Search Engine Advertising in Web Retailing: An Efficiency Analysis

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ABSTRACT

This study examines the efficiency of search engine advertising strategies employed by firms. The research setting is the online retailing industry, which is characterized by extensive use of Web technologies and high competition for market share and profitability. For Internet retailers, search engines are increasingly serving as an information gateway for many decision-making tasks. In particular, Search engine advertising (SEA) has opened a new marketing channel for retailers to attract new customers and improve their performance. In addition to natural (organic) search marketing strategies, search engine advertisers compete for top advertisement slots provided by search brokers such as Google and Yahoo! through keyword auctions. The rationale being that greater visibility on a search engine during a keyword search will capture customers' interest in a business and its product or service offerings. Search engines account for most online activities today. Compared with the slow growth of traditional marketing channels, online search volumes continue to grow at a steady rate. According to the Search Engine Marketing Professional Organization, spending on search engine marketing by North American firms in 2008 was estimated at $13.5 billion.

Despite the significant role SEA plays in Web retailing, scholarly research on the topic is limited. Prior studies in SEA have focused on search engine auction mechanism design. In contrast, research on the business value of SEA has been limited by the lack of empirical data on search advertising practices. Recent advances in search and retail technologies have created data-rich environments that enable new research opportunities at the interface of marketing and information technology. This research uses extensive data from Web retailing and Google-based search advertising and evaluates Web retailers' use of resources, search advertising techniques, and other relevant factors that contribute to business performance across different metrics. The methods used include Data Envelopment Analysis (DEA), data mining, and multivariate statistics.

This research contributes to empirical research by analyzing several Web retail firms in different industry sectors and product categories. One of the key findings is that the dynamics of sponsored search advertising vary between multi-channel and Web-only retailers. While the key performance metrics for multi-channel retailers include measures such as online sales,

conversion rate (CR), click-through-rate (CTR), and impressions, the key performance metrics for Web-only retailers focus on organic and sponsored ad ranks. These results provide a useful contribution to our organizational level understanding of search engine advertising strategies, both for multi-channel and Web-only retailers. These results also contribute to current knowledge in technology-driven marketing strategies and provide managers with a better understanding of sponsored search advertising and its impact on various performance metrics in Web retailing.

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SECTION 1: INTRODUCTION

The Internet has emerged as a cost effective communication channel between organizations and customers. In 2008, online sales were reported to be $165.9 billion, an increase of 21.8% from 2007 (Internet Retailer, 2008). This surge in online sales can be attributed to the Internet's unique characteristics as a marketing channel. Traditional marketing channels such as television, print media and radio, have focused on reaching as many people as possible. Mass media allows for neither customer targeting nor the customization of products and services. Marketers have, however, seen the need for product customization and targeting of customers through the Internet (Berthon, Pitt, & Watson, 2003; Sen, 2005). Thus the Internet creates a platform on which organizations of all sizes can compete.

Among the various Internet technologies that have changed the business landscape today are search engines. Search engines are in a unique position as they stand between millions of Web sites and customers. Search engines are now able to leverage the value of their information location tools by selling advertising linked to search keywords (Ghose & Yang, 2008c). With the number of Web sites constantly increasing, marketers have to come up with ways to increase their visibility. Unlike other forms of intrusive Internet advertising such as banner ads, search engine advertising provides a cost effective, non-intrusive way in which marketers can increase Web site traffic (Edwards, Li, & Lee, 2002). The effectiveness of search engines as a marketing tool is underlined by the fact that search engine-driven sales continue to grow at a higher rate than other traditional marketing channels (Sen, 2005).

Search engine advertising (SEA) involves the entire set of techniques used by advertisers to direct visitors from search engines to marketing Web sites. SEA is becoming a key marketing strategy due to its ability to massively increase the visibility of an organization in a cost effective manner. This study investigates the impact of search engine advertising practices, particularly sponsored search advertising, on various performance metrics in the online retailing industry. The study focuses on sponsored search advertising as it is a source of competitive advantage and an area of strategic focus for many organizations. In addition, organizations that undertake sponsored search advertising try different approaches to achieve success due to the lack of a general evaluation mechanism (Internet Retailer, 2008). Moreover, sponsored search advertising has not been widely studied in the past and it therefore represents a new area of academic research. The study focuses on Web retail firms due to the high competition in the industry, the reliance on the Web as a key marketing channel, and the high utilization of technology in general. Therefore, traditional marketing methods such as the advertising of goods and services through mass media channels and the use of customer relationship programs can no longer be solely relied upon. In order to achieve high organizational visibility, firms are utilizing the Internet as a key marketing channel due to its unique characteristics (Wang, Head, & Archer, 2000).

In sponsored search advertising, advertisers pay a fee for their ads to be displayed alongside organic search results (Ghose & Yang, 2009). Sponsored search differs from traditional marketing channels in various ways. In traditional marketing channels, also known as pay per view, advertisers are charged based on the number of impressions or exposure their advertisements received. Whereas, sponsored search advertisers are charged based on the number of times search engine users click on their advertisements (Ghose & Yang, 2009; Mangani, 2004).

Various organizations use different sponsored search strategies to achieve different objectives. However, research on sponsored search advertising is limited by the focus on individual firms and a few performance metrics. As a result, there is a lack of an evaluation framework to assess sponsored search advertising practices across different metrics. Organizations engage in sponsored search for various reasons, such as to increase their visibility, to increase traffic on their Web site, to increase Web sales, among others. In the absence of a performance evaluation framework, Web retailers tend to follow traditional rules or simply mimic their competitors (van der Merwe & Bekker, 2003). This approach, however, may lead to sub-optimal business performance (Internet Retailer, 2008). Therefore, the main objective of this research is to conceptualize sponsored search advertising as an economic process and develop a model to evaluate the efficiency of sponsored search advertising strategies employed by multi-channel and Web-only retailers. In order to achieve this objective, we address the following three research questions: How should the performance of sponsored search advertising be evaluated? What are the key performance metrics in Web retailing? And, are there differences between multi-channel retailers (MCR) and Web-only retailers (WOR)?

The study aims to contribute to the literature as well as the Web retailing industry in many ways. Previous research on SEA is characterised by the lack of data and an empirical base. Therefore, theoretical propositions are often validated based on numerical experiments using simulated data (Ghose & Yang, 2008a; Ghose & Yang, 2008b). The proposed study is data-driven and utilizes extensive industry data that has not been available previously. In addition, the study employs well-established quantitative techniques, which include data envelopment analysis (DEA), data mining, and multivariate techniques. DEA is a non-parametric method used to measure the relative efficiency of entities or decision making units that use multiple inputs to produce multiple outputs (Charnes et al., 1978). DEA overcomes the limitations of traditional efficiency measures that rely on a single performance metric. The underlying assumption is that decision making units consume a common set of inputs in the production of a common set of outputs so that those units exhibiting relatively inefficient performance could be targeted for improvement or change. In addition to DEA, the study uses data mining and multivariate statistics in the exploratory and validation phases. Therefore, the study attempts to provide broad insights into search advertising practices and the business performance implications. In summary, the study contributes to current knowledge in technology-driven marketing strategies as well as provides managers with a better understanding of SEA and its impact on various performance metrics in Web retailing.

The rest of the thesis is organized as follows. Section 2 provides a review of Internet marketing and the various channels through which marketing activities can be carried out. The section then reviews the various forms of online advertising, the key dimensions of search advertising, and a review of prior research in the area. Section 3 presents the methodology, the conceptual model and the variables that are used in the study. Section 4 describes the data that is used for the study. Section 5 delves into the various steps taken for the data analysis. Section 6 presents the results of the analysis, followed by the discussion in Section 7. Finally, Section 8 provides the conclusions drawn as well as the implications of the study and future research directions.

SECTION 2: LITERATURE REVIEW

This section provides a review of SEA literature. Our review is organized as follows: First, we discuss the different dimensions of Internet marketing. We then discuss the various forms of online advertising with a focus on SEA. This will be followed by a discussion on sponsored search advertising. Finally, we conclude this section with a discussion on the gaps in existing literature and the specific contributions of this study.

2.1 INTERNET MARKETING

Organizations carry out marketing activities through three types of channels: distribution, transaction, and communication channels (Kiang, Raghu, & Shang, 2000; Peterson, Balasubramanian, & Bronnenberg, 1997). The distribution channel facilitates the physical exchange of goods and services. The transaction channel generates sales between buyers and sellers. The communication channel enables efficient communication between buyers and sellers. Traditional marketing channels fail to serve in all three capacities, whereas the Internet is able to accommodate all three channels simultaneously in a cost effective manner.

The Internet has significantly improved the way organizations distribute goods and services, communicate with customers, and promote their goods and services. This has led to a new form of marketing known as Internet marketing. Internet marketing leverages Web technologies and applications to create new ways in which consumers and organizations can interact (Parsons, Zeisser, & Waitman, 1998). As Figure 1 shows, Internet marketing is seen to lie at the interface of Marketing, Economics, Business and Management, and Information Technology and Information Systems (Ngai, 2003).

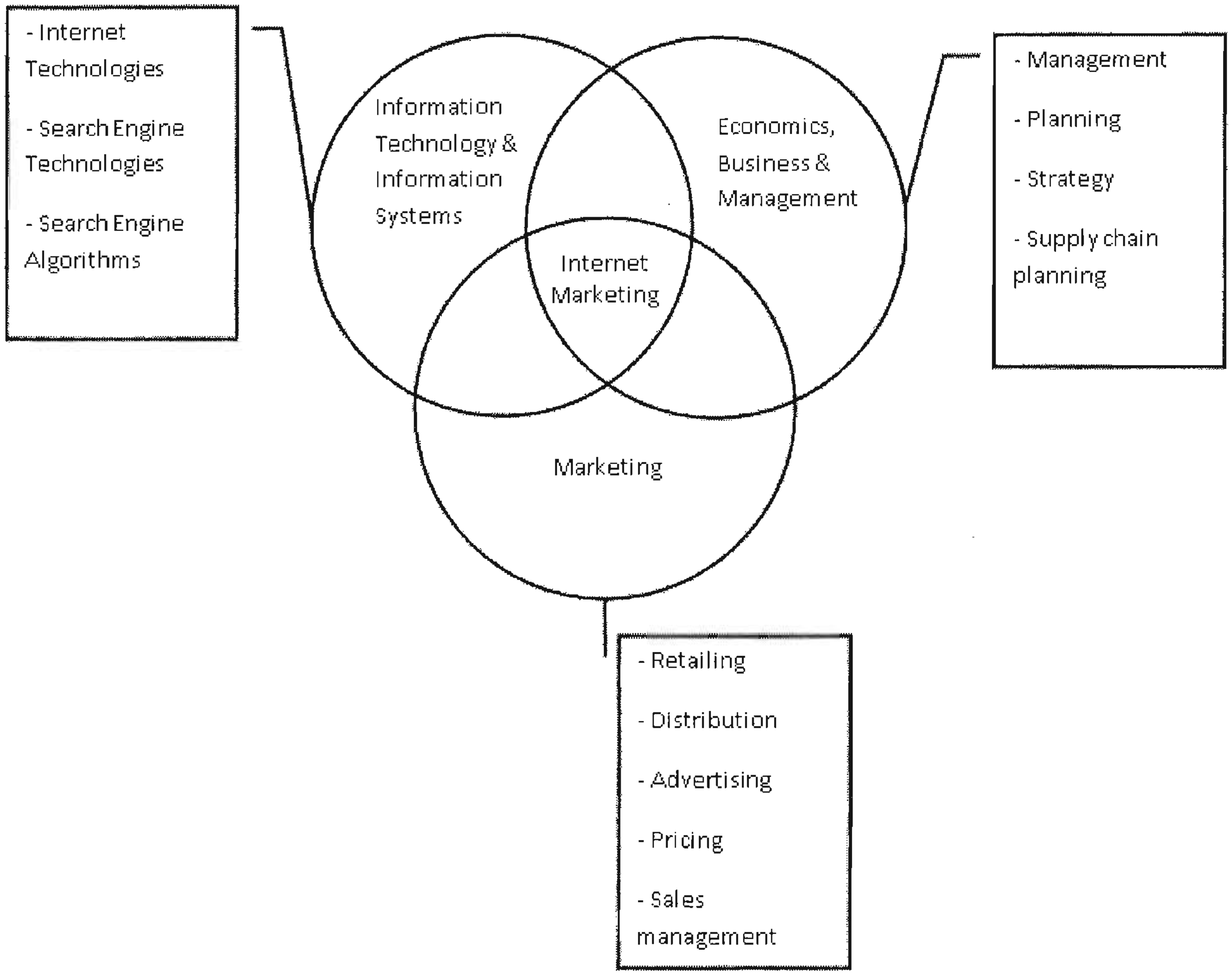

Figure 1: Internet Marketing Taxonomy (Ngai, 2003)

Distribution channels, avenues through which organizations distribute and advertise their products, can be broadly divided into direct and indirect channels. The direct channel involves an organization selling its product directly to the end user without the use of intermediaries. In the indirect channel, an organization uses intermediaries such as distributors and retailers to move the product closer to the end user. Internet marketing shares characteristics from both channels (Kiang et al., 2000; Parsons et al., 1998). The transaction channel aims at improving sales activities. It involves improving the visibility of the organization to a wider audience, exploitation of cross-selling opportunities thus leading to increased revenues, the streamlining of transaction processing and the customization of promotion and sales activities (Kiang et al., 2000; Parsons et al., 1998). The communication channel aims at improving communication between the customer and the marketer. It does this by collecting customer information that will be used to model future buying habits of customers and by use of interactive media. The Internet offers various interactive solutions that a marketer can use to reach a large number of customers or potential customers at a very low cost thus leading to a more focused marketing campaign (Kiang et al., 2000; Parsons et al., 1998). Furthermore, the Internet offers many advantages to online firms such as the shortening of the supply chain, eliminating or reducing inventories, improving organizational visibility to a wider customer base, increasing revenues through cross-selling opportunities, improving interactivity, and gathering massive amounts of information on customers via surveys and spending habits (Berthon et al., 2003; Blattberg & Deighton, 1991; Kiang et al., 2000; Peterson et al., 1997). Due to all these advantages, the Internet has emerged as a lucrative marketing channel.

2.2 EVOLUTION OF ADVERTISING

The advertising world has changed dramatically over the past few years. Two eras are clearly discernible in its evolution, the pre-Internet and the Internet era. The pre-Internet era was mainly characterized by mass media, non-targeted advertisements transmitted via print media, television, and radio (Ghose & Yang, 2008b). Today, marketers have embraced the Internet and use it as a way to target a much more relevant customer base. The Internet has, therefore, brought about a paradigm shift in the way consumers search for and purchase goods and services.

Online advertising has been recognized as an effective strategy for marketing and advertising due to its global visibility and cost effectiveness. With the rapid growth of the Internet user population and new Web technologies, a large percentage of Internet users are now purchasing goods and services on the Web. The popularity of the Internet is exemplified by the fact that in 2008, Internet users spent over $165.9 billion on the Web (Internet Retailer, 2008).

Online advertising is diverse, due to the different modes of communication the Internet offers. Some of the popular forms of online advertising include: e-mail advertising, online word of mouth (WOM) advertising, affiliate advertising, banner advertising and search engine advertising.

E-mail advertising is the use of e-mails by advertisers to carry out marketing campaigns. E-mails are used to generate sales, acquire new customers, notify existing customers on promotions and sales, and to develop a constant dialogue and relationship with customers (DuFrene, Engelland, Lehman, & Pearson, 2005). Currently, the Internet has over 1.5 billion Internet users and e-mail is the mostly widely used form of online communication with over 1.4 billion e-mail users. E-mail marketing is very successful and generated more than $21 billion in sales in the United States in 2008 and offered a strong return on investment, delivering $48 for every dollar invested (Internet Retailer, 2008). However, e-mail marketing has been plagued with the prevalence of spam. Spam refers to unsolicited e-mail messages, usually of a commercial nature, sent to individuals with whom the mailer has had no previous contact. Spam are often misleading, offending and malicious, whereas commercial e-mail messages are permission based and sent legitimately as part of an organization's marketing efforts (Cheng, 2004; Clarke, Flaherty, & Zugelder, 2005; Melville, Stevens, Plice, & Pavlov, 2006).

Online word of mouth (WOM) advertising is the informal communication on the ownership, usage and communication of particular goods and services (Brown, Broderick, & Lee, 2007; Davis & Khazanchi, 2008; de Valck, van Bruggen, & Wierenga, 2009; Dellarocas, 2003; Hennig-Thurau & Gianfranco, 2003; Liu, 2006; Westbrook, 1987). Online WOM relies on systems in which individuals in the same social circles recommend products to their friends and services via various means. Online WOM has been proven as an accurate system and is commonly used to increase sales (Bone, 1995; Brown et al., 2007). According to eMarketer.com, the number of Internet users who engaged in online WOM communication in 2008 was 28.4 million, a number which is expected to reach 34.3 million by 2011. Online WOM advertising can take different forms: social network advertising, blog advertising and viral marketing. These categories of Internet advertising fall under the umbrella of online WOM advertising because of their informal and interactive nature, thus facilitating the exchange of ideas on products and services (Davis & Khazanchi, 2008; de Valck et al., 2009; Dellarocas, 2003). Viral marketing is a stream of email marketing, in which the e-mail is generated from friends and family, rather than a commercial marketing effort. Moreover, whereas viral marketing is informal and cannot be efficiently tracked by the advertiser, e-mail marketing can be tracked by the advertiser as legitimate e-mails are only sent to users who subscribe for a particular service. Viral marketing campaigns that attempt to recruit online users to promote goods and services reduce the effectiveness of the campaign (Bampo, 2008; Subramani & Rajagopalan, 2003). Social network advertising takes advantage of the large number of Internet users on social networks and uses them as a platform for advertising (Helm, 2000). Blog marketing takes advantage of blogs, both individual and corporate, to advertise various products and services to Internet users (Kirby & Mardsen, 2006).

Affiliate Advertising involves an organization creating affiliate networks by recruiting other websites willing to put up their ads in exchange for a commission based on clicks (Constantinides, 2002; Duffy, 2005). Affiliates are paid on either a pay per conversion basis or a pay per lead basis (Libai, Biyalogorsky, & Gerstner, 2003). Affiliate networks can substantially increase an organization's visibility. However, they have to be chosen carefully as their reputation reflects on that of the advertiser (Constantinides, 2002).

Banner ads are a form of advertising that often combines animation, sophisticated graphics, audio and even video to endorse a product or service. Banner ads are usually represented by a small rectangular display on a Web page (Novak & Hoffman, 1997). Banner ads, like affiliate ads, redirect the user to the advertisers Web site when clicked on. However, even if the ad is not clicked on, banner ads have been shown to have an influence on visitor attitudes and help build the advertiser brands (Hofacker & Murphy, 1998). Banner ads are considered as a form of passive advertising exposure as the visitor does not consciously decide to view the ad. Instead, the banner ad pops up as a result of visiting a particular Web page (Novak & Hoffman, 1997). Edwards et al. (2002) consider banner ads as intrusive as visitors to a Web page are often distracted and irritated by the banner pop up ads. It is for this reason that search engine advertising is preferred by Web users as it is non-intrusive in nature.

Search engine advertising (SEA) is a new form of advertising that entails several unique features. It involves the entire set of techniques used to direct more visitors from search engines to marketing websites. According to the Search Engine Marketing Professional Organization (SEMPO), approximately 45 million searches are performed every day in North America, making search second only to email as the most popular online activity. In a recent survey, the total number of searches per month in North America was estimated at 14.5 billion, a number that increases each month (comScore.com, 2009).

Search engines have grown tremendously since the first search engine was introduced in 1993 by Michael Gray (searchenginehistory.com, 2009). This growth can be attributed to the growth in the number of Web sites and the growth of the Internet in general. The number of Web sites has increased from a mere 130 in 1993 when the first search engine was introduced, to a massive 185 million as of January 2009 (Netcraft.com, 2009). According to a report published by SEMPO in

2008, SEA has emerged as a cheaper mode of advertising than other forms of online advertisements such as e-mail, banner and affiliate advertising.

