The Impact of Sponsored Results on the Quality of Information Gatekeepers

Hemant Bhargava
University of California at Davis
Davis, CA 95616
hemantb@ucdavis.edu

Juan Feng
University of Florida
Gainesville, FL 32611
jane.feng@cba.ufl.edu

ABSTRACT

Information gatekeepers, such as Internet search engines, travel experts, comparison shopping systems, credit raters, radio deejays, and movie critics, are an essential entry point for many information search and decision making tasks. They make recommendations on these tasks based on their expertise, but also frequently due to sponsorship by interested merchants. We develop and analyze a tractable model in which consumers may prefer or dislike the use of sponsored results in the recommendations, merchants' value for sponsorship increases with the gatekeeper's user base, and when there are negative externalities among merchants competing for consumers' attention. The optimal strategy strikes a balance between sponsorship revenues from merchants and user-based revenues. The gatekeeper may employ sponsored recommendations even when doing so is detrimental to users, or may not present enough sponsored results even when these improve the quality of recommendations. Product innovations or better domain expertise give the gatekeeper greater flexibility in using sponsored results.

We thank Eitan Gerstner, Anindya Ghose, Kartik Hosanagar, Greta Hsu, Krishna Jayakar, Ramayya Krishnan, Rahul Telang, for useful comments.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Economics

Keywords

information gatekeeper, quality, sponsored result

ICEC'07, August 19–22, 2007, Minneapolis, Minnesota, USA.

1. INTRODUCTION

Individual and organizational decision makers often turn to experts—reviewers, critics, advisors, consultants, referral services, counsellors—for advice on which alternatives to consider or how much to value them. We call such entities *information gatekeepers*, due to their critical role in organizing, searching, and prioritizing massive amounts of available information. Example phenomena include financial reports from credit rating agencies, product reviews by Consumer Reports, restaurant and dining guides, movie (or drama, art) reviews, wine critiques, pharmaceutical recommendations and referrals by physicians, directories of vendors or buyers in electronic exchanges, and business school rankings. Information gatekeepers on the World Wide Web include Internet search engines (e.g., Google), comparison shopping services (e.g., mySimon.com), online travel services (e.g., Expedia.com), review and recommender systems (e.g., epinions.com), referral sites, Web portals, and other systems that filter alternatives using data and retrieval algorithms.

Because they reduce the decision maker's effort, information gatekeepers can influence the decision process: which alternatives are considered, how they are valued, and which products or merchants are chosen for trade. Positive recommendations by information gatekeepers increase merchant revenues. Famously, favorable "display bias" in the SABRE airline reservation system yielded American Airlines over $200m each year in the 1980s [6]. Favorable reviews by movie critics earn a film greater viewership and higher revenues [2, 9, 19]. Web sites that earn high rank on Internet searches obtain greater *click-through* rates [16] and revenues [8]. The correlation between good reviews and revenues induces merchants to seek better recommendations through monetary payments, pressure, ownership, or other means. [7] describes how American Airlines pioneered recommendation bias in travel search systems by giving, for a fee, preferential recommendation to host partners' flights in SABRE. On the Web, merchants compete to pay search engines for preferential recommendation on specific search terms (these auctions produce prices ranging, presently, from a few cents to several dollars per click).

We use the term *objective results* for recommendations produced by an information gatekeeper's internal resources, and *sponsored recommendations* for outputs influenced by sponsorship payments from recommended entities (merchants). Depending on context, the use of sponsored recommendations can either enhance or deplete the information value of the gatekeeper. Under certain conditions corresponding to a separating equilibrium in advertising expenditures [17], or when the gatekeeper itself is rather inaccurate in identifying high-quality merchants, sponsored slots are of higher average quality than objective results. Conversely, when the gatekeeper's internal recommendations are highly accurate, or when there is no separating equilibrium in the signalling game for advertising expenditures, the addition of sponsored results may adversely impact the user. This point is well illustrated by Dollar-Thrifty's agreement with Expedia.com, which guaranteed Dollar-Thrifty the "lowest cost provider" position in certain markets: when other rental companies offered lower prices, Expedia would simply omit them from search results.[1] There is also some evidence showing that users of gatekeeper services have a negative perception of recommendation bias ([11], [12], [15], [14]). Actually, even Google, the search system who does highly targeted sponsered search has doubts on the relevance of the paid results. A New York Times article[2] notes that "Mr. Page and Mr. Brin (the founder) were suspicious of any system that put high-bidding advertisers at the top ... They thought that if someone was willing to pay more it was a negative." and Mr. Schmidt (the CEO) "was afraid people would realize these ads were worthless."

