

December 2002

# Information Gatekeepers: Paid Placement and Competition

Hemant Bhargava  
*Pennsylvania State University*

Jane Feng  
*Pennsylvania State University*

Follow this and additional works at: <http://aisel.aisnet.org/icis2002>

---

## Recommended Citation

Bhargava, Hemant and Feng, Jane, "Information Gatekeepers: Paid Placement and Competition" (2002). *ICIS 2002 Proceedings*. 45.  
<http://aisel.aisnet.org/icis2002/45>

This material is brought to you by the International Conference on Information Systems (ICIS) at AIS Electronic Library (AISEL). It has been accepted for inclusion in ICIS 2002 Proceedings by an authorized administrator of AIS Electronic Library (AISEL). For more information, please contact [elibrary@aisnet.org](mailto:elibrary@aisnet.org).

# INFORMATION GATEKEEPERS: PAID PLACEMENT AND COMPETITION

**Hemant K. Bhargava**  
Penn State University  
University Park, PA USA  
bhargava@computer.org

**Juan Feng**  
Penn State University  
University Park, PA USA  
jifl@psu.edu

## Abstract

*Information gatekeepers such as Internet search engines and shopbots play a crucial role in the information society. Recently, such gatekeepers have begun implementing a paid placement strategy, where some content providers are given, in return for a placement fee, prominent positioning in response to user queries. Generally, users have disutility toward the bias created by paid placement, and the search engine can manipulate the placement strategy to affect users' disutility. We analyze the gatekeeper's tradeoff between revenue from paid placement and the potential loss in advertising revenue from the loss of credibility. In the optimal paid placement strategy, an increase in the gatekeeper's quality of service allows it to improve profits from paid placement, moving it closer to the ideal. However, an increase in the advertising rate motivates the gatekeeper to increase market share by reducing further its reliance on paid placement and fraction of paying providers. When there is competition between search engines of identical quality, they will choose the same bias level. For heterogeneous search engines with different qualities, the equilibrium outcome depends largely on the users' cognitive or other limitations on the number of search results they effectively consider.*

## 1 INTRODUCTION

Individual and organizational decision makers often turn to advisors (consultants or counsellors) for advice and recommendations, for help in determining which alternatives to consider or how to rank alternatives. In the case of ordinary individuals or consumers, first the transportation revolution increased the number of choices available for most decisions (e.g., decisions related to purchase of goods and services) by removing barriers related to distance, and then the information revolution dramatically increased the capability of consumers to collect information relevant to the decision. The Internet and World Wide Web present repositories of information—from text to multimedia, from amateur opinions to expert thought, from voluntary contributions to commercial interests—on every conceivable topic. Lawrence and Giles (1999) estimated the publicly indexable Web at 800 million pages, 6 terabytes of text data, on 2.8 million servers, as of February 1999. The average decision maker, whether searching for information goods or for collateral information related to some other decision or product, is presented today with a huge consideration space, much too large for unguided or enumerative search. Consequently, the last few years have witnessed tremendous growth in the area of information gatekeepers. Common examples of information gatekeepers on the Internet include Internet search engines, comparison shopping systems, recommender systems, and other information systems that filter available choices for decision makers using databases and algorithms for information retrieval.

We define an *information gatekeeper* as an information system (usually, but not necessarily, computer-based) that is able to influence decision-making behavior through its vast repository of relevant information and algorithms for matching elements of this repository to consumer requirements. The gatekeeper's influence on decision-making behavior may manifest in terms of which alternatives are seriously considered, or perhaps even how the decision maker values certain alternatives. This ability to influence decisions arises from the gatekeeper's expertise related to the decision topic, which allows it to search for, match, and evaluate alternatives, thereby partially offloading the search and evaluation tasks from the decision maker. These systems are seen as *gatekeepers* because it would be nearly impossible for most decision makers to conduct a search and evaluation without the assistance of such systems. For example, the vast amount of information on the Web would be of little value in the absence of

effective search engines. Indeed, Internet search engines serve as a gateway to the Web's information repository and have established a crucial role in today's information society. Most studies of Internet usage find that search engines play a vital role in information retrieval over the Internet. A recent *USA Today* (2000) article states that 100 million queries are made on U.S. search engines each weekday, and a study of Web usage by Jupiter Media Metrix (Sullivan 2002b) found that the top three search engines were each visited by 61 percent, 56 percent, and 40 percent of tracked Internet users during the previous month.