The dependence of the browsing population on search engines and the rapid growth in the number of Web sites make it important for online sellers to develop marketing strategies that improve their visibility (Sen, 2005). Marketing strategies of this kind are often referred to as SEA strategies. In general, advertisers target high positions on either the organic or sponsored link sections on the search engine results page (SERP) so as to achieve higher levels of traffic or visibility. Figure 2 illustrates the various advertising slots on the SERP for the keyword “plasma tv”.

SEA is divided into three categories: search engine optimization (SEO), paid inclusion, and sponsored search advertising (Green, 2003). According to SEMPO, search engine advertisers’ spending in 2008 in the United States was $13.5 billion. Moreover, of the $13.5 billion, advertising on sponsored search advertising was estimated at $10.8 billion, followed by SEO, at $1.4 billion. Sponsored search advertising accounted for 80% of all SEA spending. The following paragraphs will examine SEO, paid inclusion, contextually targeted text ads and sponsored search advertising.

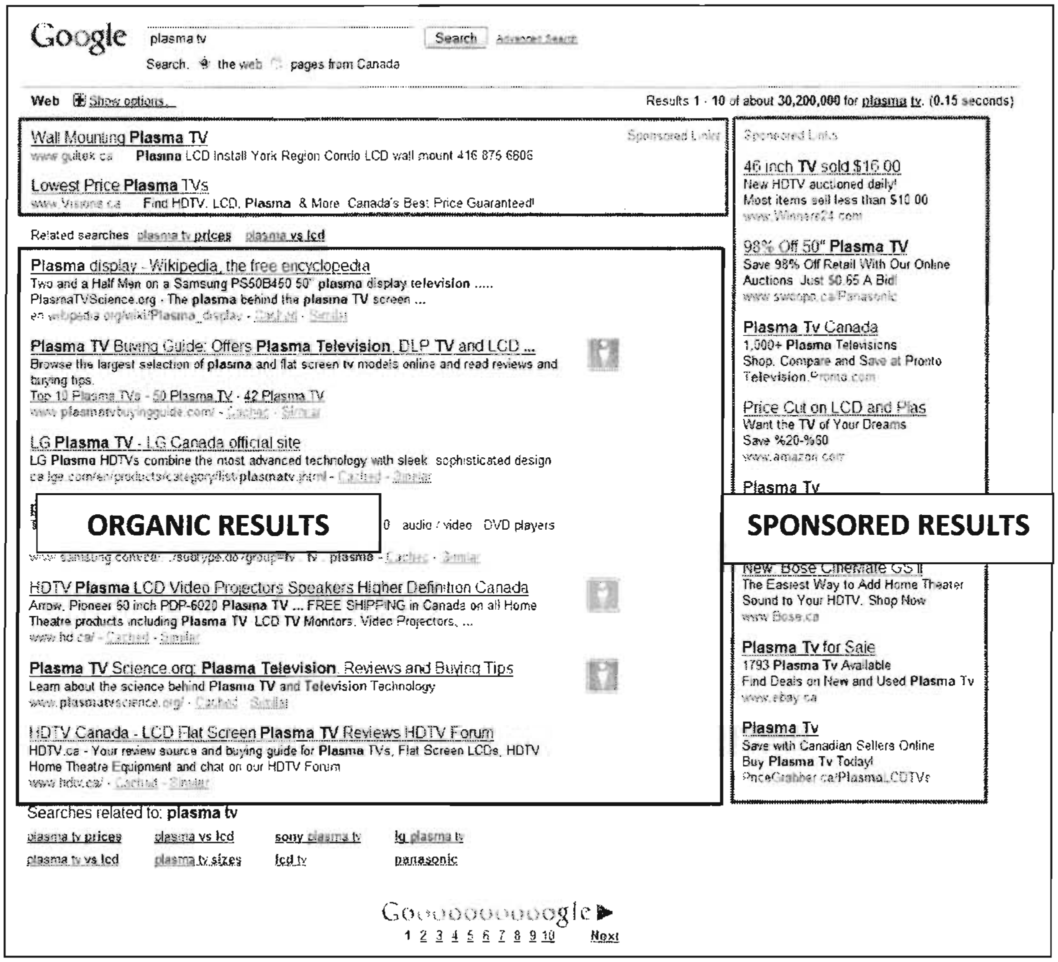

Figure 2: Search Engine Results Page

Organic SEO aims at providing a seller's site a high rank within the natural or organic results, which are the search engine's regular, unpaid results (Sen, 2005; Wilson & Pettijohn, 2006). High rankings on search engines are determined primarily by two factors, keywords and links from other sites. The more focused and clear the content is on a Web page, the greater the chances for a high organic ranking (Wilson & Pettijohn, 2006; Wilson & Pettijohn, 2007). Sponsored search differs from SEO in two ways: first, sponsored search targets sponsored listings instead of organic listings. Second, it does not involve the modification of sections of Web site code.

Paid inclusion is the practice of paying a fee to search engines so that a given Web site or Web pages may be included in the service's directory, although not necessarily in exchange for a particular position in search listings (SEMPO, 2009). Paid inclusion is an advertising practice that is declining. One notable exception to search engines that do not offer paid inclusion is Google.

Contextual targeting is whereby the content and context of a Web page is read and understood, and the resulting information is related to an organization's keywords. The relevant ads are displayed on pages when their content closely matches the provided keywords. Contextual targeting leads to a targeted audience with an established interest in the advertiser's message. Users of search engines do not have to key in the specific keywords that an advertiser has bid on, but one that contextually matches those that an organization has placed a bid on (Google.com, 2009a; Google.com, 2009b).

Sponsored search, where advertisers pay a fee for their ads to be displayed alongside organic search results, has emerged as a popular non-intrusive form of advertising (Ghose & Yang, 2008c). Sponsored search is considered non-intrusive for the potential customer as the ad only comes up when the user searches for particular keywords on the search engine. The potential customer has the option of clicking or ignoring the ad. Moreover, the ad does not provide a distraction to the potential customer. Sponsored search is also considered a cheaper mode of advertising than other online advertising practices as the advertiser only pays when their ad is clicked on. In addition, search engine advertisers set a daily budget and bid on particular keywords. Regardless of whether their ad is clicked or not, potential customers who read the ad are made aware of the existence of the marketer (Ghose & Yang, 2008d).

Keyword advertising is implemented differently across search engines. When a marketer wants to advertise on Google, they submit a list of the keywords they want to place a bid on. The keywords describe the business the marketer is involved in. Bid values are then assigned to the keywords to determine the relative placement of the ads. Given that the keywords are bid on by multiple advertisers, Google holds an instantaneous, automated auction to determine which of the advertisers currently bidding on that keyword are allocated advertising slots. Advertisers who place higher bids get better positions on the search engine results page[1].

Advertising positions are, however, continually updated throughout the day (Google Adwords, 2009), subject to new or revised bids by advertisers (Ghose & Yang, 2008d; Özlük & Cholette, 2007). The sponsored search engine advertising process is summarized in Table 1.

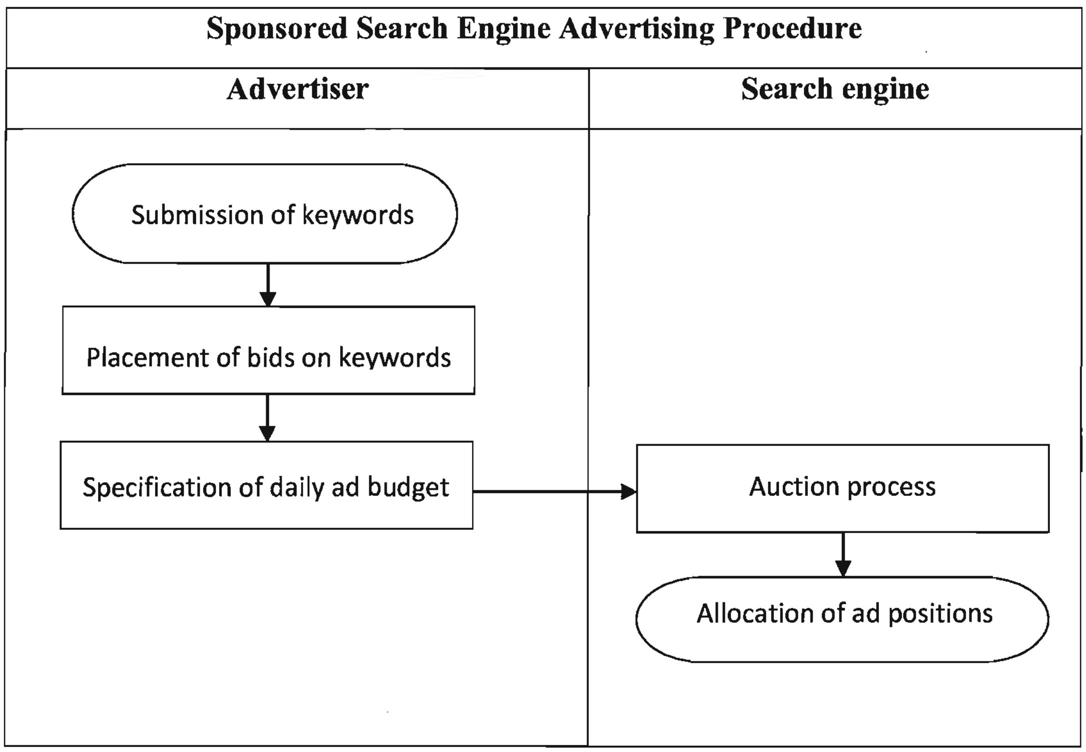

Table 1: Sponsored Search Engine Advertising Procedure (Ghose & Yang, 2008d)

[1] Allocation of advertising positions on the Search Engine Results page is based on a Quality Score. The quality score takes into account the historical click through rate, 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, the advertiser's performance in their geographical region and other relevance factors. The quality score is calculated each time an advertiser's keyword matches a search query. In general, a high quality score leads to high ad positions on the search engine result page and a low cost per click. The quality score is crucial when determining first page bids and ad position (Google.com, 2009b).

In general, ads placed higher on the page are more desirable than lower placements. This is because such ads are more noticeable (Agarwal, Hosanagar, & Smith, 2008). The position of the ads changes dynamically, hence the advertisers do not know the exact position of their ads throughout the day. Google denotes the ad position in the form of a non-integer average value which is calculated on a frequent basis (Google, 2007).

Google analyses the traffic for all advertisers competing for the same keyword and gives higher positions to the ads that generate more clicks over those who offer a similar bid price but that generate fewer clicks. In order to determine the placement of advertiser ads, Google uses both the bid price and the quality score. This approach enables Google to generate more revenue than other search engines. Yahoo on the other hand uses a keyword advertising system that is based solely on bid price (Özlük & Cholette, 2007).

2.3 PRIOR STUDIES ON SPONSORED SEARCH ADVERTISING

Research in sponsored search is relatively new and limited. Prior studies in sponsored search advertising can be categorized broadly into two areas: market mechanism design and business value and efficiency studies. Much of the existing academic literature on sponsored search has concentrated on the former.

2.3.1 MARKET MECHANISM DESIGN

The studies on market mechanism design focuses on the interaction between advertisers, search engines, and search engine users. Previous studies have focused on auction mechanisms, keyword pricing and bidding tools.

Search engine auction mechanism literature examines various types of bidding systems and their relative efficiency. Cary et al. (2007) examine the role of greedy bidding strategies for keyword auctions and their effectiveness. They investigate various greedy bidding strategies that a software robot may use in a repeat keyword auction for a particular search term. The study assumes that the recent past is the best predictor of future and that other bidders will bid exactly what they bid for the search term in the last round. The software robot therefore increases its bid in each round so as to maximize its utility relative to the postulated set of bids by other bidders. Zhou & Lukose (2007) examine the role of vindictive bidding strategies, in which a bidder forces his competitor to pay more for keywords without affecting his own payment, thereby undercutting the competitions' profits. The study proposes a stable pure strategy Nash equilibrium with vindictive bidding, which predicts the success of a vindictive campaign when several organizations bid for the same keyword. Edelman, Ostrovsky, & Schwarz (2007) examine generalized second-price (GSP) auctions and contrast GSP auctions with the Vickrey-Clarke-Groves mechanism. Asdemir (2006) develops an auction mechanism that investigates static bids and bidding war cycles. The study examines characteristics of advertisers and the auction design parameters that influence advertisers' bids in a bidding war cycle equilibrium. The study examines characteristics of advertisers and the auction design parameters that influence advertisers' bids in a bidding war cycle equilibrium. The study concludes that weaker advertisers, those without sufficient funds to enter a bidding war, compete under a static bid equilibrium model. Varian (2007) examines the equilibria of a game based on the ad auction used by Google and Yahoo. He finds that the Nash equilibria of the position auction describe the basic properties of the prices observed in Google's auction. Aggarwal, Goel, & Motwani (2006) present a truthful auction that prices the various advertising slots on a SERP. Their model captures both the Google and Yahoo auction mechanisms. Using a pure strategy Nash equilibrium, the authors find that revenue-equivalence exists between non-truthful next-price auctions and truthful auctions. Lahaie (2006) analyses slot auction designs used by Google and Yahoo. He analyses the incentive, efficiency and revenue properties of two slot auction designs:

Rank by Bid and Rank by Revenue, by performing equilibrium analysis on the two methods. Asdemir (2006) and Kitts & Leblanc (2004) analyse existing auction systems and propose an optimal bidding strategy in keyword auctions. Ghose & Yang (2009) find that advertisers are not bidding optimally with respect to keywords and are therefore not maximizing their profits. The literature on bidding strategies studies how advertising slots are allocated on search engine pages and proposes novel ideas on ad placements and auctioning mechanisms that aim to create a fair environment in sponsored search advertisement.

Other related studies include keyword pricing. Keyword pricing literature studies the factors that influence the price of advertisements and come up with models that attempt to select the best priced keywords for an advertiser. Goldfarb & Tucker (2007) analyze the factors that drive variation in prices for advertising legal services on Google and investigate how bids for context based ads depend on making a match between the search term and the advertisements.

2.3.2 BUSINESS VALUE AND EFFICIENCY

The literature on business value and efficiency of sponsored search is scant. Rutz & Bucklin (2007) focus on hotel marketing keywords and analyze the performance of individual keywords in sponsored search advertising, thus addressing the problem of sparseness, thereby allowing advertisers to analyze the effectiveness of individual keywords. Ghose & Yang (2008c) find that keyword attributes such as retailer specificity, brand specificity and keyword length affect click through rates, conversation rates and ranks and eventually, profitability. Ghose & Yang (2008b) compare various performance metrics of organic and sponsored advertising and find that keyword level characteristics have a stronger impact on the performance of natural search than on sponsored search. Ghose & Yang (2008a) analyze firm behaviour and cross selling in electronic markets and find that keywords without brand information lead to a higher conversion than advertising on brand specific keywords. Ghose & Yang (2008d) analyze the effects of cross category purchases and find that advertisers have an opportunity of pairing the items that consumers search for on search engines with other items that are associated with that keyword in prior instances thus increasing their chances of multiple sales conversions. Agarwal et al. (2008) quantify the profits associated with the various positions advertisements can have on a search engine results page. The paper finds that higher placements lead to a higher click-through-rate (CTR) and ultimately high sales. Other studies on the business value of sponsored search have focused on the prediction of click through rates. Regelson & Fain (2006) predict the CTR using a cluster of keywords; and Richardson, Dominowska, & Ragno (2007) focus on predicting the CTR of new advertisements.

Other related studies examine budget allocation models. Özlük & Cholette (2007) discuss how to allocate advertiser budget across multiple keywords. They show that the trade-off for bidding more for a particular keyword than another is dependent on their click through rates and price elasticity. Abrams, Mendelevitch, & Tomlin (2007) discuss an auction framework. They postulate that the presence of bidder budgets can have a significant impact on the ad delivery process. They go on to propose a linear programming model that takes bidder budgets into account to forecast pricing and ranking schemes.

Our literature review shows that significant work has been done in the area of market mechanism design. However, limited research has been carried out in the area of business value. In general, the gaps in prior literature can be divided into two: gaps in methodology and data.

Prior studies examine search engine advertising by analyzing one performance metric at a time. The proposed study aims at incorporating various performance metrics in order to have a better assessment of efficiency. We believe that by the use of an appropriate methodology, we can analyze multiple inputs and outputs at the same time to gain a better understanding of the dynamics involved in SEA.

Moreover, prior literature uses simulated or data from one source in empirical analysis. The use of an extensive industry data can greatly improve the insights to be obtained from empirical research and the validity of results. Our research is based on data drawn from two sources. The data includes keyword level and organizational level details on search engine metrics as well as business performance. The study has both theoretical and practical implications. The study guides managerial decisions with regard to search engine marketing strategies. It does so by providing guidelines that will aid managerial decisions on resource allocation in SEA campaigns. The study also contributes to the literature by performing an efficiency analysis of current search engine marketing strategies. It provides broader insights on the mix of input and output variables with direct implications for practice. Moreover, the study contributes to market mechanism design by enhancing understanding on the dynamics between inputs and outputs so that models, bidding mechanisms, and application tools can be better designed.

In summary, the proposed study aims to contribute to both academic literature and industry knowledge. It adds to the academic literature by providing a data-driven perspective on search advertising practices. It contributes to industry by providing a comprehensive evaluation framework by which sponsored search advertising strategies can be assessed. It therefore provides managers with general guidelines for SEA decisions. Moreover, the study aids in the development of SEA application tools such as bidding agents by analyzing multiple performance metrics simultaneously thus improving current assumptions on key parameters.

SECTION 3: METHODOLOGY

The study uses data envelopment analysis (DEA) as the primary methodology. In addition, data mining and multivariate statistics are employed at the various stages of the data analysis.

DEA is chosen as the primary methodology due to its non-parametric nature and ability to evaluate efficiency in the presence of multiple input and output variables. Input variables represent the resources organizations invest in their sponsored search advertising campaigns whereas output variables represent the outcome of sponsored search advertising campaigns. In addition, DEA does not impose any prior assumptions on the relationship between the input and output variables. Therefore, due to the relatively un-explored nature of SEA and the possible relationships among several input and output variables, DEA provides an appropriate fit for the analysis required to address our key research questions.

DEA was developed by Charnes, Cooper, & Rhodes (1978) as a tool for measuring the relative efficiency of decision making units. A decision making unit (DMU) is the unit of analysis in DEA. It can range from a single department to an economy. Each DMU consumes a common set of inputs in the production of a common set of outputs. The goal of DEA is to identify those units exhibiting relatively inefficient performance and target them for improvement or change. In this study, DEA will be used to determine the mix of resources that lead to sponsored search advertising success and efficiency. The units of analysis in this study will be retailers in two major categories - multi-channel and Web-only.

DEA has grown in popularity ever since Charnes et al. (1978) introduced the CCR (Charnes, Cooper and Rhodes) model. It now has a rich literature base of over 3000 papers and several books (Cooper, Seiford, & Tone, 2006). The literature on DEA is divided into two major categories:

methodology and application. Methodology studies aim to further and fine tune various variants of the DEA methodology and the application papers use DEA for efficiency analysis in various industries. Indeed, DEA has been applied successfully to various industries ranging from banking, airline, health care, e-commerce and educational services. DEA has been used to measure the efficiency of banks (Golany & Storbeck, 1999; Saha & Ravisankar, 2000; Sherman & Gold, 1985; Vassiloglou & Giokas, 1990), airline operations (Adler & Golany, 2001; Martín & Román, 2001; Schefczyk, 1993), health care facilities (Banker, Conrad, & Strauss, 1986; Chen, Hwang, & Shao, 2005; Prior, 2006), Internet companies (Alpar, Porembski, & Pickerodt, 2001; Barua et al., 2004; Serrano-Cinca, Fuertes-Callén, & Mar-Molinero, 2005) and educational services (Banker, Janakiraman, & Natarajan, 2004; Mayston, 2003). Moreover, studies have also been conducted on online banking and stock broking performance (Ho & Oh, 2008; Ho & Wu, 2009).

Among the main extensions of the CCR model are the BCC model (Banker, Charnes, & Cooper, 1984), the additive model (Charnes, Cooper, Golany, Seiford, & Stutz, 1985) and the imprecise DEA model (Cooper, Park, & Yu, 1999). A comprehensive taxonomy and framework of DEA can be found in Kleine (2004) and Gattoufi, Oral, & Reisman (2004). According to prior research, the most widely used DEA models are the CCR and BCC models.

