

Keyword Competition and Determinants of Ad Position in Sponsored Search Advertising

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Abstract

Given the significant growth of the Internet in recent years, marketers have been striving for new techniques and strategies to prosper in the online world. Statistically, search engines have been the most dominant channels of Internet marketing in recent years. However, the mechanics of advertising in such a market place has created a challenging environment for marketers to position their ads among their competitors. This study uses a unique cross-sectional dataset of the top 500 Internet retailers in North America and hierarchical multiple regression analysis to empirically investigate the effect of keyword competition on the relationship between ad position and its determinants in the sponsored search market. To this end, the study utilizes the literature in consumer search behavior, keyword auction mechanism design, and search advertising performance as the theoretical foundation.

This study is the first of its kind to examine the sponsored search market characteristics in a cross-sectional setting where the level of keyword competition is explicitly captured in terms of the number of Internet retailers competing for similar keywords. Internet retailing provides an appropriate setting for this study given the high-stake battle for market share and intense competition for keywords in the sponsored search market place. The findings of this study indicate that bid values and ad relevancy metrics as well as their interaction affect the position of ads on the search engine result pages (SERPs). These results confirm some of the findings from previous studies that examined sponsored search advertising performance at a keyword level. Furthermore, the study finds that the position of ads for web-only retailers is dependent on bid values and ad relevancy metrics, whereas, multi-channel retailers are more reliant on their bid

values. This difference between web-only and multi-channel retailers is also observed in the moderating effect of keyword competition on the relationships between ad position and its key determinants. Specifically, this study finds that keyword competition has significant moderating effect only for multi-channel retailers.

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Chapter 1 Introduction

1.1 Introduction

The rapid growth of the Internet over the past two decades has raised significant interest among advertisers in using it as a tool for conveying their messages. The Internet has enabled the distribution of information to be affordable, convenient, and remarkably fast. Search engines in particular have been shown to be the primary gateway for most Internet users seeking information (Jansen & Mullen, 2008). This growth of users, along with simple, targeted, and customizable advertising, has allowed search engines to be the dominant online marketing channel on the Internet. In 2010, the revenue generated in the North American search engine marketing industry was \$16.6B¹ (Econsultancy, 2011). Given the unique characteristics that advertisers encounter in this growing online marketplace (e.g., three-agent interaction², mounting competition, and increasing budget allocation), it is evident that advertisers must understand the search engine environment to develop competitive strategies to achieve their marketing goals. Not only is the display of an advertisement directly related to the marketing goals, but so is the position of the ad within the search engine result pages (SERPs). Whether the marketing goal is brand awareness (visibility), revenue maximization (profit), or lead generation (visits), advertisers need to understand the factors that affect the display and position of ads in the sponsored search marketplace and develop strategies to compete in such a marketplace.

In sponsored search advertising, firms create ads and link them to keywords in order to appear on the SERPs. When a searcher enters a keyword, the search engine

¹ Values are in US dollars.

² Search engines, advertisers and users.

retrieves the ads related to that keyword (if any) and displays the ad on the resulting search page. The displayed ads are called ad copies and they usually contain a title, a short description, and a URL linking to the advertiser's destination webpage. Whenever a user clicks on the ad copy, the advertiser will be charged according to a payment mechanism called Pay-Per-Click (Geddes, 2010). Unlike conventional advertising media, where ad slots usually have predetermined prices, search engines conduct auctions in order to allocate ad slots to advertisers. Advertisers bid on keywords (or group of keywords) to enter these auctions. Winning an auction means that the ad linked to a keyword will be displayed on the SERP.

With improvements in search engines' ad placement mechanisms, the bidding value is no longer the only winning criteria in sponsored search auctions. The displayed ads should also be relevant to the searcher's query. Viewing pertinent ads is a vital factor for consumers searching online (Jansen & Spink, 2009) and the display of relevant ads (results) on the SERP attracts more customers to the search engine. Consequently, more users would click on the sponsored ads and this will generate higher revenue for the search engines. Therefore, search engines have employed mechanisms that rank ads not only based on bidding values but also on how relevant the ads are to the users' queries (Lahaie, 2006; Liu & Chen, 2006). For example, Google uses a measure called Quality Score (Google, 2011b) to determine whether an ad is eligible (relevant) to enter the auction as well as to determine where to place the advertiser's ad on the SERP³.

³ Although Google is referenced throughout the rest of this thesis (due to its dominance in search engine market share), other search engines are also using similar approaches in their auction design. Yahoo! uses a measure called Quality Index and Microsoft Bing is also incorporating quality measures in its ranking mechanism.

Therefore, advertisers should not only implement a proper bidding strategy, but also consider the ad relevancy measures needed to optimize their ad campaigns.

From the mechanism design viewpoint, competition is an inevitable characteristic of any auction design (Brannman, Klein, & Weiss, 1987; Milgrom & Weber, 1982). To succeed in sponsored search advertising, it is crucial for advertisers to understand the impact of competition in the underlying auction design. Major search engine providers currently use Generalized Second Price (GSP) auction. To succeed in a GSP auction, advertisers need to implement proper strategies to compete with their rivals. Auctions are generally explained by game theory, which mathematically models situations where the decision of each individual influences others' welfare (Myerson, 1997). In any auction game, there might be a situation called "strategic dominance", where for each individual there is a decision that results in a best strategy independent of others' decisions. However, the GSP auction does not have equilibrium in dominant strategies (Edelman, Ostrovsky, & Schwarz, 2005; Varian, 2007). Therefore, the decision of each advertiser is dependent on the decision of its rivals. With no dominant strategy in GSP auction, the number of competitors participating in the sponsored search advertising could have a significant impact on the allocation of ad slots to competing advertisers.

Two major streams of research have studied sponsored search advertising. While some researchers have focused on the auction process and investigated the mechanism design of such a market, others have focused on empirically modeling sponsored search ad performance using different performance variables. Studies related to auction mechanism design use game theory and impose restrictions on the real world situation to explain the market place and the interaction between agents of the marketplace

(Aggarwal, Feldman, & Muthukrishnan, 2007; Aggarwal, Goel, & Motwani, 2006; Asdemir, 2006; Edelman et al., 2005; Varian, 2007). This stream has been followed by other researchers who propose new slot allocation mechanisms in the sponsored search mechanism design (Edelman & Schwarz, 2007; Feng, Bhargava, & Pennock, 2007; Lahaie, 2006; Liu & Chen, 2006). The other stream of research analyzes sponsored search market place using keyword level or firm level data. This stream is mostly related to advertising strategies and optimization of keyword bidding values (Ghose & Yang, 2008, 2009, 2010; Rutz & Bucklin, 2007, 2011; Skiera, Eckert, & Hinz, 2010). Other related empirical studies have investigated consumer search behavior in sponsored search markets (e.g., Jansen, Booth, & Spink, 2008; Jansen & Resnick, 2006; Jansen & Spink, 2009).

Yet existing research in sponsored search advertising has failed to incorporate certain essential ingredients when modeling such marketplaces. The most neglected characteristic of the sponsored search market is competition intensity (Animesh, Viswanathan, & Agarwal, 2011; Ghose & Yang, 2009; Rutz & Bucklin, 2007). This is primarily due to a lack of cross-sectional competition data, the uncertainty about the underlying proprietary ad placement algorithms, and the heterogeneous characteristics of auction markets. Previous empirical research has indicated that the position of the ads on the SERP has significant importance in measuring economic or behavioral performance metrics (Dou, Lim, Su, Zhou, & Cui, 2010; Ganchev et al., 2007; Jansen et al., 2008; Rutz & Bucklin, 2007). However, there has been very limited research that examines the effect of competition intensity in the keyword market. Furthermore, while positioning strategy has been the subject of study in other competitive markets (Ahmed, 1991;

Brooksbank, 1994; Shostack, 1987), previous empirical studies in sponsored search advertising have rarely analyzed ad position as a dependent variable.

This study investigates the effect of keyword competition on the determinants of sponsored search ad position in an Internet retailing setting. Given that Internet retailers are at the very end of the supply chain, the development of information technology has enabled them to develop new marketing strategies in their advertising campaigns. Utilizing this new form of advertising with its growing consumer exposure enables retailers to expand their market share. Therefore, in this thesis, I plan to empirically examine the effect of keyword competition on a unique cross-sectional dataset using hierarchical multiple regression analysis (Aiken & West, 1991; Montgomery, Peck, Vining, & Vining, 2001). Specifically, I address two related research questions. First, how do key sponsored search variables (e.g., bid value, ad relevancy factors) affect ad position? Second, how does competition intensity moderate the relationship between ad position and its key determinants? To address these questions, I also control market conditions to account for differences across merchant types, company sizes, advertising budgets, and search engine optimization (SEO) quality in Internet retailing.

1.2 Research Goals and Contributions

Bidding in keyword auctions, ad relevancy measures, and intense keyword competition create a very challenging environment for Internet retailers in sponsored search advertising. Bidding values are easily measurable determinants of ad position, and usually in the control of advertisers. However, the relevancy of the advertisement to the user query is determined by multiple factors, which are proprietary to search engines. My objective in this study is to analyze the determinants of ad position, and empirically

examine how the level of keyword competition affects the relationship between ad position and its key determinants in the sponsored search market.

My research provides guidelines for researchers and practitioners with respect to the determinants of sponsored ad position in a competitive setting. From an academic perspective, this thesis attempts to explain how bidding strategy affects ad position, the relationship between ad relevancy attributes and ad position, and how these relationships are affected by the level of competition in the marketplace, using a unique cross-sectional dataset of online retailers and their search advertising campaigns. From the practitioners' perspective, the results of this study may enable advertisers to better implement positioning and differentiation strategies on the SERPs. With the widespread acceptance and use of search engines, advertisers are heavily investing in sponsored search advertising. Whether the advertisers' goal is brand awareness or revenue maximization, advertisers are well aware that the position of ads has a direct effect on their marketing goals. In particular, knowing that consumers click on sponsored ads based on their position on the SERP, the results of this study can guide advertisers in their campaign strategies in order to appear in the desired ad positions.

1.3 Thesis Outline

Chapter 2 presents an overview of the literature in Internet marketing and sponsored search advertising. Chapter 3 presents the conceptual framework and the theoretical foundations. Chapter 4 outlines the research model and the hypotheses of this study. Chapter 5 describes the data collection procedure, the research methodology, and the empirical results of the study. Chapter 6 presents the discussion of the results and the

theoretical and practical implications of the study. Finally, Chapter 7 provides the conclusions, limitations, and future research directions.

Chapter 2 Background and Research Context

2.1 Internet Marketing

Internet marketing, also known as online advertising, is a relatively modern marketing technique in comparison to conventional marketing channels like newspapers, radio, and television. It origins back to the early 1990s, when product information was displayed on simple text-based websites. With advances in information technologies, other forms of Internet marketing such as affiliate marketing, e-mail marketing, banner advertising, and search engine marketing (SEM) have emerged.

Affiliate marketing, also known as associate marketing, is a strategic marketing scheme with three roles involved in it: merchants, affiliates, and consumers (Duffy, 2005). The mechanics are very simple: the affiliate takes the risk of marketing costs for promoting the merchant's products or services in order to redirect consumers to the merchant's shopping portals. In return, the merchant pays a percentage of the sales from the redirected consumer as a reward to the affiliate (pay-per-conversion) or the affiliate gets rewarded as it redirects a certain number of consumers to the merchant website (pay-per-lead) (Libai, Biyalogorsky, & Gerstner, 2003). Although affiliate marketing provides a win-win situation for both merchants and affiliates, partners should be chosen carefully to be relevant to the website content (for affiliates) (Gallaughher, Auger, & BarNir, 2001) and to redirect more consumers to shopping portals (for merchants) (Chaffey, Ellis-Chadwick, Mayer, & Johnston, 2009).

Email marketing is another form of Internet advertising, which uses email to promote products or services to consumers. A 2011 report by Pew Research Center

(Purcell, 2011) shows that over 90% of Internet users are using email with 61% using it every day. Cheaper advertising costs, faster consumer response time, and interaction with consumers are the primary reasons for the popularity of this advertising medium (Martin, Van Durme, Raulas, & Merisavo, 2003). Furthermore, marketers believe that email is among the dominant virtual mechanisms of viral marketing (word-of-mouth advertising) (Phelps, Lewis, Mobilio, Perry, & Raman, 2004). However, spamming is one of the major drawbacks of email advertising among consumers. Spam is unsolicited commercial messages sent to individuals usually by strangers. Therefore, email marketers should legitimize their email advertising campaigns by receiving permission from consumers to prevent becoming victims of spam filterers (Blanzieri & Bryl, 2008; Delany, Cunningham, & Coyle, 2005).

Banner advertising, which first appeared in 1994 (Jansen & Mullen, 2008), is a form of display advertising illustrating graphical images inside vertical or horizontal boxes on webpages. A click on a banner redirects consumers to the merchant website associated with it. In 2009, displayed ad format had 22% of online advertising revenue share, and it reached 24% in 2010 (PricewaterhouseCoopers, 2010). However, views regarding the effectiveness of banner advertising have been inconsistent among marketing experts. Some believe that online users pay less attention to banner ads and have learned to avoid banner advertisements (Dreze & Hussherr, 2003; Hollis, 2000), whereas others have proven that banner advertising has a significant effect on Internet purchase behavior (Manchanda, Dubé, Goh, & Chintagunta, 2006). Yet due to the obtrusive nature of banner advertising, it has shared its popularity among marketers in

display advertising with content-targeted text-based advertising¹ (Goldfarb & Tucker, 2010). This recently emerged content-targeted advertising is an advertising model, where ads are either manually or automatically targeted to the content of the webpages.

2.2 Search Engine Advertising

With the advent of search engines, Internet marketing also has evolved. Search engines are providing service for over 50% of Internet users on a daily basis (Purcell, 2011); therefore, they have the potential to be a new and powerful marketing channel for advertisers. Search Engine Advertising (SEA), also known as Search Engine Marketing (SEM) or Sponsored Search Marketing, has recently received significant attention from both academia and industry. According to the most recent report by SEMPO (Econsultancy, 2011), the North American search engine marketing industry has increased in value from \$14.6B in 2009 to \$16.6B in 2010 and 16% growth was estimated in 2011, reaching a value of \$19.3B by the end of 2011. The proportion of companies carrying out Search Engine Optimization (SEO) has been reported to be at around 86%, while the percentage of companies engaging in paid search marketing was almost 80% in 2011 (Econsultancy, 2011). The Interactive Advertising Bureau (IAB) reports that search engine advertising in the fourth quarter of 2010 had a 19% increase in ad revenue compared to the same quarter in 2009 and a 15% increase compared to the third quarter in 2010 (PricewaterhouseCoopers, 2010). IAB also reports that the most popular ad format in 2010 was Search Engine Advertising, representing 46% of the total online advertising revenue.

¹ Google AdSense is the dominant provider of content-targeted ads online.

Sponsored search advertising has alleviated some of the reasons that marketers avoid advertising on the Internet. Academic research has shown that perceived goal impediment, perceived ad clutter, and prior negative experiences with online ads are major problems with conventional forms of Internet marketing, such as banner ads (Chang-Hoan & Cheon, 2004). However, perceived goal impediment (showing ads that are not aligned with the consumer's goals), the strongest factor in ad avoidance on the Internet, is diminished in SEA. Matching the ads to a consumer's query is one of the primary goals of search engine providers (Ghose & Yang, 2010; Google, 2011b). Evidently, all three agents of the sponsored search marketplace (i.e. the search engine, the advertisers and the consumers) have their own significant impact on the marketplace (Yao & Mela, 2011). The nature of the interaction and the benefits are threefold: search engines provide relevant results to the user queries resulting in user satisfaction, and acquisition of more users. More users would attract more advertisers to advertise on SERPs and consequently, search engine revenue increases. At the same time, an advertiser's ads would be displayed to the users with potential interest to the products or services the advertiser is offering (see Figure 2-1). In summary, not only advertising on the search engines does not have an obtrusive nature (contrary to banner advertising), but also, it will display relevant content to the consumers (contrary to email advertising), intensifying the popularity of this new advertising channel.

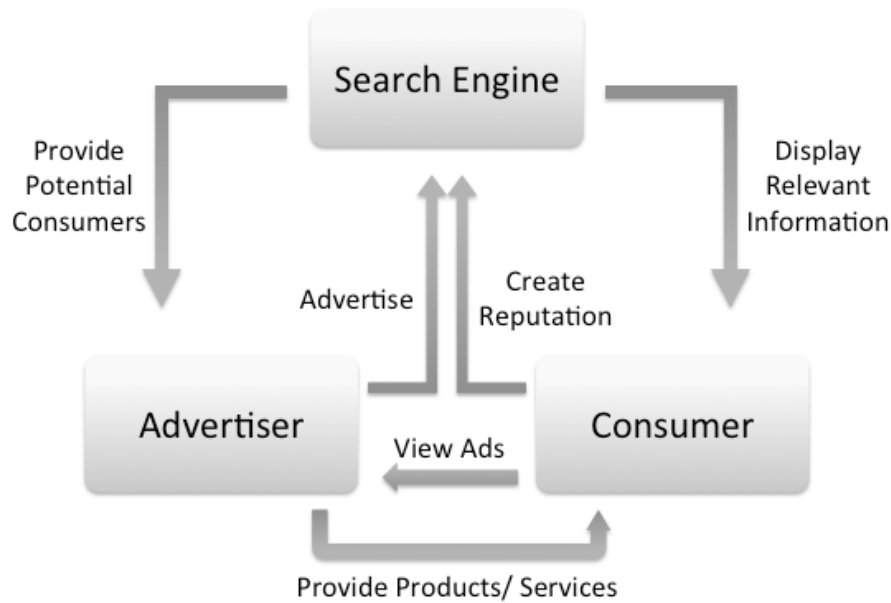


Figure 2-1: Three-way interaction of search engine, advertisers, and consumers.