Thus, how will the paid results impact the overall quality of the recommender is a complex problem, and may be influenced by many different factors. Do merchants have an incentive to pay for sponsorship? How should the gatekeeper determine the mix of objective and sponsored recommendations? Will the share of sponsored results, in equilibrium, be too much or too little? These questions are relevant to the design of many types of information gatekeepers, and particularly to Internet search engines, given the infancy of the industry and its visible influence in daily life. This article proposes such a framework, presents a tractable model for analyzing sponsored recommendations, and applies the framework to study this practice in Internet search engines.

2. MODELING FRAMEWORK

An information gatekeeper is a platform that serves two groups, users who seek information and merchants who wish to get information across to consumers. The gatekeeper responds to user queries with a list of relevant merchants, using its *technological capability* $y \in [0, Y]$ comprising its domain expertise and knowledge, index of relevant merchants, search and filtering algorithms, etc. In addition, the gatekeeper's list might be influenced by monetary signals from merchants. We model the interaction between the gatekeeper, users, and merchants as a simultaneous game in which the gatekeeper chooses the mix of objective and sponsored results and sets the fee for sponsorship, merchants choose whether or not to buy sponsorship, and users decide whether or not to visit the gatekeeper. Merchants and users are aware of the gatekeeper's technological capability. The rational expectations equilibrium outcome involves consistent realization of expectations about the mix of results and market participation.

2.1 How do Sponsored Recommendations Affect Consumer Valuation?

Let $\mathbf{V}(x; y) \in [0, 1]$ denote users' valuation of gatekeeper who has technological capability y and inserts Nx sponsored results in the consideration set. We assume $\mathbf{V}(x; y)$ is continuous and differentiable in y, and twice differentiable in x.[3] The gatekeeper's technology y measures, among other things, how many merchants it indexes, the accuracy of its knowledge regarding these merchants, and its ability to identify the best merchants with respect to the user query. The gatekeeper's output combines its own technology y and monetary bids from merchants. Intuitively, a gatekeeper with high technological quality (y close to 1) already places high quality merchants, therefore replacing some of these merchants with sponsored results can only reduce the overall quality. The opposite effect emerges when y is small. We formalize these remarks below.

- *A*-1 $\mathbf{V}_y(x; y) = \mathbf{V}(x; y)y > 0$. Better technology produces a higher quality consideration set. Therefore, user demand for the gatekeeper increases as it indexes more merchants or when it improves its knowledge about these merchants.
- *A*-2 $\mathbf{V}_{xy}(x; y) < 0$. Use of sponsored recommendations will produce diminishing gains in output quality as gatekeeper technology improves.
- *A*-3 For any given y, there exists $\bar{x}(y)$ such that $\mathbf{V}(\bar{x}(y); y) = 0$, $\mathbf{V}(x; y) > 0$ for $x < \bar{x}(y)$ and $\mathbf{V}(x; y) < 0$ for $x > \bar{x}(y)$. The use of sponsored results may improve recommendation quality (i.e., $V_x(x; y) > 0$) or hurt it ($V_x(x; y) < 0$). This effect will vary with x, the degree of sponsor influence.

Note by assuming the existence of $\bar{x}(y)$, we abstract away from the endogeneity between the consumer's behavior and the gatekeeper's output. We explore the detail interaction between the three parties in our extended work. As $\mathbf{V}(x; y)$ is unimodal in x, and for every y there is (for users) an *ideal mix* of sponsored and objective results, given by $\bar{x}(y)$. Choosing this ideal mix delivers users the maximum possible recommendation quality (given technological capability y), $\bar{\mathbf{V}}(y) = \mathbf{V}(\bar{x}(y); y)$. There are three cases of interest: (1) $\bar{x}(y) = 0$, then $V_x < 0$ for all x: if the gatekeeper has perfect technology ($y = 1$), any positive weight on the bid signal would be detrimental to the user [18]; (2) $\bar{x}(y) = 1$, then $V_x > 0$ always; and (3) $\bar{x}(y) \in (0, 1)$, users benefit from sponsored results upto some threshold and consider a greater fraction to be harmful. A trivial consequence of our assumptions is that $\bar{x}(y)$ is decreasing in y. We note that $\mathbf{V}_x$ (hence $\bar{x}$) will vary across domains. Finally, we make two additional assumptions that provide mathematical tractability and appear justified in the context.