The CCR and BCC models differ as the CCR model exhibits constant returns to scale and the BCC model exhibits variable returns to scale. The returns to scale concept represents the relationship between the inputs and the outputs when either of them are changed. Returns to scale, also known as elasticity, refers to increasing or decreasing efficiencies based on the size of the change.

Constant returns to scale is whereby a change in either the input or output results in a directly proportional change in the other. Variable returns to scale can be either increasing or decreasing. Increasing returns to scale is whereby an increase in input leads to an increase in output in greater proportion than the input increase. Decreasing returns to scale is whereby an increase in input leads to proportionally lower increase in output (Banker et al., 1984).

3.1 MODEL SPECIFICATION

The CCR model is the most widely used DEA model. The proposed study will begin with the CCR model and explores its extensions. The efficiency of a DMU, h_k, is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity. In mathematical terms:

Maximize

$$h_k = \frac{\sum_{r=1}^{s} u_r y_{rj0}}{\sum_{i=1}^{m} v_i x_{ij0}}$$

Subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1; \quad \text{j} = 1 \ldots n$$

$v_i \geq 0 \, for \, i = 1 \ldots m, \quad u_r \geq 0 \, for \, r = 1 \ldots s$

Where

$x = vector\ of\ i\ inputs\ (x_i)\ used\ in\ the\ production\ process; i > 0, x_i \geq 0, x \neq 0$

$y = vector\ of\ r\ outputs\ (y_r)\ resulting\ from\ the\ production; r > 0, y_r \geq 0$

$u_r = vector\ of\ output\ DMU\ weights\ chosen\ by\ the\ linear\ program$

$v_i = vector\ of\ input\ DMU\ weights\ chosen\ by\ the\ linear\ program$

The above DEA model is a fractional programming problem where the weights for both inputs and outputs are selected so as to maximize the efficiency of each DMU. Therefore, the original form of the DEA model is both nonlinear and non-convex problem (Po, Guh, & Yang, 2009). The normalization of the fractional form of the DEA model leads to two linear programming transformations. Hence, Charnes, Cooper, & Rhodes (1981) formulated an input oriented model (M1) and an output oriented model (M2). The first formulation (M1) is the input-based model in which the weighted sum of outputs is constrained to be unity and minimizes the inputs that are utilized. The second formulation (M2) is the output based model in which the weighted sum of inputs is constrained to unity and maximizes the outputs that can be obtained.

The choice of whether to select input or output oriented models is dependent on the application setting. The input oriented model attributes greater emphasis to a production process which aims at utilizing less input for a given level of output. The output oriented model attributes greater emphasis to a production process that aims to produce more outputs with a given level of input (Charnes et al., 1981; Kauffman & Hahn, 2005). In sponsored search advertising, the advertiser sets out a budget and aims to maximize the benefits derived from their investment. In this regard, the output oriented model provides an appropriate fit to sponsored search advertising.

The M1 and M2 models presented in Table 2 are linear programming forms of the fractional CCR model. As stated above, the BCC and CCR models differ as the former allows variable returns to scale. This property is captured by equating the sum of DMU weights used to unity. Equating the DMU weights to unity gives the BCC model the ability to have increasing or decreasing returns to scale.

Model M1 – Input Oriented	Model M2 – Output Oriented
Min $h_k = \sum_{i=1}^{m} v_i x_{ij0}$ Subject to $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$ $\sum_{r=1}^{s} u_r y_{rj} = 1$ $j = 1, \ldots, n;\ u_r, v_i \geq 0;$ $r = 1, \ldots, s; i = 1, \ldots, m$	Max $h_k = \sum_{r=1}^{s} u_r y_{rj0}$ Subject to $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$ $\sum_{i=1}^{m} v_i x_{ij} = 1$ $j = 1, \ldots, n;\ u_r, v_i \geq 0;$ $r = 1, \ldots, s; i = 1, \ldots, m$

Table 2: Input and Output Oriented CCR Models (Charnes et al., 1981)

The methodology employed in the DEA models is the production function theory. In economics, the production function theory converts multiple inputs into a single output. Hence, the general mathematical function in economics can be expressed as:

$$y = f(x_1, x_2, x_3, \ldots, x_n)$$

Where y is a quantity of output and x_n is one of the inputs. DEA however, converts multiple inputs into multiple outputs. Therefore, the general mathematical function of DEA is expressed as:

$$g(y_1, y_2, y_3, \ldots, y_n) = f(x_1, x_2, x_3, \ldots, x_n)$$

The productivity of a particular DMU is evaluated by comparing its observed inputs and outputs against an efficiency frontier, which is a convex combination of other DMUs in the dataset. Individual DMUs are measured against the efficiency frontier and their relative performance is based on their distance from the efficiency frontier. DMUs that are on or that lie closer to the efficiency frontier than other DMUs are deemed as being relatively more efficient in converting their inputs to outputs. A DMU is deemed as being inefficient if another DMU can produce the same amount of output by using less input or alternatively if another DMU can use the same level of input and produce a higher level of output.

In this study, we employ the BCC model (Banker et al., 1984) because it allows for variable returns to scale. The CCR model (Charnes et al., 1981) is less desirable for this context as it enforces constant returns to scale. This is because in the search engine advertising context, the key output variables, click-through-rate, impressions, conversion rate, sales and rank are not totally under the control of the advertiser. Therefore, even if an optimal production function is to exist and is found, the advertiser would not be able to enforce it. Enforcing of the production function would entail the advertiser dictating the behavior of the search engine user, which is not plausible (Kauffman & Hahn, 2005).

3.2 INPUT AND OUTPUT VARIABLE SELECTION

Table 3 shows the list of input and output variables that are explored in this study. The variables used in the study were chosen as a result of prior research and an analysis of industry practices. The input and output variables are grouped under two categories: Web retail (WR) and financial (F) metrics. The input variables generally represent the resources that an organization invests in their SEA activities. The output variables generally represent the results organizations attempt to achieve from their various SEA activities. Definitions for each of the input and output variables are provided in Appendix A. The various methods and data analysis techniques used in this research are summarized in Figure 3. The conceptual model for the DEA is also presented in Figure 4.

Input Variables	*Category*	*Output Variables*	*Category*
Number of paid keywords	WR	Sales	F
Number of organic keywords	WR	Impressions	WR
Cost per click	F	Click Through Rate (CTR)	WR
Length of the keyword	WR	Conversion Rate (CR)	F
Total Cost per day	F	Average Organic Rank	WR
Total Number of Ads	WR	Average Ad Rank Percentile	WR

Table 3: Organizational Level Input and Output Variables

With the exception of the cost per day, the number of ads and the sales, all the variables used has been studied in prior literature by Ghose & Yang (2008); Ghose & Yang (2009) and Yang & Ghose (2009). The cost per day, the number of ads and the sales were included in the study based on current industry trends. Web retailers track their cost per day to measure their expenditure against their maximum daily ad budget. In practice, Web retailers set a maximum daily ad budget. If the specified maximum budget is reached before the end of the day, the retailer's ads are no longer displayed. Web retailers therefore strive to keep their cost per day below their maximum daily ad budget. The cost per day is therefore a reflection of the Web retailer's efforts to minimize their cost of advertising. The total number of ads represents the different versions of an ad that an advertiser has on a particular keyword. Advertisers have different ads for the same keyword due to a limitation in the number of words; typically ads on Google are limited to 70 words. The different ads put up by advertisers represent different ideas and concepts and provide the advertiser with a way of tracking which concepts are most popular. The total number of ads is used in the study to measure the rigour and quality of an ad campaign. The sales figures are used by search engines to estimate future sales and future bid prices for Web retailers. Search engines predict the future sales of advertisers and their willingness to pay future bid prices based on their current sales. This practice ensures that search engines deal with reputable advertisers who will continue to buy ad space from them for the foreseeable future.

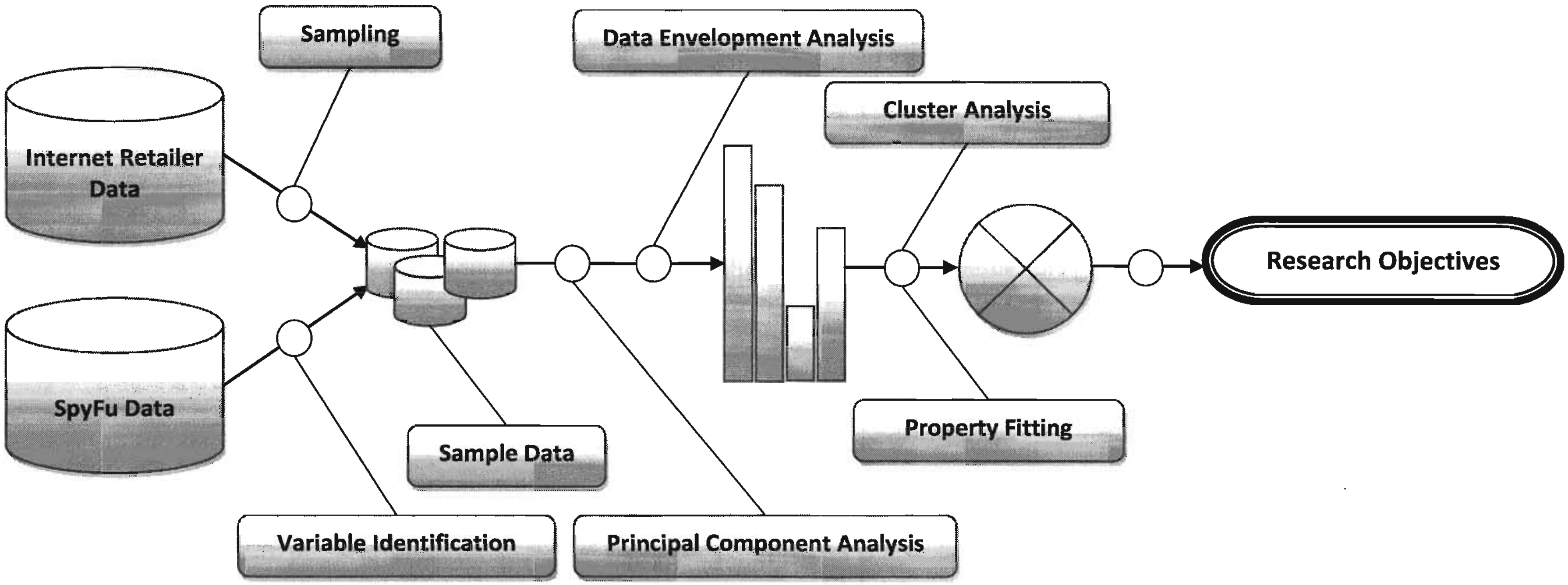

Figure 3: Data Analysis Procedure

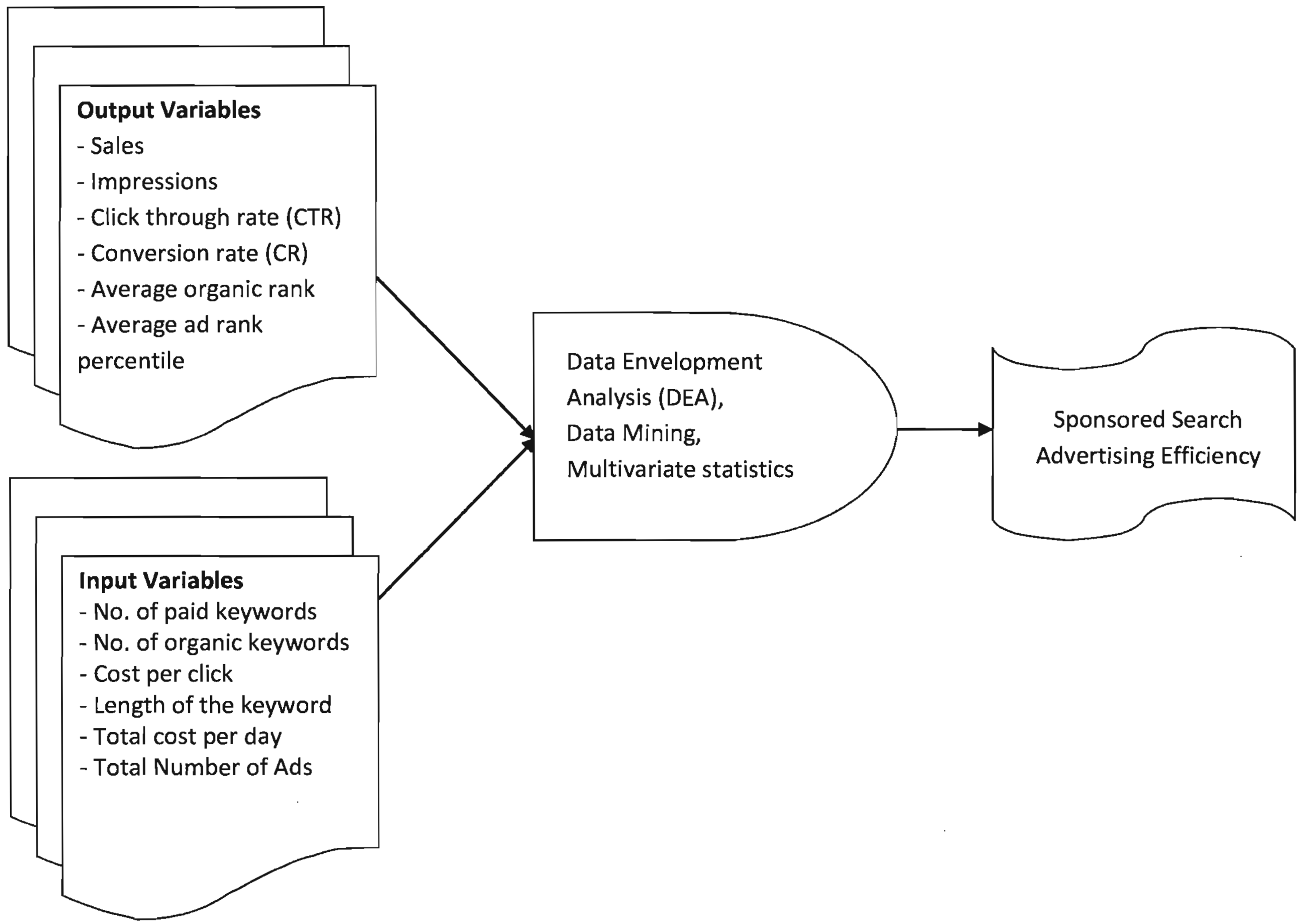

Figure 4: Conceptual Model of Sponsored Search Efficiency

SECTION 4: DATA

The data for this study was obtained from *Velocityscape* (www.spyfu.com), a privately held software product and services firm that specializes in providing search engine advertising data and products and solutions that move data between the web and a database or spreadsheet. The dataset contains search engine marketing data of Internet retailers that advertise on Google. This data presents a unique opportunity for this research due to its level of detail and the range of merchant and product categories covered. More specifically, the dataset consists of organizational level and keyword level advertising information for each company. It also includes several metrics such as *clicks per day, cost per click,* and *daily budget* of all the companies that advertise on Google. In this research, the search advertising data is supplemented by a dataset from *Vertical Web Media* (www.internetretailer.com). This dataset includes annual financial, operational, marketing, and Web site metric data about American's top 500 retailers, with ranking based on their 2007 annual online sales.

4.1 DATA PRE-PROCESSING

In order to ensure the integrity of the data, data pre-processing was performed. The pre-processing task entailed data aggregation as well as the elimination of incomplete records. Incomplete records were eliminated by identifying records that contained missing input and output variables. So as to maintain the highest possible integrity in the data, the missing values in the records were not recalculated or replaced but instead deleted from the dataset. After the elimination of the records with missing values, the Internet Retailer dataset was reduced to 430 retailers.

4.2 SAMPLING

Sampling was performed to ensure that the dataset was manageable for the proposed methodology and analysis. The original dataset contained four merchant types: Catalogue/Call Center (CC), Consumer brand manufacturer (CM), Retail Chain (RC) and Web only retailers. Due to the disproportionate distribution and representation of records across merchant types, the CC, CM and RC categories were combined to form a multi-channel retailers (MCR) category. These retailers all have other sales channels in addition to the Web. However, Web-only retailers (WOR) have only the Internet for their sales activities. Thus, in the sample, the retailers were classified into multi-channel retailers (MCR) and Web-only retailers (WOR). Table 4 summarizes the distribution of retailers in the original merchant categories and in the final MCR and WOR categories in our sample.

Merchants	**No. Of Firms**	**Firms in sample**	**% Representation**
CC	73	25	12.50%
CM	35	25	12.50%
RC	122	50	25.00%
WOR	200	100	50.00%
Merchants	**No. Of Firms**	**Firms in sample**	**% Representation**
MCR	230	100	50.00%
WOR	200	100	50.00%
Total	**430**	200	**100.00%**

Table 4: Distribution of Merchant Categories in the Sample

The sample contains 200 records, 100 retailers in the WOR category and 100 retailers in the MCR category. The representation of merchant records in the sample was made proportional thus eliminating any bias that may have existed in the original dataset. The sampling technique used was stratified random sampling. This technique is especially suitable for this dataset due to the presence of different merchant and product categories. One key advantage of stratified random sampling is that it produces characteristics in the sample that are proportional to those in the original data set, thus ensuring that all dimensions represented in the data are represented equally in the sample. Thus, strata were formed based on the number of records that have been proportionally assigned to each product group. The data contains 14 product categories, where each product category contains a varying number of records. Using stratified random sampling, the number of records under each product category was reduced proportionally to ensure that the total number of records under each merchant category corresponds to the total number of records as shown in Table 4. The records were then randomly selected within each product category to ensure a heterogeneous mix of records that captured the variations in the retailers' performance. Table 5 shows the distribution of records along product categories in the original dataset and in the sample.

Categories		**MCR (Total)**	**MCR (Sample)**	**WOR (Total)**	**WOR (Sample)**
Apparel & Accessories	AA	69	34	17	8
Books, music & video	BC	8	3	10	5
Computers & electronics	CE	19	9	28	14
Food & drug	FD	11	5	8	4
Flowers & gifts	FG	6	3	5	3
Health & beauty	HB	9	4	13	7
House wares & home furnishing	HHF	23	9	23	11
Hardware & home improvement	HHI	8	3	20	10
Jewellery	JE	4	1	8	4
Mass merchant	MM	15	6	13	7
Office supplies	OS	5	2	11	5
Sporting goods	SG	19	8	7	4
Specialty & non - apparel	SP	25	9	31	15
Toys &hobbies	TH	9	4	6	3
	Total	**230**	**100**	**200**	**100**

Table 5: Distribution of Product Categories in the Sample by Merchant Type

Table 6 shows the final distribution of records in the sample alongside that of the original dataset.

Categories		Total in original dataset	Total in sample
Apparel & Accessories	AA	86	42
Books, music & video	BC	18	8
Computers & electronics	CE	47	23
Food & drug	FD	19	9
Flowers & gifts	FG	11	6
Health & beauty	HB	22	11
House wares & home furnishing	HHF	46	20
Hardware & home improvement	HHI	28	13
Jewellery	JE	12	5
Mass merchant	MM	28	13
Office supplies	OS	16	7
Sporting goods	SG	26	12
Specialty & non - apparel	SP	56	24
Toys &hobbies	TH	15	7
	Total	**430**	**200**

Table 6: Distribution of Product Categories in the Sample

SECTION 5: DATA ANALYSIS

In order to run the DEA model, we used a data matrix consisting of the 6 input variables and 6 output variables described in Table 3, and the 200 retailers (i.e., DMUs) identified through our sampling. One limitation of DEA is the potential problem of differentiating DMUs, which can either be caused by an excessive number of input and output variables with respect to the total number of DMUs in the analysis, or the use of highly correlated input and output variables (Adler & Berechman, 2001; Nunamaker, 1985). The utility of DEA depends on its ability to calculate the relative efficiency of DMUs using multiple inputs and outputs. However, the greater the number of input and output variables, the less discerning the analysis is. In our first run of the complete model with all the input and output variables, 45% of the firms in the sample were deemed to be operating at 100% efficiency. This percentage does not portray a realistic picture of the Web retailing industry as it implies that a large percentage of firms in the industry are operating at full efficiency (Jenkins & Anderson, 2003). In order to overcome the limited distinction provided by DEA due to highly correlated variables, some studies have taken the approach of retaining only those that are perceived as being more important in an ad-hoc manner. However, the elimination of variables in an ad-hoc manner due to high correlation leaves out vital information and distorts the final DEA scores (Jenkins & Anderson, 2003). Therefore, it was necessary to test the correlation among the input and output variables used in this analysis as well as justify the number of input and output variables with respect to the total number of DMUs.