This paper develops economic models to analyze the occurrence of bias in information gatekeepers. We define bias as the deliberate perturbation of advice (or a search result) in order to derive monetary gain from a third party (content provider): the bias manifests itself as a preferential placement of one or more content providers, who anticipate increased gains in a future transaction with the decision maker as a result of the preferential placement. Bias, or preferential placement, is widespread in information gatekeepers and found also in many gatekeepers that began as independent, neutral aggregators of information. Internet search engines and comparison shopping sites (also called *shopbots*) are illustrative examples. All of the early sites began as noncommercial independent aggregators of Web content, and came to rely on advertising revenue. In the last few years, however, the drop in supply of venture capital and the fall in advertising revenues forced search engines to investigate mechanisms for generating revenue from content providers. These mechanisms, which we generically label as paid placement, include a fee for inclusion in the database, an increased relevance score in response to a query, or featured listings on the results pages. A paid placement strategy usually requires a minor modification of the ranking algorithm or to the display of results, either of which can be made at very low cost. Paid placement is widespread in search engines (e.g., *Google*), information portals (e.g., *Yahoo!*), metasearch engines (e.g., *Metacrawler*), and shopbots (e.g., *MySimon*). Nearly all major search engines and portals employ paid placement (Sullivan 2002a). Table 1 presents data on the extent of paid placement for metasearch engines. Figure 1 shows paid placement, regular listings, and advertising in an Internet search engine (*Metacrawler.com*) when searching for the keyword *Canada*. The top positions of the paid links (featured search results) increase their likelihood of being followed up. But this preferential listing may create disutility for the consumers. For example, it might be irrelevant to the user's search, but it occupies a lot of space, or it is actually relevant but the user has extra uncertainty about its relevancy because it is a paid featured result.



Figure 1. Paid Placement in MetaCrawler.com

**Table 1. Percentage of Paid Listings**

Meta Search	Paid Links	Total Links	% Paid
Dogpile	30	35	86
qbsearch	66	98	67
MetaCrawle	13	25	52
Mamma	6	15	40
Search.com	10	29	34
ProFusion	2	14	14
Ixquick	1	10	10
Vivisimo	0:	20	0

The table shows what percentage of the links shown on the first page of results from a meta search service were paid listings. The table shows what percentage of the links shown on the first page of results from a meta search service were paid listings. The search query was *Canada*, done using each meta search service's default settings.

The evolution of preferential placement in Internet-based information gatekeepers has followed a similar path as in older forms of gatekeepers. For example, it is similar to the pay for play practice in radio stations, where commercial radio stations accept money from record companies and “push” their music by playing those songs more frequently. The music played on radio stations influences sales of recorded music, since listeners tend to rely on the expertise of radio deejays. Pay-for-play is a legal practice today so long as the radio station announces the play with a sponsorship line (Gloede 1993); however, it caused huge controversy (known as the payola scandal) in the middle of the last century, leading to a conviction, in 1960, of a leading deejay in the United States for accepting payola. More recently, several Latin radio stations in the United States have been investigated for illegal practices involving payment for playing music. The movement of search engines from independent to commercial sites also finds a parallel in the radio station industry: while there were only independent radio stations in the beginning, today there are about 10,000 commercial radio stations in the United States and only about 2,500 independent stations.

In other examples, we see many information gatekeepers that are considered independent (e.g., Consumer Reports, some special interest recommendation sites on the Internet, academic survey articles such as the OR/MS Today annual survey of major software products for statistical analysis, decision analysis, linear programming, etc.) and many others that have a general information aggregation role but provide preferential treatment based on payments (e.g., commercial yellow pages, product analyses in commercial magazines). In this paper, we view preferential placement (or bias) as just one of several attributes that define the gatekeeper's quality. If consumers are negatively disposed toward preferential placement, then it simply reduces the quality perception of the gatekeeper, hence downwardly influencing its likely market share. The rest of this paper is organized as follows and, for ease of discussion, is set in the specific context of Internet search engines. In section 2, we develop our model of the search engine's revenue problem, considering network effects, the effect of paid placement, and third-party revenues. We characterize the optimal paid placement strategy in section 3, and discuss the sensitivity of the paid placement strategy to various controllable parameters such as the extent of bias and search engine quality, and other factors such as perceived disutility and the advertising rate. In section 4, we consider two cases of duopolistic competition, one in which both search engines are identical and the other in which one is endowed with superior quality. We conclude with a summary of our results and possible application of our work to other forms of Internet-based information intermediaries.

