

Research Note

Quality Uncertainty and the Performance of Online Sponsored Search Markets: An Empirical Investigation

Animesh Animesh

Desautels Faculty of Management, McGill University, Montreal, Quebec H3A 1G5, Canada,
animesh.animesh@mcgill.ca

Vandana Ramachandran

David Eccles School of Business, University of Utah, Salt Lake City, Utah 84112,
vandana.ramachandran@business.utah.edu

Siva Viswanathan

Decision, Operations, and Information Technologies, Robert H. Smith School of Business,
University of Maryland, College Park, Maryland 20742, sviswana@rhsmith.umd.edu

Online sponsored search advertising has emerged as the dominant online advertising format largely because of their pay-for-performance nature, wherein advertising expenditures are closely tied to outcomes. While the pay-for-performance format substantially reduces the wastage incurred by advertisers compared to traditional *pay-per-exposure* advertising formats, the reduction of such wastage also carries the risk of reducing the signaling properties of advertising. Lacking a separating equilibrium, low-quality firms in these markets may be able to mimic the advertising strategies of high-quality firms. This study examines this issue in the context of online sponsored search markets. Using data gathered from sponsored search auctions for keywords in a market without intervention by the intermediary, we find evidence of adverse selection for products/services characterized by high uncertainty. On the other hand, there is no evidence of adverse selection for similar products in a regulated sponsored search market, suggesting that intervention by the search intermediary can have a significant impact on market outcomes and consumer welfare.

Key words: electronic commerce; competitive impacts of IS; IT impacts on industry and market structure; econometrics

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1. Introduction

Sponsored search mechanisms, where advertisers bid for better placement in the listing of search results on services such as Yahoo! and Google, have emerged as the dominant revenue model for online search engines. Online sponsored search markets differ from traditional advertising formats in a number of important ways. First, sponsored search mechanisms enable firms to specifically target consumers actively searching for products/services offered by them. Second, the ordered listing of advertisers in sponsored search markets creates an information environment where

consumers browse through the listings from top to bottom. This “sequential search” creates a directional market, where firms listed at the top have an advantage over firms appearing lower in the listing (Arbatskaya 2007), thereby leading to intense competition for the top ranks. Researchers believe that strategies used by firms, and the resulting competitive dynamics in such directional markets may be different from those created by traditional formats such as the *Yellow Pages*, where consumers have been shown to sample firms randomly (Arbatskaya 2007, Perry and Wigderson 1986). Third, in contrast to traditional

advertising media, like television and print, where there is a clear distinction between content and advertising, sponsored search results can potentially introduce a bias in the listing of their search results because information intermediaries that deliver information about sellers and their offerings are also paid by the same sellers they “certify” (Gaudeul 2004).

Finally, and most important to our study, is the difference in the pricing of advertisements. Traditional advertising formats adopt a pay-per-exposure pricing mechanism and require advertisers to pay a lump sum or fixed fee for a given number of impressions or exposure. In contrast, online sponsored search markets use a pay-for-performance pricing mechanism, where advertisers only pay for each received click, but are not charged for exposures. However, performance-based pricing, as explained in §2, can potentially weaken the signaling properties of advertising enabling low-quality firms to mimic the advertising strategies of high-quality sellers. This issue takes on greater importance in online markets that are characterized by information asymmetries, where consumers face significant pre-purchase quality uncertainty. This is further exacerbated by the presence of a large proportion of consumers who believe that a seller listed higher in the search results is of higher quality than those listed lower (iProspect 2006); perhaps as a consequence of the directional nature of these markets. In light of these differences between traditional and online sponsored search advertising, and given the rapid growth in the popularity of the latter, we seek to better understand the performance outcomes in sponsored search markets, and their implications for market participants and policymakers.

We gather data from two of the biggest online sponsored search markets to answer the following questions: (1) Are advertisers that are ranked higher in the sponsored search listings of higher quality than advertisers appearing lower down the listings? (2) Does this relationship between an advertiser’s rank and its quality differ across purchase situations characterized by differing degrees of quality uncertainty? (3) Finally, does intervention by the online search intermediary help alleviate adverse selection, if any? Interestingly, the two premier search intermediaries—Yahoo! and Google—adopted different mechanisms

for ranking their sponsored search results at the time of the study, thereby allowing us to compare the outcomes across markets with and without intervention. Advertisers in both sponsored search markets participate in a continuous open bid auction, where they bid for placement in the listing of paid search results triggered by keyword searches conducted by search engine users. On Yahoo!, the higher the advertiser’s bid per click in the auction, the higher the placement the advertisement receives in the paid search listings.¹ On Google, the position of an advertisement is a function of the advertiser’s bid per click, its click-through rate, i.e., the number of clicks the advertisement gets, and the quality of its landing page, among others. If an ad fails to generate sufficient clicks, it is penalized and moved lower down the list. This difference between Yahoo!’s unregulated market (pure market hereafter) and Google’s regulated market (performance-adjusted market hereafter) brings to fore the question related to the effectiveness of the market maker’s intervention (or the lack thereof) in determining the ranking outcomes of paid advertisements. To the best of our knowledge, ours is the first study to investigate the relative performance outcomes of the two dominant sponsored search formats across purchase contexts characterized by differing degrees of quality uncertainty.