The rest of this section is organized as follows: Section 5.1 examines the correlation of the variables used in this study both in the input and output categories and discusses the implications of the correlations. This will be followed by Section 5.2 which presents a technique that combines principal component analysis (PCA) with data envelopment analysis (DEA). We refer to this technique as PCA-DEA in the rest of this thesis. In the PCA-DEA method, principal components of the input and output variables are used to specify various DEA models and generate the corresponding sets of efficiency scores. Section 5.3 presents the first of two different approaches we adopted to analyze the results obtained from the PCA-DEA method and conceptualize the patterns of the efficiency scores obtained from the various model specifications. The first approach uses property fitting on the efficiency scores in order to examine the manner in which different sets of model specifications lead to efficiency and the similarities among them. Property fitting involves a PCA procedure which is different from the PCA that will be conducted on the input and output variables to generate the various specifications of PCA-DEA models. Thus the PCA within property fitting will be conducted on the efficiency scores of the various PCA-DEA models to identify sets of models that lead to similar efficiency patterns. A similar technique was used by Rezaie, Dehghanbaghi, & Ebrahimipour (2009) to find models that displayed concordant behaviour leading to efficiency.

In section 5.4, we present the second approach that uses clustering on the set of efficiency scores obtained from all the specified models in order to identify similar patterns of efficiency scores and discuss their implications across merchant categories, product categories, and other performance attributes of the retailers.

5.1 CORRELATION ANALYSIS

We used correlation analysis as a means of identifying variables that may have high correlations. High correlations in the data lead to unexpected results in DEA. In addition, it is unclear how to interpret DEA results in the presence of significant correlations among the input and output variables. Eliminating high correlation is, therefore, important for the proper interpretation of the results obtained from the DEA model. However, the correlation analysis should not be used in solitary for variable reduction as it could lead to possible omission of key variables (Jenkins & Anderson, 2003). Thus, the correlation analysis was used in conjunction with other techniques to reduce the variables in such a way as to retain as much information as possible. It should be noted that correlations among variables does not necessarily mean that one of the variables can be excluded from the analysis without changing the DEA results (Nunamaker, 1985). Table 7 summarizes the significant correlations between the input and output variables used in this study. The complete correlation results are presented in Appendix B.

The input variables show several strong correlations. Among the key correlations are those between *total number of organic keywords* and *total number of paid keywords*, between *cost per day* and *total number of ads,* and between *total number of keywords* and *cost per day.*

Significant Correlations Between Input Variables		
Input Variable 1	**Input Variable 2**	**Correlation Coefficient & Relationship**
Number of paid keywords	Number of Organic keywords	0.978 (Strong positive relationship)
	Cost per day	0.988 (Strong positive relationship)
	Total number of ads	0.983 (Strong positive relationship)
Number of organic keywords	Cost per day	0.980 (Strong positive relationship)
	Total number of ads	0.944 (Strong positive relationship)
Cost per day	Total number of ads	0.948 (Strong positive relationship)
Significant Correlations Between Output Variables		
Output Variable 1	**Output Variable 2**	**Correlation Coefficient & Relationship**
Conversion rate	Click through rate (CTR)	0.297 (Weak positive relationship)
Sales	Impressions	0.866 (Strong positive relationship)
Average ad percentile	Average organic rank	-0.153 (Weak negative relationship)

Table 7: Correlations: Input and Output Variables

The output variables show correlations between *conversion rate* and *click through rate*. There is also a strong positive correlation between *sales* and *impressions*. In addition, there is a weak negative correlation between *average ad percentile* and *average organic rank*. The average ad percentile represents sponsored ad position. It is calculated by taking the average ad competition into account. In sponsored search advertising, ads move closer to the top position as the average ad percentile increases. The correlation between organic and sponsored listings is highlighted in previous research (Ghose & Yang, 2009; Yang & Ghose, 2009). Due to the high correlations in the input and output variables, we decided to perform PCA on the input and output variables separately in a bid to eliminate the correlations and reduce the number of variables used in the study, thus increasing the discerning capabilities of DEA (Adler & Golany, 2001; Adler & Golany, 2002; Nunamaker, 1985; Ueda & Hoshiai, 1997).

5.2 PCA–DEA

In addition to correlations, another limitation of DEA is its sensitivity to outlier observations. This is the likely scenario in our sample due to widely differing sizes of the retailers used in the study. In DEA, retailers like Amazon may tend to be super-efficient, due to their large relative size (Cooper et al., 2006). Hence, when DEA was carried out with the original input and output variables without applying PCA, the distribution was highly skewed. A visualization of the differences between DEA and PCA–DEA can be seen in the figure below. In Figure 5, differences between MCR and WOR across the two types of DEA can be also observed.

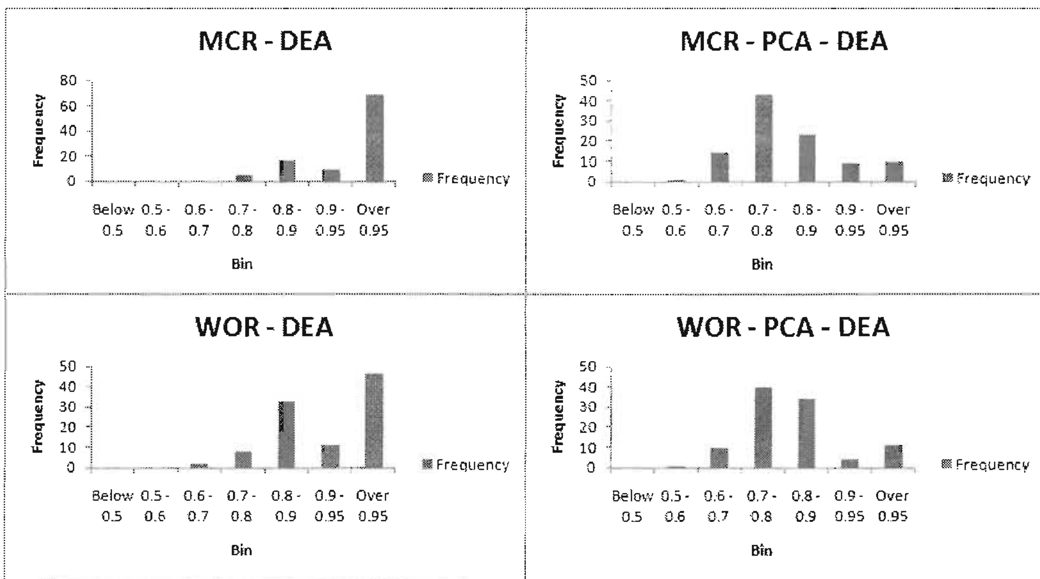

Figure 5: Distribution of MCR and WOR Firms

The histograms in Figure 5 show the differences between the efficiencies obtained by DEA *vis-à-vis* those obtained by PCA–DEA. Note that the efficiencies obtained by DEA are relatively skewed to the left, indicating that the majority of retailers engaging in sponsored search advertising are efficient. The validity of the distribution provided by the PCA–DEA model is verified by a study carried out by Forrester Research that revealed that over 50% of merchants are overpaying for keywords, sometimes even paying double the required amount so as to create barrier on the use of the keywords by other firms (Johnson, Delhagen, & Dash, 2003). In addition, a study carried out by Ghose & Yang (2008a) found that most retailers are not bidding optimally for the keywords used in their sponsored search campaigns. These results indicate that the PCA–DEA model is a more realistic evaluation of the practices in search advertising. A further examination of the skewed DEA scores is shown in Figure 6, which examines the MCR and WOR efficiency scores of established Web retailers. In general, retailers are classified as young if they were formed after 2001, that is, after the dot com bubble burst. Moreover, retailers formed prior to 2001 are classified as established.

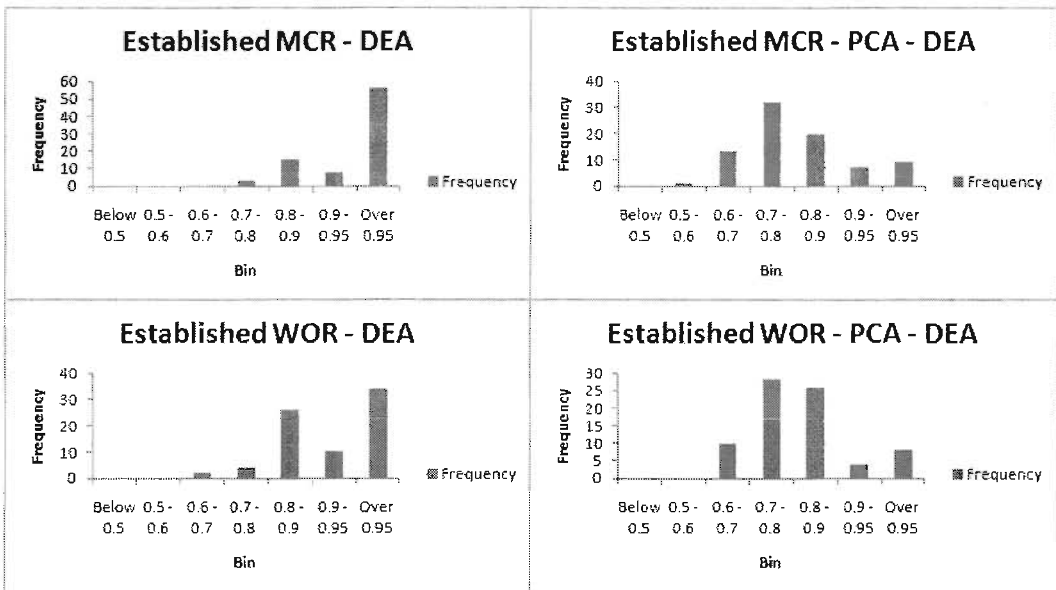

Figure 6: Distribution of Established Web Retail Firms

The poor initial results of the basic DEA model were such that we needed to reduce the number of input and output variables used in the analysis. Consequently, we used PCA in a bid to reduce the input and output variables used in the study and increase the discerning capabilities of the analysis (Adler & Golany, 2002; Adler & Yazhemsky, 2010). Using PCA allows us to reduce the number of variables used in the study by aggregating highly correlated variables. Reducing the variables based on PCA not only leads to a parsimonious model, but also increases the discerning capabilities of DEA. Various methods of reducing the number of variables used in a DEA procedure exist, such as having experts select the appropriate input and output variables based on their extended knowledge of the industry and years of experience. However, since the motivation of our study is to investigate the dynamics of various performance metrics in sponsored search advertising, we included as many relevant variables as we deemed necessary, then applied PCA to create relevant composite variables. According to prior literature, two methods for improving the discriminatory power of DEA without the use of additional preferential information exist: PCA–DEA and Variable reduction (VR). Variable reduction reduces the input and output variables based on a partial covariance analysis. This method takes into account the degree of correlation between variables so as to identify the variables that could be omitted with minimal loss of information (Jenkins & Anderson, 2003). A recent study by Adler & Yazhemsky (2010), found that when the 'true' efficiency scores are compared to those of PCA–DEA and VR, PCA–DEA produced more accurate results than the VR method consistently across numerous variations of the tests and dataset sizes. PCA explains the variance covariance structure of a matrix of data through linear combinations of variables, consequently reducing the initial dataset to a few principal components, which generally describe 80 – 90% of the variance in the data. If most of the variance can be explained by a few principal components, then they can replace the original variables without much loss of information.

As used in Johnson and Wichern (1982), let the random vector $X = [X_1, X_2, ..., X_P]$, which represents the variables to be aggregated, have the covariance matrix V with eigenvalues $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_P \geq 0$ and normalized eigenvectors $l_1, l_2, ..., l_P$. Consider the linear combinations where the superscript t represents the transpose operator. Thus,

$$X_{PCi} = l_i^t X = l_{1i}X_1 + l_{2i}X_2 + \dots + l_{pi}X_p,$$

$$Var\,(X_{PCi}) = l_i^t V l_i, \qquad i = 1,2, \dots, p,$$

$$Cov\,(X_{PCi}, X_{PCk}) = l_i^t V l_k,$$

$$i = 1, 2, \ldots, p, \qquad k = 1, 2, \ldots, p.$$

The principal components are the uncorrelated linear combinations X_{PCi} ranked by their variances in descending order. In addition to using PCA–DEA as means of improving discrimination, three ways of implementing PCA exist. First, PCA is applied to all the input and output variables. Second, PCA is applied to the input and output variables separately. Third, PCA is applied to groups of input variables and groups of output variables. We chose to apply PCA to the input and output variables separately so as maximize the discriminatory power of PCA–DEA (Adler & Golany, 2002). In addition, descriptive statistics of the input and output variables are presented in Appendix C.

5.2.1 PCA: INPUT VARIABLES

Table 8 shows the PCA results for the input variables and the components with eigenvalues of greater than 1. Table 9 shows the various constituents of the principal components. The first two principal components explain 83% of the variance in the dataset.

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.918	65.298	65.298	3.918	65.298	65.298
2	1.068	17.792	83.090	1.068	17.792	83.090
3	.927	15.455	98.545			
4	.066	1.092	99.637			
5	.020	.335	99.972			
6	.002	.028	100.000			

Table 8: Total Variance Explained: Input Variables

Component Matrix		
	Component	
	1	2
Total Number of Paid Keywords	.998	.020
Total Number of Organic Keywords	.987	.015
Average Length of Keywords	-.042	.740
Average Cost per Click	-.086	.719
Total Cost per day	.990	.012
Total Number of Ads	.979	.046

Table 9: Component Matrix: 2 Principal Components

Component Matrix			
	Component		
	1	2	3
Total Number of Paid Keywords	.998	.020	.015
Total Number of Organic Keywords	.987	.015	-.015
Average Length of Keywords	-.042	.740	-.671
Average Cost per Click	-.086	.719	.690
Total Cost per day	.990	.012	.021
Total Number of Ads	.979	.046	.011

Table 10: Component Matrix: 3 Principal Components

Table 10 presents the component matrix for the input variables when three components are selected. Though the eigenvalue of the third principal component is high relative to that of the fourth principal component, it did not add any useful information after the extraction of the first two principal components and was considered superfluous. The first principal component aggregates the total number of paid and organic keywords, the total cost per day and the number of ads. The second principal component aggregates the average length of keywords and the average cost per day. The third principal component also aggregates the average length of the keywords and the average cost per day. In that regard, the third principal component does not add any useful information and was not included in the analysis. In addition, the two principal components extracted have eigenvalues greater than one, which is a common cut-off point for determining the number of components extracted.

We label the first principal component as *Input 1* and the second principal component as *Input 2* (Figure 7).

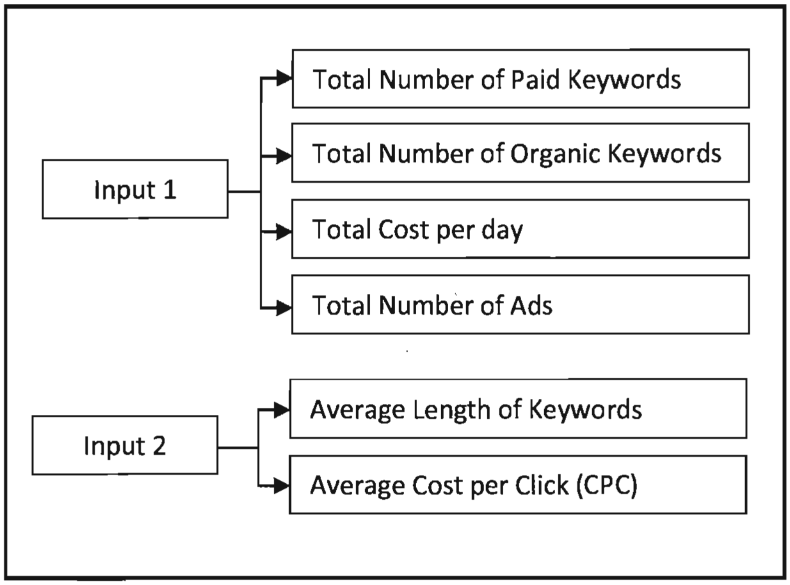

Figure 7: Input Variables

5.2.2 PCA: OUTPUT VARIABLES

Table 11 shows the PCA results for the output variables. The principal components extracted account for 72% of the variance of the dataset. Although we could have included the fourth principal component to increase the variance explained to 86%, it lacked clear intuitive meaning to be useful in the analysis. Moreover, the eigenvalue of the fourth component was less than 1 indicating that it did not extract as much variance as is required. Table 12 shows the composition of the extracted principal components.

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.873	31.220	31.220	1.873	31.220	31.220
2	1.456	24.259	55.480	1.456	24.259	55.480
3	1.002	16.706	72.186	1.002	16.706	72.186
4	.848	14.134	86.320			
5	.694	11.560	97.880			
6	.127	2.120	100.000			

Table 11: Total Variance Explained: Output Variables

Component Matrix[a]			
	Component		
	1	2	3
Conversion Rate	.011	.662	.505
Sales	.966	-.027	.057
Impressions	.958	-.136	.007
CTR	.092	.720	.311
Avg Ad Rank Percentile	.072	.482	-.605
Avg Organic Rank	-.098	-.498	.531

Table 12: Component Matrix: Output Variables

Rotated Component Matrix[a]			
	Component		
	1	2	3
Conversion Rate	-.030	.831	-.022
Sales	.965	.062	.028
Impressions	.966	-.056	.004
CTR	.035	.769	.176
Avg Ad Rank Percentile	-.001	.038	.775
Avg Organic Rank	-.025	-.095	-.728

Table 13: Rotated Component Matrix: Output Variables

The first principal component aggregates the search engine sales and the impressions (*Output 1*), the second component aggregates the Conversion rate and the CTR (*Output 2*) and the third component aggregates the average ad rank percentile and the average organic rank (*Output 3*) as shown in Figure 8. Unlike the extraction of components on the input variables, the component matrix in the output variables does not provide a clear representation of the variables represented in each principal component. In order to have a clearer representation of the output variables comprising each principal component, we run a rotation on the principal components. Table 13 represents the rotated component matrix of output variables.

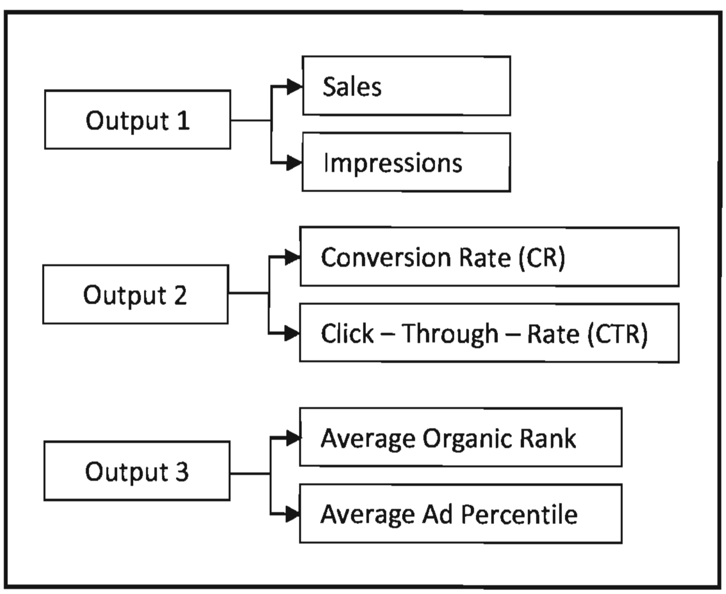

Figure 8: Output Variables

5.2.3 PCA – DEA MODEL FORMULATION

In the PCA-DEA model formulation, the original variables were replaced by the coefficients generated by the PCA. Figure 9 shows the conceptual model used in the PCA–DEA analysis. An excerpt of the PCA coefficients that were generated by the analysis can be found in Appendix D. Generally, inputs and outputs of a DEA need to be strictly positive. However, the results of PCA can be negative. An affine transformation of data can be utilized with no change in the results when using standard radial[2] constant returns to scale (CRS) and variable returns to scale (VRS) DEA models (Banker et al., 1984; Charnes et al., 1978). Using the extracted principal components in place of the original data does not affect the properties of the DEA models. The input-oriented, variable returns-to-scale, radial estimators are both units[3] and translation invariant[4] with respect to outputs (Adler & Golany, 2001; Pastor, 1996).