- *A*-4 For every y, $\mathbf{V}(x; y)$ is log-concave in x ($\ln \mathbf{V}(x; y)$ is concave in x). Equivalently, $\frac{\mathbf{V}_x(x;y)}{\mathbf{V}(x;y)}$ is monotone decreasing, i.e., $V(x; y) \times \mathbf{V}_{xx}(x; y) < (\mathbf{V}_x(x; y))^2$.
- *A*-5 For every y, $\frac{\mathbf{V}_x(x;y)}{V(x;y)} < \frac{1}{2}$.

9[1]Consumer Reports (at http://www.consumerwebwatch.org/dynamic /travel-report-booking-bidding.cfm), and Form 8-K filings by Dollar-Thrifty in May 2005.

9[2]Your Ads Here (All of Them), by SAUL HANSELL, Oct. 30, 2005, Sunday, p. BU 9

9[3]We use subscripts x and y to denote partial derivatives with respect to x and y respectively, e.g., V_x is the partial derivative of V with respect to x. We will occasionally drop the arguments of functions in order to make formulas more compact, e.g., writing V_x in place of $V_x(x, y)$.

2.2 Consumer Demand for Gatekeeper Service

We characterize the potential users of gatekeeper service by a type parameter $\theta \in [0,1]$, representing users' reservation value for using the gatekeeper. For example, users may perceive different interaction costs with a travel search engine that requires them to enter origin and destination cities, time preferences, personal information details, etc. Similarly, subscribers are heterogeneous in their ability to learn and use advanced search features, especially because these features and user interfaces differ across gatekeepers. The gatekeeper's market penetration $\mathbf{M}(x;y)$ consists of users for whom the benefit $\mathbf{V}(x;y)$ exceeds their reservation value θ. To simplify exposition, assume that θ is uniformly distributed in $[0,1]$, so that $\mathbf{M}(x;y) = \{\theta : \theta \in [0, \mathbf{V}(x;y)]\} = \mathbf{V}(x;y)$. Our formulation and results are robust across other distributions, and can be extended to cover additional factors such as brand preference or loyalty towards a search engine.

User demand for the gatekeeper service can change with the degree of sponsor influence in its outputs. We define users' *demand elasticity with respect to x* as

$$\epsilon(x;y) = \frac{-\mathbf{M}_x(x;y)x}{\mathbf{M}(x;y)} = \frac{-\mathbf{V}_x(x;y)x}{\mathbf{V}(x;y)} \qquad (1)$$

$\epsilon(x;y)$ may be positive or negative, may vary across gatekeeper domains (e.g., search for commercial products vs. information search). In some domains, subscribers may be highly sensitive to adoption of sponsored results by a hitherto independent gatekeeper, but increasing the share may have less impact. As an example, consider the drop in value of University rankings (or, say, Consumer Reports rankings) if these rankings were perturbed due to payment from Universities. In other cases, subscribers may benefit from some sponsored results, but demand may fall rapidly when x exceeds a threshold because space for objective results gets increasingly scarce. Our analysis covers a broad class of such scenarios.

2.3 Merchant Demand

To model merchant demand for sponsored recommendations, let $\gamma(x) \in \Re$ be the market-clearing fee (or subsidy) when the gatekeeper inserts Nx sponsored slots. Merchants are heterogeneous in willingness to pay for sponsored recommendations. They are sensitive to the gatekeeper's performance on the other side of the network, i.e., to the size of user base $\mathbf{M}$ (a positive cross-network externality). Merchants have higher value for sponsored slots when these slots are more exclusive because lower competition should generate more "hits" (negative externality within network). To satisfy these requirements, we adopt the quality-adjusted linear demand function employed in prior literature [1, 3]:

$$\gamma(x, \mathbf{M}(x;y)) = \frac{b}{N}\mathbf{M}(x;y) - \frac{e}{N}x \qquad (2)$$

Note in this specification, we ignore a possible inverse relationship between the merchants' demand and the gatekeeper's technological capability: sponsored recommendations made by a highly capable gatekeeper are more likely to be inferior to the objective results (because the objective ones are already very good). We explore this interaction in our extended work. Rewriting the demand function as $x = (\frac{b}{e}\mathbf{M}(x;y) - \frac{N\gamma}{e})$, $\frac{b}{e}$ is the responsiveness of merchant demand to the size of the gatekeeper's subscriber base. We note that $\gamma(x)$ may be positive or negative. A positive fee has the obvious interpretation that merchants pay the gatekeeper in order for positive recommendation, and is possible regardless of the sign of $\mathbf{V}_x$. Negative γ, possible only for x such that $\mathbf{V}_x > 0$, indicates that the gatekeeper subsidizes the merchants in return for private information that helps it improve its recommendations. The magnitude and sign of γ is endogenous to the gatekeeper's design problem.

