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Online search-based advertising strategy for e-Business platform with the consideration of consumer search cost

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Abstract

Purpose – Consumers are increasingly using search-based advertising in e-Business platforms to seek their desirable products. Platforms will choose a centralized advertising mechanism (CAM) or decentralized advertising mechanism (DAM) to offer a search advertising service to lower consumer search cost, as represented by using search time length. It is important for the platform to decide how to choose advertising mechanisms, and how to determine the optimal advertising price and search time length. To address these issues, this study aims to develop a theoretical approach under each mechanism to examine the platform's optimal search-based advertising strategy by considering search cost.

Design/methodology/approach – In this study, two models are developed to examine the optimal search-based advertising strategy by considering consumer search cost (i.e. search time length). By comparing the platform's profits under two models, the optimal advertising strategy, search time length and price are explored.

Findings – It is found that when the seller's reserve benefit is sufficiently large, the platform benefits from choosing the DAM; otherwise, the CAM is a better choice. The advertising service is usually offered with a shorter search time length accompanied by a higher charge, and a longer search time length accompanied by a lower charge. Specifically, when the seller's reserve benefit is substantially high, a DAM that benefits both the platform and seller is a better choice. This can explain why many platforms offer advertising services with a DAM.

Originality/value – This paper is the first theoretical study on addressing the search-based advertising strategy, especially the choice of advertising mechanisms, in the online advertising context. It is also the first piece of analytical research that considers the effect of consumer search cost on product demand, and then examines the optimal advertising price and search cost (i.e. search time length) for online platforms.

Keywords Advertising mechanism, Consumer search cost, e-Business platform, Search-based advertising

Paper type Research paper

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1. Introduction

Consumers are increasingly searching their desirable products and making purchases in retailing platforms (Dukes and Liu, 2015). Retailing platforms offer a convenient place for consumers to purchase, and however, consumers may face choosing one or several particular products from many similar products provided by various third-party sellers. In such a circumstance, platforms may offer an advertising service to help consumers to find their desirable products. An obtrusive advertising can reduce search cost and inform consumers, and thus can accelerate consumer searching and identifying their desirable products (Anderson and Renault, 2013; Tan *et al.*, 2013). However, an obtrusive advertising such as banner advertising may incur increased advertising costs, which will be paid by online sellers/advertisers. The primary goal of this paper is to examine the optimal online search-based advertising strategy for e-Business platforms by considering consumer search cost.

To illustrate the consideration of consumer search cost in online marketplaces, consider a consumer who wants to buy an overcoat. He knows his tastes about the product (e.g. style, size, color, etc.), but does not have a particular overcoat in his mind. In an online platform, he will search overcoat on the website and browse all possible products from top to bottom in the list of search results. Note that he may evaluate each listed product following his idiosyncratic utility. As Dukes and Liu (2015) indicated, product evaluation for each listed result is costly to consumers. In this regard, an obtrusive search-based advertising offered by the platform can easily attract his attention. Conventional wisdom suggests that consumers scale back the number of considered sellers with relatively high search costs (Anderson and Renault, 1999). Consequently, an advertising with a relatively low search cost may help consumers to find their desirable products and then increase their purchase willingness. Hence, to boost sales, online sellers may have incentives to pay for search-based advertising.

Advertising strategy specifies a particular advertising mechanism and pricing scheme, and also determines consumer search cost represented as search time length, which will directly affect consumer purchase decisions (Anderson and Renault, 2013; Dukes and Liu, 2015). Two advertising mechanisms are commonly used, namely, centralized advertising mechanism (CAM) and decentralized advertising mechanism (DAM) (Wu, 2015). CAM is a simple market-based mechanism, under which a platform (or a publisher) announces a list price for each advertising slot, and advertisers (or sellers) then self-select to purchase slots (Wu, 2015). This advertising mechanism can be observed in Tianmao Mall and JD.com. Unlike CAM, DAM is an auction-based mechanism, under which a platform sells limited advertising slots (or spaces) to sellers with auctions (Yao and Mela, 2011; Yuan *et al.*, 2015). This mechanism is widely used in online platforms such as TaoBao.com, JD.com, Amazon.com and EBay.com. Generally speaking, sellers who buy advertising services may expect to increase their product sales, and thus profitability. In practice, sellers may hold different expectations in terms of profitability for different products such as fashion products, luxury, new products and discounted products. In such a context, sellers may choose to purchase advertising services under different advertising mechanisms. Thus, it is unclear whether DAM and CAM can benefit platforms, sellers or both.

The aforementioned evidences raise two important issues:

(1) What advertising mechanism can benefit platforms, that is CAM or DAM?

(2) Under a particular advertising mechanism, how do platforms charge online sellers for designing particular search time lengths to reduce consumer search costs?

To address these two issues, in this paper, we consider a platform and a seller and develop a theoretical approach under each advertising mechanism to explore the optimal online search-based advertising strategy by considering consumer search cost. Consumer search cost is represented as search time length, which is assumed to linearly affect product demand. Under CAM, the platform first provides his price and search time length for a given advertising slot, and then the seller decides whether to purchase the advertising service. Under DAM, the platform first sets search time length, and then the seller determines auction payoff price for the service. Based on the two proposed approaches, the optimal advertising mechanism, advertising price and search time length are explored. The optimal profits of both the platform and the seller are also examined. Some important findings and insights are achieved. The rest of the paper is organized as follows. Section 2 reviews the most relevant literature. In Section 3, we present our theoretical models. The results and managerial insights are provided in Section 4. Section 5 offers the conclusions. All proofs are provided in Appendix.

2. Literature review

There is a rich body of studies on advertising strategies on online platforms. Here, we only review the most relevant studies on online advertising, which includes consumer search cost and advertising mechanism.

2.1 Consumer search cost

Diamond (1985) is the pioneer on examining consumer search cost, which is defined as cost incurred by a consumer locating an appropriate seller and purchasing a product, including opportunity cost of time spent on searching. Robert and Stahl (1993) investigate the interaction between search and price advertising, and find that advertising can adjust price distribution. Similar results are found in Stivers and Tremblay (2005). However, these studies neglect the effect of advertising on search cost. Janssen and Non (2008) explore the relationship between advertising, search cost and revenue, and find that consumers with lower search costs result in more benefits than those with higher search costs. Anderson and Renault (2013) remarkably state that advertising can effectively reduce search cost. Chan and Park (2015) show that consumer search activities can be endogenously determined by advertising positions. These studies suggest that suitable advertising strategies can reduce consumer search costs, whereas the effect of search cost on consumer behaviors is ignored. Anderson and Renault (1999) show that consumers scale back the number of considered sellers when facing relatively high search costs. By assuming that consumers only learn partial product information, Branco *et al.* (2012) find that consumers can react to high search costs by decreasing the amount of acquired information. Dukes and Liu (2015) find that high search cost prevents consumers from evaluating many sellers, but does not have a significant effect on evaluation depth within products.

According to the above-mentioned studies, we find that consumer search cost may negatively affect consumer decisions on searching or evaluating their products in the online retailing context. Thus, we assume that search cost negatively affects consumer purchasing utility, and based on this assumption, we can derive consumer utility function for this study.

2.2 Advertising mechanism

Since 1994, internet advertisement has been gradually evolved in steps over time. In 1997, Overture, GoTo and Yahoo! introduced a completely new model of selling internet advertising, that is generalized first-price auction. Under such a mechanism, an advertiser who has submitted the highest price will win the advertising slot, and the price is the highest bid. However, Overture and advertisers found that the mechanism was unstable due to the fact that bids could be changed very frequently (Edelman *et al.*, 2007). In 2002, Google recognized this problem and designed a new auction mechanism, that is generalized second-price (GSP) auction mechanism, to offer search advertising. This mechanism makes

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the market more user-friendly and less susceptible to gaming in auction process (Edelman *et al.*, 2007). Due to these advantages, Overture and Yahoo! have also switched to GSP. In recent years, many e-Business platforms have also adopted this mechanism to sell advertising services, such as TaoBao.com, JD.com, Amazon.com and EBay.com. Notably, the GSP auction mechanism uses auction payoff price to determine advertising price, which is called DAM. More recently, with the rapid growth of e-Business, many platforms such as Tianmao Mall and JD.com have applied CAM to offer advertising services. Under this mechanism, platforms provide a list price for each advertising slot, and advertisers determine whether to accept to buy the service.