Search engine marketing is performed in two ways: search engine optimization (SEO) and sponsored search advertising. SEO is the enhancement of website content and visibility to be more search engine friendly. In other words, by optimizing website content and structure, webpages can appear at higher positions in natural (organic) search results. Sponsored search advertising is like any other advertising media, where advertisers pay a fee in order to appear on the SERPs. The following scenario explains the mechanics of search engine advertising. Consider a user submitting a query (keyword) consisting of one or more words to the search engine². The search engine not only shows natural (organic) search results, but also displays sponsored search results promoted by advertisers. Placement of these sponsored results is different in various search engines, but mainly they appear at the top and right hand sides of SERPs. Figure

² User query and keyword are used interchangeably throughout this thesis.

2-2 shows an example of such a page from Google search engine, where the user query is “buy laptop”. The top and right hand side rectangles illustrate sponsored search results, whereas the left-bottom rectangle illustrates natural search results.

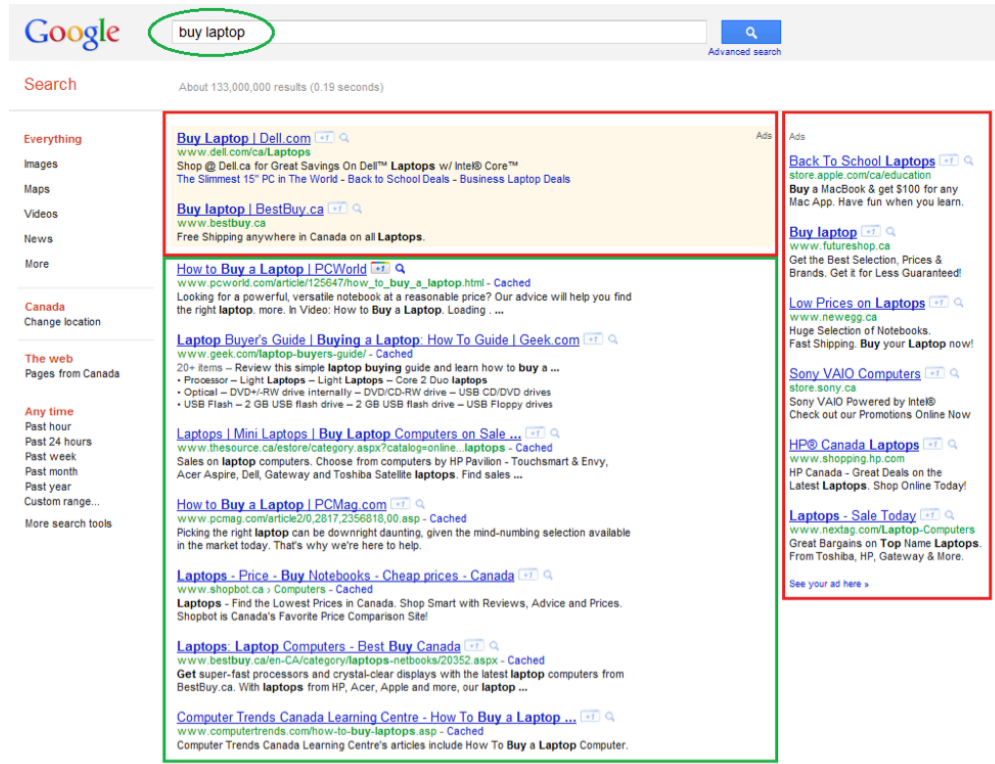


Figure 2-2: Placement of sponsored and organic search results on Google SERP.

A Generalized Second Price (GSP) auction determines where the ads (also called ad copies) should be positioned on the search engine result page (Edelman et al., 2005). With the submission of each query, an online (real time) auction is conducted among advertisers bidding on that query. To enter the auction, each ad has to be relevant to the searchers query and pass a certain minimum relevancy criteria (Google, 2011b). To position the ads on the result page, the search engine calculates the ad rank (related to the position of the ad on SERP) by multiplying an advertiser’s maximum Cost-Per-Click

(CPC) and its Quality Score. CPC is the amount that each advertiser is willing to pay for each particular keyword and Quality Score is a dynamically calculated value that determines how relevant the ad is to a user's query. If a user clicks on any ad, the corresponding advertiser will be charged slightly more than the bid value of the next advertiser's ad in the ad list (For an example and some exceptional cases, refer to (Google, 2011a)). This billing mechanism is called second price pay-per-click (PPC), which has gained a lot of attention compared to other forms of billing like pay-per-impression (CPM) as the advertisers are only paying for the ads only when they are actually being visited by the consumers (Rey & Kannan, 2010).

As mentioned above, Quality Score is a determinant of how much users of search engine find ads relevant to their keywords. Quality Score is dependent on a number of factors such as ad quality and historical performance of the advertiser's ad and is calculated every time a user submits a query. Therefore, due to the dynamic nature of the Quality Score, it is always possible for advertisers to improve their ad campaigns. Figure 2-3 shows the determinants of Quality Score according to Google (2011b). This figure shows that there is a huge emphasis on Click-Through-Rate (CTR) in the calculation of the Quality Score. CTR is the number of searchers' clicks on an ad, divided by the total number of times that the ad is displayed (also known as impressions). For example, if an ad is displayed 100 times and only 5 searchers click on that particular ad, the CTR for the ad is 0.05. The landing page is the webpage where the searcher is taken to when s/he clicks on the ad.

- *The historical CTR of the keyword and the matched ad on the Google domain*
- *Account history, measured by the CTR of all the ads and keywords in the account*
- *The historical CTR of the display URLs in the ad group*
- *The relevance of the keyword to the ads in its ad group*
- *The relevance of the keyword and the matched ad to the search query*
- *Account's performance in the geographical region where the ad will be shown*
- *The quality of the landing page*
- *Other relevance factors*

Figure 2-3: Google Quality Score factors.

As it is apparent from these criteria, controlling Quality Score is not an easy task as adjusting bidding value. A weak Quality Score can easily lead to disqualification of an ad from appearing on the SERP. Even if the ad can enter the auction with a weak Quality Score, the advertiser has to enormously overbid the true value of the ad slots to be able to secure the desired position. Furthermore, without a fixed price mechanism for ad slots, advertisers are competing in a growing competitive environment where their ad positions are highly related to their competitors' strategies and performance. Recently, there has been a growing stream of published literature (both from academia and practitioners) related to sponsored search advertising (Jansen & Mullen, 2008). The following section briefly summarizes some of the academic literature in this stream.

2.3 Sponsored Search Literature Review

Previously, sponsored search has been studied from different perspectives. While some researchers focused on the auction process and investigated mechanism design of such a market, others have empirically modeled the sponsored search ad performance. The empirical work in this area either focused on advertiser strategies or consumer search behavior in the sponsored search market.

2.3.1 Mechanism Design in Search Engine Auctions

The search engine advertising model displays ads that are based on user queries. It was first introduced by GoTo.com³, and used auctions to display ads on SERPs. In the GoTo.com model, the ads with the highest bidding values showed up at the top positions on the SERP. Later, Google started incorporating relevancy attributes into its auction design by not only displaying ads based on highest bidding values, but also based on the number of clicks that each ad receives. The total amount that the auctioneer charges the advertisers is calculated by multiplying the number of clicks by the bid value over a specific period. Therefore, an ad with high CTR value would return higher revenue compared to more expensive, less clicked ads.

In this regard, a number of studies have focused on mechanism design of sponsored search auctions. Appendix A lists an overview of existing literature in this area. Generalized Second Price (GSP) auction is the dominant mechanism design currently used by search engines. Each advertiser m submits a bid b_{mj} stating the maximum amount they are willing to pay for a click on an ad related to keyword j . Search

³ GoTo.com was created in 1998, which was then renamed to Overture in 2001, and later Overture acquired by Yahoo! In 2001 Google started its own search advertising model and introduced Google AdWords.

engine places the bidders in descending order of $b_{mj} * q_{mj}$, where q_{mj} is the quality of the advertiser m 's ad for the keyword j ; i.e., how relevant the ad is to the user's query. If the user clicks on advertiser m 's ad, the advertiser will be charged slightly more than b_{nj} , where b_{nj} is the amount that the advertiser, whose ad is listed just below advertiser m , is willing to pay for the ad.

GSP, compared to other conventional auction designs (e.g. Generalized First Price or Vickrey-Clarke-Groves (VCG) auctions), generates more profit for the search engines (Edelman et al., 2005; Jansen & Mullen, 2008). Edelman et al. (2005) proved that there is no equilibrium in dominant strategies in GSP auctions. Therefore, advertising decisions are constantly dependent on other participants of the market place. Consequently, some studies tried to constrain the GSP auction mechanism in an attempt to explain the game theory behind sponsored search auctions favoring advertisers (Aggarwal et al., 2007; Aggarwal et al., 2006; Asdemir, 2006; Edelman et al., 2005; Varian, 2007). Others have proposed new slot allocation mechanisms to maximize search engines' revenue (Edelman & Schwarz, 2007; Feng et al., 2007; Lahaie, 2006; Liu & Chen, 2006).

Derived from the Nash equilibrium, Varian (2007) proposes a "symmetric" equilibrium for slot allocation in complete information auction settings. Similar to Edelman's (2005) findings, he argues that optimal bids in sponsored search auction are dependent on the bids of the other agents in the market place. Asdemir (2006) shows patterns of bidding war cycles in sponsored search auctions. He suggests that bidding under estimated value can prevent advertisers from being in a bidding war cycle. Aggarwal et al. (2007) introduce position-based design, where advertisers are able to

specify the minimum rank they would like to appear at along with their bids. They prove that the so-called position-based design is both envy-free⁴ and bidder-optimal.

Giving more priority to the benefits of the auctioneers, Aggarwal et al. (2006) introduce a truthful “Laddered Auction” mechanism. The authors argue that truthfulness promotes simplicity in advertisers’ bidding strategy, removing incentives for under-bidding behavior, and utility maximization of both auctioneers and merchants. Lahaie (2006) compares two different auction designs used by Yahoo! and Google in existence of complete and incomplete information: Rank By Bid (RBB) and Rank By Revenue (RBR). The author implies that the existence of relevancy factors in RBR model leads to harder conditions in playing the equilibrium compared to RBB model. Liu and Chen (2006) also compare auction designs by Google and Yahoo! in an incomplete information auction setting. They imply that with higher competition in effect, Google’s mechanism design (which incorporates relevancy attributes) generates more revenue compared to Yahoo!. Likewise, Edelman and Ostrovsky (2007) argue that first price auction design originally utilized by Yahoo! has enabled bidders to strategically bid on keywords resulting in revenue losses for the search engine. Feng et al. (2007) simulate several ranking mechanisms in an incomplete information auction setting. The authors propose that incorporating relevancy attributes or editorial filtering into ranking mechanism would highly increase the search engine revenue. Edelman and Schwarz (2007) also show that GSP auction design with a reserve price for keywords is an optimal auction setting for search engines and the reserved price is independent of the number of

⁴ Envy-free in a division problem is a situation where all the players in the game think s/he has the best division possible and no other player has better piece.

competitors. Furthermore, with an increase in competition, more revenue for the search engine will be generated.

It is clear from mechanism design literature that incorporating ad relevancy metrics in the auction design has benefits for both advertisers and search engines. While it has been proven that it generates more revenue for the auctioneer, it also opens more avenues for advertisers to strategically design their advertising campaigns. One of the shortcomings of previous research in mechanism design is operationalizing the ad relevancy simply by measuring the CTR value. CTR is a key determinant of the ad's Quality Score and a higher Quality Score results in a higher position of the ads on the SERP; however, as previously discussed, CTR is not the only factor affecting the Quality Score. The mechanism design literature has rarely incorporated other factors such as ad copy content and the landing page quality in their studies. Another issue in the existing mechanism design literature is that the analysis of competition is modeled using only a few (e.g. two) advertisers (Asdemir, 2006; Liu & Chen, 2006). The sponsored search marketplace is a dynamic environment with thousands of firms continuously entering the market. Modeling the marketplace characteristics should account for competition intensity between advertisers. An increase in competition intensity has a direct effect on both sponsored search revenue (Edelman & Ostrovsky, 2007) and advertisers' bidding strategies (Varian, 2007).

Finally, as Lahaie (2006) points out, budget constraints can affect the design equilibrium. Advertisers are restricted by resource constraints in their advertising campaigns, and this could significantly affect their role in the marketplace equilibrium. Existing research has failed to specifically address the constraints that the budget

allocation can impose on the marketplace both in terms of search engines' revenue and advertisers' bidding strategies.

2.3.2 Empirical Research in Sponsored Search Ad Performance

Another stream of research in sponsored search advertising has focused on search engine ad performance metrics. This stream of research has used econometric models to model the relationships between various sponsored search variables. These variables have been measured either at keyword level (e.g. length of the keywords) or firm level (e.g. number of keywords) settings. Appendix A summarizes the existing work in this area.

Ganchev, Kulesza, Tan, Gabbard, Liu, and Kearns (2007) propose approaches that should be taken in order to model advertisers' bidding behavior in sponsored search auctions. They conclude that removing data related to certain strategies (e.g. jamming bids to deplete competitors' budgets) can contribute to finding a better fit for bidding data. Rutz and Bucklin (2007) propose a method to calculate individual keyword's cost per sale and consequently, a model to generate high performance keywords. Ghose and Yang (2009) used keyword level variables, ad position, and landing page quality to explain consumer search and purchase behavior, advertisers' cost-per-click, and search engine ranking mechanism. In another study, Ghose and Yang (2008) propose a model for calculating optimal bidding values and evaluate advertisers' overbidding and underbidding patterns based on keyword level attributes. Surprisingly, their conclusions for optimal bidding values (CPCs) are in contrast to their earlier study: the presence of retailer and brand specific information in keywords increase optimal bid price, while long tail keywords decrease optimal bid price. In another study on search data from Yahoo!,

Rey and Kannan (2010) propose a model to optimize the bidding value of the keywords based on estimated conversion rate of each keyword.

Some studies have investigated the relationship between sponsored search advertising and organic search results. Jansen and Spink (2007) report that combining organic listings together with sponsored search results decreases the CTR of sponsored search results. Yang and Ghose (2010) show that the presence of both sponsored and organic listings results in a synergy that increases the CTR on both listings. Richardson, Dominowska, and Ragno (2007) propose a logistic regression model to estimate the CTR of newly created ads. They incorporate information about terms relativity, quality, content, and scope of the ads.

A very nascent stream of research emerging in sponsored search is the effect of spillovers between different marketplace variables. Ghose and Yang (2010) have modeled the consumers' search-to-purchase behavior over different product categories. They conclude that there is a high probability that consumers searching for a product in a category might not only purchase a product in that category, but also tend to buy a product from a different category. They further elaborate their results based on keyword-level attributes such as retailer-specific keywords and brand-specific keywords. Rutz and Bucklin (2011) introduce the concept of "awareness of relevance" in keywords, and propose that there is a strong asymmetric spillover from generic search to branded search activity.

The emerging empirical research in sponsored search marketplace reveals the variety of questions and nascent development of research in this area. Apparently, difficulties in data acquisition, heterogeneous characteristics of search engines, and

uncertainty about proprietary slot allocation algorithms have led to inconsistent results in this stream of research⁵. Previous researches have used a variety of metrics for measuring and estimating search engine advertising performance. Both financial performance metrics (e.g. revenue) and consumer behavior metrics (e.g. CTR) have been the subject of measuring the performance of sponsored search campaigns. However, each metric targets a specific advertising strategy (e.g. brand awareness) and fails to provide a landscape for measuring the performance of sponsored search advertising. In fact, it is the nature of marketing and advertising where media planning, budget allocation, and performance assessment becomes challenging for managers even in traditional settings (Cheong, De Gregorio, and Kim, 2010; Lavrakas, Mane, and Laszlo, 2010).

Furthermore, most of the previous studies are based on data from only a single firm's marketing campaign. The competitive nature of the sponsored search market requires incorporating competition intensity when performing empirical analysis. The lack of competition data has also been emphasized in previous literature (e.g. Ghose and Yang, 2009; Rutz and Bucklin, 2007). Finally, search engines constantly change their ad slot allocation mechanisms. Therefore, some of the assumptions in the previous empirical research have changed, as the allocation mechanisms have evolved. An example is the evolution of ranking mechanism from being only based on bid values to integrating ad relevancy factors into the equation. Although this dynamic nature of sponsored search might have challenged the ongoing research, it has led to a fertile stream of empirical research in the information systems and marketing fields.

⁵ These are the results of advertising hassles imposed by the policies of the advertising intermediaries. Edelman (2009) lists five rights that are taken from advertisers when they sign up to these intermediaries.

