and their competitors' bidding approach might also contribute to the selection of fixed-bidding strategy. There are two implications of this observation. First, the percentage of fixed-bidding advertisers reveals the acceptance of such strategy in practice. Without proper information on the budget, management cost, campaign goals and competitors' bidding approach, one cannot conclude the optimal strategy for a specific firm. Rather, the firm should use our empirical results as a benchmark and explore the optimal bidding strategies for its specific situation. As Jansen and Mullen (2011) pointed out, "an optimal strategy for one keyword market may not be the optimal strategy for another" (p.127). Second, we find that those who change their bid value frequently and at large scale achieve better keyword performance.

These empirical results are specific to our bidding environment where around 40% of the advertisers choose the fixed-bidding strategy, and the observed improvement may not apply if a substantial number of bidders change their bidding behavior.

Future Research

There are several ways to extend the current study. First, our study is more of a descriptive nature than a normative nature. We empirically examine the differences between the fixed- and the pulse-bidding strategies in terms of their influences on keyword performance using observed bidding activities. To provide guidance on the optimal keyword bidding strategies, one needs to rely on more comprehensive information, such as company's budget, bid management cost, campaign goals, and its competitors' bidding approach. Among them, the cost of learning bid pulsing, collecting expansive and intricate data, and developing intensive algorithm for proper bid value calculation, could be substantial and moderate the choice of the bidding strategies. In addition, about 40% of the advertisers in our data choose the fix-bidding strategy, and such bidding (competitive) environment may contribute to our empirical results. Future research could examine the optimal bidding strategy theoretically and empirically if proper data are collected, and explore the optimal bidding strategy in a competitive context. Second, different keyword categories — for example, branded versus generic keywords, B2B versus B2C keywords, high-involvement versus low-involvement purchase keywords, etc. — may vary in keyword performance when bid value fluctuates. Future research can examine how the effect of bid pulsing and cost saving differ across various types of keywords. Third, advertisers pulse their bids based on different rules (such as position-based bidding, probability-based bidding, portfolio-based bidding, or even random bidding), and the effect of bid pulsing on keyword performance might differ correspondingly. A study incorporating such rules would

contribute to the understanding of keyword bidding strategies. All these questions are of great importance for search engine marketing practitioners and worth further investigation.

Conclusions

This study empirically investigates whether and how pulse-bidding affects keyword auction performance in search engine advertising. We extend previous search engine advertising literature by providing empirical evidence of pulse-bidding strategy under the GSP auction format and by exploring the consequence of such strategy. With cross-sectional and longitudinal analyses on publicly available Yahoo! Search advertising data, we find that on average, the advertisers who adopt the pulse-bidding strategy generally achieve better rank, impression, and click-through rate at a lower bid price compared to those who adopt the fixed-bidding strategy. Across four keyword categories that vary in the level of competitiveness, higher pulsing frequencies and larger, positive bid price change are associated with better keyword performance metrics, with the positive impact of bid-pulsing stronger in more competitive keyword categories. We propose that when keeping all other costs (such as the cost of learning dynamic bidding, and the time and resources to manage the bidding process) and the bidding environment (such as the distribution of fixed- and pulse-bidding advertisers) constant, search engine advertisers should consider increasing the bid pulsing frequency and pulsing scale. This is especially the case when they bid on highly competitive keyword categories. With its rapid growth in recent years, and increasing attention from marketers, we hope that our study will elicit more research interest in search engine advertising.

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Table 1: Descriptive Statistics of Four Keyword Categories

A				B				
Min.	Mean	Max.	S.D.	Variables	Min.	Mean	Max.	S.D.
	4617			Num. bidders		4501		
99.76	1332	1,000,000	20,934.37	Average bid	50	699.3	211,900	3482.67
2	4,736	1,125,000	25,606.15	Num. bids	2	3586	1,148,000	33,499.73
1	2.94	383	5.72	Num. bidders per Keyword	1	2.48	158	4.96
0.00%	24.72%	99.65%	30.96%	Pulsing intensity	0	0.00%	18.51%	98.37%
0.00%	11.35%	151.90%	17.29%	% Pulse fluctuation	0	0.00%	8.37%	120.90%
0	81.06	9,208	293.212	Pulse fluctuation	0	90.26	89220	1475.09
1	6.66	38.5	3.64	Rank	1	7.93	46.17	5.63
0	4.08	17	2.17	Rank fluctuation	0	4.62	24.4	2.92
1	13.08	4,479	100.88	Impressions	1	8.14	2,878	63.87
0	19.46	4,723	150.23	Impression fluctuation	0	9.5	3,088	62.23
0	0.08	8	0.29	Clicks	0	0.06	17.41	0.35
0	0.14	10.88	0.46	Click fluctuation	0	0.14	10.88	0.46
C				D				
Min.	Mean	Max.	S.D.	Variables	Min.	Mean	Max.	S.D.
	5675			Num. bidders		3135		
50	806.1	200,000	3007.63	Average bid	80	537.3	112,400	2,336.49
2	3,333	778,300	16586.03	Num. bidders	2	2,328	155,100	8,695.19
1	2.16	240	3.77	Num. bidders per Keyword	1	2.37	539	6.44
0.00%	24.91%	98.58%	31.01%	Pulsing intensity	0.00%	25.83%	97.72%	30.93%
0.00%	12.26%	159.70%	19.25%	% Pulse fluctuation	0.00%	12.07%	191.40%	18.35%
0	85.72	8,874	312.27	Pulse fluctuation	0	77.17	57,700	1,077.67
1	5.62	34	3.08	Rank	1	5.69	27.59	3.27
0	3.49	20	2.03	Rank fluctuation	0	3.67	19.33	2.23
1	5.14	2,315	32.44	Impressions	1	7.76	1,114	30.15
0	6.47	4,266	59.17	Impression fluctuation	0	9.93	1,389	40.14
0	0.05	7.89	0.2	Clicks	0	0.07	9.011	0.27
0	0.09	15.5	0.36	Click fluctuation	0	0.12	17.29	0.49