Despite practical applications of DAM and CAM, an increasing number of studies in the literature have examined these issues. The extant studies can be grouped into two streams. The first stream is related to DAM. Chatterjee *et al.* (2003) firstly introduce the GSP auction into online advertising to examine the effect of repeated exposure on click-through rate. Edelman *et al.* (2007) show that the GSP auction is the equilibria in search advertising auctions. Katona and Sarvary (2010) apply GSP to design online advertising auction mechanisms, and find that interactions between search results and sponsored link and inherent differences between sites and brand quality indeed affect bidding behaviors and the equilibrium prices for sponsored links. Some studies focus on examining interactions between GSP auction and consumer behaviors, for example, Animesh *et al.* (2010) and Chan and Park (2015). Through an empirical study, Yao and Mela (2011) show that online retailers are practicing dynamic bidding in sponsored search advertising. Some studies investigate the effect of advertising position on the sponsored search advertising effectiveness (Narayanan and Kalyanam, 2015), and the effect of position and time on personalized online advertising effectiveness (Bleier and Eisenbeiss, 2015). Note that most of the existing studies on advertising auctions treat advertisers' bidding prices as exogenous variables. An exception is Liu and Viswanathan (2014). In this study, we take GSP as the auction mechanism to determine payoff price for search-based advertising under DAM, and treat the auctioned payoff price as an endogenous variable.

In the second stream, only two articles focus on examining the issue of CAM. Deza *et al.* (2015) introduce a chance-constrained optimization model for the fulfillment of guaranteed display internet advertising campaigns. In their work, the display slots are allocated by considering the uncertainty of the supply of internet viewers. In a recent empirical study, Wu (2015) explores the profit of publisher and the motivation of advertiser with CAM and DAM, and finds that the publisher's profit obtained under the decentralized mechanism is close to that obtained under the centralized mechanism with perfect information. These studies suggest that CAM can be a suitable advertising mechanism under certain conditions.

To the best of our knowledge, this paper is the first theoretical study on addressing the search-based advertising strategy, especially the choice of advertising mechanisms, in the online advertising context. It is also the first piece of analytical research that considers the effect of consumer search cost on product demand, and then examines the optimal advertising price and search cost (i.e. search time length) for online platforms. Accordingly, some new findings and insights for advertising management are obtained.

3. Theoretical models

In practice, many online sellers sell the same type of product to a group of consumers in an e-Business platform. Products offered by various sellers are assumed to have no systematic quality differences. The platform offers a search-based advertising service such as search-based banner advertising for consumers to seek their desired products. To this end, the platform will choose CAM or DAM to offer advertising services, and charges sellers for

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incurred advertising costs. Generally speaking, the platform may provide multiple advertising banner slots at once, and allocate slots to sellers according to their prices. Common wisdom suggests that the number of sellers who want to buy advertising services is much larger than that of the given advertising slots in any platform, and thus each slot will be sold to one seller eventually (Balseiro *et al.*, 2015; Yuan *et al.*, 2015). For ease of analysis, we assume that advertising slots are allocated to sellers one by one. In such a circumstance, we consider only one slot in the platform. Furthermore, sellers generally make their decisions on purchasing the service independently in the platform. Thus, we further assume that there is only one seller who will buy the advertising service. It is also assumed that each consumer buys only one product, and he knows what he wants to buy. However, he does not have a clear brand or seller in his mind. When he comes to the platform, he will seek his desired product by using the search service with some key words. The platform then lists the most relevant products via search advertising to reduce his search cost. To examine the optimal search-based advertising strategy, we further assume that the platform is rational and self-interested, and his aim is to maximize his own profit. We also assume that there is no information asymmetry between the platform and the seller.

Before we provide our theoretical model, we firstly present the notions used in this study, as summarized in Table I.

We assume that product price p is presented on the website and is exogenous. Under CAM, search time length T and constant charge m are determined by the platform, and the seller only determines whether to accept the charge. If the seller accepts the charge, he will pay m to the platform for advertising his product; otherwise, he will not advertise his product. Under DAM, search time length T is a decision variable of the platform, whereas payoff price p_s for the slot is determined with auction by the seller. Furthermore, product production cost is normalized to zero. This assumption can help us to focus on the main decision issues considered in our study, while retaining analytical tractability.

We define the overall utility of purchasing a product from the seller as:

Notation	Interpretation
u	Overall utility of a product
u_0	The base utility of a product
p	Product price
T	Search time length of a product
T_0	The base product search time length without offering a search advertising service
S	Product demand function
S_0	The base product demand without offering a search advertising service
ΔS	Increase in product demand with offering a search advertising service
α	The search time length sensitivity coefficient
m	Per-click charge for a product under CAM
p_s	Per-click payoff price of a slot under DAM
$c(T)$	Search-based advertising cost function of a product
k	The cost coefficient of unit search time length reduction
x	The seller's choice of the advertising under CAM
ρ	The platform referral fee rate
λ	Conversion rate
γ	Reserve benefit per product of the seller
π_p	The platform's profit function
π_s	The seller's profit function

Table I. Summary of notations used

$$u = u_0 - p - \alpha T. \quad (1)$$

Note that the coefficient α captures the degree regarding tolerance of search time length for the seller's product, and αT corresponds to total utility from the tolerance degree for search time length. To describe consumer heterogeneity, we use u_0 to characterize the base level of utility from purchasing a product. Following Anderson *et al.* (2014) and Ji *et al.* (2016), we assume that u_0 is uniformly distributed over the interval [0, 1]. The specific utility function indicates that consumer utility decreases in both product price and search time length. The decrease effect of search time length on consumer utility is intuitive and can be widely observed in practice and in recent academic articles, for example Anderson and Renault (2013) and Dukes and Liu (2015).

In general, a consumer may purchase a product from the seller when the product overall utility is non-negative, that is $u > 0$. We denote by $\overline{u_0}$ the intrinsic usage benefit to make a difference between purchasing and not purchasing the product. When the intrinsic usage lies in the interval $[\overline{u_0},1]$, the consumer will buy the product. With the purchasing rate of $1 - \overline{u_0}$, product demand can be expressed as:

$$S = 1 - p - \alpha T. \quad (2)$$

We assume that $0 \leq p - \alpha T \leq 1$ so as to make S fall into the interval [0, 1]. Note that T_0 is assumed to be the base search time length for any product in the case when the seller does not pay for advertising fee, that is, the platform offers a basic search service rather than search-based advertising service. To provide such a search service, the platform will incur related search cost. For simplicity, the search cost in this case is assumed to be constant, and we do not consider it in this study. In particular, product demand in this case is $S_0 = 1 - p - \alpha T_0$.

When the seller is willing to pay for the advertising service, the platform will exert additional efforts to decrease search time length. Thus, this may incur additional costs for offering the service. Following Sayadi and Makui (2014) and Taylor (2002), we apply a quadratic cost function to capture the decreasing marginal effect of advertising efforts and the costs associated with the platform's efforts. Without loss of generality, it is assumed that $T_0 \geq T$. We focus on the difference between the two search time lengths, that is $T_0 - T$. Therefore, cost function for offering a search-based advertising service with time length T is defined as:

$$c(T) = \frac{1}{2}k(T_0 - T)^2, \quad (3)$$

where k is used to measure cost coefficient of such search time length reduction.

Note that, according to equation (2), an increase in product demand with offering search-based advertising service can be formulated as $\Delta S = S - S_0 = \alpha(T_0 - T)$.

