

ABSTRACT

Title of Document:

**THE IMPACT OF ONLINE SPONSORED SEARCH
ADVERTISING ON CONSUMER AND SELLER
STRATEGIES**

Animesh

Directed By:

Professor Ritu Agarwal (Co-Chair), Department
of Decision and Information Technologies
Professor Siva Viswanathan (Co-Chair),
Department of Decision and Information
Technologies

Sponsored search advertising has emerged as an important and significant forum for advertisers, accounting for 40% of all advertising spending online. The unique features of sponsored search advertising – the nature of consumer search as well as the pricing mechanisms employed – differentiate it from traditional advertising formats, and raise many interesting questions regarding consumers' search and purchase behavior, sellers' advertising strategies, and the ensuing market dynamics. However, despite the robust growth in sponsored search advertising, research on its implications is limited. My dissertation, comprising three essays, seeks to fill this gap. In addition to examining the effects of sponsored search advertising on consumers and sellers, I also investigate the validity of theories developed for traditional media in an emerging online sponsored search context.

The first essay focuses on the impact of a seller's sponsored search advertising strategies, including its rank in the sponsored listing, the unique selling proposition (USP)

employed in its advertisement text/creative, and competitive market dynamics on the performance of the focal seller's advertisement. Drawing upon prior research on consumer search and directional markets, I propose a model of the consumer search process in the sponsored search context and conduct an empirical study to test the research model. The results validate the research hypothesis that the search listing can act as a consumer filtering mechanism and competitive intensity within adjacent ranks has a significant impact on the seller's performance.

The second essay employs consumer search and quality signaling theories from information systems, marketing, and economics to understand the impact of the informational cues contained in the sponsored search listing about sellers' *relative advertising expenditure* on consumer search and purchase behavior. Contrary to conventional wisdom, I find that the unique format of the sponsored search listing significantly increases the strength of the advertising signal vis-à-vis the price signal. In addition, I find that the risk attitude of consumers has a significant impact on the valence of these different information cues in the online setting.

The third essay examines market outcomes in directional markets such as sponsored search and comparison shopping advertising. Specifically, I focus on comparison shopping advertising where advertising not only informs consumers about price and quality but also directs consumer search. I find that the relationship between a firm's price, quality, and advertising intensity in this market is strikingly different from that in traditional markets, a result attributable to the differential impact of price and quality on an advertiser's conversion rates and profit margins.

Overall, these studies provide crucial insights into consumer behavior in online sponsored search markets. These findings have significant implications for firms, as well as for the market makers. Insights from these studies will enable practitioners to develop appropriate advertising strategies and online intermediaries to optimize the design of online sponsored search markets.

THE IMPACT OF ONLINE SPONSORED SEARCH ADVERTISING ON
CONSUMER AND SELLER STRATEGIES

By

Animesh

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2007

Advisory Committee:

Professor Ritu Agarwal (Co-Chair)

Professor Siva Viswanathan (Co-Chair)

Professor Amna Kirmani

Professor G. Anandalingam

Professor John Rust

© Copyright by
Animesh
2007

ACKNOWLEDGEMENTS

I would like to take this opportunity to thank all the people who helped me directly or indirectly in my pursuit to become *Philosophiæ Doctor*.

Firstly, I would like to thank my advisors – Professor Ritu Agarwal and Professor Siva Viswanathan for their encouragement, guidance, and constant support on the dissertation and career direction throughout the doctoral program. I really appreciate the significant amount of time and effort that they spent to help me, without which I would not have been able to accomplish my dissertation.

Thanks are also due to my committee members – Professor Anand Anandalingam, Professor Amna Kirmani, and Professor John Rust for their invaluable comments, suggestions and feedback that immensely benefited the quality of this dissertation.

I would also like to thank Professor Sanjay Gosain for his intensive brainstorming sessions in the early stages of this dissertation that helped refine the focus of my dissertation topic. I also appreciate the comments and support provided by other faculty members in the Business School and the Economics Department.

I am grateful to my friends, doctoral students, both current and those who have graduated, for helping me in so many ways that I do not have words to express my gratitude. My colleagues Jason Kuruzovich, Sherae Daniel, Fei Ye, Corey Angst and Likeobe Maruping were also very supportive throughout my Phd program and I would

like to acknowledge their contributions in the successful completion of this thesis. I would like to thank Tashfeen Sohail, Kiran Panchamgam, Ashwin Aravindakshan and Nitish Sinha for the insightful discussion on the both the theory and the empirical aspects of my essays. They were also my Stata, Excel and Maple gurus. I also benefited from the social and academic interactions with Vandana Ramachandran, Steven Johnson, Ritu Narayanan, Dina Ribbink and Shweta Oza. My friends from outside the Phd life also were a source of strength. I am especially thankful to Mahesh, Neeraj and Pawan who not only gave me feedback on my research ideas and edited my drafts at short notices but also provided me encouragement and inspiration. All these academic and social interactions made my journey towards the doctoral degree as enjoyable as the destination. Thank you all for making it a wonderful experience.

My family also deserves the credit for helping me reach where I am today. They have sacrificed a lot for me and I hope that I will be able to fulfill their dreams. I am very fortunate to have such a family and a great circle of friends.

Last but not the least, I would like to thank Professor Larry Gordon and Mary Slye for taking great care of the doctoral students and making it so easy for us.

I really enjoyed the last 5 years of my life that I spent here at the R. H. Smith School of Business and will always cherish the memories and the experiences that I have had here.

TABLE OF CONTENTS

| | |
|--|------------|
| ACKNOWLEDGEMENTS..... | II |
| TABLE OF CONTENTS..... | IV |
| TABLE OF CONTENTS..... | IV |
| LIST OF TABLES..... | VI |
| LIST OF FIGURES..... | VII |
| CHAPTER 1: OVERVIEW..... | 1 |
| 1.1 ONLINE ADVERTISING: GROWTH AND TRENDS | 1 |
| 1.2 ONLINE SPONSORED SEARCH ADVERTISING..... | 3 |
| 1.2.1 <i>Sponsored Search Advertisement</i> | 4 |
| 1.2.2 <i>Comparison Shopping Advertising</i> | 6 |
| 1.2.3 <i>Comparison with Traditional Advertising Media</i> | 7 |
| 1.3 OBJECTIVE OF THE STUDY | 10 |
| CHAPTER 2: COMPETING “CREATIVELY” IN ONLINE MARKETS: EVIDENCE FROM SPONSORED SEARCH..... | 12 |
| 2.1 INTRODUCTION | 13 |
| 2.2 A CONCEPTUAL MODEL OF AD PERFORMANCE | 17 |
| 2.3 RESEARCH HYPOTHESES | 23 |
| 2.4 DATA AND METHODOLOGY | 29 |
| 2.5 RESULTS AND DISCUSSION | 33 |
| 2.6 DISCUSSION AND IMPLICATIONS | 37 |
| 2.7 CONCLUSIONS | 42 |
| CHAPTER 3: ADVERTISING OR PRICE? THE EFFICACY OF QUALITY INFORMATIONAL CUES IN ONLINE SPONSORED SEARCH MARKETS..... | 44 |
| 3.1 INTRODUCTION | 45 |
| 3.2 THEORETICAL BACKGROUND AND PRIOR RESEARCH..... | 49 |
| 3.2.1 <i>Sponsored Search and Online Information Contexts</i> | 49 |
| 3.2.2 <i>Consumer Search and Quality Signaling</i> | 52 |
| 3.3 HYPOTHESIS DEVELOPMENT..... | 54 |
| 3.3.1 <i>Advertising and Price as Signals of Quality</i> | 54 |
| 3.3.2 <i>Interaction between Price and Advertising Signals</i> | 58 |
| 3.3.3 <i>The Effects of Risk Attitudes</i> | 58 |
| 3.4 METHODOLOGY | 60 |
| 3.4.1 <i>Research Design</i> | 60 |
| 3.4.2 <i>Measurement and Data</i> | 63 |
| 3.5 RESULTS | 64 |
| 3.5.1 <i>Manipulation Check</i> | 64 |
| 3.5.2 <i>Empirical Analyses</i> | 66 |
| 3.6 DISCUSSION | 71 |
| 3.7 CONCLUSION | 74 |
| CHAPTER 4: PRICE, QUALITY AND ADVERTISING RELATIONSHIP IN ONLINE DIRECTIONAL MARKETS | 77 |
| 4.1 INTRODUCTION | 78 |
| 4.2 RELEVANT LITERATURE..... | 79 |
| 4.3 THE MODEL..... | 82 |
| 4.4 DATA..... | 85 |
| 4.5 RESULTS | 88 |
| 4.6 DISCUSSION | 91 |

| | |
|--|------------|
| 4.7 CONCLUSION | 97 |
| CHAPTER 4: EPILOGUE | 98 |
| REFERENCES | 127 |
| FIGURES..... | 100 |
| TABLES..... | 108 |
| APPENDIX A: TYPOLOGY OF ONLINE ADVERTISING..... | 113 |
| APPENDIX B1: INSTRUCTIONS FOR SHOPPING TASK..... | 114 |
| APPENDIX B2: SCREENSHOTS OF THE SHOPPING TASK | 116 |
| APPENDIX B3: SURVEY ITEMS..... | 118 |
| APPENDIX B4: LOTTERY SELECTION TASK..... | 119 |

LIST OF TABLES

| | |
|--|-----|
| TABLE 2.1 DESCRIPTIVE STATISTICS..... | 108 |
| TABLE 2.2 CORRELATION COEFFICIENTS..... | 108 |
| TABLE 2.3 REGRESSION RESULTS | 108 |
| TABLE 3.1 DESCRIPTIVE STATISTICS..... | 109 |
| TABLE 3.2 CORRELATION COEFFICIENTS..... | 109 |
| TABLE 3.3 PERCENTILES OF SEARCH INTENSITY, PRICE AND RANK PREFERENCE | 110 |
| TABLE 3.4 QUALITY BELIEFS AND SHOPPING BEHAVIOR* | 110 |
| TABLE 4.1: CONVERSION INEFFICIENCY VERSUS PROFIT MARGIN..... | 111 |
| TABLE 4.2 DESCRIPTIVE STATISTICS..... | 111 |
| TABLE 4.3 CORRELATION COEFFICIENTS..... | 111 |
| TABLE 4.4 PROBIT REGRESSION RESULTS..... | 112 |
| TABLE 4.5: TOBIT REGRESSION RESULTS | 112 |

LIST OF FIGURES

| | |
|--|-----|
| FIGURE 1.1 AN EXAMPLE OF A SPONSORED SEARCH LISTING..... | 100 |
| FIGURE 2.2 RESEARCH MODEL | 100 |
| FIGURE 2.3 SPONSORED SEARCH LISTING AS CONSUMER SEGMENTATION MECHANISM | 101 |
| FIGURE 2.4 PREDICTED RELATIONSHIP BETWEEN RANK AND CLICKTHROUGH RATE (CTR) | 101 |
| FIGURE 2.5A INTERACTION BETWEEN RANK AND USP IN THE PRESENCE OF LOW COMPETITION..... | 102 |
| FIGURE 2.5B INTERACTION BETWEEN RANK AND USP IN THE PRESENCE OF HIGH COMPETITION..... | 102 |
| FIGURE 2.6A INTERACTION BETWEEN USP AND COMPETITIVE INTENSITY AT TOP RANKS | 103 |
| FIGURE 2.6B INTERACTION BETWEEN USP AND COMPETITIVE INTENSITY AT BOTTOM RANKS..... | 103 |
| FIGURE 3.1 CONCEPTUAL MODEL..... | 104 |
| FIGURE 3.2 RESEARCH MODEL | 104 |
| FIGURE 3.3 PRICE PREMIUM AND THREE-WAY INTERACTION | 105 |
| FIGURE 4.1 ILLUSTRATION OF THE V AND R FUNCTIONAL SPECIFICATION..... | 106 |
| FIGURE 4.2 ORDERED LISTING OF FIRMS ON A COMPARISON SHOPPING ENGINE | 106 |

CHAPTER 1: OVERVIEW

The rapid growth of Internet and the emergence of advanced information and communication technologies have created an environment conducive for disruptive innovations. Today's Internet economy, fueled by such innovations, has witnessed transformation of existing business models and the emergence of new business models. Online advertising is one such innovation which is dramatically changing the dynamics of advertising industry and has the potential to have a profound impact on businesses, industries, as well as consumers. Therefore, it is not surprising that researchers and practitioners have focused their attention on understanding this online advertising phenomenon. My dissertation, comprising of three essays, examines the effect of online sponsored search advertising on consumers' search and sellers' advertising strategies. In the following paragraphs I provide a brief overview of the trends in online advertising. I then describe the mechanics of online sponsored search advertising. Finally, I provide an outline of the three essays.

1.1 ONLINE ADVERTISING: GROWTH AND TRENDS

According to recent reports Internet advertising revenues (U.S.) for the first six months of 2005 were approximately \$5.8 billion, a 26% increase over the first half of 2004 (Interactive Advertising Bureau 2005). Nevertheless, the share of online advertising in the total advertising budget is still miniscule compared to traditional advertising. According to a recent study by (PricewaterhouseCoopers 2005), Internet advertising revenues accounted for only 3.7 percent (approximately) of total U.S. advertisement spending in 2004. However, as the reach of Internet grows, and as more

consumers use the Internet to gather information and purchase products, the share of online advertising in the traditional media mix is bound to increase correspondingly. In the words of Tom Hyland, Chair PricewaterhouseCoopers New Media Group, "History shows that advertising ultimately follows the audience, and with 66% of all Americans having regular access to the Internet, we believe advertising budgets will continue to shift more online as long as the online medium continues to gain share of overall media consumption" (Interactive Advertising Bureau 2003).

The disruptive nature of online advertising business model and associated information technologies is evident from the emergence of companies like Google and other intermediaries like Overture (which was acquired by Yahoo), ValueClick and LinkShare which provide infrastructure for online advertising. Online advertising has also spawned new support businesses (for example, Efficient Frontier, Advertising.com, iProspect, etc.) which help advertisers to optimize their online advertising expenditure, conduct demographic as well as behavioral targeting campaigns and deliver customized advertisements to target audience. In addition to the emergence of new advertising intermediaries, online media has also lowered barriers of entry for publishers and advertisers, thus, enabling emergence of small and niche content publishers such as bloggers and enabling firms with small advertisement budgets to compete with large national players. Clearly this emerging advertising format has significant implications for businesses, consumers, and policy makers and opens up interesting research issues for academicians and practitioners alike.

1.2 ONLINE SPONSORED SEARCH ADVERTISING

Online advertising can be defined as delivery of digital advertisements (which may include audio, video, image and text) to Internet users. Online advertising can be classified into various categories based on the message format, interactivity, intrusiveness, etc. According to one of the industry classification, online advertising can be of following types: display advertising, search advertising, sponsorship, referral, email, rich media, slotting, email and classifieds (PricewaterhouseCoopers 2005). Appendix A provides definitions of these formats.

Advertising has been generally considered to have two roles – persuasive (changes consumers’ taste and brand loyalty) and informative (informs consumers about price and/or quality). We define sponsored search advertising broadly as online directional market where advertising not only informs consumers about existence of the firms’ product/service offerings and related information but also directs consumer search pattern/sequence. We identify two different market makers who provide sponsored search advertising – *search engines* and *comparison shopping engines*. As explained below, the sponsored advertisement markets created by these online intermediaries are similar in terms of pricing and the ordering of the sellers in an ordered list but differ primarily in terms of the kind of information available to the consumer. We will refer to the sponsored advertising markets created by search engines as *sponsored search advertising* and the sponsored advertising market created by comparison shopping engines as *comparison shopping advertising*.

The following paragraphs describe the sponsored advertising formats and pricing mechanism, and provide a comparison of sponsored advertising format with traditional advertising.

1.2.1 Sponsored Search Advertisement

Sponsored search advertisements (also known as “paid search advertising” or “pay-for-placement” or “keyword advertising”) are text-based advertisement messages displayed alongside the “organic” (i.e. algorithm based) search results, in response to a user’s search query.

A typical sponsored search advertisement contains a title line and two lines of description followed by the website address (i.e., URL) of the advertiser. Each line has between 25 and 45 characters. This text, also referred to as the “creative” plays an important role as it conveys information about the firm and its offerings to potential consumers (see Figure 1.1 for examples of ad creatives used by different advertisers selling digital cameras). Advertisers select the keywords that are relevant to their product or service and bid on them for enhanced placement (i.e., higher rank) of their advertisements in the sponsored search results. The higher the bid, the higher the advertiser’s message appears in the sponsored search list, which should lead to more sales-leads (clickthroughs), and consequently greater sales.

The sponsored search model employs an auction mechanism for pricing the placement/position of an advertisement in the sponsored search listing for each keyword. Advertisers bid on keywords relevant to their product or service, for enhanced placement (i.e., higher rank) of their advertisements in sponsored search results. The higher the bid,

the higher the advertiser's message appears in the sponsored search list, which should lead to more sales-leads (click-throughs), and consequently greater sales.

Major search engines like Google and Yahoo conduct auctions to price the advertisements on various slots in their sponsored listings. Each sponsored listing corresponds to a specific keyword and can be considered as a separate auction market. An advertiser's bid in an auction represents the amount an advertiser is willing to pay for every click on its advertisement. The rank of an advertiser's advertisement in a specific keyword search listing is determined by the advertiser's rank in the auction for that keyword. An advertiser pays only for the click-throughs (i.e. when a user clicks on an advertisement link and visits the advertiser's website) and is not charged for the exposures. The payment per click, however, is not based on advertiser's own bid but is equal to the bid of the next highest bidder.

Different sponsored search markets such as Yahoo! and Google, employ variants of the basic auction mechanism. Yahoo allocates ranks on the listing to advertisers based purely on their bids for clickthroughs. However, it uses a "click index" -- a scoring system to determine how an advertiser's listing is performing relative to a competitor's listing -- to filter low performing advertisements. It removes the listings with low click index scores. Google, on the other hand, has incorporated this feature in its auction mechanism itself. Google uses a sophisticated proprietary algorithm which takes into account the bid and historical click-throughs of the advertisers to determine their rank in the sponsored list. Thus, in effect, Google provides discount to the advertisers whose advertisements generate more click-throughs than other advertisers. Apart from the advertisement allocation mechanism, there are other differences in the auction

mechanisms employed by these intermediaries. Yahoo auctions are transparent as any bidder can see his bid and determine his position on the relevant search result pages whereas Google does not make the bids publicly available. Further, the minimal bid amount and bid increment may also vary across these intermediaries.

An interesting point to note is that these auctions are held in infinite time horizon and are dynamic. The auctions are dynamic as an advertiser cannot lock a rank for a keyword term. Since advertisers' can change their bids at any time, the rank/position of the advertisements on the listing may change dynamically depending on the rank ordering of the current bids. Thus it becomes difficult for the advertisers' to monitor and manage the bidding process. To make it easier for advertisers to bid for a specific position, auctioneers and third parties provide automated bidding tools to adjust bids in order to maintain a rank in the listing, subject to an advertiser's maximum bid constraint.

1.2.2 Comparison Shopping Advertising

Recently comparison shopping engines have gained prominence as an online consumer acquisition channel and are growing rapidly. According to Hitwise, a market research firm, 5.3% of traffic to online retailers was driven by comparison-shopping sites in December 2005, which is a 26% increase from December 2004. The future growth potential of comparison engines can be gauged by the recent acquisition of the major comparison engines. For example, PriceGrabber.com was bought by Experian for \$485 million, Shopping.com was bought by ebay for \$620 million, and Shopzilla (formerly Bizrate.com) was bought by E. W. Scripps for \$525 million (Rand 2005).

The comparison shopping advertisements display a list of advertisers selling a particular product to a potential consumer who is searching for that product on the

shopping engine. Unlike sponsored search advertisements, the comparison shopping advertisements include price and quality (i.e., the customer satisfaction ratings) of the advertisers/firms in the market along with other relevant information. This is the main difference between the sponsored search advertising and comparison shopping advertising. Another difference is that the sponsored search advertisements are displayed next to organic search result. However, the comparison shopping advertisements are solely for sellers and therefore do not include organic search results.

Comparison shopping engine conducts online auctions similar to sponsored search auctions conducted by search engines like Google and Yahoo! and allots top 3 ranks on the shopping list to the firms who emerge as the top 3 bidders in an auction conducted by the engine. Firms pay a fee known as cost-per-click (CPC) for every consumer who clicks on their advertisement and thus visits their online store. Firms willing to pay more (i.e., having higher advertising intensity) for every potential customer visit to their website gets higher rank in the listing. Other firms in the market have lower advertising intensity than these top 3 firms and are ordered in the listing based on the price of their product. We focus on comparison shopping market in the third essay.

1.2.3 Comparison with Traditional Advertising Media

One of the interesting aspects of sponsored search advertising is the integration and co-evolution of online *search* and *advertising* business models. Given that search engines have become the starting point for Internet navigation, it is not surprising that advertisers have been trying to garner the attention of online consumers through advertisements on the search engine result pages. A study shows that 88% of adults who purchase items online conduct some sort of online research at least sometimes prior to

completing their purchase and 67% of those who research online before making a purchase decision use search engines as a research tool (iCrossing 2005). This trend has led to the emergence of sponsored search and comparison shopping advertising, thus transforming search engines into a very influential and lucrative advertising media.

Sponsored search advertising and comparison shopping advertising differs from traditional (media) advertising in a number of significant ways. The closest analogue to sponsored search advertising medium in traditional media is the yellow pages directory which is also a pull media (i.e. consumer pulls the information rather than advertiser pushing the advertisement). However, the capabilities of digital media provide an unprecedented platform to create an ordered/ranked listing of sellers to be shown to the consumer searching for a product, and to operate an auction mechanism to allocate ranks on the listing to the sellers. This auction based ranking mechanism results in more intense competition among advertisers to reach out to potential consumers than traditional yellow pages. The relative ranking of advertisers, not practical in the traditional yellow pages directory, also has the potential to significantly influence consumer behavior by informing consumers about the relative advertising intensity of advertisers.

The advertisement presentation format also affects the order in which consumers visit the advertisements appearing in a listing. In the case of yellow pages directory, the order in which a consumer browses the advertisements may differ significantly across consumers due to a large variety of dimensions on which the advertisements vary. The various dimensions are text versus visual ad, large versus small ad, colored versus black and white, bold versus plain listing, and amount and type of information presented in the

advertisement (Lohse 1997). The importance that a consumer attaches to each of these numerous combinations while deciding the order in which to browse the advertisements may be difficult to determine and predict. On the other hand, the advertisements on the sponsored search listing differ primarily in terms of their rank in the listing. Though the text of the advertisement also varies but due to space constraints there is not much difference in terms of type and amount of information presented. Thus, the ordered presentation format limits the freedom/flexibility that a consumer may have in browsing the advertisements. Consequently, a consumer consciously or subconsciously browses the listing from top to the bottom (Hoque and Lohse 1999; Sherman 2005; DoubleClick 2006). Further, in related search contexts, researchers have found that the ordinal ranking of the firms is strongly related to a consumer's likelihood of visiting a firm and purchasing from it (Smith and Brynjolfsson 2001; Ellison and Ellison 2004). This pattern of search where consumers find it natural to search from top to bottom of the listing creates a *directional* market where it is "costlier" for a typical consumer to visit sellers at the bottom of the list before visiting the sellers at the top of the listing.

This directional nature of the market also affects the distribution of consumers that each firm encounters. Economists examining the traditional media generally assume that consumers sample the firms randomly while searching a media such as yellow pages (Perry and Wigderson 1986). However, sponsored search media creates an environment where the order in which the firms are searched is known (i.e. is a function of the rank of the firm on the listing). Consequently, strategies employed by the firms and the resulting competition dynamics in such an ordered media may be different than those in the traditional media (Perry and Wigderson 1986; Arbatskaya forthcoming).

1.3 OBJECTIVE OF THE STUDY

Despite the phenomenal growth in sponsored search advertising, existing research on the implications of this new form of advertising is limited. The advent of sponsored search advertising raises many interesting questions regarding consumers' search and purchase behavior, sellers' advertising strategies, and the ensuing market dynamics. Current research in this field focuses primarily on designing better rank/position allocation mechanisms (Feng, Bhargava et al. forthcoming), identifying optimal bidding strategies (Kitts and Leblanc 2004), or examining market dynamics (Animesh, Ramachandran et al. 2006; Edelman and Ostrovsky forthcoming). Very little is known about consumer search behavior in this context, or the implications of sponsored search mechanisms for seller strategies. My dissertation, comprising three essays, seeks to fill this gap by examining the effects of sponsored search advertising on consumers and sellers.

The first essay seeks to examine the impact of the interaction between a seller's sponsored search advertising strategies and consumer search behavior on advertisement's performance. I employ consumer search theory to identify the factors that affect performance of a seller's advertising strategies. The second essay employs consumer search and quality signaling theories from marketing and economics to understand the impact of the availability of informational cues about sellers' *relative advertising expenditure* on consumer search and purchase behavior. The third essay investigates the outcomes in comparison shopping engines which are also directional markets similar to sponsored search advertising. Specifically, I examine the affect of the price and quality

of a firm's product/service on its advertising intensity in comparison shopping advertising market.

The rest of this thesis is structured as follows. Chapter Two, Three, and Four present the three primary research studies that constitute my dissertation. Chapter Five describes the implications of the findings from the three research studies and concludes with suggestions for future research.

CHAPTER 2: COMPETING “CREATIVELY” IN ONLINE MARKETS: EVIDENCE FROM SPONSORED SEARCH

ABSTRACT

While the efficiency-enhancing features of online markets have been well studied much less is known about firms’ differentiation strategies in such competitive markets, or the outcomes of such differentiation. This study examines competition among firms in online sponsored search markets - one of the fastest growing and most competitive of online markets. Given the nascence of online sponsored search and the lack of sophisticated differentiation strategies, firms have primarily sought to be listed on top of the search results, leading to intense competition. With the rapid evolution of sponsored search markets from simple auctions to sophisticated forums for customer acquisition, the need to go beyond a myopic focus of competing for the top slots and seek effective differentiation strategies is becoming clear. In this chapter I develop and test a model that predicts the clickthrough rate (CTR) of a seller’s listing in a sponsored search setting. Drawing upon consumer search theory and competitive positioning strategies I theorize that the CTR is jointly driven by the seller’s positioning strategy as reflected by the unique selling proposition (USP) highlighted in its “ad-creative,” by its rank in the sponsored search listing, and the nature of competition around the focal seller’s listing. I use data from a field experiment conducted by leading firm in the mortgage industry where the firm varied its rank and USP dynamically. Results suggest that sponsored search listings can act as an effective customer segmentation mechanism, consistent with a model of consumer search in directional markets. I further find that the relationship

between the firm's positioning strategy and its rank in the listing is strongly moderated by its ability to differentiate itself from adjacent rivals. I discuss the implications of the findings for sellers' strategies in sponsored search markets and for extending understanding of consumer search behavior in directional markets.

2.1 INTRODUCTION

Online marketplaces have significantly transformed the essence of commerce, influencing the way buyers and sellers interact and transact in many industries. Among the most widely studied aspects of online marketplaces is their role in lowering buyers' search costs and the resulting impact on market efficiency (e.g., Alba, Lynch et al. 1997; Bakos 1997; Bailey, Yao et al. 1999; Smith 2001; Smith and Brynjolfsson 2001; Bakos, Lucas et al. 2005). However, while it is true that lower search costs for consumers have led to increased price competition in online markets, it is also well known the firms in competitive settings successfully differentiate themselves from their rivals to reduce price pressures. Such positioning and differentiation strategies have been extensively studied in traditional settings (Economides 1986; Deephouse 1999; Netz and Taylor 2002) but surprisingly, very few studies (for exceptions, see Lynch and Ariely 2000; Brynjolfsson, Dick et al. 2004; Kuksov 2004; Bakos, Lucas et al. 2005) have examined the differentiation strategies adopted by sellers to counteract the increased competition in online markets, or the effectiveness of such differentiation. This essay examines the outcomes of differentiation on price and quality attributes by a focal firm competing for customers, in one of the fastest growing and the most competitive online markets – sponsored search advertising.

In online sponsored search (also known as “paid search” or “pay-for-placement” or “keyword”) markets, firms compete to be listed on top of search results generated in response to a user’s query (keyword search) in search engines such as Google and Yahoo!. Sponsored search markets have evolved to become the dominant mechanism for customer acquisition online, with firms reallocating significant proportions of their advertising budgets from traditional media to online sponsored search. In 2005, for instance, sponsored search accounted for more than 40% of the total online advertising dollars spent by companies in the United States (Markoff and Ives 2005). These markets exhibit a number of unique characteristics that make them ideal test-beds for understanding the effectiveness of online differentiation strategies. As noted earlier, they are highly competitive; the intensity of competition being reflected in the staggering costs for the top slots for several product-keywords. Firms are willing to incur these costs because the market allows them to precisely target consumers that are actively searching for specific products or services. In addition, online sponsored search markets use a pay-per-click pricing mechanism in contrast to most traditional advertising formats that adopt a lump-sum pay-per-exposure pricing mechanism. This paves the way for numerous smaller, less-established, firms to compete with their larger, well-established counterparts, diminishing the role of brand name as the key differentiating factor, and further intensifying competition for the top slots. Finally, and most significantly, the ordered listing of advertisers in sponsored search markets creates an information environment such that consumers tend to browse through the listings sequentially in the order they are listed¹. This “sequential search” creates a directional market², where firms

¹ This is in contrast to traditional markets or media such as the yellow pages, where consumers have been shown to sample firms randomly (Perry and Wigderson 1986).

listed on the top have an advantage over firms appearing lower in the listing (Arbatskaya forthcoming). The directional nature of online sponsored search markets and the resulting sequential nature of consumer search, further intensifies competition for the top ranks, and the associated cost to firms of using these markets.

Given the nature of this heightened online competition, it becomes imperative for firms to successfully differentiate themselves in such settings. While firms competing in traditional contexts rely on factors such as physical location, the lack of geographical constraints requires firms to seek additional avenues for differentiation in online markets. However, very little is known about the effectiveness of differentiation strategies adopted by firms in these online markets. To the extent that sponsored search markets constitute a significant forum for customer acquisition, and to the degree that the strategic significance of these markets is likely to grow, it is clearly important to gain a more complete understanding of competition in such online contexts.

To date, extant research on sponsored search has focused primarily on designing optimal rank allocation mechanisms or on developing bidding strategies for sellers to obtain higher ranks in the search listing. Much of the research in this area builds upon earlier work on the design of auctions and optimal bidding strategies for firms (Kitts and Leblanc 2004; Feng, Bhargava et al. forthcoming), and largely treats sellers as homogenous bidders. This body of research ignores the strategic choices made by other sellers that is likely to be not only restrictive, but also misleading. Further, in addition to limited understanding about the characteristics of bidders, little is known about consumer

² In the context of sponsored search markets, the directionality arises from the cognitive costs to a consumer of visiting sellers at the bottom of the list before visiting those at the top of the listing.

search behavior in the sponsored search context, and the implications of this behavior for seller strategies.

