The Path to Click: Are You On It?

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ABSTRACT

The authors investigate the information search process consumers are engaged in when visually inspecting search engine results pages (SERP). Eye-tracking data are collected and matched with the textual content of the SERPs. A computational cognitive model with static and dynamic utilities is developed to capture the inspection process. The results show that the scan paths are heterogeneous across consumers and are affected by section intrinsic preferences, the ranking of listings, and more importantly, the semantic environment. Both the content of listings and the textual information of previously viewed listings exert a significant impact on inspection patterns. Transactional (price, promotion, store) and descriptive (attribute, quality, brand) information affect inspection decisions differently. The impact of ranking varies significantly across different screen compositions. The paper offers insights into the content design and optimal target rank selection on SERPs with respect to the content and location of search results from competitors.

Keywords: Eye-Tracking, Text Analysis, Search Engine Marketing

INTRODUCTION

Search engine marketing (SEM) is the leading customer acquisition tool of Internet marketers. In 2013, paid search advertising and search engine optimization (SEO) – two key constituents of SEM – will account for roughly $19.8 billion in the marketing budgets of U.S. businesses (eMarketer.com 2012). Marketing practitioners use search engines to reach their prospective customers in two ways – through the natural (or "organic") search results returned by a search engine in response to a user query, and through the sponsored (or paid) search. In a paid search, the advertiser specifies a certain target query (a set of keywords) and a certain advertisement such that when a user enters that query, the search engine displays that advertisement as part of a list of "sponsored links." Marketers can use multiple decision variables available to optimize the performance of paid search campaigns, including keyword choice, maximum bid amount, landing page design, textual content, and advertisement layout. In turn, the key concern of SEO is around achieving a higher rank in organic search results, which typically involves inbound link formation, optimization of a website's content, structure, and presentation tailored to a focal keyword(s).

In the academic literature, SEM has recently been getting a substantial amount of attention. Researchers have looked at such topics as keyword performance evaluation and forecasting (e.g., Ghose and Yang 2009; Rutz and Bucklin 2011; Rutz et al. 2011), optimal bidding strategies (e.g., Edelman et al. 2007; Katona and Sarvary 2010; Jerath et al. 2011;Yao and Mela 2011), the interplay between web traffic generated by organic and sponsored searches (e.g., Yang and Ghose 2010), as well as the impact of SEO on the competition in the paid search (e.g., Berman and Katona 2013). These studies have two commonalities: First, they tend to focus more on the paid search advertising aspect of SEM with less attention devoted to organic searches. Second, the vast majority of the extant studies take the firm's perspective on searches, using datasets collected from advertisers. Typically, these datasets are an amalgamation of daily summary statistics on impressions and clicks provided to a firm by a search engine (e.g., Google's AdWords) and the firm's own records of user transactions and clickstream. On the other hand, research that takes the consumer's perspective on search engine marketing and, accordingly, considers the competitive landscape of the consumer's choice environment (i.e., the entire content of the search engine results page or SERP) is still quite scarce.

This paper attempts to fill this gap in the marketing literature by looking at SEM from the consumer's viewpoint. On average, users spend just a few seconds inspecting search results (hereafter, *listings*) before clicking on one. However, during this short period of time, they make a number of decisions, including what sections of SERP (e.g. organic vs. top sponsored vs. right sponsored results) to consider, how many listings in each section to go through and to what extent a particular listing should be examined (Figure 1). These decisions are naturally dynamic and interrelated, as the outcomes of the preceding actions influence subsequent decisions (such as click-through or continued inspection of the SERP). This visual inspection by itself can be seen as a *micro search* process within a broader context of an online search.

---- Insert Figure 1 about Here -----

There is a long history in marketing of studying the information search process during decision making (e.g., Bettman and Kakkar 1977; Payne 1976; Payne et al. 1993). How consumers acquire information reflects their preference formation process and affects their decision outcomes. To understand the determinants of the information search process, collecting appropriate process data is essential (Shah and Oppenheimer 2008). Traditional process-tracing tools, such as Information Display Board, Mouselab, and Flashlight[1], require motor responses, which slow down the decision process and render the observed information search process more controlled and deliberate (Bettman et al. 1998). Eye-tracking equipment, in contrast, can capture the fast and dynamic information search process in a less obtrusive fashion. Eye movement data provide moment-to-moment fixation locations of the eyes that indicate the time-course of an information search. It has been proven to be important for the study of cognitive processes in realistic settings such as print ads , feature ads, super market shelves, product-attribute comparison matrix, and TV ads (e.g., Lohse and Johnson 1996; Liechty et al. 2003; Pieters and Warlop 1999; Pieters et al. 2007; Rayner 1998; Reutskaja et al. 2011; Russo and Leclerc 1994; Stüttgen et al. 2012; Shi et al. 2012; Teixeira et al. 2010; van der Lans et al. 2008a, 2008b), and has offered insights into optimizing information display and dynamic information search process.

Visual inspection patterns have been found to be driven by both low-level stimuli, such as size, location, color, luminance, and edges of the design elements, which direct attention through a "fast, primitive mechanism," and high-level stimuli, such as textual information, which direct attention through "cognitive, volitional control" (Itti and Koch 2000, p.1490) (e.g., Braun and Sagi 1990; Braun and Julesz 1998; Nakayama and Mackeben 1989; van der Lans et al. 2008a; Wolfe 1998; Yue et al. 2011). Most eye- tracking studies in the area of information display optimization and information search process primarily focus on low-level stimuli (e.g., Pieters et al. 2007; Teixeira et al. 2010; van der Lans et al. 2008a, 2008b). Several eye-tracking studies carried out on SERP also give attention to such stimuli (location): for instance, Sherman et al. (2005) discussed the importance of "golden triangle" (upper left corner of the page) on SERP; Guan and Cutrell (2007) investigated impact of ranking and search tasks (informational

[1]MouselabWEB, http://www.mouselabweb.org/ (retrieved December 10, 2011); Application of FlashLight, http://vlab.ethz.ch/flashlight/ (retrieved December 10, 2011).

or navigational) on consumers' search behavior. Dumais et al. (2010) and Buscher et al. (2010) studied how visual attention is distributed across different areas of the SERP controlling for type of the search task, the relevance of the listings, and order of presentation. However, the textual content of the stimuli and its role in the visual inspection process have been generally overlooked.

We argue that SERPs offer a suitable context to investigate the impact of high-level stimuli on the visual inspection process. Except for location (ranking), individual listings are not easily differentiable regarding their perceptual features such as size, color, luminance, and edges. In contrast, we speculate that the *content* of listings plays a key role in distinguishing among different listings and thus affects consumers' inspection decisions. Taking Figure 2 as an example, we propose that the consumer's decision to visually inspect the 3rd listing on the right sponsored section is affected by the semantic content (e.g., price, promotion depth, attribute information) of other listings that appear on the same page and, hence, can be a part of the consumer's visual inspection path.

---- Insert Figure 2 about Here -----

How consumers integrate information during their search process and make subsequent inspection decisions is not yet fully understood. What are the determinants of consumers' inspection patterns? Will the textual content of organic and paid sections create a long-lasting effect on the information seeking behavior? Will ranking effect vary across different sections and across different SERPs? Is information-seeking behavior affected by the competitive landscape? How does the content of other listings affect the inspection decisions of the target listing, and how does this impact vary across different types of textual information? How can companies break through the competitive clutter to attract consumers' attention given the limited variability in the perceptual attributes of listings? To shed some light on these questions, we conducted a lab study in which participants were asked to perform a series of online searches on Google's search engine to make purchase recommendations. Eye-tracking data and corresponding SERPs for each search task were recorded. These SERPs were parsed to extract the content and the pixel-level location of listings, and then matched with eye-tracking data. The mapped eye-tracking data were used to make inferences about the inspection sequence, as well as the content of a page and specific listings examined by each user on each search. A model is developed to assess the visual inspection path and the impact of semantic information on consumer's inspection decisions. We propose that a user's decision to inspect a particular listing is driven by several factors, including the type of listing (organic vs. sponsored), its location on the page (section and rank within section), and the content of previously inspected listings. Also, the evaluation process is dependent on the individual's specific search strategy as well as position and section preferences.