2.3.3 Consumer Search Behavior

Uncertainty about consumers' search behavior is one of the most prominent factors that make online advertising a challenging task. Figure 2-4 is the means-end model relating price, quality, and value, as proposed by Zeithaml (1988). The model shows that the decision process that leads to a consumer purchase combines several intrinsic and extrinsic attributes together, which is unique to each and every individual consumer. It is also clear that in the very end of the process, it is the perceived value of an item (in this context, the perceived value that each sponsored result can produce for consumers), which determines if the consumer is going to take an action (e.g. clicking the sponsored ad). In sponsored search advertising context, consumer search behavior drives the selection of the keywords, the design of the ad copies, and the overall advertising campaign strategy. In addition, it is the search engine policy to show relevant ads in the

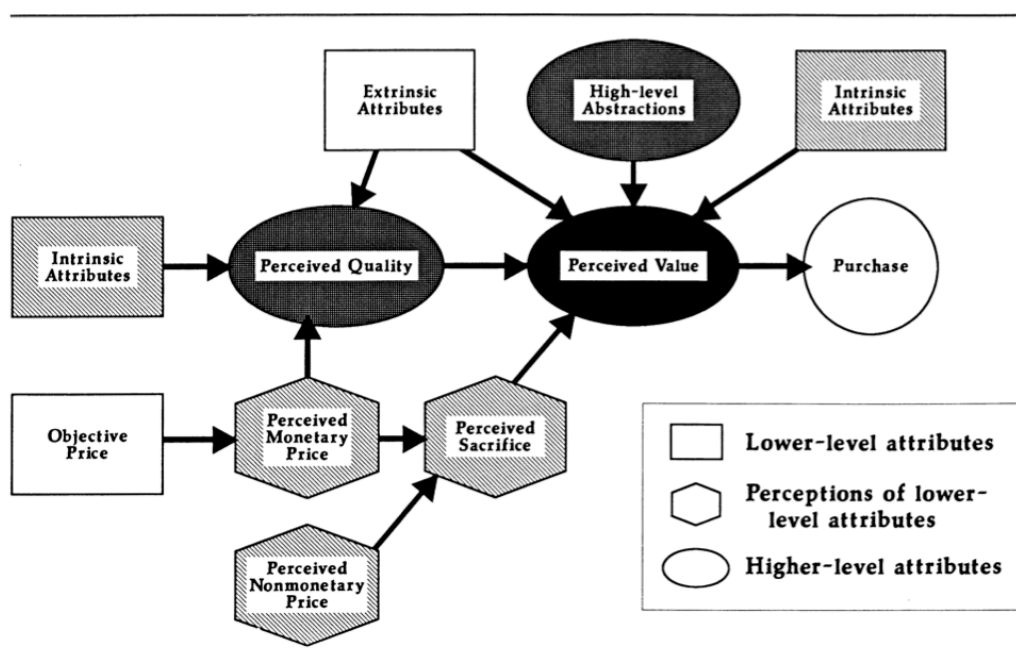


Figure 2-4: A means-end model relating price, quality, and value (Zeithaml, 1988)

higher spots, as the ads on the top spots receive more attention from users. Users have different mindsets when searching on the Internet, and search engines can show more results that are relevant if they recognize users' intent during their search session. In this regard, Jansen et al. (2008) provide a hierarchical classification of user intent on search engines, derived from previous research in sponsored search advertising. In their research, queries are categorized into informational, transactional, and navigational web queries.

Much of the work in consumer search behavior overlaps with the research reviewed in the previous section. For example, several studies by Ghose and Yang (2008, 2009, 2010) also have implications related to online consumer purchase behavior. Jansen and Resnick (2006) have reviewed a large body of literature related to consumer search behavior in search engines. They conclude that consumers' preference towards organic results is stronger; however, consumers rate the non-sponsored result pages as relevant as sponsored result pages. Furthermore, they find that integrating sponsored and non-sponsored search results do not increase user attention towards sponsored results (Jansen & Spink, 2009).

One important implication from previous research regarding consumer search behavior is how the user search behavior can be captured by click-through-rate (CTR). Due to privacy concerns as well as difficulties in data collection, it is laborious to capture a decent sample of user search behavior data. The CTR value is one of the best indicators of the consumer search behavior, as it incorporates both impressions and actual user clicks. While impressions define how many consumers are searching for a particular product (much like reach and frequency in traditional advertising media), consumer

clicks are an indicator of relevancy of the advertisement based on consumer evaluation. More specifically, a click by the consumer indicates that the position, information content, and presentation of the ad have been reliable enough to be regarded as a relevant search result. Interpreting CTR as a measure of consumer involvement also provides the rationale for RBR ranking mechanisms discussed in the previous section.

2.4 Internet Retailers

This study focuses on Internet retailers and their competition in sponsored search advertising. Being at the very end of supply chain, the online retailing industry has shown to be excessively competitive, especially with the emergence of new website technologies (Agrawal & Smith, 2009). With the worldwide spread of the Internet, not only the “brick and mortar” companies have adopted this new technology to become “click and mortar” companies, but also a new form of pure-play businesses have emerged. Reports show that seasonally adjusted 2010 e-commerce sales were \$164.6 billion and represented 4.2% of total retail spending (InternetRetailers, 2011). Reported profits and sales indicate that Internet retailing is a firmly established and increasingly profitable market (Venkatesan, Mehta, & Bapna, 2007).

Competition is an indisputable characteristic of the retail industry. Striving for a greater market share has forced retailers to adopt differentiation strategies in order to be on top of their market. The online world has even intensified this competition by removing the geographical boundaries and its worldwide exposure. It is no surprise that advertising in this growing high competitive online market could be quite challenging. Merchants, regardless of their channel category, size, and product category, utilize all forms of Internet marketing to advertise their products and services. Therefore, focusing

on Internet retailers in studying the sponsored search market not only sheds light on the design characteristics of the sponsored search advertising campaigns, but also provides an appropriate environment to understand the effect of competition intensity on the relationship between ad position and its key determinants.

Chapter 3 Conceptual Model and Theoretical Foundation

This chapter proposes the conceptual model used in this study (Figure 3-1). The positioning strategy of the firm in sponsored search marketplace is correlated with the actual position of its ads on SERP. The ad position itself is an outcome of a strategic mixture of sponsored search auction determinants, which is observable in the form of bidding values and ad relevancy attributes. Furthermore, this relationship takes place in a competitive environment, where the competition intensity is projected in a high-stakes battle for keywords and ad slots. The following sections will explain the proposed research framework. First, I will explain why the outcome of positioning strategy can be reflected in ad position and how it can be compared to other performance metrics in previous studies. Then I will discuss the key determinants of ad position based on existing academic and practitioners' findings. Finally, I will provide an overview of the keyword market with a focus on keyword competition.

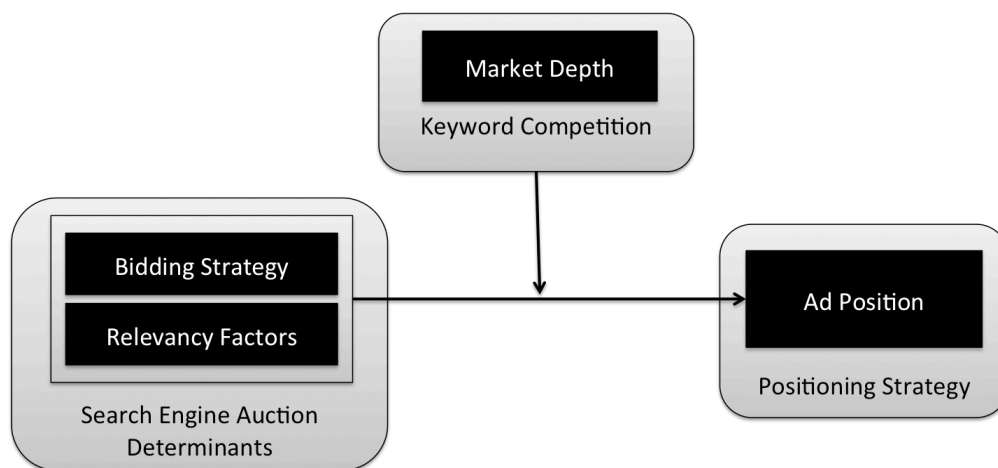


Figure 3-1: Conceptual model.

3.1 Positioning Strategy and Ad Performance

The following quote by Ries and Trout (2000, p. 3) gives a clear definition of positioning:

“... positioning is not what you do to a product. Positioning is what you do to the mind of the prospect. That is, you position the product in the mind of the prospect.”

A similar analogy can be drawn for the sponsored search marketplace by conceptualizing ad copies as products that advertisers are willing to sell to consumers (by drawing consumers' attention to it). The term “positioning” in sponsored search can be simply understood as the placement of the ads on a search page. However, on a more complex level, positioning strategy is a direct reflection of how a firm wants to appear in a consumer's mind. For example, consumers may perceive high priced items as having premium quality compared to their lower priced equivalents. Within the sponsored search context, the higher the position of the ads can suggest better product quality and a higher reliability of the advertiser. In the end, it is the consumers' perceived value of an item that drives his/her decision process (Ahmed, 1991; Zeithaml, 1988) and advertisers are constantly studying consumer behavior and strategizing their marketing campaigns to target their audiences more accurately. Positioning and differentiation strategies have been the focus of marketing in various contexts such as service positioning (Shostack, 1987), positioning in tourism industry (Ahmed, 1991), and positioning in retail computer market (Brooksbank, 1994).

Providing a ranked list of ads, search engines have enabled advertisers to target different consumer segments. This has been done by applying demographic filters¹ and by providing a competitive positioning setting. Advertisers can pursue their marketing goals through targeting a certain ad position on SERPs. For example, one advertiser might aim for top advertising slots to pursue brand awareness and recognition (Dou et al., 2010; Rutz & Bucklin, 2011). Whereas, by aiming at middle positions (cheaper ads and more conversion rate), another advertiser might be interested in revenue maximization (Ghose & Yang, 2009). The directional nature of the sponsored search marketplace has enabled advertisers to strategize their campaigns based on consumers' perception of different ad positions (Animesh et al., 2011).

The examples above demonstrate that advertisers have some guidelines for their advertising goals based on implications from consumer search behavior (e.g., top position leads to brand awareness, or lower position implies lower product cost). Unfortunately, previous research on ad performance has used different performance metrics that make comparisons difficult and implications inconsistent. Consumer behavior metrics (such as CTR) (Agarwal, Hosanagar, & Smith, 2008; Animesh et al., 2011) and financial metrics (such as revenue per click) (Agarwal et al., 2008; Rutz & Bucklin, 2007) have all been used as performance metrics; often dependent on the ad position, informational content of the ad copies, and other sponsored search variables. However, the relationship between ad position and ad performance is not a one-way relationship (Figure 3-2). As such, the ad position is partly determined by the historical performance of the ad campaign (e.g., CTR). On the other hand, advertisers are becoming more aware of consumer behavior

¹ Advertisers can target a specific geographic region, or a certain period for their ads to be displayed. However, these demographic factors are not the focus of this study.

and it is their interest to develop and implement their marketing strategies according to different consumer segments. For example, knowing that the quality seeking consumers usually surf the ads in the premium positions, advertisers offering higher quality products are interested in securing premium ad slots for their advertisement. Therefore, one fundamental question is how to design the ad campaign to reach the desired ad position which takes into account the marketing goals of the advertiser.

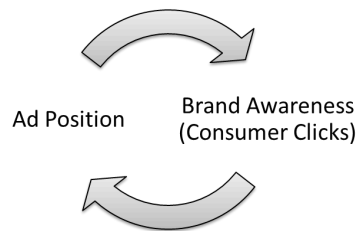


Figure 3-2: Sample two-way relationship between ad position and consumer clicks.

Previous research has focused on either optimizing bid values of sponsored search keywords or explaining the strategies that would maximize economic welfare (revenue). However, despite ample practical evidence in the industry regarding the importance of the ad position, empirical research in sponsored search advertising has given limited attention to ad position as a dependent variable. This study uses ad position as the dependent variable and investigates how sponsored search variables are related to the position of the ads on the SERP in a competitive environment.

3.2 Determinants of Ad Position

To achieve the desired ad position, advertisers need to know how to customize, control, and strategize the ad position determinants. Analyzing and describing the key factors of the sponsored search ad position has also been the focus of the mechanism design literature (Edelman & Ostrovsky, 2007; Rutz & Bucklin, 2011; Varian, 2007). For

example, Rutz and Bucklin (2011) model the change in ad position as a function of awareness carryover, current CPC, historical CTR, and seasonality indicators. Also, Feng et al. (2007) suggest that auction designs that incorporate both bidding value and relevancy attributes are producing more revenue for the search engines. Most of the research related to mechanism design has focused on winning the top position in the auction process. This stream of research mainly focuses on strategies for bid adjustment, rarely incorporating CTR as the determinant of the slot allocation process (Liu & Chen, 2006). Furthermore, as it was previously discussed, the search engine ad rank formula is much more complicated than just being conveyed by the CTR value.

An overview of the mechanism design literature in sponsored search (Appendix A) reveals that both bidding strategies and ad relevancy attributes contribute to the position of the ads on SERP. Bidding strategies are mainly in control of the advertiser in terms of setting bidding values and budget limits. Advertisers are in control of setting bid values for each keyword in the auction process. However, as the auction mechanism follows the GSP auction rules, they will be charged by the highest bid value submitted by the next competitors. In the end, it is the advertiser who can strategize the bid value either to win the competition and spend the maximum cost per click or bid on the keyword as much as his evaluation of the keyword's value (Aggarwal et al., 2006; Asdemir, 2006; Ghose & Yang, 2008).

On the other hand, ad relevancy attributes are mainly in control of the search engine as the auctioneer in the auction process. Advertisers can indirectly influence their ad quality (e.g., by following SEO practices or creating relevant ad copies). However, in the end, it is the search engines proprietary algorithm that determines the relevancy score.

These two dimensions also conform to the guidelines published by the search providers (see Section 2.2). Likewise, this study categorizes the sponsored search determinants into bidding and relevancy dimensions to evaluate their main effects on ad position (Figure 3-3).



Figure 3-3: Bidding strategy and ad relevancy attributes as determinants of ad position.

3.3 Competition Intensity

Similar to other marketplaces, competition in online sponsored search markets has forced advertisers to adopt differentiation strategies (e.g. quality or price) in order to distinguish themselves from their rivals. Fortunately for the advertisers, the pay-per-click mechanism employed by search engines allows them to enter the competition from diverse demographics. Even smaller companies with low advertising budgets, and without well-known brands, can enter the competition. However, with the increase in the number of advertisers, the competition is becoming increasingly intense. Auction theory states that an increase in the number of competitors increases the winning bids (Brannman et al., 1987). Sponsored search marketplace as an adopter of auction mechanism design is no different. Competition in the marketplace causes the per-click values to vary across different advertising slots and even if the position is cost free (organic results), it might not be desirable (Xu, Chen, & Whinston, 2008). Furthermore, in a GSP auction setting,

the per-click value is related to the allocation of the slots and bids of the other competitors, not solely on the advertisers' own bid (Jansen & Mullen, 2008; Varian, 2007). From the users' perspective, not only does the order of the ads affect the user behavior, but also the probability of an ad getting clicked is dependent on other ads on the result page (Aggarwal, Feldman, Muthukrishnan, & Pál, 2008). Therefore, it is vital to account for the competition intensity while analyzing ad performance in the sponsored search market.

Previous empirical research in search engine advertising has always questioned the impact of competition on the marketplace variables. Yet, lack of publicly available data both from search engines and advertisers, as well as difficulties in capturing users behavior due to privacy concerns are main reasons for limited consideration of competition in empirical evaluations. A recent exception (closely related to the topic of this study) is the work by Animesh et al. (2011). In their work, the authors model the competition by calculating the number of firms with similar unique selling propositions in relation to the focal firm's ads. However, like other empirical studies in sponsored search, they are focusing on competition intensity around a focal firm. To the best of my knowledge, this study is the first empirical research that uses ad position as the dependent variable and investigates the determinants of ad position in sponsored search in a cross-sectional setting where the level of competition in the keyword market is explicitly incorporated in terms of the number of firms competing for similar keywords.

Chapter 4 Research Hypotheses

In this chapter, I derive the research model (Figure 4-1) from the conceptual framework presented in previous chapter and formulate several hypotheses for the proposed study. As it was stated previously, positioning strategy of the firm is reflected in the position of the ad on the SERPs. The ad position is not the only mechanism for implementing positioning strategies; in addition, other factors such as ad content also contribute to the positioning strategy of the firm. However, the focus of this study is the ad position as one of the main anticipating mechanisms of achieving positioning strategy of the firm. The following sections present theoretical arguments leading to the relationships between sponsored search ad position and its key determinants based on the relevant literature and industry practices.

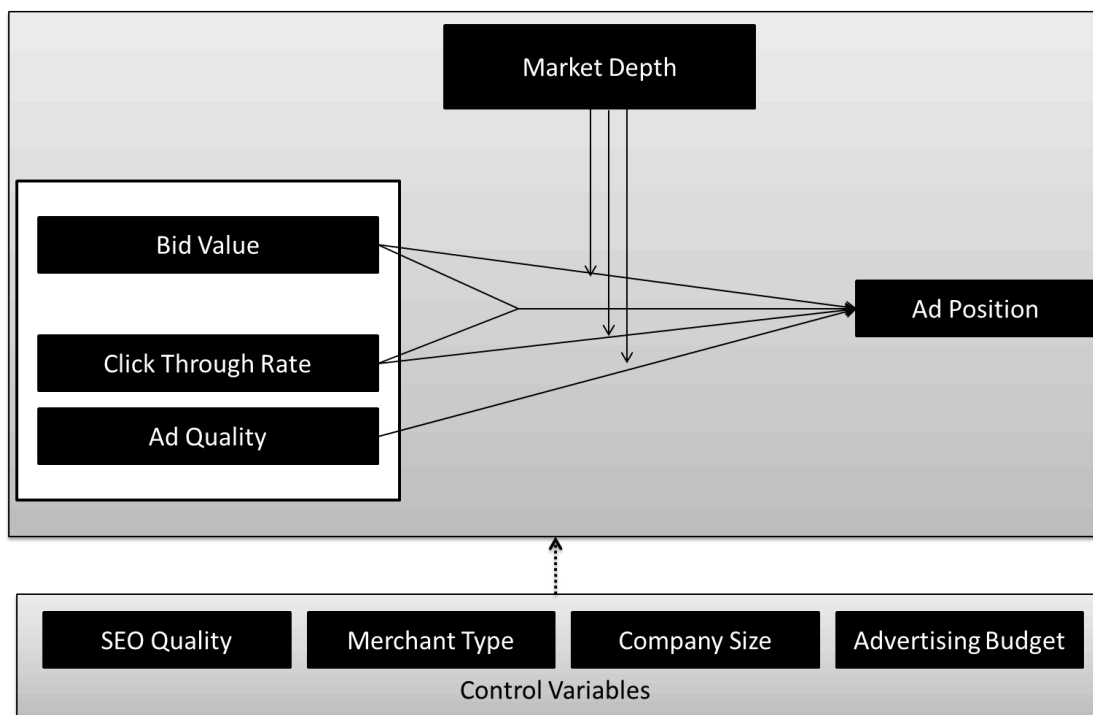


Figure 4-1: Research model

4.1 Main Effects of Ad Position Determinants

4.1.1 Bidding Strategy

Bid value is one of the most important determinants of ad position. It is the maximum amount of money that an advertiser is willing to spend on each of its keywords. The more the advertiser bids on its keywords, the higher the likelihood that the advertiser wins the auction. Most previous research in sponsored search advertising (except some related to consumer search behavior) use the bid value as a key variable in their models. For example, some researchers have tried to propose models for either predicting optimal bidding values or controlling the determinants of bidding values (Ghose & Yang, 2009; Yang & Ghose, 2010). According to auction theory, setting the bidding value is a challenging task prone to winner's curse¹ (often called a Pyrrhic victory). However, market equilibrium is not the only factor affecting how much advertisers are willing to spend on each keyword². Advertising goals are also reflected in the bidding values. An advertiser may intentionally overbid on some of its keywords to receive a higher CTR by appearing at higher positions, leading to a better Quality Score for future ads. Another example can be adjusting the bid value based on either "keyword level bid ideas" or "group level bid ideas" (refer to Google, 2012). Looking at the ad ranking formula presented in Section 2.2, it can be easily seen that the bid value has a direct impact on the final ad position. Therefore:

¹ Winner's curse is a phenomenon where the auction winner overpays for the items won and the paid price is more than what actually the item is worth.