## 2 MODEL OF GATEKEEPER'S REVENUE PROBLEM

In developing an economic model of gatekeeper, we consider three types of entities: users of the gatekeeper, content providers, and third-parties such as advertisers and licensing firms. The gatekeeper benefits content providers by providing preferential placement.

## 2.1 Network Effects

We conceptualize the gatekeeper as offering network benefits to both users and content providers. The overall value of the gatekeeper to users increases in the total number of content providers, and the value to content providers increases in the number of users. Content providers also face a negative externality when evaluating paid placement: the benefits from paid placement go down if the gatekeeper also provides preferential placement to many other content providers.

Consider first the market for users of a monopolist gatekeeper. The demand for the search service is determined by the overall quality of the gatekeeper, which is composed of the extent of bias, and all of the other quality measures other than bias. Let  $\xi$  represent such a technological or service measure. Let  $x$  represent bias level, denoted by the number of paid placement among all the content providers. Let  $\beta(\xi; x)$  be the relative bias level with respect to its technological features. In general, the more advanced the technological level or the higher the service level of the gatekeeper, the more consumers can bear higher bias. So  $M_x(\xi; x) < 0$ , and  $M_\xi(\xi; x) > 0$ . The demand function  $M(\xi; x)$  is decreasing in the bias level  $x$ , while increasing in the other quality measures  $\xi$ . For simplicity, we use  $M(\xi; x)$  to represent  $M(\beta(\xi; x); x)$  in most of the rest of the paper.

The gatekeeper generates revenues on the basis of its user base, including revenues from third-party firms such as advertisers and fees for licensing their information retrieval technologies. Advertisers are interested in exposure to users of the gatekeeper, hence advertising revenues are a function of the search engine's user base. For simplicity in exposition, we denote all user-based revenues as advertising revenues. Let  $s$  represent the advertising value per user, so that the gatekeeper's revenues from its user base equal  $\pi_u M(\xi; x)$ .

## 2.2 Effect of Paid Placement

Internet search engines execute a user's search query on a database index and typically return a set of results ranked according to their *relevance score*. Given these results, the user selects specific content providers in the list for further transactions. It is well known that the ranking of a result term is strongly correlated with the probability that the user will follow up on the result term (McLuhan 2000). Commercial content providers are interested in *clickthroughs* and *conversion rates*, i.e., the likelihood that a search engine user will enter into a commercial transaction with the content provider. For this reason, content providers have an incentive for *paid placement*: to pay the search engine in order to be included, ranked highly, or prominently featured in the search result (*USA Today* 2000). In practice, this may mean a higher relevance score, a featured listing, or perhaps even a guaranteed retrieval for certain search terms.

What is the impact of paid placement on a search engine's perceived quality? Here we assume that search engines cannot hide the fact that they perform paid placement, because this does not define a long run equilibrium (users will finally perceive the bias, or it may cause serious legal issues as did pay-for-play in the radio industry) (Sullivan 2002b). Articles in the business press and data from commercial research firms suggest that paid placement strategies have a *negative impact* on a search engine's perceived quality and credibility. Goodman (2000) argues that search engines must act as "referees—fair arbiters of relevance" or they will lose market share. Since loss of market share causes a fall in advertising revenue, search engines must trade off potential revenues from paid placement with those from advertising.