2.4 Gatekeeper Revenues and Objective Function

The gatekeeper sponsorship revenues from merchants are

$$R(x;y) = \gamma \cdot (Nx) = (b\mathbf{M}(x;y) - ex)x. \qquad (3)$$

The gatekeeper second revenue source is on account of its subscriber base, including revenues from for-fee services, sale of user data, traditional advertising, and other indirect revenues that treat user base as an asset. Let $s\mathbf{M}(x;y)$ represent the gatekeeper's user-based revenues when Nx results are sponsored, where s is the per-user revenue.[4] The gatekeeper's second revenue source is sponsorship fees from merchants. Eq. 2 yields a sponsorship revenue function

$$R(x;y) = \gamma \cdot (Nx) = (b\mathbf{M}(x;y) - ex)x. \qquad (4)$$

The gatekeeper's per-subscriber expected payoff from promoting a merchant is b, lessened by merchants' desire for exclusivity in sponsorship, captured by e. The gatekeeper's profit combines sponsorship revenues and direct user-based revenues, so that

$$\pi(x;y) = s\mathbf{M}(x;y) + (b\mathbf{M}(x;y) - ex)x \qquad (5)$$

LEMMA 1. *$\pi(x;y)$ is unimodal in x. There is at most one critical point $x^m \in (0,1)$, if so it is the global maximum. The derivative $\pi_x(x;y)$ is positive for $x < x^m$ and negative for $x > x^m$.*

COROLLARY 1. *The user-based revenues ($s\mathbf{V}(x,y)$) and sponsorship revenues ($R(x,y)$) are both unimodal in x, first increasing and then decreasing (one of the regions may be empty).*

The profit function is well-behaved and the optimal value x^m can be obtained from first-order conditions (FOC). The two parts of Corollary 1 follow from, respectively, Assumption 3 and by setting $s = 0$ in Lemma 1. Choosing x^m requires making the optimal balance between user-based and sponsorship revenues. When $\mathbf{V}_x > 0$ in some region, it is possible for the gatekeeper to increase both revenues at the same time. However, such an x cannot be optimal. The

9[4]If s includes subscription fees paid by the user, its effect on the demand model may be captured by adjusting the reservation cost θ.

optimal level, x^m, always occurs in a region where increasing user-based revenues requires changing x in the opposite direction needed to increase sponsorship revenues. Formally,

3. OPTIMAL MIX OF OBJECTIVE AND SPONSORED RECOMMENDATIONS

We describe the properties of the optimal solution in this section; our use of the terms "excessive" or "inadequate" sponsored results is from the user's perspective. From Lemma 1, if the FOC has an interior solution, it is unique and yields $x^m \in (0, 1)$, otherwise x^m is 0 (when $\pi_x(x; y)$ is always positive) or 1 ($\pi_x(x; y)$ always negative).

Corollary 2. *The optimal level of sponsored recommendations, x^m, is*

1. $x^m = 0$ *when* $s\mathbf{V}_x(0; y) + b\mathbf{V}(0; y) < 0$, *and*

2. $x^m = 1$ *when* $(s + b)\mathbf{V}_x(1; y) + b\mathbf{V}(1; y) - 2e > 0$.

Intuitively, gatekeepers maintain objectivity when adoption of sponsored results causes a sharp drop in subscriber base ($\mathbf{V}_x$ significantly negative, or high y), or when s is substantially larger than b (merchants' willingness-to-pay for sponsored results is low, relative to direct per-user revenues). Corollary 2 provides a precise measure and, in combination with econometric estimates, offers the potential to explain design differences across various information gatekeeper domains. For example, users of *Consumer Reports* (or of *Business Week* rankings of business schools) strongly expect objective analysis, so it is best to generate objective rankings and forego sponsorship revenues in such markets. On the other hand, Internet search engines appear to exhibit a lower s value and weaker expectation for objectivity, consistent with $x^m > 0$. At the extreme, the "all sponsored results" outcome ($x^m = 1$) may be realized for very low y (a common example of this outcome is the "Yellow Page" directories, which provide a listing of merchants but no intrinsic expertise in providing recommendations). Other factors that cause differences between markets include whether the gatekeeper is for- or non-profit, the type of search query, and the size of investment consumers must make in the product they are searching for.