Principal components represent the selection of a new coordinate system obtained by rotating the original system with $x_1, \ldots, x_m$ as the coordinate axes. Because it is not the parallel translation of the coordinate system, PCA–DEA could be applied to all basic DEA models irrespective of their lack of translation or units' invariance (Adler & Yazhemsky, 2010).

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[2] Radial (technical) inefficiency means that all inputs and outputs can be simultaneously reduced without altering the proportions in which they are utilized, ignoring the presence of non-zero slacks

[3] Units invariance means that the efficiency measure is independent of the units in which the input and output variables are measured

[4] Translation invariance means that the efficiency measure is independent of the linear translation of the input and output variables

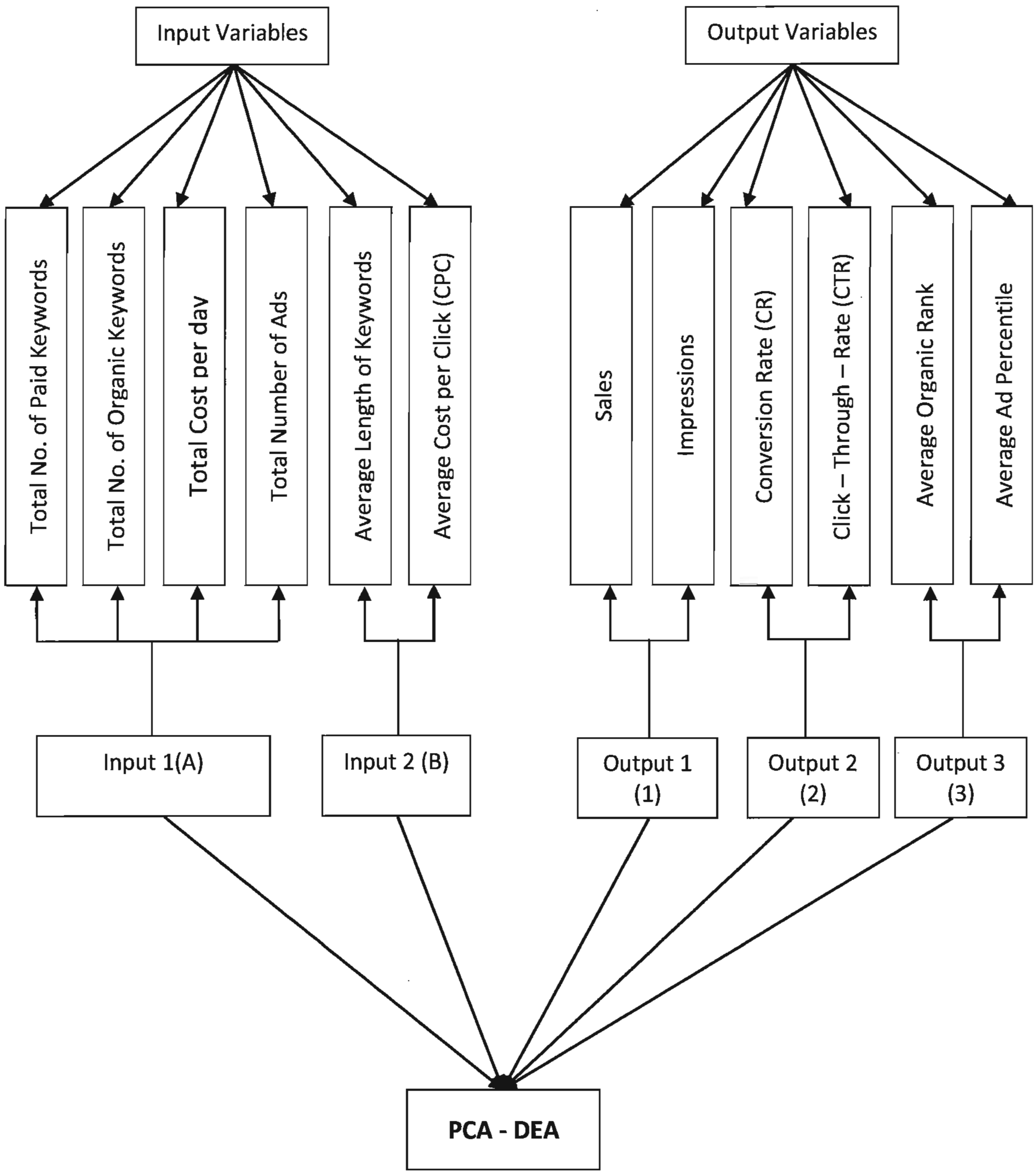

Figure 9: PCA DEA Model

Due to the translation invariance of the DEA models, all principal component input and output data used in the DEA analysis was increased by the most negative number in the vector plus one when necessary, thus ensuring strictly positive data. The formula used for the transformation is as follows:

$$\tilde{X}_{PCi} = X_{PC} + b, \quad \text{where } b = \text{Min } \{X_{PCi}\} + 1$$

The transformed principal components that were used for the DEA analysis can be found in Appendix E. With two input components and three output components, 21 different DEA models were specified as shown in Table 14. We categorized the components as follows: We use the label A for *Input 1*, B for *Input 2*, 1 for *Output 1*, 2 for *Output 2*, and 3 for *Output 3*.

DEA Models		
A1	B1	AB1
A2	B2	AB2
A3	B3	AB3
A12	B12	AB12
A13	B13	AB13
A23	B23	AB23
A123	B123	AB123

Table 14: DEA Models

The PCA-DEA procedure runs analysis for all the models presented above except the ones with one input and one output variable as this represents a simple ratio analysis and is considered trivial. PCA-DEA has the advantage of investigating the mix of input and output variables through the formulation of the DEA models that represent all possible combinations of the input and output components. The results of the PCA-DEA analysis reveal several distinguishing features across firms and model specifications. Retailers that are efficient under one model specification are not necessarily efficient under other model specifications. The efficiency scores generated by PCA–DEA can be analyzed using two different approaches: a property fitting procedure as was done by Cinca, Molinero, & Queiroz (2003); Ho & Wu (2009) and Serrano-Cinca et al. (2005) or a cluster analysis as was done by Brown & Ragsdale (2002); Helmig & Lapsley (2001) and Johnes & Johnes (1993). Section 5.3 and 5.4 discuss these two approaches, respectively.

5.3 PROPERTY FITTING

Property fitting, Pro-Fit for short, is a regression based technique, originally proposed by Schiffman, Reynolds and Young (1981), that examines various patterns in the PCA-DEA efficiency scores. The objective of property fitting is to provide an efficiency pattern analysis. Efficiency pattern analysis involves a PCA procedure followed by a visualization procedure that graphically represents the relationship between the various DEA model specifications.

Following the PCA on the original input and output variables, the variables were reduced to 2 input components and 3 outputs components. We would like to reiterate that the PCA procedure in the property fitting analysis was conducted on the efficiency scores obtained from the various DEA model specifications (i.e., Table 14). In this study, we aim to not only identify efficient and non-efficient retailers, but also identify which models in particular lead to efficiency by identifying pattern similarities of the sets of efficiency scores obtained from the various model specifications.

Therefore, the goal of the PCA in this section is to conceptualize the patterns of the efficiency scores obtained from the different model specifications. The dataset for this analysis defines the various model specifications as variables and the retailers as observations. The efficiency score of each retailer under each model specification represents the values for the PCA. Figure 10 shows the conceptual framework that includes the PCA conducted on the input and output variables as well as on the efficiency scores of the various model specifications. The efficiency matrix in our setting contained 15 model specifications and 200 observations. PCA was, therefore, conducted on the 15 models and their corresponding efficiency scores in a bid to examine which models in particular lead to efficiency and the similarities between them. The results of the PCA analysis on the models are shown in Tables 15 and 16.

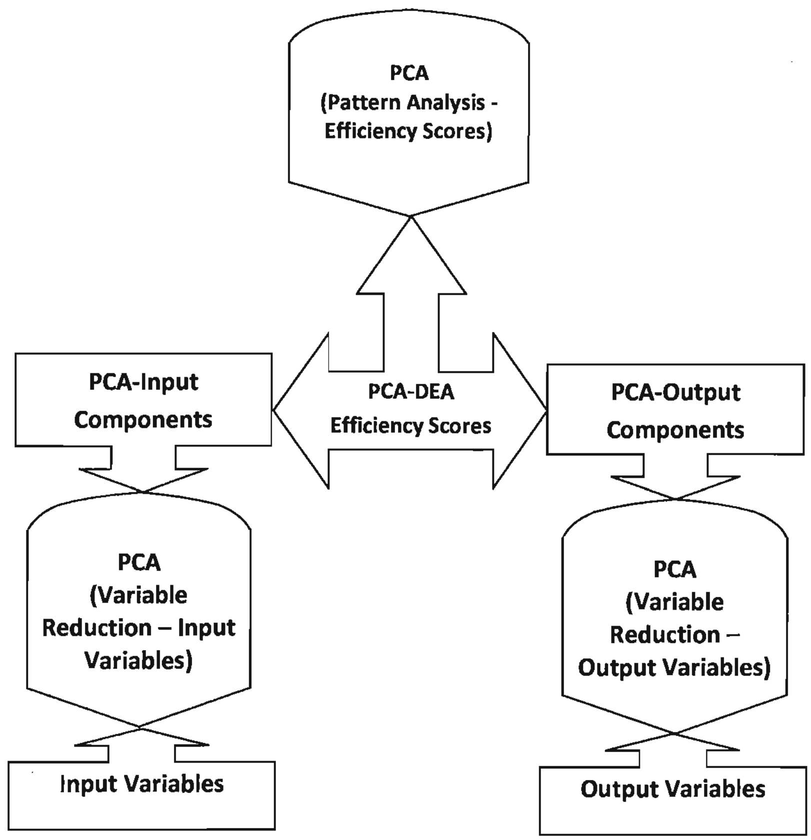

Figure 10: Use of PCA

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.981	53.208	53.208	7.981	53.208	53.208
2	4.269	28.462	81.670	4.269	28.462	81.670
3	1.210	8.067	89.737	1.210	8.067	89.737
4	.771	5.140	94.877			
5	.373	2.489	97.366			
6	.172	1.150	98.516			
7	.072	.483	98.999			
8	.060	.402	99.400			
9	.032	.212	99.612			
10	.020	.134	99.746			
11	.014	.095	99.841			
12	.013	.084	99.925			
13	.006	.043	99.967			
14	.004	.023	99.991			
15	.001	.009	100.000			

Table 15: Total Variance Explained: DEA Efficiency Scores

	Component		
Model	**1**	**2**	**3**
A13	.900	-	-.391
A123	.900	-	-.384
AB23	.877	-.219	.278
B123	.851	-.412	-
A23	.835	-.495	-
AB13	.830	.423	-.116
B23	.823	-.502	.150
AB123	.816	.489	-
AB3	.804	-.476	.114
B13	.770	-.541	-
AB12	.476	.857	-
B12	.462	.572	.407
AB1	.416	.831	-
AB2	.394	.603	.640
A12	.358	.704	-.430

Table 16: Component Matrix: DEA Efficiencies

Three principal components are associated with eigenvalues greater than 1, the usual cut-off point in PCA. The first principal component accounts for 53% of the total variance. The second principal component accounts for 28% of the total variance, and the third accounts for 8% of the total variance. The first two principal components account for 81% of the variance of the original dataset.

The interpretation of the principal components is based on the information in the component matrix, which is shown in Table 16. The models have been arranged in descending order according to the first principal component. In the first principal component, all the models load with a positive sign on the component. In a situation such as this, the first principal component is normally interpreted as an overall measure of size. It is therefore useful in the ranking of the various DMUs in terms of their efficiencies.

In the second and third principal components, small component loadings have been ignored to ease interpretation (Serrano-Cinca et al., 2005). In the second principal component, the models with negative loadings incorporate *Output 3* in their calculation. The most positive loadings incorporate *Output 1 (Sales and Impressions)* and *Output 2 (CTR and CR)* in their calculation. The second principal component is therefore a contrast between *Output 3 (Average organic rank and average ad percentile)* and *Output 1* and *Output 2*. The second principal component therefore provides a differentiation between DMUs that maximize *Output 1 and 2* versus those that maximize *Output 3*. In the third principal component, all the negative loadings include *Output 1 (Sales and Impressions)*, whereas the most positive loadings include *Output 2 (CTR and CR)*. Therefore, the third principal component provides a differentiation between DMUs that maximize *Output 1* versus those that maximize *Output 2*.

When the first two principal components are plotted against each other, several interesting relationships can be seen. To avoid cluttering of the plot, the retailers used in this analysis will be the ones that have positive scores for the first principal component. The first principal component has been identified as an overall measure of size; we are therefore more interested in firms that score positively on this scale as they are more likely to have a well-defined sponsored search advertising activity. To further avoid cluttering of the plot, we divided the firms into two samples (Sample 1 and 2) based on the mean of the first principal component. Sample 1 consists of retailers whose component score falls above the mean of the first principal component and Sample 2 consists of retailers whose component score falls below the mean. The first sample examines the retailers that score highly on the first principal component (Figure 11), whereas the second sample examines retailers that do not score as high as those in the first sample on the first principal component (Figure 12). This approach enables us to visualize the different strategies used by Web retailers in sponsored search advertising.

Figure 11 and 12 examine the relative efficiency of firms in a 2-dimensional plot. Retailers that appear on the extreme left have relatively lower degree of efficiency than those that appear on the right (Cinca & Molinero, 2004).

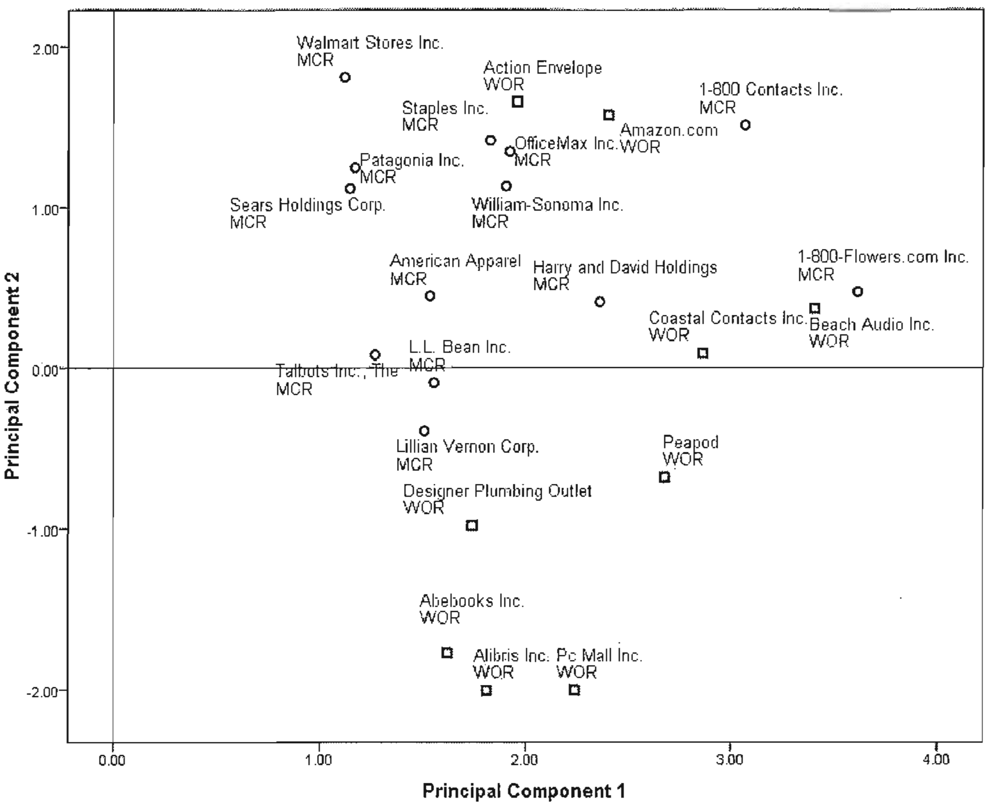

Figure 11: Distribution of Web Retailers on an Efficiency Map: Sample 1

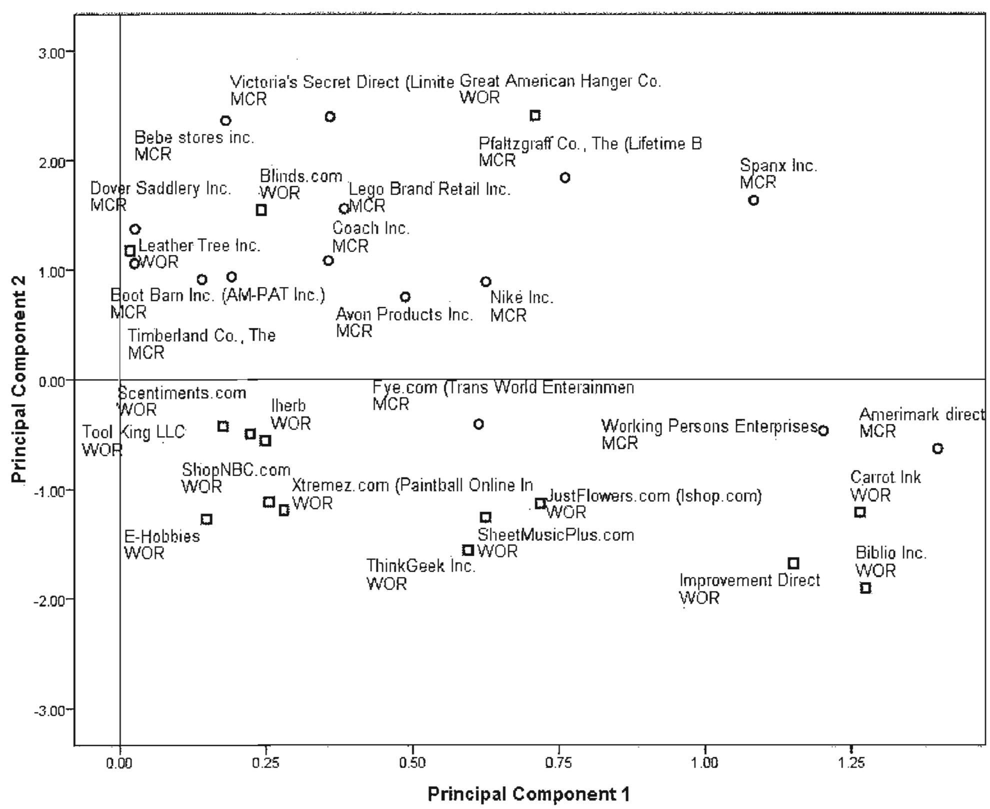

Figure 12: Distribution of Web Retailers on an Efficiency Map: Sample 2

Figure 11 and 12 show the relative position of retailers with respect to each other on the basis of their efficiency score. However, the various strategies used to achieve efficiencies are not presented on the map. To investigate and graphically represent the relationship between the principal components (Component 1 and 2) and the various PCA–DEA models, we use Pro-Fit. In Pro-Fit, vectors are drawn in such a way that, for a particular DEA model, the efficiency value obtained increases in the direction of the vector. The direction of the vector is calculated as a result of a regression analysis. The regression model is formed by using the efficiency scores derived from a particular model as dependent variables and the components scores obtained from PCA as independent variables. In our case, we used the component scores of the three principal components that were extracted as the independent variables.

Pro-Fit identifies model specifications that are closely related by the use of correlation. The angle between the various models indicates how similar the models are in terms of their patterns of results. The smaller the angle, the more correlated and similar the adjacent models are. In order to ensure the validity of the models, vectors are included only if they are significant and their coefficient of determination, R^2, is deemed high enough. Despite the numerous DMUs in our study, the lowest R^2 value is 0.702, which indicates a good fit for all the models. We therefore included all the models in our Pro-Fit analysis as they are all significant and have high R^2 values. All the vectors point out towards the right, indicating that the various ways of achieving efficiency are all correlated (see Figure 13). The results of the Pro-Fit regression, the directional cosines (γ_1, γ_2) and their significance level are shown in Table 17.