Our results show that the semantic content plays an important role in driving users' inspection decisions. We confirm a common SEM practitioners' perception that a higher rank in the SERP tends to result in more attention from the consumer; however, the role of the position is strongly moderated by the competitive landscape. Through a series of simulations, we show that for some advertisers, a change in position may have a much more significant impact on getting "noticed" by consumers than for others. These findings imply that the value of a certain position on the SERP is context dependent; hence, it is important for the firms to take the entire semantic context into account when setting a target position for their listings.

Understanding the decision mechanism and the factors driving a user's choice is an invaluable asset for both SEO and paid search practitioners, because it has implications for designing text ads (paid search), optimizing web sites for search engines indexing (organic search), choosing an optimal position on a results page with respect to the location and the content of listings from competing firms (paid and organic searches). To the best of our knowledge, this is the first study in the marketing literature that looks at SEM literally through the eyes of the consumers by empirically investigating the impact of the semantic environment on the information search process on SERPs. Contributing to both eye-tracking and search engine marketing research domains, it enables us to identify drivers behind eye movements and offers insights into the content design of listings.

The paper proceeds as follows. First, we present a conceptual framework and summarize the relevant literature on eye-tracking research and search engine marketing. We then present our model, dataset, and results. Next, we discuss the implications of our findings to SEM practitioners. We finish with the conclusion and discussion of the directions for future research.

CONCEPTUAL FRAMEWORK

Given the critical role the location of a listing plays in generating clicks, competition for top ranked positions on SERPs is fierce. Not surprisingly, almost all of the existing empirical SEM studies include an ad's rank as one of the key predictors of its performance. A number of studies go beyond a mere position effect and incorporate elements of the competitive landscape. It is common for these studies to focus on only one section of the search results (typically, sponsored search) while assuming a sequential choice process in which consumers inspect listings from top-to-bottom (e.g., Animesh et al. 2011; Agarwal et al. 2011; Arbatskaya 2007; Park and Park 2012).

Our exploratory analysis of eye-tracking data reveals that top-to-bottom inspection is indeed the dominating strategy *within each results section*; nevertheless, when taking the entire

SERP screen as a choice context faced by consumers, we observe a significant amount of variability in inspection patterns. For example, it is quite common for consumers to skip individual listings and/or ignore entire section(s) of the results. To illustrate, Figure 3 plots four distinct inspection patterns on SERPs observed in our experiments. These patterns differ across both subjects and search results pages.

---- Insert Figure 3 about Here -----

Let O, S, and T represent the organic, right sponsored, and top sponsored sections, respectively, and let the numbers represent the position (rank) of a specific listing in that section (e.g., O5 represents the 5^{th} listing from the top in the organic section). Figure 4 shows a visual inspection path for the consumer who is looking to buy a shot glass. She starts SERP inspection with the first listing in the top sponsored section (T1). T1 does not contain any attribute, quality, or brand information of the shot glass that she might be interested in, so she moves down to the first listing in the organic section (O1).

Apparently, she is not satisfied with listing O1, perhaps because it lacks specificity and the retailer's focus is on a broad range of products (e.g., "beer bongs," "party gear," "bar stuff"). So subsequently, she inspects T2, O2, O5, O4, O3, and O2. Finally she arrives at O4, customink.com, possibly attracted by a "free shipping" offer or an option to personalize a shot glass. As apparent from the example, this consumer ignored the right sponsored section, skipped through the second listing on the top on the first pass (T2) and never made it below organic listing 5 (O5) on the page that has ten organic results. Also, there was a notable number of back and forth transitions across listings.

---- Insert Figure 4 about Here -----

As can be seen from the above example, the visual path goes beyond a top-to-bottom pattern typical to traditional reading. Instead, what we observe in eye-tracking data is a visual sampling (skimming) from different sections of the SERP with frequent re-inspections of already viewed listings and a certain amount of "stickiness" within a section. It also seems that consumers have individual preferences for certain types of search results (e.g., all results, organic and top-sponsored, organic only). Moreover, inspection paths for the same individual are not necessarily consistent across different searches. Hence, we speculate that the SERP content plays a role in affecting the inspection path, as previously inspected listings influence consumers' subsequent inspection decisions. Based on these observations, we develop our conceptual framework depicted in Figure 5. We propose that there are three main factors driving the information search process on SERPs: intrinsic section preference, low-level stimuli, and high-level stimuli.

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Intrinsic Section Preference

The organic and sponsored sections on the SERP are quite different in nature. Sponsored links are paid advertising, and a mixed preference has been found for these sections: Hotchkiss et al. (2004) and Greenspan (2004) proposed that users prefer organic listings relative to sponsored links, yet Jansen and Resnick (2006) suggested that if sponsored links provided a high level of relevance, consumers would still consider them. This may be due to the fact that sponsored advertising links deliver relevant and targeted texts, making them less obtrusive and less annoying compared to other forms of online advertising like banners or pop-ups (Ghose and Yang 2009). Consumers pre-consciously identify different sections of the SERP and direct their attention accordingly. The eye movement data collected in our study also reflects such heterogeneity in section preference: the consumer in Figure 3c does not consider sponsored sections at all during this process, while the consumer in Figure 3b inspects all three sections. In addition, the inspection patterns indicate a "section stickiness" effect. Instead of entering and exiting sections immediately, consumers tend to continue exploring multiple listings within the section (Figures 3 and 4). Thus, we expect that consumers' intrinsic section preferences will influence subsequent listing inspections through a lag effect, and such lag effect may differ across organic and sponsored sections. These propositions will be addressed in our model formulation with *static utility* and *dynamic utility,* respectively.

Low-Level Stimuli

The second factor affecting the information search process is *low-level stimuli*, or low-level attributes of the visual scene, such as size, location, color, luminance, and edges of the design elements. Low-level attributes have been used to evaluate the most salient areas and to predict information-seeking behavior (e.g., Itti and Koch 2000; Pan et al. 2007; van der Lans et al. 2008a). Given the relatively low variability in perceptual attributes across SERP listings, we focus on the *ranking* of search results. Search engine's proprietary algorithms use website content and the "importance" of inbound links to determine the relevance and, hence, the ranking of each listing for the organic section. The key concern of organic search marketing is to achieve a higher rank, which typically involves optimizing a website's content, structure, presentation, and external inbound links. The ranking in the right sponsored section is determined by the keyword, the ad, the landing page's quality and the maximum bid amount. Ads that exceed a certain quality and maximum bid amount threshold might be placed by the search engine algorithm in the top sponsored sections. Thus, managers can strategically choose the keywords and the bid amount to compete for top placement in the paid section. How the ranking effect varies across different sections and competitive landscapes, and when the minor improvement (as in a position change) may lead to a significant payoff, are all very relevant issues for managers given their cravings for higher positions on the SERP.

High-Level Stimuli

High-level stimuli are defined as “meaningful objects that include higher order scene structure, semantics, context or task-related factors” (Cerf et al. 2008, p.1). They have proven to be of critical importance in studying search tasks (e.g., Henderson and Hollingworth 1999; Neider and Zelinsky 2006) and contextual effects (e.g., Torralba et al. 2006). The content of listings is an important high-level stimulus that influences the adaptive information search process, especially when the perceptual features of listings do not substantially differ from each other. The decision about which listing to inspect next might be influenced by the content of other listings the consumer has already inspected. These listings create an information-rich semantic environment where each listing competes for consumers’ scarce attention. Therefore, to better understand the impact of the competitive landscape on adaptive information search, the textual information acquired from previously viewed listings and the content of the target listing (if re-inspected) should be taken into account. Yet given the undisputed role played by high-level stimuli, the semantic environment is often overlooked in examining the information search behaviors on the SERP. For instance, Ghose and Yang (2009), Yang and Ghose (2010) focused on the impact of “keywords” specified by the advertisers, rather than the listing content, on consumer search and purchase behavior. Rutz and Trusov (2011) studied the impact of an ad’s content on click-through and purchase decisions; however, they did not take the content of other listings shown on the SERP into account. Park and Park (2012) analyzed the competing advertisements and consumers’ click and stop decisions, yet limited their content analysis to the “number of products offered” and “price discount offered” in the sponsored sections. Our study examines a broader range of semantic factors and considers the content of the entire SERP.