The focus of this study is on the unanswered questions regarding sellers' positioning strategies, consumers' search behavior, and the ensuing market dynamics in sponsored search settings. Drawing on the consumer search, directional markets, and competitive positioning literatures, I identify factors that influence the performance (as measured by clickthrough rates) of a focal firm's advertisement over and above the effect its rank in the listing. I use data from a field experiment to examine how a seller's positioning strategy (i.e. its Unique Selling Proposition (USP)) as highlighted in its "ad-creative" influences the effectiveness of its listing in the sponsored search market. I also examine the performance effects of the interaction between the firm's positioning strategy and its rank in the sponsored search listing. Consistent with a model of consumer search in directional markets, the results suggest that sponsored search listings can act as an effective customer segmentation mechanism. I further investigate the influence of competition on the performance of the focal seller's advertisement, and find that the relationship between the seller's positioning strategy and its rank in the listing is strongly moderated by its ability to differentiate itself from its rivals. Overall, the findings yield important implications for sellers' strategies in sponsored search markets as well as for extending understanding of consumer search behavior in directional markets.

The rest of the chapter is organized as follows. Section 2.2 reviews the sponsored search literature and other relevant literature from economics, marketing and information systems that has studied consumer search, as well as competitive and positioning strategies. In section 2.3, I present research hypotheses. The research methodology is

described in section 2.4, followed by results in section 2.5. Section 2.6 provides a discussion of the findings and their implications, and Section 2.7 concludes the chapter.

2.2 A CONCEPTUAL MODEL OF AD PERFORMANCE

As described in Chapter 1, major search engines such as Google and Yahoo! conduct auctions to price advertisements on various ranks in their sponsored listings. Since sellers can change their bids in real time, their rank on a listing may change dynamically depending on the rank ordering of the current bids. Thus a seller cannot lock-in a rank for a keyword and has to constantly monitor and actively manage the bidding process. To make it easier for sellers to bid for a specific rank, auctioneers and third parties provide automated bidding tools to adjust bids in order to maintain a rank in the listing, subject to the seller's maximum bid constraint. Given the dynamic nature of these advertising auctions, sponsored search markets require significant strategizing by sellers. Seller strategies need to be shaped not only by the normative implications of auction design but also by the expected response of end-consumers to the adopted differentiation strategy. Yet, despite the phenomenal growth of these markets, research providing insight into the implications of these relatively new markets for sellers' strategies is limited. This study seeks to fill this gap by examining the effects of a firm's positioning and differentiation strategies in sponsored search markets on the performance of its sponsored search listings.

The conceptual model guiding this study is shown in Figure 2.1. The performance of a firm's advertisement in a sponsored search listing is the observable consumer behavior in the form of a clickthrough; representing the culmination of a search process. The search

process, in turn, takes place in a context characterized by the strategic decisions made by the seller in regard to ad rank and USP, together with the competitive landscape within which the ad is displayed. Below I briefly review relevant literature that provides the theoretical foundation for the proposed conceptualization.

Sponsored Search Listings and Consumer Search

Research on sponsored search advertising is still in a nascent stage. As noted earlier, current research in this field predominantly adopts an auctions perspective to examine the interaction between the search intermediary who conducts the sponsored search auction and sellers who bid in these auctions. One stream of research focuses on designing better rank/position allocation mechanisms from the perspective of the search intermediary (Aggarwal, Goel et al. 2006; Asdemir 2006; Lahaie 2006; Edelman, Ostrovsky et al. forthcoming; Feng, Bhargava et al. forthcoming; Varian forthcoming), while a second identifies optimal bidding strategies from the perspective of sellers (Kitts and Leblanc 2004; Borgs, Chayes et al. 2006; Rusmevichientong and Williamson 2006). In addition, a few studies examine the market dynamics that result from these sponsored search auctions (Animesh, Ramachandran et al. 2006; Edelman and Ostrovsky forthcoming).

However, limited research has examined consumer search behavior in this context, or the implications of sponsored search mechanisms for seller strategies. In one of the few scholarly studies on consumer behavior in sponsored search context, Jansen and Resnick (2005) examine the perception of searchers towards sponsored search listings and find that compared to organic search listings, consumers are skeptical of sponsored search results and trust them less. This study adds to this stream of research by highlighting the

importance of understanding consumer search behavior in these markets and its implications for the effectiveness of various sponsored search differentiation strategies.

Research in economics and information systems suggests that a consumer's search cost has a significant impact on the price, product positioning, advertising and other strategic decisions of a firm (Stigler 1961; Bakos 1997). Search costs also determine the competitive dynamics and structure of a market (Stahl 1982) as well as consumer welfare (Salop and Stiglitz 1977). Given that the Internet and online marketplaces have radically lowered the consumer's search cost, researchers have employed models of consumer search to examine the implications of online markets on various stakeholders (Alba, Lynch et al. 1997; Lal and Sarvary 1999; Smith and Brynjolfsson 2001). Since sponsored search advertising also significantly influences consumers' search costs in online markets (Arbatskaya forthcoming), a consumer search perspective provides an appropriate framework to study sellers' strategies in sponsored search markets.

The Nature of Consumer Search

Two key aspects of the search process are relevant to the conceptualization: one, how *much* consumers are willing to search (i.e., their search intensity), and two, the *nature* of the search process in terms of the specific information sought.

Determinants of Search Intensity

The economics and marketing literature employs a cost-benefit framework to understand consumers' information search and choice behavior (Stigler 1961; Ratchford 1982).

Researchers suggest that consumers differ in terms of their search intensity, i.e., the time and effort spent in searching for sellers in a market. Ratchford (1982) observes that higher relative valuation and large dispersion of prices increases the gains from search,

thus leading to greater search. He suggests that education, a proxy for search efficiency, has a positive impact on search whereas income, a proxy for opportunity costs of time, has a negative impact on search intensity. Using a survey methodology, Ratchford and Srinivasan (1993) also find that search intensity (measured as the time spent searching for price) increases with perceived benefits of search, whereas it decreases with consumer knowledge and hourly wage.

Schmidt and Spreng (1996) provide an extensive review of research on the determinants of search intensity and develop a model integrating the psychological search and economics of information (EOI) literatures. They propose that the individual, situational, and environmental variables determining search are mediated by ability to search, motivation to search, and the cost and benefits of search. Such a cost benefit framework has also been employed in online markets (Klein and Ford 2003) and thus, is likely to be relevant within the sponsored search context.

Price Search versus Quality Search

A fundamental tenet underlying descriptive and normative models of consumer search is that consumers differ in terms of their needs and product attribute preferences (Bell and Lattin 1998). The two most important attributes of a product or service are price and quality, and consumers vary in terms of the weight that they attach to these attributes in their purchase decision (Wolinsky 1983; Levin and Johnson 1984). As a result, the type of information (i.e., price versus quality) sought and acquired by a consumer depends on their product attribute preference. For example, quality seeking consumers have higher willingness to pay for any quality level as compared to low quality valuation consumers

(Wolinsky 1983; Desai 2001) and therefore will search for high quality sellers rather than low price sellers.

Quality versus price preferences are known to affect a consumer's search cost, as collecting and comparing quality information is costlier than collecting and comparing price information (Nelson 1970). Today, Internet technologies alter the cost of collecting price and/or quality information and thus, significantly affect consumer behavior (Smith 2001). For instance, research on consumer search behavior in an online environments suggests that the differential search cost for obtaining quality information vis-à-vis price information may affect price sensitivity (Lynch and Ariely 2000; Diehl, Kornish et al. 2003). Given the importance of the price and quality attributes from consumers' as well as sellers' perspectives, I focus on differences across consumers in terms of their price versus quality preference and their search objectives.

Positioning Strategies and Competition

Sellers in a market compete with each other by employing different positioning strategies to attract their target consumer segment. There is an extensive literature on the impact of competitive positioning on firms' performance in traditional non-directional markets (Economides 1986; Deephouse 1999; Netz and Taylor 2002). Researchers examining such traditional markets or media generally assume that consumers sample firms randomly while searching a medium such as the yellow pages (Perry and Wigderson 1986). However, the sponsored search medium creates an environment where the order in which the firms are searched is known i.e., the order in which the firms are searched is a function of the rank of the firm on the listing (Arbatskaya forthcoming). The ordered presentation format limits the freedom and flexibility that a consumer may have in

browsing advertisements. In related search contexts, researchers have found that the ordinal ranking of the firms is strongly related to a consumer's likelihood of visiting a firm and purchasing from it (Smith and Brynjolfsson 2001; Ellison and Ellison 2004). This pattern of search where consumers find it natural to search from top to bottom of the listing creates a *directional* market.

A directional market is one where a consumers' search cost or transportation cost to visit sellers in the market depends not only on the distance between the consumers' location and the location of the firm, but also on the direction in which a firm is located (Nilssen 1997). For example, parking garages on a one-way street represent a directional market, where it is more costly for a driver to return to the garage that is behind her versus going to a garage ahead, irrespective of the distance between the garages (Lai 2001). Another dimension on which markets may exhibit directionality is temporal space, as in markets for radio or television programming and transportation services such as airline flights. Here, it might be less costly for a consumer to wait a while, relative to her ideal time, than to arrive earlier (or later depending on the context) in order to get serviced (Cancian, Bills et al. 1995; Nilssen 1997).

In sponsored search markets, the directionality arises due to cognitive burden as it is cognitively "costlier" for a typical consumer to visit sellers at the bottom of the list before visiting the sellers at the top of the listing. This directionality, where consumers search the sellers in the market in the order in which their ads are displayed in the listing, affects the distribution of consumers that each firm encounters. As one might expect, both the strategies employed by firms as well as the resulting competition dynamics in such an ordered medium are likely be different than those in the traditional medium (Perry and

Wigderson 1986; Arbatskaya forthcoming). Much of the consumer search literature addresses behaviors in traditional non-directional search market with one notable exception (Arbatskaya forthcoming). As sponsored search markets become increasingly popular venues for advertising, research examining the relationship between consumer behavior and seller strategies in such directional markets is needed.

In summary, the unique attributes of sponsored search markets and the nature of online competition in these markets require firms to seek appropriate means to differentiate themselves from their rivals. Prior research has suggested that consumers vary in the intensity with which they search and have heterogeneous preferences in regard to the product attributes (price or quality) they value. To the extent that the sponsored search market is inherently directional in nature, consumer search behavior is also affected by the order in which firms are listed in the search results. I use these insights from prior work to develop testable hypotheses in the following section.

2.3 RESEARCH HYPOTHESES

Specific instantiations of the conceptual constructs are depicted in the research model (see Figure 2.2). The key outcome of interest is the performance of the focal firm in the sponsored search market, operationalized as the CTR of its ad. Theoretical arguments for each of the proposed relationships are provided below.

Sequential Search

The typical format of a sponsored search listing is a display of an ordered list of firms along with their advertising messages. It has been observed that when presented with an ordered list of items, individuals tend to browse through them sequentially in the order in

which they are listed. For instance, a recent eye motion study shows that searchers scan a listing from top to bottom and they pay more attention on the advertisements appearing on the top of the listing (Sherman 2005). This sequential search creates a directional market, where firms listed on the top have an advantage over firms appearing lower in the listing. In addition, consumers are likely to vary in their search intensity due to differences in perceived search costs and benefits (Stigler 1961). Thus, while all consumers may search sequentially from the top to the bottom, consumers with higher search costs (or lower search intensity) will restrict their search to the top sellers in the list. By contrast, consumers with lower search costs (higher search intensity) are more likely to search further down the listing. Given the tendency for consumers to search sequentially and the heterogeneity in consumer search intensity, more consumers are likely to click on sellers with a higher rank/placement. I therefore test:

H1: *Sellers ranked higher in a sponsored search listing have higher CTR than those ranked lower in the search listing.*

The Impact of a Firm's Unique Selling Proposition (USP)

While a naive sequential search strategy might be realistic in simple settings, it is likely to be less so in a more complex and high-involvement setting such as shopping or purchase. In a shopping situation consumers typically seek products and services that meet their needs. As discussed earlier, consumers can broadly be classified as price-seeking or quality-seeking, based on their preference for price and quality (Wolinsky 1983; Levin and Johnson 1984; Desai 2001). A price-seeking consumer is more likely to search for low-priced offerings, while a quality-seeking consumer is likely to search for high-quality offerings. Thus, while all consumers may search sequentially through the

ordered listing, consumers with specific preferences for certain attributes are likely to filter out those sellers which do not appear to provide the feature/attribute that is being sought. In other words, a consumer who is quality seeking has higher likelihood of visiting sellers signaling higher quality, while a price seeking consumer is more likely to sample sellers that signal lower prices. Because firms use their ad creative to differentiate themselves and convey their unique selling proposition (USP) to potential customers, consumers will select sellers whose USP signals the attribute they value. Thus, the seller's USP as highlighted in the ad creative, in addition to its rank in the listing, would affect the performance of sponsored search advertisements. I therefore test:

H2a: *The CTR of a seller in a sponsored search listing is influenced by the seller's positioning strategy as highlighted by the USP in its ad creative.*

Sponsored Search Listing as a Filter

Given the directional nature of the sponsored search market, the effectiveness of a firm's positioning strategy is likely to be moderated by its rank in the listing. Prior research suggests a correspondence between consumers' needs and search intensity, stemming from differences in perceived costs and benefits of search. For instance, search costs and benefits for a consumer are a function of the consumer's individual characteristics (i.e., income, education, etc.) as well as the product attribute that is being searched (i.e., cost of searching and comparing different attributes and the utility derived from the attributes). Therefore, consumers searching for product attributes that have greater net marginal

benefit from an additional search or/and who have lower opportunity cost of time due to their individual characteristics would exhibit higher search intensity (Schmidt and Spreng 1996). Because consumers search sequentially from top to bottom of the listing, those with higher search intensity will search further down the listing whereas those with lower search intensity would restrict their search to the top few advertisers in the listing. It follows then that the proportion of consumers with a specific product attribute preference will vary as an ad is moved down the listing. I label this phenomenon that changes the composition of consumers likely to see a seller on the sponsored search listing as the “*sponsored search filter*” (see Figure 2.3). Because the proportion of consumers searching for a specific product attribute varies across different ranks due to the sponsored search filter effect, the performance of a seller’s USP would depend on the rank on which the seller appears on the listing. Therefore, I test:

H2b: *The effect of a seller’s USP on CTR will be moderated by the rank at which the seller appears on the sponsored search listing.*

Next I develop specific hypotheses regarding the differential effect of price and quality USPs at different ranks. In general, price seeking consumers are likely to have higher search intensities than quality seeking consumers for at least three reasons. First, searching for quality can be more time consuming than searching for price – research suggests that quality information is more expensive to collect and process as compared to price information (Nelson 1970). Assessing and comparing quality of sellers in an online environment is even more difficult than offline markets where other “physical” signals of quality are frequently available, whereas price comparison across sellers online is more objective and thus easier. Therefore, quality seeking consumers would not consider it

worthwhile to search more, and will be more likely to restrict their search to sellers in the top ranks.

A second effect is due to the relationship between income, search cost, and preferences of a consumer. Research suggests that income is associated with preferences for higher quality products. According to the “relative income hypothesis,” income is linearly and positively related to consumption of expensive or high quality products (Schaninger 1981). High income consumers are less price sensitive across various product categories (Ainslie and Rossi 1998) and low income consumers typically search for low prices (Andrews and Currim 2002). Income has also been identified as a determinant of the search cost. As might be expected, the marginal cost of an incremental search effort (i.e., the opportunity cost of time) is higher for a consumer with a higher income (Stigler 1961; Ratchford 1982; Ratchford and Srinivasan 1993). Given the existence of a sponsored search filter effect, a larger proportion of consumers that reach the bottom ranks in the listing would belong to the low income group. To the degree that the higher income group attaches greater weight to the quality dimension than the price dimension vis-à-vis the low income group, firms at higher ranks will receive a larger proportion of quality seeking consumers as compared to firms at lower ranks.

Finally, if consumers believe that sellers on the top positions are of higher quality – either due to 1) awareness of sponsored search mechanism along with advertisement signaling beliefs or 2) a lack of knowledge about the distinction between organic and sponsored ads and a transfer of positive experience from top ranked results on the organic search listing to the sponsored listing – quality seeking consumers would concentrate their search efforts on the sellers appearing on the top of the listing. As a consequence, a

larger proportion of consumers that reach the bottom ranks in the listings are more likely to be price seekers. I therefore test:

H2c: *The relative performance (i.e., CTR) of a price USP as compared to a quality USP will improve at lower ranks in the sponsored search listing.*

The Impact of Competition

Given limited attention and memory, consumers are more likely to compare adjacent sellers offering the attribute that is being sought before visiting a seller's website. As stated earlier, consumers are likely to click on the seller with a USP that matches their preference. To the extent that a consumer's comparison set consists of adjacent sellers in a listing, the constitution of this comparison set should influence the CTR received by a focal firm. In particular, the greater the number of firms with an identical USP within the comparison set, the higher the competitive intensity. Assuming that consumers select a subset of sellers from a group of adjacent sellers employing a similar USP while searching sequentially from top to bottom of the listings, due to market fragmentation, the presence of higher competitive intensity in the seller's USP space will lower the clickthrough received by the firm. Hence,

H3a: *In a sponsored search listing, higher competitive intensity (i.e., more firms around a focal firm that are using the same USP) for a USP will lead to lower CTR for a seller with that USP.*

Finally, since quality seeking consumers have higher search costs and lower search intensity, they will sample fewer sellers from their comparison set vis-à-vis price seeking consumers who have higher search intensity. Therefore the effect of competition will be more pronounced for a quality USP than for a price USP.

H3b: *The impact of competitive intensity will be stronger for a seller using a quality USP relative to a seller using a price USP.*

2.4 DATA AND METHODOLOGY

Empirical Context

The analysis is based on data from a field experiment field experiment conducted in conjunction with a firm in the mortgage industry (henceforth MorgSeller) that bids for placement on one of the largest sponsored search markets. The key strategic choices facing the firm are the rank at which it will be displayed in the listing (determined by the amount it bids) and the specific differentiation it will highlight in the text message accompanying its advertisement. MorgSeller randomly varies the keywords and associated USP it utilizes in the market, and changes its bids for placement dynamically. Through this experimentation, its objective is to find the optimal rank given a choice of keyword such that CTR is maximized. The data contains MorgSeller's bids for the top 36 (based on clickthroughs) keywords (e.g., loans, mortgages, home loans, etc.) and the ranks obtained in the sponsored search listings corresponding to each of those bids. MorgSeller provided us with data for a period of three months in 2006. The key variables of interest are MorgSeller's rank in the sponsored search listings, and the USP as highlighted in its ad creatives, while the key outcome of interest is the CTR obtained. The bids were updated frequently and resulted in different ranks over time and for different keywords. In addition, the ad creative (i.e., two lines of text advertisement with 30-40 characters in each line) to be displayed on the listings, used by MorgSeller was varied over time and across keywords. Two broad positioning strategies were chosen – price and quality, and the ad creatives employed highlight either a *quality* or a *price* USP. Ad creatives using a quality USP generally included words such as “customer satisfaction”, “trusted”, “secure and confidential”, “quick and easy” whereas price USP

ads used phrases such as “no closing cost”, “low rates”, “lowest price”, “low interest”, “compare offers”.

In addition to data on MorgSeller’s strategic choices with regard to rank and ad USP, I also obtained the corresponding performance data, i.e., clickthrough rate. To measure competition, I further, collected data on the USP of competitors in the sponsored search listing on the selected keywords. The competition data were compiled by extracting the keywords in the sample from the search engine result page every two hours. Then, using content analysis and identifying a set of words that capture the essence of price and quality USPs, I classified the ad creatives used by these competitors as a *price* or a *quality* USP. Four marketing experts, who were blind to the objective of the research study, were asked to classify a sample of ads into quality and price USPs. The agreement of the experts for the USP classification was assessed using inter-rater reliability tests for nominal data (Hughes and Garrett 1990). I obtained a Cohen's kappa agreement index of 0.69, indicating a high degree of inter-rater reliability (Landis and Koch 1977).

I used different “windows of competition” to identify competitors adjacent to the seller. I created multiple competition indices based on different windows to test for the robustness of the results. For the smallest window, I used one advertisement above MorgSeller’s advertisement and one advertisement below MorgSeller to define adjacent competitors. The competitive intensity for a USP is obtained by dividing the number of advertisements using that USP by the number of adjacent ads.

The unit of analysis is the combination of a unique advertisement (i.e., unique text) appearing on a listing on a specific day. Descriptive statistics and correlation coefficients between the variables used in this study are shown in Table 2.1 and Table 2.2,

respectively. The sample contains 1556 observations appearing at ranks in the range of 1 to 7. Of these observations, 757 ads employed a quality USP and 799 ads contained a price USP. The competitive intensity ranges between 0 and 1, with a mean of 0.54.

Empirical Analyses

I employ moderated multiple regression (MMR) analysis to test the hypotheses. I log transform the rank variable to capture the exponential decay in clickthrough rate as a function of seller rank on the listing³. The dependent variable, CTR, is defined as the number of clicks received by a seller (i.e., the number of consumers who clicked on the seller) divided by the number of impressions received by the seller (i.e., the number of consumers who were shown the seller's ad). The use of such a normalized dependent variable is necessary to avoid the problem due to variations in the number of impressions obtained by sellers' ads.

Finally, although the CTR by virtue of being normalized takes into account differences in clicks due to differences in impressions, it still suffers from some measurement issues. I assume that the CTR obtained by a seller is a reliable estimate of the true effectiveness of the seller's ad. However the estimate of effectiveness is not reliable if the number of impressions obtained by an advertisement is small. I, therefore, weight each observation in the regression model such that observations with higher impressions get a larger weight when the least square errors are minimized in the regression analysis. I assume that after a threshold number of impressions the CTR estimate would be very close to the true value. In other words, I model the reliability of

³ I tested a linear model (i.e., without log transformation) and find that log-transformation explains larger variation in the data. I also conducted additional regressions to examine the model using linear relationships between rank and click-through and obtained results similar to those with the exponential relationship.

an ad's effectiveness measure as a concave function of impressions and therefore weight the observations by $\log(\text{impressions})$. I analyzed the data without using the weights and found the results to be consistent. The results reported here are based on the weighted regression.

The regression model that I employ to test the research hypotheses is shown below.

$$\text{CTR} = \alpha_0 + \beta_1 * \log(\text{Rank}) + \beta_2 * \text{USP} + \beta_3 * \log(\text{Rank}) * \text{USP} + \beta_4 * \text{CI} + \beta_5 * \text{CI} * \text{USP} + \beta_6 * \text{CI} * \log(\text{Rank}) + \beta_7 * \text{CI} * \log(\text{Rank}) * \text{USP} + \sum_{i=2..j} (\delta_i * \text{Keyword}_i) + \varepsilon$$

where j = total number of keywords
 CTR: Clickthrough rate
 Rank: Position of a seller's ad on the listing. Top rank is coded as 1
 USP: Unique selling proposition employed by the seller in its ad. USP is coded as 1 for price and 0 for quality USP
 CI: Competitive intensity on the USP that is employed by the seller.

As described earlier, CTR is calculated by dividing the number of clicks received on an advertisement by number of impressions for the advertisement. Rank represents the rank (daily average) at which the advertisement was shown in the sponsored listing. Rank equals 1 for the advertisement shown on top of the listing, 2 for the advertisement shown below it and so on. Thus, a lower value of rank implies that the advertisement appeared towards the top of the listing. USP is a dummy variable which equals 1 if the advertisement conveys a low price USP and is 0 if the ad conveys a high quality USP. CI represents the competitive intensity around an advertisement on the specific USP dimension that the ad employs. A seller one rank above the focal seller and a seller one rank below the focal seller are used to create the competitive intensity measure⁴. Finally

⁴ To test the robustness of the results, I also used windows of two as well as three sellers above and below to create the competitive intensity variable. The results are consistent across these different "windows of competition". I present the results based on the smallest "window of competition" – comprising of one seller above and one below the focal firm.

keyword dummies are used as a control variable to account for differences in CTR due to the inherent nature of the keyword.

2.5 RESULTS AND DISCUSSION

The results of the regression analysis are presented in Table 2.3. In Model 1, I include only the keyword dummies to account for the differences in CTR across different keywords. The results show, not surprisingly, that keywords have a significant impact on the CTR of an ad, suggesting that consumers differ in the likelihood of clicking on a particular ad on the basis of the keywords that they use to search. Next, in model 2 I include rank of the ad as an independent variable. I find that, as expected, advertisements placed higher in the listings get higher CTR. I graph the predicted relationship between rank and CTR in Figure 2.4. Model 3 includes the effect of USP after controlling for the rank of the ad. In Model 4, I include the interaction effect between rank and USP to test hypothesis H2b and H2c. Model 5 introduces the competitive intensity (CI) variable to test hypothesis H3a and Model 6 introduces the interaction term between CI and USP to test hypothesis H3b. Although, *a priori*, I did not hypothesize a higher order interaction between CI, USP, and rank, such a relationship is possible. Since omitting higher order interactions if the true effects are non-zero would bias the lower order coefficients, I also test for the presence of a three-way interaction in Model 7 (Aiken and West 1991)⁵.

I find that the coefficient of the higher order interaction is significant (beta=-0.063; p<.001) and the increase in r-square by including this interaction is also significant (ΔR -square=0.02; F=25.21). Due to the presence of the 3-way interaction, it is advisable to

⁵ The multicollinearity diagnostics were acceptable (VIF scores were less than 10) thus alleviating concerns regarding unstable coefficients.

focus on the fully specified model (i.e., Model 7) rather than interpreting the partial models (Aiken and West 1991). Therefore, I plot the three-way interaction to validate the hypotheses.

In Figure 2.5a and 2.5b, I graph the interaction between rank and USP at different levels of competition. Results show that CTR decreases at lower ranks. For the price USP this difference is significant at a 10% level of significance for both low and high competition (difference=0.01; $p=0.062$ and difference=0.008; $p=.053$, respectively). For the quality USP the difference is significant at 5% in both low and high competition cases (difference=0.075; $p<.01$ and difference=0.026; $p<.01$, respectively). Thus I find support for H1.

The graphs also show that the quality USP performs better than the price USP in generating higher CTR at the top ranks but the relationship reverses at the bottom ranks. In the presence of low competition, the difference between the price and quality USPs is -0.028 ($p<0.01$) at the top and 0.036 ($p<.01$) at the bottom. In cases with higher competition, the results are similar but are not statistically significant. The difference between price and quality USP is -0.01 ($p=0.117$) at the top and 0.01 ($p=0.163$) at the bottom. I do not find a significant main effect of USP on CTR. Thus H2a is not supported. Though the main effect is not significant, as hypothesized, I find that the effect of USP on CTR varies as a function of rank. However the results show that the relationship between the ad's USP and its rank in the listing is strongly moderated by the advertiser's ability to differentiate itself from its rivals. Thus, I find conditional support (i.e., only when competitive intensity is low) for H2b and H2c.

I graph the three-way interaction in Figure 2.6a and 2.6b to examine the relationship between competitive intensity and USP at top and bottom ranks. Results show that high competitive intensity significantly decreases the CTR for the quality USP (difference=-0.22; $p<0.01$) at the top ranks. The effect of competition on the price USP is also in the same direction but is not significant (difference=-0.003; $p=0.577$). This is consistent with hypotheses H3a and H3b. At the bottom ranks, the effect of competition on price USP is similar as in top ranks (difference=-0.00002; $p=0.997$). However the effect of competition on the quality USP at the bottom ranks is quite surprising and contrary to expectations. I find that higher competitive intensity on the quality USP at the bottom rank leads to higher CTR as compared to lower competitive intensity (difference=-0.027; $p<0.01$).

In summary, I find that the magnitude of decrease in CTR as an ad is moved from top rank to bottom rank is much larger for the quality USP in comparison to the price USP. This result is consistent with the sponsored search filter effect described earlier, and I find that the performance of the price USP vis-à-vis the quality USP improves as I move down the listing. Further, competitive intensity has a significant effect on CTR but the effect is present only in the case of the quality USP. At the top ranks, higher competitive intensity lowers the CTR for the quality USP but surprisingly, higher competition on quality USP increases the CTR at the bottom ranks.

The effect of competition at lower ranks in the listing for the quality USP is unexpected and seemingly counter-intuitive. One possible explanation for this effect is that it is caused by differences in the profile of consumers who reach the bottom of the listing as compared with that of consumers who stop searching at the top of the listing.

High competitive intensity affects the quality USP more at the top as quality seeking consumers are sampling fewer of the adjoining quality USP ads, in contrast to price seeking consumers who are sampling more (perhaps, exhaustively) adjoining price USP ads. However at the bottom, more intense competition does not have the same effect for quality as it is not the quality seeking consumers but the price seeking consumers who are clicking on these ads. As I argued earlier (and based on the indirect evidence provided by the results) a majority of consumers who visit a seller's ad at the bottom of the listing would be price seeking. Also, recall that I assumed that though consumers are more likely to click on an ad that has the USP which matches their preferences, some consumers (i.e. β proportion of quality seeking and γ proportion of price seeking) may sample ads that do not specifically claim the attribute that they are seeking when they do not have enough⁶ ads to sample in a "sliding window". Of the price seeking consumers who may click on the quality USP ad, a larger number would click on the quality USP if they do not have enough price USP alternatives to sample. This is the case when there is high quality competition (i.e., adjoining sellers have the quality USP) and therefore we may see the counterintuitive result.

Limitations

Prior to discussing the implications of the findings, I acknowledge the limitations of the study. Our empirical analysis is restricted to data from a single firm, that somewhat limits its generalizability. Nevertheless, it is important to note that the unit of analysis is not the firm but rather the specific differentiation strategy, i.e., USP deployed at a given rank.

MorgSeller experimented with both these key strategic variables, permitting us to test the

⁶ Number of ads that a consumer would sample from a window would also depend on their search intensity. The larger the search intensity, the larger the number of ads clicked in any sliding window.

assertions in the research model. Moreover, the use of a single firm allows us to control for a number of other firm-specific factors such as brand-name (Wu et al. 2005), that might affect the outcomes of interest in this study. By focusing on a single firm I was able to effectively isolate the impact of the firm's competitive and positioning strategies, in these markets. The data used in this study is also limited to the mortgage industry. This choice is primarily driven by the popularity of online mortgage services which provides us sufficient number of clickthroughs to perform empirical analyses. I believe the results would also hold in other industries, though the strength of the relationships may vary. Extending this study to encompass other sectors would be an interesting avenue for future studies. Another potential limitation of this study is that I measure only CTRs rather than actual purchases. However, CTRs are considered to be the primary performance metric by practitioners as they are a good predictor of sales. To the degree that different product categories may have different conversion rates, it would be important for future researchers to understand the effect of firms' positioning strategies on conversion rates and sales. Finally, while I am able to observe consumers' actions (i.e. their click-throughs) I do not directly observe individual consumers' search behavior, or their preferences. Future research should validate the assumptions of this study by conducting complementary studies employing lab experiment and survey methodology.