**Table 2: Cross-Sectional Data:
Comparison between Fixed Bidding and Pulse Bidding**

Fixed Bidding: A (N = 1,890)				Pulse Bidding: A (N = 2,727)				
Min	Mean	Max	S.D.		Min	Mean	Max	S.D.
100	2,153.20	999,990	32,658.83	Average Bid	100	763.64	37,530	1,482.37
2	392.27	69,733	2,179.13	Number of Bids	2	7,746.29	1,125,397	32,936.79
1	6.97	38.50	4.55	Average Rank	1	6.44	22.80	2.83
0	3.72	17.00	2.42	Rank Fluctuation	0	4.32	14.41	1.95
1	10.74	4,479.13	124.01	Average Impressions	1	14.70	1,909.94	81.04
0	13.22	4,722.67	147.06	Impression Fluctuation	0	23.78	3,553.07	152.26
0	0.05	8.00	0.26	Average Clicks	0	0.10	5.71	0.31
0	0.09	6.00	0.32	Click Fluctuation	0	0.18	10.88	0.53

Fixed Bidding B (N=2,039)				Pulse Bidding B (N=2,462)				
Min	Mean	Max	S.D.		Min	Mean	Max	S.D.
58	754.80	211,900	4,621.84	Average Bid	50	632.30	11,320	988.96
2	714.90	214,900	7,491.74	Number of Bids	2	5964.00	1,148,000	44,643.75
1	8.55	46.17	6.88	Average Rank	1	7.42	37.78	4.26
0	4.46	24.40	3.29	Rank Fluctuation	0	4.75	18.07	2.56
1	6.49	232.90	12.60	Average Impressions	1	10.12	2,878.00	93.85
0	8.40	459.20	20.70	Impression Fluctuation	0	10.81	3,088.00	89.61
0	0.06	17.41	0.48	Average Clicks	0	0.07	3.13	0.17
0	0.09	24.42	0.72	Click Fluctuation	0	0.12	5.81	0.30

Fixed Bidding C (N=2,400)				Pulse Bidding C (N=3,275)				
Min	Mean	Max	S.D.		Min	Mean	Max	S.D.
50	954.60	200,000	4,465.35	Average Bid	63	695.60	18,750	1,237.83
3	372.20	59,530	1,947.12	Number of Bids	3	5716.00	778,300	21,879.75
1	5.69	34.00	3.64	Average Rank	1	5.59	26.45	2.52
0	3.16	20.00	2.18	Rank Fluctuation	0	3.87	14.58	1.81
1	3.67	233.90	8.72	Average Impressions	1	6.44	2315.00	42.78
0	3.75	396.90	13.58	Impression Fluctuation	0	8.82	4266.00	78.37
0	0.04	2.97	0.12	Average Clicks	0	0.06	7.89	0.24
0	0.06	5.75	0.20	Click Fluctuation	0	0.12	15.50	0.44

Fixed Bidding: D (N = 1,271)				Pulse Bidding: D (N = 1,864)				
Min	Mean	Max	S.D.		Min	Mean	Max	S.D.
80	577.20	31,140	1,327.61	Average Bid	88	510.08	112,444	2,824.94
2	391.84	14,375	1,195.10	Number of Bids	2	3,648.16	155,123	11,041.41
1	5.88	27.59	3.81	Average Rank	1	5.42	21.40	2.83
0	3.11	19.33	2.34	Rank Fluctuation	0	4.06	15.80	2.07
1	7.11	1113.71	39.04	Average Impressions	1	8.21	520.93	22.13
0	7.81	1388.55	43.45	Impression Fluctuation	0	11.37	887.26	37.65
0	0.05	9.01	0.28	Average Clicks	0	0.08	6.00	0.27
0	0.09	17.29	0.51	Click Fluctuation	0	0.15	10.19	0.46

Table 3a: Cross-Sectional Analyses: Pulsing Intensity and Keyword Performance / Performance' Fluctuations