3.1 Centralized advertising mechanism

Under this mechanism, the platform first provides price and search time length for the advertising slot, and then the seller may determine whether to buy the advertising slot. The platform's profit can be formulated as:

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$$\max \pi_p = x\left(\frac{\Delta S}{\lambda}m + \rho p \Delta S - c(T)\right) + \rho p S_0$$
$$s.t.\ (1-\rho)p - \frac{m}{\lambda} \geq \gamma. \tag{4}$$

Note that when $x = 1$, the seller accepts to buy the platform's advertising service, and will pay m for per click of the advertising; however, when $x = 0$, he will not accept. In model (4), λ measures the conversion rate which is defined as the purchasing rate through advertising clicks. Following some prior articles such as Athey and Ellison (2011) and Katona and Sarvary (2010), we treat the conversion rate as an input parameter. Thus, it is assumed to be constant within a short time for a specific advertising slot, and fall into the interval [0, 1]. When $\lambda = 1$, the platform will use the PPS (i.e. pay per sale) pricing scheme to charge for the advertising service, whereas when $0 < \lambda < 1$, the pricing scheme will be PPC (i.e. pay per click). Note that, PPS and PPC are known as two members of the pay-for-performance pricing scheme (Sundararajan, 2003). As a widely used pricing model in online advertising setting, we use the PPC model as the pricing scheme in this study. Note that $\Delta S/\lambda$ can be seen as total number of clicks or impressions. Thus, $(\Delta S/\lambda)m$ refers to the charge for the advertising service. Note that profit referral rate ρ falls into the interval [0, 1]. Specifically, when $\rho = 0$, the platform such as Tianmao.com cannot deduct any profit from seller sales.

Note that γ refers to reserve benefit per unit product. This is treated as a minimum profit criterion when deciding whether to purchase the advertising service. This criterion (i.e. minimum profit constraint) is used to avoid very low profit scenario (García-González *et al.*, 2007). Similar assumption are found in Jedidi *et al.* (2003) and Athey and Ellison (2011). Because the seller may gain additional profit $[(1-\rho)p - m/\lambda]\Delta S$ from the advertising service, per unit product benefit from the advertising service is $(1-\rho)p - m/\lambda$. Hence, when $\gamma > (1-\rho)p - m/\lambda$, the seller will not accept to buy the slot; otherwise, he will accept to buy. It is also assumed that the platform can learn the seller's reserve benefit from the previous experiences. Consequently, profit function of the seller is expressed as:

$$\max \pi_s = x\left[(1-\rho)p - \frac{m}{\lambda}\right]\Delta S + (1-\rho)pS_0$$
$$s.t.\ x \in \{0, 1\}. \tag{5}$$

We solve the model starting with the platform's profit function. The platform first determines the optimal search time $T^*(m)$ in terms of the advertising slot price m by solving the first condition of the objective function in model (4). Then, the seller chooses whether to purchase the advertising service. Notably, the platform can learn the seller's reserve benefit from historical experiences, that is the platform has the ability to know the seller's reserve benefit. Thus, the advertising price $(m = (1-\rho)p\lambda - \gamma\lambda)$ can be obtained with respect to the seller's response (Wu *et al.*, 2011).

3.2 Decentralized advertising mechanism

As a widely used auction mechanism, GSP is directly applied to determine the auction price for the advertising slots. Guided by GSP, the platform first provides the advertising slot for auction, and then sellers will bid for the given advertising slot. The payoff price for the slot is determined as the second bid price. In particular, the seller who bids the highest price is selected to be assigned the advertising slot with paying the second-highest bid price. As mentioned earlier, we consider only one seller in this study. Thus, the auction for the slot can be seen as a virtual auction scenario, in which the seller and other many virtual sellers participate in the auction, and the seller wins the slot eventually.

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Under such a mechanism, when the seller wins, the platform's profit can be formulated as:

$$\pi_p = \rho p S_0 + \left(\frac{p_s}{\lambda} + \rho p\right)\Delta S - c(T). \tag{6}$$

The seller's profit can be expressed as:

$$\pi_s = (1 - \rho) p S_0 + \left(p - \frac{p_s}{\lambda} - \rho p\right)\Delta S. \tag{7}$$

We solve the model starting with the platform's problem and working backwards. Note that the second order conditions for the platform's maximization problem are satisfied, and the first order necessary conditions of this optimization problem can be solved to yield the platform's best search time $T^*(p_s)$ in terms of the seller's payoff price p_s. By substituting the best response function $T^*(p_s)$ into the seller's profit maximization problem in model (7), the optimal payoff price can then be obtained through solving the model. Once the optimal payoff price is known, the optimal value of search time length can be obtained from the first order conditions of the optimization problem in model (6).

4. Analysis

In this section, we will first derive the optimal online search-based advertising strategies, and then examine the optimal profits of both the platform and the seller.

4.1 Optimal online search-based advertising strategy

What mechanism can benefit the platform to offer a search advertising service? The following theorem characterizes the platform's optimal choices and the conditions.

Theorem 1. When $\gamma > \bar{\gamma}$, DAM is a better choice for the platform; otherwise, CAM is a better choice.

Note that in Theorem 1, $\bar{\gamma} = p/2$ when $p_s = p_s^*$, and $\bar{\gamma} = (1 - \rho)p - p_s/\lambda$ when $p_s > p_s^*$. p_s^* is the optimal auction payoff price obtained by solving models under DAM. When $p_s < p_s^*$, which means that payoff price is lower than the optimal auction payoff price, the seller will not gain the optimal profit through the auction. In this case, the seller would not submit any price less than p_s^* to win the advertising slot during the auction. Thus, this case has been included in the case when $p_s = p_s^*$.

Theorem 1 shows that when the seller's reserve benefit per product ("reserve benefit" for short) γ exceeds a particular threshold $\bar{\gamma}$, the platform is better off choosing DAM; otherwise, it is better off choosing CAM. Indeed, when the seller's reserve benefit is sufficiently high, the platform might be worse off choosing CAM to meet the reserve benefit. Thus, the platform has less incentive to choose CAM but more to choose DAM. In contrast, when the reserve benefit is relatively low, the platform's better choice is CAM. Wu (2015) suggests that when the profit generated from advertising service for the seller exceeds zero, the seller will choose to buy the advertising service, and CAM is a better choice. To boost sales, enormous firms or companies have advertised their products without gaining any benefit from advertising services in Taobao.com (Clover, 2014). Such findings suggest that these sellers may have sufficiently low reserve benefits for buying advertising services. This can explain why Taobao.com uses CAM to offer promotion advertising services.

Note that $\gamma > \bar{\gamma}$ can be equivalently transformed into $m \leq (1/2 - \rho)p\lambda$ and $m < p_s$ when $p_s = p_s^*$ and $p_s > p_s^*$, respectively. This indicates that when the charge under CAM is less than a particular threshold, the platform is better off using DAM; otherwise, it is better to use CAM to gain more profit. Specifically, when $p_s > p_s^*$, if $m < p_s$, the platform may benefit more from choosing DAM than CAM; otherwise, CAM is a better choice.

What advertising mechanism provides a shorter search time length is characterized by *P1*:

P1. When $\gamma > \overline{\gamma}$, $T_d^* < T_c^*$; otherwise, $T_c^* \leq T_d^*$. In particular, when $\gamma = \overline{\gamma}$, $T_c^* = T_d^*$.

P1 shows that when $\gamma > \overline{\gamma}$, DAM offers a shorter search time length; otherwise, CAM offers a shorter search time length than (or the same search time length as) that offered by DAM. Actually, when the seller's reserve benefit is sufficiently large, the platform's profit gained from the advertising service will be relatively low, and thus the platform has less incentive to provide a shorter search time length for the service under CAM. In such a case, DAM may generate more profit, and thus the platform may offer a shorter search time length under DAM. As suggested in Theorem 1, the platform in this case is better off choosing DAM to provide the advertising service, which further illustrates the reasonability of this proposition. Similar to the case when $\gamma > \overline{\gamma}$, if $\gamma < \overline{\gamma}$, the platform has less incentive to offer a shorter search time length under DAM but more under CAM.