2.6 DISCUSSION AND IMPLICATIONS

My goal in this essay was to extend understanding of the performance of ads in sponsored search listings by moving beyond a uni-dimensional focus of ad rank as the determinant of performance. We examined, both theoretically and empirically, how the

interaction between an advertiser's USP as highlighted in its "ad-creative", the rank of the ad, and the competitive intensity around the ad influences the effectiveness of the sponsored search ad. Results largely support our predictions, suggesting that these factors are important strategic variables for firms competing in these markets.

The study makes several theoretical contributions. It integrates consumer search theory with directional search to provide insights into consumer search and seller's differentiation strategy in sponsored search markets. I proposed and found evidence that the sequential nature of search in such markets results in the sponsored search listing becoming a consumer segmentation filter. Not only is the number of consumers who click at the top larger than those who click at the bottom, as might be expected, a striking finding is that consumers who reach the bottom may be more homogenous in certain characteristics such as search intensity, income, product attribute preferences, etc. The findings provide indirect evidence of consumer search patterns in sponsored search listings, and can assist analytical modelers and auction designers in developing more realistic models.

In addition to theoretical contributions, the study yields several managerial implications. First, I reaffirm the widespread belief that higher ranking of the advertisement leads to better performance (i.e., higher clickthroughs). However, the ranking in the search results explains only a small (around 5%) proportion of the variance in the clickthrough rates that the firm obtains. A key implication of this finding is that the forecasting models used by the search engine marketers and advertisers that only include rank as the predictor of clickthroughs would not only be misleading, but may also result in sub-optimal bidding strategies.

The results indicate that both the firm's USP as well as the competitive intensity around the focal firm's position have a significant impact on the advertisement's performance. In general, the price USP performs better than the quality USP at lower ranks. This finding yields a number of interesting and important implications. First, most of the advertisers (or search engine marketers who advertise on behalf of their clients) typically treat rank and USP as independent decisions. However the results suggest that firms should seek to jointly optimize these two decision variables.

A second implication is the need for sellers to build web-based information systems capable of capturing the rank of the ad in the sponsored search listing at which the consumer clicked to visit a seller's site. This information can then be used in conjunction with consumers' demographics and psychographics (if available) to obtain insights into the differences between the profile of consumers who encounter the seller's ad at different ranks in the listing, and to make sharper predictions about consumer purchase behavior.

Third, a seller would find it useful to customize its landing page (i.e., the web page that a consumer is taken to when she clicks on an ad in the sponsored search listing) for ads shown at different ranks. For example, if a seller's ad is appearing at the bottom rank, then the seller can customize its page to fit the information needs and preferences of a price seeking consumer profile and may even post lower prices. By contrast, if a seller is listed at the top, it can afford to set higher prices and customize its site to cater to quality seeking consumers. Further, a seller can dynamically set the price on a landing page depending on the rank at which the ad linked to this landing page appears on the listing. Finally, a quality seller may benefit more from bidding higher to appear at the top

of the listing as a majority of the consumers who are quality seeking may not even see the seller if its ad appears at the bottom of the listing. Sellers competing on price can, however, afford to be at the lower ranks. Although this strategy would lower their clickthrough (due to the lower rank), it would draw a more homogenous set of consumers (in terms of their search intensity and other factors that determine search intensity or are related to search intensity) to the seller's website and thus, a seller may be able to get higher sales by developing a more targeted marketing strategy.

The assertion that quality seeking consumers may be concentrated at the top of the listing also has implications for the design of the sponsored search mechanism. The search engine intermediaries need to design the ranking mechanism to ensure that the sellers at the top of the listing are high quality sellers. Else, in the long run at equilibrium the quality seeking consumers may stop using the sponsored search results.

Interestingly, I also find that the quality USP is strongly affected by competitive intensity. As expected, the effect is negative at the top ranks but reverses at the bottom ranks. The proposed explanation suggests that this is due to price seeking consumers clicking on the quality USP ads when they do not have enough price USP ads to sample at the bottom. This may, however, have implications for the conversion rate (i.e., the number of sales divided by the number of clicks/visits) of the quality ads when they are at the bottom amidst high quality USP competition. It is possible that in such an environment the conversion rate of an ad may be lower. Although I did not examine the conversion rate, future research can investigate this issue more closely and study the impact of clickthroughs on conversion rate. One important implication of this finding is that advertisers, especially those who are using a quality USP, should develop

information systems to monitor the competition on the sponsored search listing to better predict fluctuations in their CTR, and to make more informed decisions regarding what ranks to obtain for their ads for different keywords in the advertiser's keyword portfolio. As opposed to just the rank of the ad, the advertisers should also include the historical competitive intensity, USP and the ad's rank to forecast future CTR to obtain better forecasting estimates and to arrive at an optimal bidding strategy for the sponsored search auctions.

Future Research

Several promising new avenues for research in this nascent field emerge from this study. First, researchers can build on this study by using complementary research methods. Controlled lab experiments can be designed to directly examine the consumer behavior that was inferred in this study and to address some of the other limitations of the study described earlier. Consumer surveys can also be conducted to identify the profile of consumers who search till the bottom of the listing and how this profile differs from those who stop at the top. Further, if sellers start tracking the rank at which a consumer saw an ad, researchers can use this secondary data to triangulate findings about consumer search behavior in the sponsored search listings.

I examined competition in terms of the USP on which the firms were competing. Future research can develop alternative metrics for competitive intensity (for instance, competition based on a firm's brand equity). It is possible that competition from firms which have greater market share (or brand recognition) than the focal firm would lower the performance of focal firm's advertisement. Finally, researchers can analyze data

collected from firms in different industries to examine the sensitivity and robustness of the findings.

2.7 CONCLUSIONS

Researchers believe that differentiation strategies employed by firms and the resulting competitive dynamics in directional markets may be different from those created by traditional formats (Perry and Wigderson 1986; Arbatskaya forthcoming). However, very few empirical studies have examined the nature and outcomes of competition in such online markets and the various differentiation strategies adopted by firms competing in an environment characterized by very high competitive intensity and a growing number of rivals. The exclusive focus on the rank of firms in the sponsored search listings as a driver of performance adopted both researchers and practitioners fails to account for the unique characteristics of sponsored search markets, and the ability of firms to differentiate themselves in such contexts. In contrast to extant research that has adopted an auction perspective to understand the dynamics between search intermediaries and sellers, in this study I adopted an alternative consumer search perspective. Findings from this study can aid firms in optimizing their sponsored search strategies. Tracking and accounting for a range of variables (in addition to rank) in forecasting models can improve the prediction accuracy of clickthrough rates. The results of this study are not only likely to be useful for managers seeking to analyze the competition and craft their best response to their competitors' positioning strategies, they also extend existing research on directional markets to a new and emerging empirical context. Finally, to the

best of my knowledge, this is the first study to examine the impact of positioning strategies and competition in a directional market such as sponsored search.

CHAPTER 3: ADVERTISING OR PRICE? THE EFFICACY OF QUALITY INFORMATIONAL CUES IN ONLINE SPONSORED SEARCH MARKETS

ABSTRACT

The digitization of commerce has caused fundamental changes in consumer information search and use. With an increasing number of consumers using search engines as an integral component of their online purchase process, online sponsored search markets, such as those provided by Google and Yahoo!, have emerged as a dominant customer acquisition mechanism for sellers. Given the extent of information asymmetry in online markets, consumers rely on a number of informational cues or signals to infer the quality of sellers in these markets – advertising and price being the two most important among them. While the importance of advertising and price as signals of quality has been well established in traditional markets, online sponsored search markets have a number of unique characteristics that differentiate them from traditional settings. This calls for an examination of the efficacy of different informational cues for consumers' search and transaction behaviors in online sponsored search markets. Using a lab experiment, I examine how the knowledge of firms' relative advertising expenditures and prices affect consumers' search and purchase decisions. Contrary to earlier findings of the dominance of price signals in traditional markets, I find that firms' relative advertising expenditures serve as a stronger signal of quality in online sponsored search markets – a result attributable to the directional nature of these markets. I also find that the risk attitude of consumers has a significant impact on consumer beliefs and market outcomes. I discuss

the implications of the findings for sellers and consumers using sponsored search markets, as well as for search intermediaries.

3.1 INTRODUCTION

It is well established that the digitization of commerce has fundamentally altered the nature of information search and use for consumers. Over 53% of prospective buyers search online, and 67% of online consumers seeking information use search engines as part of their purchase process (iCrossing 2005). To the extent that this population of consumers represents an important set of prospects for firms seeking to sell products and services, it is not surprising that the growth of online markets has been accompanied by a concomitant increase in the popularity of online advertising. Recent reports suggest that online advertising revenues in the U.S. for the first six months of 2005 were approximately \$5.8 billion, representing a 26% increase over the first half of 2004 (Interactive Advertising Bureau 2005).

Among the various online advertising formats, sponsored search advertising is witnessing the fastest growth and has emerged as the dominant advertising format, accounting for nearly 40% of all advertising spending online (PricewaterhouseCoopers 2005). Sponsored search advertisements are text-based advertisements that are typically displayed alongside “organic” (algorithm-based) search results on major search engines such as Google and Yahoo! In sponsored search advertising, also known as “paid search,” “pay-for-placement” or “keyword” advertising, firms compete to be listed on top of search results generated in response to a user’s keyword query. This form of promotion offers a number of significant advantages over traditional approaches,

including the ability to precisely target messages to potential consumers who are actively searching for sellers, and enabling sellers to more directly relate advertising expenditures to outcomes.

A unique aspect of sponsored search is the integration and co-evolution of *search* and *advertising* business models. While it is well understood that search and advertising are two sides of the same coin – the objective of each being to match buyers and sellers – the ability of firms to target their advertising to consumers, or the ability of consumers to selectively seek out advertisements has been limited by the constraints imposed by traditional media. Sponsored search mechanisms enable firms to overcome these limitations and, recognizing their value potential, firms are aggressively reallocating significant proportions of their advertising budgets from traditional media to online sponsored search.

The sponsored search model employs an auction mechanism where firms bid on keywords relevant to their product or service for enhanced placement (i.e., higher rank) of their advertisements in the search results. Competition for the top slots in the search listings is predicated on the fact that consumers primarily tend to click on sellers that appear higher on the list (DoubleClick 2006). However, a vast majority of consumers (62%) are unaware of the distinctions between sponsored search and organic (algorithm-based) search results (Fallows 2005). In addition, a large proportion of consumers believe that a seller listed higher in the search results is of higher quality than those listed lower (iProspect 2006). It is not clear how consumer behavior would change if they were aware of the fact that a seller appearing higher on the list pays more than the seller ranked lower. This question becomes especially important in markets where consumers cannot

easily distinguish the quality of competing sellers, i.e., when the market exhibits quality uncertainty.

Research suggests that in markets characterized by quality uncertainty consumers rely on informational cues or signals to infer the quality of sellers (Kirmani and Wright 1989), *advertising* and *price* being the two most important among them. This is particularly true in online settings where consumers confront significant information asymmetries (Baylis and Perloff 2002). While it has been found that consumers shopping online rely on brand name to infer retailer's quality in non-contractible aspects of the product and service bundle such as shipping reliability (Smith and Brynjolfsson 2001), the nascence of online markets and the lack of geographical constraints expose consumers to new firms and unknown sellers. This "long tail" of tens of thousands of small businesses, not being served by conventional means of advertising (Anderson 2005), diminishes the role of brand name in consumer decision making, and increases the reliance on other indirect informational cues such as advertising and the price charged by the sellers.

Although the importance of advertising and price as signals of quality have been well established in traditional markets (Peterson 1970; Gerstner 1985; Milgrom and Roberts 1986; Kirmani and Wright 1989), little is known about their effects on consumer behavior in electronic markets. In particular, online sponsored search markets have several unique characteristics that differentiate them from traditional contexts. Unlike traditional media settings where firms pay for advertising using a pay-per-exposure model, in online sponsored search contexts, firms pay-per-click. The former mode of advertising requires significant lump-sum investments, while the latter makes it economically feasible for smaller and less well-established firms to compete more

intensely for customers. Further, sponsored search listings create a “directional” market where consumers find it easier to search and visit the sellers in a sequential order from top to bottom. The implications of market directionality on consumer behavior have not been addressed in the literature.

This research is motivated by the growing popularity of online markets and the fact that consumer behavior in the type of unique informational environment created by sponsored search advertising is not well understood. I focus on the effects of informational cues on consumer behavior and examine the relative importance of price and advertising as quality signals in search and purchase decisions. I use data from a laboratory experiment to address four specific research questions: 1) Can sponsored search advertising serve as a signal of quality and if so, under what circumstances? 2) How do perceptions about the correlation between a seller’s advertising expenditure and quality affect consumers’ search and purchase behavior? 3) How does the price signal influence consumers’ reliance on advertising signals in their purchase decisions? , and 4) How does the risk attitude of consumers affect their reliance on indirect cues provided by the informational environment?

The findings show that in contrast to behavior in traditional markets where price tends to be the dominant signal of quality, firms’ relative advertising expenditures serve as a stronger signal of quality in online sponsored search markets – a result attributable to the directional nature of the online setting. I also find that the risk attitude of consumers has a significant impact on consumer beliefs and market outcomes. I discuss the implications of the findings for sellers and consumers using sponsored search markets, as well as for search intermediaries.

The rest of the chapter is organized as follows. Section 3.2 previews the sponsored search literature and other relevant literature from economics, marketing and information systems that has studied consumer search and purchase behavior under quality uncertainty. In section 3.3, I present the research hypotheses. The research methodology is described in section 3.4, followed by results in section 3.5. Section 3.6 provides a discussion of the findings and their implications and Section 3.7 concludes the chapter.

3.2 THEORETICAL BACKGROUND AND PRIOR RESEARCH

Research from a variety of disciplines is relevant to understanding consumer behavior in the presence of information asymmetries. I first review work focused specifically on the sponsored search context and studies that have examined the availability of information in online markets. This is followed by a discussion of research related to *consumer search*, and *quality signaling* in markets with asymmetric information. The overall conceptual model depicting the relationship between quality signals and consumer behavior that frames this research is shown in Figure 3.1. Consumers are exposed to different signals of quality in online markets and use these signals to form beliefs about the extent to which specific signals denote higher quality. These beliefs then influence online search and purchase behavior.

3.2.1 Sponsored Search and Online Information Contexts

Research on sponsored search advertising is still in a nascent stage. Prior research in this field predominantly approaches the phenomenon from an auctions perspective to examine the interaction between market-makers and sellers who bid in these auctions. One stream of research focuses on designing better rank/position allocation mechanisms from the perspective of the search intermediary (Aggarwal, Goel et al. 2006; Asdemir 2006;

Lahaie 2006; Edelman, Ostrovsky et al. forthcoming; Feng, Bhargava et al. forthcoming; Varian forthcoming), while a second identifies optimal bidding strategies from the perspective of sellers (Kitts and Leblanc 2004; Borgs, Chayes et al. 2006; Rusmevichientong and Williamson 2006). In addition, a few studies examine the market dynamics that result from sponsored search auctions (Animesh, Ramachandran et al. 2006; Edelman and Ostrovsky forthcoming). However, there is limited research examining consumer search behavior in this context, or the implications of sponsored search mechanisms for seller strategies. In one of the few academic studies on consumer behavior in the sponsored search context most directly related to this work, Jansen and Resnick (2005) examine the perception of searchers towards sponsored search listings and find, not surprisingly, that compared to organic search listings, consumers are skeptical of sponsored search results and trust them less.

Other work in information systems has examined the impact of online markets on the availability of price and quality information, and how the online provision of such information affects consumer welfare (Bakos 1997; Brynjolfsson and Smith 2000; Smith 2001; Smith and Brynjolfsson 2001; Baye and Morgan 2002; Baylis and Perloff 2002; Bakos, Lucas et al. 2005). A significant body of research also examines online consumer behavior (Jarvenpaa, Tractinsky et al. 2000; Koufaris 2002; Gefen, Karahanna et al. 2003; Pavlou 2003), however, there is limited research that investigates the impact of online advertising on consumer behavior (Gao, Koufaris et al. 2004; Hong, Thong et al. 2004; Wu, Cook Jr. et al. 2005). In one of the few information systems studies on online advertising, Gao et al. (2004) conduct an experiment to compare the effect of animated versus pop-up advertisements on consumers' perceptions. They suggest that the online

format and presentation of information has significant consequences for consumers' perceptions and attitudes.

As noted earlier, the sponsored search format differs from traditional mass media in three key respects: 1) the spatial and temporal proximity of price and advertising information in sponsored search advertising facilitates consumer access to and comparison between the two pieces of information, 2) sellers presented in list are sorted by their advertisement intensity, and 3) there is no search effort required to assess the relative advertisement expenditure information, however gathering price information imposes a search cost (in terms of time and effort), although this is typically lower than in the traditional channel. As a result of these unique characteristics, consumer behavior in the sponsored search market is likely to differ significantly from offline shopping and purchase behavior and, therefore, warrants systematic examination.

Studies suggest that subtle changes in information presentation formats can influence information search costs and subsequent consumer choice behavior (Payne, Bettman et al. 1993; Hoque and Lohse 1999; Lynch and Ariely 2000; Mandel and Johnson 2002). For instance, Hoque and Lohse (1999) conduct an experiment to examine consumer behavior in online settings and find that consumers search sellers in sequential order and therefore suggest that, unlike traditional yellow pages, online yellow pages should charge advertisers based on their rank in the advertising list. They recommend that since online media exhibit different relationships than print media for some variables, researchers should strive to obtain a deeper understanding of consumer information processing and decision making processes. Consistent with this stream of research, I examine the

efficacy of different quality signals – primarily, price and advertising intensity - in the sponsored search setting and their impacts on consumer behavior and market outcomes.

3.2.2 Consumer Search and Quality Signaling

Consumer search behavior has been extensively studied in various disciplines such as economics, marketing, psychology, and information systems. Recognizing the importance of understanding consumers' online search behavior for the design of search engines and other information systems, researchers have turned their attention on consumer search in online markets (Browne, Pitts et al. 2007). One important stream of consumer search literature relevant to the current study examines consumer search behavior in markets that exhibit price dispersion (Stigler 1961). Analytical models (Stigler 1961; Bakos 1997) and empirical evidence (Schotter and Braunstein 1981; Ratchford and Srinivasan 1993; Zhang, Fang et al. 2006) suggest that consumers searching for a low price adopt a reservation price strategy. According to this strategy, a consumer calculates the reservation price based on the price dispersion and unit search cost, and buys from the first seller who meets this reservation price. However, much of the research in this stream either ignores quality dispersion or assumes quality to be identifiable prior to purchase. This study, on the other hand, examines consumer search behavior in markets where consumers cannot ascertain quality attributes prior to purchase.

It has been argued that markets with information asymmetries break down unless there are effective quality-signaling mechanisms. A signaling mechanism refers to informational cues provided by a seller that reveal his/her true quality. Researchers have identified various external cues (i.e., cues not directly related to product performance) – such as advertising, warranty, brand name, and product price – that can act as quality

signals (Grossman 1981; Milgrom and Roberts 1986). Of particular interest in the current context is the role of advertising expenditure and prices in providing informational cues related to quality. Studies in traditional settings show that consumers associate higher advertising expenditure with higher quality (Kirmani and Wright 1989). Unlike traditional media, the rank of the advertiser in the sponsored search listings by itself provides information about the seller's advertising expenditure (and possibly the seller's quality) relative to other sellers in the listing. Since a consumer using a sponsored search listing can also choose to search for prices across various sellers, it becomes important to understand how consumer's search behavior may be affected by the presence of the advertising signal.

Finally, in situations characterized by uncertainty such as the sponsored search market where consumers do not have *ex ante* knowledge of quality, evidence suggests that risk attitudes play a role in consumers' reliance on informational signals and their search strategies. A consumer faced with uncertainty about price and quality acquires information that may reduce the risk inherent in such an uncertain environment. Since there is heterogeneity among consumers in risk attitudes, their information acquisition strategy also varies. Prior findings indicate that risk-averse consumers search less than risk-neutral consumers in a search with recall scenario (Nachman 1975; Schotter and Braunstein 1981). Surprisingly, research on the role of advertising and price signals on consumer perceptions overlooks the effects of the risk attitude of consumers. Given the uncertainty faced by consumers in online markets, their risk attitudes are likely to strongly influence their reliance on the informational cues available in these markets. To obtain better insights into the relationship between consumer search and consumer's

reliance on signals, I extend this literature and examine the impact of consumers' risk attitude on search behavior and purchase decisions.

3.3 HYPOTHESIS DEVELOPMENT

Building upon the theoretical logic and findings reviewed above, Figure 3.2 depicts the research model that forms the foundation for this study. As shown there, I seek to explain three key outcomes in the sponsored search context: the consumers' *search intensity*, his/her *rank preference*, and the *price premium* paid. I define *rank preference* as a consumer's propensity to purchase from a seller appearing higher on the sponsored search listing. The three consumer outcomes are collectively determined by the interaction between consumers' quality beliefs related to advertising and price, and their risk attitudes. I define an advertisement (price) belief as the consumer's perception of a positive correlation between the seller's advertising expenditure (price) and quality. Thus, a consumer with a higher price belief relies more on the seller's price as a signal of quality as compared with a consumer with a lower price belief. These beliefs are shaped by the availability of quality signals related to advertising and price in the sponsored search market. Specific hypotheses for empirical testing are developed below.

3.3.1 Advertising and Price as Signals of Quality

Prior research shows that in offline settings firms' advertising expenditures can signal quality when consumers cannot infer the sellers' service/product quality prior to purchase. Experimental studies find that consumers associate higher advertising expenditure with higher quality (Kirmani and Wright 1989). In the sponsored search context, sellers are sorted on the basis of their advertising expenditure (i.e., the sellers who bid more get listed higher in the search results). However, as noted earlier, a large

proportion of consumers are unaware of how sellers obtain specific ranks in the sponsored search market, i.e., they are not aware that those appearing higher on the list have paid more. To the degree that consumers believe that higher advertising intensity is associated with higher quality, awareness of the advertisement allocation mechanism should enable them to infer the relative quality of the sellers in a sponsored search listing. Hence I test,

H1: *In a sponsored search market, consumers who are aware of the ranking mechanism will have a stronger advertisement belief than consumers who are unaware of the ranking mechanism.*

Researchers suggest that consumers may also use price as an informational cue to infer seller quality (Milgrom and Roberts 1986). A review of empirical studies provides evidence for a robust (though moderate) price-quality relationship (Rao 2005) across a variety of settings. I expect this relationship to hold in the online sponsored search context as well. However, while a firm's prices may serve as a signal of quality, the strength of this signal is likely to be attenuated in the presence of additional signals of quality (e.g., advertising) (Broniarczyk and Alba 1994). Thus I expect:

H2: *In a sponsored search market, consumers who are aware of the ranking mechanism will have a weaker price belief than consumers who are unaware of the ranking mechanism.*

Earlier studies find that consumers' beliefs about the price-quality correlation affects their search patterns (Roedder, Scott et al. 1986). Provided that quality dispersion is sufficiently high compared to price dispersion (i.e., there is a need to distinguish between

sellers), a strong belief in price as a signal of quality leads consumers to search for the highest price and pay a high price premium. Hence I test:

H3a: *In a sponsored search market, the stronger the consumer's price belief, the higher the price premium paid by the consumer.*

While information about a firm's relative advertising expenditure can be obtained from its ranking in the sponsored search results, consumers need to invest a greater effort (i.e., visit each seller's website) to obtain information about the prices charged by competing sellers. Because consumers incur a search cost to obtain price information, the benefits of additional search will be realized only in the presence of a strong price belief. That is, consumers who believe that price is a signal of quality will be willing to invest the time and effort necessary to locate the seller with the highest price. I define search intensity as the number of alternative sellers the consumer visits in the online market and test:

H3b: *In a sponsored search market, the stronger the consumer's price belief, the higher the consumer's search intensity.*

Finally, consumers relying on price as a signal of quality will tend to buy from a high price seller irrespective of the rank at which the seller appears on the listing. Thus, under the assumption that sellers' price is uncorrelated with sellers' rank in the search listing, consumers will not systematically attempt to purchase from the top ranked sellers in the search listings. Hence, I posit that:

H3c: *In a sponsored search market, the stronger the consumer's price belief, the lower the consumer's rank preference.*

Consumers who are aware of the ranking mechanism and believe in advertising as a signal of quality (i.e., they perceive a positive rank-quality correlation) would prefer to buy from sellers ranked higher on the list. Their awareness of the ranking mechanism would enable them to infer that sellers higher on the rank have higher advertising expenditure. Therefore I test:

H4a: *In a sponsored search market, for consumers who are aware of the ranking mechanism, the stronger the consumer's advertising belief, the higher the consumer's rank preference.*

Since a consumer with a strong advertising belief would prefer to buy from the topmost sellers in the listing, his/her search would be restricted to the few top ranked sellers. It follows that the extent to which this consumer engages in searching for sellers will be lower vis-à-vis consumers who have a weaker advertising belief. I test this expectation in the following hypothesis.

H4b: *In a sponsored search market, the stronger the consumer's advertising belief, the lower the consumer's search intensity.*

Finally, a consumer with a strong advertising belief will attempt to purchase from sellers appearing higher on the sponsored list, and is less likely to sample sellers appearing lower in the listing. Due to this constrained sampling, the consumer would not always be able to discover high-priced sellers in the market. As a result, on average, the price premium paid by this consumer would be lower. Thus, I posit:

H4c: *In a sponsored search market, the stronger the consumer's advertising belief, the lower the price premium paid by the consumer.*

3.3.2 Interaction between Price and Advertising Signals

Researchers have called for the need to understand the interactions among various signals of quality (Kirmani and Rao 2000; Purohit and Srivastava 2001). This takes on added significance in the context of sponsored search as a consumer has access to not only relative advertising expenditures, but also the relative prices charged by competing firms. In prediction tasks, it has been found that consumers' reliance on the price signal is stronger than their reliance on the advertising signal (Broniarczyk and Alba 1994). However, the tradeoff between these two signals has not been studied in the context of a purchase task. Earlier I theorized that a strong price belief influences the price premium paid, and a strong advertising belief influences the consumer's rank preference. Since a consumer would tend to rely on the signal in which he/she has a stronger belief (at the expense of other signals) and make a purchase decision consistent with the stronger quality signal, I hypothesize that:

H5: *In a sponsored search market, the stronger the consumer's advertising belief, the weaker the impact of the price belief on the price premium paid by the consumer.*

H6: *In a sponsored search market, the stronger the consumer's price belief, the weaker the impact of the advertising belief on the consumer's rank preference.*

3.3.3 The Effects of Risk Attitudes

Analytical models developed to derive optimal search strategies as well as signaling equilibria generally assume that the searcher is risk neutral. However, a consumer's optimal strategy may differ if this assumption is violated. As noted previously, researchers examining consumers' price search behavior in markets with quality uncertainty find that risk-averse searchers search less than risk-neutral searchers in a search with recall scenario (Nachman 1975). This is due to the fact that the benefit of

additional search is uncertain and hence, risky. Therefore, a risk-averse consumer would be satisfied with the current alternative even if the *expected* marginal benefit of searching for the next alternative is larger than the marginal search cost⁷. I test this expectation in the following hypothesis:

H7a: *In a sponsored search market, risk-averse consumers will have lower search intensity than risk seeking consumers.*

Although reliance on quality signals is unavoidable in markets with quality uncertainty, because the signal may not always be perfectly correlated with quality, risk-averse consumers are likely to prefer an informational cue which minimizes any potential loss. In situations where either price or advertising may signal quality, acting on the basis of a price signal can lead to larger loss than acting on the basis of an advertising signal, as in the former case, the consumer might end up paying a price premium for a low quality product. In other words, relying on a false advertising signal is less detrimental than relying on a false price signal. Therefore, a risk-averse consumer would prefer to use the advertising signal whereas a risk-seeking consumer would prefer to act on the price signal. Recall that reliance on the price signal results in a higher price premium while reliance on the advertisement signal yields a higher rank preference. I test the following hypotheses related to these effects:

H7b: *In a sponsored search market, risk-averse consumers will pay a lower price premium as compared to risk-seeking consumers. This effect will be stronger for consumers with advertising beliefs.*

⁷ In an experimental study, Schotter and Braunstein (1981) found support for this analytical proposition.

H7c: *In a sponsored search market, risk-seeking consumers will have a lower rank preference as compared to risk-averse consumers. This effect will be stronger for consumers with price beliefs.*

In summary, I drew from and extended research on quality uncertainty and signaling and consumer information search to propose hypotheses related to consumer outcomes in a sponsored search setting. Two key theoretical extensions to existing work embedded in the proposed model are first, the explicit incorporation of risk attitudes, and second, predictions about the relative efficacy of price and advertisement signals on consumer outcomes in the new context of online sponsored search. The experiment conducted to test the research hypotheses is described next.

3.4 METHODOLOGY

The dominant empirical strategy in prior research on quality signaling and consumer search behavior is that of an experiment as it is viewed as the most appropriate method for achieving a precise test of theory (Schotter and Braunstein 1981; Lynch and Ariely 2000; Srivastava and Lurie 2001; Zwick, Rapoport et al. 2003). Following this tradition, I employ an experimental methodology to test the research hypotheses.

3.4.1 Research Design

The experiment employs a one factor (knowledge of sponsored search mechanism) between-subjects factorial design where one group of subjects is informed that sellers are ranked in descending order on the sponsored search listing according to how much they pay per click (treatment group), and the other group of subjects is informed that all sellers in the market are randomly assigned a rank in the directory listing (control group). The

subjects are presented one set of general instructions and a set of specific instructions for their assigned experimental condition (See Appendix B1 for details).

The *control* group has 38 subjects, each of whom is informed that sellers are ordered randomly in the listing, while the treatment group consists of 42 subjects⁸, each of whom is informed that sellers are ordered in the listing based on their relative advertising expenditures. As is common in such experimental settings, undergraduate students in a large northeastern business school were recruited for this experiment. The subjects participate for course credits. In addition they are provided performance-based monetary incentives.

The experiment consists of three tasks: (1) A shopping task in which subjects make search and purchase decisions (See Appendix B2), and (2) A follow-up survey (see Appendix B3) in which subjects are asked questions about their beliefs about price and advertising as signals of quality. (3) A lottery selection task (see Appendix B4) to assess risk attitudes (Holt and Laury 2002).