We first examine data on sponsored search listings collected from Yahoo!’s pure sponsored search market for two categories of keywords characterized by different levels of uncertainty for consumers. Using different measures of advertiser quality, we examine the relationship between an advertiser’s ranking within the sponsored search listings for each keyword, and the advertiser’s quality. Our findings indicate that in contexts characterized by high quality uncertainty, firms listed at the top of the search results are not always of higher quality compared to firms listed lower down the listing for a given search keyword. However, for the same set of keywords, we find no

¹ Yahoo! subsequently changed its ranking algorithm to a more “regulated” mechanism (similar to Google’s) in Feb. 2007. However, our data were collected in late (September–November) 2006, when Yahoo! still used a pure market mechanism to rank sellers in paid listings.

evidence of such adverse selection on Google, highlighting the beneficial impact of intervention by the search intermediary.

The rest of the paper is organized as follows. Section 2 outlines related research that informs our theoretical arguments in the study. Section 3 describes the data, measures, and methodology, while §4 presents the results and robustness checks. Section 5 concludes with a discussion of the implications of our findings.

2. Theoretical Background

The impressive growth of online advertising in recent times has fueled new interest in this field. Extant academic work in sponsored search advertising is, however, nascent and predominantly adopts an auctions perspective to examine the interaction between market makers and bidders. One stream of research focuses on developing better rank allocation mechanisms from the perspective of the search intermediary (e.g., Asdemir 2006, Edelman et al. 2007, Feng et al. 2007, Weber and Zheng 2007), while a second identifies optimal bidding, and keyword selection strategies for advertisers (e.g., Kitts and Leblanc 2004, Ghose and Yang 2007, Hosanagar and Schwarz 2007). Much of the research in this area builds on earlier work on auction design, and largely treats advertisers as homogenous bidders. Sponsored search auctions, however, are unique in that they are primarily an advertising forum for firms. Consequently, understanding the characteristics of bidders' in these auctions is important, as they can have significant welfare implications for consumers, and given the extent of information asymmetries, a study of the outcomes in these markets becomes paramount.

2.1. Advertising and Quality Signaling.

As is well known, advertising can serve to reduce information asymmetries and help improve the efficiency of markets. Starting with the pioneering work of Nelson (1974), a substantial body of research has examined how conspicuous advertising expenditures can enable firms to signal the quality of their offerings to imperfectly informed consumers (Kihlstrom and Riordan 1984, Milgrom and Roberts 1986, Linnemer 2002). A broad conclusion of the theoretical models in this context is a positive correlation between sellers'

quality and advertising expenditures.² Of particular relevance to our study, is the finding that firm-specific nonsalvageable or "sunk" costs are sufficient to ensure that high-quality firms honor their commitment to supply a high level of quality, especially when quality is costly to determine prior to purchase (Klein and Leffler 1981). The "potential wastage" associated with the lump sum investments required by traditional advertising formats serves to credibly signal quality by creating an opportunity cost for firms that renege on their promise to supply high quality (Ippolito 1990). Thus, firms that invest more in *fixed cost* advertising are more likely to be higher-quality firms that can hope to recoup their investments. However, the same is not true if these investments are salvageable or are tied to output. As noted earlier, a crucial feature of online sponsored search advertising formats is the pay-per-click pricing mechanism, where firms' advertising expenses are closely tied to potential sales (clicks). This *variable cost* advertising is less wasteful as there is little dissipation, making it attractive to advertisers. However, this reduction in wastage also reduces the bonding ability of the signal (Ippolito 1990), and consequently, its potential to signal quality reliably. In other words, while the dissipative nature of traditional advertising formats is capable of providing a separating equilibrium where it is unprofitable for low-quality firms to incur lump sum investments in advertising, the variable cost nature of online sponsored search advertising may lack the potential to signal quality.³ The absence of a separating equilibrium in the case of pay-for-performance advertising can potentially enable low-quality firms to mimic the advertising strategies of

² While empirical studies (e.g., Kirmani and Wright 1989, Thomas et al. 1998, Moorthy and Zhao 2000) provide broad support for a positive correlation between advertising and expected quality in many cases, it is acknowledged that market characteristics and the extent of information asymmetries, among others, can significantly affect this relationship (cf. Horstmann and MacDonald 2003).

³ A few studies (for instance, see Hernandez-Garcia 1997, Esteban et al. 2006) have examined the role of variable cost advertising, and find that it, unlike fixed-cost advertising, can lead to quality distortions and lower social welfare. Other research also suggests that a performance-based advertising format cannot effectively screen out low-quality clients or advertisers (Sundararajan 2003) and lends itself better to products with lower product market uncertainty (Hu 2004).