To model the effect of paid placement, suppose that the search engine offers priority placement to content providers who pay a placement fee  $\gamma$ . Providers that receive preferential treatment expect additional profits due to increased transactions with users. As mentioned earlier, paid placement is more beneficial when there are only few sites that receive such preferential treatment: more paid listings reduce the additional benefits due to increased competition. Therefore, we use a specific quality adjusted linear demand function (as in Banker et al. 1998) to represent the demand for paid placement by the content providers. We write the demand function implicitly as  $\gamma = bM - cx$ , where  $M$ , the market coverage of the search engine, can be understood as the search engine's quality measure from the content providers' perspective, and  $b$  and  $c$  are nonnegative constants. The search engine now gets additional revenues  $\pi_p = \gamma \cdot x$ .

## 2.3 Search Engine's Profit Function

The search engine obtains revenues from two sources: third party firms and paid placement. The first type of revenue,  $\pi_u = s \cdot M(\xi; x)$ , is a function of the search engine's market coverage,  $M(\xi; x)$ , and profit rate brought by each user,  $s$ . The search engine's placement revenue is  $\pi_p = \gamma \cdot x$ . Substituting for  $\gamma$  and rearranging terms, we get

$$\gamma_p = (bM(\xi; x) - ex)x = bM(\xi; x)x - ex^2$$

The search engine's total profits are  $\pi = \pi_u + \pi_p$  and it aims to choose the optimal fraction of paid placement  $x$  in order to maximize  $\pi$ .

## 2.4 Literature Review

In related work, Bhargava and Choudhary (2001) and Corbett and Karmarkar (1999) study the case where an information intermediary has the option to charge subscription fees for customers and listing fees for suppliers. However, Bhargava and Choudhary consider only a one-sided network benefit, and their model does not incorporate advertising revenue. Corbett and Karmarkar model two-sided network benefits, but assume homogeneous content providers and do not incorporate advertising revenue. Baye and Morgan (2001) applied a game theoretic model to study a similar question. None of these papers consider the possibility that the gatekeeper may bias its outputs due to payments from content providers. Dewan et al. (2002) study the problem faced by content Web sites to balance content and advertising by an infinite horizon control program. Gabszewicz et al. (1999) analyze the case of two TV channels competing in both the audience market and the advertising market. In both of these models, however, advertising is the only revenue source, hence no trade-off between different resources is considered.

## 3 OPTIMAL PLACEMENT STRATEGY

Solving first-order conditions for the search engine's profit function, we see that the optimal degree of independence  $x^*$  is given by

$$sM_x(\xi; x) + bM(\xi; x) - (2e - b)x = 0 \tag{1}$$

It can be verified that the profit function is concave and that the *optimal*  $x^*$  given by (1) satisfies second-order conditions for optimality. To understand Eq. (1), we rearrange the terms and get:

$$(bM(\xi; x) - ex)\Delta x = sM_x(\xi; x)\Delta x - \gamma_x \Delta x \tag{2}$$

This shows that with a small amount of change in the paid placement strategy, the left hand side represents the increase in the placement revenue. The first term on the right hand side is the fall in revenue from lower demand and the second term is the fall in revenue from a lower placement fee. This equation shows that the marginal benefit from paid placement should be balanced by the marginal cost in the optimal situation.

Next we examine the sensitivity of the placement strategy to exogenous factors and factors that the information gatekeeper can control. One of the controllable factors of the information gatekeeper is its quality of service. The gatekeeper can improve quality via investments in these areas. Intuitively, the gatekeeper could give up some placement revenues, improve  $\xi$ , attract more customers and get more advertisement revenues. What is the trade-off between the search engine's quality and the placement revenue?

**Proposition 1:** *An increase in the gatekeeper's technological or service level  $\xi$  allows it to increase its total profit. If  $|M_x(\xi; x)/M(\xi; x)| < b/s$ , it is allowed to increase its bias level as well; otherwise its optimal bias level should be reduced.*

We note that the increase in paid placement links is accompanied by a reduction in the placement fee, yet there is an unambiguous increase in placement revenues since the placement level moves closer to its ideal (i.e., the level the gatekeeper would set if there were no negative effect on users). Thus, the search engine must examine potential investments in quality  $\xi$  based on its impact not only on user-based revenues but also on revenues from paid placement.

Next, we consider the impact of per user profit. How do changes in  $s$  affect the search engine's paid placement strategy?