Shopping Task: The shopping task requires subjects to conduct 10 shopping trips using a simulated online yellow pages directory. In each shopping trip, subjects query the directory for a particular product. The online directory presents a list of 10 sellers (identified by fictitious names) along with a link to visit their websites, in a rank-ordered listing. The information provided to consumers about the ordering of the sellers in the directory listing differs across different experimental treatments. The subjects are also informed about the price dispersion and the quality dispersion among sellers in each market. The quality dispersion (i.e., range of seller quality in a market) is four times the

⁸ Originally there were 43 subjects. However, one subject who did not complete the experiment was dropped.

price dispersion (i.e., range of prices in a market)⁹. Subjects can observe the price being charged by a seller but they have to incur a specified search cost to visit a seller's website and obtain the price being charged by that seller. The search cost at any point in time in a shopping trip is displayed on the top panel of the computer screen. Information about seller quality is not revealed to the subjects in any treatment at any time during the experiment. Subjects can, however, use advertising and/or price informational cues to infer a seller's quality. Subjects are asked to maximize their payoffs by buying from the highest quality seller at the lowest price while minimizing the total search cost.

The payoff function given to subjects is to maximize $U = Q - P - n * c$, where "Q" is the quality of the product purchased, "P" is the price paid for the purchased product, "c" is the cost to discover a seller's price and "n" is the total number of sellers searched. This utility function is similar to that used by Diehl, Kornish et al. (2003), except that it explicitly includes search cost in the specification. Price, seller quality, and search cost are all expressed in experimental dollars. The subjects are provided monetary incentives based on their performance in maximizing their payoff function (i.e., utility derived from the purchase).

Lottery Selection Task: I use a standard lottery selection task to assess the risk attitude of the subjects that requires them to make 10 decisions regarding lottery preferences. The ten lottery decisions are designed to evaluate choices between risky prospects when the probability of the higher payoff is varied in a systematic manner. Each decision involves choosing between a pair of lotteries referred to as option "A" and option "B". The subject is shown the payoff and the winning probability associated with

⁹ The rationale for higher quality dispersion is to ensure that the quality attribute - the key outcome of interest - is salient in the decision making process.

each lottery, and has to choose one of these lotteries to play. The subject is told to make each decision carefully as one of these decisions will be randomly selected to calculate subject's payoff. After the subject has submitted the 10 lottery decisions, one of the decisions is chosen randomly as the outcome. This lottery selection task is performed twice. In the second round, the procedure remains the same, except for the payoffs, which are incremented at a higher rate.

3.4.2 Measurement and Data

Knowledge of the sponsored search advertising mechanism is included as a dummy variable that is used to identify those subjects who have different sets of information. As noted earlier, this variable is manipulated by providing information about the existence of sponsored search advertising mechanism to the subjects in the treatment groups before they make search and purchase decisions. Subjects in the control group, on the other hand, are informed that the ordering of sellers in the listing is random.

After completing the shopping task, subjects report their beliefs about the correlation between sellers' price and sellers' quality as well as sellers' rank on the listing and sellers' quality. Since the relative advertising expenditures of sellers are determined by their rank in the sponsored search listing (in the *treatment* sample), I use the term rank-quality as being synonymous with advertising-quality. Quality beliefs are operationalized using self reported measures, the items for which are adapted from existing literature (Kirmani and Wright 1989; Kirmani 1997). I used a 7-point Likert scale for assessing the strength of the advertising and price beliefs where 7 represents "strongly agree that there is a positive correlation" and 1 represent "strongly disagree that there is a positive correlation". A composite of 3 items is used to create advertisement belief scale – HRHQ (cronbach's alpha=0.85) and a composite of 2 items is used to

create price belief scale – HPHQ (cronbach’s alpha=0.78). I conducted a factor analysis to assess the convergent and divergent validity of the scales. The results suggest that HRHQ and HRPQ are two distinct constructs. The items and factor analysis results are presented in Appendix B3.

The *dependent variables* -- *search intensity*, *price premium*, and *rank preference* – are calculated based on observed behavior, and are recorded using click-stream data. *Search intensity* (SearchIntensity) is measured as the total number of sellers visited by a subject in a given shopping trip. *Price premium* (PricePremium) is the difference between the price at which the subject purchased the product during a shopping trip and the lowest price in that market. *Rank preference* (RankPreference) is the rank of the seller from whom the subject made the purchase. It is reverse coded where 1 represents the highest rank (i.e., top rank on the list), and 10 represents lowest rank (i.e., the bottom rank on the list). Thus, a lower value of RankPreference reflects a higher rank preference, i.e., indicating an inclination towards selecting a seller located higher in the listing.

As described above, the risk attitude of subjects is assessed using the lottery selection task. Each lottery involves a choice between a high-risk and a low-risk (“safe”) option. The number of safe choices (captured in the variable Safe) reflects the risk aversion of a subject. Subjects who make 10 safe choices out of 10 decisions are considered to be extremely risk averse while subject who did not make any safe choices are risk-seekers (Holt and Laury 2002).

3.5 RESULTS

3.5.1 Manipulation Check

Recall that the key manipulation in the experiment is to provide information about the relative advertising expenditures of participating firms to the *treatment* group but not to

the *control* group. In the follow-up survey, subjects are asked two questions about the ranking of the sellers in the listing to test whether the treatment manipulation was successful or not. These two questions are “in your opinion, did the seller on the third rank incur a higher advertising cost than the seller on the fourth rank on the list” and “in your opinion, did the seller on the first rank incur the highest advertising cost than the rest of the sellers on the list”. Subjects responded on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). I create an “AdvertisingExpenditure” variable using these two items (cronbach’s alpha=.91) and conduct a t- test to examine if the two groups differ in terms of their knowledge about firms’ relative advertising expenditures. I find that subjects’ beliefs about the seller ordering differs significantly. The mean score for the treatment group is 5.93 whereas the mean score for the control group is 3.54 ($p < 0.001$), indicating that subjects in both the groups read and understood the instructions and the manipulation was successful.

Descriptive statistics shown in Table 3.1 suggest that as expected, subjects in the treatment group have a higher advertisement belief than subjects in the control group but the two groups are similar in terms of price beliefs. Interestingly, though the rank of the seller from whom the subjects purchase is not significantly different across the control and treatment groups, subjects in the treatment group pay a lower price premium than do control group subjects. I also find that, as desired, subjects in the two groups do not differ in terms of the risk attitude due to the random assignment procedure.

Variable correlations are shown in Table 3.2. The correlation coefficients suggest that the subjects in the treatment group have a stronger advertising belief and pay a lower price premium than those in the control group. Further, I find that subjects with price

beliefs pay a higher price premium. Subjects with strong advertising beliefs, on the other hand, pay a lower price premium and have a higher rank preference (i.e., more likely to purchase from sellers appearing on top of the listing). Interestingly, I also find that the price premium and the rank preference are positively correlated suggesting that subjects who have a rank preference also pay a high price premium.

3.5.2 Empirical Analyses

I hypothesized that awareness of the sponsored search allocation mechanisms will lead consumers to believe that sellers higher on the listing are of higher quality. A comparison of the distributions of seller quality beliefs held by subjects in the control and treatment group provides support for the hypothesis, H1. The results show that the advertisement belief (HRHQ) for the treatment group is significantly stronger than that for the control group. The mean score for the treatment group is greater than 4 (mean=4.60, $p<0.01$) which is the midpoint of the Likert scale, suggesting a neutral belief. On the other hand, the mean score for the control group is significantly lower than 4 (mean=2.44, $p<0.01$), indicating that subjects in the control group do not believe that seller rank and seller quality are related.

With respect to price beliefs, I find that subjects in both the groups have a high mean score on the scale measuring the perceived relationship between seller price and quality (HPHQ). The mean is 4.97 and 4.90 for control and treatment group, respectively. I compare the mean price belief scores across the two groups to test if the presence of the advertising signal lowers subjects' belief in the price signal. T-test results suggest that the strength of price belief does not differ across groups ($p=0.81$); hence I reject hypothesis H2.

Before examining specific hypotheses regarding impact of quality beliefs on consumer behavior, I take a closer look at differences in the shopping behavior of the subjects in the treatment and the control group. The distribution of the dependent variables is shown in Table 3.3. There is no difference in search intensities across the treatment and the control group. Approximately 50% of the subjects in both groups visit only two or three sellers. The distribution of the price premium paid shows that subjects in the treatment group pay a much smaller price premium as compared to the subjects in control group at every percentile. The distribution of the rank of the sellers from whom subjects bought the product shows that subjects in the treatment group buy from sellers higher on the listing (i.e., had a higher rank preference) as compared to subjects in the control group in every percentile, except 75th and 99th percentile. However the difference between ranks is small.

To statistically validate the differences in the subjects' behavior across the control and treatment groups, I conduct a MANOVA with SearchIntensity, PricePremium, and RankPreference, as the dependent variables, and the treatment dummy as the independent variable. Though the subjects in the treatment group (i.e., subject who are aware of advertising mechanism) pay a lower price premium than those in the control group (mean difference=10 units) and the subjects in the treatment group buy from sellers higher on the list compared to those in the control group (mean difference=0.4 unit), the difference between the groups is not significant (Wilks' lambda=0.93; p=0.13). However, the lack of any significant differences in the behaviors of the two groups could stem from the aggregation of subjects with one of the four different beliefs about quality – belief in neither signal, only advertising beliefs, only price belief, or beliefs in both advertising

and price signals. Therefore, I examine the subjects' behavior after taking into account their quality signal beliefs as proposed in the research model (see Figure 3.2).

The hypotheses related to consumer search and purchase behavior are tested using a set of three regression equations as specified below:

$$\begin{aligned} \text{SearchIntensity}_i = & \alpha_1 + \alpha_2 * \text{HRHQ}_i + \alpha_3 * \text{HPHQ}_i + \alpha_4 * \text{Safe}_i + \alpha_5 * \\ & \text{HRHQ}_i * \text{HPHQ}_i + \alpha_6 * \text{HRHQ}_i * \text{Safe}_i + \alpha_7 * \text{HPHQ}_i * \text{Safe}_i + \alpha_8 * \text{HRHQ}_i * \text{HPHQ}_i * \\ & \text{Safe}_i + e_i \end{aligned} \quad (4)$$

$$\begin{aligned} \text{PricePremium}_i = & \beta_1 + \beta_2 * \text{HRHQ}_i + \beta_3 * \text{HPHQ}_i + \beta_4 * \text{Safe}_i + \beta_5 * \text{HRHQ}_i * \text{HPHQ}_i \\ & + \beta_6 * \text{HRHQ}_i * \text{Safe}_i + \beta_7 * \text{HPHQ}_i * \text{Safe}_i + \beta_8 * \text{HRHQ}_i * \text{HPHQ}_i * \text{Safe}_i + e_i \end{aligned} \quad (5)$$

$$\begin{aligned} \text{RankPreference}_i = & \gamma_1 + \gamma_2 * \text{HRHQ}_i + \gamma_3 * \text{HPHQ}_i + \gamma_4 * \text{Safe}_i + \gamma_5 * \\ & \text{HRHQ}_i * \text{HPHQ}_i + \gamma_6 * \text{HRHQ}_i * \text{Safe}_i + \gamma_7 * \text{HPHQ}_i * \text{Safe}_i + \gamma_8 * \text{HRHQ}_i * \text{HPHQ}_i * \\ & \text{Safe}_i + e_i \end{aligned} \quad (6)$$

where i stands for the subject.

Because the dependent variables in these three equations are generated as the result of a subject's action, the error terms may be correlated across the equations. I conduct a Breusch-Pagan test and find that the error terms are correlated (Chi-Sq[3] = 22.189, $p < 0.01$). Therefore, to account for correlated error terms, I use a seemingly unrelated regression (SUR) model¹⁰. Because the independent variables across the equations do not change, the regression coefficients in the SUR model will be the same as ordinary least square (OLS) model, however, the SUR model will be more efficient as the error terms are correlated. The results of SUR analysis are presented in Table 3.4. I first test a model without risk attitude (i.e., Model A) and then introduce risk attitude and the corresponding interactions in the next model (i.e., Model B). The coefficients of quality signals are similar across the two models.

¹⁰ I also conducted multivariate regression and the results are consistent with SUR analysis.

The SUR results indicate that subjects with varying types and levels of quality signal beliefs do not differ in terms of their search intensity. Thus I do not find support for hypotheses H3b and H4b. Further, I find that the subjects' risk attitude does not affect their search intensity (results are in the expected direction but not significant) leading to the rejection of hypothesis H7a.

In examining how the price premium that subjects' pay depends on their beliefs in price and advertising as signals of quality, I find that subjects with a stronger price belief pay a larger price premium. A unit increase (from the mean levels) in the strength of the price belief leads to an increase of 4.98 units in the price premium paid by subjects. On the other hand, subjects who believe in a positive advertising-quality correlation pay a lower price premium. A unit increase (from the mean levels) in the strength of the advertisement belief decreases the price premium paid by 4.20 units. These results provide support for hypotheses H3a and H4c.

In examining the effect of interaction between price beliefs and advertising beliefs on price premium I find that the interactions are not significant, suggesting the lack of any moderating effects of the advertisement belief on the relationship between the price belief and the price premium paid. While the risk attitudes of the subjects do not directly impact their price or rank premium, I find some evidence of a higher level interaction between price beliefs, advertisement beliefs, and the risk attitude of subjects ($\beta=-0.78$; $p=0.09$). This suggests that the risk attitude of the subjects moderates the impact of the price and advertising beliefs on the outcomes. The three-way interaction graphs are presented in Figure 3.3.

Panel A and Panel B graph the interaction between the price belief and the advertising-belief for subjects with different risk attitudes. It is clear that the price belief leads to higher price premium whereas the advertisement belief lowers the price premium. As seen in Panel A which represents risk-averse subjects, the impact of the price belief on price premium is significantly weaker for those risk-averse subjects who believe in a positive correlation between advertising expenditure and quality. Panel B presents the interaction graph for risk-seekers. The graph suggests that risk-seekers who have a stronger advertisement belief but not price belief, pay a lower price premium. However, risk-seekers who have a stronger price belief pay a similar price premium irrespective of their belief in the advertising-quality signal. Thus, I find qualified support for hypothesis H5 (i.e., the advertisement belief moderates the relationship between price beliefs and price premium); however, the strength of the moderation is determined by the risk attitude of the subject.

Panel C and D present an alternative representation of three way interaction by plotting the graph between price beliefs and the risk attitude for subjects with differing levels of advertisement beliefs. The results show that the price beliefs lead to a higher price premium and the advertising-quality signal lowers the price premium. Further, I find that, in the absence of advertisement beliefs, risk-averse subjects are more likely to act on the price signal and pay a higher price premium than risk seeking subjects. However, in the presence of strong advertisement beliefs, risk averse subjects switch to an advertising signal and pay a lower price premium than risk seekers (irrespective of their price beliefs). Thus I find qualified support for Hypothesis 7b (i.e., risk-averse

consumers will pay a lower price premium as compared to risk-seeking consumers in the presence of an advertisement belief).

The result of the rank preference regression shows that subjects with a stronger belief in the advertising-quality signal tend to buy from sellers higher on the list, supporting hypothesis H4a. The main effect of price beliefs on rank preference as well as the interaction effect is not significant. Thus, I do not find support for hypothesis H3c (i.e., price belief lowers the rank preference), hypothesis H6 (i.e., price belief weakens the effect of the advertisement belief on rank preference) and H7c (i.e., risk seeking consumers have a lower rank preference than risk averse consumers).

3.6 DISCUSSION

This research was motivated by the observation that online search has become a consequential activity for consumers using electronic markets. As a result, sellers are increasingly relying on new and emerging mechanisms such as sponsored search advertising to reach these consumers. The sponsored search context creates a unique informational environment that is characterized by a number of features including significant information asymmetry, directionality, readily available comparative information about advertising expenditure, and price information for which consumers incur a search cost. I sought to understand how consumer search and purchase processes unfold in this emerging context.

Empirical results suggest that awareness of the sponsored search allocation mechanism (i.e., firms ranked higher incur higher advertising expenditure) has the potential to influence consumers' online shopping behavior. While this awareness does not change the consumer's search intensity (i.e., overall click-through rates), the click-

through as well as conversion rates increase at higher listing ranks. Consumers who have information about the sponsored search allocation mechanism use the rank of the firms as a proxy of relative advertising intensity of the firms, and form beliefs about advertising as a signal of quality. Their beliefs are reflected in their search and purchase behavior. In addition to the advertising signal, consumers also use price as a signal of quality.

Price versus Advertising as Signals of Quality

I find interesting dynamics between *advertising* and *price* as signals of quality in the sponsored search context. The results show that consumers who have knowledge of the allocation mechanism of the sponsored search results believe that firms appearing higher on the listings are of higher quality (i.e., they exhibit a strong advertisement belief) and therefore, behave differently than those who are unaware of the rank allocation mechanism. Specifically, I find that consumers who have a stronger belief in price as a signal of quality pay a higher price premium and consumers who have a stronger belief in advertising as a signal of quality have a higher rank preference (i.e., are more likely to buy from firms appearing on the top). However, a belief in advertising as a signal of quality weakens the price signal, and leads a consumer to pay a lower price premium. A belief in price as a signal of quality, on the other hand, does not influence the rank preference. This finding is contrary to extant research which suggest that price signals strongly dominate advertising signals (Broniarczyk and Alba 1994). The striking difference can be attributed to the unique characteristic of the sponsored search advertising medium which informs consumers about the relative advertising intensity/expenditure of all the firms within the market.

Risk Aversion and Reliance on Signals

The results also highlight the importance of understanding consumers' attitudes towards risk in order to explain their reliance on price and advertising signals. I argued that risk seeking and risk-averse subjects are likely to adopt different strategies when they hold different beliefs about price and advertisement signals. As expected, I find that risk-averse subjects differ from risk seekers in terms of their reliance on signals. However, contrary to expectations, I find that among those consumers who do not have advertising signal beliefs, risk-averse consumers pay a higher price premium than risk seekers. Interestingly, the price premium paid by risk-averse consumers is significantly lower than risk seeking consumers in the presence of an advertisement belief. Thus, the results indicate that while risk-averse consumers are more likely to rely on signals under uncertainty, given a choice of signals they prefer signals that are less risky.

Prior to discussing its implications, I acknowledge the limitations of the study. First, the use of student subjects may weaken the external validity of the findings. However, this should not be a serious concern as students routinely make purchase decisions therefore should have formed their beliefs about signals based on their experiences, like any other consumer. Even if the findings may not be generalized to larger population, the results should hold for an important demographic -- students. Second, to tease out the marginal effects of the two competing quality signals, I focused on market situations where price and advertising are uncorrelated. However, it is possible that some markets exhibit a positive or negative correlation between price and advertising. It is not clear whether these findings will be applicable to those market situations. For example, it is possible that positive correlation between price and advertising may strengthen consumers' belief in both the quality signals. Thus, the

congruent signals may lead to high price premium as well as higher rank preference. On the other hand, negative correlation between price and quality may weaken consumers' beliefs in signals, and the incongruent signals may either make consumer disregard any signal or rely on the stronger signal. Therefore, it would be interesting to extend this study by examining consumer behavior in the present of congruent versus incongruent signals.

3.7 CONCLUSION

Overall, the results of this study have significant implications for the sellers using sponsored search listings, as well as for online intermediaries managing sponsored search auction markets. It appears that though the overall click through rate might not change as more consumers become aware of the sponsored search mechanism, the click through and conversion rate at higher ranks may increase. Consumers may buy from a seller on a higher rank regardless of whether the price is higher or lower than other sellers. Thus, sellers need to take into account both the pricing as well as the advertising strategies to maximize their profits. Online intermediaries, on the other hand, need to ensure that their advertisement allocation mechanism remains consistent with the consumer's advertisement belief. Otherwise, in the long-run consumers may avoid clicking and buying at the top ranks, thus leading to the collapse of the auction mechanism to allocate the advertisement ranks.

Search intermediaries such as Yahoo! and Google are constantly experimenting with various rank allocation mechanisms -- such as "pay per click", "pay per action" or willingness to "pay per impression" (Lee 2002; Newcomb 2005), with the objective of getting the advertisers to reveal their true valuation for appearing on higher ranks in the

search listings. The findings suggest that search intermediaries as well as researchers developing analytical models to compare different rank allocation mechanisms should also take into account the possibility that information about the allocation mechanism may itself affect consumers' behavior which in turn may influence sellers' valuations and ultimately search intermediaries profits.

The results also underscore the fact that consumer behavior in online markets is significantly different than that in traditional markets due to the unique informational environments created by the online medium. The findings provide further evidence that subtle changes in the online format and presentation of information and/or the amount of information consumers have about the online market mechanisms, such as sponsored search advertising, may have significant consequences on consumers' perceptions and attitudes. These beliefs and perceptions in turn will dictate consumers' interactions with the online markets and information systems and their online behavior. An understanding of the factors that may affect consumers behavior is important, especially in the context of sponsored search advertising, because consumer search and purchase strategy – manifested in the click-through and conversion rate at various ranks in the sponsored search listing significantly affects the revenues and strategies of advertising intermediaries and the advertisers in this multi-billion emerging industry. Consumer welfare is also affected as a result of the interaction of sellers advertising strategies and consumer search strategies, which has implications for policy makers.

As noted earlier, a large proportion of consumers are unaware that the sponsored search listing are generated as a result of auction outcomes where advertisers bid against each other to get better placement. Based on the findings, I believe that making

consumers aware of the allocation mechanism may help the search engines and advertising intermediaries. The advertisement beliefs of consumers may increase the conversion rates at top ranks, thereby increasing the competition in the sponsored search auctions for the top slots in the listing, and a consequent increase in the monetization of the online real estate. Future studies should also examine how different interface design and provision of additional information about seller quality and price in the listing may affect consumer search and purchase behavior. This study focused on the “pay per click” mechanism. Future work should extend this study and compare consumers’ advertising-quality belief across different allocation mechanisms and to examine its impact on search intermediary profits, advertiser profits and consumer welfare.

This study makes several important contributions. It is among the first to examine whether knowledge of the sponsored search advertising mechanism affects consumer perceptions about the quality of sellers, and their subsequent purchase behavior. It is also among the very few that examines the interactions among different informational cues/signals on consumer behavior. Further, in contrast to extant research investigating the role of advertising as a signal of quality, this study measures the effect of advertising expenditure not only on perceived quality, but also on observed behavioral outcomes such as search intensity, price sensitivity and consumers’ purchase decisions. Finally, to the best of my knowledge, this is the first study to examine the influence of consumers’ risk attitudes on their use of informational cues.

CHAPTER 4: PRICE, QUALITY AND ADVERTISING RELATIONSHIP IN ONLINE DIRECTIONAL MARKETS

ABSTRACT

Though there is extensive literature examining the relationships between price, quality and advertising in the traditional market, it is not clear how the unique characteristics of online directional advertising medium, such as comparison shopping, may affect these relationships. Given the lack of research in this field, I empirically examine the relationship between advertising intensity of the advertisers and their price and quality attributes in online directional markets. Interestingly, I find that unlike majority of the traditional results, higher quality firms and lower priced firms are more likely to have higher advertising intensity. I attribute these results to the tradeoff between a firm's conversion rate and its profit margin and the counteracting effect of price and quality on these two forces.

4.1 INTRODUCTION

Comparison shopping engines provide a platform to the firms to advertise and reach the consumers who are actively searching for a specific product. However, unlike traditional advertising, comparison shopping advertising not only informs consumers about price and quality but also directs consumers' search (Arbatskaya Forthcoming). While there is extensive literature examining the relationships between price, quality and advertising in the traditional market, it is not clear how the unique characteristics of online directional advertising medium, such as comparison shopping, may affect these relationships. It is important to understand firms' strategies and market outcomes in directional markets as advertising directs consumer search which would have a significant impact on consumer welfare, profitability of the firms in the market and the profitability of the advertising platform provider. Given the lack of research in this field, I empirically examine the relationship between advertising intensity of the advertisers and their price and quality attributes in online directional markets. Interestingly, I find that unlike majority of the traditional results, higher quality firms and lower priced firms are more likely to have higher advertising intensity.

The rest of the chapter is organized as follows. Section 4.2 presents a brief overview of the research on advertising, price and quality in traditional and online markets. Section 4.3 formulates the economic model for the advertising decision of a firm in the comparison shopping context. The research methodology is described in section 4.4, followed by results in section 4.5. Section 4.6 provides a discussion of the findings and their implications, and Section 4.7 concludes the chapter.

4.2 RELEVANT LITERATURE

While there is a large amount of research examining online consumer behavior (Jarvenpaa, Tractinsky et al. 2000; Koufaris 2002; Gefen, Karahanna et al. 2003; Pavlou 2003) and impact of online advertising on consumer behavior (Gao, Koufaris et al. 2004; Hong, Thong et al. 2004; Wu, Cook Jr. et al. 2005), there is limited research that investigates the online advertising strategies of firms. In this study, I examine the affect of the price and quality of a firm's product/service on its advertising intensity in online markets. Specifically, I focus on directional markets created by online intermediaries such as search engines and comparison shopping engines.

As mentioned earlier, online directional markets provide an ordered listing of firms selling a specific product and consumers generally search the listing sequentially from top to bottom. Researchers suggest that strategies employed by the firms and the resulting competition dynamics in such directional markets may be different from those in the traditional media (Perry and Wigderson 1986; Arbatskaya forthcoming). For instance, Arbatskaya (Forthcoming) suggests that these markets would exhibit positive correlation between advertising expenditure and price (i.e., firms paying more to appear higher on the listing will charge higher price). However, this proposition has not been tested empirically. To the best of my knowledge, there is no study that examines the relationship between quality and price and/or quality and advertising in online directional markets, with the notable exception of Animesh et al. (2006) and Edelman (2006). I extend this stream of research by empirically examining the relationship between price and quality, and price and advertising in a comparison shopping market.

Economists have employed analytical models to examine the relationship between price, quality and advertising decisions of a firm in traditional markets. However, the results are inconclusive. Nelson (1974) argued that lower price and higher quality products are more likely to advertise. Kihlstrom and Riordan (1984) also suggest that higher quality firms will advertise more, given that the cost difference between low and high quality firms is sufficiently low. On the other hand, Schmalensee (1978) argues that lower quality firms may advertise more, especially if consumers are responsive to advertising. Comanor and Wilson (1979) also suggest that high priced and low quality products are more likely to be advertised. There is another stream of research which claims that higher quality firms (Orzach, Overgaard et al. 2002) and higher priced firms (Bagwell and Overgaard 2005) will have modest advertising expenditure (i.e., neither too low not too high) or may even have lower advertising levels (Zhao 2000).

Given the conflicting results in the theoretical literature, Archibald et al. (1983) suggest that “the relationship between advertising and quality is an empirical question”. Interestingly, empirical research investigating the relationships between the three important variables – price, quality and advertising in traditional markets is also inconclusive (Oxenfeldt 1950; Wills and Mueller 1989; Caves and Greene 1996; Nichols 1998; Thomas, Shane et al. 1998). One stream of empirical studies examines the impact of advertising on the price and/or quality across markets with different advertising regimes. Benham (1972) compared the eyeglasses market in different American states and found that prices were lower in states where advertising was allowed. Kwoka (1984) examined optometry market and observed that when firms are allowed to advertise, firms that advertise lower their price and their quality whereas the non-advertisers increase

their quality. Other stream of empirical research focuses on the differences across firms in terms of their advertising, pricing, and quality. Thomas et al. (1998) examined firm's advertising intensity as a function of unobserved quality and price¹¹. They found that, in automobile market where product quality cannot be completely determined until after purchase, higher price products and higher quality products will have higher advertising levels. Archibald et al. (1983) also show that both price and quality are positively correlated to advertising expenditure. Caves and Greene (1996), on the other hand, conclude that advertising and quality are unrelated across brand in the 200 product categories that they studied. It is important to note here that this stream of research has primarily relied on the signaling role of advertising to understand the relationship between price, quality and advertising. I extend this stream of research in the domain of online directional markets where the main role of advertising is to direct consumer search in addition to providing information about price and quality.

The model that I employ is closest to the one developed by Tellis et al. (1988). They propose a set of equations predicting relative advertising, market share, relative cost, and profit of a firm. In the equation predicting relative advertising they model advertising as a linear function of relative price and relative quality (where both variables are exogenous variables), in addition to other variables. Their results suggest that higher quality products have higher advertising intensity.

¹¹ However, they do not include both price and quality in the same model.

4.3 THE MODEL

I develop a simple model to understand the relationship between price, quality and advertising intensity in online directional markets. The profit function for the firm participating in a comparison shopping advertising market can be written as:

$$\pi(p, q, A) = [V(p, q) * R(p, q) * X(p, q, A)] - [A * X(p, q, A)]$$

where V is the *profit margin per unit*, A is the unit cost of attracting a consumer to the firm's store, X is the number of consumers who visit the firm's store (i.e., *click-through rate*), R is the probability that a visitor will actually purchase (i.e., *conversion rate*), p and q are the *price* and *quality* of the product/service, respectively.

I assume that a firm's quality is exogenously determined. A consumer in the market cannot observe the real quality of the firms with certainty. Therefore, following the tourist-native logic (Salop and Stiglitz 1977; Baylis and Perloff 2002), firms may charge different prices which may not necessarily be a function of their real quality (i.e., some firms are good and some are bad). Given the quality and price, a firm can choose to influence the demand by advertising to maximize its profits. Assuming this to be so, the optimal advertising (A^*) be derived as:

$$V(p, q) * R(p, q) \frac{\partial X(p, q, A)}{\partial A} - X(p, q, A) - A^* \frac{\partial X(p, q, A)}{\partial A} = 0 \quad (1)$$

$$A^* = V(p, q) * R(p, q) - \frac{X(p, q, A)}{\frac{\partial X(p, q, A)}{\partial A}} \quad (2)$$

I chose the following specifications for profit margin per unit, click-through and conversion rate functions. Profit margin per unit (V) is expected to increase with P but decrease with increasing Q as specified below:

$$V = \exp(\gamma_0 + \gamma_1 p - \gamma_2 q) \quad (3)$$

It has been observed that the number of potential customer visits to a firm's website is an exponential function of the rank of a firm on the listing (Animesh, Viswanathan et al. 2007). Now, we know that by increasing the per unit advertising bid (i.e., cost per click) a firm can obtain higher rank in the comparison shopping market by outbidding other firms in the online auction. Thus I model X (clickthrough rate or potential demand) as an increasing function of A (advertising expenditure). Further, the number of visits received by a firm (i.e., potential consumers/demand) is also expected to vary as a function of price (P) and quality (Q) of the firm's product/service. I assume that X will be an increasing function of Q and a decreasing function of P. This specification is similar to that of Cowling and Cubbin (1971).

$$X = \exp(\beta_0 - \beta_1 p + \beta_2 q) A^{\beta_3} \quad (4)$$

The specification for R (conversion rate) is similar to X. However, I do not model conversion rate to vary as a function of A.

$$R = \exp(\alpha_0 - \alpha_1 p + \alpha_2 q) \quad (5)$$

Though the particular functional form is chosen primarily for analytical and empirical tractability, the specifications model the essence of the relationship between variables. The reason for assuming these specific functional forms is to transform the model to a version that is linear in the parameters of interest and thus facilitate empirical estimation. The impact of P and Q on V and R is depicted in Figure 4.1.