Table 1 Definition of Measures Used in Empirical Analysis

Panel A		Panel B				
Low	High	Type	Measure	Definition	Scale	
Apparel	Brokerages	POSITION	<i>PaidRank</i> *	Average rank obtained by the seller during the 60-day period	Continuous	
Books	Carpet cleaners					
Cameras	Cruises		<i>OrdRank</i>	Rank of the seller based on ordering <i>PaidRank</i> within a keyword	Ordered	
Cell phones	Driving school	QUALITY_UNC	<i>High_Uncertainty</i>	Dummy = 1 for high uncertainty keywords	Binary	
Computers	Kitchen appliance repair	QUALITY	<i>TrafficRank</i> **,**	A combination of historical page view rank (per million) and page reach (% of all Internet users).	Continuous(Log)	
Flight tickets	Moving and storage					
Music CDs	Plumbing		<i>Rating</i>	Customer-generated score/rating for the seller	1–5 (Log)	
PDA	Real estate brokers		<i>Inlinks</i> **	Number of links pointing into the seller's site	Continuous(Log)	
Printers	Remodeling		<i>QualityFactor</i>	Factor of <i>TrafficRank</i> , <i>Inlinks</i> , and <i>Rating</i>	Continuous	
Refrigerators	Special event planners	Interaction	—	The product of QUALITY and QUALITY_UNC (<i>High_Uncertainty</i>)	Centered product	
Television	Tailors	Controls	AGE	Days since firm was first established online	Continuous	
Toys	Tax services		ORGANIC	Whether the seller appeared in organic results	Binary	
			LOCAL	Whether the seller is local or national	Binary	

*Lower *PaidRank* indicates top POSITION in the listings and vice versa. **Lower *TrafficRank* indicates higher QUALITY and vice versa. ***Measures normalized by AGE.

higher-quality firms, thereby leading to adverse selection. More important, absent any intervention, such mimicking strategies would be more successful, the more costly it is for consumers to identify the differences in quality prior to purchase.

In summary, with increasing quality uncertainty, low-quality sellers who can successfully masquerade as high-quality sellers would find it the most profitable (as a consequence of their low costs and higher profitability) to compete for the top advertising slots in online sponsored search markets. We examine if lower-quality sellers are indeed more likely than higher-quality sellers to appear in higher ranks in sponsored search listings. Also, given that consumers face different levels of quality uncertainty across products, we expect that low-quality sellers would bid more aggressively in markets with greater uncertainty. However, active intervention by the search intermediary might help alleviate this problem. Our empirical analysis examines this issue as well.

3. Data Description and Analysis

Fundamental to sponsored search advertising is the *keyword* or *query* that advertisers bid for. Of particular importance here is the extent of prepurchase quality uncertainty faced by consumers who search for products/services represented by the keywords.

We examine if sellers of offerings characterized by varying degrees of quality uncertainty exhibit differences in their bidding behavior that manifest in sponsored search outcomes.

3.1. Description of Data

We selected 12 keywords each to represent two levels of quality uncertainty⁴—*Low* and *High*—across product/service categories as shown in Table 1, Panel A. The choice of keywords was driven by their popularity, the adequacy of the number of sellers advertising in each keyword market, and the availability of data on other measures of interest. For each of these keywords, we automated the collection of data on advertisers' positions or ranks achieved on the sponsored search listings from Yahoo! and Google once every day over a period of 60 consecutive days in late 2006. The sample represents the collection of sellers that appeared in all the available ranks on paid listings for our sample of keywords. Within each keyword market, we collapsed the ranks obtained for each

⁴Low (High) uncertainty keywords in our classification correspond to products (services), and map well to Search (Experience/Credence) product categories (Nelson 1970). The *Search*, *Experience*, and *Credence* (SEC) goods framework is widely used in the economics and marketing literature to examine consumer search and firms' advertising strategies (cf. Ekelund et al. 1995).

seller across all the days that the seller bid, producing 1,027 observations for Yahoo! and 942 observations for Google. The following steps ensured appropriateness of the sellers included in our estimation sample. We excluded sellers who exhibit noisy or sporadic behavior patterns by discarding outliers, including bidders who bid sporadically (fewer than 20 days), and bidders whose deviation in rank exceeded the 90th percentile (among the days that they appeared in paid listings). We discarded nonsellers such as aggregators, link farms, comparison shopping engines, and infomediaries that appear in the search listings. Additionally, we also removed from our data irrelevant sellers, i.e., those sellers who were selling products/services that were different from that searched (intended by the user), and different from the majority of products/services sold by other sellers on a search listing. We visited the websites of the sellers in our sample, and classified nearly 16% of sellers on Yahoo! and 12% of sellers on Google as irrelevant. After applying these restrictions, we had 560 observations for Yahoo! and 441 observations for Google. This final sample of sellers was ordered by average rank within each keyword market.

3.2. Measures

The description of the measures is presented in Table 1, Panel B. The dependent variable of interest, the POSITION (rank) advertisers receive on sponsored search listings on Yahoo! and Google, is measured in two ways. *PaidRank* is a measure of the average POSITION in the paid results obtained by the seller over all the days that she bid, while *OrdRank* is the corresponding ordinal rank for each seller within a keyword market.