To better illustrate *P1*, we apply a numerical example in what follows. We set $k = 0.5$, $T_0 = 0.7$, $\lambda = 0.4$, $\rho = 0.03$, $\alpha = 0.5$, $p_s = 0.2$ and $p = 0.6$. According to *P1*, the optimal search time lengths with respect to γ are shown in Figure 1.

Figure 1 shows that the optimal search time length under CAM increases in γ when γ varies from 0 to 0.6, whereas under DAM, it remains constant regardless of whether $p_s = p_s^*$ or $p_s > p_s^*$. Furthermore, the optimal search time length under CAM is smaller than that under DAM (i.e. $T_c^* < T_d^*$) when $\gamma < \overline{\gamma}$, whereas larger than or equal to that under DAM when $\gamma \geq \overline{\gamma}$. Note that in this example, $\overline{\gamma} = p/2 = 0.3$ and $\overline{\gamma} = (1-\rho)p - p_s/\lambda = 0.082$ when $p_s = p_s^*$ and $p_s > p_s^*$, respectively.

In what follows, we will compare payoff prices under the two mechanisms.

P2. When $\gamma > \overline{\gamma}$, $m^* < p_s$; otherwise, $m^* \geq p_s$. In particular, when $\gamma = \overline{\gamma}$, $m^* = p_s$.

P2 shows that when $\gamma > \overline{\gamma}$, payoff price under CAM is less than that under DAM; otherwise, payoff price under CAM is larger than or equal to that under DAM. We take the case $\gamma > \overline{\gamma}$ as an example to illustrate the rationale of *P2*. As *P1* suggested, when $\gamma > \overline{\gamma}$, the platform has less incentive to provide a shorter search time length under CAM but more under DAM.

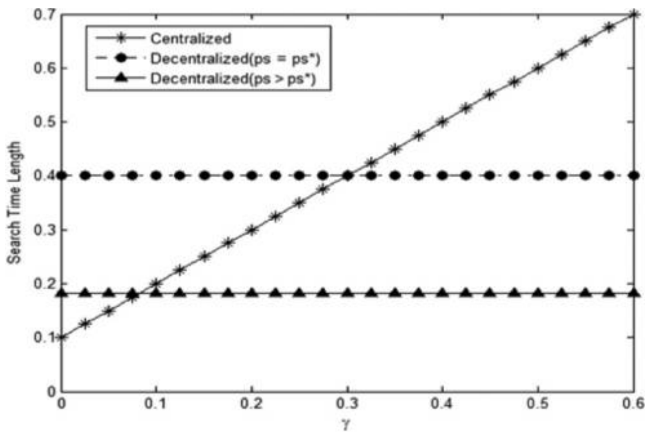

Figure 1. Optimal search time length with respect to γ

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Therefore, in such a circumstance, the platform may charge less under CAM than that under DAM. A numerical example based on the same data as used in *P1* is applied to illustrate *P2*. The optimal payoff prices regarding γ are depicted in Figure 2.

Figure 2 shows that when $\gamma > \overline{\gamma}$, the platform charges lower fees for the advertising service under CAM than those under DAM. Note that $\overline{\gamma} = 0.3$ and $\overline{\gamma} = 0.082$ when $p_s = p_s^*$ and $p_s > p_s^*$, respectively.

According to *P1* and *P2*, we can obtain *P3*.

P3. The platform offers the advertising service with a shorter search time length accompanied by a higher charge, and a longer search time length accompanied by a lower charge.

P3 is intuitive that a shorter search time length means a higher search cost, and thus a higher charge or payoff price, and vice versa. Ye *et al.* (2015) and Narayanan and Kalyanam (2015) present similar results. Specifically, Narayanan and Kalyanam (2015) points out that a high position of an advertising needs more costs. This finding suggests that a shorter search time length for an advertising needs a larger payoff price. In practice, many platforms such as Ebay.com and JD.com provide obtrusive advertising locations with relatively high payoff prices.

4.2 Profit analysis

Based on the optimal profits of the platform under the two advertising mechanisms, the following conclusion can be directly achieved.

Lemma 1. The platform always benefits from offering search-based advertising service rather than not offering.

Lemma 1 shows that the platform will earn more profit from offering search-based advertising service than not offering. This observation can be directly supported by many practical evidences that many platforms offer their online advertising services, for example banner advertising and search-based advertising. For example, Amazon has gained roughly \$800m from online advertising services in addition to its sales commissions during the year 2013 (emarket.com).

We next characterize properties of the platform's profits under both advertising mechanisms in Theorem 2.

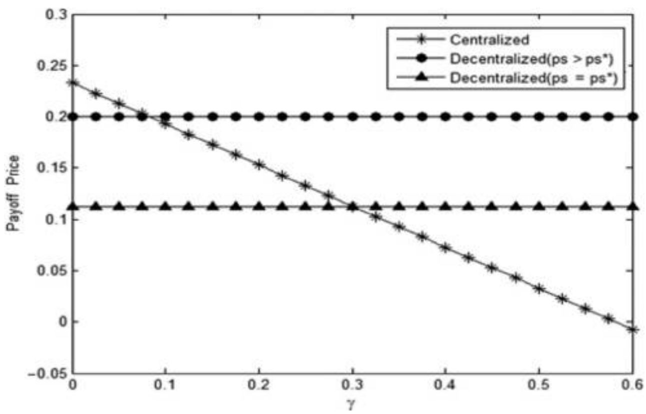

Figure 2.
Payoff price with respect to γ

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Theorem 2. The platform's optimal profit meets the following rules:

(a) Under CAM, when $\gamma \in [0,p]$, the optimal profit is decreasing in γ; in particular, the platform can gain the maximum profit $\rho p S_0 + (\alpha^2/2k)p^2$ and the minimum profit $\rho p S_0$ when $\gamma = 0$ and $\gamma = p$, respectively.

(b) Under DAM, when $p_s \in [p_s^*, p_s^-]$, the optimal profit is increasing in p_s; in particular, the platform can gain the maximum profit $\rho p S_0 + (\alpha^2/2k)p^2$ and the minimum profit $\rho p S_0 + p^2\alpha^2/8k$ when $p_s = p_s^-$ and $p_s = p_s^*$, respectively.

Note that p_s^- is the critical value or the maximum value of the seller's payoff price for the advertising slot.

Theorem 2(a) indicates that the platform's optimal profit under CAM increases in γ, when $\gamma \in [0,p]$. In particular, when $\gamma = 0$, the platform can gain the maximum profit $\rho p S_0 + (\alpha^2/2k)p^2$. Under such a situation, the platform extracts all the profit generated from the advertising service. In contrast, when $\gamma = p$, the platform gains the minimum profit $\rho p S_0$. In such a case, the seller gains all the profit generated from the advertising service. Theorem 2(a) is intuitive that when the seller's reserve benefit is high, the platform's profit is low, and vice versa.

Similarly, Theorem 2(b) implies that the platform's optimal profit is increasing in the payoff price p_s. The platform gains the maximum and minimum profits, that is $\rho p S_0 + (\alpha^2/2k)p^2$ and $\rho p S_0 + p^2\alpha^2/8k$, when $p_s = p_s^-$ and $p_s = p_s^*$, respectively.

Note that relative to the minimum profit, the platform's maximum profit is easy to obtain. Due to limited advertising slots, some sellers may be eager to purchase advertising slots to promote their products regardless of what profit the advertising service can bring for them (Pawels *et al.*, 2003).

By comparing the platform's maximum profits under the two mechanisms, the following conclusion can be directly achieved:

P4. The maximum platform's profit obtained under CAM is equal to that obtained under DAM.