Extracting semantic information from listings by itself presents a significant challenge. In the extreme, each word or combination of words can be treated as a unique factor. The downside of this approach is dimensionality of the problem – the space formed by unique words can easily become unmanageably large. We follow the approach proposed by Rutz et al. (2011), in which dimensionality reduction is achieved by creating a set of semantic factors and each factor is associated with multiple words.

---- Insert Figure 6 about Here -----

On the top level of our hierarchy (Figure 6), there are two broad categories of semantic factors: *descriptive information* that describes the product, and *transactional information* that helps consumers find information about purchasing process. According to the marketing 4Ps, we then subdivided these two categories into: *price, promotion, place (store),* and *product information*. Product information is further divided into *attribute, quality,* and *brand information*. Finally, for each category, we build a list of words (cognitive synonyms and hyponyms) that reflect the conceptual-semantic and lexical relations with that category.

Consumers trade off the costs and benefits of inspecting listings on the SERP. Transactional information, such as price and promotion, is mostly in numeric format and is meaningful through comparison. Alternatively, descriptive information (product attribute and quality) of a certain product may not be substantially different across listings and may require further cognitive processing. Therefore, transactional information is easier to compare and evaluate than descriptive information; looking for a listing that contains more transactional information will generate utilities at a lower evaluation cost compared to inspecting the listing that focuses on descriptive information. Cumulatively viewed listings may unconsciously prime consumers with certain search goals and direct the search towards certain types of information. More transactional information viewed on the SERP will prime consumers with a price/promotion-oriented goal, where evaluating as many options (listings) as possible would be preferred to find the "best deal." Therefore, we predict that more cumulatively viewed transactional information will encourage consumers to inspect more listings. However, viewing more descriptive information will prime consumers with an attribute/quality-learning goal. Because the amount of attribute and quality information consumers need to learn about a product is limited, inspecting several relevant listings would suffice. Thus, we predict that more cumulatively viewed descriptive information deters consumers from inspecting additional listings.

To summarize, intrinsic section preference, low-level stimuli, and high-level stimuli influence the information search process, and decisions regarding which section or listing to inspect are interrelated over time. We propose that at each inspection decision point on the SERP, the utility of a particular listing is formed by *static* and *dynamic* components. The *static utility* (i.e., stays constant over search process) includes intrinsic section preferences, as well as the listings' ranking and content (in re-inspection). The *dynamic utility* changes as the decision making progresses and may come from (1) the lag effect of intrinsic section preference, i.e., "section stickiness," and (2) the content of previously inspected listings. This updating process is driven by the lexical and visual properties of the inspected sections and listings, which can be identified through eye-tracking data. The information search behavior is thus believed to be interdependent: the section or listing viewed previously influences subsequent inspection decisions. The basic premise of this proposition is the adaptive decision process. When making decisions, consumers incorporate new information, develop new standards, and adapt subsequent information search behaviors. Their preferences are constructed over time (Bettman et al. 1998) and strongly influenced by contextual factors (Gigerenzer and Selten 2001; Simonson 1989).

MODEL

While there might be different ways to model visual inspection processes, for the objectives of this study we found "path" representation to be a suitable formalization. Marketing literature offers several approaches to model path data in physical and virtual environments. Hui et al. (2009) developed an integrated individual level probability model of consumers' shopping path through the store. The key proposition is that each area within the store is associated with a certain attractiveness measure, and this measure is being updated as the consumer navigates through the store. The updated latent utility is used to calculate the visiting probability of the next step, which is similar to the "choose one out of *n*" choice problem. Van der Lans et al. (2008a) proposed that the saliency map directs attention to the visual target in the localization state, and selected objects are verified in the identification state. During this process, consumers' refixation strategies and their left-to-right/right-to-left zigzag systematic search strategies are updated after each fixation, while the perceptual feature of the screen remains constant. The navigation path across webpages has been modeled with a similar approach under the Information Foraging Theory framework (Pirolli and Card 1999). Fu and Pirolli (2007) proposed that after reviewing the webpage, consumers develop an updated assessment of the website's potential usefulness, thus adapting their page viewing strategies based on their ongoing evaluation of the website's utility and inspection cost. What is common among these methodologies is that researchers are able to infer the updated utilities of the alternatives (e.g., zones, categories, area on the shelf, webpages) with path data and then model subsequent decisions based on these updated assessments.

In line with these studies, the basic premise of our model is that the expected utilities of all listings are updated after each fixation and used as predictors for the inspection path on SERPs. Our empirical model is based on the proposition that a user's decision to inspect a particular section or listing is driven by an intrinsic section preference, as well as high and low-level stimuli, and these contextual factors update the listing's utilities. Given the heterogeneity of the inspection patterns, we model the inspection choice with a mixed multinomial logit model (MNL) with random coefficients, which supports unrestricted substitution patterns across alternatives and correlation in unobserved factors over time (Train 2003).

Let $s_{i,t}$ represents a discrete choice among S listings $s_{i,t} \in$ *(O1,…,O10, S1,…, S8, T1, T2, T3)* for consumer i at fixation point t. Let U_{ist} represents the utility of listing s for consumer i at fixation t. We define the consumer's utility of viewing a listing as follows:

$$\begin{aligned} U_{ist} = \beta_{0,i,j} + \beta_{1,i,j} STICK_{i,j,t} + \beta_{2,i} REP_{i,s,t} + \beta_{3,i,j} Rank_{s,j} + \beta_{4,i} REP_{i,s,t} \cdot TEXT_s + \\ \beta_{5,i} \cdot CUMTEXT_{i,j,t} + \beta_{6,i} \cdot Direction_{i,t} + \varepsilon_{i,s,t} \end{aligned} \quad , \qquad (1)$$

where:

- $\beta_{0,i,j}$ is the intrinsic preference of section j for consumer i that is unknown to researchers and contributes to *static* utilities. The section preference is embedded with the listing inspection decisions. Note that the right sponsored section (S) is used as the baseline category.

- $STICK_{i,j,t}$ is a dummy variable that captures the "stickiness" of section j at fixation t for consumer i. It equals one if section j was viewed at fixation $t-1$ for consumer i, and zero otherwise. This variable reflects the impact of the lag effect of section choice on subsequent inspection decisions. Parameters $\beta_{1,i,j}$ are set to be different across sections and across individuals.

This captures how intrinsic section preference *dynamically* influences the information search process.

- $REP_{i,s,t}$ is a dummy variable that captures the re-inspection of listing *s* at fixation *t* for consumer *i*. It equals one if listing *s* has already been viewed previously (up to fixation *t-1*) for consumer *i*, and zero otherwise. We assume that once the listing has been inspected, its content will be "remembered" for the subsequent comparison and evaluation. Since consumers do not always assess all listings available on the SERP prior to click through (Brumby and Howes 2003), we speculate that the previously viewed listing has a higher chance of entering the consideration set and being inspected again.

- $Rank_{s,j}$ represents the rank of listing *s* in its corresponding section *j*. Parameters $\beta_{3,i,j}$ are set to be different across sections and across individuals, since we expect to see the position (rank) effect varies across S, O, and T, and across consumers. This is a low-level stimulus that contributes to *static* utilities[2].

- $TEXT_s$ is a vector of textual information of listing *s* constructed following the hierarchy presented in Figure 6. The interaction term $REP_{i,s,t} \cdot TEXT_s$ reflects the semantic impact of listing *s*, if the listing *s* has been viewed before fixation *t* by consumer *i*. Parameters $\beta_{4,i}$ are set to be different across individuals.