DEPENDENT VAR	A			B			C			D		
RANK	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	7.457	0.163	0.000	7.865	0.138	0.000	6.116	0.084	0.000	6.035	0.118	0.000
Average Bid Value	-6.19E-04	7.90E-05	0.000	-6.69E-05	1.85E-05	0.000	-4.41E-04	3.49E-05	0.000	-9.72E-05	2.31E-05	0.000
Pulsing Intensity	-1.255	0.283	0.000	-1.167	0.318	0.000	-0.273	0.148	0.065	-0.251	0.225	0.264
IMPRESSIONS	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	2.883	2.573	0.263	5.006	0.409	0.000	5.899	1.456	0.000	6.081	0.928	0.000
Average Bid Value	4.15E-03	1.25E-03	0.001	1.12E-04	5.47E-05	0.040	8.96E-04	6.06E-04	0.139	2.81E-04	1.81E-04	0.121
Pulsing Intensity	11.967	4.458	0.007	5.137	0.942	0.000	-0.193	2.569	0.940	4.562	1.762	0.010
CLICKS	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	0.024	0.015	0.104	0.038	0.006	0.000	0.024	0.008	0.003	0.042	0.011	0.000
Average Bid Value	3.81E-05	7.14E-06	0.000	8.44E-07	7.43E-07	0.256	2.56E-05	3.34E-06	0.000	8.89E-06	2.22E-06	0.000
Pulsing Intensity	0.105	0.026	0.000	0.090	0.013	0.000	0.051	0.014	0.000	0.083	0.022	0.000
RANK FLUCTUATION	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	4.649	0.110	0.000	4.729	0.083	0.000	3.841	0.060	0.000	3.874	0.086	0.000
Average Bid Value	-4.15E-04	5.33E-05	0.000	-4.33E-05	1.11E-05	0.000	-2.76E-04	2.50E-05	0.000	-7.04E-05	1.68E-05	0.000
Pulsing Intensity	0.001	0.191	0.996	0.169	0.114	0.140	0.506	0.106	0.000	0.502	0.164	0.002
IMPRESSION FLUCTUATION	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	1.187	4.726	0.802	5.643	0.671	0.000	7.884	2.667	0.003	6.986	1.578	0.000
Average Bid Value	7.17E-03	2.29E-03	0.002	1.67E-04	8.98E-05	0.063	1.36E-03	1.11E-03	0.222	4.09E-04	3.08E-04	0.185
Pulsing Intensity	24.381	8.187	0.003	7.787	1.546	0.000	-0.010	4.707	0.998	9.606	2.997	0.001
CLICK FLUCTUATION	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	0.036	0.026	0.165	0.064	0.010	0.000	0.041	0.015	0.006	0.072	0.019	0.000
Average Bid Value	6.64E-05	1.26E-05	0.000	1.57E-06	1.28E-06	0.219	4.62E-05	6.19E-06	0.000	1.15E-05	3.78E-06	0.002
Pulsing Intensity	0.207	0.045	0.000	0.171	0.022	0.000	0.101	0.026	0.000	0.159	0.037	0.000

Table 3b: Cross-Sectional Analyses: Pulsing Variations and Keyword Performance / Performance' Fluctuations

DEPENDENT VAR	A			B			C			D		
RANK	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	7.308	0.137	0.000	7.836	0.114	0.000	6.105	0.066	0.000	6.121	0.093	0.000
Average Bid Value	-5.98E-04	7.86E-05	0.000	-6.22E-05	1.85E-05	0.001	-4.35E-04	3.47E-05	0.000	-9.31E-05	2.31E-05	0.000
Pulsing Variation	-2.002	0.435	0.000	-1.413	0.492	0.004	-0.521	0.203	0.010	-0.972	0.327	0.003
IMPRESSIONS	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	4.390	2.154	0.042	5.490	0.338	0.000	5.466	1.152	0.000	6.309	0.732	0.000
Average Bid Value	3.95E-03	1.24E-03	0.002	1.01E-04	5.48E-05	0.065	8.99E-04	6.04E-04	0.137	2.35E-04	1.81E-04	0.195
Pulsing Variation	18.703	6.870	0.007	9.048	1.461	0.000	1.581	3.523	0.654	8.750	2.560	0.001
CLICKS	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	0.031	0.012	0.013	0.041	0.005	0.000	0.029	0.006	0.000	0.053	0.009	0.000
Average Bid Value	3.65E-05	7.09E-06	0.000	4.85E-07	7.39E-07	0.512	2.46E-05	3.33E-06	0.000	8.15E-06	2.22E-06	0.000
Pulsing Variation	0.195	0.039	0.000	0.183	0.020	0.000	0.083	0.019	0.000	0.127	0.031	0.000
RANK FLUCTUATION	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	4.702	0.092	0.000	4.633	0.069	0.000	3.958	0.048	0.000	4.043	0.068	0.000
Average Bid Value	-4.16E-04	5.31E-05	0.000	-5.55E-05	1.11E-05	0.000	-2.86E-04	2.50E-05	0.000	-7.31E-05	1.69E-05	0.000
Pulsing Variation	-0.252	0.294	0.391	0.338	0.297	0.404	0.527	0.146	0.000	0.246	0.239	0.302
IMPRESSION FLUCTUATION	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	4.350	3.957	0.272	6.575	0.555	0.000	7.221	2.111	0.001	7.705	1.244	0.000
Average Bid Value	6.75E-03	2.28E-03	0.003	1.46E-04	9.00E-05	0.104	1.35E-03	1.11E-03	0.221	3.16E-04	3.08E-04	0.305
Pulsing Variation	37.653	12.618	0.003	17.230	2.398	0.000	3.015	6.455	0.640	11.540	4.353	0.008
CLICK FLUCTUATION	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	0.051	0.022	0.019	0.071	0.008	0.000	0.052	0.012	0.000	0.092	0.015	0.000
Average Bid Value	6.31E-05	1.25E-05	0.000	9.12E-07	1.27E-06	0.474	4.41E-05	6.17E-06	0.000	1.01E-05	3.78E-06	0.008
Pulsing Variation	0.178	0.069	0.010	0.143	0.034	0.000	0.052	0.036	0.150	0.111	0.053	0.037