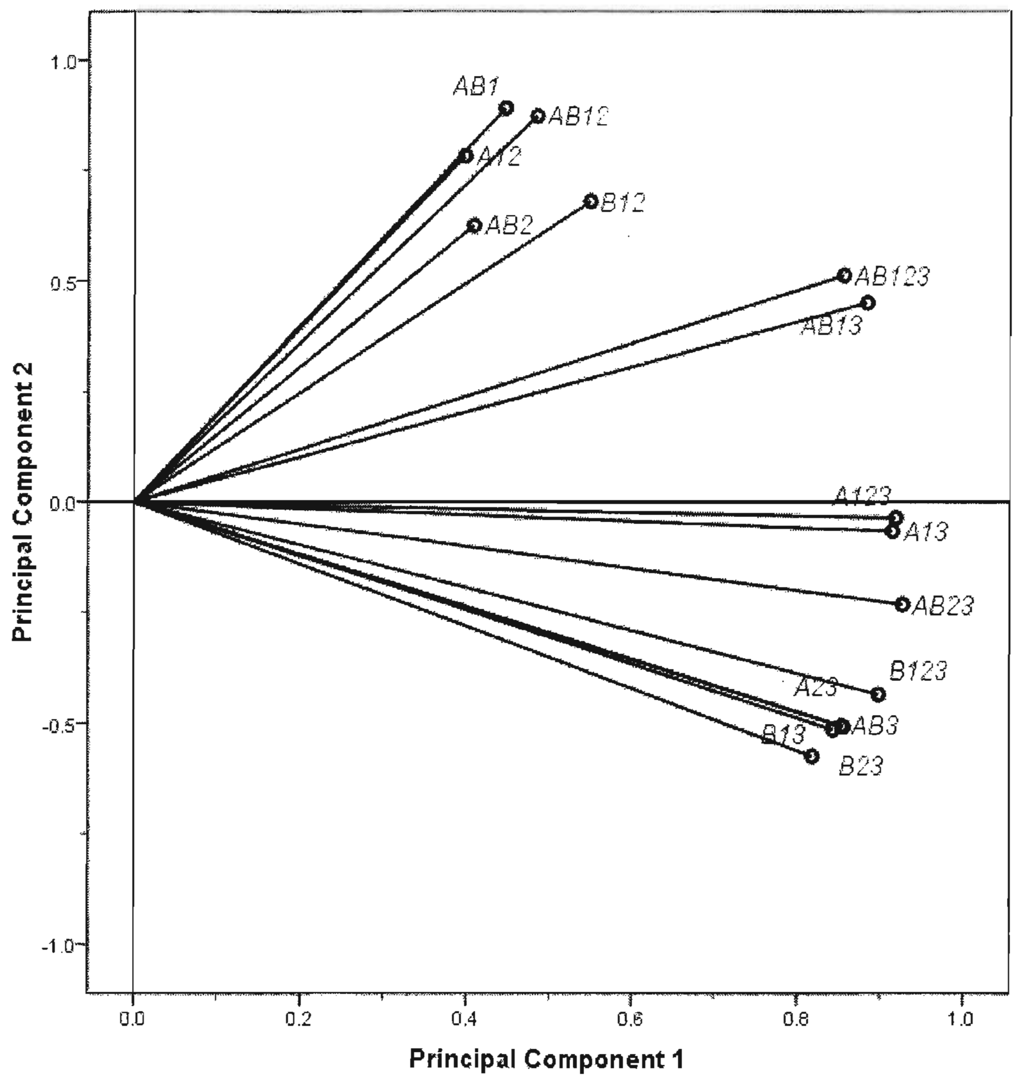

Figure 13: Pro-Fit Analysis Vector Diagram: All Models

In Pro-Fit, highly correlated models are often adjacent to each other; the degree of correlation between any two model specifications is proportional to the angle between the lines representing the models. Such models can be interchangeable without significant effects on the patterns of the efficiency results. As can be seen in Figure 13, DMUs achieve efficiency by maximizing various combinations of output variables. However, as far as DMU ranking is concerned, no single model should contribute solely to the position of a DMU. This is because all considerations need to be taken into account when ranking efficient DMUs. Thus, ranking on the first principal is appropriate (Cinca & Molinero, 2004). Appendix F shows the rankings of the most efficient retailers based on the first principal component.

Models	Gamma$_1$ (γ_1)	Gamma$_2$ (γ_2)	Gamma$_3$ (γ_3)	F	R Sq.	Adj R Sq.
AB1	0.45	0.89	-0.08	434.46	0.869	0.867
	(16.123)**	(32.185)**	(-2.745)*			
AB12	0.48	0.87	0.04	1684.88	0.963	0.962
	(34.477)**	(62.117)**	(2.744)*			
A12	0.40	0.78	-0.48	277.73	0.810	0.807
	(11.482)**	(22.598)**	(-13.809)**			
B12	0.55	0.68	0.48	157.51	0.707	0.702
	(11.944)**	(14.797)**	(10.531)**			
A123	0.92	-0.04	-0.39	1540.41	0.959	0.959
	(62.482)**	(-2.416)	(-26.672)**			
A13	0.92	-0.07	-0.40	1963.27	0.968	0.967
	(70.231)**	(-5.031)**	(-30.530)**			
AB13	0.88	0.45	-0.12	489.90	0.882	0.881
	(33.893)**	(17.274)**	(-4.750)**			
AB123	0.86	0.51	-0.06	643.71	0.908	0.906
	(37.627)**	(22.531)**	(-2.770)*			
AB23	0.93	-0.23	0.29	557.88	0.895	0.894
	(37.938)**	(-9.479)**	(12.020)**			
AB3	0.85	-0.51	0.12	509.26	0.886	0.885
	(33.394)**	(-19.758)**	(4.716)**			
B23	0.84	-0.51	0.15	1284.87	0.952	0.951
	(52.377)**	(-31.933)**	(9.571)**			
A23	0.86	-0.51	0.09	1233.92	0.950	0.949
	(52.107)**	(-30.888)**	(5.704)**			
AB2	0.41	0.63	0.66	848.27	0.928	0.927
	(20.614)**	(31.558)**	(33.526)**			
B13	0.82	-0.57	-0.02	508.29	0.886	0.884
	(31.956)**	(-22.434)**	(-0.645)			
B123	0.90	-0.44	0.06	572.48	0.898	0.896
	(37.239)**	(-18.031)**	(2.356)			
*** Significant at the 0.01 level (Two-tailed test)**						
**** Significant at the 0.05 level (Two-tailed test)**						

Table 17: Pro-Fit Linear Regression Results

5.4 CLUSTER ANALYSIS

Cluster analysis is an exploratory data analysis tool that aims to assign different entities into groups. The entities are assigned to different groups in such a way that the distance between two similar entities is minimized and the distance between entities assigned to different groups is maximized (Rao, 1971). Cluster algorithms are used in various application domains in order to organize observed data into meaningful taxonomies that were previously unknown (Ayanso & Yoogalingam, 2009). Cluster analysis is traditionally used for the empirical classification of objects due to its partitioning ability. For example, Bhatnagar & Ghose (2004) segmented web shoppers based on demographics and benefit by using latent class modeling. Wen-Jang & Su-Fang Lee (2003) segmented cellular phone users according to their retail shopping motives, and Okazaki (2006) segmented mobile Internet adopters by using a two-step clustering approach. Therefore, clustering was deemed appropriate in forming disparate groups within the generated efficiency scores of the PCA –DEA model according to the similarity of the various groups in the study.

We used the Two-Step clustering implementation available in SPSS 17.0. The Two-Step approach is suited for this dataset which is relatively large with several model specifications which will be defined as variables for the cluster analysis. The method employs a distance measure that efficiently clusters both categorical and continuous variables and determines the final number of clusters automatically based the Bayesian Information Criterion (BIC) or Akaiki Information Criterion (AIC). The distance between any two clusters is derived from a probabilistic model that equates it to the decrease in the log-likelihood function as a result of merging (Chiu, Fang, Chen, Wang, & Jeris, 2001).

Two-step clustering is comprised of pre-clustering and clustering steps. The pre-cluster step uses a sequential clustering approach. The method scans the data records sequentially and decides if the current record should be merged with the previously formed clusters or starts a new cluster based on the distance criterion. Therefore, based upon the similarity to existing pre-clusters, each successive case is added to form a new pre-cluster using a log-likelihood distance measure as the similarity criterion. Data records are assigned to a pre-cluster that maximizes a log-likelihood function.

In the final clustering step, the pre-clusters are grouped using the standard agglomerative hierarchical clustering algorithm. The algorithm produces a range of solutions, which are then reduced to the most appropriate number of clusters on the basis of the BIC. BIC is known as a useful and objective selection criteria as it avoids the arbitrariness in traditional clustering in which the number of clusters is required as an input (Okazaki, 2006).

The Two-Step auto-clustering algorithm indicated that a two cluster solution was the best cluster formation. The results of the auto-clustering are presented in Table 18.

Auto-Clustering				
Number of Clusters	Schwarz's Bayesian Criterion (BIC)	BIC Change[a]	Ratio of BIC Changes[b]	Ratio of Distance Measures[c]
1	-10283.375			
2	**-10503.387**	**-220.012**	**1.000**	**1.143**
3	-10413.418	89.969	-.409	1.225
4	-10272.285	141.133	-.641	1.652
5	-10122.941	149.344	-.679	.902
6	-9975.777	147.164	-.669	1.002
7	-10203.211	-227.434	1.034	1.006
8	-10238.179	-34.968	.159	1.125
9	-10096.320	141.859	-.645	1.229
10	-9975.707	120.613	-.548	1.008
11	-9825.709	149.998	-.682	1.052
12	-9684.336	141.373	-.643	1.179
13	-9530.885	153.450	-.697	1.034
14	-9381.141	149.744	-.681	1.079
15	-9232.949	148.192	-.674	1.109

[a] The changes are from the previous number of clusters in the table
[b] The ratios of changes are relative to the changes for the two cluster solution
[c] The ratios of distance measures are based on the current number of clusters against the previous number of clusters

Table 18: Two-Step Auto-Clustering Results

The SPSS implementation of the Two-Step clustering method selects the final number of clusters based on two criteria. One is that the model with the lowest BIC coefficient is chosen. The second criterion selects the model that yields a large BIC ratio of change and a large ratio of distances. When the model chosen by the auto-clustering algorithm does not have the lowest BIC coefficient, the algorithm judges that the gain in information from having more than the number of clusters specified by the BIC coefficient alone is not worth the increased complexity of the model. The Two-Step clustering algorithm therefore selects the most parsimonious model.

The validity of the two clusters identified by the auto-clustering is further verified by ANOVA tests. The ANOVA tests measure the significance of the distance between the centers of the clusters. The results of the ANOVA are presented in Appendix G. The clusters formed by the two-step algorithm represent valid cluster formations as the distances between them are all significant.

An examination of the DMUs under the two clusters formed revealed that the clustering was carried out along two logical dimensions: efficient and non-efficient retailers. The efficient DMUs, that is, the retailers who achieved efficiency scores of 100% in a majority of the model specifications, were all found to belong to one cluster. The non-efficient DMUs, that is, the retailers who achieved relatively lower efficiency scores, were all found to belong to a separate cluster. The first cluster, which contains the efficient retailers has 22 retailers and the second cluster contains which contains the non-efficient retailers has 178 retailers. Interestingly, the DMUs that were identified in Sample 1 in the previous section fell into the efficient retailers clusters, whereas the DMUs that were identified in Sample 2 fell predominantly in the non-efficient retailers cluster. The profile of retailers in Sample 1 is presented in Appendix F.

Due to the large difference in size of the two clusters, we were not able to perform any inferential statistics. The results from the cluster analysis are therefore intended to provide some insights in hypothesis formulation in future studies rather than provide significant empirical evidence of relationships within the data. Therefore, the results obtained from the cluster analysis are descriptive and exploratory in nature and show variations in the two clusters across certain dimensions in the data.

SECTION 6: RESULTS

This section presents the results of the data analysis section. In this section, various exogenous and endogenous variables have been analyzed against the models generated in the previous section in order to provide some insight into the Web retailing sector.

6.1 PROPERTY FITTING RESULTS

According to the results of the PCA on the efficiency scores from the various model specifications, the models with the highest efficiency are A13, A123. However, various strategies lead to efficiency in sponsored search advertising. Figure 14 combines Figure 11 (Sample 1) and Figure 13, and Figure 15 combines Figure 12 (Sample 2) and Figure 13 in a bid to show several interesting patterns.

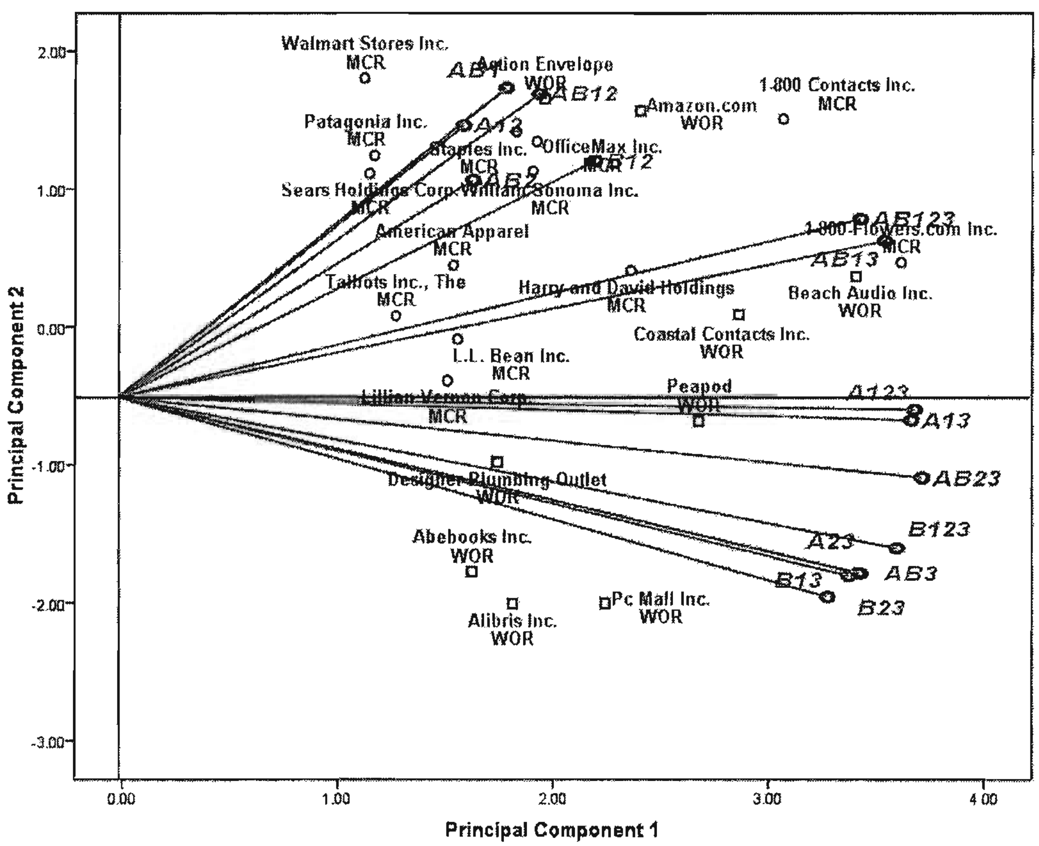

Figure 14: Pro-Fit Analysis Vector Diagram: Cluster Identification (Sample 1)

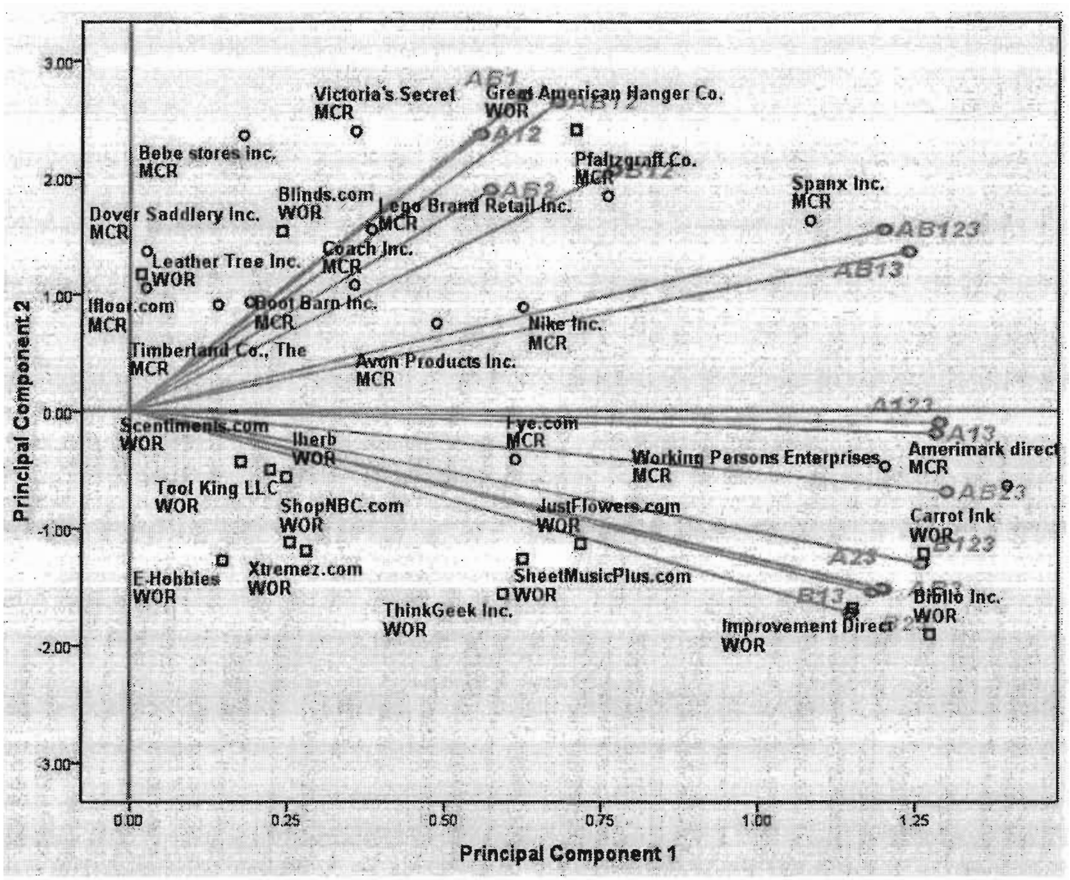

Figure 15: Pro-Fit Analysis Vector Diagram: Cluster Identification (Sample 2)

Figure 14 and 15 show the distribution of the models in a 2-dimensional map. DMUs increase in efficiency from left to right. According to the PCA of the efficiency scores, the first principal component was labelled as the overall measure of efficiency. The three models that have the highest measure of overall efficiency (Component 1) are A13, A123 and AB23 (Table 16). In these three models, all the input and output components are represented. However, other strategies of achieving efficiency exist. Models that load positively and highly on the second component contain *Output 1 and Output 2* but not *Output 3* (Figure 16). On the other hand, models that load negatively on the second component all contain *Output 3* (Figure 17).