- $CUMTEXT_{i,j,t}$ is a vector of cumulatively viewed textual information of section *j* at listing fixation *t* for consumer *i*. It reflects the influence of the competitive semantic landscape generated by the previously viewed listings on subsequent inspection decisions. The

[2] To allow for potential non-linearity in position effect we tested our model with listing rank coded as dummy variables. The results largely point to the linear reltaionship between the rank and the inspection probabilty of the listing. Therefore, we develop a more parsimonious model with a linear ranking effect within each section. Also see Table 2 for descriptive stats.

cumulatively viewed textual information is calculated as the total number of words that have been viewed up to the listing inspected at fixation *t-1* in section *j* for consumer *i*. Parameters $\beta_{5,i}$ are set to be different across individuals. This is a high-level stimulus that *dynamically* influences the information search process.

We also include a control variable "$Direction_{i,t}$" to capture a top-to-bottom inspection pattern. If fixation *t* is below the fixation *t-1* in terms of screen coordinates, it is coded as one, zero otherwise. Error term $\varepsilon_{i,s,t}$ follows a double exponential distribution. Table 1 presents a summary of these variables.

---- Insert Table 1 about Here -----

The probability of inspecting listing *s* at fixation *t* for consumer *i* is specified as:

$$P_{it}(s) = \frac{\exp(U_{ist})}{\sum_{s' \in S} \exp(U_{is't})} \tag{2}$$

To capture heterogeneity among consumers, we allow parameters Θ_i $\{\beta_{m,i}\ m = 0 \sim 6\}$ to follow multivariate normal distribution: $\Theta_i \sim MVN(\overline{\Theta}, \Sigma)$. This is a full random coefficient, mixed GLM (multinomial logit) model. The log likelihood function can be written as:

$$\mathrm{L}(\mathrm{s},\Theta) = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \ln\left\{ \int_{-\infty}^{\infty} \phi\left(\Theta_i \mid \overline{\Theta}, \Sigma\right) P_{it}\left(s_{i,t} \mid \Theta_i\right) d\Theta_i \right\}, \tag{3}$$

Where $P_{it}(\cdot)$ is defined in equation (2), $\phi(\cdot)$ is the density function of Θ_i (normal distribution), and T_i is the total number of fixations a consumer had. The likelihood cannot be estimated directly because there is no closed form. The typical estimation procedure for this type of mixed model is simulated likelihood (Bhat 2001): we draw a value of Θ_i, Θ_i^r, from distribution $\phi(\Theta_i \mid \overline{\Theta}, \Sigma)$, and insert into the log likelihood function (3), resulting in value $L(\Theta_i^r)$.

Then, we repeat this process R (1000) times, and take the average of the log likelihood value

($\frac{1}{R}\sum_{R=1}^{R} L(\Theta_i^r)$) as the approximate log likelihood $L(s,\Theta)$ in equation (3).

EXPERIMENT AND DATA COLLECTION

We conducted a lab experiment in which 39 participants (undergraduate business students) were asked to perform a series of online searches and make purchase recommendations to a friend. Each participant was successively presented with shopping objectives that came from a set of ten consumer products commonly purchased on the Internet and reasonably appealing to our subject pool (e.g., "Colored contact lenses," "GPS navigation systems," "Poker chip sets"). The order of these ten products was randomized for each participant to avoid the possible impact from the sequence of search tasks. The participants were instructed to start each new search on Google's website and use as much time as needed to come up with a good product recommendation. Their eye movements were recorded. An example of a specific search task (e.g., GPS navigation systems) reads as follows:

Your friend would like to buy a GPS system that can be carried into a car for navigation and mapping. • *At which site should your friend buy this?* • *What is the name of the product?* • *What is the price you found?* *Use Google's search engine to do your search.*

Note that in our procedure we do not rely on preset ("canned") search result pages, trying to keep subjects' online shopping experience as close as possible to the natural settings. Indeed, with canned pages it can be hard to match SERP content with a particular search term used by the participant in each individual case. Any discrepancies between the results returned to the subject and the search term used may affect visual inspection process and search behavior. Our setup assures that (a) searches have "transactional" focus (instead of "informational" or "navigational" as in Guan and Cutrell 2007), (b) subjects are roughly in the same stage of the shopping cycle, and (c) there is natural variation in SERP content which results from variation in search terms used by the subjects.

The experiment was conducted with binocular Tobii® infrared corneal reflection eye-tracking equipment[3], which collects eye movement with minimum obtrusiveness and allows insights into the individual cognitive process on the SERP. Cameras in the rim of the monitor track the position of the eyes and the head, allowing continuous correction of position shifts. Measurement precision of the eye-tracking equipment was better than 0.5 degree of visual angle, and measurements were taken with a frequency of 35Hz. Instructions and stimuli were presented on a 21-inch LCD monitor in full-color bitmaps with a 1,280 x 768 pixel resolution. The specific eye-tracking equipment applied leaves participants free to move their heads, and closely mimics real-life situations in which consumers make decisions on the SERP.

Eye-movements consist of two main components: fixations and saccades. Fixations are brief moments (around 200-500 ms) where the eye is still and an area of a visual stimulus is projected onto the fovea for detailed visual processing (Rayner 1998). Fixations have been shown to be valid indicators of elementary information processing (e.g., Liechty et al. 2003; Russo and Leclerc 1994; Reutskaja et al. 2011; Shi et al. 2012; Teixeira et al. 2010) and thus well suited to monitor information searches on SERPs. Their duration, however, is largely beyond cognitive control. Saccades are ballistic movements (20-40 ms) that serve to redirect the line of sight to a new location, or re-fixate on the current one, up to 3 to 4 times per second. Visual processing is suppressed during saccades (also known as visual saccadic suppression), so

[3]See detailers at: http://www.tobii.com/en/eye-tracking-research/global/products/hardware/tobii-t60t120-eye-tracker/

that the gap in visual perception is not discernible for viewers. Saccades from one location on an information display to another thus form a semi-continuous measure of information acquisition activity during decision making.

SERP Content Analysis

To understand what listings have been inspected on the SERP page, we need two pieces of information – screen coordinates of each eye fixation and screen coordinates of each textual object (listing) presented to the subject during the experiment. The standard software that comes with the Tobii® eye-tracking equipment provides only the first piece. Unfortunately, the software does not store raw HTML files or allow extracting textual objects under gaze locations. All of these software limitations present serious challenges for data collection. Coding individual pages from screen-captured images manually would be too labor intensive given that we used real SERPs produced by Google in response to subjects' queries, rather than presets typical to extant eye-tracking studies. To overcome these obstacles we developed our own software that, while working in conjunction with the Tobii® tools, allowed us to capture SERPs (i.e. raw HTML files), extract content, identify pixel-level locations of all textual elements on each page, and map textual elements to the eye-tracking data (Figure 7).

---- Insert Figure 7 about Here -----

Next, we categorized individual words for each listing in accordance with the proposed semantic hierarchy depicted in Figure 6. We conducted the textual categorization based on the procedure developed by Rutz et al. (2011). Firstly, using semantic factors defined in Figure 6, we "seeded" each category with a reasonable number of words that strongly represent this category. For instance, for the promotion category, we seeded it with the words like "discount," "sale," and "free"; for the quality category, we seeded it with words like "exclusive," "high-end," and "professional." Secondly, we used the WordNet – a large lexical electronic database for the English language (Miller 1995) – to identify synonyms and hyponyms for these words.[4] This process resulted in a group of words that were meaningfully related within a category. Then, we reviewed the list of classified keywords, expanded the list of synonyms as needed, and repeated the first and second steps.[5] Clearly, this procedure does not allow us to classify every possible word that occurs in the listings. Rather, we focus on a subset of words that can be categorized into predetermined semantic factors proposed in our conceptual framework. Further research is needed to explore other semantic categories and their possible impact on visual inspection path.

Equipped with the above procedure, we parsed all the listings and assigned individual words into appropriate semantic categories. Table 2a presents average counts of textual information for each listing, across ten search tasks.