**Table 4: Longitudinal Analyses
Mixed Two-Stage Least Square Model Results**

Main Model Results												
DEPENDENT VAR	A			B			C			D		
RANK	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	8.423	0.102	0.000	7.707	0.295	0.000	4.923	0.300	0.000	4.260	0.103	0.000
Bid Value	-3.22E-04	3.38E-06	0.000	-1.16E-04	4.60E-06	0.000	-6.89E-05	1.07E-05	0.000	-4.53E-05	9.52E-06	0.000
Pulsing Dummy	-0.169	0.005	0.000	-0.094	0.009	0.000	-0.073	0.004	0.000	-0.065	0.007	0.000
Pulsing Strength	-0.021	0.003	0.000	-0.012	0.001	0.000	-0.014	3.24E-04	0.000	-0.002	0.001	0.208
sd(γ_0^R)	9.819			7.614			7.144			4.922		
sd(γ_1^R)	8.07E-09			5.18E-08			9.89E-09			7.62E-08		
sd(γ_2^R)	7.59E-06			6.23E-05			7.07E-06			8.10E-06		
sd(γ_3^R)	7.26E-06			8.94E-07			5.53E-07			3.55E-06		
<i>-2 LogLike/AIC</i>	<i>1.31E+08</i>	<i>1.31E+08</i>		<i>1.02E+08</i>	<i>1.02E+08</i>		<i>1.14E+08</i>	<i>1.14E+08</i>		<i>4.45E+07</i>	<i>4.45E+07</i>	
IMPRESSIONS	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value	Estimate	S.D.	<i>P</i> -value
Intercept	10.541	1.960	0.000	10.046	1.152	0.000	12.008	0.942	0.000	7.324	0.423	0.000
Bid Value	0.015	0.001	0.000	0.008	2.89E-04	0.000	0.011	4.65E-04	0.000	2.51E-04	3.53E-05	0.000
Pulsing Dummy	8.391	0.850	0.000	5.175	0.648	0.000	5.933	0.221	0.000	0.087	0.053	0.102
Pulsing Strength	6.653	0.266	0.000	3.414	0.172	0.000	1.492	0.076	0.000	0.050	0.008	0.000
sd(γ_0^I)	10.262			11.467			13.339			13.540		
sd(γ_1^I)	3.40E-06			7.17E-07			1.09E-06			7.43E-08		
sd(γ_2^I)	7.06E-04			2.77E-03			8.48E-04			2.22E-04		
sd(γ_3^I)	1.36E-03			9.56E-04			6.04E-05			5.79E-05		
<i>-2 LogLike/AIC</i>	<i>3.54E+08</i>	<i>3.54E+08</i>		<i>2.09E+08</i>	<i>2.09E+08</i>		<i>2.62E+08</i>	<i>2.62E+08</i>		<i>9.24E+07</i>	<i>9.24E+07</i>	

(Cont'd in the next page)