² For example, bidding under item's true estimation to avoid winner's curse.

Hypothesis 1 (H1): There is a positive relationship between a firm's bid value and its ad position on the SERP.

4.1.2 Ad Relevancy Factors

According to previous studies related to search behavior in sponsored search advertising, consumers' clicks indicate how they find search engine results relevant to their queries. In fact, number of impressions and CTR are extensively used to understand consumer search behavior (Animesh et al., 2011; Ghose & Yang, 2009; Jansen & Spink, 2009). Furthermore, search engines and anecdotal evidence from practitioners indicate that CTR has a direct effect in determining Quality Score. The number of clicks an ad receives is an indicator of how good the quality of the ad is and how relevant the ad is to consumer search goals. It is also the search engines' revenue strategy to value the ads with higher CTR (Aggarwal et al., 2006). In the long run, the product of bid value and clicks will generate higher revenue as opposed to ads with higher bid value and fewer clicks. Therefore:

Hypothesis 2 (H2): There is a positive relationship between a firm's click-through-rate (CTR) and its ad position on the SERP.

Research in advertising and marketing highly emphasize on the information-content of the ads displayed to consumers (Abernethy & Franke, 1996; Resnik & Stern, 1977b). The more customized the content of the ads to the consumer needs, the higher the likelihood of dragging consumers' attention to the ads. Non-informative advertising would distract consumers. Consumers are becoming information-seeking experts and the search process is relatively less expensive than before. Designing targeted ads would result in better relevancy metrics, leading to higher Quality Score. The guidelines by

search engines for ad design also conform to the academic findings (Google, 2011c). Ad copies can contain catchwords related to the brand, price, and even location of the product. Besides, they display the landing page URL of the advertisement. As a result, they are composed of several relevancy metrics recommended by the search engine guidelines. Advertisers are given the option to design multiple ads for each ad group and provide customized ad content for their ad groups. Therefore:

Hypothesis 3 (H3): There is a positive relationship between a firm's ad quality and its ad position on the SERP.

4.1.3 Competition Intensity

Although the direct effect of competition on the ad position is not the main hypothesis of interest in this study, it is necessary to include it when analyzing its impact on other market variables. It is logical to think that an increase in the market competition will significantly impact the position of the ads on the SERP. The following scenario simplifies why an increase in competition intensity affects ad position. With only one firm bidding on a keyword, there is only one advertiser willing to pay for an advertising space. If the ad passes minimum relevancy criteria, the probability of appearing on the top spot is 100%. However, an increase in the number of advertisers (e.g. 10 competitors bidding on the same keyword), keeping other factors constant between competitors, the probability of securing the top position becomes 10%. With further increase in the number of competitors bidding on the same keyword (e.g. 100 competitors), the probability will decline further. Therefore:

Hypothesis 4 (H4): There is a negative relationship between the level of competition intensity in the marketplace and a firm's ad position on the SERP.

4.2 Interaction Effects

4.2.1 The Interaction between CTR and CPC

It is evident from the ad ranking mechanism that CTR and bid value simultaneously effect the ad position. Practitioners' experience indicates that in order to decrease the advertising costs in sponsored search advertising, it is important to increase the CTR of the ads. Bidding excessively to create brand awareness in the beginning of the sponsored search marketing campaign would direct more customers to the retailers' websites. With an increase in impressions and customer clicks, the bid value is less likely to be the major determinant of the firm's ad position on the SERP. Therefore, when ads with higher CTR exist in the competition, the impact of bidding values will be lower on the ad position. On the other hand, CTR is an important element of the ads' Quality Score. As previously mentioned, an increase in the Quality Score would increase minimum relevancy threshold that an ad requires to enter the auction. Therefore, ads with high bid values and low Quality Scores will be automatically removed from the auction and subsequently the bidding value will lose its advantage in determining the ad position.

Hypothesis 5 (H5): The positive relationship between a firm's bid value and ad position is affected by CTR, such that with higher CTR, the impact of bid value on Ad Position will be diminished.

4.2.2 Moderating Effects of Competition Intensity

Consumers have different objectives when they are making a purchase. With variety of products available, the consumer compares different products and decides which product is better according to her quality metrics. According to Zeithaml (1988), “evaluations of the quality take place in a comparison context”. Comparison context inevitably resembles competition context: While consumers are busy comparing ads from different advertisers³, advertisers are competing to target their desired audience in the market place. Adapted from Edelman & Schwarz (2007), I use the term “market depth” to refer to the number of advertisers bidding on the same keyword. Increase in the “market depth” mirrors that the keyword is favorable by many advertisers; therefore, “market depth” is an indicator of competition intensity in the sponsored search marketplace.

An increase in competition intensity increases the winning bids in auctions (Brannman et al., 1987). But how would an increase in winning bid impact the ad position? Advertisers increase their bidding values to secure a higher ad position. With an increase in the competition intensity, the winning bids will be higher than in a less competitive environment. Therefore, the increase in bid value will compensate for the increase in competition, diminishing its direct effect on the ad position (the main effect). In other words, with an increase in competition intensity, the average winning bid will increase among competitors and if a company is strategizing to appear on top spots just by increasing its bid value, it should increase the bid value taking the level of competition into consideration. For example, consider a situation where few advertisers are bidding on a similar keyword. If the advertiser is willing to spend twice as the suggested bid

³ The same argument holds within organic results context where consumers are deciding which organic result is meeting their demands.

value by Google, its ad appears at the top spot. With an increase in the competition, the advertiser should bid more than twice of the keyword estimated price to implement the same strategy (i.e. securing the top spot). Furthermore, an increase in winning bids would exhaust the advertising budget in a short time (if it is not set properly). With no advertising budget, no matter how optimized the rest of the factors are, the ads will not show up in the result page. Therefore, the average ad position will diminish in time. The following hypothesis translates the above arguments.

Hypothesis 6a (H6a): The positive relationship between a firm's bid value and ad position is moderated by keyword competition, such that this positive relationship is weakened by an increase in keyword competition.

A study by Liu and Chen (2006) shows that in order to maximize their revenue, search engines should favor advertisers with low CTR values when the number of competitors increases. An increase in the number of competitors decreases the competitive advantage of the CTR value and the placement of the ads will be more based on bidding values. An example would clearly explain the logic behind this assumption. Consider a situation where only one advertiser is bidding on the keyword. Clearly, regardless of how relevant the ad is to the searcher's query, the advertiser would bid minimally as he is the only one appearing on the SERP. With a few advertisers bidding on the keyword (keeping the bid value constant between advertisers), the companies benefit from having a high CTR value. The one with the highest product of CTR⁴ and bidding value will secure the top spot and others will follow. An increase in the number

⁴ CTR is one of the determinants of relevancy (quality score), but here the situation is simplified for the sake of clarity.

of advertisers would increase the number of advertisers with higher CTR values. Therefore, existence of several companies with high CTR value would reduce the advantage of having a high CTR value⁵. Therefore, ads will be positioned by their corresponding bid values (the product of CTR and bid value will be higher for such ads). On the other hand, existence of many companies with high CTR values increases the minimum ad relevancy threshold that ads require to enter the auction pool for a given keyword. This increase in the minimum ad relevancy threshold will create a pool of ads with similar CTR values, reducing the competitive advantage of having a high CTR value. This example will formally translate to the following hypothesis:

Hypothesis 6b (H6b): The positive relationship between a firm's CTR value and ad position is moderated by keyword competition, such that this positive relationship is weakened by an increase in keyword competition.

The ad copy content creation and customization is an in-house strategy, which is in control of each advertiser. The message that each ad copy contains can significantly define positioning and differentiating strategies of the firm. The use of the search term in the ad copy content and using buzzwords such as “cheap” or “discount” can clearly convey the message of the advertisement. However, with competitors' ads listed around the focal retailer's ad, attention of the searchers might be dragged away from the ad (Animesh et al., 2011). With few ads displayed on the SERP, each ad has better chance of differentiating itself from the rivals. An increase in the number of competitors with

⁵ Section 2.2 explains how Google enters the advertisers into the auction by first evaluating them based on minimum relevancy criteria.

similar offerings might result in distraction from the focal ad's unique differentiating message. Therefore:

Hypothesis 6c (H6c): The positive relationship between a firm's ad quality and ad position is moderated by keyword competition, such that this positive relationship is weakened by an increase in keyword competition.

4.3 Control Variables

Given the diversity of the Internet retailers and the complexity of the sponsored search market, some variables should be controlled in order to accurately evaluate the proposed model.

Advertising resources are always limited for any firm. Firms cannot allocate unlimited advertising budget to their campaigns. Operationalization of the advertising budget has been the focus of many previous studies (see Mitchell, 1993). In fact, setting the advertising budget is a critical decision in media planning when budgets are allocated to different media outlets (Little & Lodish, 1969).

Setting the advertising budget has certainly an impact in the sponsored search market equilibrium (Auerbach, Galenson, & Sundararajan, 2008; Lahaie, 2006). The budget limit is not reflected directly in the ad rank formula; however, it has an effect on the average ad position. If it is set too low, the firm runs out of the daily ad budget quickly. Consequently, even if other factors of ad rank were optimal, the search engine would not display the ads when the firm's daily ad budget is depleted. Therefore, searchers would not see the ads in subsequent searches, and eventually the ad rank will be affected.

The quality of the landing page is constantly on the list of sponsored search optimization criteria. Landing page quality is also highly correlated with the SEO practices and incorporates, but is not limited to the quality of the page header, website description, URL of the page and structure of the website. Impact of SEO strategy, a closely related Internet marketing strategy to SEA, has also been the center of attention in many studies before (Rutz & Bucklin, 2011). Improving the landing page quality results in a better campaign performance, such as an increase in profits (Ghose & Yang, 2009). Previously, spillover effects of organic and sponsored results have proved that SEO and ad rank are in direct correlation (Ghose & Yang, 2010). Also, practitioners constantly recommend SEO practices as a strategy in sponsored search campaigns to decrease bidding costs; and usually companies invest both in SEO and sponsored search at the same time (Econsultancy, 2011). Therefore, the impact of SEO quality should be considered in the formulation of sponsored search advertising.

Finally, measures have to be taken to control for the size and merchant category of the Internet retailers. The sponsored search environment has enabled companies from diverse demographics advertise their products and services online. Therefore, not only the performance of the companies should be measured in their own market sector (Ayanso, Lertwachara, & Thongpapanl, 2010; Ayanso, Lertwachara, & Thongpapanl, 2011), but also their differences in size should be considered (Ghose & Yang, 2009). In summary, this study uses advertising budget, SEO quality, merchant category, and company size as control variables in the proposed research model.

Chapter 5 Data and Methodology

This chapter presents the data collection procedure, the research methodology, and the empirical results of the study. Figure 5-1 illustrates an overview of the operational variables derived from the proposed research model. The variables in parentheses are the constructed variables corresponding to each research variable.

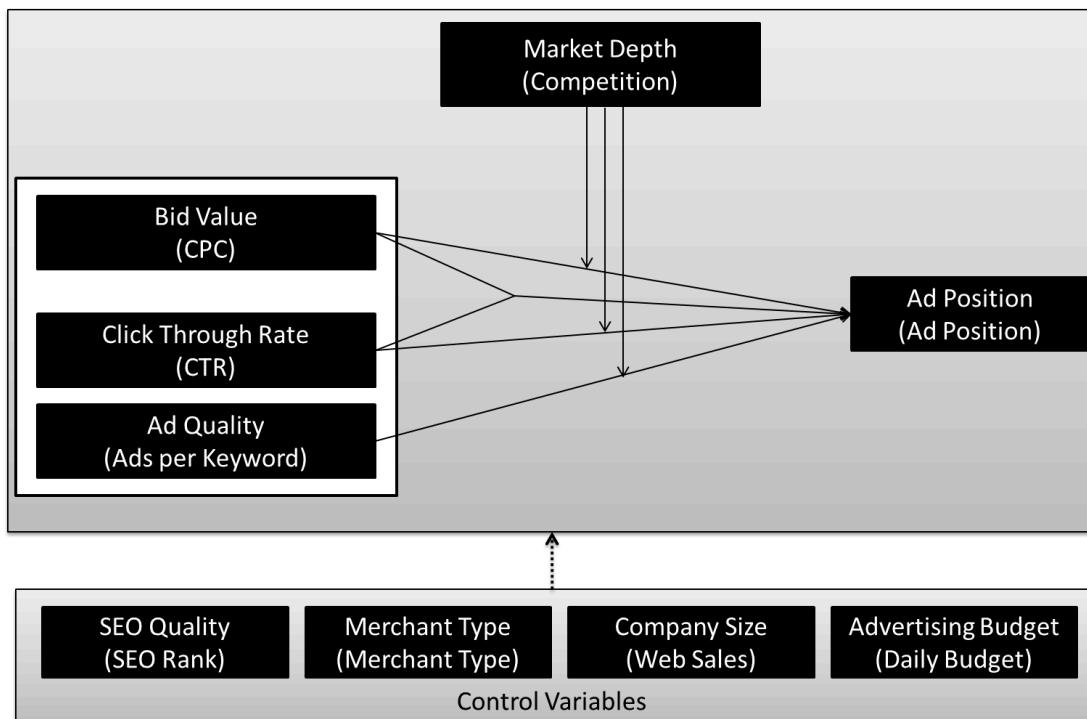


Figure 5-1: Research model and the operational variables.

5.1 Description of Variables

In this study, three sources of data are used to test the aforementioned hypotheses. The first dataset is the data related to the market segment addressed in the analysis. As discussed in the introduction section, this study focuses on online retailers' sponsored

search advertising campaigns. To obtain a list of retailers relevant to the study, the most recent list published by Internet Retailer's "Top 500 Guide" is used (Vertical Web Media, 2011). This list ranks top five hundred retailers by their annual sales in 2011. Vertical Web Media has been publishing data about Internet retailers since 1999 and is one of the leading companies providing business intelligence for the e-commerce market. The top 500 guide not only ranks the Internet retailers based on their annual sales, it also categorizes companies into four merchant types (i.e. web only, retail chain, consumer brand manufacturer, and catalog/call center) and 15 merchandise categories (Appendix B).

The other two datasets contain sponsored search ad campaign data for the top 500 retailers. The analysis in this study is based on campaign data from Google search engine. Obviously, the primary source of data collection is Google itself. However, sponsored search data are proprietary data only available to each advertiser in its AdWords account. Google has provided a set of tools for advertisers in order to get some estimates when designing their own sponsored ad campaigns¹. Moreover, lots of third party tools are also providing sponsored search data by crawling Internet websites, including Google search engine result pages, and using Google provided application programming interfaces (APIs) to generate comprehensive data for search engine marketers. To collect campaign data, data from Spyfu (SpyFu, 2012) and KeywordSpy (KeywordSpy, 2012) are used. Both companies are leading providers of keyword research technology and competitive intelligence to search engine advertisers. IBM, Toyota, and American Express are some of the major companies using KeywordSpy tools for their sponsored search advertising

¹ Google AdWords Keyword tool, Google Trends, Google Search Insights, etc. For an example look at: <https://adwords.google.com/select/KeywordToolExternal>

and SpyFu has been endorsed in The Washington Post, The Wall Street Journal, and Forbes.

Table 5-1 summarizes the definition of the variables that are used in this study. To measure bid value, estimated minimum and maximum CPC values are averaged across all keywords for each company. Although the CPC cannot replace the advertiser's true bidding value (as GSP is a second price auction), it can be regarded as a close estimate of bid value. Advertisers constantly adjust their bid values based on the actual market outcomes (Asdemir, 2006). Therefore, if they observe they are overbidding on a keyword, compared to its actual CPC, they will adjust the bid value accordingly. A similar argument holds for the daily budget. Although it is unknown how much a company has dedicated to its sponsored search advertising campaign, the actual average daily ad spending gives an estimation of the allocated budget. Furthermore, data regarding both CPC and daily spending values are collected with similar methodology for all companies; therefore, the values are consistent across different companies. The CTR value is calculated by dividing clicks per day by the number of daily searches. Unfortunately, ad impressions are proprietary for each company and only each advertiser has access to the real values. In this study, instead of using ad impressions, the number of times that a firm's keywords are searched is used. For example, if a company is bidding on 2 keywords and the first keyword has been searched 20 times and the second keyword has been searched for 30 times during a day, the total number of daily searches for the company would be 50 daily searches. The number of searches cannot truly reflect the

Table 5-1: Definition of variables

Dependent Variable	Description	Source
Ad Position	The monthly average position of the company's ads across all of its keywords.	<i>Average Ad Position</i>
Independent Variables		
Cost-per-Click	The amount that Google charges an advertiser every time someone clicks on their ads. The value is averaged over a month across all keywords.	$(Min\ CPC + Max\ CPC) / 2$
Click-Through-Rate	Number of clicks that a company received during a day on all of its keywords divided by the number of keyword searches in a day.	<i>Clicks per Day / Daily Searches</i>
Ads-per-Keyword	Number of ads that a company runs divided by the number of keywords that a company is bidding on.	<i>Number of Ads / Number of Keywords</i>
Competition	The average number of companies that their ads are displayed along with the focal firm's ads.	<i>Average Ad Competitors</i>
Control Variables		
SEO Quality	The firm's ranking in the organic results across all of its keywords (Rank 1 is the top rank on the SERP)	<i>ln(Organic Rank)</i>
Web Sales	The year 2010 online only sales of the firm.	<i>ln(Web Sales)</i>
Budget	The firm's average daily spending for sponsored search advertising.	<i>ln(Daily Budget)</i>
Merchant	Indicates whether the merchant is a web only channel (coded as 1) or has multiple sales channels (coded as 0)	<i>Merchant Type</i>

exact number of impressions (ads might not show up when a user searches for a keyword); however, it can estimate the number of impressions with reasonable probability.