---- Insert Table 2a about Here -----

In Table 2b, we aggregate these counts across search tasks and report averages for three sections of the SERP: top sponsored (T), organic (O) and right sponsored (S) sections. Across all SERPs, the count of price information is significantly higher in the S (.634) and T (.642) sections than the O section (.378, S versus O: $p=.007$; T versus O: $p=.080$); and the count of promotion information is significantly higher in T (1.618) than O (1.084, T versus O: $p=.062$); O (5.213) has significantly more attribute information than T (1.977, O versus T: $p<.000$) and S (1.635, O versus S: $p<.000$), as well as quality information (O (1.942) versus S (1.233): $p=.004$; O versus

[4] WordNet® is a popular tool widely used in computational linguistics and natural language processing. It groups nouns, verbs, adjectives and adverbs into sets of cognitive synonyms (synsets), each expressing a distinct concept. Access to the database can be fully automated using an application programming interface (API).
[5] Due to the space consideration we do not decsribe the employed word classification procedure in detail. Rather we refer interested reader to the Rutz et al. 2011, "Web Appendix C – Extracting Semantic Information from Keywords" where this approach is discussed in-depth.

T (1.110): *p=.002*). Store and brand information is not significantly different across the three sections.

---- Insert Table 2b about Here -----

Descriptive Analysis of Eye Fixations

Since the number of listings displayed by the search engine in the top sponsored section (T) varies from one search to another, we only kept the SERPs that have three listings in the top sponsored section and eight listings on the right sponsored section, so that all pages used for the analysis have the same layout. Overall, 1,746 fixations across 154 unique SERPs were recorded.[6] Table 3 shows the total number of fixations each listing received. In general, higher ranked listings received more attention across the three sections.

---- Insert Table 3 about Here -----

On average, consumers spent 11.23 seconds (*sd*=9.76) before making a click and viewed 7.18 (*sd*=3.82) out of 21 listings. They inspected 4.95 (*sd*=2.83) listings in the O section, 1.31 (*sd*=.92) listings in the T section, and .92 (*sd*=1.71) listings in the S section. We have also calculated empirical transition probabilities across sections (Table 4) and across listings (Table 5). As shown in the Markov transition matrix of section inspection decisions in Table 4, consumers exhibit significant stickiness within the current section (O: .843, S: .754, T.358).

---- Insert Table 4 about Here -----

The transition matrix for all listings is presented in Table 5. High transition probabilities in the block diagonal also suggest that all three sections demonstrate a strong "stickiness" effect. High switching probabilities from T1 and T3 to O1 reflects the natural top-to-bottom reading

[6] We treat multiple consecutive fixations within the same listing as a single fixation.

tendency. Yet the transition matrix also shows that this is not the only inspection pattern; for example, the probability of going "up" from O1 to T3 is quite high at .364.

---- Insert Table 5 about Here -----

In the following section, we provide details of the computational cognitive model that was used to captures the consumers' dynamic listing inspection decisions.

MODEL RESULTS

In this section, we present model estimation results and discuss managerial implications. Table 6 features three sets of results with Model 1 being our main model discussed in the section above; Model 2 – a simplified version of Model 1 with all *Descriptive* and *Transactional* semantic variables combined into two predictors; and Model 3 - a base model that does not account for semantic effects. Based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), Model 1 is the best model out of the three supporting our proposition that semantic predictors help in explaining consumer visual inspection decisions on the SERP. Hence, in most of the following discussion we refer to the results of Model 1, unless explicitly noted otherwise. [7]

Listing Inspection Choice

In line with our prediction, intrinsic section preference plays an important role in the information search process. Consumers show highest preference for listings in the organic section (Baseline for O: β=1.671, p<.000, sd = .079), followed by the listings in the top sponsored section (Baseline for T: β=1.559, p<.000, sd = .128). Although the baseline inspection propensity of the top sponsored section is lower than that of the organic section, the section

[7] Due to a scarcity of fixations at lower positions, we exclude the bottom three listings in the organic section and the bottom four listings in the right sponsored section from our analysis. We ended up with 14 listings in total.

stickiness is higher (Stickiness for T: β=1.099, p=.001, sd = .304 vs. Stickiness for O: β=.941 p=.005, sd= .151), which may be interpreted as consumers who are open to sponsored advertising tend to explore the top section more diligently compared to the organic section. Taking these results together, we conclude that the top sponsored section, which gets consumers' attention, is indeed a desirable area on the SERP. In addition, top sponsored listings create a strong stickiness effect on the scan path that encourages consumers to view more advertisements within the section.

Low-level stimuli, i.e., the ranking of listings, also influence the inspection probabilities: lowering the rank of a listing in the organic and top sponsored sections will significantly decrease the probability of the listing being viewed (Rank in O Section: β= -.080, $p<.000$, sd = .036; Rank in T Section: β= -.107, p<.000, sd = .042; Rank in S Section: β= -.075, $p=.102$, sd = .043). The negative impact of ranking in the top sponsored section is the strongest among the three sections, followed by that in the organic section. This result suggests that the benefit (loss) of getting (losing) one position rank for different sections is not the same and is more substantial for top sponsored results. The top-to-bottom reading tendency manifests itself through "Direction" covariate ($\beta=.263$, $p=.046$, $sd = .104$): the probability of moving down the page from the currently inspected listing is higher than moving upwards from the current position.

High-level stimuli, i.e., semantic environment, significantly influence the inspection patterns on SERPs. The results indicate that both the semantic environment and the textual information of the target listing affect the listing re-inspection decisions.

The content of the target listing exerts its impact through repeated listing inspection. Once the listing has been inspected, it has a higher likelihood of being inspected again (Repeat Dummy: β=.132, p=.001, sd = .033). We speculate that after viewing the listing, consumers use the listing's content information in subsequent evaluations. Increasing the amount of descriptive information in the target listing (Model 2 – Repeatedly Viewed Descriptive: β= -1.021, p=.002, sd = .439), especially the attribute information (Repeatedly Viewed Attribute: β= -1.546, p=.002, sd = .451), significantly decreases the probability of the target listing being inspected again. Having more transactional information in the target listing (Model 2 – Repeatedly Viewed Transactional: β=1.740, p=.008, sd = .611), especially price (Repeatedly Viewed Price: β=2.195, p=.045, sd = .602) and store information (Repeatedly Viewed Store: β=1.539, p=.019, sd = .404), significantly increases the probability of repeated inspections. A likely reason for repeated inspections is to compare information. Most transactional information (price, promotion) can be easily evaluated through numeric comparison while this might not the case with descriptive information (attribute). Consumers trade off the costs and benefits of inspecting additional listings when making (re)inspection decisions on the SERP. The cost of inspecting additional listings with transactional information is lower than that of listings with descriptive information. Therefore, listings with more transactional information tend to get more repeat visits.

The competitive landscape, reflected by the cumulatively viewed textual information, also affects the scan path on the SERP. Since cumulatively viewed textual information is changing as information search progresses, the semantic environment that consumers face is dynamic in nature. Our results show that more transactional information viewed (Model 2 – Cumulatively Viewed Transactional: β=.834, p=.068, sd = .217), especially the price information (Cumulatively Viewed Price: β=.669, p=.020, sd = .211) and store information (Cumulatively Viewed Store: β=1.020, p=.098, sd = .409), will significantly increase the inspection probability of the target listing in that particular section (i.e., increase the section's attractiveness). However, cumulatively viewed attribute (Model 2 – Cumulatively Viewed Descriptive: β= -.303, p=.047, *sd* = .123) and quality (Cumulatively Viewed Quality: β= -.373, p=.060, *sd* = .105) information significantly decreases the inspection probability of the listings in the corresponding section. We speculate that the semantic content extracted from inspected listings unconsciously primes consumers with certain search goals and generates a momentum that directs the search towards certain types of information. Note that this is different from the conscious search goal reflected in the search query. Cumulatively viewed transactional information primes the consumer with an active price/promotion-oriented search goal. Such search momentum motivates consumers to find the "best deal" for the product, which requires them to inspect more listings, or ideally, to exhaust all possible alternatives. The semantic environment generated by cumulatively viewed descriptive information, however, primes consumer with an active attribute/quality-learning goal. The amount of attribute and quality information of a certain product consumers want to learn about might be limited, and they tend to reach a saturation point quicker with descriptive information than with transactional information.