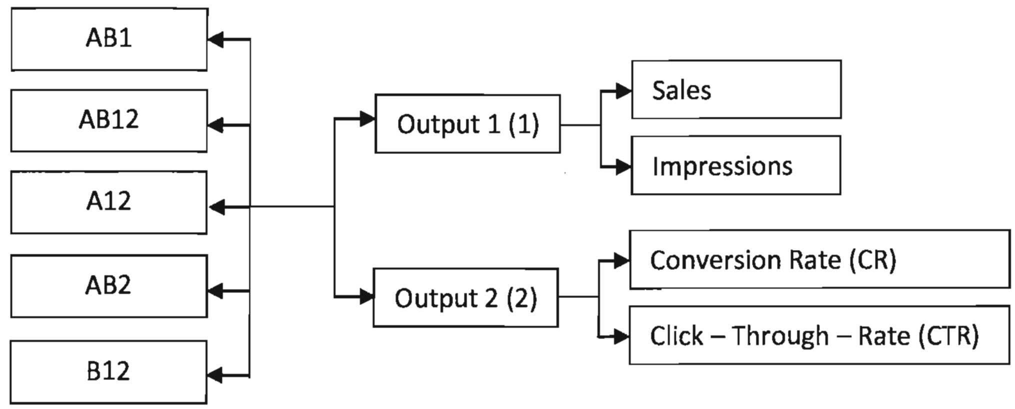

Figure 16: PCA - DEA Models that Incorporate Output 1 & 2

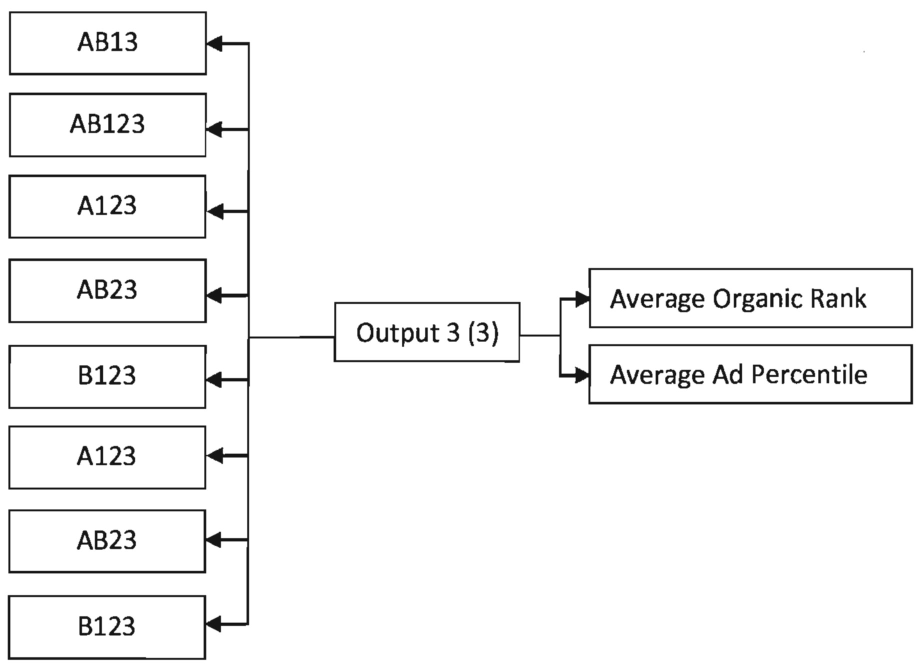

Figure 17: PCA - DEA Models that Incorporate Output 3

Figure 14 and 15, in addition to the names of the companies also indicate the merchant category that the retailers belong to. Variations in sponsored search strategies along merchant categories can be seen clearly in the above diagrams. All the input and output variables are important in the formulation of a sponsored search advertising strategy. However, some output variables are seen as being more important that others in the formulation of a sponsored search strategy for particular merchant types. Figures 14 and 15 indicate that *Output 1 (Impressions and*

Sales) and / or *Output 2 (CTR and CR)* are integral components in the sponsored search advertising strategy of MCRs that achieve high efficiencies. Similarly, *Output 3 (Average organic rank and average ad percentile)* can be seen as an integral component in the sponsored search advertising strategy of WORs that achieve high efficiencies.

This is an interesting finding as it indicates some of the key performance metrics in the two merchant categories. WORs are seen to achieve efficiency along 8 DEA models (Figure 17). In each of these models *Output 3* is the one recurring component across the models, thus indicating its importance in leading to efficiency of WORs. Visibility of an organization on a search engine result page is key in gaining market share and in the promotion of the goods and services a Web retailer is selling. WORs only have one channel, the Internet, through which they market their goods and services. Therefore, both organic rank and sponsored rank, are found to be important in WORs advertising strategy. MCRs achieve efficiency along 7 DEA models (Figure 16). In each of these 7 models, *Output 1 and / or Output 2* are present. This finding indicates that *Output 1 and Output 2* are important components in the sponsored search advertising strategy of MCRs.

The results of the above model indicate that MCRs that maximize *Output 1 (Sales and Impressions) and Output 2 (CTR and CR)* achieve high efficiencies, whereas WORs that make *Output 3 (Average ad percentile and average organic rank)* an integral part of their sponsored search campaigns also achieve high efficiencies. The validity of the above models is further highlighted by the correlation analysis in Table 19 and 20. The correlations of the models that load positively on the second principal component, Figure 16, are shown in Table 19. In addition, the correlations of the models that load negatively on the second principal component, Figure 17, are shown in Table 20. The correlation analysis shows that models that are adjacent to each other, as identified above, are all significantly correlated. Moreover, the correlation analysis is an indication that significantly correlated models lead to efficient DMUs in a similar pattern (Cinca & Molinero, 2004). Table 19 and 20 show the correlations between the various models that lead to efficiency of both MCRs and WORs. The correlations indicate that the models are not only closely related but also represent similar patterns in achieving efficiency.

Correlations						
	A12	B12	AB1	AB2	AB12	AB13
B12	.548**					
AB1	.642**	.525**				
AB2	.346**	.774**	.571**			
AB12	.723**	.699**	.953**	.701**		
AB13	.522**	.444**	.769**	.478**	.761**	
AB123	.562**	.525**	.786**	.550**	.809**	.980**
** Correlation is significant at the 0.01 level (2-tailed)						

Table 19: Correlations: DEA Models and Efficiency patterns for MCRs

Correlations							
	A13	A23	A123	B13	B23	B123	AB3
A23	.764**						
A123	.993**	.744**					
B13	.727**	.867**	.706**				
B23	.704**	.926**	.700**	.920**			
B123	.758**	.868**	.760**	.936**	.969**		
AB3	.710**	.951**	.680**	.859**	.863**	.803**	
AB23	.684**	.891**	.678**	.700**	.846**	.796**	.871**
** Correlation is significant at the 0.01 level (2-tailed)							

Table 20: Correlations: DEA Models and Efficiency patterns for WORs

6.2 CLUSTERING RESULTS

The clustering results of Section 5.4 were further analyzed along various dimensions of the Internet Retailer dataset. As mentioned before, the cluster analysis led to two clusters which we label here as "efficient retailers" and "non-efficient" retailers for discussion purposes. The efficient cluster contains 22 retailers and the non-efficient cluster contains the remaining 178 retailers in our sample. Sections 6.2.1 through 6.2.3 present the results across the main dimensions of the Internet Retailer dataset.

6.2.1 PRODUCT CATEGORY AND MERCHANT TYPE

The dataset is segmented along 14 product categories, ranging from apparel to food. However, the distribution of goods along product lines does not provide any conclusive insights into what products predominantly fall in the efficient and non-efficient retailer clusters (Table 21).

	Categories	Efficient Retailers	Non-Efficient Retailers
Apparel & Accessories	AA	4 (10%)	38 (90%)
Books, music & video	BC	2 (25%)	6 (75%)
Computers & electronics	CE	3 (13%)	20 (87%)
Food & drug	FD	2 (22%)	7 (78%)
Flowers & gifts	FG	1 (17%)	5 (83%)
Health & beauty	HB	2 (18%)	9 (82)
House wares & home furnishing	HHF	2 (10%)	18 (90%)
Hardware & home improvement	HHI	1 (8%)	12 (92%)
Jewellery	JE	0 (0%)	5 (100%)
Mass merchant	MM	3 (23%)	10 (77%)
Office supplies	OS	3 (43%)	4 (100%)
Sporting goods	SG	0 (0%)	12 (100%)
Specialty & non - apparel	SP	0 (0%)	24 (100%)
Toys &hobbies	TH	0 (0%)	7 (100%)

Table 21: Classification of Retailers based on Product Category

Due to the relatively small number of the efficient retailers, none of the product categories is predominantly identified with this cluster. However, past literature on product categories on the Internet as well as several empirical studies have empirically found that books, hobby items, music, software, flowers, CD's and videos have a higher likelihood of being sold online as they are highly differentiable, and require minimal physical interaction between the salesperson and the consumer (Elliot & Fowell, 2000; Grewal, Iyer, & Levy, 2004; Teo, 2002).

In addition, Monsuwé, Dellaert, & Ruyter (2004) noted that consumers tend to shop online for standardized, familiar products in which the product uncertainty is negligible. Therefore, for items like personal care products, cars and home furnishings in which quality of the product is a major consideration, offline shopping may be preferred. In general, if personal interaction with a salesperson is required for the product under consideration, consumers' intention to shop on the Internet is low. Moreover, if consumers need to pre-trial the product under consideration, or have the necessity to feel, touch or smell the product, then their intention to shop online is low as well. However, in case of standardized and familiar goods, or certain sensitive products that require a level of privacy and anonymity, consumers' intention to shop on the Internet is high (Grewal et al., 2004). Some of the patterns of online purchase described above are present in the dataset. However, clear patterns representing the product categories cannot be seen in the sample used for this study. In order to alleviate this problem, we classified the product categories into two disparate groups, low outlay and high outlay products, as proposed by Phau & Poon (2000).

Peterson et al. (1997) also introduced a classification scheme in which products can be classified along three dimensions: Cost and frequency of purchase, value proposition and degree of differentiation. Goods vary along the first dimension from low cost, frequently purchased items to high cost, infrequently purchased items. Goods vary along the second dimension according to their value proposition, that is, if they are tangible or intangible. The third dimension reflects the extent to which a seller is able to create a sustainable competitive advantage through product and service differentiation. Differentiation is important as it alleviates intense price competition due to commonality between various products. Therefore, the product categories in the dataset can be better classified into two categories.

Dimension 1	**Dimension 2**	**Dimension 3**	**Product Categories**	**Category**
Low outlay, frequently purchased goods	Value proposition, **tangible or physical**	Differential potential **high**	**AA, BC, FD, FG, HB, HHI, MM, TH**	**Low Outlay**
High outlay, infrequently purchased goods	Value proposition, **tangible or physical**	Differential potential **high**	**CE, HHF, JE, OS, SG, SP**	**High Outlay**

Table 22: Product Categorization (Peterson et al. 1997)

The product categories in the dataset fit into two categories: Low and high outlay. The proportions of the classification based on the above model are presented in Table 23.

	Product Category
Efficient retailers	
Low Outlay	**15 (68%)**
High Outlay	7 (32%)
Non - efficient retailers	
Low Outlay	**94 (53%)**
High Outlay	84 (47%)

Table 23: Classification of Retailers based on the Modified Product Category

The classification scheme proposed by Peterson et al. (1997) provides a better fit to the dataset as clear differences are visible across the efficient and non-efficient retailers. In the efficient retailers, the low outlay category is more prevalent. However, in the non-efficient retailers, the low outlay products are slightly more prevalent than those of the high outlay category. This may indicate that low outlay products have a higher likelihood of being sold online than high outlay products (Grewal et al., 2004). In addition, the product categorization may indicate that low outlay products have a high likelihood of success on search engine advertising. Table 24 presents the classification of the two merchant types (i.e., MCR and WOR) across the clusters.

	Merchant Type
Efficient retailers	
WOR	9 (41%)
MCR	**13 (59%)**
Non - efficient retailers	
WOR	**91 (51%)**
MCR	87 (49%)

Table 24: Classification of Retailers based on Merchant Type

The efficient retailers are predominantly MCRs whereas the majority of the non-efficient retailers are WORs (Elliot & Fowell, 2000). This can be attributed to the relative size of the companies in the dataset. In the dataset, MCRs are larger in size, have higher sales, than WORs. Appendix H presents the variations of retailers across product and merchant types.

6.2.2 WEB TRAFFIC: MONTHLY VISITS AND MONTHLY UNIQUE VISITS

The monthly visits (MV) and monthly unique visits (MUV) represent the Web traffic that a Web site generates. These two measures are commonly used to evaluate overall site performance (Karayanni & Baltas, 2003). Moreover, the two measures have been used to measure the performance of the search engine market (Gandal, 2001) and government sectors (Steyaert, 2004).

A correlation analysis of the monthly visits and monthly unique visits with the variables used in the efficiency analysis was conducted and the results are presented in Appendix I. We found significant correlations between MV and MUV with sales, as well as impressions. These results may also imply that the total number of keywords a retailer uses is correlated to Web traffic. A possible explanation to the correlation could be that use of a large number of keywords could be associated with high traffic and possible high sales.

Table 25 shows the categorization of retailers across the two clusters. It is expected that due to the high performance of the efficient retailers and their strength in generating sales[5], they would be more dominant than the non-efficient retailers in generating Web traffic.

	MV	MUV
Efficient Retailers		
Avg	**15,943,185.68**	**5,788,772.73**
Min	100,000.00	55,000.00
Max	207,671,000.00	52,295,000.00
Non – Efficient Retailers		
Avg	**4,383,096.73**	**1,944,495.70**
Min	95,000.00	42,000.00
Max	164,703,000.00	40,884,000.00

Table 25: Classification of Retailers based on MV and MUV

The MV and MUV of the efficient retailers are on average higher than those of the non-efficient retailers. This may imply that the efficient retailers are more productive at generating sales and impressions than the non-efficient retailers.

[5]A break down on the sales by product category and merchant category is presented in Appendix H

6.2.3 AVERAGE TICKET AND STOCK KEEPING UNIT

The average ticket is the average amount of money spent by a consumer online in one visit. Although the average ticket and the frequency with which online consumers visit Web sites has been increasing over recent years, online purchases are mostly dominated by low ticket items (Internet Retailer, 2008). High ticket items are usually associated with higher perceived risk of transaction on the Internet. Most merchants steer away from high ticket items as they are infrequently purchased leading to dead stock (Hoffman & Novak, 2000; Molesworth & Suortfi, 2002).

A stock keeping unit (SKU) is a unique item, which is held in inventory with a specific number to allow for tracking and reordering. In general, large retailers carry more SKUs than smaller retailers due to their ability to have a wider variety of inventory items (D'Andrea, Lopez-Aleman, & Stengel, 2006). Table 26 shows the distribution of the average ticket and SKUs across the two clusters.

	Average Ticket	SKU
Efficient retailers		
Avg	**$ 176.24**	**10,818,410.00**
Min	$ 26.00	800
Max	$ 600.00	110,000,000
Non - efficient retailers		
Avg	**$ 205.26**	**1,625,237.28**
Min	$ 9.00	150
Max	$ 5,629.00	150,000,000

Table 26: Classification of Retailers based on Average Ticket and SKU

As shown in Table 26, the efficient retailers have a lower average ticket than the non-efficient retailers, thus indicating that the products sold by the efficient retailers have a higher likelihood of being sold on the Internet (Hoffman & Novak, 2000; Molesworth & Suortfi, 2002). The average number of SKUs is relatively greater for the efficient retailers, indicating that on average, efficient retailers maintain inventories with a wider variety than non-efficient retailers (D'Andrea et al., 2006).

A correlation analysis, presented in Appendix J, of the average ticket and SKU with the variables used in the efficiency analysis reveals some interesting characteristics. The average ticket is positively correlated with the cost per click (CPC) and negatively correlated with the conversion rate. This is consistent with previous studies that indicate low ticket items have a higher likelihood to be sold online (Hoffman & Novak, 2000; Molesworth & Suortfi, 2002).

SECTION 7: DISCUSSION

Due to the heterogeneity of retailers in the sample, we sought to answer certain questions. First, how should the performance of search engine advertising be evaluated? Second, what are the key performance metrics in Web retailing? Third, are there differences in the evaluation of sponsored search engine strategies of multi-channel retailers and Web-only retailers?

The study finds that search engine advertising strategies should be evaluated by taking multiple variables into account. The efficiency of search engine strategies depends on an advertiser's ability to effectively maximize their outputs given a specified amount of resources. The study finds that various strategies can be used to maximize efficiency of the sponsored search strategies of Web retailers.

The key performance metrics identified by both clustering and Pro-Fit analysis were *Output 1 (Sales and Impressions) and Output 2 (Conversion Rate and Click – through – rate)* for MCRs and *Output 3 (Average ad percentile and average organic rank)* for WORs. WORs are seen to achieve efficiency by including *Output 3* as a priority. The importance of rank, however, cannot be over-estimated. A recent study by Ghose & Yang (2009) found that efficient ranking strategies inevitably lead to profitability of keywords. The results suggest that WORs that do not achieve high efficiency scores should therefore evaluate their performance on the sponsored and organic rank sections. MCRs focus primarily on *Output 1 (Sales and Impressions) and Output 2 (Conversion Rate and Click – through – rate)*. The Pro-Fit analysis indicates that MCRs focus more on sales than WORs. One reason for this could be the presence of several large MCRs in our dataset. Generally, customers will tend to shop with larger retailers than smaller retailers (Balabanis & Reynolds, 2001; Elliot & Fowell, 2000). Larger MCRs have an advantage over smaller WORs as prior customer attitude toward offline retailers are transferred to an online environment. Therefore, successful MCRs are more likely to be successful than newer WORs (Balabanis & Reynolds, 2001).

The clustering and Pro-Fit results show variations along merchant category. The clustering results indicate that MCRs are generally more efficient in their sponsored search strategies than WORs. This finding goes contrary to common belief, which is that WORs are more efficient than MCRs in an online environment as the Internet is their only channel and therefore are more likely to show expertise in it. The Pro-Fit results indicate that retailers who are efficient at generating *Output 1 (Sales and Impressions)* are established MCR, categorized in the Top 100. However, retailers that are efficient securing high advertising slots on search engine result pages are WORs. This finding indicates that WORs are more inclined to ensure a high ranking than MCRs. The results also indicate that MCRs and WORs adopt different strategies when competing in their sponsored search campaigns.

This research has identified various factors that influence the success of sponsored search campaigns. As shown in the clustering results, retailers that stocked primarily low ticket items that are highly differentiable, and maintained a high number of SKUs, were found to be efficient retailers. This may be because consumers are reluctant to make high ticket purchases on the Internet due to trust and security issues.

The dataset contained 14 different product categories. When the 14 product categories were assessed, none of them was found to be especially prevalent within the efficient and non-efficient retailers. However, when the 14 product categories were reduced to two categories, differences were found. In the efficient retailers' cluster, low outlay, frequently purchased products that were highly differentiable were predominant. In the non-efficient retailers cluster, however, the distribution of the aforementioned product type and high outlay, infrequently purchased products that were highly differentiable was more or less even. This pattern is in line with current research on products that have a high propensity to be sold in an online environment (Grewal et al., 2004; Peterson et al., 1997). Highly differentiable, low outlay products that are frequently purchased are more likely to be purchased on the Internet as they experience lower price competition. Since most of them are standardized products, quality uncertainty is very low.

SECTION 8: CONCLUSION

The research sought to answer questions that, to the best of our knowledge, had not been addressed in a satisfactory manner by previous research. Using a unique dataset composed of organizational and keyword data, we were able to explore several questions. We sought to explore the key differences between merchant types in the Web retail industry. In addition, we sought to explore the key performance metrics given that the industry lacks clear evaluation metrics.

MCRs and WORs were found to differ across product categories and key performance metrics. MCRs were found to focus more on improving their sales as well as CR, impressions and CTR, whereas WORs were found to focus more on rank, both organic and sponsored. A cluster analysis of the efficiency scores generated by DEA revealed that efficient firms were predominantly MCRs and non–efficient firms were predominantly WORs. In addition, low outlay products were found to have a higher likelihood of success on the Internet *vis-à-vis* high outlay products. These findings are critical when determining the success factors of retailers on the Internet and in the evaluation of the efficiency of current sponsored search advertising strategies.

The implications of the study are divided in three categories: managerial, market mechanism design and academic. We then discuss the limitations and future research opportunities as a consequence of this study.

8.1 MANAGERIAL IMPLICATIONS

Managerial decisions regarding the structure of sponsored search strategies are key to the success of the campaigns. Managerial decisions regarding resource allocation and key performance metrics can be aided by this study. Managers of MCRs and WORs have to position themselves appropriately so as to achieve maximum efficiency and utility from their sponsored search campaigns. MCRs achieve the highest efficiency when maximizing *Output 1 (Sales and Impressions)* and *Output 2 (Click-through-rate and Conversion rate).* Impressions are highly correlated to sales and therefore, efficiency in achieving impressions could be related to higher sales. Just to reiterate, this finding does not indicate that *Output 3* is not important for MCRs. It only indicates that *Output 1 and Output 2* are more critical to the success of a sponsored search engine marketing strategy carried out by MCRs. Managers should therefore focus on how to attain more impressions. SEA differs from other modes of advertising due to its payment scheme. In sponsored search, advertisers pay the search engine only when their ad is clicked on; whereas advertisers on mass media channels pay based on the number of views or impressions their ads receive. Pay-per-click presents an efficient mode of payment for retailers as they have more control over their expenditure through the different keyword bids that they make (Dennis, 2004). Our results, however, show that retailers should maximize impressions even though they are not directly charged on impressions.