To measure the ad copy quality, a proxy is defined by dividing the number of ad copies to the number of all paid keywords. This ratio is used to represent the level of the firm's "Ad Quality". Greater levels of ad quality imply that the firm has put more effort into crafting these ad copies for each keyword (or keyword group).

To operationalize the market depth, the number of companies that their ads appear along with each focal firm's ads is used. Generally "Mass Merchants" encounter higher number of competitors as they are bidding on keywords related to multiple categories of products. For example, if an ad appears on the third position on the SERP and there are 9 other ads displayed alongside the ad, the ad position will be 3 and the number of competitors would be 9 (the focal advertiser itself is excluded) for that keyword. The "Ad Position" and "Competitors" variables are both averaged over a period of a month. Furthermore, the value of the ad positions has been subtracted from the highest value to make the interpretation of the results easier. With this transformation, a high number depicts better ad position, while a lower one presents ads that are displayed at bottom positions.

The operationalization of the remaining control variables is straightforward. To control for company size, annual sales figures published by retailers themselves are used. Sales figures have been extensively used in various disciplines such as economic and accounting (Adams, Hill, & Roberts, 1998; Hart & Oulton, 1996). Specifically, annual web sales instead of total sales are used for controlling the company size. This would lead

to identification of active online retailers instead of inclusion of retailers generating high sales via offline sales channels. It is logical to assume that companies advertising online are more interested in promoting their online sales channels instead of their offline sales channels.

To control for SEO quality of the companies, the overall organic rank of the companies are log transformed. To qualify to appear on the top organic results, companies need to rigorously optimize their SEO strategies. Therefore, organic rank could be a good candidate to control for overall SEO efforts of the company.

Finally, to control for the type of the merchants, the merchants are categorized into “web-only” firms, denoting firms without physical store, and “multi-channel” firms, denoting firms with both physical and online stores (click and mortar). The second category includes retailers from catalog/call center, consumer brand manufacturer, and retail chain.

5.2 Data Collection

Data was collected for the 500 retailers for the month of February 2012 from all three data sources: Top 500 Retailers, KeywordSpy, and SpyFu. The top 500 retailers were used as the starting pool of companies. Some of the companies in the pool had multiple Internet domains listed for their online channels. Either the first domain (i.e. the primary domain) or the domain targeting North American population was selected for multi-domain companies. For example, Amazon has specific domain names for each country but only “Amazon.com” was selected as the primary domain and “Amazon.co.uk” and similar domains were removed from the options. This assumption does not create any bias in the data as the sponsored search data are collected based on

each domain instead of each company. Furthermore, all the “Mass Merchant” companies were removed from the pool as they appear to bias the competition in the market. The mass merchant companies (e.g., Amazon.com) work across several product categories. Therefore, they can appear as competitors in every product category.

An astute reader might ask if the selection of retailers based on being “top Internet retailer” creates any bias in the results. To address this issue it is important to note that being the top Internet retailer does not necessarily mean that the firm has optimized sponsored search campaigns. Selection of top Internet retailers is important, as it is evident that these companies are successful in utilizing Internet as one of their retailing channels. Table 5-2 shows dispersion of firms over merchandise categories and merchant types after the data collection procedure.

Table 5-2: Dispersion of firms over merchandise categories and merchant types

Merchandise Category	Multi-Channel	Web Only	Total
Apparel/Accessories	89	20	109
Automotive Parts/Accessories	2	3	5
Books/Music/Video	5	7	12
Computers/Electronics	21	12	33
Flowers/Gifts	7	2	9
Food/Drug	11	3	14
Hardware/Home Improvement	6	8	14
Health/Beauty	11	10	21
Housewares/Home Furnishings	20	8	28
Jewelry	5	7	12
Office Supplies	3	4	7
Specialty/Non-Apparel	15	20	35
Sporting Goods	12	7	19
Toys/Hobbies	7	8	15
Total	214	119	333

The pool of the Internet domains from the “Top 500 Guide” was submitted to the two other third party data providers. The data from all three data sources were matched and domains with missing values in their sponsored search data were removed. The missing values were either due to the limitation of the third parties in collecting data for those companies or because the domains did not have sponsored search campaigns.

To test whether the sample population is representing companies with diverse search engine advertising skills, the pay-per-click (PPC) rank score for each retailer estimated by SpyFu is used. The PPC rank score estimates how well the advertisers’ ads are ranked on the sponsored search results across all of their keywords and how often users click on these ads. Figure 5-2 reveals that the distribution of the companies over PPC score has a normal distribution. Values from 1 to 5 show high PPC rank and Low PPC rank respectively. This indicates that the sample population of retailers comprises companies with low, medium, and high performance PPC campaigns.

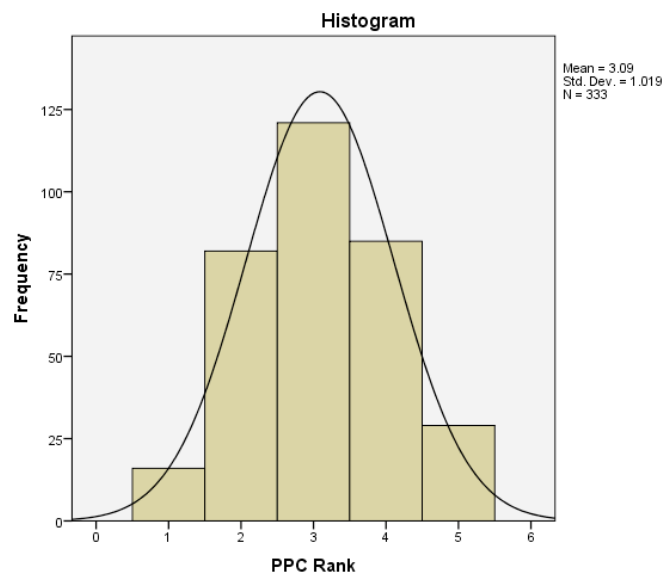


Figure 5-2: Distribution of companies over their “PPC Rank” scores.

Table 5-3 presents descriptive statistics and Pearson correlations of the key research variables. Evidently, *CPC* and *CTR* are positively correlated to the *Ad Position*. The numbers provide preliminary support for H1 and H2 and show a significant positive correlation of these variables with the *Ad Position*. Moreover, the *Competition* variable is correlated with the *Ad Position* with a significant negative value. This high correlation was expected and provides preliminary support for H4.

It is also interesting to look at two other correlations in the results. First, *SEO Quality* has a significant negative correlation with *Ad Position*. *SEO Quality* is measured capturing SEO rank of each merchant over all of its organic keywords. A smaller number shows a better rank in the organic listings. Second, the positive correlation between *CPC* and *Competition* conforms to the expectations in auction theory. With an increase in competition intensity, the bid values to win the auction tend to be higher (Brannman et al., 1987).

Table 5-3: Means, standard deviations and correlations of key variables (February 2012).

Variable	Mean	S.D.	N	1	2	3	4	5	6	7	8	9
1 Ad Position	5.2037	1.83503	333	1.000								
2 SEO Quality	8.0855	1.45142	333	-.131*	1.000							
3 Daily Budget	7.407	1.3218	333	-0.004	-.583**	1.000						
4 Web Sales	17.7208	1.21407	333	-0.032	-.196**	.238**	1.000					
5 Merchant Type	0.36	0.48	333	-0.075	.212**	-.189**	-0.106	1.000				
6 CPC	0.3571	0.09219	333	.310**	0.080	.128*	-0.030	-0.055	1.000			
7 CTR	0.0561	0.07025	333	.144**	0.017	0.084	-0.073	.173**	.246**	1.000		
8 Ads Per Keyword	1.8493	0.68673	333	-0.032	-0.035	.268**	.114*	-.204**	.205**	-0.051	1.000	
9 Competition	7.1758	1.06647	333	-.568**	.184**	0.099	-0.028	-0.072	.438**	0.007	.244**	1.000

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

5.3 Research Methodology

To evaluate the research model presented in this study, hierarchical multiple regression (Aiken & West, 1991; Montgomery et al., 2001) is used. To explain the relationships between the predictor variables and the ad position, eight different models based on the proposed research framework were created (Table 5-4). In all models, α_i is the intercept, β_i s are the regression coefficients, and ε_i captures the unexplained error term. Model 1 incorporates only control variables to account for the variability of companies in terms of size, budget, SEO quality, and merchant type. All Control variables except the merchant type have been transformed using natural log function to derive a linear relationship between dependent and independent variables. Model 2 and 3 enter main effect variables to test the main effect hypotheses. To test the moderating effects, models 4 to 7 are constructed by entering interaction effects one at a time, and model 8 by entering all moderators simultaneously. The interaction terms in models 4 to 7 provide the necessary results to test the hypotheses involving the moderating effects individually.

The empirical analyses have been performed in two stages. First, all the February 2012 data were tested to fit the regression model. A significant effect of the merchant type was found in the models using the full dataset; therefore, the data set was divided into two datasets representing each merchant type. Then, the analysis was performed for each merchant type separately.

Table 5-4: Hierarchical multiple regression equations.

Model 1	$AdPosition = \alpha_1 + \beta_1 * \ln(WebSales) + \beta_2 * \ln(DailyBudget) + \beta_3 * \ln(SEOQuality) + \beta_4 * MerchantType + \varepsilon_1$
Model 2	$AdPosition = \alpha_1 + \beta_1 * \ln(WebSales) + \beta_2 * \ln(DailyBudget) + \beta_3 * \ln(SEOQuality) + \beta_4 * MerchantType + \beta_5 * CPC + \beta_6 * CTR + \beta_7 * AdsPerKeyword + \varepsilon_2$
Model 3	$AdPosition = \alpha_1 + \beta_1 * \ln(WebSales) + \beta_2 * \ln(DailyBudget) + \beta_3 * \ln(SEOQuality) + \beta_4 * MerchantType + \beta_5 * CPC + \beta_6 * CTR + \beta_7 * AdsPerKeyword + \beta_8 * Competition + \varepsilon_3$
Model 4	$AdPosition = \alpha_1 + \beta_1 * \ln(WebSales) + \beta_2 * \ln(DailyBudget) + \beta_3 * \ln(SEOQuality) + \beta_4 * MerchantType + \beta_5 * CPC + \beta_6 * CTR + \beta_7 * AdsPerKeyword + \beta_8 * Competition + \beta_9 * CPC * CTR + \varepsilon_4$
Model 5	$AdPosition = \alpha_1 + \beta_1 * \ln(WebSales) + \beta_2 * \ln(DailyBudget) + \beta_3 * \ln(SEOQuality) + \beta_4 * MerchantType + \beta_5 * CPC + \beta_6 * CTR + \beta_7 * AdsPerKeyword + \beta_8 * Competition + \beta_9 * Competition * CPC + \varepsilon_5$
Model 6	$AdPosition = \alpha_1 + \beta_1 * \ln(WebSales) + \beta_2 * \ln(DailyBudget) + \beta_3 * \ln(SEOQuality) + \beta_4 * MerchantType + \beta_5 * CPC + \beta_6 * CTR + \beta_7 * AdsPerKeyword + \beta_8 * Competition + \beta_9 * Competition * CTR + \varepsilon_6$
Model 7	$AdPosition = \alpha_1 + \beta_1 * \ln(WebSales) + \beta_2 * \ln(DailyBudget) + \beta_3 * \ln(SEOQuality) + \beta_4 * MerchantType + \beta_5 * CPC + \beta_6 * CTR + \beta_7 * AdsPerKeyword + \beta_8 * Competition + \beta_9 * Competition * AdsPerKeyword + \varepsilon_7$
Model 8	$AdPosition = \alpha_1 + \beta_1 * \ln(WebSales) + \beta_2 * \ln(DailyBudget) + \beta_3 * \ln(SEOQuality) + \beta_4 * MerchantType + \beta_5 * CPC + \beta_6 * CTR + \beta_7 * AdsPerKeyword + \beta_8 * Competition + \beta_9 * CPC * CTR + \beta_{10} * Competition * CPC + \beta_{11} * Competition * CTR + \beta_{12} * Competition * AdsPerKeyword + \varepsilon_8$

5.4 Empirical Results

The results from the analysis on the full dataset can be found in Table 5-5. The baseline specification is presented in Model 1. In this model, the variations between retailers are explained by entering only control variables to the model. The coefficient of *SEO Quality* is negative and highly significant ($\beta = -0.248$, $p < 0.01$). The smaller *SEO Quality* value indicates better SEO rank on the SERP (Table 5-1) and the negative coefficient is expected: companies with higher SEO rank have better ad positions. Model 2 shows that *CPC* has a significant positive effect on the *Ad Position* ($\beta = 6.871$, $p < 0.01$) supporting H1. A higher *CPC* value is related to a higher *Ad Position*. The coefficients for *CTR* and *AdsPerKeyword* are not significant and they do not support H2 and H3, respectively.

Inclusion of the *Competition* variable in Model 3 has a significant impact on the model fit and significantly increases the R^2 ($R^2_{\text{Change}} = 0.559$). It also has a significant negative coefficient ($\beta = -1.506$, $p < 0.01$) providing support for H4. With more competitors bidding on the same keyword, the ad will be displayed at a lower position. The coefficient of *CPC* is still significant in model 3 supporting H1. A higher *CPC* value is related to a higher *Ad Position*. However, there is no support for H2 and H3.

Table 5-5: Regression results (February 2012 data)

Dependent Variable: Ad Position	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	9.803 (1.897)	10.67 (1.817)	7.442 (1.054)	7.764 (.999)	7.375 (1.055)	7.765 (1.034)	7.404 (1.05)	7.759 (.985)
Web Sales	-0.073 (.085)	-0.029 (.08)	-0.07 (.046)	-0.082 (.044)	-0.069 (.046)	-0.083* (.045)	-0.072 (.046)	-0.088* (.043)
Daily Budget	-0.164 (.094)	-0.283** (.094)	-0.063 (.055)	-0.052 (.052)	-0.061 (.055)	-0.069 (.053)	-0.058 (.055)	-0.049 (.051)
SEO Quality	-0.248** (.085)	-0.342** (.082)	-0.048 (.049)	-0.064 (.046)	-0.046 (.049)	-0.055 (.048)	-0.047 (.049)	-0.061 (.045)
Merchant Type	-0.232 (.214)	-0.258 (.206)	-0.375** (.119)	-0.353** (.113)	-0.399** (.121)	-0.351** (.117)	-0.387** (.119)	-0.401** (.112)
CPC		6.871** (1.087)	13.688** (.68)	14.573** (.66)	13.528** (.694)	14.12** (.674)	13.8** (.68)	14.517** (.665)
CTR		2.303 (1.409)	0.03 (.816)	1.612* (.814)	0.083 (.817)	0.052 (.799)	0.022 (.813)	1.645* (.811)
Ads per Keyword		-0.172 (.147)	0.098 (.086)	0.104 (.081)	0.099 (.086)	0.106 (.084)	0.045 (.09)	0.067 (.085)
Competition			-1.506** (.059)	-1.529** (.056)	-1.493** (.06)	-1.572** (.06)	-1.5** (.059)	-1.535** (.057)
CPC*CTR				-47.76** (7.715)				-45.069** (8.358)
Competition*CPC					0.538 (.473)			1.148* (.484)
Competition*CTR						-3.77** (.955)		-2.166* (1.038)
Competition* Ads per Keyword							0.148 (.079)	0.115 (.078)
R-Squared	0.032	0.164	0.723	0.753	0.725	0.736	0.726	0.763
R-Squared Change	0.032**	0.132**	0.559**	0.03**	0.002	0.013**	0.003	0.04**
Number of observations	333	333	333	333	333	333	333	333

Standard errors in parentheses.

** p<.01

* p<.05

Model 4 results show that the interaction between *CPC* and *CTR* is significant ($\beta = -47.76$, $p < 0.01$). Therefore, H5 is supported. Figure 5-3 illustrates the interaction plot between *CTR* and *CPC*. The *CPC* has a positive influence on the *Ad Position*. However, at higher *CTR* values, *CPC* values will have a lower significant positive impact on the *Ad Position*. Similarly, at lower *CTR* values, *CPC* values will contribute more to the *Ad Position*. This is in line with the study expectation in H5. The *CTR* has a positive influence on overall Quality Score. Consequently, when ads with higher Quality Scores enter the auction, the minimum Quality Score threshold for entering the auction will increase. Therefore, ads with high bid values and low Quality Scores are less likely to qualify for entering the auction, thus the impact of *CPC* diminishes.

Model 5 tests the impact of *Competition* on the relationship between *CPC* and *Ad Position*. The interaction is not significant and does not provide support for H6a.