We use a dummy—*High_Uncertainty*—to represent keywords with high levels of prepurchase quality uncertainty, *QUALITY_UNC*. Of primary interest is *QUALITY* of the advertiser, which encompasses the quality of the seller's offerings as well as the seller's reliability/trustworthiness—i.e., the propensity of the advertiser to truthfully represent the quality of its offerings. Given the multidimensional nature of advertiser's quality, we collect seller quality measures from multiple sources, which are particularly relevant in online settings. Our first measure

of quality is *TrafficRank*, or traffic-based ranking of a seller,⁵ computed from the average fraction of page views per million by a Web user that go to a particular website (page view), and the proportion of all Web users that visit the website (page reach). The second measure, *Rating*, is an aggregate of consumer-provided scores on a 5-point scale of a seller's overall reliability.⁶ Both measures are obtained from Alexa.com, which collects detailed site use data from the tens of millions of users who participate and contribute this information by using the online Alexa toolbar. For *TrafficRank*, a lower value indicates higher quality and vice versa. Prior research in information systems (IS) (e.g., Brynjolfsson and Smith 2000, Palmer 2002) has also used Alexa data as a proxy for firm's brand equity or social capital, among others. Furthermore, *TrafficRank* is a measure of online market share, which, as an aggregation of dispersed information across customers, has been shown to correlate with seller quality, especially in the presence of uncertainty (Caminal and Vives 1996, Moorthy and Zhao 2000).

We supplement seller quality with two additional measures. We collect data on the number of incoming links to a website, *Inlinks*, from Alexa.com. Originally popularized by search engines, links pointing to a website are now commonly regarded as a positive recommendation by the originator of that link, whereby *Inlinks* offers a measure of seller importance or quality. Finally, we conduct a factor analysis of the three described measures of quality—*TrafficRank*, *Rating* (reversed) and *Inlinks* (reversed), and obtain the common underlying construct that succinctly captures the multidimensional structure of seller quality. We use principal component factor analysis with varimax rotation, and retain one factor with eigenvalue >1 , where all the variables load high on the factor. This

⁵ This traffic is generated by Alexa toolbar users. Search engines are just one of the several sources that drive traffic to a website. Consequently, a seller's *TrafficRank* on Alexa, while certainly influenced by rank on sponsored listings, is not synonymous with it. This is further confirmed by our tests for endogeneity and the robustness checks (for details, see §4).

⁶ We also obtained data on (customer) ratings for the sellers in our sample from other popular public sources—BBB.com, bizrate.com. However, because of the sparseness of this data, we are unable to use them in our analyses.

Table 2 Sample Description and Correlations

Variables	Sample descriptives					Correlations				
	<i>N</i>	Mean	S.D.	Min.	Max.	(1)	(2)	(3)	(4)	(5)
Pure market										
(1) <i>PaidRank</i>	560	19.010	10.490	1.040	38.100	1				
(2) <i>TrafficRank</i>	560	549,931	1,144,143	1	7,242,732	0.070	1			
(3) <i>Rating</i>	317	3.010	1.400	1	5	0.050	-0.310	1		
(4) <i>Inlinks</i>	555	4,203.320	19,711.260	1	170,900	0.050	-0.100	0.180	1	
(5) <i>QualityFactor</i>	317	-0.039	0.970	-1.870	2.810	-0.020	0.530	-0.680	-0.340	1
Performance-adjusted market										
(1) <i>PaidRank</i>	441	13.720	7.690	1	28.620	1				
(2) <i>TrafficRank</i>	441	515,158.200	1,208,959	1	8,322,110	0.200	1			
(3) <i>Rating</i>	246	3.120	1.460	1	5	-0.150	-0.390	1		
(4) <i>Inlinks</i>	426	4,485.190	21,134.670	1	170,900	-0.010	-0.080	0.160	1	
(5) <i>QualityFactor</i>	246	0.010	1.020	-2	2.500	0.190	0.550	-0.760	-0.350	1

QualityFactor displays satisfactory reliability ($\alpha = 0.74$) and explains 68% variance in the items.

Finally, the validity of our analyses relies on the inclusion of several controls that address the possibility of confounding and alternate explanations. To control for the effect of older firms being associated with better *TrafficRank* and *Inlinks*, we normalize the said measures by AGE—the number of days the firm has existed online, as provided by Alexa.com. An important variable that might influence the position that a seller obtains on paid listings is given by the rank of the seller on organic search results.⁷ We find that only a small fraction of sellers appear on both during our data collection period. Furthermore, organic rank for these sellers neither correlates well with the other three measures of quality nor loads well on the *QualityFactor*. Yet, it is possible that unobserved factors that contribute to a seller’s ability to achieve better organic ranking might also have a parallel effect on the sponsored search ranking. We therefore control for sellers’ simultaneous presence on organic listings using a dummy labeled ORGANIC. A final concern arises from the possibility that paid listings for *High_Uncertainty* keywords are also likely to contain a higher proportion of *local* or regional (versus national) sellers. By virtue of their operations, local sellers would tend to have a lower measure of *TrafficRank* and/or *Inlinks*. We add a dummy, LOCAL, to address this confound.