Note that although the maximum profits obtained under both advertising mechanisms are equivalent, the corresponding conditions are different. However, in practice, the condition $p_s = p_s^-$ is hard to be satisfied. This means that under DAM, the platform's maximum profit may not be equal to but be close to the maximum profit $\rho p S_0 + (\alpha^2/2k)p^2$. A similar result is found in Wu (2015).

Regarding the seller's optimal profit, we have the following conclusion:

Theorem 3. The seller's profit satisfies the following rules:

(a) Under CAM, the profit increases in γ when $\gamma \in [0, p/2]$, whereas decreases in γ when $\gamma \in [p/2, p]$; in particular, the seller gains the maximum profit $\rho p S_0 + (\alpha^2/4k)p^2$ when $\gamma = p/2$, and the minimum profit $(1-\rho)pS_0$ when $\gamma = 0$ or $\gamma = p$.

(b) Under DAM, the optimal profit decreases in p_s when $p_s \in [p_s^*, p_s^-]$; in particular, the seller gains the maximum profit $\rho p S_0 + (\alpha^2/4k)p^2$ and the minimum profit $(1-\rho)pS_0$ when $p_s = p_s^*$ and $p_s = p_s^-$, respectively.

Theorem 3(a) shows that unlike the platform's optimal profit under CAM as indicated in Theorem 2(a), the seller's optimal profit increases in γ when $\gamma \in [0,p/2]$, whereas it decreases when $\gamma \in [p/2,p]$. To be specific, when $\gamma \in [0,p/2]$, which suggests that the seller's reserve benefit is relatively low, the platform can earn a relatively high profit. In such a case, the platform may provide the advertising service with a shorter time length as shown in *P1*, which can boost product demand. Thus, the seller's profit increases. In contrast, when the seller's reserve benefit is sufficiently high, that is $\gamma > p/2$, the platform's profit decreases

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when γ increases. In such a circumstance, the platform has less incentive to provide the advertising service with a shorter time length, which leads to a decrease in product demand. Thus, the seller's profit will decrease in γ when $\gamma \in [p/2,p]$. Accordingly, the seller achieves the maximum profit $\rho pS_0 + (\alpha^2/4k)p^2$ when $\gamma = p/2$, and the minimum profit $(1-\rho)pS_0$ when γ is at the two endpoints of the interval $[0,p]$.

Theorem 3(b) indicates that in contrast to the platform's optimal profit under DAM, the seller's optimal profit is decreasing in p_s when $p_s \in [p_s^*, p_s^-]$. This is intuitive that when the platform's profit increases, the seller's profit decreases, and vice versa. In particular, when $p_s = p_s^*$, which indicates that the seller pays relatively low fee for the advertising service, the seller achieves the maximum profit $\rho pS_0 + (\alpha^2/4k)p^2$, while the platform gains his minimum profit $\rho pS_0 + p^2\alpha^2/8k$. When $p_s = p_s^-$, which indicates that the seller will bear the highest cost for the advertising service, the seller's profit reaches the minimum profit $(1-\rho)pS_0$, while the platform achieves the maximum profit $\rho pS_0 + (\alpha^2/2k)p^2$.

Interestingly, the seller can gain the same maximum profits (i.e. $\rho pS_0 + (\alpha^2/4k)p^2$) and minimum profits $(1-\rho)pS_0$ under both CAM and DAM. Specifically, the seller's minimum profit is equal to that without purchasing the advertising service. Indeed, under CAM, when $\gamma = 0$, the platform will extract all the profit generated from the service; when $\gamma = p$, the platform may gain no profit from offering the service, and thus he has no inventive to offer the service. Similarly, under DAM, when $p_s = p_s^-$, the profit generated from the advertising service will be completely extracted by the platform.

To better illustrate Theorems 2 and 3, two numerical examples based on the same data as used earlier are considered. The first example is used to illustrate the profits of the platform and the seller under CAM [i.e. Theorems 2(a) and 3(a)], and the second example is used to illustrate Theorems 2(b) and 3(b). For these purposes, we let γ increase from 0 to 0.6, and p_s increase from 0.1692 (the optimal auction payoff price) to 0.36 in both examples, respectively. The optimal profits of the platform and the seller under both mechanisms are displayed in Figures 3(a) and (b), respectively.

Figure 3(a) shows that the platform's profit decreases from 0.0914 when $\gamma = 0$ to 0.0014 when $\gamma = 0.6$. The seller's profit increases from 0.0466 when $\gamma = 0$ to 0.0916 when $\gamma = p/2 = 0.3$, and then decreases to 0.0466 when $\gamma = 0.6$. Figure 3(b) shows that the platform's profit increases from 0.0239 to 0.0914, whereas the seller's profit decreases from 0.0916 to 0.0466 when p_s increases from 0.1692 to 0.36.

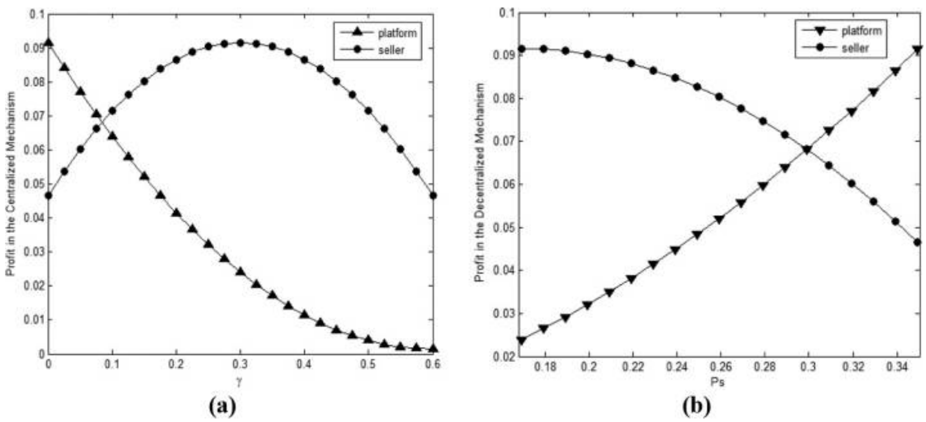

Figure 3.
(a) The profits under the CAM; (b) The profits under the DAM

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According to Theorems 1, 2 and 3, advertising mechanisms have significant effects on the optimal profits of both the platform and the seller, which are characterized as the following two corollaries:

Corollary 1. When $p_s = p_s^*$, if $\gamma > \overline{\gamma}$, the choice of DAM benefits both the platform and the seller; otherwise, it only benefits the seller.

Corollary 1 shows that the seller is always better off choosing DAM when the auction payoff price is equal to the optimal payoff price under DAM, that is $p_s = p_s^*$. As shown in Theorem 3, when $p_s = p_s^*$, the seller can always gain his maximum profit $\rho p S_0 + (\alpha^2/4k)p^2$ under DAM, which is also the maximum profit under CAM. Note that only when $\gamma = \overline{\gamma} = p/2$, the seller can achieve this profit under CAM. Corollary 1 suggests that when the seller's reserve benefit is sufficiently high, the platform will definitely choose DAM. This case can be illustrated by using a numerical example based on the same data used earlier, which is shown in Figure 4.

Note that, for ease of analysis, we use the difference between the profit obtained under DAM and that under CAM instead of the profits for either of the platform or the seller under both mechanisms. Figure 4 shows that when $\gamma > \overline{\gamma} = 0.3$, the profit differences of both the platform and the seller under both mechanisms are larger than zero. This indicates that DAM in this case benefits both the platform and the seller. However, when $\gamma < 0.3$, DAM will benefit only the seller.

Corollary 2. When $p_s > p_s^*$, the choice of advertising mechanisms depends on:

(a) If $\gamma < \overline{\gamma}$, CAM benefits the platform but hurts the seller, whereas DAM is the opposite.

(b) If $\overline{\gamma} \leq \gamma < \hat{\gamma}$, DAM benefits the platform but hurts the seller, whereas CAM is the opposite.

(c) If $\gamma > \hat{\gamma}$, DAM benefits both the platform and the seller.