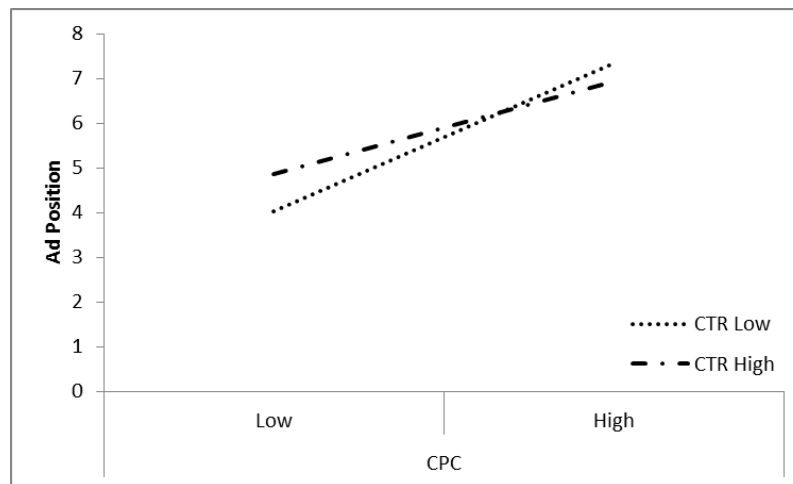


Figure 5-3: Effect of *CTR* on the *CPC-Ad Position* relationship

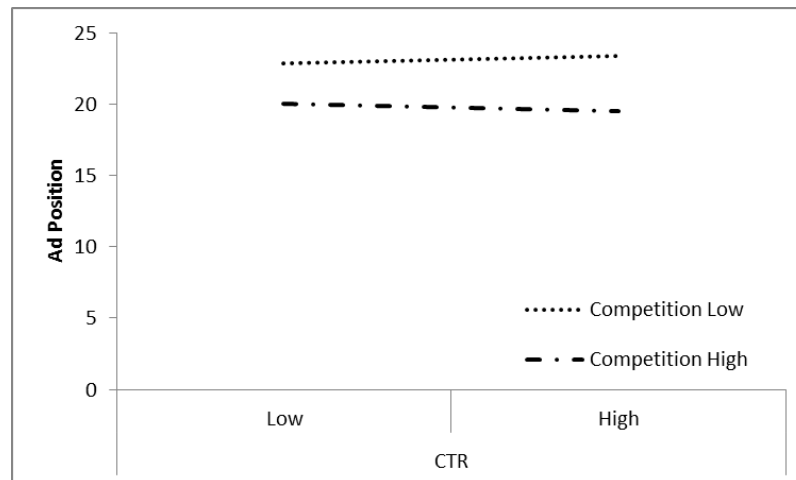


Figure 5-4: Effect of level of *Competition* on *CTR-Ad Position* relationship

Model 6 investigates the interaction between *Competition* and *CTR*. The interaction coefficient is significant ($\beta = -3.77$, $p < 0.01$) and therefore H6b is supported. At a higher keyword competition level, the impact of *CTR* on ad position will be diminished. The interaction plot is illustrated in Figure 5-4. With more advertisers bidding on the same keywords, most of the ads in the auction pool will have high *CTR* values. Consequently, an ad's *CTR* value loses its competitive advantage among other ads.

The interaction plot illustrated in Figure 5-5 indicates that the interaction between *Competition* and *AdsPerKeyword* is slightly significant at 10% ($\beta = 0.148$, $p < 0.1$). The figure illustrates that at higher levels of keyword competition, quality of ads has a significant positive relationship with the position of the ads (opposing H6c). However, the significance level is not strong enough to develop this hypothesis further, and more evidence is needed to make such a claim.

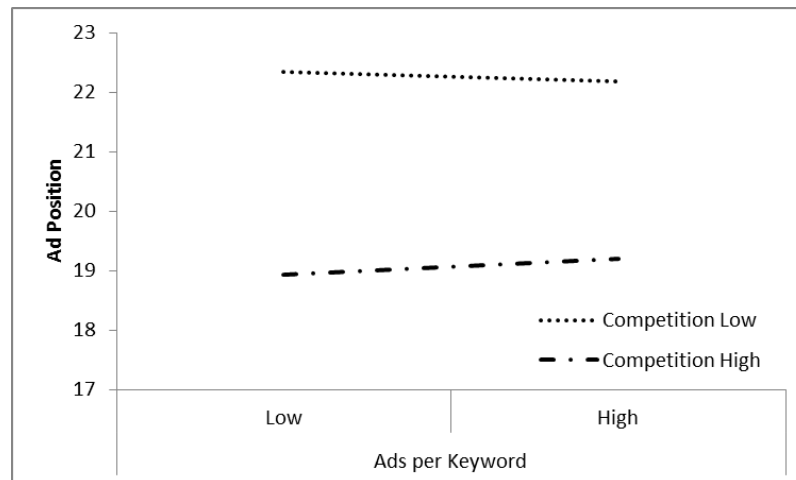
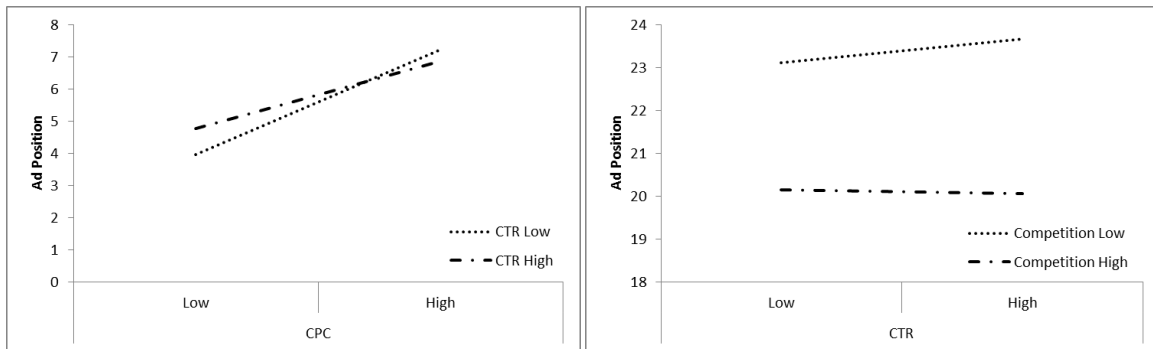
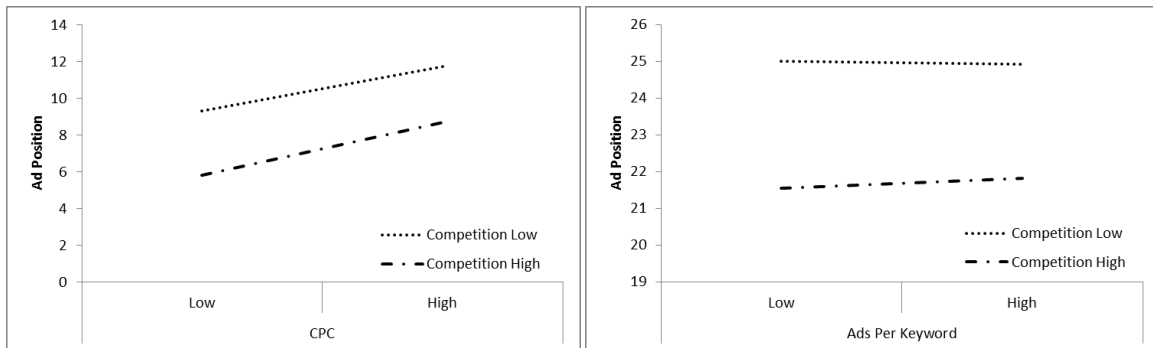


Figure 5-5: Effect of level of *Competition* on *Ads per Keyword-Ad Position* relationship

Finally, Model 8 takes all of the main and interaction effects into account (Hair, Anderson, Tatham, & William, 1998). The interaction plots for the full model are demonstrated in Figure 5-6. The results from this model find support for hypotheses H6a and H6b. It is important to note that it is possible to construct two other higher-order interactions in the study: the three-way interaction between *CPC*, *CTR*, and *Competition* and the three-way interaction between *CPC*, *AdsPerKeyword*, and *Competition*. However, the coefficients and the increase in R-square of the aforementioned three-way interactions were not significant, and, therefore, as Aiken and West (1991) suggest, partially constructed models should be investigated in the study of the two-way interactions and predictor variables.

In summary, the study indicates that a firm's *CPC* value has a positive relationship with its *Ad Position* on the SERP. However, evidence of such a relationship does not exist for *CTR* and *AdsPerKeyword*. This positive effect is moderated by *CTR*. With higher levels of *CTR* values in place, *CPC* loses its advantage in positioning the ads

on the SERP. Furthermore, the level of keyword competition in the marketplace has significant impact on the positioning of the ads on the SERP. At a higher level of keyword competition, both *CTR* and *CPC* values lose their competitive advantage on determining the *Ad Position*. The impact of Competition on *AdsPerKeyword* is not consistent across different models; however, the slight significance of the interaction in Model 7 provides contradictory results to the study assumptions. It appears that an increase in keyword competition intensity would positively impact the relationship between ad content quality and ad position on the SERP.

a: Effect of *CTR* on*CPC-Ad Position* relationshipb: Effect of level of *Competition* on*CTR-Ad Position* relationshipc: Effect of level of *Competition* on*CPC-Ad Position* relationshipd: Effect of level of *Competition* on*Ads per Keyword-Ad Position* relationship**Figure 5-6: Full model interaction effects**

Careful examination of the results in Table 5-5 indicate that the dummy coded variable, *Merchant Type*, has negative significant effect on Models 3 through 8 ($\beta \leq -0.351$, $p < 0.01$). To investigate further how the market characteristics change based on the type of the merchant, the original dataset was divided to two categories: “web-only” and “multi-channel” retailers. Table 5-6 presents summary statistics representing each group and Table 5-7 and Table 5-8 present regression results for each category.

Looking at the mean values in Table 5-6 provides interesting preliminary results. Note that the mean *CTR* value for web-only retailers is higher than the corresponding value for the multi-Channel retailers. Another significant observation regarding web-only retailers is the correlation between *SEO Quality* and *Ad Position*. Firms with higher *SEO Quality* (smaller values denote better quality) have better *Ad Position*, which conforms to the study expectation.

Finally, not only a high negative correlation between *Competition* and *Ad Position* favors the study assumptions, but also the correlations between *Ad Position* and *CPC*, as well as *Ad Position* and *CTR* for each merchant type provides interesting insights. It seems that the ad positions for multi-channel merchants are more reliant on their *CPC* values, whereas, web-only retailers benefit more from their *CTR* values in position of their ads.

Table 5-6: Means, standard deviations and correlations of key variables (divided by *Merchant Type*).

Multi-Channel	Variable	Mean	S.D.	1	2	3	4	5	6	7	8
	1 AdPosition	5.3059	1.86104	1.000							
	2 SEO Quality	7.8561	1.43406	-0.084	1.000						
	3 Daily Budget	7.5932	1.25588	-0.075	-.620**	1.000					
	4 Web Sales	17.8167	1.2799	-0.048	-0.093	.200**	1.000				
	5 CPC	0.3608	0.0882	.469**	0.010	0.115	0.009	1.000			
	6 CTR	0.0471	0.06649	0.102	-0.102	.187**	-0.020	.224**	1.000		
	7 AdsPerKeyword	1.9535	0.74121	-0.025	-0.001	.218**	0.114	.178**	-0.030	1.000	
	8 Competition	7.233	1.02737	-.552**	.189**	0.113	-0.002	.307**	-0.026	.227**	1.000
Web-Only	Variable	Mean	S.D.	1	2	3	4	5	6	7	8
	1 AdPosition	5.0197	1.78024	1.000							
	2 SEO Quality	8.4979	1.39571	-.184*	1.000						
	3 Daily Budget	7.0722	1.37579	0.080	-.475**	1.000					
	4 Web Sales	17.5482	1.06931	-0.021	-.370**	.274**	1.000				
	5 CPC	0.3502	0.09897	0.038	.232*	0.127	-0.125	1.000			
	6 CTR	0.0724	0.07406	.259**	0.116	0.023	-0.125	.312**	1.000		
	7 AdsPerKeyword	1.6618	0.52916	-0.110	0.033	.304**	0.037	.257**	0.015	1.000	
	8 Competition	7.0729	1.13055	-.622**	.232*	0.047	-0.103	.624**	0.088	.267**	1.000

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 5-7: Regression results (web-only retailers)

Dependent Variable:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Ad Position (web-only)								
Intercept	10.418	9.606	9.08	9.33	8.97	9.059	8.894	9.078
	3.587	3.538	2.003	1.962	2.035	2.014	2.007	1.978
Web Sales	-0.173	-0.118	-0.132	-0.147	-0.129	-0.132	-0.127	-0.143
	(.165)	(.16)	(.091)	(.089)	(.092)	(.091)	(.091)	(.089)
Daily Budget	0.004	0.012	-0.013	-0.015	-0.01	-0.012	-0.005	0
	(.135)	(.143)	(.081)	(.079)	(.082)	(.082)	(.081)	(.08)
SEO Quality	-0.282*	-0.306*	-0.194*	-0.182*	-0.193*	-0.194*	-0.192*	-0.176*
	(.138)	(.142)	(.08)	(.079)	(.081)	(.081)	(.08)	(.079)
CPC		0.519	11.677**	12.417**	11.518**	11.653**	11.456**	12.269**
		(1.804)	(1.251)	(1.26)	(1.334)	(1.261)	(1.265)	(1.335)
CTR		6.501**	3.686**	3.866**	3.767**	3.725**	3.755**	4.22**
		(2.246)	(1.285)	(1.259)	(1.31)	(1.303)	(1.285)	(1.284)
Ads per Keyword		-0.383	0.009	0.007	0.005	0.006	-0.112	-0.155
		(.324)	(.185)	(.181)	(.186)	(.187)	(.214)	(.211)
Competition			-1.596**	-1.658**	-1.587**	-1.591**	-1.56**	-1.608**
			(.103)	(.104)	(.107)	(.106)	(.108)	(.108)
CPC*CTR				-35.782*				-47.859**
				(14.608)				(16.294)
Competition*CPC					0.224			-0.009
					(.632)			(.743)
Competition*CTR						0.32		1.728
						(1.499)		(1.906)
Competition*							0.218	0.27
Ads per Keyword							(.193)	(.206)
R-Squared	0.043	0.13	0.724	0.738	0.724	0.724	0.727	0.747
R-Squared Change	0.043	0.087*	0.594**	0.014*	0	0	0.003	0.023*
Number of observations	119	119	119	119	119	119	119	119

Standard errors in parentheses.

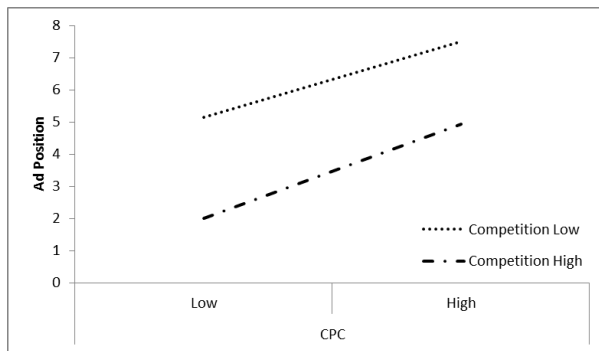
** p<.01

* p<.05

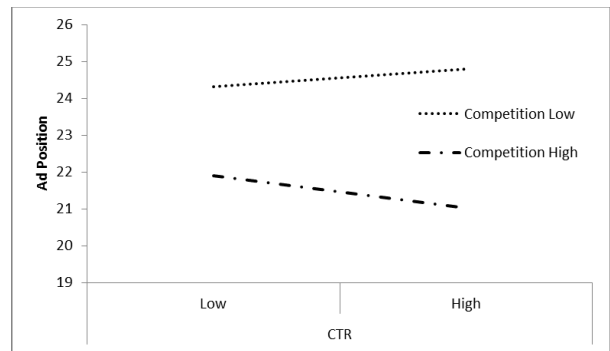
Model 1 from Table 5-7 indicates that there is a positive significant relationship between *SEO Quality* and *Ad Position* for the web-only merchants ($\beta = -0.282$, $p < 0.05$). This result conforms to our expectations as web only retailers actively engage in improving quality of their online content and landing pages as the Internet is their only selling channel. This result is also consistent in Models 2 and 3 where direct effects of the predictors are investigated. Model 2 reveals that *CTR* has significant positive impact on the position of the ads ($\beta = 6.501$, $p < 0.01$) supporting H2. Model 3 indicates that entering competition intensity into the model would not only increase the model fit significantly ($R^2 = 0.724$, $p < 0.01$), but impacts the coefficients and significance of *CTR* and *CPC*. Results from this model provide support for hypotheses H1, H2, and H4. Model 4 provides support for the interaction effect of *CTR* on *CPC-Ad Position* relationship. Contrary to the study assumptions, there is no interaction between *Competition* and each of the variables, *CTR*, *CPC*, and *AdsPerKeyword* (models 5, 6, and 7, respectively). Finally, it is most likely that the significant change in R^2 in Model 8 ($R^2_{\text{Change}} = 0.023$, $p < 0.05$) is mainly due to the interaction between *CPC* and *CTR* variables.