⁷ We thank the review team for this suggestion.

Key summary statistics are in Table 2. The average number of sellers per keyword listed on paid search results is significantly higher for Yahoo! than Google ($t = 8.88, p = 0.00$). The average *TrafficRank*, *Rating*, and *QualityFactor* are only slightly better on Google than Yahoo!, whereas the average *Inlinks* is marginally better for Yahoo! than Google. However, these differences across *TrafficRank* ($t = 0.47, p = 0.64$), *Rating* ($t = -0.90, p = 0.37$), *Inlinks* ($t = -0.22, p = 0.83$), and *QualityFactor* ($t = 0.62, p = 0.50$) are not significant, ensuring that our results reported in §4 are not driven by systematic biases in seller composition across Yahoo! and Google.

3.3. Methodology and Analysis

As mentioned earlier, our primary goal in this study is to examine how the relationship between seller QUALITY and POSITION varies across the pure and performance-adjusted sponsored search mechanisms, and across low- and high-QUALITY_UNC categories. Our model shown in Equation (1) is estimated using two alternate specifications. First, we use the continuous outcome *PaidRank* in a keyword fixed-effects model with clustered standard errors to account for unobservables at the level of the keyword (such as level of competition, demand for product in online markets) that can systematically affect a seller’s rank and other covariates. Here, we ignore the structure of ranks within keyword markets. Second, we use *OrdRank* and rank-ordered logit to model the preferences of sellers over a discrete set of items based on ranked orderings of the alternatives (paid search

positions) within each keyword market (see Beggs et al. 1981). For seller i and keyword k , we estimate

$$\begin{aligned} \text{POSITION}_{ik} &= \gamma_1 + \gamma_2 \text{QUALITY}_i + \gamma_3 \text{QUALITY}_i \\ &\quad * \text{QUALITY_UNC}_k + \gamma_4 \text{ORGANIC}_{ik} \\ &\quad + \gamma_5 \text{LOCAL}_i + \sum \gamma_{6k} \text{KEYWORD} + \epsilon_{ik}. \end{aligned} \quad (1)$$

We note that for *TrafficRank* and *QualityFactor* (*Rating* and *Inlinks*), a positive coefficient on *QUALITY* depicts that, on average, higher-quality firms are present in higher (lower) positions. The main effect of *QUALITY* in our analyses is interpreted as the effect on *POSITION* arising from one unit change in seller *QUALITY* for the left out category, or *Low_Uncertainty* keywords. The primary test of the

presence of adverse selection across the two categories of keywords is given by the interaction between *QUALITY* and *QUALITY_UNC*, which is created as a product of centered main effects. While the main effect of *QUALITY_UNC* is not separately identified as it is collinear with keyword fixed effects, the interaction represents by how much the effect of *QUALITY* on *POSITION* (for *Low_Uncertainty* keywords) is changed when considering the *High_Uncertainty* keywords.

4. Results

In Table 2, we observe significant correlations among the measures of *QUALITY* for Yahoo! and Google, suggesting that *TrafficRank*, *Rating*, *Inlinks*, and *QualityFactor* are correlated for the sellers who appear on their paid search lists. Tables 3(a) and 4(a) present the results of our analyses for the two sponsored search

Table 3 Pure Market

Model	A. <i>TrafficRank</i>		B. <i>Rating</i>		C. <i>Inlinks</i>		D. <i>QualityFactor</i>	
	A1 FE	A2 ROLOGIT	B1 FE	B2 ROLOGIT	C1 FE	C2 ROLOGIT	D1 FE	D2 ROLOGIT
(a) Regression analyses for alternate measures of <i>QUALITY</i> (DV = <i>POSITION</i>)								
<i>QUALITY</i>	2.836** (1.012)	0.331** (0.137)	-1.597** (0.733)	-0.200** (0.091)	-2.304** (1.110)	-0.227* (0.136)	2.868*** (0.797)	0.348*** (0.094)
<i>QUALITY</i> * <i>QUALITY_UNC</i>	-4.826*** (1.017)	-0.542*** (0.139)	4.989*** (0.950)	0.538*** (0.134)	4.690*** (1.152)	0.468*** (0.146)	-6.456*** (0.888)	-0.709*** (0.129)
<i>ORGANIC</i>	-0.790 (2.622)	-0.111 (0.253)	-2.150 (2.425)	-0.096 (0.256)	-1.342 (2.573)	-0.164 (0.266)	1.511 (2.556)	-0.038 (0.283)
<i>LOCAL</i>	5.166* (2.544)	0.552* (0.302)	-8.399* (4.512)	-1.350** (0.682)	5.199* (2.465)	0.567† (0.298)	-7.348* (4.157)	-1.160* (0.701)
Constant	19.487*** (0.710)		19.690*** (0.900)		19.477*** (0.629)		19.566*** (0.951)	
<i>N</i>	560	560	317	317	555	555	317	317
<i>F</i> (4, 32) or Wald χ^2 (4)	7.070***	24.270***	9.470**	17.380***	6.760***	22.810***	17.180***	39.490***
<i>R</i> ² or Log pseudolikelihood	0.057	-1,267.812	0.073	-567.150	0.048	-1,257.587	0.102	-562.792
(b) Test of the absolute quality coefficient across quality uncertainty categories								
<i>Low_Uncertainty</i>	2.836*** (1.012)	0.331** (0.137)	-1.597** (0.733)	-0.200** (0.091)	-2.304** (1.110)	-0.227* (0.136)	2.868*** (0.797)	0.348*** (0.094)
<i>High_Uncertainty</i>	-1.990*** (0.615)	-0.211*** (0.059)	3.392*** (0.652)	0.338*** (0.101)	2.385*** (0.636)	0.241*** (0.060)	3.588*** (0.887)	-0.361*** (0.136)