Corollary 2(a) indicates that when the seller's reserve benefit is relatively low, that is $\gamma < \overline{\gamma}$, the platform can gain a higher profit under CAM than DAM (Theorem 1). The effect of γ on the seller's profit is opposite to that of the platform, and is intuitive. When $\gamma < \overline{\gamma}$, under CAM, the platform gains more but the seller earns less, whereas under DAM, the platform gains less profit but the seller obtains more.

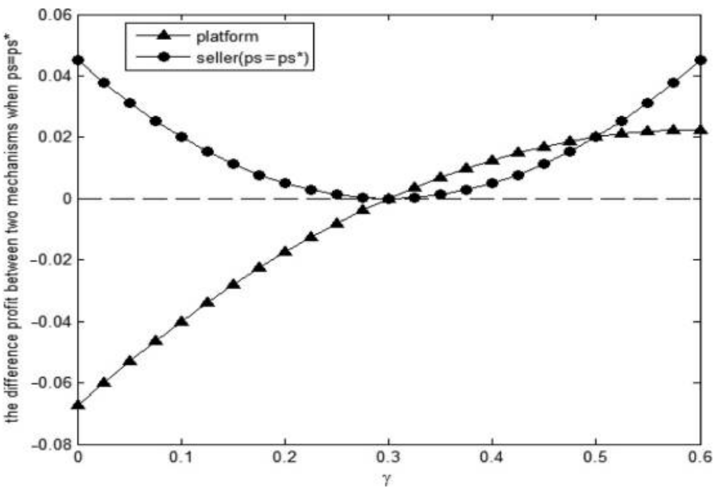

Figure 4. The profit difference results under CAM and DAM when $p_s = p_s^*$

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Note that in Corollaries 2(b) and (c), $\hat{\gamma} = \rho p + p_s / \lambda$. When γ is sufficiently large, that is $\gamma \geq \bar{\gamma}$, the platform is better off under DAM rather than under CAM (Theorem 1). In such a case, the platform will gain more profit under DAM, and the seller will earn less accordingly. However, as γ is relatively large ($\bar{\gamma} \leq \gamma < \hat{\gamma}$), the seller can gain more profit under CAM. Specifically, when γ is substantially large, that is $\gamma > \hat{\gamma}$, the platform may have less incentive to offer the advertising service under CAM but more under DAM. As shown in Theorem 3(a), when $\gamma \geq \bar{\gamma}$, the seller is worse off when γ increases. This, in turn, partly suggests that when $\gamma > \hat{\gamma}$, the seller is better off under DAM.

Similar to Corollary 1, we use the same example to better illustrate Corollary 2. For ease of illustration, we also use profit differences instead of the platform's profits and the seller's profits under DAM and CAM when $p_s > p_s^*$. The results are shown in Figure 5.

Figure 5 shows that when $\gamma < \bar{\gamma} = 0.082$, the seller's profit differences under both mechanisms exceed zero, whereas the platform's profits are less than zero. This indicates that DAM benefits the seller rather than the platform. When $0.082 < \gamma < \hat{\gamma} = 0.518$, DAM only benefits the platform. When γ is substantially large, that is $\hat{\gamma} > 0.518$, DAM benefits both the platform and the seller.

It can be seen from Corollaries 1 and 2 that when γ is sufficiently large, DAM is the better choice, in that both the platform and the seller will be better off in this case. This finding can be used to explain why many platforms offer advertising services with DAM in practice. For example, Google Ads, JD CPC Alliance and Taobao Train use DAM to offer advertising services. Furthermore, many academic studies suggest that DAM is the widely used advertising mechanism in practice, for example Balseiro *et al.* (2015) and Yuan *et al.* (2015). These evidences can directly support Corollaries 1 and 2.

4.3 Discussion

In this study, we assume that there is no information asymmetry between the platform and the seller. In particular, the platform can learn the seller's reserve benefit. However, when this assumption is relaxed, the platform can estimate a reserve benefit for the seller, which is denoted as γ'. The platform's decision may be slightly affected by this information asymmetry. To be specific, when $\gamma' = \gamma$, the platform's optimal decisions have already been examined in this study. Note that when $\gamma' < \gamma$, this means that the platform may gain more profits from selling advertising services. In such a case, the seller may not accept to buy the advertising service, and

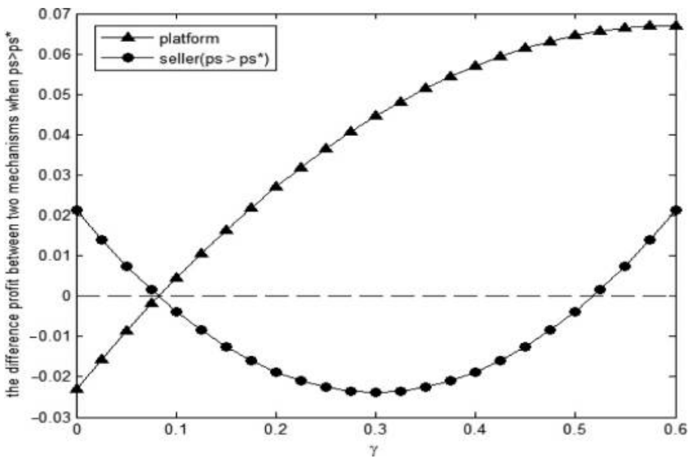

Figure 5.
The profit difference results under CAM and DAM when $p_s > p_s^*$

this case is reduced to be the case without offering the advertising service. When $\gamma' > \gamma$, the platform may sacrifice some profits, which may benefit the seller. We will discuss the platform's decisions under this condition by using the following three cases:

(1) When $\gamma' > \gamma > \overline{\gamma}$, according to Theorem 1, the condition $\gamma > \overline{\gamma}$ holds, and thus the platform would be better off choosing DAM to sell advertising services. Nevertheless, the platform may gain less profit than that when $\gamma' = \gamma > \overline{\gamma}$. In this case, according to Corollary 2(c), the seller may accordingly be better off.

(2) When $\gamma' > \overline{\gamma} > \gamma$, the platform may choose the advertising mechanism according to his estimated reserve benefit γ', and following Theorem 1, he may also adopt DAM to offer the advertising service. However, because the actual reserve benefit γ is less than the particular threshold $\overline{\gamma}$, according to Theorem 1, the platform would be worse off but the seller would be better off in this case.

(3) When $\overline{\gamma} > \gamma' > \gamma$, according to Theorem 1, the platform will use CAM instead of DAM to provide advertising services. In such a case, because $\gamma' > \gamma$, although the platform can be benefit from using CAM, the platform will gain less profit than that when $\overline{\gamma} > \gamma' = \gamma$.

According to these statements, it would be better for the platform to exert efforts (e.g. market analysis) to learn the seller's reserve benefit before deciding to choose CAM or DAM to sell advertising services in the online retailing context.

5. Conclusions

Consumers are increasingly using online search-based advertising to search their desirable products. Search-based advertising services can help to reduce consumer search costs, and thus boost sales. However, such services will incur costs for platforms. To offer such services, platforms may adopt CAM or DAM, under which platforms may use differentiated pricing schemes to charge for the advertising service. Hence, it is important for platforms to decide how to choose the optimal advertising mechanism and charge sellers for advertising services with a typically designed search cost (i.e. search time length) under the chosen advertising mechanism. To address these two issues, in this study, we consider one platform and one seller, and develop a theoretical model under each mechanism to examine the optimal search-based advertising strategy for the platform by taking search cost into consideration. The platform's optimal choice of advertising mechanisms and the optimal search time lengths and charges are derived. The optimal profits of both the platform and the seller are also examined.

Some important findings are achieved. First, when the seller's reserve benefit is sufficiently large, the platform is better off choosing DAM to offer search-based advertising service; otherwise, CAM is a better choice. Particularly, the platform's maximum profits under both mechanisms are equivalent. Second, the platform usually offers search advertising service with a shorter search time length accompanied by a higher charge, and a longer search time length accompanied by a lower charge. Third, when the seller's reserve benefit is substantially large, DAM will benefit both the platform and the seller; otherwise, whether the platform chooses CAM or DAM may hurt one player. Our results also show that the platform can gain more profit by offering the search-based advertising service than that without offering.