**Proposition 2:** *An increase in per user profit,  $s$ , decreases the fraction of paid placements  $x^*$ , hence the gatekeeper increases its market coverage  $M$ . The search engine also improves its total profits  $\pi$ .*

To understand this result, consider the gatekeeper’s tradeoff between its two revenue sources. As  $s$  increases, the potential for advertising revenue increases, hence a partial sacrifice of revenues brought by users imposes a greater cost on the gatekeeper. Therefore, it reduces its level of paid placement in order to provide greater utility to users, and captures a greater percentage of potential advertising revenues.

#### 4 COMPETITION BETWEEN GATEKEEPERS

Now consider two gatekeepers in the market. Suppose that originally they are endowed with the same quality and capture equal market share in the users market. Now they have the option to adapt to a paid placement strategy. Let  $x_1$  and  $x_2$  represent the bias levels of the two engines. Users are heterogeneous in their tolerance toward bias. Those users with high tolerance toward bias (higher than  $\text{Max}\{x_1, x_2\}$ ) are indifferent to the services provided by either gatekeeper, so we assume that this segment is equally likely to visit either service. Those with a lower bias will prefer the less biased search engine.

Since the two gatekeepers have the same technological or service level, we omit  $\xi$  in the demand function and write it as  $M(x_i, x_j)$ , which represents the demand for the gatekeeper with bias level  $x_i$  when the competing gatekeeper has bias level  $x_j$ . The gatekeeper with the higher bias splits, with its competitor, the demand from users with tolerance levels greater than its bias. The engine with lower bias gets its own market for customers with lower tolerance toward bias, plus the market shared with the engine with higher bias levels. Hence we write the demand function as:

$$M(x_i, x_j) = \begin{cases} M(x_i) - \frac{1}{2}M(x_j) & \text{if } x_i \leq x_j \\ \frac{1}{2}M(x_i) & \text{if } x_i > x_j \end{cases}$$

Where  $M(x_1)$ , and  $M(x_2)$ , are the demand functions presented in the monopoly analysis, and represent the demand when there is only one gatekeeper with bias levels  $x_1$  or  $x_2$  respectively.

Consider gatekeeper 1. If  $x_1 > x_2$ , it captures half its monopoly market,

$$M_1(x_1; x_2) = 1/2 M(x_1)$$

and  $\pi_1 = \frac{1}{2}M(x_1) \cdot ex_1$ . The gatekeeper’s profit function is:

$$\pi_1 = s \cdot \frac{1}{2}M(x_1) + b \cdot \frac{1}{2}M(x_1)x_1 - ex_1^2 \tag{3}$$

On the other hand, if  $x_1 < x_2$ , then search engine 1 has a larger market share:

$$M_1(x_1; x_2) = M(x_1) - \frac{1}{2}M(x_2).$$

Then  $\pi_1 = bM(x_1) - \frac{1}{2}M(x_2) \cdot ex_1$ . Given the competitor’s bias level  $x_2$ , the gatekeeper’s profit function is:

$$\pi_1 = sM(x_1) - \frac{1}{2}M(x_2) + bM(x_1)x_1 - \frac{1}{2}M(x_2)x_1 - ex_1^2 \tag{4}$$

Now we solve gatekeeper 1’s best response to gatekeeper 2’s bias level, they are the solution to the first order condition to Eq. (3) and Eq. (4) respectively. Since the two gatekeepers are symmetric, the unique pure strategy Nash equilibrium is determined by:

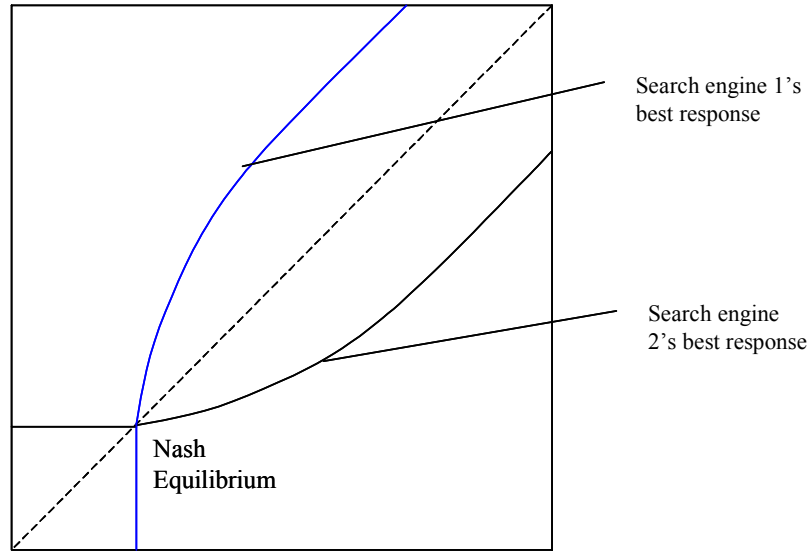
$$x_1^* = \arg \max \quad s \cdot M(x_2) + b \cdot \frac{1}{2}M(x_1)x_1 - ex_1^2 \tag{5}$$