Using equation (3), (4), and (5) and solving for A* as defined in equation (2), we get:

$$\frac{A^{*(\beta_3+1)}}{\beta_3} = \exp(\gamma_0 + \gamma_1 p - \gamma_2 q) * \exp(\alpha_0 - \alpha_1 p + \alpha_2 q)$$

Let $k = \frac{(\beta_3+1)}{\beta_3}$. Taking log on both sides we get.

$$\log(kA^*) = \gamma_0 + \alpha_0 + (\gamma_1 - \alpha_1)p + (\alpha_2 - \gamma_2)q$$

$$\text{i.e. } A^* = \theta_0 + \theta_1 p + \theta_2 q \quad (6)$$

$$\text{where } \theta_0 = \gamma_0 + \alpha_0; \theta_1 = \gamma_1 - \alpha_1; \theta_2 = \alpha_2 - \gamma_2$$

I use equation (6) as the basis of the econometric model. If $\theta_1 > 0$ then one can infer that $\gamma_1 > \alpha_1$ (i.e., the positive effect of higher price on per unit margin is larger than the negative impact of higher price on R or in other words, loss of conversion efficiency is compensated by larger profit margin per unit). If $\theta_2 > 0$ then one can infer that $\alpha_2 > \gamma_2$ (i.e., the positive effect of higher quality on R is larger than the negative impact of higher quality on the cost of production).

Further, it is possible that price and quality attributes of a firm may interact to determine the firm's advertising intensity. Given the two dimensions -- price and quality, we can construct a 2X2 matrix to understand the tradeoff between conversion rate and profit margin due to varying price and quality attributes of a firm (refer Table 4.1). The firms having lowest price and highest quality product/service would be the best deal for the consumers and I refer to them as "cherries". These firms would have lowest profit margin (as per equation 3) but highest conversion rate (as per equation 5). On the other extreme are the firms having highest price and lowest quality and I term them as "lemons" as these firms offer the worst deal to the consumers. These firms would have highest profit margin (as per equation 3) but lowest conversion rate (as per equation 5). The other 2 types of firms which either have high price and high quality or have low price and low quality can be considered as offering "fair deal" and their profit margin and conversion rate would lie somewhere between the two extremes of "cherries" and "lemons". To examine which of these four types of firms are most likely to advertise, we

can modify the model shown in equation 6 by including an interaction term between price and quality.

$$A = \beta_0 + \beta_1 p + \beta_2 q + \beta_3 pq \quad (7)$$

Based on the profit margin and conversion rate tradeoff that drives the advertising intensity, I expect that either the cherries or the lemons will have the highest advertising intensity. Which one of these two types of firms will advertise more would depend on strength of the effect of price and quality on conversion rate vis-à-vis contribution of the price and quality attribute on a firm's profit margin (per unit).

4.4 DATA

Caves and Greene (1996) call for “studies that are more closely focused (individual product markets?) or gain access to better data on the extent and adequacy of buyers' information sets”. Unlike traditional studies, I examine the relationship at the most granular level i.e., individual product markets having only those firms who are in a consumer's information set.

Data Description

I collect data from a comparison shopping engine, hereafter referred as CompShop, which is one of the largest comparison shopping engines. This shopping engine reaches 15% of online shoppers each month and held more than 15% of the market share in 2005. As shown in Figure 4.2, the engine displays a list of firms selling a specific product to the consumer who searched for that product.

The listings provide the price charged by the firms and the quality ratings of the firms, in addition to other relevant information. CompShop allots top 3 ranks on the

shopping list to the firms who emerge as the top 3 bidders in an auction conducted by it. Firms willing to pay more (i.e., having higher advertising intensity) for every potential customer visit to their website get higher rank in the listing. Other firms in the market have lower advertising intensity than these top 3 firms and are ordered in the listing based on the price of their product. I examine the relationship between price, quality and advertising (i.e., reflected in the rank that a firm buys on the listing) in this market.

I collect data for 221 specific products (such as “Canon EOS 400D / Rebel XTi Body Only Digital Camera”, “Coby CX-CD114 Personal CD Player”, “Casio Exilim EX-S600 Digital Camera”, etc.) within 6 broad electronics product categories (camcorder, camera, notebook, palm/PDA, CD/DVD player, CD/DVD Recorder) over a period of 28 days. Data includes the rank of the firms in the listing, quality rating of the firms (provided by consumers), number of consumers who rated the firm, price of the product, shipping and tax, presence of logo and other special text/image, etc.

I use the rank of a firm in a product listing as a proxy of its advertising intensity as the top three featured firms are ranked based on their advertising intensity. However, since the firms below the third slot are ordered based on their price instead of their advertising bids, I do not observe their relative advertising/bidding intensity. In other words the advertising intensity is censored and ranges between 1 and 3. I code the rank variable as 3 for the featured firm on the first rank, 2 for the second featured firm, 1 for the third featured firm, and zero for the rest of the firms in the listing (i.e., the firms that had bid lower than the 3rd highest bidder). The price variable captures the total price that a consumer would have to pay to buy from a firm. The quality proxy is calculated by multiplying the average customer ratings for a firm (which range from 0 to 5) by log(total

number of customers who rated the firm)¹². I create average rank, average price and average quality across the 28 days time period for each of the firms in a market. Then, I create AdRank variable by sorting the firms in ascending order, based on the average rank within a product market, and assigning a rank such that the firm which had the highest average rank was assigned Adrank=(n-1) where n is the number of firms in that product market¹³. Similarly I create PriceRank, and QualityRank variables. I also create a dummy variable, “Advertiser”, which is equal to one if a firm advertises in a product market (i.e., appears in the top 3 ranks) and zero otherwise. To distinguish between firms who sell a wide variety of products from the firms who specialize in fewer products, I create “MarketPresence” variable which measures the number of product markets in which a firm competes (i.e., a proxy for product variety/assortment).

Further, I supplement this dataset by collecting additional information about firms’ characteristics from Alexa.com. Specifically, I collect a firm’s overall traffic rank (which is a proxy for the brand equity of a firm) and the duration of a firm’s online existence. Similar to AdRank, PriceRank, and QualityRank, I create TrafficRank¹⁴ and AgeRank variable by sorting the firms within a product market by traffic rank and age respectively, and assigning ranks. The dataset contains 2421 observations from 121 firms across 221 products in 6 product categories. Descriptive statistics are presented in Table 4.2. The average rank (i.e., advertising intensity), excluding zeroes, ranges from 1 to 3 with a mean of 1.9 and a standard deviation of 0.8. The non-advertiser group (i.e., firms which never advertised) charge lower price (mean=622.7) than advertiser group (mean=671.1). However the price difference is not significant (t=-0.57, p=0.57). On the

¹²We weight the ratings by log(number of raters) to get reliable quality measure.

¹³ The AdRank of the firms which had an average rank of zero were assigned Adrank=0

¹⁴ TrafficRank is reverse coded such that lower number means higher brand equity or more traffic.

other hand, the quality (i.e., RatingsXlog(Raters)) of advertisers is higher (mean=27.2) than quality of non-advertisers (mean=25.4) and the quality difference is significant ($t = -3.69, p < 0.01$)¹⁵.

The correlation coefficients are shown in Table 4.3. However, these correlations, especially those with respect to AdRank, should be interpreted with caution as they do not correct for the fact that AdRank is not observed for a large number of observations and is set to be zero for such firms. It seems that those firms that have higher quality charge a higher price. Similarly, firms which have stronger brand equity (i.e., more traffic or lower TrafficRank) as well as firms which have longer online presence charge higher price. Firms which have a broader product assortment, on the other hand, charge a lower price.

4.5 RESULTS

The empirical model to test the relationship between price, quality and advertising, as shown below, is based on equation 6:

$$\text{AdRank}_{ij} = \alpha_0 + \beta_1 * \text{PriceRank}_{ij} + \beta_2 * \text{QualityRank}_{ij} + \beta_3 * \text{TrafficRank}_{ij} + \beta_4 * \text{AgeRank}_{ij} + \beta_5 * \text{MarketPresence}_{ij} + \varepsilon_{ij} \quad (7)$$

The main variables of interest are PriceRank and QualityRank. I use TrafficRank, AgeRank and MarketPresence as control variables. Before estimating this model where the dependent variable, AdRank, is a continuous variable measuring the relative advertising intensity of firms, I test a model to predict which firm is more likely to advertise. Therefore, instead of AdRank, I use Advertiser (a binary variable denoting

¹⁵ The mean of ratings as well as mean of number of raters for advertisers group is also significantly higher than those of non-advertisers.

whether a firm is advertiser or non-advertiser) as dependent variable and employ probit regression.

$$\text{Advertiser}_{ij} = \alpha_0 + \beta_1 * \text{PriceRank}_{ij} + \beta_2 * \text{QualityRank}_{ij} + \beta_3 * \text{TrafficRank}_{ij} + \beta_4 * \text{AgeRank}_{ij} + \beta_5 * \text{MarketPresence}_{ij} + \varepsilon_{ij} \quad (8)$$

The results of probit regression are presented in Table 4.4. In Model 1, I only include the control variables. I add PriceRank and QualityRank in Model 2 to estimate equation 8. I add the interaction term between price and quality in Model 3 to examine the possibility of a more complicated relationship between price and quality.

Model 2 suggests that price and quality explain variation in a firm's propensity to advertise above and beyond the control variables ($\chi^2(2)=39.38$; $p<0.01$). I find that the lower price firms ($\beta=-0.013$) and higher quality firms ($\beta=0.016$) are more likely to be among the advertiser group. Further, the results suggest that firms with larger brand equity ($\beta=-.057$), firms with relatively less online experience, and firms having smaller product assortment are more likely to advertise. Model 3 includes the interaction term between price and quality and explains significantly larger variance than Model 2. The interaction term is significant and is shown in Figure 4.3. Firms with low price and higher quality are most likely to advertise. However, among the firms charging high price, lower quality firms are more likely advertise than high quality firms.

Next, I examine the relative advertising intensity of firms by using the continuous dependent variable -- AdRank. As mentioned earlier, AdRank is a proxy of the advertising intensity of the firms. However, I do not observe the advertising intensity of the firms whose advertising intensity is lower than a threshold such that they are either unwilling to or unable to come to the top three ranks in the comparison shopping listing.

The advertising intensity of these firms is recorded as zero. Thus, the appropriate empirical model is a censored tobit model where A^* is the latent advertising intensity:

$$A_i^* = \beta x_i + \varepsilon_i$$

However, we observe A , such that

$$A_i = A_i^* \text{ if } A_i^* > c, \text{ and } A_i = 0 \text{ if } A_i^* \leq c$$

Using ordinary least square regression on the full sample or on the non-zero observations will bias the coefficients as the sample consists of two different sets of observations. The first set contains the observations for which we know only the values of the independent variables (i.e., X 's) and the fact that dependent variable (A^*) is less than or equal to threshold c . The second set consists of all observations for which the values of both X and A^* are known. Therefore, I use a censored tobit model (Tobin 1958) to estimate the advertising intensity of firms as specified by equation 7. Further, since the advertising rank is assigned to the firms based on their average rank on the listing over the sampling time period, we need to take into account that some firms may appear consistently in the top three ranks (i.e., advertising slots) whereas others may appear in the top three ranks irregularly. I, therefore, weight each observation in the tobit regression model, by the total number of days on which they appeared in the top three positions, such that firms who appear more frequently in the top ranks get a larger weight in the likelihood function¹⁶.

The tobit regression results, shown in Table 4.5, are similar to the probit results with binary advertising dependent variable. In model 2 which maps to equation 7, I find that lower the price charged by a firm higher is its advertising intensity (beta=-0.037) and

¹⁶ We analyzed the data without using the weights and found the results to be consistent.

higher the quality of a firm higher is its advertising intensity ($\beta=0.064$). Comparing the empirical coefficients on P and Q with coefficients in equation 6, we can infer that in the comparison shopping market, higher price reduces conversion efficiency (i.e., leads to lost advertising expenditure) much more strongly than what can be compensated by the higher price. Further, lower quality also reduces conversion inefficiency much more strongly than what can be compensated by the lower cost of producing/serving lower quality. Therefore, I find firms with lower price and higher quality to advertise more and obtain top ranks in the listing.

Last, in model 3, I empirically test the interaction effect between price and quality. The interaction term is significant and the effect is depicted in Figure 4.4. Results suggest that the lower the price and higher the quality, higher will be a firm's advertising intensity. However, lower quality firm's advertising intensity increases the higher the price charged by the firm.

Also, similar to probit regression, I find that firms that have stronger brand name and that sell smaller product assortment are more likely to advertise.

4.6 DISCUSSION

The results indicate that price and quality are related to advertising intensity of firms in the online directional markets. However, I find that the relationship between price, quality and advertising in the online directional markets is very different than traditional markets. Unlike the empirical findings in traditional market that suggests that higher price and higher quality firms advertise most (Archibald, Haulman et al. 1983; Thomas,

Shane et al. 1998), the results of this study show that directional markets lead to better outcomes where higher quality but lower price firms advertise the most.

I suggest that this unique outcome is a consequence of the directional nature of the online market which determines consumers' search and purchase behavior which in turn influences firms' advertising strategies in directional markets (such as comparison shopping engine). These results provide support to the theoretical arguments that unique nature of directional market makes firms employ different strategies than traditional markets and thus leads to different market outcomes (Perry and Wigderson 1986; Arbatskaya forthcoming). However, contrary to the suggestion that firms which appear higher on the advertisement listing would have higher price (Arbatskaya forthcoming), I find that low price and high quality firms are more likely to spend more on advertising and appear higher on the comparison shopping listing.

To understand this outcome, we need to examine the factors that may affect the value that a firm gets from appearing higher on the listing. *Ceteris paribus*, appearing on higher ranks is more valuable to all the firms as it brings more traffic to a firm's online store. However, I argue that the value that a firm gets from appearing higher on the listing not only depends on the rank but also on the price and the quality of the firm, among other firm attributes such as brand name/equity. Specifically, I suggest that higher price will decrease the clickthrough and conversion rate whereas higher quality will increase both clickthrough and conversion rate. The lower conversion rate would increase the cost of customer acquisition due to higher inefficiency and wastage of advertising expenditure. Increasing conversion rate/efficiency by lowering price and increasing quality, however, comes at the cost of lower profit margin. Thus the outcome of the tradeoff between these

opposing effects of price and quality on the profits of a firm would determine what type of firm (in terms of price and quality) is more likely to advertise more. Based on the result that firms with lower price and higher quality value higher ranks more than others, it seems that higher price and lower quality have a very strong negative impact on the conversion rate that cannot be compensated by the higher profit margin¹⁷.

Consistent with the conversion rate versus profit margin tradeoff logic, we find that as the gap between a firm's price and quality becomes larger, the advertising intensity of the firm increases. Though lower price and higher quality firms have higher advertising intensity (refer Figure 4.4), the likelihood of a firm that charges higher price and offers lower quality to have higher advertising intensity increases as the price becomes higher and the quality becomes lower (i.e., the profit margin becomes larger to overcome the loss due to lower conversion rate).

As seen above, advertising in directional market allows two extreme type of firms -- cherries and lemons (refer Table 4.1) – to appear on the top of the listing. Given the comparison shopping engine displays the firms in ascending order of price right below the three advertising spots, one would expect that firms with higher price would want to advertise to get ahead of the other low price sellers. On the other hand, one would not expect that the *cherries* (firms that offer the best deal in terms of price and quality) would not need to advertise in a shopping comparison market as consumers can easily spot them by sorting the list in the descending order of price (if needed) and then picking those firms which have high quality ratings. However, the fact that cherries find it beneficial to pay advertising fee to appear on the top ranks (and are able to outbid other firms to obtain

¹⁷ Given the maximum price that a firm can charge and the lowest quality that can be offered in a market.

top ranks) suggests that a large proportion of consumers visiting the online market incurs a high cognitive search cost and does not make an effort to resort the list and/or to include firms lower down the listing in their consideration set (Brynjolfsson, Dick et al. 2004).

Further, our observation that lemons too are able to pay more to get valuable rank in the listing suggests that a significant proportion of consumers buys from these lemon firms -- either because they are not sophisticated enough to identify the lemons in the market (in spite of the presence of quality ratings) or they do not carefully evaluate the price quality tradeoff due to bounded rationality. However, the fact that cherries are more likely than lemons to have higher advertising intensity and thus obtain higher rank suggests that the proportion of consumers who chose lemons -- referred as uninformed consumers or tourists in analytical literature (Salop and Stiglitz 1977; Riordan 1986; Bagwell and Riordan 1991) -- is small. We believe that the increase in the number of informed consumers would reduce the likelihood of lemons obtaining high ranks.

Since occurrence of lemons on the top of the listing adversely affects consumer welfare, we suggest that the comparison shopping engine should attempt to design advertisement allocation mechanisms such that possibility of lemons' advertising is minimized. One direct measure could be to weight the bids of the advertisers by their quality ratings. An alternative approach could be to weight the bids by the conversion rate. However it requires that advertisers' conversion rate data be available to the comparison shopping engine and there are sufficient informed consumers in the market.

A comparison shopping engine can also add functionality to its website to make it easier for consumers to identify the cherries. Currently, almost all the shopping engines

allow consumers to sort the list by only one attribute at a time which makes the search process costly for a consumer who is trying to find the firm that is best on more than one attributes. Allowing consumers to sort the list on multiple attributes (such as weighted average of price and quality) and providing filtering tools may increase the efficiency and effectiveness of consumers decision making. It has been shown that subtle changes in information presentation formats can influence consumer choice behavior (Payne, Bettman et al. 1993; Hoque and Lohse 1999; Mandel and Johnson 2002) and we suggest that allowing more flexibility to the consumer to modify the information format may increase the probability of consumers to find cherries. It would be interesting to examine how such change in the interface may affect consumer behavior, advertiser's strategies and market outcomes.

The results also suggest that firms that have higher brand awareness/equity (i.e. higher traffic) have higher advertising intensity. This result is surprising as firms with strong brand name competing with unknown firms should be able to attract consumers even at the lower ranks and should not incur cost to appear on top ranks. However, the result is consistent with the previous inference that consumers (at least a significant number) are naturally predisposed to visit the firms in the order in which they appear in the listing. Thus, the directional nature of this market makes it valuable for even a branded firm to pay advertising cost to appear on top of the listing.

Another interesting result is regarding the product assortment and advertising intensity. In a traditional market, it has been argued that advertising is most valuable to low cost firm which offer low prices and large product variety and therefore firms with lower price and large product variety will advertise more (Bagwell and Ramey 1994).

On the other hand, I found that firms with lower product variety advertise more in a directional market. It is possible that, in online markets, firms with a large product assortment do not have the significant cross-selling advantage due to consumers' use of search engines as a starting point in their purchase process; also the firms with a specialized/narrow product assortment have cost advantages. Future research should examine the underlying reasons for the higher advertising intensity of firms with lower product variety.

Currently, we do not know how many consumers are aware that top ranks are advertisements and firms compete in an auction to obtain those slots. It would be interesting to see how that information affects or would affect consumer search and purchase behavior. It is possible that consumers may use advertising expenditure as a signal of quality and may prefer to buy from the top ranked firms. Future research should examine the impact of such advertising signal beliefs on consumer behavior and the consequent strategies of firms.

I investigated the linkage between price, quality and advertising in a directional market where price and quality information about a seller is provided in the advertisement itself. However, it would be interesting to examine other directional markets such as sponsored search advertising where obtaining price and quality information is relatively costlier.

4.7 CONCLUSION

Extant research examining online markets has focused on the relationships between quality and price or between quality and advertising. This is the first study that examines the advertising intensity in an online market as a function of price and quality.

Advertising has been generally considered to have two roles – persuasive (changes consumers' taste and brand loyalty) and informative (informs consumers about price and/or quality). I examine an online directional market, specifically a comparison shopping engine, where advertising not only informs consumers about price and quality but also directs consumer search pattern/sequence. I find that the advertising outcomes in this market are strikingly different than the traditional markets. This study shows that low price and high quality firms exhibit high advertising intensity and are able to obtain high rank in the advertisement listing. I suggest conversion versus profit margin tradeoff as a potential explanation for this outcome.

This study empirically tests the conclusions of the analytical model that proposes a positive relationship between price and quality in such directional markets (Arbatskaya, Forthcoming). In addition the results will also allow a researcher to develop analytical model that describes the real market relationships.

This research will have significant implications for welfare and public policy. The findings will also help market makers such as comparison shopping engines to understand the market dynamics and develop mechanisms to provide better outcomes to consumers as well as to increase their profits.

CHAPTER 4: EPILOGUE

Sponsored search and comparison shopping advertising, enabled by Internet technologies, present new opportunities and challenges to the market participants. The two primary features that differentiate these new forms of advertising from other traditional advertising media are the nature of consumer search and the mechanism to price the advertisements. Consumers typically search the sponsored search advertisements from top to the bottom of the listing and sellers compete in an auction to obtain better positions on the sponsored search advertisement listing. However, the impact of these features on consumers and advertisers is not clear. This dissertation examines the validity of theories developed for traditional media in an emerging online sponsored search context and provides valuable insights for future research. Investigation of consumer behavior in online sponsored search markets will enable researchers to develop more realistic normative models and help practitioners develop better advertisements campaigns.

The first essay draws on the consumer search and directional markets literature to understand the implications of seller's strategies on seller's advertisement performance. The results validate the research hypothesis that search listing can act as a consumer filtering mechanism and competition intensity within adjacent ranks has significant impact on a seller's performance. The essay also contributes to the directional search literature by examining the effect of directional search on the performance of a firm.

The second essay provides evidence that like traditional markets, consumers rely on quality signals in electronic markets. However, the unique format of the sponsored

search listing significantly increases the strength of the advertising signal vis-à-vis price signal. The essay also adds to the signaling literature by introducing and empirically testing the moderating role of risk attitude on the usage of quality signaling cues.

The third essay examines the market outcomes in directional markets such as sponsored search and comparison shopping advertising. Specifically, we focus on comparison shopping advertising where advertising not only informs consumers about price and quality but also directs consumer search pattern/sequence. We find that the advertising outcomes in this market are strikingly different than the traditional markets. Our study shows that low price and high quality firms exhibit high advertising intensity and are able to obtain high rank in the advertisement listing. We suggest conversion versus profit margin tradeoff as a potential explanation for this outcome.

Overall, the findings of this dissertation will have significant implications for the sellers/advertisers on online sponsored search and comparison shopping mechanisms, as well as for the online intermediaries managing these online advertising markets. Insights from these studies will enable practitioners to develop appropriate advertising strategies and to choose effective and efficient position allocation mechanisms for the sponsored listings. Online intermediaries would also benefit from a better alignment of the advertisement allocation mechanisms with consumers' beliefs and behaviors.

FIGURES

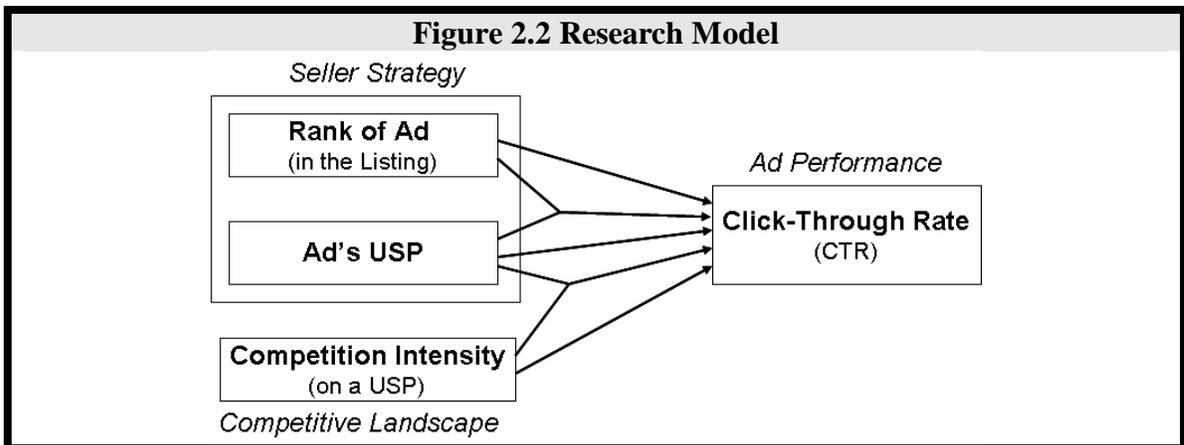
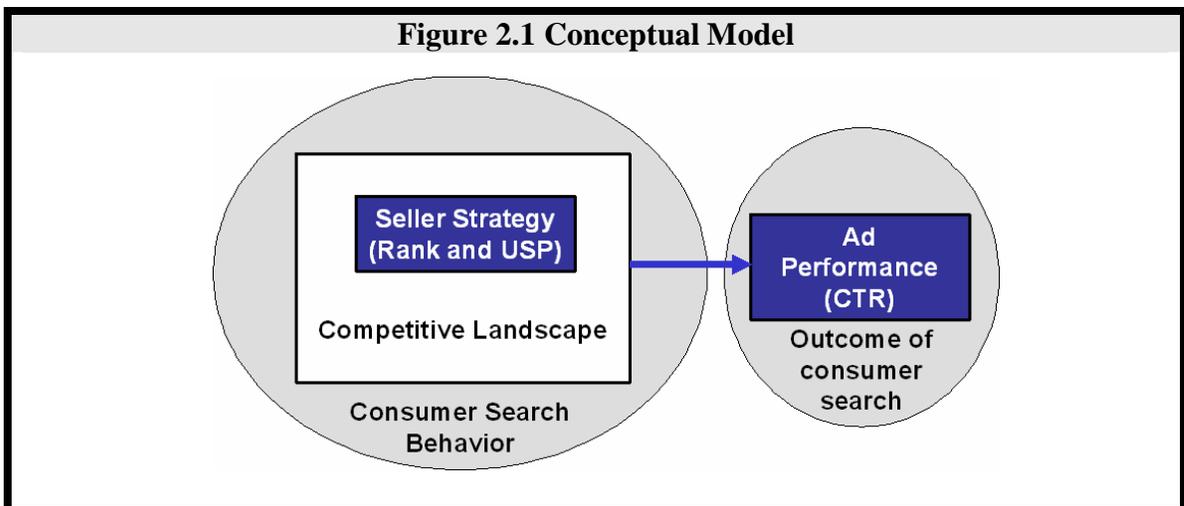


Figure 2.3 Sponsored Search Listing as Consumer Segmentation Mechanism

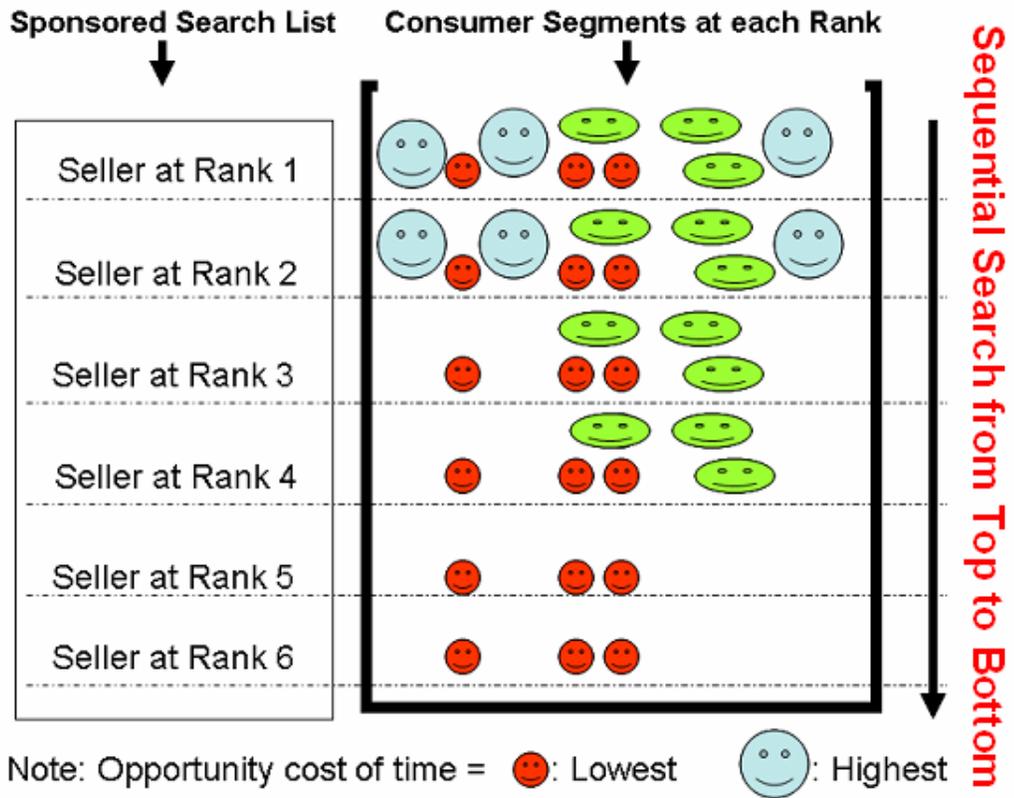


Figure 2.4 Predicted Relationship between Rank and Clickthrough Rate (CTR)