---- Insert Table 6 about Here -----

To summarize, our results demonstrate that in contrast to on-the-spot, saliency based visual search, consumer's inspection decisions are dynamic and strongly intertwined with previous inspection path. This adaptive inspection pattern is driven by intrinsic section preference, bottom-up, low level screen perceptual features, and top-down, high level cognitive processes. We found that the consumers' inspection path is not uniformly top-to-bottom. Rather, scan paths are quite heterogeneous and cannot be simply explained by the top-to-bottom natural reading tendency. Inspection decisions are driven by intrinsic section preference as well as the section stickiness, and more importantly, the textual information of previously inspected listings. At each fixation, consumers assimilate new information and develop new standards for their inspection decisions based on the newly updated listing utilities. The competitive landscape of the SERP thus creates a dynamic, constantly changing choice environment.

From a practitioner's perspective, our results suggest that the amount of visual attention a particular listing gets from a consumer is not solely determined by the listing's rank, but is a function of the competitive landscape of the entire SERP. Hence, when setting a target position for a particular listing, SEM practitioners should account for semantic environment, as a listing's performance in a certain rank in one context may be quite different for the same rank in a different context. In the next subsection, we present a number of business scenarios and quantify the effects of listing's position and semantic context on listing's performance.

Managerial Implications

Optimizing performance of SEM campaigns is a quite elaborate and multifaceted process. There is a number of decision variables involved from keyword and bid amount selection (for paid search), to inbound link formation (for SEO) and landing page design. Clearly, the entire process is beyond the scope of this paper. Instead, we focus on one specific question, which nevertheless, directly relates to all SEM activities: How much of a consumer's attention a listing is likely to get if it is placed in a certain position in a given semantic context on the SERP? Being noticed is a prerequisite for getting clicked; therefore, the question is clearly of high importance to SEM practitioners.

It is well known that higher placements are typically more attractive, but also more costly (either in terms of the cost-per-bid in a paid search or SEO efforts in an organic search). The key proposition advocated in this paper is that the amount of attention the listing gets is a function of the competitive landscape. In some semantic contexts improving the rank may not be worth the effort, while in other contexts the benefits might be substantial. In addition, the content change in surrounding listings may influence the inspection probability of the target listing. Hence, before setting hard goals for a target position, it is advisable to assess the visual attractiveness of the position in a given context. Our model helps to address these questions.

Role of listing's position in a fixed semantic environment. To illustrate how the semantic context moderates the effect of a listing's position on a consumer's attention, we consider several SERPs of different competitive landscapes and calculate a listing's probability of being inspected in each of these contexts. We selected three sample SERPs: one has relatively balanced counts of descriptive and transactional textual information (denoted as "*balanced*"); the second has more descriptive than transactional textual information (denoted as "*descriptive oriented*"); and the third has more transactional than descriptive textual information (denoted as "*transactional oriented*"). Specifically, on the "balanced" screen, there are only eight more descriptive text elements than transactional text elements; on the "descriptive oriented" screen, there are 57 more descriptive than transactional text elements; one "transactional oriented" screen, there are 43 more transactional than descriptive text elements. Using the model developed in this paper, we calculated the probability of inspecting each listing on the corresponding SERP by exploring the space of possible visual inspection paths.[8] Next, within each section, we increased the target listing's rank by (a) one and (b) two units, and calculated the percentage changes in the inspection probabilities of the target listing. To illustrate the impact of intrinsic section preference, we also calculated the percentage changes in probabilities when we moved the first listing in the right sponsored section to the top sponsored section. The results are presented in Table 7.

[8] Probabilty of an inspection path (calculated as a product of conditional probabilities of all inspected listings) rapidly decreases in number of steps (inspections) and reaches e-07 after the 5th inspection. Thus, when calculating listing's inspection probability for a given SERP we consider all possible paths up to the length 5, ignoring longer paths.

On average across all three conditions, improving the rank of the target listing by one unit increases the likelihood of the listing's being inspected by 16.00% (*sd=.102)*. For two unit improvement, the increase is 34.73% (*sd=.207)*. The effect is even stronger if the target listing is in the sponsored section (one unit improvement: mean=22.95%, *sd=.103;* two unit improvement: mean=43.66%, *sd=.254*). In addition, when we moved the first listings in the right sponsored section to the top sponsored section, the inspection probabilities increased substantially (mean=387.10%, *sd=1.423*).

Importantly, the competitive landscape (semantic environment) has a strong influence on the magnitude of the ranking effect: the ranking effect in the case of the "descriptive oriented" SERP is much stronger than that of the "transactional oriented" SERP (average improvement: 93.65% versus 58.66%); while the ranking effect of the "balanced" SERP is in-between the two (average improvement: 67.93%). It is possible that the "transactional oriented" SERP creates a search momentum that focuses on transactional information and makes consumers more price/promotion conscious. To find the "best deal," consumers are encouraged to review more listings on the screen, and thus the ranking of the listings is less important in getting consumer's attention. However, the "descriptive oriented" screen facilitates a search momentum that centers on sampling product descriptive information. Since there is not a significant difference among listings, the higher ranked listings are more likely to be inspected based on consumers' natural top-to-bottom reading habit. As consumers are getting saturated with descriptive information about the product, they are less likely to go further down the screen. Therefore, having a higher ranking in this case is critical to the firm.

---- Insert Table 7 about Here -----

Role of a semantic context. While the example above demonstrates how the amount of attention that each rank gets varies with the semantic composition of the entire SERP, next we explore how the semantic content of an individual listing may affect visual inspection probabilities of other listings. For managers, it is important to understand how the content change in surrounding listings affects the inspection likelihood of their own listing. Assuming the advertiser positioned right above your listing has changed the ad copy to include price discount information. What are the implications in terms of the inspection probability for your listing? Should you rush in trying to outbid your competitor to obtain a higher position? Or competitor's change to the ad will not have a dramatic impact on your listing?

To illustrate these effects, we increase the counts of two text categories ("attribute" as descriptive information and "price" as transactional information) in the target listing by one unit. Then, we calculate the percentage changes in terms of the inspection probabilities of the other listings on the SERP. The resulting changes in inspection probabilities are presented in Table 8.

---- Insert Table 8 about Here -----

As Table 8 depicts, for example, when we increased the count of attribute information by one unit for listing O1, all the other listings in the organic section were negatively affected (percentage changes range from -6.39% to -23.42%,). In addition, this content change drove attention away from the current section (mean= - 12.08%). However, increasing the count of price information of O1 by one unit increased the inspection probabilities of all the other listings in the organic section (percentage changes range from 5.57% to 20.43%) and drew attention from other sections to the current section (mean= 10.24%). Because of the natural top-to-bottom reading tendency, the target listing is likely to exert the strongest influence on the listing that is immediately below it when there is a content change. For example, on average, the percentage change in the inspection probabilities of the listing immediately below the target listing was -14.5% (*sd=.061*) when increasing the attribute information of the target listing by one unit, and the number was 12.93% (*sd=.065*) when increasing the price information by one unit.

To visualize the impact of changes in the target listing on the others within and outside of the corresponding section, we generated several area maps (selected plots are shown in Figure 8a and 8b; also see Online Appendix B). As we can see, the listing immediately below the target listing was affected most. For the other listings within the section, the magnitude of the impact decreased as the distance increased between the listing and the target listing.

---- Insert Figures 8a and 8b about Here -----

DISCUSSION

To the best of our knowledge, this is the first study that explores the impact of the semantic environment on consumers' information search process on search engine results pages. We found that consumers exhibit a variety of inspection patterns; and top-to-bottom visual inspection sequence does not always hold. For example, the probability of reaching the 1st listing in the organic results (O1) by strictly following a top-to-bottom inspection path (i.e., T1 → T2→ T3→O1) is only .173. However, if all possible paths that may eventually lead consumers to O1 are considered (e.g., T1 → S1 → O5 → O1; or O3 → O1), the probability of reaching O1 is about 4 times higher at 0.703. Besides ranking and intrinsic section preference, previously viewed textual information, listing content, and section stickiness all influence the scan path on SERPs. Hence, to better understand the behavioral mechanism of the SERP inspection, it is important to: (1) consider the entire screen as a competitive landscape that influences inspection decisions; (2) incorporate both the perceptual features of the listings as well as a semantic environment that directs attention; (3) keep in mind that from the consumer's perspective, the choice environment of the SERP keeps changing as the consumer progresses through the page, and subsequent visual inspection decisions are based on previously viewed listings. These three aspects have been often overlooked in the extant SEM studies.