so that the two gatekeepers choose the same bias level, obtain equal market share, and make the same profits.

How does this competition affects the users’ and content providers’ welfare?

*Proposition 3: The bias level of the two gatekeepers is less than the bias level if they are monopolists. The competition among search engines increases users' welfare, while the total gatekeeper surplus and the total surplus of content providers are both reduced.*

Figure 2 demonstrate the Nash equilibrium.



**Figure 2. Nash Equilibrium**

## 5 GATEKEEPERS WITH DIFFERENT QUALITY

Now consider the case where the gatekeepers were endowed with different quality levels in the beginning. If they face the choice of choosing their own paid placement strategy, what bias levels are they going to use?

Similar with the case above, the demand function of the gatekeeper is:

$$M(\xi_i, x_i; \xi_j, x_j) = \begin{cases} M(\xi_i, x_i) - \frac{\xi_2}{\xi_1 + \xi_2} M(\xi_j, x_j) & \text{if } M(\xi_i, x_i) \geq M(\xi_j, x_j) \\ \frac{\xi_2}{\xi_1 + \xi_2} M(\xi_i, x_i) & \text{otherwise} \end{cases}$$

where  $M(\xi_i, x_i)$  represents the demand when there is only one gatekeeper with quality level  $\xi_i$  and bias level  $x_i$ , or we can view it as one indirect measure of the composite quality level of one gatekeeper. This is to say that the one gatekeeper with higher composite quality measure will gain a larger market share, while the lower composite quality gatekeeper only serves part of the market with higher tolerance level toward bias.

Without loss of generality, let's assume that  $\xi_1 > \xi_2$ . Following the same logic as before, taking  $\xi_1$  and  $\xi_2$  given, we get compute the equilibrium bias level of each gatekeeper. It may be seen here that  $x_1$  is increasing in  $\xi_1$  and  $x_2$  as before, but is decreasing in  $\xi_2$ . More specifically,

**Propositon 4:** Multiple equilibria exist. Define the market responsiveness with respect to bias  $\varepsilon$  to be  $\frac{\partial M}{\partial x} \cdot \frac{x}{M}$ . The sufficient

condition to have an equilibrium where  $x_1 < x_2$  is  $|\varepsilon| > b - \frac{\xi_2}{\xi_1 + \xi_2}$ . More than one equilibria may exists where  $x_1 > x_2$ , where



either  $M_1 \geq M_2$  or  $M_1 < M_2$ , depending upon the market situation.

Figures 3 and 4 show the cases when  $|\epsilon| > b - \frac{\xi_2}{\xi_1 + \xi_2}$  and  $|\epsilon| < b - \frac{\xi_2}{\xi_1 + \xi_2}$ .

The intuition behind this result is that, if the market responsiveness toward bias is great, then the higher quality gatekeeper (1) will have a lower bias level to maintain a good reputation, and this is more possible when the two gatekeepers' quality levels are not obviously differentiated. But if the market is not sensitive to the bias, then gatekeeper 1 can have higher bias level because its quality is better, and this is more possible when the two gatekeepers quality levels are greatly differentiated.