Based on these key findings, some practical implications can be derived. For products with relatively high profitability such as fashion products (e.g. shoes and apparel), luxury products and those best sellers, platforms are better off choosing DAM rather than CAM to sell advertising services. In contrast, regarding relatively low profitable products such as

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mature products in terms of technology or market (e.g. digital products or household appliances), sellers may have relatively low reserve benefits. For these products, it is better for platforms to adopt CAM to offer advertising services. Specifically, when selling discounted products to clear stocks and promoting new products and even those fashion products, sellers may also have relatively low reserve benefits. In such a case, platforms can benefit from using CAM to provide advertising services. These implications can explain why Taobao.com and JD.com apply promotion display advertising for most products such as computer, camera and new brand products. Notably, platforms can determine preferable search time lengths according to advertising prices regardless of whether adopting CAM or DAM in the retailing context. In addition, platforms may initiate some efforts to learn sellers' reserve benefits (especially for those new entrants or new products) to better choose advertising mechanisms.

This paper presents some key findings that can help online platforms to better manage their advertising services. Nevertheless, this paper also leaves some limitations that may serve as future research topics. First, in this study, we consider only one seller and one advertising slot. It is interesting to examine the optimal online search-based advertising strategy with several advertising slots and more sellers under the competitive market environment. The consideration of these issues based on our models may provide some new insights for platforms to manage advertising services. Second, we develop our models based on the assumption that demand function is deterministic. It may generate different results by considering the stochastic demand. Third, we only use numerical examples to illustrate our findings. Practical applications of our proposed approaches can further test their validities, and this may identify more practical insights for online platforms to better determine their advertising strategies according to the market environment. These issues can be seen as future research topics of our study. Notably, only one platform is considered in our work. It would be interesting to examine the optimal advertising strategy decisions with two or more competing platforms, who adopt CAM, DAM or both to sell advertising services. This issue will also constitute an important topic in our future research.

References

Anderson, E.G., Parker, G.G. and Tan, B. (2014), "Platform performance investment in the presence of network externalities", *Information Systems Research*, Vol. 25 No. 1, pp. 152-172.

Anderson, S. and Renault, R. (1999), "Pricing, product variety, and search costs: a Bertrand-Chamberlin-Diamond model", *The RAND Journal of Economics*, Vol. 30 No. 4, pp. 719-735.

Anderson, S. and Renault, R. (2013), "The advertising mix for a search good", *Management Science*, Vol. 59 No. 1, pp. 69-83.

Animesh, A., Ramachandran, V. and Viswanathan, S. (2010), "Research note – quality uncertainty and the performance of online sponsored search markets: an empirical investigation", *Information Systems Research*, Vol. 21 No. 1, pp. 190-201.

Athey, S. and Ellison, G. (2011), "Position auctions with consumer search", *The Quarterly Journal of Economics*, Vol. 126 No. 3, pp. 1213-1270.

Balseiro, S., Besbes, O. and Weintraub, G. (2015), "Repeated auctions with budgets in ad exchanges: approximations and design", *Management Science*, Vol. 61 No. 4, pp. 864-884.

Bleier, A. and Eisenbeiss, M. (2015), "Personalized online advertising effectiveness: the interplay of what, when, and where", *Marketing Science*, Vol. 34 No. 5, pp. 669-688.

Branco, F., Sun, M. and Villas-Boas, J.M. (2012), "Optimal search for product information", *Management Science*, Vol. 58 No. 11, pp. 2037-2056.

Downloaded by University of Liverpool At 07:13 28 February 2017 (PT)

Chan, T. and Park, Y. (2015), "Consumer search activities and the value of ad positions in sponsored search advertising", *Marketing Science*, Vol. 34 No. 4, pp. 606-623.

Chatterjee, P., Hoffman, D. and Novak, T. (2003), "Modeling the clickstream: implications for Web-based advertising efforts", *Marketing Science*, Vol. 22 No. 4, pp. 520-541.

Clover, C. (2014), available at: http://tech.ifeng.com/bat3m/detail_2014_06/30/37085940_0.shtml

Deza, A., Huang, K. and Metel, M.R. (2015), "Chance constrained optimization for targeted Internet advertising", *Omega*, Vol. 53, pp. 90-96.

Diamond, P.A. (1985), *Search Theory*, New Palgrave.

Dukes, A. and Liu, L. (2015), "Online shopping intermediaries: the strategic design of search environments", *Management Science*, Vol. 62 No. 4.

Edelman, B., Ostrovsky, M. and Schwarz, M. (2007), "Internet advertising and the generalized second-price auction: selling billions of dollars worth of keywords", *American Economic Review*, Vol. 97 No. 1, pp. 242-259.

García-González, J., Parrilla, E. and Mateo, A. (2007), "Risk-averse profit-based optimal scheduling of a hydro-chain in the day-ahead electricity market", *European Journal of Operational Research*, Vol. 181 No. 3, pp. 1354-1369.

Janssen, M.C.W. and Non, M.C. (2008), "Advertising and consumer search in a duopoly model", *International Journal of Industrial Organization*, Vol. 26 No. 1, pp. 354-371.

Jedidi, K., Jagpal, S. and Manchanda, P. (2003), "Measuring heterogeneous reservation prices for product bundles", *Marketing Science*, Vol. 22 No. 1, pp. 107-130.

Ji, Y., Xu, X. and Sun, Y. (2016), "Cooperation strategies for e-commerce platforms with seller classification", *Kybernetes*, Vol. 45 No. 9, pp. 1369-1386.

Katona, Z. and Sarvary, M. (2010), "The race for sponsored links: bidding patterns for search advertising", *Marketing Science*, Vol. 29 No. 2, pp. 199-215.

Liu, D. and Viswanathan, S. (2014), "Information asymmetry and hybrid advertising", *Journal of Marketing Research*, Vol. 51 No. 5, pp. 609-624.

Narayanan, S. and Kalyanam, K. (2015), "Position effects in search advertising and their moderators: a regression discontinuity approach", *Marketing Science*, Vol. 34 No. 3, pp. 388-407.

Pawels, K., Srinivasan, S., Silva-Risso, J. and Hanssen, D.M. (2003), "New products, sales promotions and firm value with application to the automobile industry", *Journal of Marketing*, Vol. 68 No. 4, pp. 22-38.

Robert, J. and Stahl, D.O. (1993), "Informative price advertising in a sequential search model", *Econometrica: Journal of the Econometric Society*, Vol. 61 No. 3, pp. 657-686.

Sayadi, M.K. and Makui, A. (2014), "Optimal advertising decisions for promoting retail and online channels in a dynamic framework", *International Transactions in Operational Research*, Vol. 21 No. 5, pp. 777-796.

Stivers, A. and Tremblay, V.J. (2005), "Advertising, search costs, and social welfare", *Information Economics and Policy*, Vol. 17 No. 3, pp. 317-333.

Sundararajan, A. (2003), "Pricing digital marketing: information, risk sharing and performance", Leonard N. Stern School of Business Working Paper.

Tan, S., Chong, S.C. and Lin, B. (2013), "Intention to use internet marketing: a comparative study between Malaysians and South Koreans", *Kybernetes*, Vol. 42 No. 6, pp. 888-905.

Taylor, T.A. (2002), "Supply chain coordination under channel rebates with sales effort effects", *Management Science*, Vol. 8 No. 8, pp. 992-1007.

Wu, C. (2015), "Matching value and market design in online advertising networks: an empirical analysis", *Marketing Science*, Vol. 34 No. 6, pp. 906-921.

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Wu, Z., Zhu, W. and Crama, P. (2011), "The newsvendor problem with advertising revenue", *Manufacturing & Service Operations Management*, Vol. 13 No. 3, pp. 281-296.