Table 5-8 presents the results for multi-channel merchants. The results are quite different from those obtained for the web-only retailers. Similar to web-only merchants, Models 1 and 2 indicate significant negative coefficient for *SEO Quality* variable ($\beta < -0.274$, $p < 0.05$); however, the coefficient is not significant in Models 3 to 8. Model 2 shows significant positive coefficients for *CPC* ($\beta = 10.792$, $p < 0.01$), providing support for H1. Model 3 provides significant results supporting H1 ($p < 0.01$) and H4 ($p < 0.01$). The interaction between *CPC* and *CTR* is significant in Model 4 ($\beta = -44.588$,

$p < 0.01$) and H5 is supported. Models 5 and 6 provide significant results for the interaction between *Competition* and *CPC*, and *Competition* and *CTR*, supporting H6a and H6b, respectively. However, H6a assumes that *Competition* has a negative effect on *CPC-Ad Position* relationship, whereas results show that the impact is positive. The interaction between *Competition* and *AdsPerKeyword* is not significant in Model 7 and H6c is not supported. Finally, Model 8 provides similar results compared to the previous models.



a: Effect of level of *Competition* on
CPC-Ad Position relationship



b: Effect of level of *Competition* on
CTR-Ad Position relationship

Figure 5-7: Interaction plots for multi-channel retailers

Table 5-8: Regression results (multi-channel retailers)

Dependent Variable: Ad Position (multi-channel)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	10.43	11.654	6.96	7.317	6.914	7.314	6.915	7.446
	2.301	2.051	1.195	1.137	1.183	1.161	1.196	1.11
Web Sales	-0.04	-0.02	-0.075	-0.08	-0.081	-0.095	-0.077	-0.099*
	(.101)	(.087)	(.05)	(.048)	(.05)	(.049)	(.05)	(.047)
Daily Budget	-0.297*	-0.428**	-0.065	-0.06	-0.062	-0.064	-0.06	-0.058
	(.13)	(.119)	(.07)	(.067)	(.07)	(.068)	(.071)	(.065)
SEO Quality	-0.274*	-0.348**	0.022	-0.009	0.033	0.02	0.026	0.006
	(.112)	(.099)	(.059)	(.057)	(.059)	(.058)	(.06)	(.055)
CPC		10.792**	15.269**	16.166**	15.065**	15.728**	15.346**	16.078**
		(1.298)	(.773)	(.757)	(.771)	(.759)	(.778)	(.747)
CTR		0.353	-1.965	0.282	-2.007*	-1.457	-1.982*	0.259
		(1.721)	(.991)	(1.049)	(.981)	(.969)	(.991)	(1.022)
Ads per Keyword		-0.13	0.093	0.105	0.102	0.104	0.071	0.124
		(.156)	(.09)	(.085)	(.089)	(.087)	(.093)	(.087)
Competition			-1.418**	-1.417**	-1.392**	-1.512**	-1.42**	-1.444**
			(.069)	(.065)	(.069)	(.071)	(.069)	(.069)
CPC*CTR				-44.588**				-38.606**
				(9.202)				(9.706)
Competition*CPC					1.588*			1.977**
					(.688)			(.667)
Competition*CTR						-4.977**		-3.209*
						(1.305)		(1.364)
Competition*							0.079	-0.01
Ads per Keyword							(.085)	(.082)
R-Squared	0.034	0.287	0.768	0.792	0.774	0.783	0.769	0.806
R-Squared Change	0.034	0.253**	0.481**	0.024**	0.006*	0.015**	0.001	0.038**
Number of observations	214	214	214	214	214	214	214	214

Standard errors in parentheses.

** p<.01

* p<.05

5.5 Model Validation and Robustness

5.5.1 Regression Assumptions

To verify the assumptions of the regression analysis, several tests have been performed. Appendix C provides statistical results for testing these assumptions. To evaluate the impact of unusual and influential data, Cook's D influence measure (Cook, 1977, 1979) is used. Cook's D measure simultaneously takes into account the residual outliers and the observations with extreme values on the predictor variable. Results demonstrate that reasonable Cook's D measures were obtained from the model (Cook's D $< 4 / \text{number of observations}$).

To assess the normality of the model residuals, two statistical tests were performed: Shapiro-Wilk test (Shapiro & Francia, 1972; Shapiro & Wilk, 1965) and Kolmogorov-Smirnov test (Lilliefors, 1967). Both tests fail to reject the null hypothesis of normality in all models. Thus, the normality assumption is met in all models.

To test for homoscedasticity, White's test (White, 1980) and Breusch-Pagan test (Breusch & Pagan, 1979) were performed on all models. Both tests fail to reject the null hypothesis of no heteroscedasticity in all models except Model 2.

To test whether there is collinearity between predictor variables, Variance Inflation Factors (VIFs) were calculated for each independent variable before mean centering the data. All the VIF values were less than 2 which are lower than recommended thresholds (e.g. 10) (Montgomery et al., 2001).

5.5.2 Robustness

It is important to also check for model specification issues. The proposed research model was tested to see if it can yield similar results for data in a different period. For this purpose, sponsored search campaign data for March 2012 have been collected. The same procedure for data preparation has been performed and 352 samples collected for March 2012. Appendix D provides summary statistics and regression results for the new dataset. Except for the slight change in the model fit, results are consistent with the February 2012 data across all the study models.

In studying the robustness of the model, it is also important to check for endogeneity. In conventional econometric contexts, the regression model is usually used to predict values for a dependent variable and endogeneity becomes critical if there is a recursive relationship between the dependent variable and any of the predictor variables. Endogeneity has been tested in previous research in sponsored search advertising (e.g., Animesh, Ramachandran, & Viswanathan, 2007; Ghose & Yang, 2009). Although the research setting in this study is different compared to keyword level econometric settings in previous studies, existence of endogeneity can affect the Ordinary Least Squares (OLS) estimation in above analyses. Consequently, the following test was performed to validate the above results.

Specifically, the results of the OLS regression can be biased if the problem of endogeneity exists between dependent and independent variables. If in a regression model, independent variable X causes dependent variable Y , and vice versa (Y causes X), the model suffers from simultaneous causality bias. The simultaneity bias arises in many econometric contexts and can be detected by using instrument variables and two stage

least-squares (2SLS) estimation. In sponsored search advertising, simultaneity can bias the results of the OLS estimation. For example, Animesh, Ramachandran, and Viswanathan (2007) use “age” of the website as an instrument variable for “traffic rank” in order to examine the simultaneous relationship between “traffic rank” and “position” of the seller on sponsored listings.

In this study, there is a high probability that the *CTR* is an endogenous variable and *Ad Position* has a positive relationship with *CTR*. To verify the endogeneity of the *CTR* variable, Hausman’s test (Hausman, 1978) is used to check the presence of bias in the OLS estimates. Under H_0 of no measurement error OLS is efficient, while under H_1 , 2SLS is consistent. The following equations were used to estimate the model using 2SLS:

Equation 1: Model 8

Equation 2: $CTR = \alpha_2 + \gamma_1 Ad\ Position + \gamma_2 Conversion_Rate$

Theoretically, the conversion-rate of the merchant is correlated to the *CTR*. A high conversion rate indicates that the products of the merchant are suitable for customer needs, similar to the high *CTR*, where ads of the merchant are matching the customer query. The results from the Hausman’s test are presented in Table 5-9. The results indicate that there is no significant difference between OLS and 2SLS estimates and therefore there is no need to use an instrument variable (i.e., *CTR* is not endogenous) (Bowden Roger & Turkington, 1984).

Table 5-9: Hausman specification test

Hausman's Specification Test Results				
Efficient under H_0	Consistent under H_1	DF	Statistic	Pr > ChiSq
OLS	2SLS	16	2.69	0.9999

Chapter 6 Discussion and Implications

In this chapter, I discuss the results presented in chapter 5 to address the research questions as well as the theoretical and practical implications of the study.

Table 6-1: Supporting results for the hypotheses of the study.

Hypothesis	Web Only	Multi Channel	Full Data
Hypothesis 1 (H1): There is a positive relationship between a firm's bid value and its ad position on the SERP.	Yes	Yes	Yes
Hypothesis 2 (H2): There is a positive relationship between a firm's click-through-rate (CTR) and its ad position on the SERP.	Yes	No	No
Hypothesis 3 (H3): There is a positive relationship between a firm's ad quality and its ad position on the SERP.	No	No	No
Hypothesis 4 (H4): There is a negative relationship between the level of competition intensity in the marketplace and a firm's ad position on the SERP.	Yes	Yes	Yes
Hypothesis 5 (H5): The positive relationship between a firm's bid value and ad position is affected by CTR, such that with higher CTR, the impact of CPC on Ad Position will be diminished.	Yes	Yes	Yes
Hypothesis 6a (H6a): The positive relationship between a firm's bid value and ad position is moderated by keyword competition, such that this positive relationship is weakened by an increase in keyword competition.	No	Yes	No
Hypothesis 6b (H6b): The positive relationship between a firm's CTR value and ad position is moderated by keyword competition, such that this positive relationship is weakened by an increase in keyword competition.	No	Yes	Yes
Hypothesis 6c (H6c): The positive relationship between a firm's ad quality and ad position is moderated by keyword competition, such that this positive relationship is weakened by an increase in keyword competition.	No	No	No

6.1 Discussion and Implications

Search engines have provided advertisers with a new marketing channel to promote their products or services on the Internet. The consumer search behavior literature clearly indicates that ad position is an important performance indicator for the potential success of Internet retailers' positioning strategies. The main objective of this study was to investigate how competition intensity in the keyword market influences the relationships between ad position and its key determinants. I used a unique cross-sectional dataset collected from the top 500 Internet retailers to empirically test the relationships between keyword competition, ad position, and ad position determinants, in a competitive setting. Hierarchical multiple regression was used to estimate the model parameters. To this end, the study draws on the auction mechanism design literature and the empirical research on sponsored ad performance and consumer search behavior.

In particular, the conceptual model is built on the consumer search behavior literature to explain firms' ad positioning strategies. The position of the ads on the SERP is used as an indicator of the advertising and marketing performance. Given that consumers perceive different values depending on the position of the ads on the SERP (Animesh et al., 2011), the location of the ad on the SERP has significant importance for sponsored search advertisers in achieving their marketing goals. In addition, the ad position has significant effect on a firm's revenue (Agarwal et al., 2008). The significance of ad position for search engine advertisers conforms to similar studies in other advertising channels such as television, radio, and newspapers (Brunel & Nelson, 2003; Pieters & Bijmolt, 1997; Terry, 2005). The primacy (ads appearing in premium ad

positions) and recency (recalling the last seen ads) effects both have significant impact on persuasiveness of the ads on consumers.

Arguably, price is one of the main determinants of ad position across various advertising outlets. Clearly, it is the nature of any auction to favor the highest bidder. Our study indicates that Search engine auctions are no different; they allocate the better ad positions to the advertisers with the highest bids (i.e. CPC). Moreover, the impact of bid values on ad position is consistent in all the three variants of datasets (i.e. full, web-only, and multi-channel retailers). The results are consistent with advertising via other channels as well. The newspapers and magazines charge premium prices for showing the ads on the front and back cover page; likewise, ads displayed at the beginning of the commercial breaks on television and radio have higher rates.

Another determinant of ad position in sponsored search auctions can be also explained by the consumers' search behaviors. More specifically, consumers' perceptions of the ads have significant effect on the ad positions of search engine advertisers. Previous studies in sponsored search advertising have also emphasized the importance of the relationship between consumers' search behaviors and the ad position on the SERP (Lahaei, 2006; Liu and Chen, 2006). Ads with higher quality (e.g. rich information content) will receive more clicks from consumers. Therefore, search engines have incorporated measures to apply the consumer's click behavior into ranking of the ads. Results of this study show that consumers' clicks (CTR) are an important factor for web-only retailers. The average ad position from web-only advertisers is influenced by both average bidding value and CTR. These results provide evidence that web-only retailers are highly customizing their only store front (the Web) for search advertising.

CTR does not have a direct significant effect on the ad position of the multi-channel merchants. This might be due to the fact that multi-channel merchants are looking at sponsored search advertising like other conventional advertising channels (e.g. television, newspapers), where location of the ad has a price, and forfeiting that price will guarantee a spot. The other reason might be that the web-only advertisers are highly focused on their Internet advertising, and prevent their multi-channel rivals dominate their only storefront. Therefore, they are constantly monitoring their CTR performance and do not let the rivals steal the competition from them.

Giving priority to consumers' opinion about ads has roots in conventional advertising channels. The quality of the ads "is an important influence on consumers' responses to the ad and the brand" (Abernethy & Franke, 1996). In sponsored search advertising, CTR is a widely accepted indicator of the consumers' responses (Cheong, de Gregorio, & KiM, 2010). Furthermore, non-informative advertising might result in self-destruction of the ads (Resnik & Stern, 1977a). Therefore, and especially in sponsored search context, both bidding value and quality of the ad play a significant role in determining ad position.

Another interesting observation in this study is the relationship between the price and the quality of the ads in determining ad position. Ads with low CTR values indicate that consumers are less attracted to them. For example, uncommon keywords (e.g. "shop laptop sz340 in Canada, Ontario") are rarely entered by searchers looking for information. Consequently, the chances of the corresponding ads getting clicked is lower compared to ads linked to more popular keywords (e.g. "shop laptop"). Therefore, the

lower the minimum quality threshold is, the impact of aggressive bids will be more significant in determining premium positions.

The situation in a high CTR setting is quite different. Ads with high CTR values most likely have high quality content. Therefore, the quality threshold for those ads entering the auction is much higher than the low CTR ads (search engines adjust the minimum quality threshold automatically when the competition for a keyword increases and more firms are willing to advertise on a similar keyword). An increase in the minimum quality threshold results in elimination of the ads with high bidding values and low CTR values. Therefore, ads with unrealistic high bid values (aggressive bidders with low CTR values) will be removed from the auction pool, and the average bid value will be lower in a high CTR setting.

The results of this study also shed light on another characteristic of the sponsored search market place. The sponsored search market place is built on auction mechanism design and the existence of competition in such a market is undeniable (Milgrom & Weber, 1982). On one hand, the negative impact of keyword competition on the ad position is probably the most expected outcome of this study. The number of merchants bidding on the same keywords certainly has a negative effect on the average ad position of the focal firm. The same result has been reflected in conventional advertising channels (e.g. TV) by referring to “advertising clutter” (all non-program material, e.g., commercials). The number of advertisements on a newspaper page or during a TV Commercial break, as well as length of the ads has significant impact on the advertising performance (Brown & Rothschild, 1993; Pieters & Bijmolt, 1997; Webb & Ray, 1979).

The number of competing advertisers has negative impact on consumers' memory, and increases the advertising expenses (Asdemir, 2006; Brannman et al., 1987).

On the other hand, the keyword competition also has significant impact on other variables of the market place. Results of this study indicate that for multi-channel retailers, competition has a significant negative moderating effect on the relationship between bidding values and ad position. Existence of higher levels of keyword competition would require higher average bidding values in order to maintain the average ad position. This is also in line with previous results in mechanism design and auction theory literature (Asdemir, 2006; Brannman et al., 1987), where, an increase in competition intensity increases the winning values.

Contrary to multi-channel merchants, there is no such evidence for their web-only counterparts. The level of keyword competition does not have a significant effect on the relationship between the bid values and the average ad positions of web-only merchants. This might be due to the fact that web-only merchants have a different mindset in their online advertising and they do not follow traditional advertising strategies as multi-channel merchants do. As previously mentioned, web-only merchants are constantly monitoring their online content and are optimizing their only storefront (i.e. Internet). This optimized targeting of online consumers might have developed the web-only merchants' ads to be competent in the sponsored search advertising, and any change in the level of keyword competition does not affect such advertising strategies.

The level of keyword competition also has significant effect on the relationship between CTR and ad position. The positive relationship between CTR and ad position will be weakened at higher levels of keyword competition between multi-channel

merchants. This impact has one direct and one indirect explanation. First, the direct impact of CTR on ad position is identical to the impact of CPC on ad position. Firms with higher CPC or/and CTR values have a better ad position in the market place. Therefore, the impact of level of keyword competition on the relationship between CTR and ad position can be interpreted in a similar manner to the previous arguments. Second, to enter the auction pool, ads should pass certain minimum ad relevancy criteria. An increase in the number of competitors increases the number of advertisers with high CTR value, resulting in an increase in the minimum ad relevancy threshold. This would lead to a new auction pool, where ads have higher overall CTR values. Therefore, ads with high CTR values would lose their competitive advantage when they are among their equivalent counterparts.

Results of this study also provide guidelines for practitioners. Convenience of Internet technologies and online advertising has enabled web only retailers to easily utilize this marketing channel. Web only retailers should carefully monitor their bid values and CTR performance simultaneously as both factors are significant indicators of ad position. A weak ad copy might result in disqualification of the ad from being displayed on the SERP. This might lead to an increase in bidding values to return to the same spot. On the other hand, multi-channel retailers should start developing strategies to increase their ad quality, particularly CTRs. An increase in the quality of the ads for multi-channel retailers can significantly decrease their advertising costs.

The results from the relationship between bidding values and CTR values indicate that bidding aggressively on keywords will not work if the competitors have already developed reasonable CTR scores in their campaigns. Excessive bidding on ads with a

low quality score will not guarantee a place on the SERP, as the ad is still not meeting the minimum quality thresholds to enter the auction. Therefore, advertisers should implement strategies for bid management and monitor their ads' quality constantly.

Finally, an increase in the competition has significant negative impact on the position of the ads. However, selecting keywords without much competition does not result in a successful advertising campaign. Not only the quality of the ad copies are important for a premium position on the SERP, but also advertisers should select keywords that receive fair amount of impression from consumers. Selecting keywords with no competition (e.g. specific-long tail keywords) which consumers do not search for will reduce the overall ad campaign performance and lowers the overall quality of the ads. Therefore, advertisers should select keywords that have reasonable competition on them and then strategize their campaigns to distinguish themselves from their competitors.

Chapter 7 Conclusions, Limitations and Future Research

This chapter provides limitations, future research opportunities, and conclusions related to this study. First, limitations of the study are outlined. The limitations create several avenues for future research in the same subject area. Finally, the chapter ends with the conclusion of this thesis.

7.1 Limitations and Future Research

The limitations of this study can be described in two categories. The first category is limitations due to the nature of the data that was used in this study. The empirical data used in this study were collected during the months of February and March. It is important to run the analysis for other months of the year in order to see if the results are consistent. For example, during November and December the marketplace characteristics could change as the competition for the end of the year sales grows. However, consistent results between the current two months of data provide promising results for consistency of the model over remaining months of the year. Although this study assumes that analyzing data from top 500 retailers did not create bias in modeling the sponsored search advertising, inclusion of more Internet retailers would benefit the study, especially when analysis is performed on “web-only” and “multi-channel” merchants separately. Dividing the data to these two merchant categories provides smaller samples of each group and therefore collection of more data might change some of the findings.