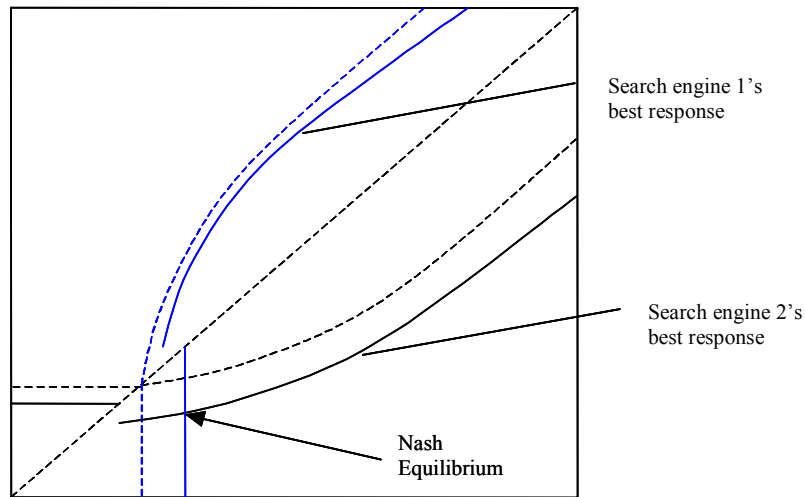


Figure 3. Market Responsiveness to Bias is Greater

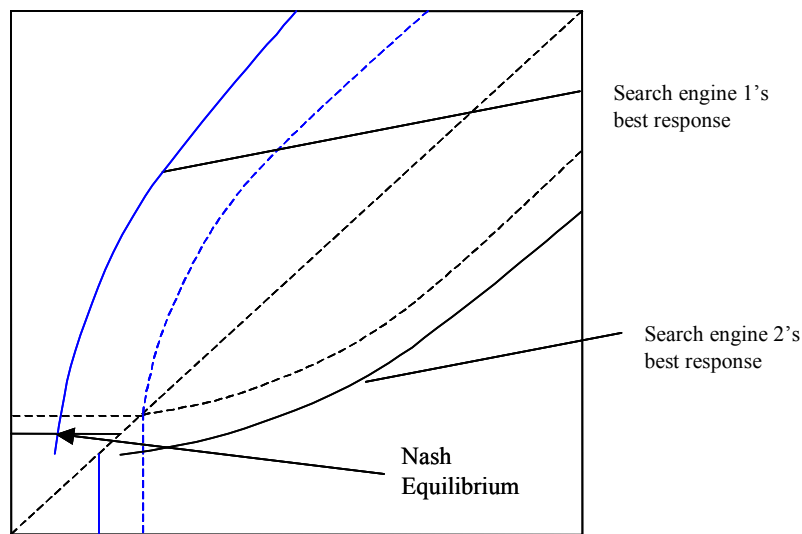


Figure 3. Market Responsiveness to Bias is Less

## 6 SOCIAL WELFARE ANALYSIS

Until now, we have only considered the profit maximizing problem for the gatekeeper(s). Here we just provide some primary results. The details are available from the authors.

**Proposition 6:** *When there is only one gatekeeper, whether or not the gatekeeper's profit maximizing bias level is greater than the socially optimal bias level will be determined by the consumer market responsiveness. When there are two gatekeepers, it is socially optimally for them to set bias levels such that one is greater than the monopoly case and one less than the monopoly case.*

## 7 CONCLUSION

This article considers paid placement information gatekeepers and analyzes the optimal strategy in the specific context of Internet search engines. On the one hand, paid placement appears to be a financial necessity, embraced by most major Web search engines. On the other, paid placement can hurt the search engine's market share and its potential for revenues brought by users. We have developed a mathematical model for optimal design of a paid placement strategy, examined this tradeoff, and analyzed sensitivity of the placement strategy to users' perceived disutility, the service quality of the gatekeeper, and the advertising rate. We also considered the case where there is competition between search engines. We showed that when the search engines are otherwise identical in quality, they will choose the same bias level. But for heterogeneous search engines with different qualities, the equilibrium outcome depends largely on the users' cognitive or other limitations on the number of search results they effectively consider.