We took advantage of recent developments in technology and studied the dynamic decision making process using eye-tracking equipment. We mapped textual information that appear on the SERP to eye-tracking data to analyze the semantic impact, i.e., the content of target listings and of previously viewed listings, on consumers' information search behavior.

Our study offers a number of substantive findings. In line with existing eye-tracking studies, we found that the top sponsored section gets a substantial amount of visual attention, while the right sponsored section gets relatively little consideration. Moreover, in contrast to the right sponsored section, the top sponsored section shows a strong stickiness effect – once consumers "enter" the top sponsored section, they are likely to inspect more than one listing within the section before switching to other sections. Finally, the transition from the top sponsored section to organic results is much more likely than the transition to the right sponsored section. While these findings *per se* might be not particularly surprising, they have some important implications for paid search practitioners and academics who employ predictive models to link ad rank with ad performance. First, it might be advisable to treat the effects of rank on ad performance in top sponsored and right sponsored sections differently (e.g., by having fixed effects for each section, or even each listing's position).[9] Second, caution should be taken when assuming adjacency of listings in positions 1 through 4. This is of a particular concern

[9] Technically, this might be difficult since Google's AdWords service does not report if the ad was shown in the top or right sponsored section. Nevertheless, there are some workarounds available to practitioners.

when a sequential listings' inspection mechanism is assumed by the modeler (e.g., in studying competitive effects).

We also found a strong influence of the semantic environment on the dynamic information search process. Specifically, both the content of the target listing and the cumulatively viewed textual information of the current section affect the (re-)inspection probability of the target listing. Price and store information of the target listing are likely to elicit repeated inspections, while the attribute information of the target listing could produce an opposite result. We speculate that this might be due to the fact that transactional information is mainly numerical and thus easier to compare. In addition, price and promotion information is more meaningful through comparison. Generally, as more attribute and quality information are inspected in the target section, consumers are less likely to remain in the same section and explore more listings. Cumulatively viewed transactional information (price and store) in the section, in contrast, draws attention away from the other sections and creates a stickiness effect in the current section. Furthermore, adding attribute information to the listing may decrease the inspection probability for other listings in the same section, while adding price information creates a reverse effect. Cumulatively viewed descriptive information (attribute and quality) creates a search momentum that primes consumers with a product learning (descriptive) goal, making it unnecessary to exhaust all listings on the SERP since inspecting several relevant listings would suffice.

Understanding the impact of the semantic environment on information search behaviors has direct implications for managers. To gain consumers' scarce attention, it is imperative for managers to choose a listing's position strategically based on a composition of the entire screen and close monitoring of the competing listings. Our results suggest that fitting the target listing into a section with more transactional information is more likely to draw consumers' attention to the listing than placing it in a section rich in product attribute and quality information. Another issue pertaining to managers is to how assess the value of a given position in the search results. Intuitively, higher ranked listings receive more attention; however, as we show in this paper, rank effects vary across different screen compositions. In SEM, higher ranks are typically achieved either through search engine optimization (SEO) or higher bidding. Since both might be quite costly to the firm, the objective for managers is to find an optimal trade-off between the cost associated with priority positions and the incremental revenue gained with higher ranking. Our model allows us to assess how improving the ranking in a given semantic context translates into increased visual attention received from the customers.

We see a number of potential extensions of our work. In this paper we do not model click-through behavior, mainly due to the relatively small number of clicks observed in our dataset to make statistical inference feasible. While our focus is primarily on the visual inspection patterns, future research could link the click-through decisions with the scan path and study how it is interrelated and affected by high and low-level stimuli. For this kind of study, however, it would be necessary to employ a considerably larger subject pool to assess the effects reliably, which, with the eye-tracking research, could become expensive. Another potential extension to our study would be to incorporate subsequent visual inspections of the same SERP. In our experiment, some consumers return to the SERP after clicking on their first selected listing and continue inspecting the other listings shown on the page. Future research could address this behavior. Also, in the presented framework we do not model fixation duration. Wedel and Pieters (2000) suggested that the duration of fixations has an approximately constant termination hazard, and therefore might not add much additional insight over an analysis of fixation counts only. In line with their work, our exploratory analysis shows no significant correlation between fixation duration and consumers' click-through decision conditional on the listing's inspection. Nevertheless, future research may look at how semantic landscape influences inspection duration for the entire SERP and incorporate duration component for modeling "blended" search that include rich media elements (e.g., embedded YouTube videos). Finally, information overload problem in the information-rich search engine results page, optimal allocation of sponsored and organic search spaces, interactions between search queries and inspection patterns, and state-dependent model for click and inspection choices, are all promising areas for further exploration.

We believe that our work makes an important contribution to the marketing literature by being the first to look at visual inspection paths of search engine results pages and highlighting the importance of the semantic competitive landscape in driving consumers' attention. SEM has become a clear leader among tools available to internet marketing practitioners. Equipped with eye-tracking, now we are able to gain unique insights into micro-level decision making processes on search engine websites. It is of both academic and managerial interests to further our understanding of the impact of contextual factors on dynamic information search behavior, as well as on search engine marketing.

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Table 1: Summary of Variables in the Model

Covariates		Description
Intrinsic Section Preference	$\beta_{0,i,j}$	• Intrinsic preference of the section *j* for consumer *i* (contributes to *static* utilities)
	$STICK_{i,j,t}$	• Dummy variables that capture the "stickiness" of section *j* at fixation *t* for consumer *i* (contributes to *dynamic* utilities)
Low Level Stimuli	$REP_{i,s,t}$	• Dummy variables that capture the re-inspection of listing *s* at fixation *t* for consumer *i* (contributes to *dynamic* utilities)
	$Rank_{s,j}$	• Rank of listing *s* in its own section *j* (contributes to *static* utilities)
High-level stimuli	$REP_{i,s,t} \cdot TEXT_s$	• Semantic impact of listing *s*, if the listing *s* has been viewed before fixation *t* by consumer *i* (contributes to *static* utilities)
	$CUMTEXT_{i,j,t}$	• Cumulatively viewed textual information of section *j* at listing fixation *t* for consumer *i* (contributes to *dynamic* utilities)
Control Variable	$Direction_{i,t}$	• Control variable that captures the natural top-to-bottom reading tendency

Table 2a: Summary of Screen Features (Unit: count-per-listing)

	Semantic Categories					
Search Task	**Promotion**	**Price**	**Store**	**Attribute**	**Quality**	**Brand**
Subscription	.524	2.810	.952	1.857	1.143	.000
Poker Chip	.645	1.319	2.205	2.919	1.844	.070
Sopranos DVD	.560	1.113	2.143	4.295	1.533	.063
GPS	.357	.958	1.298	6.649	1.482	1.095
iPhone	.469	.956	1.680	3.439	1.184	.483
Contact Lenses	.356	1.376	1.639	1.887	1.316	.378
Razr Battery	.737	.882	1.712	2.762	1.341	.028
Shot Glasses	.378	.974	1.672	2.601	2.743	.024
Show Ticket	.394	1.249	1.930	3.379	1.048	.050
USB Flash Drive	.714	1.229	1.590	4.086	1.895	1.552

Table 2b: Summary of Section Features (Unit: count-per-listing)

Semantic Group	Organic (O)	Right Sponsored (S)	Top Sponsored (T)
Price	.378	.634	.642
Promotion	1.084	1.415	1.618
Store	1.938	1.461	1.420
Attribute	5.213	1.635	1.977
Quality	1.942	1.233	1.110
Brand	.640	.097	.192

Table 3: Listing Rank and Number of Fixations (w/o re-fixations)