Another limitation of the study is that it uses several proxies to operationalize the research variables. For example, to capture the retailers’ bidding values, this study uses CPC values. Although CPC values have been extensively used in previous literature

(Ghose & Yang, 2009; Rutz & Bucklin, 2007; Yao & Mela, 2011), CPC values cannot truly capture the actual bidding values posted by the retailers. Another proxy defined in this study was ad quality, captured by number of ads per keyword for each advertiser. This proxy can only give a naïve approximation of the quality of the designed ads. However, estimating the quality of ad copy itself can be a topic of another study.

The other category of limitations can be defined as methodological limitations. The regression analysis in this study has been performed in a cross-sectional setting. Performing the same analysis using panel data (incorporating time series data into analysis) could provide additional insights. This study also accounted for the possibility of endogeneity for CTR. However, with the existence of panel data, more sophisticated econometric models can be investigated to analyze the sponsored search market place. For example the recursive effect of the ad position and CTR can be modeled taking endogeneity of the CTR values into account. Moreover, the endogeneity test can be performed using alternative instrument variables if data becomes available.

The limitations of this study provide several avenues for future research. First, a better proxy for ad copy quality should be created to more accurately examine the relationship between ad (content) quality and ad position. The quality of the ad copies can be facilitated using techniques like text mining to extract marketing cues in ads related to a specific keyword. Another roadmap closely related to the ad content quality is constructing the ad Quality Score, using its core determinants such as CTR and landing page quality. Then the resulting Quality Score can be used to investigate its relationship with ad position on the SERP.

Another extension to the results of this study can be use of simultaneous regression equations (e.g. two-stage least squares - 2SLS) and panel data to model the relationship between ad position and its determinants (both endogenous and exogenous variables). Finally, a closely related area of research which has recently emerged in this area (Chang, Oh, Pinsonneault, & Kwon, 2010) is the investigation of competition between search engines as market place auctioneers. A possible future research problem could be how search engine market share dominance can affect advertisers in developing their advertising strategies in such market places.

7.2 Conclusion

This study has combined theories from positioning strategy, consumer search behavior, and auction mechanism design to draw a conceptual model explaining the position of ads on the search engine result pages. The proposed conceptual model was tested on a unique cross-sectional dataset from Internet retailers. This study is the first empirical research that uses ad position as the dependent variable in the sponsored search market place. The importance of the ad position on the SERP can be mapped to a similar concept in conventional marketing channels like television and radio (the order of appearance in the commercial break between programs) or newspapers and magazines (ads on the front and back covers). This study is also the first of its kind to investigate the determinants of ad position in sponsored search in a cross-sectional setting where the level of keyword competition is explicitly incorporated in modeling such market places.

The results indicate that consumers' responses to ads (captured in CTR) and the placed bids (CPC) as well as their interaction affect the position of the ads on the search engine result pages. These relationships are further influenced by the level of the

competition intensity in the market place. More specifically, the position of the ads from web-only retailers is more dependent on the relevancy metrics, whereas, multi-channel retailers are more reliant on their bid values. This difference between web-only and multi-channel retailers can also be seen in the moderating effects of keyword competition. Specifically, keyword competition has significant moderating effects only for multi-channel retailers. Although there are several avenues for future research, the findings of this study contribute to our understanding of keyword competition and its effect on search advertising performance.

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Appendices

A. Summary of Literature Review

Table A-1: Summary of existing mechanism design literature.

Author(s)	View Point	Auction Determinants	Implications
Edelman et al. (2005)	Advertiser	Bid Value CTR	GSP generally does not have equilibrium in dominant strategies, and truth-telling is not equilibrium of GSP. Applying locally envy-free restrictions on GSP leads it to have the same equilibrium as VCG design in dominant strategies. The locally envy-free equilibrium is the best equilibrium for advertisers.
Varian (2007)	Advertiser	Bid Value CTR	Optimal bids in the sponsored search auction will in general depend on the bids made by other agents. Proposing a set of symmetric equilibria based on Nash equilibria in a full-information auction setting. Introduces a method for calculating bounds for unobserved values of advertisers that can be used to estimate the bidding price.
Lahaie (2006)	Search Engines Advertisers	Bid Value Relevancy	Bidders do not show their true valuation of ad slots. RBR model is more complicated compared to RBB due to underlying informational requirements. RBR model is efficient in terms of sum of bidders' revenue in equilibrium. Future work: Budget constraints might have significant effect in equilibrium.
Asdemir (2006)	Search Engines Advertisers	Bid Value	Bidding war cycles can result from a symmetric Markov-perfect equilibrium strategy. Advertisers can bid below their valuation.
Liu and Chen (2006)	Search Engines Advertisers	Bid Value Relevancy	Biasing results toward low CTR advertisers, search engines can be more efficient. Weighted UPC auctions can reduce bidders' risk. Google's auction design can generate more revenue compared to Yahoo! when the number of competitors is large.

Feng et al. (2007)	Search Engines	Bid Value Relevancy	The revenue of the search engine is highly correlated to willingness to spend and content relevancy of the advertiser. Ranking ad slots based on bidding value and relevancy at the same time provides higher revenue for the search engines.
Edelman and Schwarz (2007)	Search Engine	Bid Value Relevancy	Reserve price of a keyword is independent of the number of competitors. Increased competition creates more revenue for the search engine in GSP.
Edelman and Ostrovsky (2007)	Search Engine	Bid Value	Strategic behavior of advertisers results in great revenue loss for search engines.
Aggarwal et al. (2006)	Search Engines Advertiser	Bid Value Relevancy	Proposing a truthful auction mechanism, next-price auction yields same revenue as truthful auction with a pure-strategy Nash equilibrium. In next-price auction, there is not a general characterization of the Nash equilibrium.
Aggarwal et al. (2007)	Advertiser	Bid Value Ad position	Introduce a position-based auction mechanism, which is envy-free, has Nash equilibrium, and is bidder optimal.
Aggarwal et al. (2008)	Search Engines Advertiser	Bid Value Relevancy	A model to capture the user behavior and designing a slot allocation mechanism accordingly to affect the game theory between search engine and advertisers.
Abrams and Schwarz (2007)	Search Engines	Bid Value	A mechanism for incorporating social welfare into search engine performance reducing users' diversion from clicking on sponsored results. Accounting hidden costs in the sponsored search slot allocation increases efficiency for search engines.

Table A-2: Summary of empirical studies.

Author(s)	Data	Methodology	Implications
Ghose and Yang (2010)	Six month data of paid search advertising from a nation-wide retail chain	Hierarchical Bayesian modeling	Consumers searching for a product in a category might eventually purchase a product from different category. Retailer-specific keywords show more interdependence across categories compared to brand-specific keywords.
Ghose and Yang (2008)	Three month data of paid search advertising from a nation-wide retail chain	Hierarchical Bayesian modeling, Markov Chain Monte Carlo Methods, Simulation	A method for calculating optimal bid values. Advertisers are either overbid or underbid based on their keyword characteristics. Brand information, rank, and keyword length do not have any impact on consumers spend on the searched category. Brand information highly increases consumer spending in another product category while rank and keyword length do not.
Ghose and Yang (2009)	Six month data of paid search advertising from a nation-wide retail chain	Hierarchical Bayesian modeling, Markov Chain Monte Carlo Methods	Retailer-specific and brand-specific information in the keyword increase CTR while, increase in keyword length decreases CTR. Decrease in ad rank results in decrease in both CTR and conversion rate. Increase in landing page quality increases conversion rate, while decrease CPC. While CTR is higher in prominent ad positions, profits are not necessarily higher. Current bid value has stronger effect on ad rank than historical CTR.
Yang and Ghose (2010)	Three month data of paid search advertising from a nation-wide retail	Markov Chain Monte Carlo Methods	Modeling the relationship between ad rank and keyword level attributes and consumer responses, advertiser CPC and

	chain		search engine ranking mechanism. Analyzing nature of interdependence between sponsored and organic search results in terms of consumer clicks and advertiser profits.
Jansen and Spink (2007)	Log data from 7 million interaction of users from a major meta-search engine	Classification Algorithm, Statistical analysis of aggregated data	Classifying search queries as informational, navigational, and transactional queries. Combining sponsored and organic links in the same listing lowers overall sponsored link CTR. Navigational queries have higher CTR than transactional.
Rey and Kannan (2010)	2 month of Yahoo! search clicks for training and 2 weeks of data for testing	Simple linear regression	A solution for automatically adjusting the bid price for advanced matched keywords.
Rutz and Bucklin (2007)	Three month data of paid search campaign for a major lodging chain from Google	Binary logit model Shrinkage procedures	Ad position, click-through rate, and keyword characteristics such as brand or location are significant predictors of conversion rates for keywords. Proposing a model to generate keywords outperforming generic model-free approaches.
Rutz and Bucklin (2011)	Daily information on paid search campaign of a large lodging chain on both Google and Yahoo! search engines.	Dynamic linear model (DLM) estimated in a Bayesian framework	Generic keywords have a positive significant effect on awareness of relevance of branded keywords. Spillover from generic keywords significantly influences number of branded searches. The relationship between generic and branded keywords is asymmetric.
Ganchev et al. (2007)	Microsoft search engine data from 10000 advertisers	Logistic Regression Model	Proposing a model to estimate CTR values of newly created ads. 30% increase in estimation accuracy.
Animesh et al. (2011)	Data for 36 keywords with top CTR in mortgage industry during three month.	Moderate Multiple Regression	Sponsored search ads are targeted to different consumer segments. Firms differentiation strategy strongly moderates the relationship between

positioning strategy and CTR.

B. Data Descriptions

Table A-3: Name, description, and sources of variables.

Variable	Description	Source
<i>Average Ad Rank</i>	<i>Where a domain was placed in the order of results.</i>	<i>SpyFu</i>
<i>Organic Rank</i>	<i>Shows where a domain places in the standings against all other domains when it comes to having the most organic results on the most valuable keywords.</i>	<i>SpyFu</i>
<i>Estimated Daily Budget</i>	<i>How much a domain spends in PPC each day. This is from activity spread out over the month, broken down into daily spending.</i>	<i>SpyFu</i>
<i>Web Sales (2010)</i>	<i>2010 Internet sales (only online sales channels)</i>	<i>Top 500 Guide</i>
<i>Merchant Type</i>	<i>Indicating whether the merchant is web only, retail chain, consumer brand manufacturer, or catalog and call center.</i>	<i>Top 500 Guide</i>
<i>Min/ Max Average CPC</i>	<i>The minimum and maximum estimated cost per click averaged over all the keywords for each domain (monthly)</i>	<i>SpyFu</i>
<i>Estimated Total Clicks per Day</i>	<i>the number of clicks a domain receives across all of its paid keywords</i>	<i>SpyFu</i>
<i>Daily Searches</i>	<i>How many times a day do people search for all the keywords that a domain is bidding on.</i>	<i>SpyFu</i>
<i>PPC Ad Copies</i>	<i>Number of the advertisement copies that KeywordSpy indexed for each domain</i>	<i>KeywordSpy</i>
<i>PPC Keywords</i>	<i>Number of PPC keywords being used by each domain.</i>	<i>KeywordSpy</i>
<i>Average Ad Competitors</i>	<i>Reflects the average number of competitors a domain has when spread out over its entire paid keyword list (each month).</i>	<i>SpyFu</i>

**Table A-4: Dispersion of firms over merchant categories and merchant types
(before cleaning the data)**

Merchandise Category	Catalog/ Call Center	Consumer Brand Manufacturer	Retail Chain	Web Only	Total
Apparel/Accessories	20	33	51	24	128
Automotive Parts/Accessories	1	0	2	4	7
Books/Music/Video	5	0	7	16	28
Computers/Electronics	8	10	12	23	53
Flowers/Gifts	3	1	3	3	10
Food/Drug	6	3	6	6	21
Hardware/Home Improvement	2	1	5	13	21
Health/Beauty	3	3	6	17	29
Housewares/Home Furnishings	10	5	15	17	47
Jewelry	1	0	4	10	15
Mass Merchant	5	0	14	12	31
Office Supplies	2	0	4	12	18
Specialty/Non-Apparel	11	0	7	30	48
Sporting Goods	3	2	12	10	27
Toys/Hobbies	3	2	4	8	17
Total	83	60	152	205	500

C. Methodology Assumptions (February 2012)

Table A-5: Residual normality tests

Model	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	D.F.	Sig.	Statistic	D.F.	Sig.
Model 2	0.032	333	.200*	0.993	333	0.146
Model 3	0.033	333	.200*	0.994	333	0.245
Model 4	0.036	333	.200*	0.996	333	0.554
Model 5	0.036	333	.200*	0.995	333	0.297
Model 6	0.041	333	.200*	0.994	333	0.203
Model 7	0.035	333	.200*	0.994	333	0.182
Model 8	0.03	333	.200*	0.996	333	0.663

* This is a lower bound of the true significance.

Table A-6: Homoscedasticity tests

Model	White's Test			Breusch-Pagan		
	Statistic	D.F.	Pr > ChiSq	Statistic	D.F.	Pr > ChiSq
Model 1	9.19	13	0.7588	3.42	4	0.49
Model 2	55.64	34	0.011	27.92	7	0.0002
Model 3	46.94	43	0.3141	10.89	8	0.2081
Model 4	42.14	52	0.8338	14.6	9	0.1027
Model 5	50.46	52	0.5346	10.61	9	0.3031
Model 6	47.88	52	0.6365	13.65	9	0.1354
Model 7	50.02	52	0.5521	10.69	9	0.2977
Model 8	52.93	81	0.9933	17.66	12	0.1265

Table A-7: Collinearity among variables (before mean-centering)

Variable	Collinearity Statistics	
	Tolerance	VIF
LogSales	0.924	1.082
LogBudget	0.551	1.816
LogSEO	0.574	1.743
Merchant	0.881	1.135
CPC	0.731	1.368
CTR	0.874	1.144
AdsPerKeyword	0.832	1.202
Competitors	0.731	1.368

Table A-8: Collinearity among variables (after mean-centering)

Variable	Collinearity Statistics	
	Tolerance	VIF
LogSales	0.918	1.089
LogBudget	0.547	1.827
LogSEO	0.572	1.749
Merchant	0.855	1.17
CPC	0.664	1.507
CTR	0.768	1.301
AdsPerKeyword	0.737	1.358
Competitors	0.663	1.508
CPC*CTR	0.661	1.513
Competitors*CPC	0.76	1.316
Competitors*CTR	0.69	1.449
Competitors*AdsPerKeyword	0.799	1.252

Table A-9: Correlation between error terms and independent variables

Correlations	Unstandardized Residual
Unstandardized Residual	1
LogSEO	0
LogBudget	0
LogSales	0
Merchant	0
CPC	0
CTR	0
AdsPerKeyword	0
Competitors	0

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

D. March 2012 Results

Table A-10: Means, standard deviations and correlations of key variables (March 2012 data).

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9
1 Ad Position	5.2368	1.82267	1.000								
2 SEO Quality	8.2912	1.47306	-.138**	1.000							
3 Daily Budget	7.3616	1.35362	-0.004	-.593**	1.000						
4 Web Sales	17.7152	1.21538	-0.045	-.203**	.215**	1.000					
5 Merchant Type	0.6364	0.48173	0.049	-.216**	.202**	.116*	1.000				
6 CPC	0.3592	0.09528	.265**	0.069	.139**	-0.035	0.048	1.000			
7 CTR	0.0574	0.0723	.153**	0.016	0.088	-0.091	-.156**	.256**	1.000		
8 Ads Per Keyword	2.2697	1.00351	-0.028	-0.059	.278**	.106*	.196**	.166**	-0.011	1.000	
9 Competition	7.1697	1.18094	-.565**	.164**	.107*	-0.028	0.089	.473**	0.028	.168**	1.000

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table A-11: Regression results (March 2012 data)

Dependent Variable:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Ad Position								
Intercept	10.425 (1.854)	11.24 (1.809)	7.657 (1.078)	8.02 (1.039)	7.541 (1.081)	7.946 (1.061)	7.659 (1.079)	7.936 (1.029)
Web Sales	-0.099 (.082)	-0.058 (.078)	-0.086* (.046)	-0.098** (.044)	-0.085* (.046)	-0.095** (.045)	-0.087* (.046)	-0.101** (.044)
Daily Budget	-0.171* (.089)	-0.289*** (.09)	-0.069 (.054)	-0.065 (.052)	-0.064 (.054)	-0.079 (.053)	-0.07 (.054)	-0.061 (.052)
SEO Quality	-0.272*** (.082)	-0.356*** (.08)	-0.075 (.049)	-0.088* (.047)	-0.074 (.049)	-0.08* (.048)	-0.075 (.049)	-0.087* (.046)
Merchant Type	0.133 (.206)	0.169 (.201)	0.384*** (.119)	0.373*** (.114)	0.407*** (.12)	0.369*** (.117)	0.386*** (.119)	0.414*** (.114)
CPC		5.565*** (1.024)	13.066*** (.674)	13.768*** (.66)	12.966*** (.677)	13.499*** (.671)	13.101*** (.676)	13.823*** (.658)
CTR		2.663** (1.337)	0.493 (.795)	2.078** (.818)	0.511 (.794)	0.834 (.785)	0.485 (.795)	2.188*** (.811)
Ads per Keyword		-0.068 (.098)	0.007 (.058)	0.019 (.056)	0.008 (.058)	0.017 (.057)	-0.002 (.059)	0.016 (.056)
Competition			-1.365*** (.054)	-1.386*** (.052)	-1.356*** (.054)	-1.431*** (.056)	-1.36*** (.054)	-1.397*** (.054)
CPC*CTR				-42.217*** (7.786)				-38.903*** (8.599)
Competition*CPC					0.509 (.392)			1.034*** (.385)
Competition*CTR						-3.438*** (.902)		-2.106** (.984)
Competition* Ads per Keyword							0.04 (.05)	0.053 (.048)
R-Squared	0.036	0.139	0.7	0.724	0.702	0.712	0.701	0.733
R-Squared Change	0.036***	0.103***	0.561***	0.024***	0.002	0.012***	0.001	0.033***
Number of observations	352	352	352	352	352	352	352	352

Standard errors in parentheses.

*** p<.01

** p<.05

* P<.10