DEPENDENT VAR	A			B			C			D		
CLICKS	Estimate	S.D.	P-value	Estimate	S.D.	P-value	Estimate	S.D.	P-value	Estimate	S.D.	P-value
Intercept	0.131	0.009	0.000	0.240	0.019	0.000	0.064	0.033	0.055	0.159	0.004	0.000
Bid value	6.49E-05	1.97E-06	0.000	2.04E-05	2.68E-06	0.000	5.57E-05	4.38E-06	0.000	4.27E-06	1.99E-07	0.000
Pulsing Dummy	0.086	0.008	0.000	0.071	0.002	0.000	0.041	0.001	0.000	0.058	0.003	0.000
Pulsing Strength	0.052	0.002	0.000	0.040	0.004	0.000	0.002	2.54E-04	0.000	0.001	5.49E-05	0.000
sd(γ_0^C)	0.042			0.116			0.058			0.025		
sd(γ_1^C)	1.30E-09			7.98E-09			2.97E-09			7.54E-10		
sd(γ_2^C)	7.78E-06			5.96E-06			5.28E-06			6.25E-06		
sd(γ_3^C)	8.37E-06			8.26E-06			5.39E-07			8.31E-08		
-2 LogLike/AIC	1.11E+08	1.11E+08		8.43E+07	8.43E+07		1.04E+08	1.04E+08		3.18E+07	3.18E+07	
RANK CHANGES	Estimate	S.D.	P-value	Estimate	S.D.	P-value	Estimate	S.D.	P-value	Estimate	S.D.	P-value
Intercept	0.023	0.004	0.000	0.019	0.006	0.001	0.015	0.003	0.000	0.006	0.013	0.660
Bid value	-6.45E-05	2.39E-06	0.000	-3.51E-05	2.61E-06	0.000	-3.40E-05	1.07E-06	0.000	-9.00E-06	9.53E-07	0.000
Pulsing Dummy	-0.013	0.005	0.021	-0.007	0.001	0.000	-0.012	0.004	0.001	0.002	0.006	0.771
Pulsing Strength	-0.022	0.004	0.000	-0.013	0.007	0.070	-0.006	0.002	0.015	-0.001	3.14E-04	0.001
sd(γ_0^{RC})	15.174			21.109			6.712			15.776		
sd(γ_1^{RC})	3.70E-09			5.72E-09			7.49E-10			8.30E-09		
sd(γ_2^{RC})	9.23E-06			2.19E-06			2.20E-06			7.84E-05		
sd(γ_3^{RC})	2.00E-05			4.80E-05			5.09E-06			5.37E-07		
-2 LogLike/AIC	1.44E+08	1.44E+08		1.02E+08	1.02E+08		1.14E+08	1.14E+08		4.92E+07	4.92E+07	
IMPRESSION CHANGES	Estimate	S.D.	P-value	Estimate	S.D.	P-value	Estimate	S.D.	P-value	Estimate	S.D.	P-value
Intercept	0.862	0.124	0.000	0.460	0.109	0.000	0.469	0.041	0.000	-0.042	0.062	0.503
Bid value	0.014	0.001	0.000	0.004	1.30E-04	0.000	0.007	0.001	0.000	2.61E-04	2.73E-05	0.000
Pulsing Dummy	5.558	1.098	0.000	3.384	0.662	0.000	3.692	0.427	0.000	-0.109	0.087	0.210
Pulsing Strength	12.154	0.749	0.000	7.052	0.274	0.000	4.042	0.259	0.000	0.102	0.016	0.000
sd(γ_0^{IC})	15.628			16.397			21.339			22.960		
sd(γ_1^{IC})	1.56E-06			3.13E-07			7.27E-07			1.50E-07		
sd(γ_2^{IC})	7.51E-03			9.00E-04			1.20E-03			2.29E-04		
sd(γ_3^{IC})	8.95E-04			8.53E-04			6.22E-04			9.11E-05		
-2 LogLike/AIC	1.31E+08	1.31E+08		2.09E+08	2.09E+08		2.7E+08	2.7E+08		9.74E+07	9.74E+07	

(Cont'd in the next page)

DEPENDENT VAR	A			B			C			D		
	Estimate	S.D.	P-value	Estimate	S.D.	P-value	Estimate	S.D.	P-value	Estimate	S.D.	P-value
Intercept	0.013	0.003	0.000	0.011	0.002	0.000	0.006	0.001	0.000	-0.002	0.102	0.981
Bid value	3.19E-05	1.03E-06	0.000	1.92E-05	8.48E-07	0.000	5.93E-06	4.35E-07	0.000	5.34E-06	3.95E-07	0.000
Pulsing Dummy	0.039	0.006	0.000	0.026	0.007	0.000	0.017	0.003	0.000	3.61E-04	0.001	0.714
Pulsing Strength	0.109	0.002	0.000	0.073	0.001	0.000	0.018	0.001	0.000	0.002	4.08E-04	0.000
sd(γ_0^C)	3.59E-06			0.001			1.01E-04			9.36E-07		
sd(γ_1^C)	6.44E-09			6.26E-09			7.15E-10			3.31E-09		
sd(γ_2^C)	9.34E-06			7.07E-06			2.77E-06			8.95E-07		
sd(γ_3^C)	1.33E-06			1.36E-06			8.55E-07			6.60E-07		
-2 LogLike/AIC	1.26E+08	1.26E+08		9.29E+07	9.29E+07		1.09E+08	1.09E+08		3.68E+07	3.68E+07	