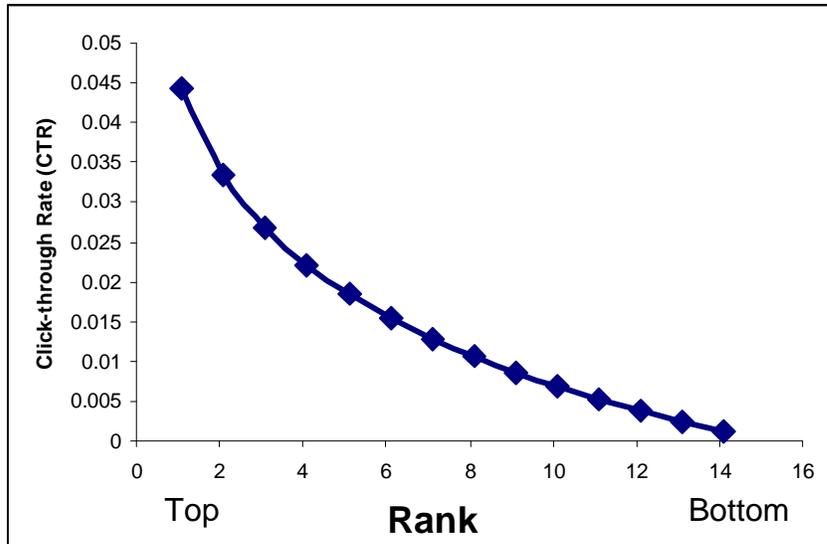


Figure 2.5a Interaction between Rank and USP in the Presence of Low Competition

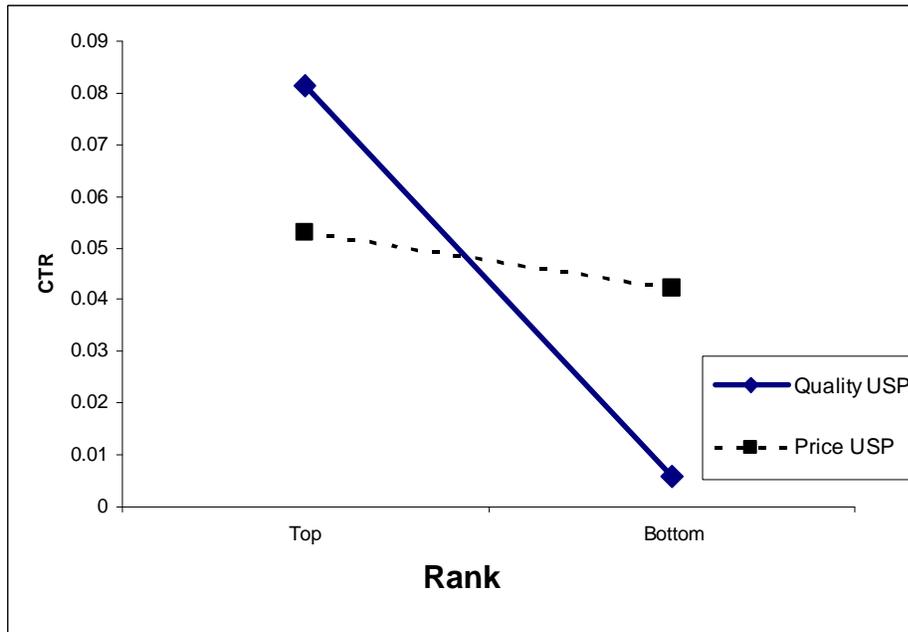


Figure 2.5b Interaction between Rank and USP in the Presence of High Competition

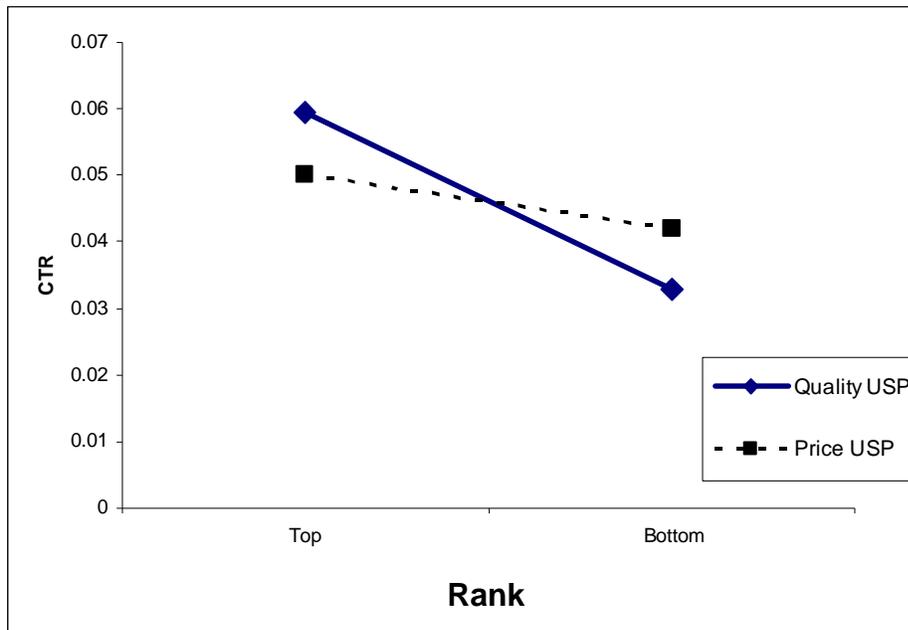


Figure 2.6a Interaction between USP and Competitive Intensity at Top Ranks

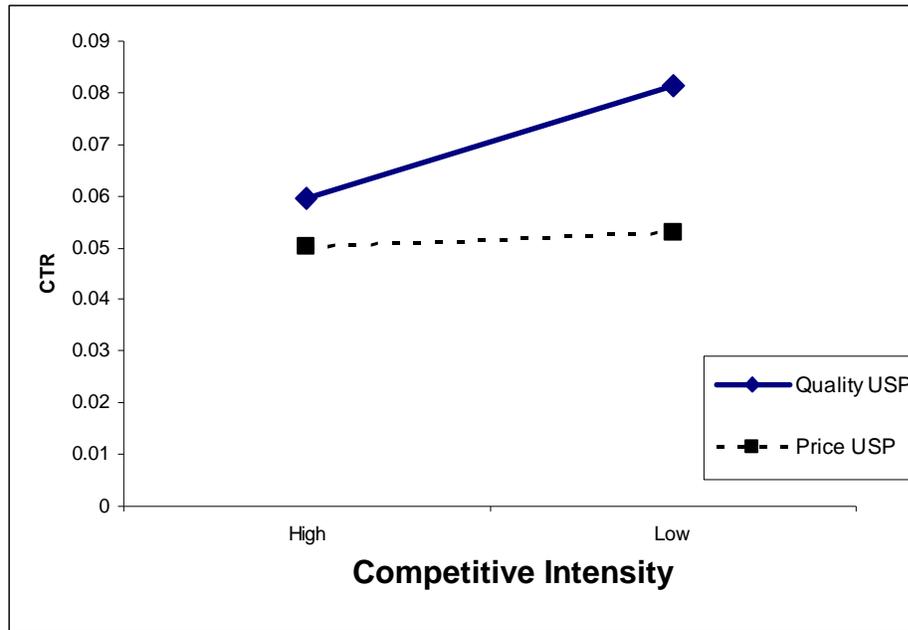
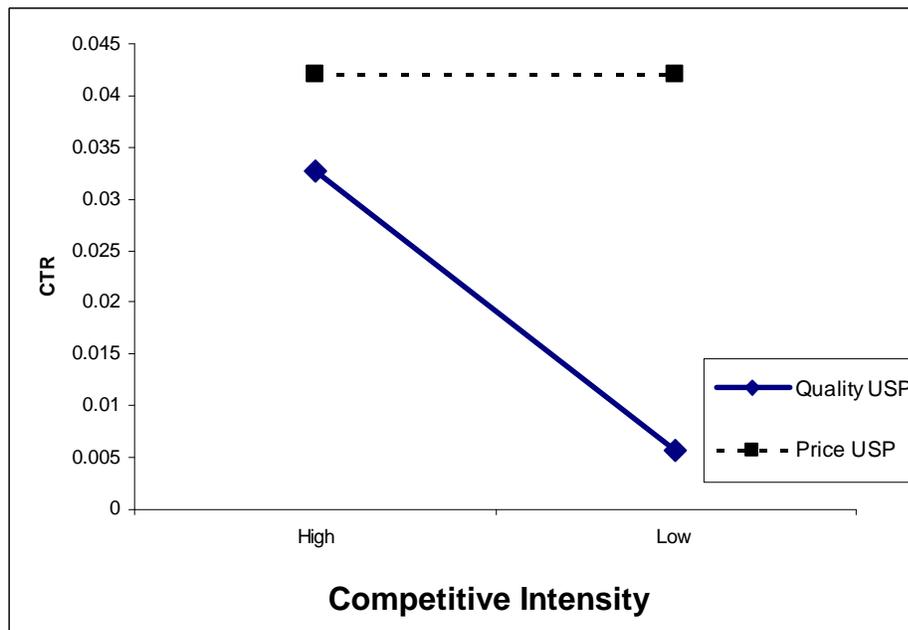


Figure 2.6b Interaction between USP and Competitive Intensity at Bottom Ranks



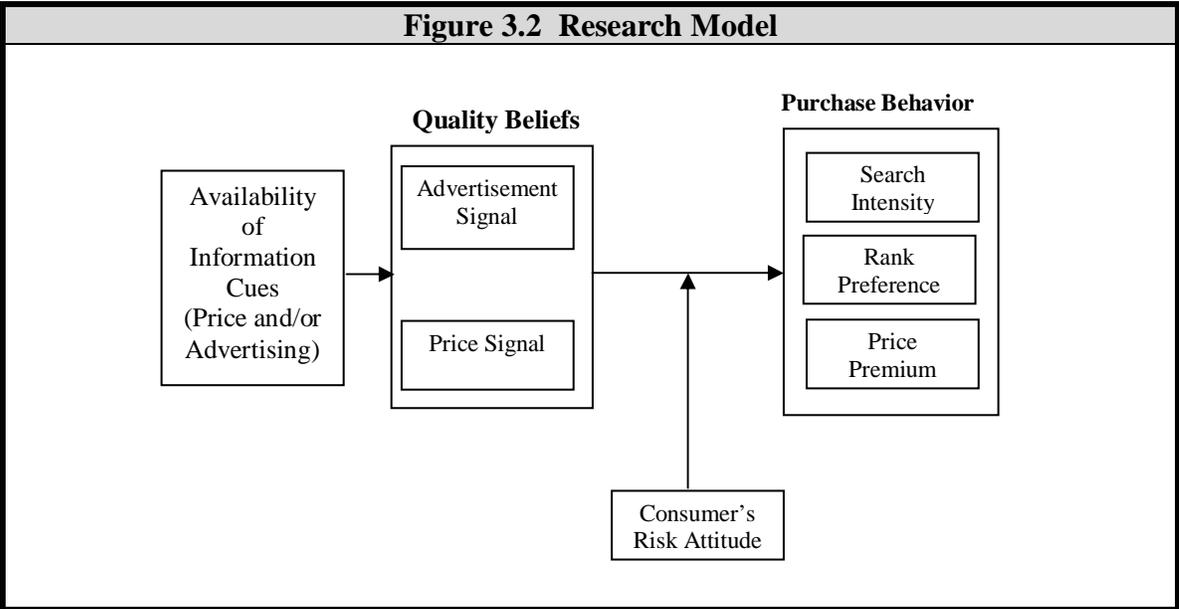
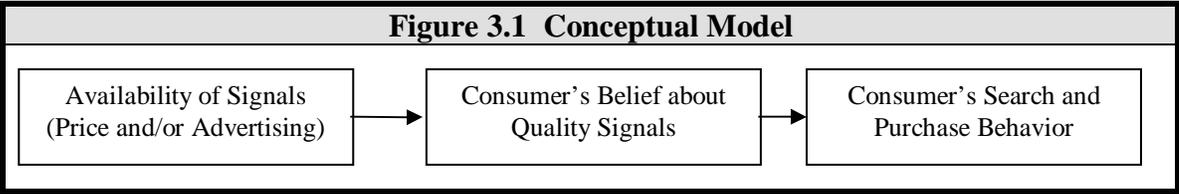
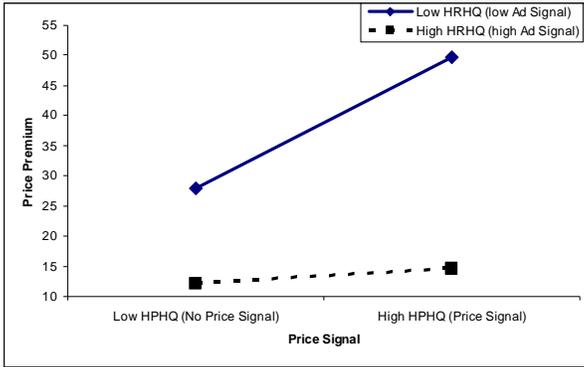
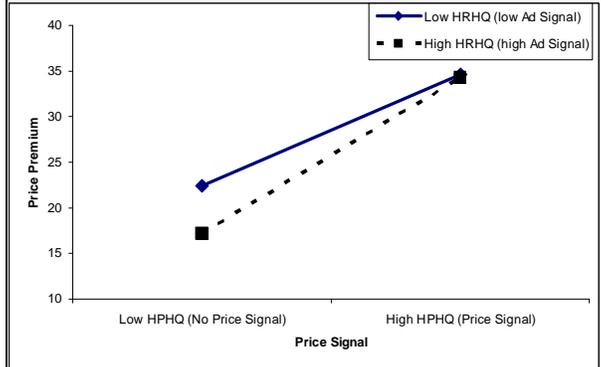


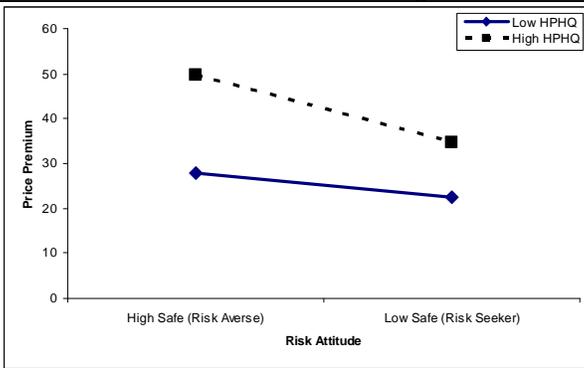
Figure 3.3 Price Premium and Three-way Interaction



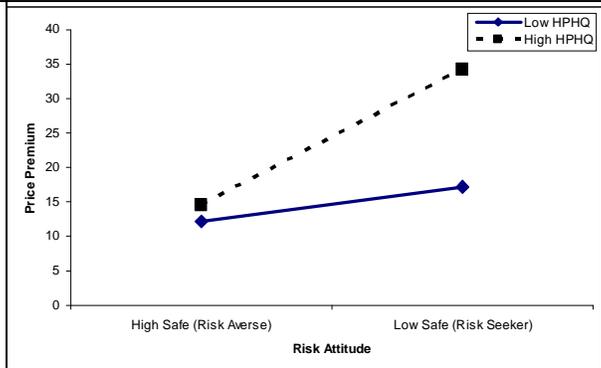
Panel A: Risk Averse (High Safe)



Panel B: Risk Seeker (Low Safe)



Panel C: Low HRHQ



Panel D: High HRHQ

Figure 4.1 Illustration of the V and R functional specification

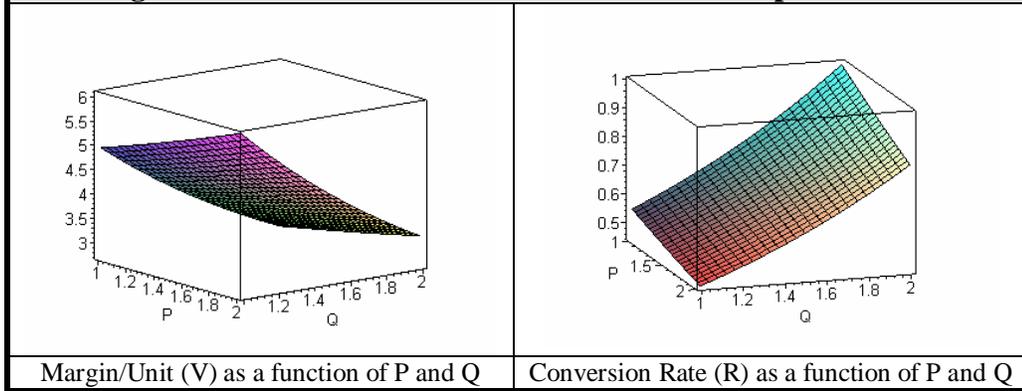


Figure 4.2 Ordered listing of Firms on a Comparison Shopping Engine

Product image — Points to the Nikon D200 camera image.

More information — Points to links for 'Consumer & expert reviews', 'See product details', and 'See product accessories'.

Stock status — Points to the 'In stock' status for various stores.

Featured placement sorted by bid — Points to the top three store listings.

Base price, state tax, ground shipping — Points to the breakdown of costs for a store listing.

Smart Buy: The lowest price from a trusted store — Points to the 'Smart Buy' badge on the third store listing.

Total price — Points to the final price including tax and shipping.

Trusted stores sorted by price — Points to the 'Trusted Store' badge on the fourth store listing.

All other stores sorted by price — Points to the remaining store listings at the bottom.

| Store Name | Store Information | Notes | Price |
|---------------------------|---------------------|---|--|
| Best Buy | 25 store reviews | In stock | Price: \$1,299.00 + Tax: \$0.00 + Shipping: \$0.00 = \$1,299.00 |
| B&H Photo-Video-Pro Audio | 3,738 store reviews | In stock LIMITED TIME OFFER | Price: \$1,399.00 + Tax: \$0.00 + Shipping: \$15.00 = \$1,354.40 |
| Adorama | 3,045 store reviews | In stock New | Price: \$1,194.00 + Tax: \$0.00 + Shipping: \$0.00 = \$1,234.00 |
| Digital | 2,433 store reviews | In stock Smart Buy | Price: \$1,299.00 + Tax: \$0.00 + Shipping: \$0.00 = \$1,298.00 |
| Camera Camera | 409 store reviews | In stock Authorized Nikon USA Dealer | Price: \$1,315.00 + Tax: \$0.00 + Shipping: \$0.00 = \$1,315.00 |
| Planet Photo | 1,335 store reviews | In stock | Price: \$1,339.00 + Tax: \$0.00 + Shipping: \$15.23 = \$1,358.23 |
| Adorama | 3,045 store reviews | In stock | Price: \$1,339.00 + Tax: \$0.00 + Shipping: \$15.23 = \$1,359.95 |
| PhotoCup | 227 store reviews | In stock | Price: \$1,307.00 + Tax: \$0.00 + Shipping: \$13.35 = \$1,410.35 |
| PhotoCup | 227 store reviews | In stock | Price: \$1,315.00 + Tax: \$0.00 + Shipping: \$0.00 = \$1,315.00 |
| Amazon.com | 1,467 store reviews | In stock Free Shipping orders \$35+ | Price: \$1,339.00 + Tax: \$0.00 + Shipping: \$19.23 = \$1,358.23 |

Figure 4.3: Price and Quality Interaction Effect - Based on Probit Results (model 3)

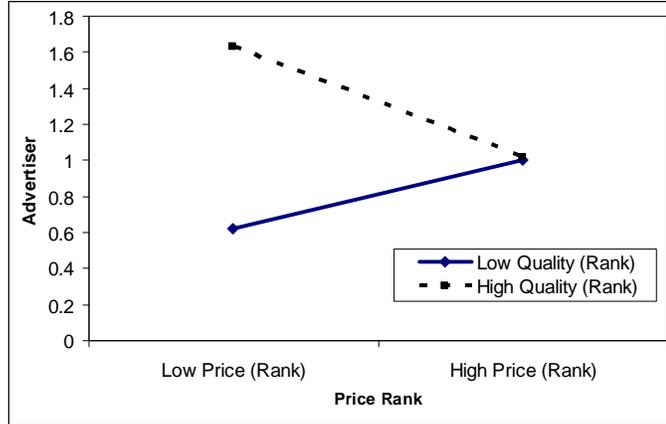
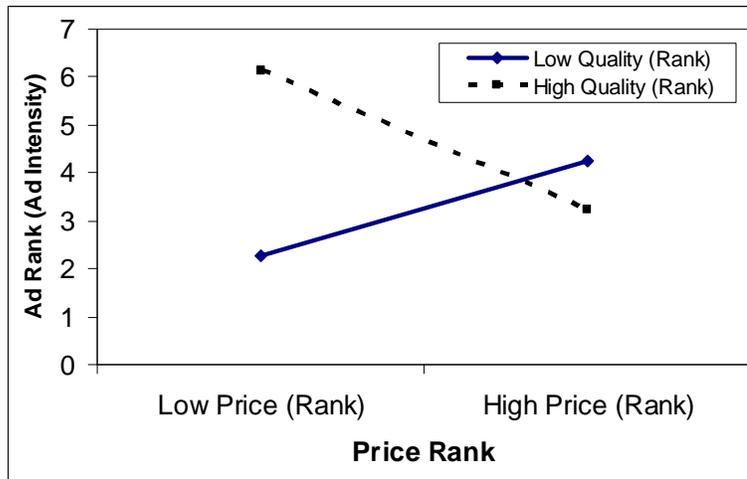


Figure 4.4: Price and Quality Interaction Effect - Based on Tobit Results (model 3)



TABLES

| Table 2.1 Descriptive Statistics | | | | | |
|----------------------------------|------|----------|-----------|----------|----------|
| Variable | Obs | Mean | Std. Dev. | Min | Max |
| CTR | 1556 | 0.049636 | 0.047139 | 0 | 0.401 |
| Log(Rank) | 1556 | 0.574577 | 0.399923 | 0.086178 | 1.957274 |
| USP | 1556 | 0.513496 | 0.499979 | 0 | 1 |
| CI | 1556 | 0.541292 | 0.458159 | 0 | 1 |

| Table 2.2 Correlation Coefficients | | | | | | | | |
|------------------------------------|-----------------|-----------------|-----------------|-------------------|-----------------|------------------|-----------------|----------------------|
| | CTR | log(Rank) | USP | log(Rank) XUSP | CI | log(Rank) XCI | USPX CI | log(Rank) XCIXUSP |
| CTR | 1.00 | | | | | | | |
| log(Rank) | -0.13 (0.00) | 1.00 | | | | | | |
| USP | -0.10 (0.00) | 0.19 (0.00) | 1.00 | | | | | |
| log(Rank)XUSP | 0.05 (0.04) | 0.32 (0.00) | -0.01 (0.68) | 1.00 | | | | |
| CI | -0.16 (0.00) | 0.01 (0.71) | 0.42 (0.00) | -0.12 (0.00) | 1.00 | | | |
| log(Rank)XCI | 0.11 (0.00) | 0.02 (0.54) | -0.12 (0.00) | 0.25 (0.00) | -0.12 (0.00) | 1.00 | | |
| USPXCI | 0.07 (0.00) | -0.13 (0.00) | -0.03 (0.32) | -0.07 (0.00) | -0.09 (0.00) | 0.20 (0.00) | 1.00 | |
| log(Rank)XCIXUSP | -0.14 (0.00) | 0.25 (0.00) | 0.02 (0.52) | 0.03 (0.30) | 0.19 (0.00) | 0.18 (0.00) | -0.09 (0.00) | 1.00 |

p values below the correlation coefficients

| Table 2.3 Regression Results | | | | | | | |
|------------------------------|--------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | CTR | CTR | CTR | CTR | CTR | CTR | CTR |
| Log(Rank) | | -0.037 (10.61)** | -0.037 (10.61)** | -0.044 (12.59)** | -0.043 (12.43)** | -0.043 (12.27)** | -0.039 (10.82)** |
| USP (Price=1; Quality=0) | | | 0.000 (0.11) | -0.001 (0.28) | 0.001 (0.11) | 0.000 (0.09) | 0.001 (0.15) |
| Log(Rank)XUSP | | | | 0.064 (9.20)** | 0.063 (9.04)** | 0.062 (8.94)** | 0.051 (7.18)** |
| CI | | | | | -0.004 (1.74) ‡ | -0.004 (1.56) | 0.000 (0.07) |
| CIXUSP | | | | | | 0.005 (0.98) | -0.003 (0.62) |
| CIXlog(Rank) | | | | | | | 0.037 (5.73)** |
| CIXlog(Rank)XUSP | | | | | | | -0.063 (4.83)** |
| Keyword Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 0.045 (23.35)** | 0.051 (26.27)** | 0.051 (21.65)** | 0.046 (19.92)** | 0.046 (19.78)** | 0.046 (19.39)** | 0.046 (19.82)** |
| Observations | 1554 | 1554 | 1554 | 1554 | 1554 | 1554 | 1554 |
| R-squared | 0.29 | 0.34 | 0.34 | 0.38 | 0.38 | 0.38 | 0.40 |

(Absolute value of t statistics in parentheses) ‡ significant at 10%; * significant at 5%; ** significant at 1%

| Table 3.1 Descriptive Statistics | | | | | | | | | | | |
|----------------------------------|---------------|-------|-----------|------|-------|-----------------|-------|-----------|------|------|--------------------------------|
| Variable | Control Group | | | | | Treatment Group | | | | | t-Test for difference of means |
| | N | Mean | Std. Dev. | Min | Max | N | Mean | Std. Dev. | Min | Max | |
| SearchIntensity | 38 | 2.87 | 1.38 | 1 | 9.20 | 42 | 3.05 | 1.68 | 1.30 | 10 | -0.38 |
| PricePremium | 38 | 32.69 | 20.62 | 2.40 | 78.70 | 42 | 22.67 | 16.58 | 1.70 | 53.8 | 2.27** |
| RankPreference | 38 | 4.60 | 1.14 | 2.40 | 6.90 | 42 | 4.20 | 1.45 | 1.80 | 7.5 | 1.48 |
| HPHQ | 38 | 4.97 | 1.43 | 1 | 7.00 | 42 | 4.90 | 1.27 | 1 | 7 | 0.30 |
| HRHQ | 38 | 2.44 | 1.09 | 1 | 4.33 | 42 | 4.60 | 1.36 | 2 | 7 | -7.78*** |
| Safe | 38 | 5.42 | 1.91 | 0 | 9 | 42 | 4.92 | 1.64 | 0 | 9 | 1.23 |

t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

| Table 3.2 Correlation Coefficients | | | | | | | | |
|------------------------------------|------------------|------------------------|-----------------|------------------------|------------------------|-----------------|-----------------|------|
| | | A | B | C | D | E | F | G |
| A. | Treatment | 1.00 | | | | | | |
| B. | Search Intensity | 0.04 (0.70) | 1.00 | | | | | |
| C. | Price Premium | -0.25 (0.03) | -0.02 (0.87) | 1.00 | | | | |
| D. | Rank preference | -0.16 (0.14) | -0.03 (0.80) | 0.56 (0.00) | 1.00 | | | |
| E. | HPHQ | -0.03 (0.76) | -0.07 (0.55) | 0.44 (0.00) | 0.19 (0.09) | 1.00 | | |
| F. | HRHQ | 0.66 (0.00) | -0.01 (0.95) | -0.33 (0.00) | -0.29 (0.01) | -0.06 (0.57) | 1.00 | |
| G. | Safe | -0.14 (0.22) | -0.13 (0.27) | 0.01 (0.95) | 0.07 (0.52) | -0.12 (0.31) | -0.18 (0.11) | 1.00 |

Significance (i.e., p values) of each correlation are printed under it in parenthesis

| Percentile | Search Intensity | | Price Premium | | Rank Preference | |
|------------------|------------------|-----------|---------------|-----------|-----------------|-----------|
| | Control | Treatment | Control | Treatment | Control | Treatment |
| 1% | 1 | 1.3 | 2.4 | 1.7 | 2.4 | 1.8 |
| 5% | 1.2 | 1.6 | 3.2 | 2.5 | 2.5 | 2 |
| 10% | 1.4 | 1.7 | 5.8 | 3.1 | 3 | 2.3 |
| 25% | 2.1 | 2.2 | 15 | 10.1 | 4 | 3.1 |
| 50% | 2.6 | 2.6 | 33.55 | 18.6 | 4.7 | 3.9 |
| 75% | 3.5 | 3.4 | 46.8 | 44.3 | 5.2 | 5.4 |
| 90% | 4.2 | 4.3 | 60.5 | 48.1 | 6 | 5.8 |
| 95% | 4.6 | 6.1 | 76.3 | 49.8 | 6.5 | 6.4 |
| 99% | 9.2 | 10 | 78.7 | 53.8 | 6.9 | 7.5 |
| N | 38 | 42 | 38 | 42 | 38 | 42 |
| Mean | 2.87 | 3.05 | 32.69 | 22.167 | 4.60 | 4.20 |
| Std. Dev. | 1.38 | 1.68 | 20.62 | 16.58 | 1.14 | 1.45 |

| | Model A: Without Risk Attitude | | | Model B: With Risk Attitude | | |
|-------------------|--------------------------------|----------------------------|----------------------------|-----------------------------|-----------------------------|----------------------------|
| | Search Intensity | Price Premium | Rank Preference | Search Intensity | Price Premium | Rank Preference |
| HPHQ [‡] | -0.063 (-0.48) | 5.87 (4.26)*** | 0.14 (1.35) | -0.159 (1.10) | 4.981 (3.38)*** | 0.177 (1.50) |
| HRHQ [‡] | 0.018 (0.17) | -3.98 (-3.54)*** | -0.23 (-2.65)*** | -0.033 (0.30) | -4.209 (3.71)*** | -0.213 (2.35)** |
| safe [‡] | | | | -0.154 (1.51) | -0.267 (0.26) | 0.071 (0.85) |
| HPHQ*HRHQ | 0.05 (0.69) | -0.74 (-0.93) | -0.04 (-0.68) | 0.060 (0.64) | -0.830 (0.86) | -0.008 (0.10) |
| HPHQ*safe | | | | -0.031 (0.48) | -0.266 (0.41) | 0.073 (1.40) |
| HRHQ*safe | | | | -0.065 (0.84) | -1.852 (2.34)** | -0.040 (0.62) |
| HPHQ*HRHQ*safe | | | | -0.054 (1.16) | -0.784 (1.65)* | -0.009 (0.23) |
| Constant | 2.97 (17.46)*** | 26.67 (15.06)*** | 4.36 (31.43)*** | 2.968 (16.97)*** | 26.042 (14.58)*** | 4.370 (30.61)*** |
| Observations | 80 | 80 | 80 | 80 | 80 | 80 |
| R-square | 0.01 | 0.31 | 0.11 | 0.05 | 0.36 | 0.14 |
| Chi-square | 0.95 | 36.54 | 10.09 | 4.38 | 45.59*** | 13.52* |

z statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%
[‡] These variables are mean centered to avoid multicollinearity.