While this research is set in the context of Internet search engines, our model and results apply more generally to many other contexts that share similar characteristics as search engines. This broader category, often called information gatekeepers, intermediates between a set of users (buyers or consumers) and a set of products (content providers or vendors). Baye and Morgan (2001) argue that modern markets for information tend to be dominated by information gatekeepers that specialize in collating, aggregating, and searching the massive amounts of information available on the Web and that can often charge consumers, advertisers, and information providers for their ability to acquire and transmit information. Wise and Morrison (2001) emphasize the increasing role of information gatekeepers in today's economy, noting that in business-to-business markets, "value has shifted from the product itself to information about the product." Specific categories of information gatekeepers to which our work applies include recommender systems (e.g., Amazon.com), comparison shopping services (e.g., mySimon.com), e-marketplaces and exchanges (e.g., FreeMarkets), and more traditional information gatekeepers such as investment advisors and television networks. Like search engines, many information gatekeepers generate user-based revenues, but also seek to obtain revenues from their provider-base by offering some form of preferential placement. For example, some Internet booksellers are influenced by advertising fees in determining their *bestseller* lists. Similarly, certain Internet exchanges provide preferential service (such as real time notification or favorable recommendation to buyers) to some clients in return for higher fees.

Our models can be extended to examine conditions under which the information gatekeeper will begin to charge users, and specifically the case where the gatekeeper differentiates between users by offering two versions: a fee-based premium service with no bias in the query results and a free basic version with paid placement bias. The fee-based premium version will bring additional user revenues to the search engine; however, it may reduce placement revenues because paid placement becomes less attractive to content providers. In addition, the search engine's market coverage and placement fee may change as well, and the models can be used to determine if it is optimal for the gatekeeper to offer differentiated service. Similar models can be developed to examine the impact of differentiation based on advertising. Some search engines have already begun to offer fee-based premium search services that contain no advertising. If this is the trend, it may eventually change people's view of Internet search engines as a free resource for fair information.

## 8 REFERENCES

- Banker, R. D., Khoslam I., and Sinha, K. K. "Quality and Competition," *Management Science* (45:9), 1998, pp. 1179-92.
- Baye, M. R., and Morgan, J. "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets," *American Economic Review* (91:3), June 2001, pp. 454-474.
- Bhargava, H. K., and Choudhary, V. "Economics of Electronic Intermediary with Aggregation," Graduate School of Industrial Administration Working Paper 2000-20, Carnegie Mellon University, July 2001.

- Corbett, C. J., and Karmarkar, U. S. "Optimal Pricing Strategies for an Information Intermediary," Working Paper 99-001, Andersen Graduate School of Management, University of California, Los Angeles, 1999 (available online at [http://www.anderson.ucla.edu/acad\\_unit/dotm/papers/99-001.pdf](http://www.anderson.ucla.edu/acad_unit/dotm/papers/99-001.pdf)).
- Dewan, R. M., Freimer, M. L., and Zhang, J. "Managing Web Sites For Profitability: Balancing Content and Advertising," paper presented at the Hawaii International Conference on System Sciences, Kona, Hawaii, 2002 (available online at <http://rdewan.ssb.rochester.edu/re.htm>).
- Gabszewicz, J., Laussel, D., and Sonnac, N. "TV-Broadcasting Competition and Advertising," Working Paper, Center for Operations Research and Economics, Université Catholique de Louvain, 1999 (available online at <http://www.core.ucl.ac.be/services/psfiles/dp00/dp2000-6.pdf>).
- Gloede, W. F. "Play-for-Pay Comes of Age," *Mediaweek* (3:8), February 1993, p. 18.
- Goodman, A. "Why Search Engines Must Continue to be Referees," *Traffick*, November 2000 (available online at [www.traffick.com](http://www.traffick.com)).
- Lawrence, S., and Giles, C. L. "Accessibility of Information on the Web," *Nature* (400:6740), 1999, pp. 107-109.
- McLuhan, R. "Search for a Top Ranking," *Marketing*, October, 2000, pp. 47.
- Sullivan, D. "Buying Your Way In To Search Engines," *Search Engine Watch*, June 29, 2002a (available online at <http://searchenginewatch.com/webmasters/paid.html>).
- Sullivan, D. "Jupiter Media Metrix Search Engine Ratings," *Search Engine Watch*, April 29, 2002b (available online at <http://searchenginewatch.com/reports/mediametrix.html>).
- USA Today*. "Firms Pay for Search Engine Play." December 11, 2000 (available online at <http://www.usatoday.com/life/cyber/tech/cti985.htm>).