Yao, S. and Mela, C.F. (2011), "A dynamic model of sponsored search advertising", *Marketing Science*, Vol. 30 No. 3, pp. 447-468.

Ye, S., Aydin, G. and Hu, S. (2015), "Sponsored search marketing: dynamic pricing and advertising for an online retailer", *Management Science*, Vol. 61 No. 6, pp. 1255-1274.

Yuan, Y., Zeng, D., Zhao, H.M. and Li, L.J. (2015), "Analyzing positioning strategies in sponsored search auctions under CTR-based quality scoring", *IEEE Transactions on Systems Man Cybernetics-Systems*, Vol. 45 No. 4, pp. 688-701.

Appendix. Proofs

Proof of Theorem 1

Under CAM, by solving models (4) and (5), we have $m^* = ((1-\rho)p - \gamma)\lambda$ and $T^* = T_0 - (\alpha/k)(\rho p + m/\lambda)$. Then, the seller's profit is $\pi_s^c = (1-\rho)pS_0 + (\alpha^2/k)(p-\gamma)\gamma$, and the platform's profit is $\pi_p^c = \rho pS_0 + (\alpha^2/2k)(\rho p + m/\lambda)^2 = \rho pS_0 + (\alpha^2/2k)(p-\gamma)^2$.

Under DAM, by solving models (6) and (7), we have $T^* = T_0 - (\alpha/k)(p_s/\lambda + \rho p)$ and $p_s^* = (1/2 - \rho)p\lambda$. When $p_s = p_s^*$, the seller's profit is $\pi_s^d = (1-\rho)pS_0 + (p\alpha)^2/4k$ and the platform's profit is $\pi_p^d = \rho pS_0 + (p\alpha)^2/8k$. When $p_s > p_s^*$, we have $\pi_s^d = (1-\rho)pS_0 + (p\alpha^2/k)(p_s/\lambda + \rho p) - (\alpha^2/k)(p_s/\lambda + \rho p)^2$ and $\pi_p^d = \rho pS_0 + (\alpha^2/2k)(p_s/\lambda + \rho p)^2$, respectively.

When $p_s = p_s^*$, by comparing π_p^c and π_p^d, it is easy to verify that if $\gamma > p/2$, it is better for the platform to choose DAM; otherwise, it is better to choose CAM.

When $p_s > p_s^*$, similar to Case 1, if $\gamma \geq (1-\rho)p - p_s/\lambda$, DAM is a better choice; otherwise, CAM is a better choice. This completes the proof.

Proof of P1

Based on the optimal solutions under both mechanisms as shown in the proof of Theorem 1, we consider the following two cases:

Case 1: When $p_s = p_s^*$, by comparing T_c^* and T_d^*, it is easy to verify that when $\gamma > p/2$, $T_c^* > T_d^*$; otherwise, $T_c^* \leq T_d^*$. Specifically, if $\gamma = p/2$, $T_c^* = T_d^*$.

Case 2: When $p_s > p_s^*$, similar to Case 1, when $\gamma > (1-\rho)p - p_s/\lambda$, $T_c^* > T_d^*$; otherwise, $T_c^* \leq T_d^*$. Particularly, if $\gamma = (1-\rho)p - p_s/\lambda$, $T_c^* = T_d^*$. This completes the proof.

Proofs of P2 and P3

According to proof of Theorem 1, this two propositions can be easily verified, and thus omitted here.

Proof of Lemma 1

Without offering the advertising service, the platform's profit is $\pi_p = \rho pS_0$ under both CAM and DAM, which can be directly achieved from models (4) and (6), respectively. When the seller purchases the advertising service, the platform's profits under CAM and DAM are $\pi_p^c = \rho pS_0 + (\alpha^2/2k)(\rho p + m/\lambda)^2 = \rho pS_0 + (\alpha^2/2k)(p-\gamma)^2$ and $\pi_p^d = \rho pS_0 + (\alpha^2/2k)(p_s/\lambda + \rho p)^2$, respectively. Thus, it can be easily observed that $\pi_p^c > \pi_p$ and $\pi_p^d > \pi_p$. This completes the proof.

Proof of Theorem 2

Under CAM, the platform's optimal profit is $\pi_p^c = \rho pS_0 + (\alpha^2/2k)(p-\gamma)^2$. By solving the first order condition of the platform's profit, we have $\rho pS_0 + (\alpha^2/2k)p^2$ when $\gamma = 0$, and the minimum profit is ρpS_0 when $\gamma = p$.

Under DAM, the platform's optimal profit is $\pi_p^d = \rho pS_0 + (\alpha^2/2k)(p_s/\lambda + \rho p)^2$. Because $p_s \in [p_s^*, p_s^-]$, we have $\rho pS_0 + (\alpha^2/2k)p^2$ when $p_s = p_s^-$, and the minimum profit is $\rho pS_0 + p^2\alpha^2/8k$ when $p_s = p_s^*$. Note that $p_s^* = (1/2 - \rho)p\lambda$ and $p_s^- = (1-\rho)p\lambda$. This completes the proof.

Proof of P4

This proposition can be directly obtained from Theorem 2, and thus omitted here.

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Proof of Theorem 3

Under CAM, the seller's optimal profit is $\pi_s^c = (1-\rho)pS_0 + (\alpha^2/k)(p-\gamma)\gamma$. Thus, $\partial\pi_s^c/\partial\gamma = (\alpha^2/k)(p-2\gamma)$. Clearly, π_s^c is increasing in γ when $\gamma\in[0,p/2)$, whereas decreasing when $\gamma\in[p/2,p]$. Thus, the seller's maximum profit $(1-\rho)pS_0 + (\alpha^2/4k)p^2$ can be obtained when $\gamma = p/2$, and the minimum profit $(1-\rho)pS_0$ is obtained when $\gamma = 0$ or $\gamma = p$.

Under DAM, the seller's optimal profit is $\pi_s^d = (1-\rho)pS_0 + (\alpha^2/k)((1-\rho)p - p_s/\lambda)(p_s/\lambda + \rho p)$. Thus, $\partial\pi_s^d/\partial\gamma = (\alpha^2/\lambda k)(p - 2(p_s/\lambda + \rho p))$. In this case, $p_s^* = (1/2-\rho)p\lambda$ and $p_s^- = (1-\rho)p\lambda$. Therefore, when $p_s\in[p_s^*,p_s^-]$, π_s^d is decreasing in p_s, and the seller's maximum and minimum profits are $(1-\rho)pS_0 + (\alpha^2/4k)p^2$ and $(1-\rho)pS_0$, respectively. This completes the proof.

Proof of Corollary 1

Theorem 1 shows that when $p_s = p_s^*$, if $\gamma > p/2$, DAM is better for the platform; otherwise, CAM is better for the platform. This, in turn, indicates that if $\gamma \leq p/2$, DAM is worse for the platform. On the other hand, as shown in the proof of Theorem 1, the seller's optimal profits are $\pi_s^c = (1-\rho)pS_0 + (\alpha^2/k)(p-\gamma)\gamma$ and $\pi_s^d = (1-\rho)pS_0 + (\alpha^2/4k)p^2$ under CAM and DAM, respectively. By comparing π_s^c and π_s^d, the seller can always obtain $(1-\rho)pS_0 + (\alpha^2/4k)p^2$ under DAM, which is the maximum profit under CAM. This completes the proof.

Proof of Corollary 2

When $p_s > p_s^*$, the conclusion in Corollary 2 for the platform has already been shown in Theorem 1, and we here only prove the conclusion regarding the seller. By comparing π_s^d and π_s^c as shown in the proof of Theorem 1, we can easily find that when $\gamma < \bar{\gamma} = (1-\rho)p - p_s/\lambda$ or $\gamma > p_s/\lambda + \rho p$, DAM is better for the seller; otherwise, CAM is a better choice for the seller. This completes the proof.

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