Proposition 1. *Except for the two boundary cases covered in Corollary 2,*

1. x^m *is the unique solution of:*

$$b\mathbf{V}_x(x; y)x + b\mathbf{V}(x; y) - 2ex = -s\mathbf{V}_x(x; y). \qquad (6)$$

2. $x^m > \bar{x}$ *when* $\frac{b}{e} > \frac{2\bar{x}(y)}{\mathbf{V}(y)}$, *in this case* $\mathbf{V}_x < 0$ *at* x^m. *(Excessive sponsored results.)*

3. $x^m < \bar{x}$ *when* $\frac{b}{e} < \frac{2\bar{x}(y)}{\mathbf{V}(y)}$, *in this case* $\mathbf{V}_x > 0$ *at* x^m. *(Inadequate sponsored results.)*

3.1 Sponsored Results: Too Few or Too Many?

Because information gatekeepers function as intermediaries in markets with positive search costs, they have the potential to increase social welfare by efficiently matching buyers and sellers (see e.g., [4, 5]), however their incentive to appropriate some surplus can distort the way they make recommendations. In general, the share of sponsored recommendations will be *excessive* when merchants anticipate large gains from recommendation or when exclusivity is not critical (b is very large relative to e). Media and industry attention on sponsored recommendations generally highlights only its detrimental aspects (see e.g., [13, 12]; and series of articles in *The Washington Post* (Nov. 22-24, 2004) on information abuse by ratings agencies). This attitude is exemplified by the evolution of sponsored results in Google, whose founders and top executives were initially "suspicious of any system that put high-bidding advertisers at the top".[5] In contrast (Proposition 1, part 3) "too little" advertising can also be a distortion ($x^m < \bar{x}$). A weak gatekeeper, who would benefit more by employing sponsored results, may employ too few, for instance, because merchants place a strong premium on exclusivity in promotion. In addition, when the choice set is horizontally differentiated, limits on the mix of sponsored results make some consumers worse off due to reduced variety. Thus, consumer advocacy groups' efforts to ban or restrict sponsored results[6] may produce detrimental results under certain conditions.

Part 1 of Proposition 1 highlights the design problem with regard to sponsored recommendations. Gatekeepers can improve profit by choosing and displaying sponsored items in a way that increases $\mathbf{V}_x$. For example, Internet search engines display paid slots as text, having learnt that users dislike graphics and animation displays. Similarly, search engines employ measures of relevance in allocating sponsored slots, instead of giving them to the highest bidders [10]. For example, Google allocates paid slots by weighting merchant bids by estimated relevance, while Yahoo/Overture requires merchant relevance (as determined by an editorial staff) to exceed a threshold value. In making the tradeoff between user and sponsorship revenues, a greater emphasis on sponsorship revenues results in a larger gap between ideal and actual mix of sponsored results ($|\bar{x} - x^m|$). This deviation may involve too many sponsored results when preferential recommendation is highly valuable to merchants (b is large); this is more likely for search tasks with commercial interest (e.g., a search on "Harry Potter" or on hotels in the Caribbean) than for information searches (e.g., "information systems economics" or the website of a university professor). The deviation may also involve too few sponsored results when merchants have strong demand for exclusivity (large e), which is likely for price-comparison engines or recommendations involving homogeneous goods. Conversely, we should expect a smaller gap $|\bar{x} - x^m|$ when demand is highly sensitive to share of sponsored results ($\frac{-\mathbf{M}_x(x;y)}{\mathbf{M}(x;y)}$ is large).

9[5]The New York Times, October 30, 2005, Section 3, pages 1-9. "Your Ads Here (All of Them)".

9[6]For instance, travel search systems are subject to detailed regulations on access and design of search results; Sen. Joe Lieberman argued (Congressional testimony, March 20, 2002) for regulatory oversight of ratings agencies; the Kaiser health system limits doctors' links to medical firms that recommend drugs (*Sacramento Bee*, April 22, 2005); and search engine watch groups routinely imply that consumers would be better off with fewer sponsored results.

4. CONCLUSION

This article provides a conceptual framework for studying preferential recommendation, observed in many forms of information gatekeepers including credit raters, radio deejays, travel experts, movie critics, and Internet search engines.