| Table 4.1: Conversion Inefficiency versus Profit Margin | | | |
|---|------|--|--|
| | | Quality | |
| | | High | Low |
| Price | High | Fair Deal | Lemons Worst Deal for consumers therefore should be translated to lowest conversion rate; Highest profit margin for the firm |
| | Low | Cherries Best Deal for consumers therefore should be translated to highest conversion rate; Lowest profit margin for the firm. | Fair Deal |

| Table 4.2 Descriptive Statistics | | | | | | | | | | |
|----------------------------------|------|--------|--------|-------|---------|-------------|--------|--------|-------|---------|
| Non-Advertisers | | | | | | Advertisers | | | | |
| Variable | Obs | Std. | | | | Obs | Std. | | | |
| | | Mean | Dev. | Min | Max | | Mean | Dev. | Min | Max |
| AverageRank | 1635 | 0.0 | 0.0 | 0.0 | 0.0 | 786 | 1.9 | 0.8 | 1.0 | 3.0 |
| Average | | | | | | | | | | |
| TotalPrice | 1635 | 662.7 | 774.9 | 8.0 | 7504.2 | 786 | 671.1 | 834.7 | 29.9 | 5340.2 |
| Ratings | 1635 | 3.9 | 0.7 | 0.0 | 5.0 | 786 | 4.0 | 0.9 | 0.0 | 5.0 |
| Raters | 1635 | 1727.9 | 2977.6 | 0.0 | 44294.3 | 786 | 1988.9 | 3083.1 | 0.0 | 44299.8 |
| RatingsX | | | | | | | | | | |
| log(Raters) | 1635 | 25.4 | 9.0 | 0.0 | 48.3 | 786 | 27.2 | 9.9 | 0.0 | 48.3 |
| AdRank | 1635 | 0.0 | 0.0 | 0.0 | 0.0 | 786 | 3.3 | 2.1 | 1.0 | 11.0 |
| PriceRank | 1635 | 16.1 | 11.7 | 1.0 | 55.0 | 786 | 11.0 | 9.1 | 1.0 | 54.0 |
| QualityRank | 1635 | 15.8 | 11.1 | 1.0 | 56.0 | 786 | 13.5 | 11.2 | 1.0 | 55.0 |
| TrafficRank | 1635 | 131548 | 330872 | 26.0 | 6288723 | 786 | 214401 | 764784 | 26.0 | 6288723 |
| OnlineAge | 1635 | 3581.1 | 1284.0 | 382.0 | 7337.0 | 786 | 3478.7 | 1233.5 | 385.0 | 7337.0 |
| MarketPresence | 1635 | 27.2 | 18.9 | 0.4 | 73.8 | 786 | 27.9 | 15.9 | 0.4 | 73.8 |

| Table 4.3 Correlation Coefficients | | | | | | | | | | | | |
|------------------------------------|------------------|---------------|---------------|----------------|---------------|---|----------------|----------------|----------------|----------------|---------------|---|
| | Only Advertisers | | | | | | All Firms | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 4 | 5 | 6 |
| 1. AdRank | 1 | | | | | | 1 | | | | | |
| 2. PriceRank | 0.12 (0.0) | 1 | | | | | -0.14 (0.0) | 1 | | | | |
| 3. QualityRank | 0.14 (0.0) | 0.23 (0.0) | 1 | | | | -0.04 (0.0) | 0.31 (0.0) | 1 | | | |
| 4. TrafficRank | 0.03 (0.4) | 0.00 (0.9) | 0.44 (0.0) | 1 | | | -0.21 (0.0) | 0.17 (0.0) | 0.28 (0.0) | 1 | | |
| 5. AgeRank | 0.12 (0.0) | 0.79 (0.0) | 0.50 (0.0) | 0.00 (0.9) | 1 | | -0.11 (0.0) | 0.67 (0.0) | 0.43 (0.0) | -0.06 (0.0) | 1 | |
| 6. MarketPresence | 0.01 (0.7) | 0.04 (0.2) | 0.15 (0.0) | -0.36 (0.0) | 0.23 (0.0) | 1 | 0.01 (0.5) | -0.11 (0.0) | -0.08 (0.0) | -0.42 (0.0) | 0.16 (0.0) | 1 |

P values below the correlation coefficients in parentheses

| Table 4.4 Probit Regression Results | | | |
|---|----------------------------|----------------------------|----------------------------|
| | Model 1 | Model 2 | Model 3 |
| | Advertiser | Advertiser | Advertiser |
| TrafficRank | -0.050 (14.27)** | -0.057 (14.35)** | -0.065 (15.58)** |
| AgeRank | -0.025 (9.20)** | -0.023 (5.44)** | -0.032 (6.99)** |
| MarketPresence | -0.008 (4.53)** | -0.010 (5.49)** | -0.009 (5.14)** |
| PriceRank | | -0.013 (3.41)** | 0.024 (3.83)** |
| QualityRank | | 0.016 (5.30)** | 0.051 (9.14)** |
| PriceRankXQualityRank | | | -0.002 (7.24)** |
| Constant | 0.668 (8.01)** | 0.714 (8.16)** | 0.395 (4.08)** |
| Observations | 2421 | 2421 | 2421 |
| Pseudo R-square | 0.10 | 0.12 | 0.14 |
| Absolute value of z statistics in parentheses; * significant at 5%; ** significant at 1% | | | |

| Table 4.5: Tobit Regression Results | | | |
|---|----------------------------|----------------------------|----------------------------|
| | Model 1 | Model 2 | Model 3 |
| | AdRank | AdRank | AdRank |
| TrafficRank | -0.182 (13.19)** | -0.209 (13.48)** | -0.238 (15.13)** |
| AgeRank | -0.104 (9.67)** | -0.106 (6.46)** | -0.137 (8.24)** |
| MarketPresence | -0.013 (2.01)* | -0.021 (3.07)** | -0.019 (2.91)** |
| PriceRank | | -0.037 (2.55)* | 0.131 (5.68)** |
| QualityRank | | 0.064 (5.46)** | 0.215 (10.48)** |
| PriceRankXQualityRank | | | -0.010 (8.70)** |
| Constant | 2.369 (7.48)** | 2.495 (7.59)** | 1.024 (2.88)** |
| Observations | 2348 | 2348 | 2348 |
| Pseudo R-square | 0.05 | 0.06 | 0.07 |
| 1562 observations left censored; 786 uncensored observations Absolute value of z statistics in parentheses; * significant at 5%; ** significant at 1% | | | |

APPENDIX A: TYPOLOGY OF ONLINE ADVERTISING

Display Advertising—advertiser pays an online company for space to display a static or hyper-linked banner or logo on one or more of the online company's pages.

Sponsorship—advertiser sponsors targeted Web site or email areas (e.g., entire web site, site area, an event, parts or all of an email message). Sponsorships can and usually do contain some banner elements. To the extent possible, separate and report revenues for other formats contained within the sponsorship campaign.

E-mail—banner ads, links or advertiser sponsorships that appear in e-mail newsletters, e-mail marketing campaigns and other commercial e-mail communications. Includes all types of electronic mail (e.g., basic text or HTML-enabled).

Search—fees advertisers pay online companies to list and/or link their company site domain name to a specific search word or phrase (includes paid search revenues). Search categories include:

- Paid listings**—text links appear at the top or side of search results for specific keywords. The more a marketer pays, the higher the position it gets. Marketers only pay when a user clicks on the text link.

- Contextual search**—text links appear in an article based on the context of the content, instead of a user-submitted keyword. Payment only occurs when the link is clicked.

- Paid inclusion**—guarantees that a marketer's URL is indexed by a search engine. The listing is determined by the engine's search algorithms.

- Site optimization**—modifies a site to make it easier for search engines to automatically index the site and hopefully result in better placement in results.

Referrals / Lead Generation*—fees advertisers pay to online companies that refer qualified purchase inquiries (e.g., auto dealers which pay a fee in exchange for receiving a qualified purchase inquiry online) or provide consumer information (demographic, contact, behavioral) where the consumer opts into being contacted by a marketer (email, postal, telephone, fax). These processes are priced on a performance basis (e.g., cost-per-action, -lead or -inquiry), and can include user applications (e.g., for a credit card), surveys, contests (e.g., sweepstakes) or registrations.

Classifieds and auctions—fees advertisers pay online companies to list specific products or services (e.g., online job boards and employment listings, real estate listings, automotive listings, auction-based listings, yellow pages).

Rich media—advertisements that integrate some component of streaming video and/or audio and interactivity, in addition to flash or java script ads, and can allow users to view and interact with products or services (e.g., a multimedia product description, a "virtual test-drive"). "Interstitials" have been consolidated within the rich media category and represent full-or partial-page text and image server-push advertisements which appear in the transition between two pages of content. Forms of interstitials can include splash screens, pop-up windows and superstitials.

Slotting fees—fees charged to advertisers by online companies to secure premium positioning of an advertisement on their site, category exclusivity or similar preference positioning (similar to slotting allowances charged by retailers).

Source: PricewaterhouseCoopers (2005), "IAB Internet Advertising Revenue Report: 2005 Second Quarter Results"

APPENDIX B1: INSTRUCTIONS FOR SHOPPING TASK

Welcome to the Experiment

The experiment consists of **3 parts** and will take approximately 60 minutes to complete.

- 1: **Shopping** task.
- 2: **Survey** consisting of multiple choice questions.
- 3: **Lottery selection** task.

You will **earn experimental currency (referred as E\$)** based on your decisions in the shopping and lottery selection task.

After the experiment is over, 25 participants (out of approximately 125 participants) who have earned the highest experimental currency will be given cash award (or equivalent gift coupons). You will be notified about the results by email.

The higher the experimental cash you earn, the higher will be the monetary reward (if you are among the top 25 earners). The amount of cash will be proportional to the experimental currency earned.

The experimental currency will be converted at the rate of E\$1 = US \$0.025.

The value of each cash reward (or gift coupon) can be upto US \$25.

I: SHOPPING TASK:

Instructions: GENERAL

You will go on 10 different online shopping trips. In each trip you will **buy a different product**.

Each product is sold by a **different set of 10 sellers**.

Assume that you are in a shopping situation where all the sellers are unknown/unfamiliar to you. The **sellers shown are real sellers** but their identities (name and actual website content) have been hidden to simulate unfamiliar markets conditions.

Search Procedure:

The sellers **differ in quality** (i.e. product condition, delivery time, customer service, etc.,) and **charge different price** for the product.

You can discover the price charged by a seller by visiting the seller's website. However, **you do not have any information about the quality of the sellers**. You cannot identify the quality even after visiting a seller's website.

Quality is an important factor in your purchase decision, you will have to **make your own inferences about the quality of the sellers**.

Search Effort:

You will incur a search effort of **E\$ 5** every time you visit a new seller's website (i.e. click on the seller's link)

In other words, the time and effort spent in visiting a seller is worth E\$ 5 to you.

The more new sellers you visit, the higher will be your total search effort.

For example, if you visit 4 sellers, your total search effort will be equal to $4 \times E\$5 = E\20

Your total search effort at any given point during a shopping trip will be displayed on the top of the screen.

Search Sequence:

You may stop after visiting the first seller, or you may continue searching as many times as you wish.

Recall:

Each time you see a seller's price, you may either accept it and stop searching, or you may reject it and search more.

You **will NOT incur a search effort again** if you visit a previously visited seller.

After each shopping trip, you will be shown the **total cost (i.e. the price of purchased product and total search effort)** incurred by you in that trip. Then, you will be asked to provide your perception about the quality of the seller.

[Click here to go to NEXT page](#)

Objective : In each shopping trip, you will be purchasing a different product. Your objective is to maximize your payoff by buying the product from **highest quality seller** at the **lowest price** while minimizing your **search effort**.

Your payoff in each shopping trip will be calculated (but not shown to you during the experiment) as follows:

Payoff = (Quality of the seller chosen) - (Price Paid for the product) – (Total Search Effort to visit new sellers)

where **Total Search Effort = (Total number of sellers visited)*(search effort to visit one seller)**

At the end of the experiment, **one of your 10 trips will be randomly selected .**

We will use the quality of the seller chosen by you on this trip to calculate your payoffs. **This payoff will be your final payoff.**

Range of Quality in each product market (i.e. shopping trip)

Quality of sellers in each product market **varies significantly**. The actual quality of the sellers will not be revealed during the experiment. However, you will be informed about the maximum and minimum seller quality (denoted in E\$) in each product market.

Range of Price in each product market (i.e. shopping trip)

Price range in each product market also varies. You will be informed about the expected maximum and minimum price available in each product market (i.e. shopping trip).

Payoff Calculation Example:

Assume that you bought the product at price equal to **E\$150** after visiting **4** sellers.

Since **search effort to visit a seller is E\$5** , therefore your total search effort is **E\$ 20** (i.e. 4*5).

Your total cost = E\$ 150 + E\$ 20 = E\$ 170

Then, quality of the seller (from whom you bought the product) is obtained by using the satisfaction ratings provided by real customers for that seller.

If we find that the quality of the seller (from whom you bought the product) is **E\$ 500** then your payoff will be: 500 - 170 = **E\$ 330**;

However, if we find that the quality of the seller is **E\$ 300** then your payoff will be: 300 - 170 = **E\$ 130**

[Click here to go to PREVIOUS page](#)

[Click here to go to NEXT page](#)

Instructions: Summary

- There will be **10 shopping trips** . In each shopping trip, you will buy a different product. You will have the option to observe one or more sellers' prices. Sellers are real but their identities have been hidden.

- **Quality** of sellers in each product market **varies significantly**.

The range of quality (i.e. maximum and minimum quality) in each product market will be provided to you.

- **Price** in each product market also varies.

The range of prices (i.e. maximum and minimum price) in each product market will be provided to you.

- You may stop the search sequence at any time and accept any offer observed thus far.

There is **no limit** to the number of sellers you can visit.

However, you incur a **search effort** worth **E\$ 5** to visit an unvisited seller.

- At the end, **one of your 10 trips will be randomly selected**.

Your payoffs for this trip will be calculated and this payoff will be treated as your final payoff.

25 best performers (based on the their payoff in the randomly selected round) will be given monetary reward.

The higher the final payoff, the higher will be the reward. You can earn a reward upto **US \$ 25**.

You will be notified about your payoff by email.

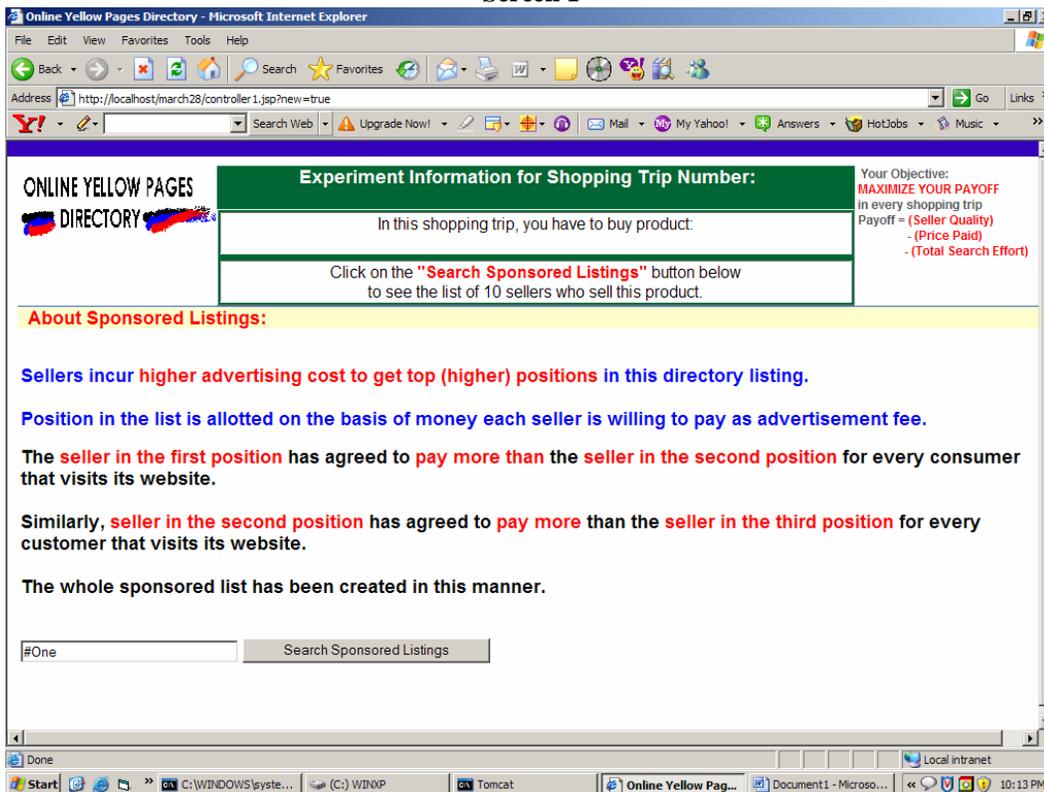
NOTE: You should try to maximize your payoff in EVERY shopping trip as any one of the shopping trips may be randomly picked to determine your payoff.

[Click here to go to the PREVIOUS page](#)

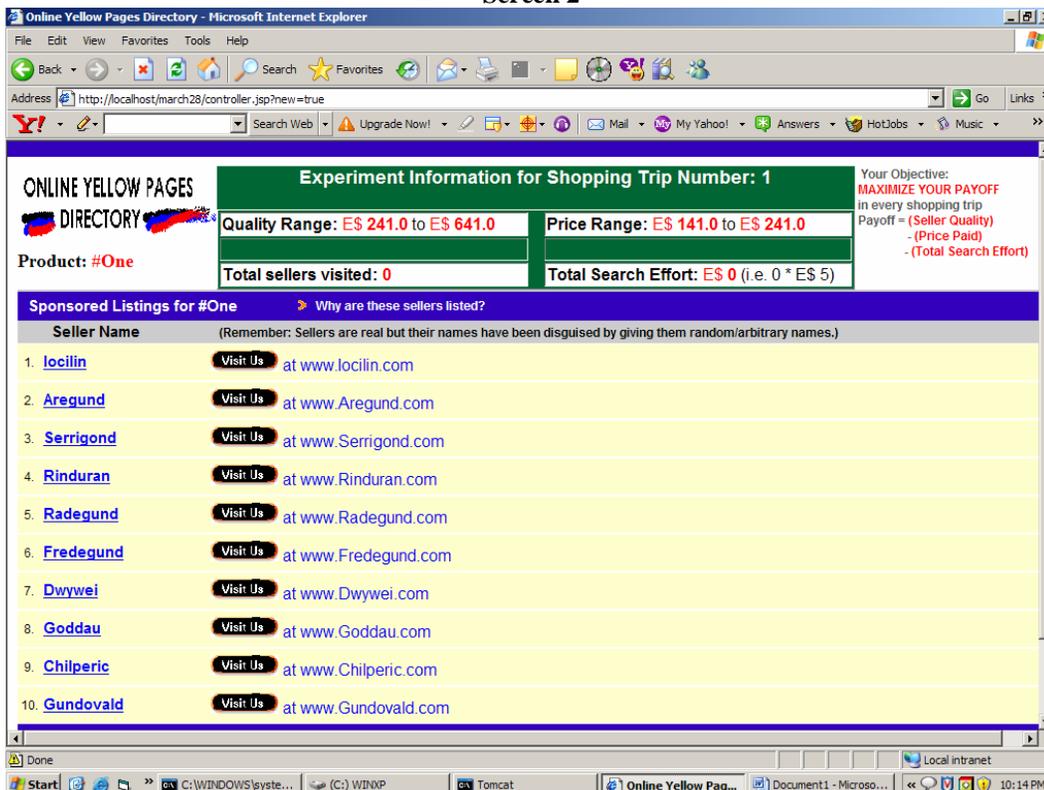
[Click here to START the Shopping Task](#)

APPENDIX B2: SCREENSHOTS OF THE SHOPPING TASK

Screen 1



Screen 2



Screen 3

The screenshot shows a Microsoft Internet Explorer window titled "Seller's Homepage". The address bar contains "http://localhost/march28/homepage.jsp?row=2". The page content includes:

- Top left: "ONLINE YELLOW PAGES DIRECTORY" logo.
- Top center: "Experiment Information for Shopping Trip Number:"
- Top right: "Your Objective: MAXIMIZE YOUR PAYOFF in every shopping trip. Payoff = (Seller Quality) - (Price Paid) - (Total Search Effort)".
- Table with two columns: "Quality Range: ES 241.0 to ES 641.0" and "Price Range: ES 141.0 to ES 241.0".
- Table with two columns: "Total sellers visited:" and "Total Search Effort: ES (i.e. 1 * ES 5)".
- Blue banner: "www.Aregund.com".
- Large blue text: "Aregund".
- Text: "Product: #One" and "Price: ES 241".
- Orange button: "Buy It".
- Text below button: "Once you click this button, your purchase will be final.".
- Text: "Go back to the sponsored listing (online yellow pages directory)".
- Blue button: "Back".

The browser's taskbar shows the "Seller's Homepag..." window active, with a system clock of 10:16 PM.

Screen 4

The screenshot shows a Microsoft Internet Explorer window titled "Next Trip". The address bar contains "http://localhost/march28/perception.jsp?last=false&round=1&draw=1&row=%202". The page content includes:

- Yellow background box with text: "Now, you will go for another shopping trip.".
- Text: "Price and quality dispersion in the next product market may be different.".
- Text: "The next product is sold by a **different set of 10 sellers.**" (where "different set of" is in blue and "10 sellers." is in red).
- Text at the bottom: "Please wait for 5 seconds. You will be automatically taken to the Online Directory".

The browser's taskbar shows the "Next Trip - Micros..." window active, with a system clock of 10:18 PM.

APPENDIX B3: SURVEY ITEMS

Rank-Quality Belief (HRHQ)

| Please answer all questions (to the best of your ability) on a scale of 1 to 7. | Strongly Disagree | | | Strongly Agree | | | |
|---|-------------------|---|---|----------------|---|---|---|
| I believe that highest quality sellers were on the top of the list. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I believe that a seller on top of the list was more established than other sellers. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I believe that a seller on top of the list was more reputable than other sellers. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Price-Quality Belief (HPHQ)

| Please answer all questions (to the best of your ability) on a scale of 1 to 7. | Strongly Disagree | | | Strongly Agree | | | |
|---|-------------------|---|---|----------------|---|---|---|
| I believe that there was a correlation between the price being charged by a seller and his quality . | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| I believe that the seller charging higher price was the higher quality seller. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Ad Expenditure Manipulation

| Please answer all questions (to the best of your ability) on a scale of 1 to 7. | Strongly Disagree | | | Strongly Agree | | | |
|---|-------------------|---|---|----------------|---|---|---|
| The seller on the first position incurred the highest advertising cost than the rest of the sellers on the list | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| The seller on the third position incurred higher advertising cost than the seller on the fourth position on the list | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

APPENDIX B4: LOTTERY SELECTION TASK

Instructions

In this part of the experiment there will be **two rounds** of the same lottery selection task.

You will be making choices between two lotteries, such as those represented as "Option A" and "Option B" below. The money prizes are determined by the computer equivalent of throwing a ten-sided die. Each outcome, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, is equally likely.

| Decision | Option A | Option B | Your Choice |
|-----------------|---|---|--|
| 1 st | E\$2.00 if the die is 1 E\$1.60 if the die is 2 – 10 | E\$3.85 if the die is 1 E\$0.10 if the die is 2 - 10 | A: <input type="checkbox"/> or B: <input type="checkbox"/> |

Thus if you choose Option A, you will have a 1 in 10 chance of earning \$2.00 and a 9 in 10 chance of earning \$1.60. Similarly, Option B offers a 1 in 10 chance of earning \$3.85 and a 9 in 10 chance of earning \$0.10.

You will make 10 such decision in each round. Even though you will make ten decisions, **only one** of these will end up being used. Once again, the selection of the one to be used depends on the "throw of the die" that is determined by the computer's random number generator. No decision is any more likely to be used than any other, and you will not know in advance which one will be selected, **so please think about each one carefully.** This random selection of a decision fixes the row (i.e. the Decision) that will be used.

| Decision | Option A | Option B | Your Choice |
|------------------|---|---|--|
| 1 st | E\$2.00 if the die is 1 E\$1.60 if the die is 2 – 10 | E\$3.85 if the die is 1 E\$0.10 if the die is 2 - 10 | A: <input type="checkbox"/> or B: <input type="checkbox"/> |
| 2 nd | E\$2.00 if the die is 1 - 2 E\$1.60 if the die is 3 – 10 | E\$3.85 if the die is 1 - 2 E\$0.10 if the die is 3 - 10 | A: <input type="checkbox"/> or B: <input type="checkbox"/> |
| . | | | |
| . | | | |
| . | \$2.00 if the die is 1 – 9 \$1.60 if the die is 10 | \$3.85 if the die is 1 - 9 \$0.10 if the die is 10 | A: <input type="checkbox"/> or B: <input type="checkbox"/> |
| 9 th | | | |
| 10 th | \$2.00 if the die is 1 - 10 | \$3.85 if the die is 1 - 10 | A: <input type="checkbox"/> or B: <input type="checkbox"/> |

For example, suppose that you make all ten decisions and the throw of the die is 9, then your choice, A or B, for decision 9 below would be used and the other decisions would not be used. After the random die throw fixes the Decision row that will be used, we need to obtain a second random number that determines the earnings for the Option you chose for that row. In Decision 9 below, for example, a throw of 1, 2, 3, 4, 5, 6, 7, 8, or 9 will result in the higher payoff for the option you chose, and a throw of 10 will result in the lower payoff. For decision 10, the random die throw will not be needed, since the choice is between amounts of money that are fixed: \$2.00 for Option A and \$3.85 for Option B

- **Making Ten Decisions:** After you finish these instructions, you will see a table with 10 decisions in 10 separate rows, and you choose by clicking on the buttons on the right, option A or option B, for each of the 10 rows. You may make these choices in any order and change them as much as you wish until you press the Submit button at the bottom.
- **The Relevant Decision:** One of the rows is then selected at random, and the Option (A or B) that you chose in that row will be used to determine your earnings. **Note:** Please think about each decision carefully, since each row is equally likely to end up being the one that is used to determine payoffs.

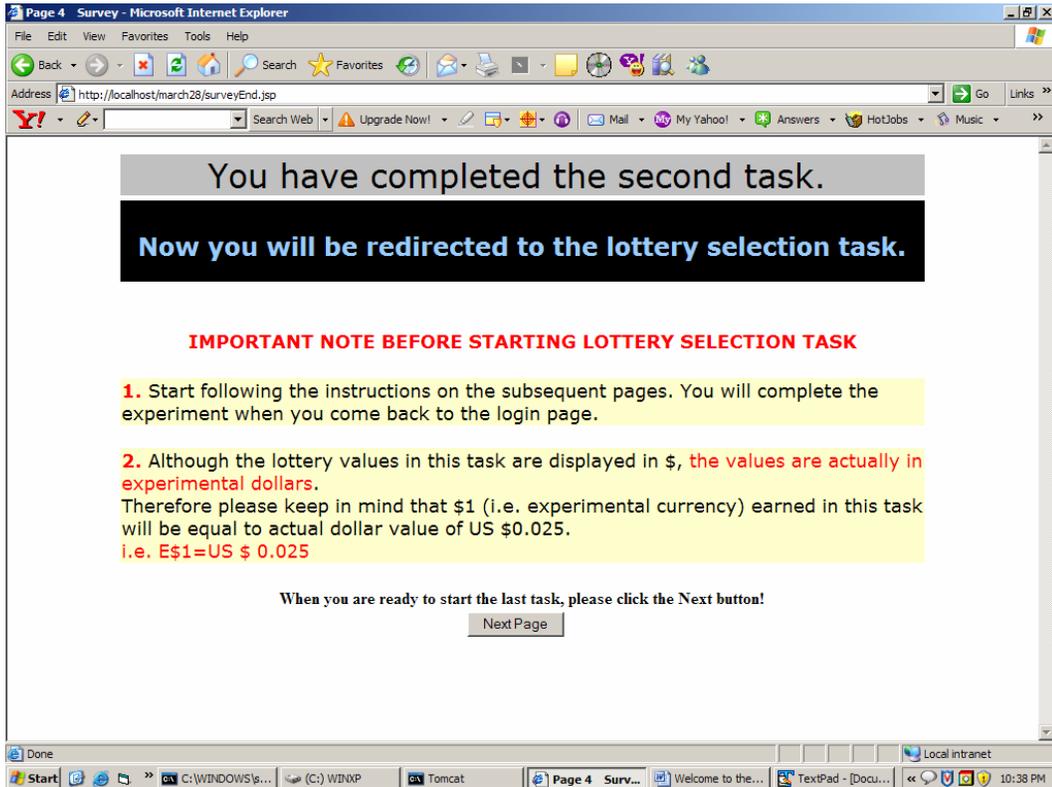
- **Determining the Payoff for Each Round:** After one of the decisions has been randomly selected, the computer will generate another random number that corresponds to the throw of a ten sided die. The number is equally likely to be 1, 2, 3, ... 10. This random number determines your earnings for the Option (A or B) that you previously selected for the decision being used.
- **Determining the Final Payoff:** There will be 2 rounds, and therefore, you will encounter 2 choice menus, each with 10 rows. You will find out your earnings for each of these menus as one of the rows is randomly selected. **Please Note:** We will use **all rounds** to determine your final earnings. Your total earnings will equal the sum of your earnings for the 2 menus.

Instructions: Summary

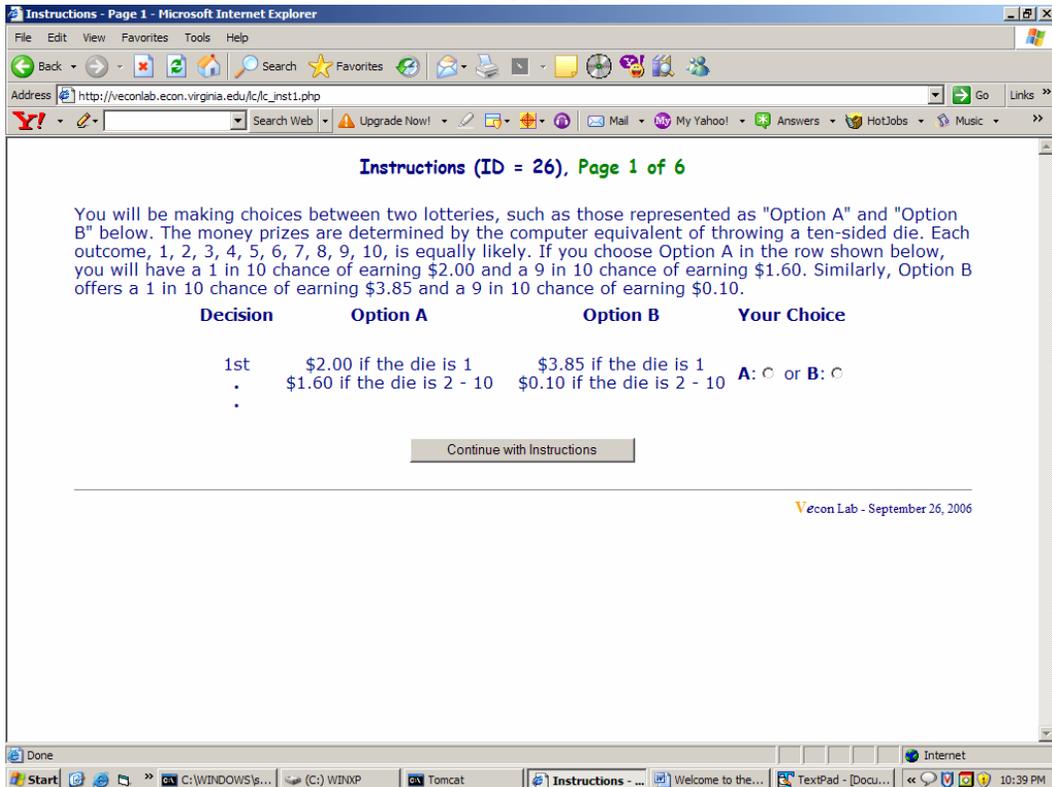
- You will indicate an option, A or B, for each of the rows by clicking on the "radio buttons" on the right side of the table.
- Then a random number fixes which row of the table (i.e. which decision) is relevant for your earnings.
- In that row, your decision fixed the choice for that row, Option A or Option B, and a final random number will determine the money payoff for the decision you made.
- This whole process will be repeated, but the prize amounts may change from one round to the next, so look at the prize amounts carefully before you start making decisions.
- The computer keeps track of your total earnings, i.e. the sum of the amounts earned in each round (negative earnings, if any, will be subtracted). Your final earnings will be the sum of all earnings in all rounds.