Figure 1: Illustration of Pulse Bidding

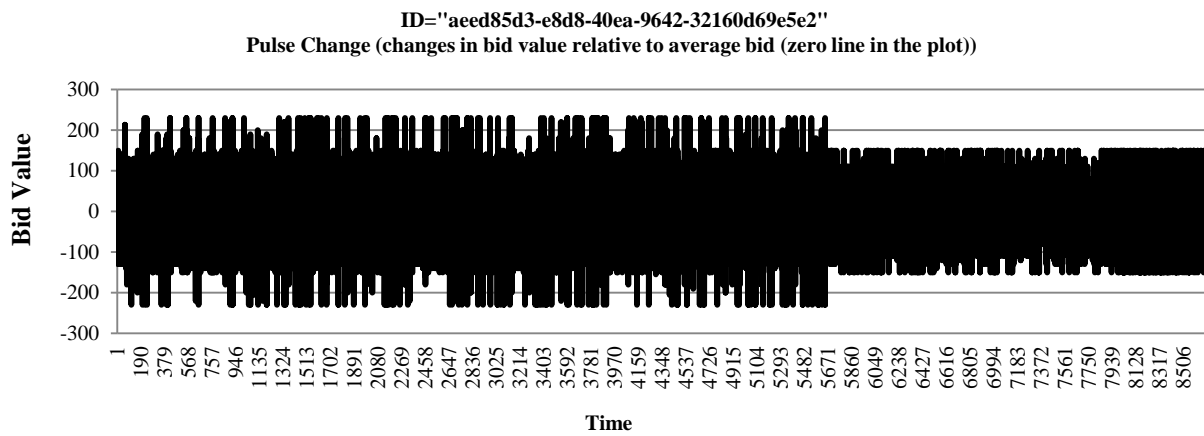
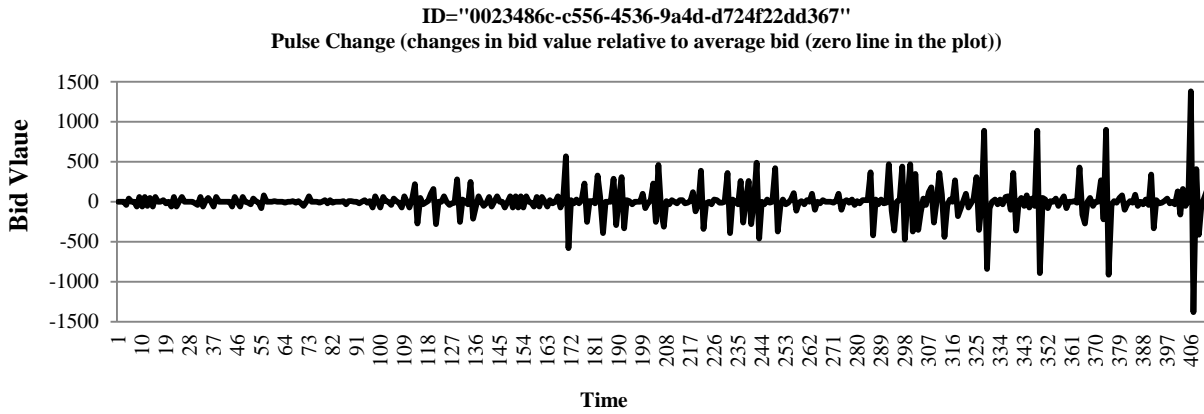
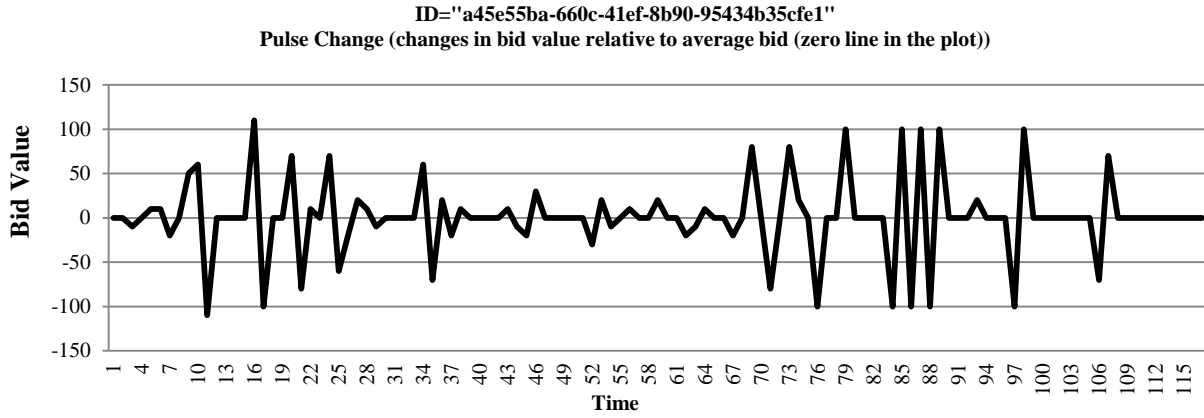