Notes. Panels A–D represent models with alternate measures of seller quality regressed on *POSITION*. A1–D1 (DV = *PaidRank*) are fixed-effects models. A2–D2 (DV = *OrdRank*) are rank-ordered logit models. All models report cluster robust standard errors. Model fit is given by *R*² in A1–D1, and Wald χ^2 in A2–D2.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4 Performance-Adjusted Market

(a) Regression analyses for alternate measures of QUALITY (DV = POSITION)								
Model	A. <i>TrafficRank</i>		B. <i>Rating</i>		C. <i>Inlinks</i>		D. <i>QualityFactor</i>	
	A1 FE	A2 ROLOGIT	B1 FE	B2 ROLOGIT	C1 FE	C2 ROLOGIT	D1 FE	D2 ROLOGIT
QUALITY	1.251*	0.247**	-1.074*	-0.187*	-1.199*	-0.150	1.447***	0.262**
	(0.618)	(0.115)	(0.592)	(0.107)	(0.652)	(0.089)*	(0.469)	(0.103)
QUALITY * QUALITY_UNC	0.029	-0.043	-0.918	-0.163	0.124	-0.030	0.175	-0.099
	(0.785)	(0.158)	(0.933)	(0.196)	(0.840)	(0.131)	(0.998)	(0.201)
ORGANIC	-2.969***	-0.361***	-2.969***	-0.387***	-3.084***	-0.469***	-5.231***	-0.345**
	(0.761)	(0.116)	(0.947)	(0.148)	(0.776)	(0.213)	(0.642)	(0.147)
LOCAL	0.658	-0.052	-0.605	-0.069	0.233	-0.135	-1.302	-0.257
	(3.379)	(0.420)	(3.363)	(0.534)	(3.488)	(0.372)	(3.561)	(0.556)
Constant	14.503***		14.231***		13.769***		14.008***	
	(0.205)		(0.336)		(0.146)		(0.149)	
<i>N</i>	441	441	246	246	426	426	246	246
<i>F</i> (4, 23) or Wald χ^2 (4)	10.470***	29.870***	6.900***	15.520***	7.620**	14.370***	7.040***	17.270***
<i>R</i> ² or Log pseudo-likelihood	0.061	-902.793	0.073	-395.594	0.042	-865.130	0.066	-396.259

(b) Test of the absolute quality coefficient across quality uncertainty categories								
Model	A. <i>TrafficRank</i>		B. <i>Rating</i>		C. <i>Inlinks</i>		D. <i>QualityFactor</i>	
	A1 FE	A2 ROLOGIT	B1 FE	B2 ROLOGIT	C1 OLS	C2 ROLOGIT	D1 FE	D2 ROLOGIT
<i>Low_Uncertainty</i>	1.251*	0.247**	-1.074*	-0.187*	-1.199*	-0.150*	1.447***	0.262**
	(0.618)	(0.115)	(0.592)	(0.107)	(0.652)	(0.088)	(0.469)	(0.103)
<i>High_Uncertainty</i>	1.280**	0.204*	-1.991**	-0.349**	-1.075*	-0.180*	1.621*	0.163
	(0.531)	(0.116)	(0.750)	(0.162)	(0.597)	(0.097)	(0.885)	(0.173)

Notes. Panels A–D represent models with alternate measures of seller quality regressed on POSITION. A1–D1 (DV = *PaidRank*) are fixed-effects models. A2–D2 (DV = *OrdRank*) are rank-ordered logit models. All models report cluster robust standard errors. Model fit is given by *R*² in A1–D1, and Wald χ^2 in A2–D2.

p* < 0.10; *p* < 0.05; ****p* < 0.01.

markets, with the fixed-effects model in columns A1–D1 and the rank-ordered logit model in columns A2–D2. Additionally, to test our hypotheses, we provide *absolute* coefficients for QUALITY across low and high uncertainty keyword categories in Tables 3(b) and 4(b).