Retailers can increase the number of impressions in various ways. They can increase the number of paid and organic keywords they buy, thus ensuring that their ads are seen more often. Managers of WORs firms need to focus on the rank of their ads. WORs achieve high efficiencies once they have secured top advertising slots on search engine results pages. In order to achieve high rankings, advertisers have to bid optimally for keywords. However, there is a trade-off between ranking and cost per click; the higher the ranking, the higher the cost per click. Retailers need to be wary of a high cost per click because research shows that there is minimal difference in effect between the first, second and third advertising slots on a page. There is, however, a large price difference between the different advertising slots. In Google, the advertising slots that a retail firm can get depend on the quality score of the retailer's Web site. The criteria taken into account by Google when calculating the quality score includes the CTR, the quality of the landing page, the relevance of the keyword to its ad group and the geographical performance of the retailer. Retailers can increase their CTR by increasing the number of ads that they have and by bidding on the right keywords. In addition, retailers should ensure their Web site metrics all exceed expectations in order to ensure the quality and interactivity of their landing page. WORs who maintain high quality score ensure a high rank and therefore increasing the efficiency of their sponsored search campaigns.

8.2 MARKET MECHANISM DESIGN

Various bidding tools exist in the market. These tools provide automated bidding mechanisms, keyword generation capabilities, tracking of keyword performance and reports on the efficiency of a sponsored search campaign. These bidding tools come with preconceived notions about the evaluation of sponsored search campaigns (Ghose, 2009). Most of the bidding tools assume that the CTR is the key performance indicator across various industries. The Pro-Fit analysis, however, indicates that efficiency can be achieved through various means such as the optimization of rank and impressions.

This study aims at aiding in the development of bidding tools and agents by informing the search advertising industry of variables important to sponsored search success. This in turn will guide in the development of bidding tools and agents that take into account not only the variables that are currently in use, but also some of the key variables that are found to be important in the different models examined in this study. By incorporating these variables, retailers in the various merchant categories can track and improve the performance of their sponsored search advertising campaigns.

8.3 ACADEMIC IMPLICATIONS

The study contributes to academic research in various ways. First, the study performs extensive data driven analysis on actual data that encompasses various merchant and product types. Previous research in the sponsored search advertising has been characterised by lack of an empirical base. This research is, therefore, a milestone in sponsored search advertising not only due to the extensive nature of the data in use, but also due to the range of quantitative techniques used to analyze the data. Second, as stated in the literature review, prior research was focused on few variables to explain the dynamics of the sponsored search advertising process. This study, however, uses multiple input and output variables in an exploratory bid to find out the key performance metrics over a range of relevant variables. The variables used in the empirical model are drawn from both industry and prior literature, which provide an extensive analysis of the dynamics in sponsored search advertising. Third, this study used well-established quantitative techniques, which include, PCA, DEA, and cluster analysis to extensively analyze the sponsored search advertising efficiency. The use of these techniques adds to the methodologies used to study search engine advertising in the literature.

8.4 LIMITATIONS AND FUTURE RESEARCH DIRECTION

Due to the relatively unexplored nature of sponsored search engine marketing, future research holds a truly exciting prospect. The study could be extended in a number of ways. First, the sample could be controlled to ensure that the size of retail firms is within a specified range. Secondly, the age of retailers could be controlled to ensure an even number of young and established retailers in the dataset. The dataset used in the study was skewed, both in the size of the retailers used and in their age. It was composed of mostly large established retailers and represents the top retailers in terms of their online sales. However, even in this group, this study has found noticeable variations along several performance dimensions. Another direction in which future research could take is to analyze the efficiency of sponsored search campaigns on a keyword level. This would entail creating an evaluation mechanism through which retailers analyze the efficiency of each of their marketing keywords so as to ensure only profitable keywords are retained. In addition to the keyword level analysis, future research could also look to a cluster of keywords as a unit of analysis in the research. Natural clusters such as keywords with brand information, retailer information and product information can be formed in a bid to find out which cluster leads to higher sponsored search performance.

One of the strengths of this research was the use of DEA. Numerous variables have been used in the analysis in a bid to single out key performance metrics in sponsored search engine advertising. However, one major pitfall of using DEA is its sensitivity to variations in data. DEA is a data driven methodology, therefore small changes in data could change the results. The use of PCA as a data reduction technique has the advantage of aggregating the correlated inputs and outputs. PCA however, may make the results of the data opaque. We have, however, graphically explained the components in a bid to make interpretation easy. Another limitation of DEA is its lack of statistical tests of significance and the exact functional form of the key relationships between input and output variables found in the analysis. The verification of DEA results is not available from within DEA, we therefore had to use Pro-Fit and clustering to verify the results and further analyze them. This, however, presents future research opportunities to analyze the exact form of functional relationships between the key input and output variables identified in this research.

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APPENDIX A: DEFINITIONS OF KEY TERMS AND VARIABLES

1. Average ad competitors: The average of all other firms that advertise on a domain's keywords
2. Average ad percentile: A measure of ad position that takes into account average ad competitors. As the average ad percentile approaches 100%, it indicates that the domain is closer to dominating the first position
3. Average clicks per day: This refers to the average number of times a firm's advertisements on Google are clicked on
4. Average cost per day: This is the average amount of money an advertiser expects to pay Google if it does not exceed its daily budget.
5. Average organic position: This is the average organic position of all the keywords that a firm advertises on
6. Click Though Rate (CTR): CTR is currently used by search brokers as the primary measure of the success of an online advertising campaign. It is obtained by dividing the number of users who clicked on an ad on a Web page by the number of times the ad was delivered (i.e., impressions)
7. Conversion Rate: Conversion rate is the number of visitors that eventually make a purchase.
8. Cost per click: The amount of money an advertiser pays Google when their ad is clicked on
9. Daily advertising budget: It is an estimate of the amount of money a firm spends on Google per day
10. Impressions: The number of users who view an ad, also known as exposure.
11. Length of keyword: The length of a keyword refers to the number of words that are contained in a paid keyword

12. Number of organic keywords: The total number of keywords with which a firm optimizes its Web site
13. Number of paid keywords: The total number of keywords a firm advertises on
14. Online word of mouth (WOM): Online WOM is defined as informal communication about the ownership, usage and characteristics of particular goods and services or sellers
15. Sales: Annual online sales that can be directly attributed to search engine traffic
16. SEA: Search engine advertising is the entire set of techniques used to direct more visitors from search engines to marketing websites
17. SEMPO: Search Engine Marketing Professional Organization is a non-profit professional association for search engine marketing firms.
18. SEO: Search engine optimization is the practice of using a range of page optimization techniques in order to improve the page rank of a particular Web page by matching specific keywords to the text on the Web page
19. SERP: The search engine result page is the listing of Web pages returned by a search engine in response to a keyword query
20. Total clicks per day: This refers to the total number of times a firm's advertisements on Google are clicked on
21. Total cost per day: This is the total amount of money an advertiser expects to pay Google if it does not exceed its daily budget

APPENDIX B: CORRELATIONS: INPUT AND OUTPUT VARIABLES

Correlations					
	Paid Keywords	Total Organic Results	Length of Keyword	Est Avg CPC	Total cost per day
Total Organic Results	.978**				
Length of Keyword	-0.037	-0.02			
Est Avg CPC	-0.06	-0.083	0.073		
Total cost per day	.988**	.980**	-0.046	-0.061	
Total No. of Ads	.983**	.944**	-0.014	-0.044	.948**
**. Correlation is significant at the 0.01 level (2-tailed).					

Correlations: Input Variables

Correlations					
	Conversion Rate	Sales	Impressions	CTR	Ad Rank Percentile
Sales	0.026				
Impressions	-0.059	.866**			
CTR	.297**	0.073	-0.017		
Ad Rank Percentile	0.07	0.031	0.005	0.137	
Avg Organic Rank	-0.094	-0.043	-0.02	-0.132	-.153*
**. Correlation is significant at the 0.01 level (2-tailed).					
*. Correlation is significant at the 0.05 level (2-tailed).					

Correlations: Output Variables

APPENDIX C: DESCRIPTIVE STATISTICS: INPUT AND OUTPUT VARIABLES

Descriptive Statistics				
	Minimum	Maximum	Mean	Std. Deviation
Total Number of Paid Keywords	72.00	1384081.00	19207.88	99598.60
Total Number of Organic Keywords	28.00	3152589.00	36848.57	227104.26
Average Length of Keywords	1.90	3.46	2.69	0.19
Average Cost per Click	0.15	0.71	0.37	0.10
Total Cost per day	10.67	49129799.83	415988.25	3487833.81
Total Number of Ads	941.00	11820588.00	249683.35	897018.73

Descriptive Statistics: Input Variables

Descriptive Statistics				
	Minimum	Maximum	Mean	Std. Deviation
Sales	1714608.00	5180000000.00	89509776.91	394732524.63
Impressions	31070.00	1721873275.00	46557049.96	147224017.01
CTR	0.00	0.05	0.01	0.01
Conversion Rate	0.05	6.84	1.20	1.08
Avg Ad Rank Percentile	0.17	0.79	0.53	0.12
Avg Organic Rank	6.49	35.81	22.58	4.69

Descriptive Statistics: Output Variables

APPENDIX D: REGRESSION COEFFICIENTS GENERATED BY PCA

Unit name	Keyword Metrics	CPC	Sales	CTR	Rank
1-800 Contacts Inc.	-0.25149	3.17308	0.13568	4.60254	0.7151
1-800-Flowers.com Inc.	0.11362	0.68816	0.41268	6.52598	3.69371
Abazias Inc.	-0.21633	1.25871	-0.25253	-0.25857	-0.9764
Abebooks Inc.	-0.09031	-0.02797	-0.24246	-0.48778	2.12264
Abt Electronics Inc.	-0.08138	-0.74363	-0.28843	-1.52346	0.8898
Ace Hardware Corp.	-0.08089	-0.4312	-0.28462	-0.69467	1.05375
Action Envelope	-0.23773	1.13986	-0.10122	2.65093	0.03923
Adidas America Inc.	-0.11801	-2.49021	-0.37495	-1.51002	0.30202
Aeropostale Inc.	-0.13977	-1.27094	-0.19933	-0.13281	-0.41262
Alibris Inc.	0.1688	-1.99622	-0.1002	-0.90363	2.45049
AllergyBuyersClub.com	-0.21819	1.58039	-0.19605	0.25298	-1.14955
Altrec Inc.	-0.05667	-1.013	-0.10324	-0.28959	-0.016
Amazon.com	13.73121	-0.10697	12.58605	-0.33971	0.55174
America musical supply	-0.05136	-0.45324	-0.21626	-0.49934	0.24095
American Apparel	-0.16133	-0.7449	-0.15854	0.82965	1.06315
American Eagle Outfitters Inc.	-0.1146	-0.64268	-0.11041	-0.33083	-0.55077
American Girl	-0.18115	0.07237	-0.27233	-0.36535	-0.1946
American blinds.com	-0.17192	0.23206	-0.22651	0.02762	-0.59116
Amerimark direct	-0.14646	-0.51083	-0.26797	0.48712	1.46823
Ann taylor stores corp	-0.1567	-0.30413	-0.15714	-0.1674	-0.74093
Apple Inc.	0.10805	1.23826	0.48975	0.26393	-0.82115

Regression Coefficients Generated by PCA

APPENDIX E: TRANSFORMED REGRESSION COEFFICIENTS

Unit name	Keyword Metrics	CPC	Sales	CTR	Rank
1-800 Contacts Inc.	1	7.83464	1.57013	7.20581	4.53317
1-800-Flowers.com Inc.	1.36511	5.34972	1.84713	9.12925	7.51178
Abazias Inc.	1.03516	5.92027	1.18192	2.3447	2.84167
Abebooks Inc.	1.16118	4.63359	1.19199	2.11549	5.94071
Abt Electronics Inc.	1.17011	3.91793	1.14602	1.07981	4.70787
Ace Hardware Corp.	1.1706	4.23036	1.14983	1.9086	4.87182
Action Envelope	1.01376	5.80142	1.33323	5.2542	3.8573
Adidas America Inc.	1.13348	2.17135	1.0595	1.09325	4.12009
Aeropostale Inc.	1.11172	3.39062	1.23512	2.47046	3.40545
Alibris Inc.	1.42029	2.66534	1.33425	1.69964	6.26856
AllergyBuyersClub.com	1.0333	6.24195	1.2384	2.85625	2.66852
Altrec Inc.	1.19482	3.64856	1.33121	2.31368	3.80207
Amazon.com	14.9827	4.55459	14.0205	2.26356	4.36981
America musical supply	1.20013	4.20832	1.21819	2.10393	4.05902
American Apparel	1.09016	3.91666	1.27591	3.43292	4.88122
American Eagle Outfitters Inc.	1.13689	4.01888	1.32404	2.27244	3.2673
American Girl	1.07034	4.73393	1.16212	2.23792	3.62347
American blinds.com	1.07957	4.89362	1.20794	2.63089	3.22691
Amerimark direct	1.10503	4.15073	1.16648	3.09039	5.2863
Ann taylor stores corp	1.09479	4.35743	1.27731	2.43587	3.07714
Apple Inc.	1.35954	5.89982	1.9242	2.8672	2.99692

Transformed Regression Coefficients

APPENDIX F: RETAILERS IN THE EFFICIENT CLUSTER

RankNo	Unitname	Year	Category	MerchantType	KeywordMetrics	CPC	Sales	CTR	Rank_A	PC_1	PC_2	PC_2	Cluster_mem
36	1-800-Flowers.com Inc.	1995	FG	MCR	1.36511	5.34972	1.84713	9.12925	7.51178	3.61456	0.4716	1.51077	1
373	Beach Audio Inc.	2002	CE	WO	1.16162	1	1.14822	2.92447	6.28115	3.40539	0.36779	3.2106	1
98	1-800 Contacts Inc.	1996	HB	MCR	1	7.83464	1.57013	7.20581	4.53317	3.06759	1.50965	0.57241	1
120	Coastal Contacts Inc.	2001	HB	WO	1.04576	6.37667	1.31526	5.52022	6.09958	2.8635	0.09035	0.4859	1
45	Peapod	1989	FD	WO	1.08372	4.17481	1.21293	2.99233	6.1615	2.67742	-0.68039	0.01016	1
1	Amazon.com	1995	MM	WO	14.9827	4.55459	14.0205	2.26356	4.36981	2.40392	1.57093	-2.22178	1
80	Harry and David Holdings	1996	FD	MCR	1.05216	6.23505	1.36041	5.39191	5.53598	2.36091	0.41002	0.49873	1
61	Pc Mall Inc.	1995	CE	WO	1.07589	5.43267	1.09437	1	6.28991	2.24214	-2.00395	-1.96774	1
439	Action Envelope	2000	OS	WO	1.01376	5.80142	1.33323	5.2542	3.8573	1.95779	1.65576	1.33811	1
6	OfficeMax Inc.	1995	OS	MCR	1.1606	7.05825	2.39985	2.94197	4.71806	1.92173	1.34546	-3.25115	1
21	William-Sonoma Inc.	1999	HHF	MCR	1.08051	4.80833	1.63326	3.20189	4.83723	1.90399	1.12974	-1.25493	1
2	Staples Inc.	1998	OS	MCR	1.5753	6.04628	3.55089	2.75592	4.74408	1.82696	1.41588	-3.51138	1
112	Alibris Inc.	1997	BC	WO	1.42029	2.66534	1.33425	1.69964	6.26856	1.81134	-2.00496	0.482	1
452	Designer Plumbing Outlet	2003	HHI	WO	1.0872	3.71173	1.06428	1.60367	5.37987	1.73982	-0.98105	-0.2832	1
73	Abebooks Inc.	1996	BC	WO	1.16118	4.63359	1.19199	2.11549	5.94071	1.62184	-1.7721	-0.44281	1
23	L.L. Bean Inc.	1995	AA	MCR	1.25157	4.0327	1.63094	3.74315	5.41811	1.55402	-0.09001	0.29736	1
262	American Apparel	2003	AA	MCR	1.09016	3.91666	1.27591	3.43292	4.88122	1.53364	0.44749	0.84698	1
105	Lillian Vernon Corp.	1999	HHF	MCR	1.10377	4.37718	1.23703	3.34991	5.28898	1.50742	-0.39124	0.56459	1
64	Talbots Inc., The	1999	AA	MCR	1.08997	4.15899	1.27095	3.05308	4.85154	1.26779	0.07944	0.36197	1
279	Patagonia Inc.	1998	AA	MCR	1.12784	3.68397	1.37929	4.27108	4.04737	1.16908	1.24326	1.86085	1
8	Sears Holdings Corp.	1998	MM	MCR	2.06341	5.13716	3.59885	1.87093	4.27811	1.14579	1.11286	-3.34158	1
14	Walmart Stores Inc.	2000	MM	MCR	2.53154	4.84738	4.30197	1.28424	3.56154	1.11882	1.80787	-4.79389	1

Ranking of Retailers based on the Overall Size of the Firm

APPENDIX G: TWO-STEP CLUSTERING ALGORITHM: ANOVA RESULTS

ANOVA				
	Sum of Squares	Mean Square	F	Sig.
A12	.489	.489	52.747	.000
A13	1.078	1.078	199.070	.000
A23	1.109	1.109	71.580	.000
A123	1.047	1.047	204.335	.000
B12	.615	.615	45.835	.000
B13	1.122	1.122	83.728	.000
B23	.956	.956	76.718	.000
B123	1.127	1.127	105.473	.000
AB1	.338	.338	30.819	.000
AB2	.435	.435	14.376	.000
AB3	1.307	1.307	65.167	.000
AB12	.424	.424	40.929	.000
AB13	.729	.729	114.017	.000
AB23	1.099	1.099	67.971	.000
AB123	.688	.688	111.101	.000

ANOVA Results for Two-Step Cluster Analysis

APPENDIX H: TOTAL SALES

Total Sales					
MCR	**CE**	$ 15,566,699,525.00	**MM**	$ 6,490,272,975.00
WOR		$ 2,430,233,493.00		$ 16,552,058,895.00
MCR	**FG**	$ 609,900,000.00	**OS**	$ 8,762,800,700.00
WOR		$ 117,707,000.00		$ 89,925,600.00
MCR	**HB**	$ 850,543,466.00	**SP**	$ 858,489,820.00
WOR		$ 304,447,611.00		$ 912,032,032.00
MCR	**HHF**	$ 1,686,684,722.00	**TH**	$ 676,708,920.00
WOR		$ 400,835,552.00		$ 34,802,496.00
MCR	**HHI**	$ 497,944,472.00	**Total**	**$ 44,007,744,854.00**
WOR		$ 200,804,252.00		**$ 23,158,412,406.00**

Total Sales across Merchant and Product Categories

APPENDIX I: CORRELATIONS: MONTHLY VISITS AND MONTHLY UNIQUE VISITS

	MV	MUV	Paid Keywords	Organic Keywords	Total cost per day	Total Number of Ads	Sales	Impressions
MV		*.950***	*.770***	*.761***	*.752***	*.777***	*.788***	*.773***
MUV	*.950***		*.718***	*.693***	*.680***	*.758***	*.747***	*.801***
**. Correlation is significant at the 0.01 level (2-tailed)								
*. Correlation is significant at the 0.05 level (2-tailed)								

Correlations: Monthly Visits and Monthly Unique Visits

APPENDIX J: CORRELATIONS: AVERAGE TICKET WITH CPC AND CONVERSION RATE

	Est Avg CPC	Conversion Rate
AVGTKT	.146*	*-.146**
SKU	-0.048	0.066
**. Correlation is significant at the 0.01 level (2-tailed).		
*. Correlation is significant at the 0.05 level (2-tailed).		

Correlations: Average Ticket with CPC and Conversion Rate