Figure 2: Illustration of Keyword Performance

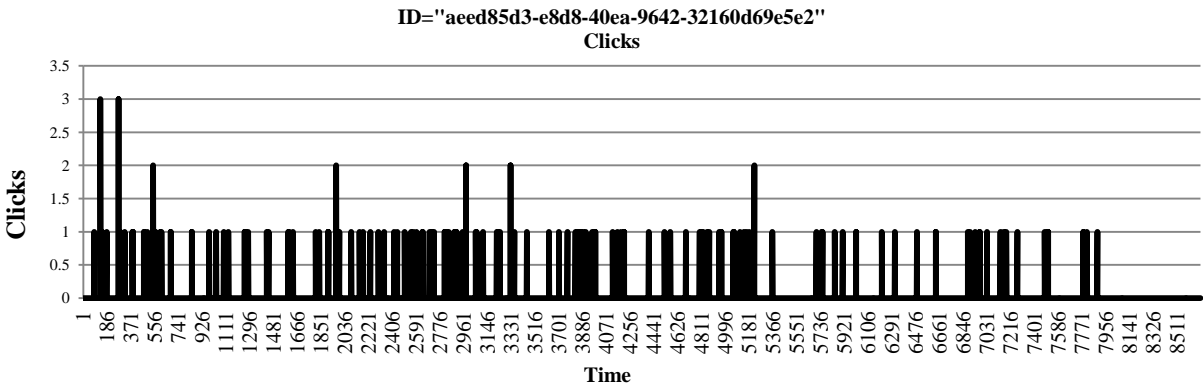
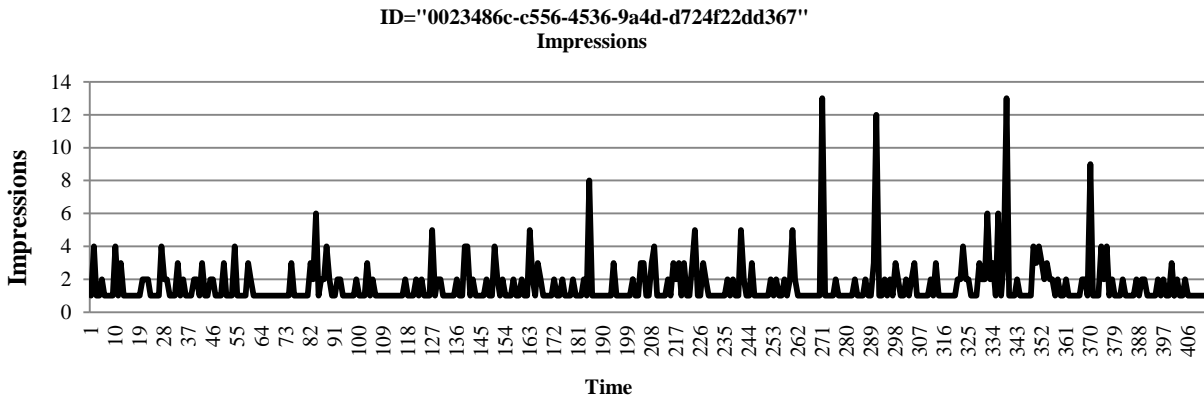
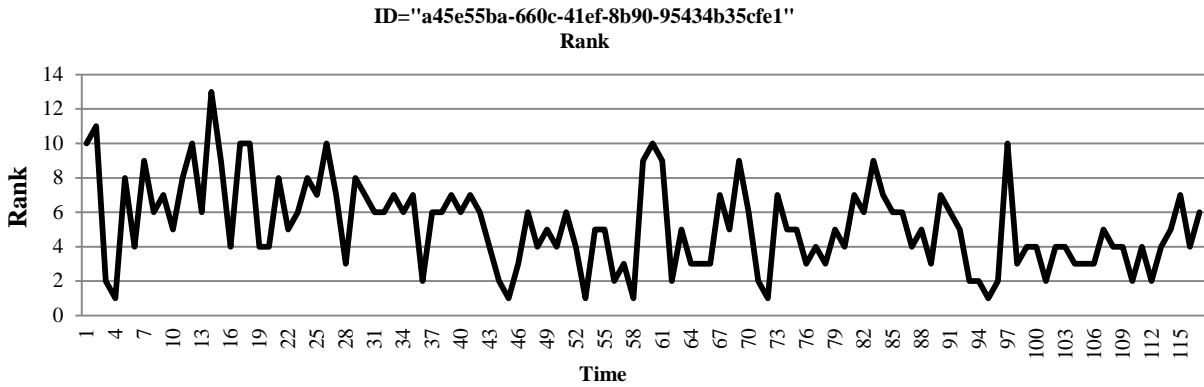


Figure 3a: Histogram of Pulsing Intensity of Pulse-bidding Group in Four Keyword Categories

X-axis represents pulsing intensity; Y-axis represents the number of observations.