We first examine the results from the fixed-effects models using alternate measures of seller quality for Yahoo! (see Table 3(a)). We find that, using *TrafficRank* (column A1), QUALITY is positively correlated with average POSITION obtained by the firm in the sponsored search listings on Yahoo!. More interestingly, we find that the coefficients of the interaction between seller QUALITY and QUALITY_UNC is negative and significant for *High_Uncertainty* goods on Yahoo!. Using *Rating* (column B1), we obtain

similar findings.⁸ Specifically, the average effect of QUALITY is negative and significant, while the interaction between QUALITY and QUALITY_UNC

⁸ We conduct additional analyses to gauge the presence of selection bias in the sample for *Rating*. There are no significant differences in the composition of sellers with available *Rating* information in terms of *TrafficRank* (*t* = -0.49, *p* = 0.62) and *Inlinks* (*t* = -0.32, *p* = 0.75) across Yahoo! and Google, suggesting that such differences do not drive our results. Furthermore, these dropped sellers are uniformly distributed across *avgRank*, indicating that they are not systematically missing across ranks. Within each search engine, we find that sellers with nonmissing *Rating* have better *TrafficRank* (*t* = 7.22 on Yahoo!, *t* = 4.35 on Google) and higher *Inlinks* (*t* = 4.09 on Yahoo!, *t* = 3.76 on Google) than firms without (all *p* < 0.00). Thus our analyses using better-quality firms still finds adverse selection in Yahoo!'s sponsored results, thereby strengthening the finding.

is positive and significant. These findings suggest that the relationship between seller QUALITY and POSITION achieved in listings are significantly different for low and high uncertainty goods in Yahoo!'s pure market. These results are consistent with those obtained by using *Inlinks* (column C1) and *QualityFactor* (column D1) as alternate measures of seller quality. Given our research objective to examine whether high-quality or low-quality sellers obtain better POSITION in Yahoo!'s paid listings, it is more informative to examine the *absolute* relationship between QUALITY and POSITION for low and high uncertainty product categories. We do so using tests of linear combinations in Table 3(b), corresponding to columns in Table 3(a). We find that using *TrafficRank* and *Rating*, the coefficient of QUALITY for low uncertainty goods indicates that high-quality sellers appear in higher/better positions on paid listings, whereas the opposite is true for high uncertainty goods, where lower quality sellers appear in higher positions on Yahoo!. We obtain similar results for the models using *Inlinks* and *QualityFactor* as the quality measures. These findings clearly point to the presence of low-quality sellers in top positions on Yahoo!'s paid search listings, albeit only when the prepurchase uncertainty for consumers is high. This result combined with buyers' higher propensity to click on/visit sellers found in the top positions highlights the presence of adverse outcomes in the pure market for purchase contexts with high uncertainty. We obtain the same pattern of results from rank-ordered logit models (columns A2–D2 in Tables 3(a) and 3(b)) that preserve the structure of rankings within keyword markets, reinforcing our main findings for Yahoo!.

Next, we wish to examine whether such adverse outcomes are mitigated in a market with intervention by the search intermediary, as in the case of Google's paid search mechanism. The corresponding results for Google are presented in Tables 4(a) and 4(b). In contrast to the findings in the pure market, the absolute coefficients for QUALITY in Table 4(b) provide evidence that higher-quality sellers obtain higher/better ranks on paid listings in the performance-adjusted market across both low and high uncertainty product categories. These results are consistent across all QUALITY measures.

Table 5 Summary of Quality Position Relationships

Advertising mechanism	Low uncertainty	High uncertainty
Pure market	Positive	Negative
Performance-adjusted market	Positive	Positive

We conduct two additional robustness checks. We examine the possible endogeneity between a seller's POSITION on paid listings and her *TrafficRank* using a 2SLS model. We, however, find that endogeneity is not a problem in our data.⁹ Finally, we address the concern that not all our measures capture the same dimension of seller QUALITY. Specifically, *TrafficRank* may capture a seller's online popularity/marketshare more than her trustworthiness. Because *Rating* is more closely reflective of consumers' satisfaction with a seller's true quality, we estimate an augmented model that includes both *Trafficrank* and *Rating*, and their interactions with QUALITY_UNC. This allows us to factor out the popularity effect, and observe the influence of quality on POSITION. For high uncertainty goods on Yahoo!, we continue to obtain an adverse effect of *Rating* on POSITION, but the same effect is not observed for low uncertainty goods on Yahoo!, and high/low uncertainty keywords on Google. Table 5 summarizes our key findings.