In general, gatekeepers will employ sponsored recommendation even when it reduces their overall quality ($\mathbf{V}_x < 0$). Under other conditions, gatekeeper may not present enough sponsored results even when they are beneficial to the users ($\mathbf{V}_x > 0$). The resultant equilibrium depends on the balance between appealing to both the market of users and sponsors, and the competition among the sponsors. Product innovations – better search technology, bundle of complementary tools, or ease of use – give the gatekeeper greater flexibility in including sponsored results. The application of these results to Internet search engines is of particular interest as search engines become an increasingly significant factor in competition between merchant firms and in consumer decision making. Currently, most search engines set predetermined *ad hoc* limits on the number of sponsored search links (e.g., Google limits such links to 8 on the sidebar and 2 on the top), but our results may help managers of information gatekeepers in designing a more systematic sponsored recommendation strategy. Our results also indicate that demands to regulate gatekeepers (e.g., search engines must be "neutral arbiters of content") might be exaggerated, and underline the need for a more careful design of safeguards and regulation. While neutrality may be valuable in some contexts (automobile safety ratings, for example), it does not always maximize societal or consumer welfare. Thus, a targeted construction of safeguards where they are warranted is more effective than a universal and unfounded claim for complete neutrality.

We have developed and analyzed a tractable model that covers a gatekeeper's decision on the amount of sponsored results and how this decision is influenced by consumer attitude towards sponsored results and merchant demand for sponsored slots. One limitation of our model is that it abstracts away the endogeneity between consumer attitude and merchant demand. Our extended work is to build a detailed model about consumer behavior and merchants responses when the quality levels of the merchants are uncertain, and explore what is its impact on the overall quality of the gatekeeper and consumer welfare, when sponsored results can serve as a mechanism for signalling merchant quality.

5. REFERENCES

[1] R. D. Banker, I. Khosla, and K. K. Sinha. Quality and competition. *Management Science*, 44(9):1179–92, September 1998.

[2] S. Basuroy, S. Chatterjee, and S. A. Ravid. How critical are critical reviews? the box office effects of film critics, star power and budgets. *Journal of Marketing*, 67:103–117, October 2003.

[3] H. K. Bhargava and V. Choudhary. Economics of information intermediaries with aggregation benefits. *Information Systems Research*, 15(1):22■36, March 2004.

[4] G. Biglaiser. Middlemen as experts. *RAND Journal of Economics*, 24:212–223, 2002.

[5] Y. Chen, G. Iyer, and V. Padmanabhan. Referral infomediaries. *Marketing Science*, 21(4):412–434, 2002.

[6] D. G. Copeland, R. Mason, and J. L. McKenney. Sabre: The development of information-based competence and the execution of information-based competence. *IEEE Annals of the History of Computing*, 17(3):30–56, 1995.

[7] D. G. Copeland and J. L. McKenney. Airline reservation systems: Lessons from history. *MIS Quarterly*, 12(3):353–370, September 1988.

[8] M. Cotlier. The payoff of paid search listings. *Catalog Age*, 18, Aug 2001.

[9] J. Eliashberg and S. M. Shugan. Film critics: Influencers or predictors? *Journal of Marketing*, 61(2):68–78, April 1997.

[10] J. Feng, H. K. Bhargava, and D. Pennock. Implementing paid placement in search engines: Computational evaluation of alternative mechanisms. *INFORMS Journal of Computing*, forthcoming.

[11] G. Hsu and J. M. Podolny. Critiquing the critics: An approach for the comparative evaluation of critical schemas. *Social Science Research*, 34(1):189–214, 2005.

[12] L. D. Introna and H. Nissenbaum. Shaping the web: Why the politics of search engines matters. *The Information Society*, 16(3), 2000.

[13] G. F. Lastowka. Do paid placement listings infringe trademarks? *Intellectual Property & Technology Law Journal*, 14:1–7, July 2002.

[14] L. Lessig. *Code and other laws of cyberspace*. Basic Books, 1999.

[15] R. W. McChesney. *Rich media, poor democracy: Communication politics in dubious times*. The New Press, New York, NY, 1999.

[16] R. McLuhan. Search for a top ranking. *Marketing*, page 47, October 2000.

[17] P. Milgrom and J. Roberts. Price and advertising signals of product quality. *Journal of Political Economy*, 94(4):796–821, 1986.

[18] T. A. Weber and E. Z. Zheng. A model of search intermediaries and paid referrals. Technical report, 02-12-01, The Wharton School, University of Pennsylvania, 2005.

[19] R. O. Wyatt and D. P. Badger. How reviews affect interest in and evaluation of film. *Journalism Quarterly*, 61:874–878, 1984.