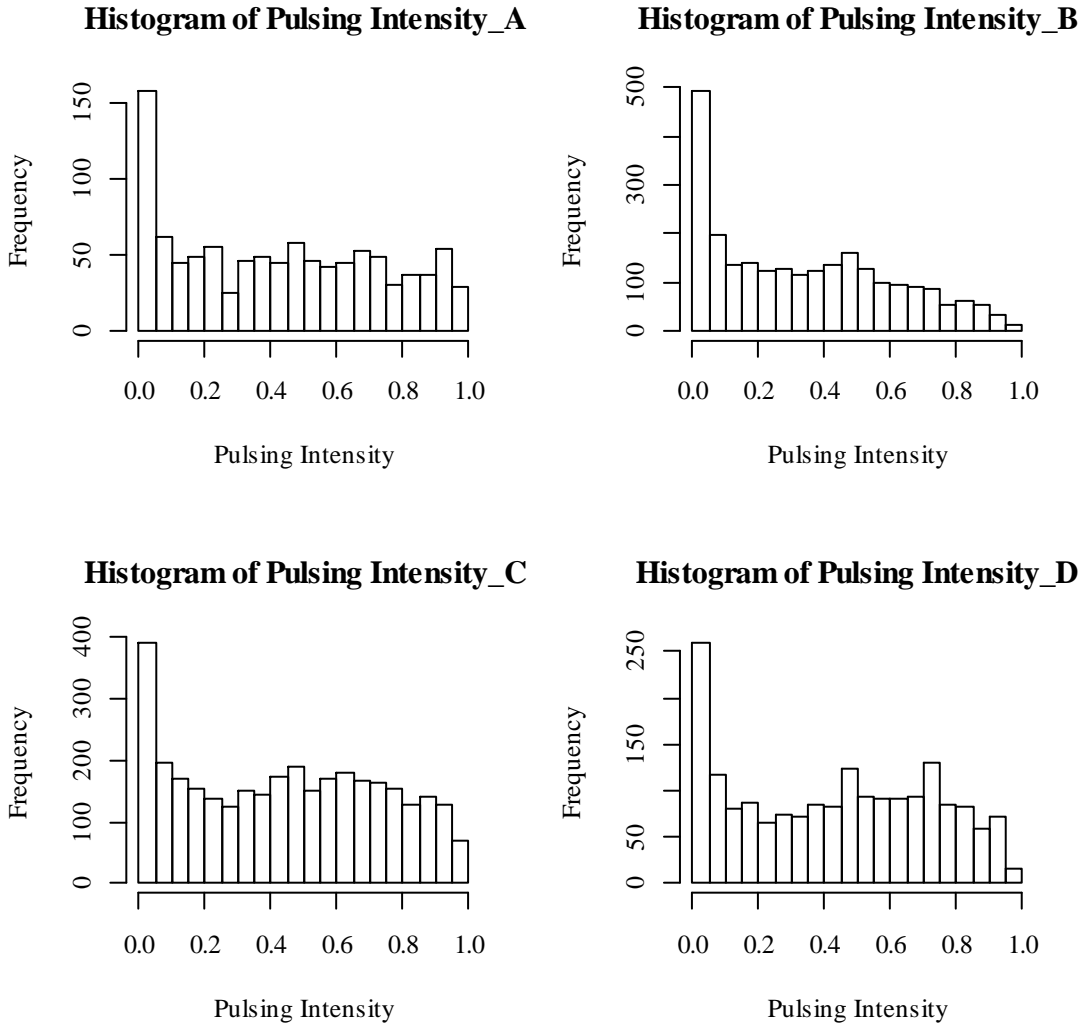
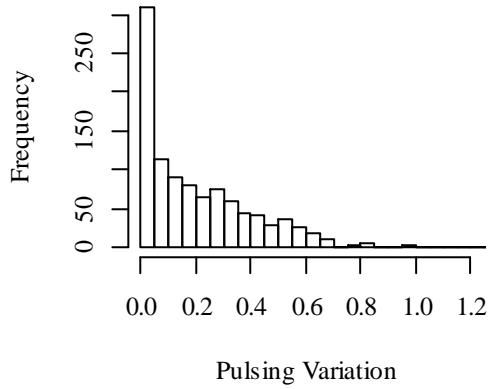


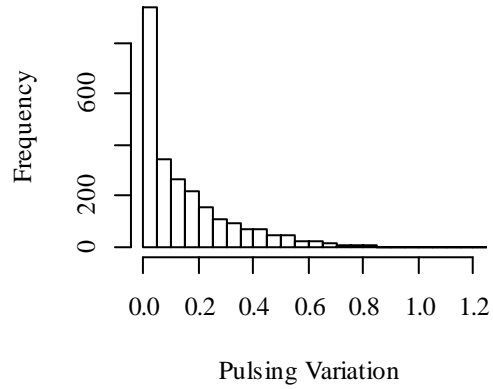
Figure 3b: Histogram of Pulsing Variation of Pulse-bidding Group in Four Keyword Categories

X-axis represents pulsing variation; Y-axis represents the number of observations.

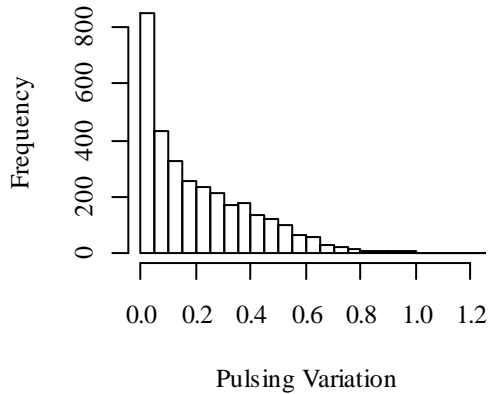
Histogram of Pulsing Variation_A



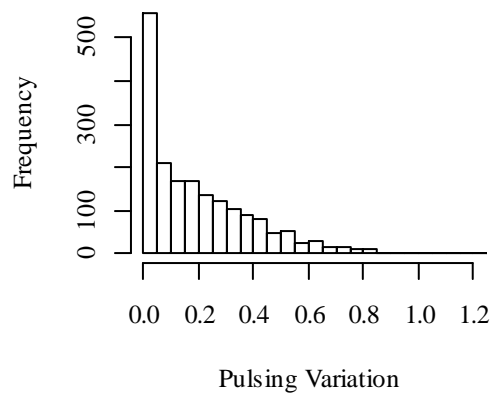
Histogram of Pulsing Variation_B



Histogram of Pulsing Variation_C



Histogram of Pulsing Variation_D



Appendix: Illustration of Sawtooth Pattern