5. Discussion and Conclusion

One of the key elements of a firm's marketing mix that has undergone significant changes because of information technology is advertising (Esteban et al. 2006). Two key developments that have revolutionized advertising are improvements in targetability and more sophisticated pricing mechanisms. While improvements in targetability have been beneficial to advertisers, intermediaries, and consumers alike, the benefits from the move to performance-based pricing mechanisms are not so clear-cut. While performance based pricing mechanisms reduce the wastage associated with traditional advertising formats, the also

⁹ The 2SLS and augmented model results are not presented here, but are available from the authors. We use *page views per user* (average share of users' page views that go to a seller) as the instrument—it measures the stickiness/attractiveness of a website and satisfies both validity and relevancy. The Hausman test of ordinary least squares (OLS) versus 2SLS (sans fixed effects) is not rejected, leading us to prefer OLS.

weaken firms' abilities to use advertising as a signaling mechanism. The difficulties for consumers in ascertaining quality prior to purchase in certain product categories can exacerbate this problem. Particularly in the case of online sponsored search advertising, a vast majority of online consumers (62%) are unaware of the distinction between *organic search* results and *sponsored search* results (Fallows 2005). Even among the aware consumers, a majority believes that advertisers ranked higher (lower) in the sponsored search results are of higher (lower) quality (iProspect 2006). These beliefs are reflected in the substantially higher number of clickthroughs that high-ranked firms receive, compared to those placed lower in the listings. Given the current state of consumer beliefs and clicking behaviors, sponsored search mechanisms where low-quality sellers can obtain top ranks in the search listings are able to lower consumer welfare and reduce the utility of such mechanisms for consumers. Our results show that this is indeed the case; however, the intensity of such adverse selection differs across markets as well as across keyword categories. While adverse selection is almost nonexistent in the market for products with low prepurchase uncertainty, we find significant evidence of its presence in the case of services with higher prepurchase quality uncertainty, in the pure market mechanism used by Yahoo!. However, Google's intervention mechanism of ranking bidder advertisements appears capable of circumventing the problem of adverse selection for both low as well as high uncertainty products/services. Google's quality scoring/weighting of advertisers reinstates the quality signal that is lost in the move from traditional dissipative advertising to online performance-based advertising.

Adverse selection issues in online markets are of increasing interest to IS researchers. Prior research has documented the presence of adverse selection costs stemming from the lack of information about quality in online (relative to offline) markets ranging from financial brokerages (Bakos et al. 2005), stamp auctions (Dewan and Hsu 2004), and sports card trading markets (Jin and Kato 2006), among others. Our study contributes to this growing body of work by investigating outcomes in online sponsored search advertising markets. We show that while online paid search

markets might lower search costs for consumers, their benefits are counteracted by sellers potentially distorting or hiding crucial information in the presence of uncertainty about unobservable quality characteristics. Biases in sponsored search listings cannot only reduce consumer welfare, but can also drive out higher-quality firms, and eventually, reduce the profitability of the intermediary as well. The future of pay-for-performance advertising formats thus rests critically on the intermediary's ability to curb adverse selection, especially in markets for services.

It is, perhaps, in recognition of such issues of adverse selection that Yahoo! has more recently adopted a quality-weighted mechanism similar to Google. Just as other online markets have resorted to technology-aided mechanisms such as online reputation systems (see Resnick et al. 2006, Lucking-Reiley et al. 2007), sponsored search markets would do well by incorporating similar mechanisms to aid consumers in their decision making for online purchases. Our findings suggest that additional signals of quality would serve to improve the efficiency and welfare properties of the sponsored search markets, particularly in situations where consumers are faced with high-quality uncertainty. Our results also have implications for sellers' choice of advertising strategies as well. Given the lack of quality signaling ability of online sponsored search markets, high-quality sellers might benefit from investments in additional signaling mechanisms, including pay-per-exposure formats. Although the pure market mechanism of Yahoo! studied here has been replaced with a performance-adjusted mechanism since 2007, our findings provide a useful benchmark that highlights the potential negative consequences of pure bid-based pay-for-performance advertising mechanisms. These findings can help generate useful guidelines for other evolving advertising formats such as "pay-per-call" and "pay-per-sale," which are much more closely tied to performance.

Our study is not without limitations. While Alexa is among the few publicly available comprehensive sources for website statistics, the usual caveat of representativeness for data collected using toolbar users applies. As discussed earlier, it is possible that in some contexts, low *TrafficRank* indicates low popularity, but not necessarily low quality—as may be the

case for niche sellers. In such cases, the presence of less popular (but high-quality) sellers can promote variety and increase consumer welfare, rather than increase adverse selection. Additionally, intervention by the search intermediary in such a context could prevent less popular sellers from appearing on higher ranks, thereby potentially reducing variety and consumer welfare.

Our study suggests a number of avenues for further research. The keywords in our study were chosen based on their popularity (as published in publicly available sources), and on the availability of quality measures. It would be interesting to examine whether our results hold for niche or less popular keywords with fewer bidders. While we focused here on generic and nonbranded keywords, it would be useful to examine the bidding patterns for keyword combinations as well as for keywords representing brands (such as Sony Vaio or Dell Inspiron). Future studies could also examine consumer behavior in response to the sponsored search phenomena. Laboratory studies designed to analyze the differential search strategies adopted by consumers would help understand how consumers search across different search formats. Studies of this nature are sparse, given the novelty of the phenomenon. Whether findings of studies relating to consumer behavior in traditional channels translate well to online settings is an empirical question yet to be answered.

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