Screenshots

Screen 1



Screen 2



Screen 3

Instructions - Page 2 - Microsoft Internet Explorer

Address http://veconlab.econ.virginia.edu/lc/lc_inst2.php

Instructions (ID = 26), Page 2 of 6

- Each row of the decision table contains a pair of choices between **Option A** and **Option B**.
- You make your choice by clicking on the "A" or "B" buttons on the right. Only one option in each row can be selected, and you may change your decision as you wish.
- **Note:** Note, try clicking on one of the radio buttons, then change by clicking on the other one.

| Decision | Option A | Option B | Your Choice |
|----------|---|---|--|
| 1st | \$2.00 if the die is 1 \$1.60 if the die is 2 - 10 | \$3.85 if the die is 1 \$0.10 if the die is 2 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |

Vecon Lab - September 26, 2006

Screen 4

Instructions - Page 3 - Microsoft Internet Explorer

Address http://veconlab.econ.virginia.edu/lc/lc_inst3.php

Instructions (ID = 26), Page 3 of 6

Even though you will make ten decisions, **only one** of these will end up being used. The selection of the one to be used depends on the "throw of the die" that is the determined by the computer's random number generator. No decision is any more likely to be used than any other, and you will **not** know in advance which one will be selected, so please think about each one carefully. This random selection of a decision fixes the row (i.e. the Decision) that will be used. For example, suppose that you make all ten decisions and the throw of the die is 9, then your choice, A or B, for decision 9 below would be used and the other decisions would not be used.

| Decision | Option A | Option B | Your Choice |
|----------|---|---|--|
| 9th | \$2.00 if the die is 1 - 9 \$1.60 if the die is 10 | \$3.85 if the die is 1 - 9 \$0.10 if the die is 10 | A: <input type="radio"/> or B: <input type="radio"/> |

Vecon Lab - September 26, 2006

Screen 5

Instructions (ID = 26), Page 4 of 6

After the random die throw fixes the Decision row that will be used, we need to obtain a second random number that determines the earnings for the Option you chose for that row. In Decision 9 below, for example, a throw of 1, 2, 3, 4, 5, 6, 7, 8, or 9 will result in the higher payoff for the option you chose, and a throw of 10 will result in the lower payoff.

| Decision | Option A | Option B | Your Choice |
|------------------|---|---|--|
| 9 th | \$2.00 if the die is 1 - 9 \$1.60 if the die is 10 | \$3.85 if the die is 1 - 9 \$0.10 if the die is 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 10 th | \$2.00 if the die is 1 - 10 | \$3.85 if the die is 1 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |

For decision 10, the random die throw will not be needed, since the choice is between amounts of money that are fixed: \$2.00 for Option A and \$3.85 for Option B.

Vecon Lab - September 26, 2006

Screen 6

Instructions (ID = 26), Page 5 of 6

- Making Ten Decisions:** After you finish these instructions, you will see a table with 10 decisions in 10 separate rows, and you choose by clicking on the buttons on the right, option A or option B, for each of the 10 rows. You may make these choices in any order and change them as much as you wish until you press the Submit button at the bottom.
- The Relevant Decision:** One of the rows is then selected at random, and the Option (A or B) that you chose in that row will be used to determine your earnings. **Note:** Please think about each decision carefully, since each row is equally likely to end up being the one that is used to determine payoffs.
- Determining the Payoff for Each Round:** After one of the decisions has been randomly selected, the computer will generate another random number that corresponds to the throw of a ten sided die. The number is equally likely to be 1, 2, 3, ... 10. This random number determines your earnings for the Option (A or B) that you previously selected for the decision being used.
- Determining the Final Payoff:** There will be 2 rounds, and therefore, you will encounter 2 choice menus, each with 10 rows. You will find out your earnings for each of these menus as one of the rows is randomly selected. **Please Note:** We will use **all rounds** to determine your final earnings. Your total earnings will equal the sum of your earnings for the 2 menus.

Vecon Lab - September 26, 2006

Screen 7

Instructions Summary (ID = 26)

- To summarize, you will indicate an option, A or B, for each of the rows by clicking on the "radio buttons" on the right side of the table.
- Then a random number fixes which row of the table (i.e. which decision) is relevant for your earnings.
- In that row, your decision fixed the choice for that row, Option A or Option B, and a final random number will determine the money payoff for the decision you made.
- This whole process will be repeated, but the prize amounts may change from one round to the next, so look at the prize amounts carefully before you start making decisions.
- The computer keeps track of your total earnings, i.e. the sum of the amounts earned in each round (negative earnings, if any, will be subtracted). Your final earnings will be the sum of all earnings in all rounds.
- There will be an announcement at the start of each round that will indicate whether earnings will be paid in cash or whether earnings are hypothetical and will not be paid.

Vecon Lab - September 26, 2006

Screen 8

| Decision | Option A | Option B | Your Choice |
|----------|---|---|--|
| 1st | \$2.00 if the die is 1 \$1.60 if the die is 2 - 10 | \$3.85 if the die is 1 \$0.10 if the die is 2 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 2nd | \$2.00 if the die is 1 - 2 \$1.60 if the die is 3 - 10 | \$3.85 if the die is 1 - 2 \$0.10 if the die is 3 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 3rd | \$2.00 if the die is 1 - 3 \$1.60 if the die is 4 - 10 | \$3.85 if the die is 1 - 3 \$0.10 if the die is 4 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 4th | \$2.00 if the die is 1 - 4 \$1.60 if the die is 5 - 10 | \$3.85 if the die is 1 - 4 \$0.10 if the die is 5 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 5th | \$2.00 if the die is 1 - 5 \$1.60 if the die is 6 - 10 | \$3.85 if the die is 1 - 5 \$0.10 if the die is 6 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 6th | \$2.00 if the die is 1 - 6 \$1.60 if the die is 7 - 10 | \$3.85 if the die is 1 - 6 \$0.10 if the die is 7 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 7th | \$2.00 if the die is 1 - 7 \$1.60 if the die is 8 - 10 | \$3.85 if the die is 1 - 7 \$0.10 if the die is 8 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 8th | \$2.00 if the die is 1 - 8 \$1.60 if the die is 9 - 10 | \$3.85 if the die is 1 - 8 \$0.10 if the die is 9 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 9th | \$2.00 if the die is 1 - 9 \$1.60 if the die is 10 | \$3.85 if the die is 1 - 9 \$0.10 if the die is 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 10th | \$2.00 if the die is 1 - 10 | \$3.85 if the die is 1 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |

Vecon Lab - September 26, 2006

Screen 9

Submit Page, Round 1, ID 26 - Microsoft Internet Explorer

Address: http://veconlab.econ.virginia.edu/c/c_submit.php

Please select either A or B for each of the ten Decisions below.
Remember: Each decision has an equal chance of being used to determine your earnings.

Real Money Payoffs: The choices that you make on this page will be used to determine your earnings, these are real money payoffs that will be paid to you in cash.

| Decision | Option A | Option B | Your Choice |
|----------|---|---|--|
| 1st | \$2.00 if the die is 1 \$1.60 if the die is 2 - 10 | \$3.85 if the die is 1 \$0.10 if the die is 2 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 2nd | \$2.00 if the die is 1 - 2 \$1.60 if the die is 3 - 10 | \$3.85 if the die is 1 - 2 \$0.10 if the die is 3 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 3rd | \$2.00 if the die is 1 - 3 \$1.60 if the die is 4 - 10 | \$3.85 if the die is 1 - 3 \$0.10 if the die is 4 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 4th | \$2.00 if the die is 1 - 4 \$1.60 if the die is 5 - 10 | \$3.85 if the die is 1 - 4 \$0.10 if the die is 5 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 5th | \$2.00 if the die is 1 - 5 \$1.60 if the die is 6 - 10 | \$3.85 if the die is 1 - 5 \$0.10 if the die is 6 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 6th | \$2.00 if the die is 1 - 6 \$1.60 if the die is 7 - 10 | \$3.85 if the die is 1 - 6 \$0.10 if the die is 7 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 7th | \$2.00 if the die is 1 - 7 \$1.60 if the die is 8 - 10 | \$3.85 if the die is 1 - 7 \$0.10 if the die is 8 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 8th | \$2.00 if the die is 1 - 8 \$1.60 if the die is 9 - 10 | \$3.85 if the die is 1 - 8 \$0.10 if the die is 9 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 9th | \$2.00 if the die is 1 - 9 \$1.60 if the die is 10 | \$3.85 if the die is 1 - 9 \$0.10 if the die is 10 | A: <input type="radio"/> or B: <input type="radio"/> |
| 10th | \$2.00 if the die is 1 - 10 | \$3.85 if the die is 1 - 10 | A: <input type="radio"/> or B: <input type="radio"/> |

Press here after you have made ALL 10 decisions.

Screen 10

Confirm Page, Round 1, ID 26 - Microsoft Internet Explorer

Address: http://veconlab.econ.virginia.edu/c/c_confirm.php

Confirm Decision for Round 1, ID: 26

Lottery Decision 1st 2nd 3rd 4th 5th 6th 7th 8th 9th 10th
 Option Selected A A A A A A A A A A

If you wish to reconsider your decisions, please press **Change Decision** below.
 Otherwise, press **Confirm Decision** to obtain the results for this round.

To rechoose: To continue:

Vecon Lab - September 26, 2006

Screen 11

Results for Round 1, ID: 26

Lottery Decision 1st 2nd 3rd 4th 5th 6th 7th 8th 9th 10th
Option Selected A A A A A A A A A A A

The random number determined by the first die throw is: **5** so we will use **Decision 5**.
Your chose **Option A** for this decision.

| Decision | Option A | Option B | Your Choice |
|----------|---|---|-----------------|
| 5 | \$2.00 if the die is 1 - 5 \$1.60 if the die is 6 - 10 | \$3.85 if the die is 1 - 5 \$0.10 if the die is 6 - 10 | Option A |

Now we will generate the random number that determines the throw of the 10-sided die in such a manner that each outcome, 1, 2, 3, 4, 5, 6, 7, 8, 9, or 10 is equally likely.

Vecon Lab - September 26, 2006

Screen 12

Results for Round 1, ID: 26

The random number determined by the first die throw was: **5** so we use **Decision 5**.
Your chose **Option A** for this decision.

| Decision | Option A | Option B | Your Choice |
|----------|---|---|-----------------|
| 5 | \$2.00 if the die is 1 - 5 \$1.60 if the die is 6 - 10 | \$3.85 if the die is 1 - 5 \$0.10 if the die is 6 - 10 | Option A |

The second die throw is: 7

Therefore, your earnings for round 1 will be **\$1.60**
Your cumulative money earnings for all completed rounds are: **\$1.60**

Vecon Lab - September 26, 2006

REFERENCES

- Aggarwal, G., A. Goel and R. Motwani (2006). Truthful auctions for pricing search keywords. 7th ACM Conference on Electronic Commerce, Ann Arbor, MI.
- Aiken, L. S. and S. G. West (1991). Multiple Regression: Testing and Interpreting Interactions. Sage, Newbury Park, CA.
- Ainslie, A. and P. E. Rossi (1998). "Similarities in Choice Behavior across Product Categories." Marketing Science **17**(2): 91-106.
- Alba, J., J. Lynch, B. Weitz, C. Janiszewski, R. Lutz, A. Sawyer and S. Wood (1997). "Interactive home shopping: incentives for consumers, retailers, and manufacturers to participate in electronic marketplaces." Journal of Marketing **61**(7): 38-53.
- Anderson, C. (2005). "Google's Long Tail." (May 18, 2006)
<http://www.webcitation.org/5G2Vsty28>
- Andrews, R. L. and I. S. Currim (2002). "Identifying segments with identical choice behaviors across product categories: An Intercategory Logit Mixture model." International Journal of Research in Marketing **19**(1): 65-79.
- Animesh, A., V. Ramachandran and S. Viswanathan (2006). "Quality Uncertainty and Adverse Selection in Online Sponsored Search Markets." Working Paper, R. H. Smith School of Business, University of Maryland.
- Animesh, A., S. Viswanathan and R. Agarwal (2007). "Competing "Creatively" in Sponsored Search Markets: The Impact of Rank, Unique Selling Proposition, and Competition on the Effectiveness of Sponsored Search Listings." Working Paper, University of Maryland.
- Arbatskaya, M. N. (forthcoming). "Ordered Search." Rand Journal of Economics.
- Archibald, R. B., C. A. Haulman and J. Carlisle E. Moody (1983). "Quality, Price, Advertising and Published Quality Ratings." Journal of Consumer Research **9**: 347-356.
- Asdemir, K. (2006). "Bidding Patterns in Search Engine Auctions." Working Paper, University of Alberta.
- Bagwell, K. and P. B. Overgaard (2005). "Look How Little I'm Advertising." Working Paper.
- Bagwell, K. and G. Ramey (1994). "Coordination Economies, Advertising, and Search Behavior in Retail Markets." The American Economic Review **84**(3): 498-517.
- Bagwell, K. and M. H. Riordan (1991). "High and Declining Prices Signal Product Quality." The American Economic Review **81**(1): 224-239.
- Bailey, J. P., Y. Yao and S. Faraj (1999). Price dispersion among internet retailers. Workshop on Information Systems and Economics, Charlotte, NC.
- Bakos, J. Y. (1997). "Reducing buyer search costs: implications for electronic marketplaces." Management Science **43**(12): 1676-1708.
- Bakos, Y., H. C. Lucas, W. Oh, G. Simon, S. Viswanathan and B. W. Weber (2005). "The Impact of E-Commerce on Competition in the Retail Brokerage Industry." Information Systems Research **16**(4): 352-371.
- Baye, M. R. and J. Morgan (2002). "Information Gatekeepers and Price Discrimination on the Internet." Economics Letters **76**(1): 47-51.

- Baylis, K. and J. Perloff (2002). "Price Dispersion on the Internet: Good Firms, Bad Firms." Review of Industrial Organization **21**(3): 305-324.
- Bell, D. R. and J. M. Lattin (1998). "Shopping Behavior and Consumer Preference for Store Price Format: Why "Large Basket" Shoppers Prefer EDLP." Marketing Science **17**(1): 66-88.
- Benham, L. (1972). "The Effect of Advertising on the Price of Eyeglasses." Journal of Law and Economics **15**: 337-351.
- Borgs, C., J. Chayes, O. Etesami, N. Immorlica, K. Jain and M. Mahdian (2006). Bid optimization in online advertisement auctions. Second Workshop on Sponsored Search Auctions, Ann Arbor, Michigan.
- Broniarczyk, S. M. and J. W. Alba (1994). "Theory versus data in prediction and correlation tasks." Organizational behavior and human decision processes **57**(1): 117-139.
- Browne, G. J., M. G. Pitts and J. C. Wetherbe (2007). "Cognitive Stopping Rules for Terminating Information Search in Online Tasks." MIS Quarterly **31**(1): 89-104.
- Brynjolfsson, E., A. A. Dick and M. D. Smith (2004). "Search and Product Differentiation at an Internet Shopbot." Working Paper, Carnegie Mellon University.
- Brynjolfsson, E. and M. D. Smith (2000). "Frictionless Commerce? A Comparison of Internet and Conventional Retailers." Management Science **46**(4): 563-585.
- Cancian, M., A. Bills and T. Bergstrom (1995). "Hotelling Location Problems with Directional Constraints: An Application to Television News Scheduling." The Journal of Industrial Economics **43**(1): 121-124.
- Caves, R. E. and D. P. Greene (1996). "Brands' quality levels, prices, and advertising outlays: empirical evidence on signals and information costs." International Journal of Industrial Organization **14**(1): 29-52.
- Comanor, W. S. and T. A. Wilson (1979). "Advertising and Competition: A Survey." Journal of Economic Literature **17**(2): 453-476.
- Cowling, K. and J. Cubbin (1971). "Price, Quality and Advertising Competition: An Econometric Investigation of the United Kingdom Car Market." Economica **38**(152): 378-94.
- Deephouse, D. L. (1999). "To be different, or to be the same? It's a question (and theory) of strategic balance." Strategic management journal **20**(2): 147-166.
- Desai, P. S. (2001). "Quality Segmentation in Spatial Markets: When Does Cannibalization Affect Product Line Design?" Marketing Science **20**(3): 265-283.
- Diehl, K., L. J. Kornish and J. G. Lynch (2003). "Smart Agents: When Lower Search Costs for Quality Information Increase Price Sensitivity." Journal of Consumer Research **30**(1): 56-71.
- DoubleClick (2006). "Search Trend Report Q4 2005." (May 9, 2006) <http://www.webcitation.org/5Fmwx1gAZ>
- Economides, N. (1986). "Minimal and maximal product differentiation in Hotelling's duopoly." Economics letters **21**(1): 67-71.
- Edelman, B. (2006). "Adverse Selection in Online "Trust" Certifications." Working Paper (<http://www.benedelman.org/publications/advsel-trust-draft.pdf>).
- Edelman, B. and M. Ostrovsky (forthcoming). "Strategic Bidder Behavior in Sponsored Search Auctions." Decision Support Systems.

- Edelman, B., M. Ostrovsky and M. Schwarz (forthcoming). "Internet Advertising and the Generalized Second Price Auction: Selling Billions of Dollars Worth of Keywords." American Economic Review.
- Ellison, G. D. and S. F. Ellison (2004). "Search, Obfuscation, and Price Elasticities on the Internet." Working Paper, MIT Department of Economics No. 04-27.
- Fallows, D. (2005). Search Engine Users. PEW Internet and American Life Project.
- Feng, J., H. K. Bhargava and D. M. Pennock (forthcoming). "Implementing Sponsored Search in Web Search Engines: Computational Evaluation of Alternative Mechanisms." INFORMS Journal on Computing.
- Gao, Y., M. Koufaris and R. H. Ducoffe (2004). "An Experimental Study of the Effects of Promotional Techniques in Web-based Commerce." Journal of Electronic Commerce in Organizations **2**(3): 1-20.
- Gefen, D., E. Karahanna and D. W. Straub (2003). "Trust and TAM in Online Shopping: An Integrated Model." MIS Quarterly **27**(1): 51-90.
- Gerstner, E. (1985). "Do Higher Prices Signal Higher Qualities?" Journal of Marketing Research **22**: 209-215.
- Grossman, S. J. (1981). "The informational Role of Warranties and Private Disclosure about Product Quality." Journal of Law and Economics **24**(3): 461-483.
- Holt, C. A. and S. K. Laury (2002). "Risk Aversion and Incentive Effects." American Economic Review **92**: 1644-1655.
- Hong, W., J. Y. L. Thong and K. Y. Tam (2004). "Does Animation Attract Online Users' Attention? The Effects of Flash on Information Search Performance and Perceptions." Information Systems Research **15**(1): 60-86.
- Hoque, A. Y. and G. L. Lohse (1999). "An Information Search Cost Perspective for Designing Interfaces for Electronic Commerce." Journal of Marketing Research **36**(3): 387-394.
- Hughes, M. A. and D. E. Garrett (1990). "Intercoder Reliability Estimation Approaches in Marketing: A Generalizability Theory Framework for Quantitative Data." Journal of Marketing Research **27**: 85-195.
- iCrossing (2005). How America Searches: Online Shopping Report.
- Interactive Advertising Bureau (2003). "IAB / PWC Release Final Full Year 2002 Internet Ad Revenue Figures." (Jan 6) http://iab.net/news/pr_2003_06_12.asp
- Interactive Advertising Bureau (2005). "IAB/PwC Release First Half 2005 Internet Ad Revenue Figures." (Jan 6) http://www.iab.net/news/pr_2005_9_26.asp
- iProspect (2006). "Search Engine User Behavior." (May 9, 2006) <http://www.webcitation.org/5FmxuJBfl>
- Jansen, B. J. and M. Resnick (2005). Examining Searcher Perceptions of and Interactions with Sponsored Results. 1st Workshop on Sponsored Search Auctions, Vancouver, Canada.
- Jarvenpaa, S. L., N. Tractinsky and M. Vitale (2000). "Consumer Trust in an Internet Store." Information Technology and Management **1**(1): 45-71.
- Kihlstrom, R. E. and M. H. Riordan (1984). "Advertising as a signal." Journal of Political Economy **92**(3): 427-450.
- Kirman, A. (1997). "Advertising Repetition as a Signal of Quality: If It's Advertised So Often, Something Must Be Wrong." Journal of Advertising **XXVI**(3): 77-86.

- Kirman, A. and A. R. Rao (2000). "No Pain, No Gain: A Critical Review of the Literature on Signaling Unobservable Product Quality." Journal of Marketing **64**(2): 66-79.
- Kirman, A. and P. Wright (1989). "Money Talks: Perceived Advertising Expense and Expected Product Quality." Journal of Consumer Research **16**: 344-353.
- Kitts, B. and B. Leblanc (2004). "Optimal Bidding on Keyword Auctions." Electronic Markets **14**(3): 186-201.
- Klein, L. R. and G. Ford (2003). "Consumer search for information in the digital age: an empirical study of prepurchase search for automobiles." Journal of Interactive Marketing **17**(3): 29-49.
- Koufaris, M. (2002). "Applying the Technology Acceptance Model and Flow Theory to Online Consumer Behavior." Information Systems Research **13**(2): 205-223.
- Kuksov, D. (2004). "Buyer search costs and endogenous product design." Marketing Science **23**(4): 490-499.
- Kwoka, J. E., Jr. (1984). "Advertising and the Price and Quality of Optometric Services." The American Economic Review **74**(1): 211-16.
- Lahaie, S. (2006). "An Analysis of Alternative Slot Auction Designs for Sponsored Search." 7th ACM Conference on Electronic Commerce.
- Lai, F.-C. (2001). "Sequential locations in directional markets." Regional science and urban economics **31**(5): 535-546.
- Lal, R. and M. Sarvary (1999). "When and how is the Internet likely to decrease price competition?" Marketing Science **18**(4): 485-503.
- Landis, J. R. and G. G. Koch (1977). "The Measurement of Observer Agreement for Categorical Data." Biometrics **22**: 79-94.
- Lee, K. (2002). "Google and Overture: CPM in Disguise?"
<http://www.webcitation.org/5JeI08Dax>
- Levin, I. P. and R. D. Johnson (1984). "Estimating Price-Quality Tradeoffs Using Comparative Judgments." The Journal of Consumer Research **11**(1): 593-600.
- Lohse, G. L. (1997). "Consumer eye movement patterns on Yellow Pages advertising." Journal of Advertising **26**(1): 61-73.
- Lynch, J. G. and D. Ariely (2000). "Wine Online: Search Costs Affect Competition on Price, Quality, and Distribution." Marketing Science **19**(1): 83-103.
- Mandel, N. and E. J. Johnson (2002). "When Web Pages Influence Choice: Effects of Visual Primes on Experts and Novices." Journal of Consumer Research **29**(2): 235-45.
- Markoff, J. and N. Ives (2005). "Web Search Sites See Clicks Add Up to Big Ad Dollars." (May 9, 2006) <http://www.webcitation.org/5FmwsRaq9>
- Milgrom, P. and J. Roberts (1986). "Price and Advertising Signals of Product Quality." Journal of Political Economy **94**(4): 796-821.
- Nachman, D. C. (1975). "Risk Aversion, Impatience and Optimal Timing Decisions." Journal of Economic Theory **11**(2): 196-246.
- Nelson, P. (1970). "Information and Consumer Behaviour." Journal of Political Economy **78**(2): 311-329.
- Nelson, P. (1974). "Advertising as Information." Journal of Political Economy **82**(4): 729-754.

- Netz, J. S. and B. A. Taylor (2002). "Maximum or minimum differentiation? Location patterns of retail outlets." The review of economics and statistics **84**(10): 162-175.
- Newcomb, K. (2005). "Google's CPM Ads Meet Lukewarm Reception." <http://www.webcitation.org/5JeHVLPCe>
- Nichols, M. W. (1998). "Advertising and Quality in the U. S. Market for Automobiles." Southern Economic Journal **64**(4): 922-939.
- Nilssen, T. (1997). "Sequential location when transportation costs are asymmetric." Economics letters **54**(2): 191-201.
- Orzach, R., P. B. Overgaard and Y. Tauman (2002). "Modest Advertising Signals Strength." The RAND Journal of Economics **33**(2): 340-358.
- Oxenfeldt, A. R. (1950). "Consumer Knowledge: Its Measurement and Extent." The Review of Economics and Statistics **32**(4): 300-314.
- Pavlou, P. A. (2003). "Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model." International Journal of Electronic Commerce **7**(3): 69-103.
- Payne, J. W., J. R. Bettman and E. J. Johnson (1993). The adaptive decision maker. Cambridge University Press, Cambridge, England.
- Perry, M. and A. Wigderson (1986). "Search in a Known Pattern." The Journal of Political Economy **94**(1): 225-230.
- Peterson, R. A. (1970). "The Price-Perceived Quality Relationship: Experimental Evidence." Journal of Marketing Research **7**: 525-528.
- PricewaterhouseCoopers (2005). "IAB Internet Advertising Revenue Report." http://www.iab.net/resources/adrevenue/pdf/IAB_PwC_2004full.pdf
- Purohit, D. and J. Srivastava (2001). "Effect of Manufacturer Reputation, Retailer Reputation, and Product Warranty on Consumer Judgments of Product Quality: A Cue Diagnosticity Framework." Journal of Consumer Psychology **10**(3): 123-134.
- Rand, M. (2005). Comparison Shopping on Sale. Forbes.
- Rao, A. R. (2005). "The Quality of Price as a Quality Cue." Journal of Marketing Research **42**(4): 401-405.
- Ratchford, B. T. (1982). "Cost Benefit Models for Explaining Consumer Choice and Information Seeking Behavior." Management Science **28**(2): 197-212.
- Ratchford, B. T. and N. Srinivasan (1993). "An Empirical Investigation of Returns to Search." Marketing Science **12**(1): 73-87.
- Riordan, M. H. (1986). "Monopolistic Competition with Experience Goods." Quarterly Journal of Economics **101**(2): 265-79.
- Roedder, J., D., C. A. Scott and J. R. Bettman (1986). "Sampling Data for Covariation Assessment: The Effect of Prior Beliefs on Search Patterns." Journal of Consumer Research **13**: 38-47.
- Rusmevichientong, P. and D. P. Williamson (2006). An Adaptive Algorithm for Selecting Profitable Keywords for Search-Based Advertising Services. Seventh ACM Conference on Electronic Commerce.
- Salop, S. and J. Stiglitz (1977). "Bargains and Ripoffs: A Model of Monopolistically Competitive Price Dispersion." The Review of Economic Studies **44**(3): 493-510.
- Schaninger, C. M. (1981). "Social Class versus Income Revisited: An Empirical Investigation." Journal of Marketing Research **18**(2): 192-208.

- Schmalensee, R. (1978). "A Model of Advertising and Product Quality." Journal of Political Economy **86**(3): 485-503.
- Schmidt, J. and R. Spreng (1996). "A Proposed Model of External Consumer Information Search." Journal of the Academy of Marketing Science **24**(3): 246-256.
- Schotter, A. and Y. M. Braunstein (1981). "Economic Search: An Experimental Study." Economic Inquiry **19**(1): 1-25.
- Sherman, C. (2005). "A new F-word for Google search results." (May 9, 2006) <http://www.webcitation.org/5FmwyPgDv>
- Smith, M. D. (2001). "The Law of One Price? The Impact of IT-Enabled Markets on Consumer Search and Retailer Pricing." Working Paper, Carnegie Mellon University.
- Smith, M. D. and E. Brynjolfsson (2001). "Consumer Decision Making at an Internet Shopbot: Brand Still Matters." The Journal of Industrial Economics **49**(4): 541-558.
- Srivastava, J. and N. Lurie (2001). "A Consumer Perspective on Price-Matching Refund Policies: Effect on Price Perceptions and Search Behavior." Journal of Consumer Research **28**: 296-307.
- Stahl, K. (1982). "Differentiated Products, Consumer Search, and Locational Oligopoly." The Journal of Industrial Economics **31**(1): 97-113.
- Stigler, G. J. (1961). "The economics of information." Journal of Political Economy **69**(3): 213-225.
- Tellis, G. J. and C. Fornell (1988). "The Relationship between Advertising and Product Quality over the Product Life Cycle: A Contingency Theory." Journal of Marketing Research **25**(1): 64-71.
- Thomas, L., S. Shane and K. Weigelt (1998). "An empirical examination of advertising as a signal of product quality." Journal of Economic Behavior & Organization **37**(4): 415-430.
- Thomas, L., S. Shane and K. Weigelt (1998). "An empirical examination of advertising as a signal of product quality." Journal of Economic Behavior & Organization **37**: 415-430.
- Tobin, J. (1958). "Estimation of Relationships for limited dependent variables." Econometrica **26**: 24-36.
- Varian, H. R. (forthcoming). "Position Auctions." International Journal of Industrial Organization.
- Wills, R. L. and W. F. Mueller (1989). "Brand Pricing and Advertising." Southern Economic Journal **56**(2): 383-395.
- Wolinsky, A. (1983). "Prices as Signals of Product Quality." The Review of Economic Studies **50**(4): 647-658.
- Wu, J., V. J. Cook Jr. and E. C. Strong (2005). "A Two-Stage Model of the Promotional Performance of Pure Online Firms." Information Systems Research **16**(4): 334-351.
- Zhang, J., X. Fang and O. L. Sheng (2006). "Online Consumer Search Depth: Theory and New Findings." Journal of Management Information Systems **23**(3).
- Zhao, H. (2000). "Raising Awareness and Signaling Quality to Uninformed Consumers: A Price-Advertising Model." Marketing Science **19**(4): 390-396.
- Zwick, R., A. Rapoport, A. K. C. Lo and A. V. Muthukrishnan (2003). "Consumer Search: Not Enough Or Too Much?" Marketing Science **22**(4): 503-519.