Rank	Organic (O)	Right Sponsored (S)	Top Sponsored (T)
1	226	53	167
2	189	48	157
3	153	36	111
4	127	31	
5	117	25	
6	104	14	
7	93	10	
8	35	9	
9	28		
10	13		

Table 4: Transition Matrix for Three Sections

		To		
		Right sponsored section (S)	**Organic section (O)**	**Top sponsored section (T)**
From	**Right sponsored section (S)**	.754	.196	.050
	Organic section (O)	.034	.843	.122
	Top sponsored section (T)	.045	.597	.358

Table 5: Transition Matrix for All Listings

		To																				
		O1	**O2**	**O3**	**O4**	**O5**	**O6**	**O7**	**O8**	**O9**	**O10**	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**T1**	**T2**	**T3**
From	**O1**	0	0.448	0.057	0.011	0.011	0.015	0	0.004	0	0	0.008	0.019	0.004	0.008	0	0	0.004	0	0.011	0.034	0.364
	O2	0.300	0	0.444	0.074	0.008	0.012	0.021	0.004	0	0.004	0.016	0.021	0	0	0.004	0	0	0	0.008	0.021	0.062
	O3	0.066	0.346	0	0.423	0.071	0.027	0.016	0	0	0	0.005	0.005	0.005	0.005	0.011	0	0	0	0	0.011	0.005
	O4	0.053	0.046	0.328	0	0.443	0.076	0.023	0.008	0	0	0	0	0.008	0	0	0	0	0	0	0	0.015
	O5	0.025	0.057	0.049	0.205	0	0.508	0.074	0.016	0	0	0.008	0.016	0.008	0.008	0	0	0	0	0.016	0	0.008
	O6	0.028	0.046	0.019	0.028	0.343	0	0.417	0.046	0	0.009	0	0.009	0.009	0	0	0	0	0	0.019	0.019	0.009
	O7	0.025	0.076	0.025	0.025	0.063	0.278	0	0.367	0.051	0.013	0	0	0.013	0.013	0	0	0	0	0.025	0.013	0.013
	O8	0	0	0.043	0.022	0	0.022	0.261	0	0.522	0.087	0.022	0	0	0	0	0	0	0	0.022	0	0
	O9	0	0.063	0	0	0.031	0	0.063	0.156	0	0.656	0	0	0	0	0	0.031	0	0	0	0	0
	O10	0	0.154	0.038	0	0.115	0.077	0	0.154	0.231	0	0.038	0	0.038	0	0	0	0.038	0	0	0.038	0.077
	S1	0.079	0.053	0.079	0	0.026	0	0.026	0	0	0.026	0	0.500	0.026	0.105	0	0.026	0	0	0	0	0.053
	S2	0.021	0.021	0.021	0	0.063	0.021	0	0	0	0	0.333	0	0.354	0.021	0	0.021	0	0	0.042	0.042	0.042
	S3	0	0.034	0.034	0	0.034	0	0.034	0	0	0	0.172	0.310	0	0.276	0.069	0.034	0	0	0	0	0
	S4	0	0.042	0	0.042	0	0.042	0	0	0	0	0.083	0.083	0.125	0	0.458	0.042	0.042	0	0	0	0.042
	S5	0.050	0.050	0.050	0	0	0.050	0	0	0	0	0.050	0	0.050	0.300	0	0.300	0.100	0	0	0	0
	S6	0	0	0	0	0	0	0	0	0	0	0	0.091	0	0	0.273	0	0.455	0.182	0	0	0
	S7	0	0	0.143	0.143	0	0	0.286	0.143	0	0	0	0	0	0.143	0	0.143	0	0	0	0	0
	S8	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0.500	0	0	0	0	0	0
	T1	0.241	0.093	0.056	0.037	0.019	0	0	0	0	0	0.074	0.037	0	0	0	0	0	0	0	0.111	0.333
	T2	0.171	0.071	0.043	0.014	0	0.029	0	0	0	0	0.014	0.014	0	0	0	0	0	0	0.157	0	0.486
	T3	0.522	0.145	0.043	0.016	0.005	0.005	0.005	0	0	0	0.022	0.011	0	0	0	0	0	0	0.059	0.167	0

Table 6: Model Estimation Results

Model 1			Model 2			Model 3	
Covariates	**Coef (S.D)**	**P-value**		**Coef (S.D)**	**P-value**	**Coef (S.D)**	**P-value**
Baseline for O	**1.671(.079)**	.000	Baseline for O	**1.887 (.063)**	.000	**1.973 (.055)**	.000
Baseline for T	**1.559 (.128)**	.000	Baseline for T	**1.214 (.247)**	.000	**1.266 (.354)**	.001
Stickiness for O	**.941 (.151)**	.005	Stickiness for O	**.618 (.175)**	.021	**.761 (.179)**	.000
Stickiness for T	**1.099 (.304)**	.000	Stickiness for T	**.947 (.299)**	.002	**1.196 (.167)**	.000
Repeat dummy	**.132 (.033)**	.001	Repeat dummy	**.350 (.143)**	.001	**.294 (.095)**	.003
Rank in O section	**-.080 (.036)**	.000	Rank in O section	**-.089 (.035)**	.000	**-.084 (.028)**	.003
Rank in S section	-.075 (.043)	.102	Rank in S section	-.045 (.089)	.121	.058 (.042)	.158
Rank in T section	**-.107 (.042)**	.000	Rank in T section	**-.132 (.035)**	.000	**-.126 (.038)**	.001
Direction (top-to-bottom)	**.263 (.104)**	.046	Direction (top-to-bottom)	**.233 (.094)**	.039	**.241 (.082)**	.004
Repeatedly viewed attribute	**-1.546 (.451)**	.002	Repeatedly viewed descriptive	**-1.021 (.439)**	.002		
Repeatedly viewed promotion	.542 (1.037)	.973	Repeatedly viewed transactional	**1.740 (.611)**	.008		
Repeatedly viewed price	**2.195 (.602)**	.045	Cumulatively viewed descriptive	**-.303 (.123)**	.047		
Repeatedly viewed store	**1.539 (.404)**	.019	Cumulatively viewed transactional	**.834 (.217)**	.068		
Repeatedly viewed quality	-1.354 (1.023)	.225					
Repeatedly viewed brand	.424 (.915)	.812					
Cumulatively viewed attribute	**-.288 (.092)**	.038					
Cumulatively viewed promotion	.797 (1.011)	.752					
Cumulatively viewed price	**.669 (.211)**	.020					
Cumulatively viewed store	**1.020 (.409)**	.098					
Cumulatively viewed quality	**-.373 (.105)**	.060					
Cumulatively viewed brand	.068 (.219)	.368					
AIC		***11328.26***			***11810.19***		***12707.64***
BIC		***11560.52***			***11953.97***		***12807.18***

Note: the bold font indicates that the parameter is statistically significant (please, refer to p-values).

Table 7: Moderating Role of Semantic Content in Rank/Attention Relations

BALANCED (Screen is balanced between transactional and descriptive text)											
	Organic						**Right Sponsored**			**Top Sponsored**	
increased rank of target listing by 1 unit	O1←O2*	O2←O3	O3←O4	O4←O5	O5←O6	O6←O7	S1←S2	S2←S3	S3←S4	T1←T2	T2←T3
	16.70%	12.10%	10.00%	7.70%	5.20%	3.60%	18.80%	22.60%	20.20%	18.80%	24.90%
increased rank of target listing by 2 units	O1←O3	O2←O4	O3←O5	O4←O6	O5←O7		S1←S3	S2←S4		T1←T3	
	28.60%	25.90%	21.70%	19.50%	13.10%		29.90%	30.90%		32.20%	
move from right sponsored to top sponsored section	T1←S1	T2←S1	T3←S1								
	574.10%	301.00%	257.00%								
DESCRIPTIVE ORIENTED (Screen has more descriptive than transactional text)											
	Organic						**Right Sponsored**			**Top Sponsored**	
increased rank of target listing by 1 unit	O1←O2*	O2←O3	O3←O4	O4←O5	O5←O6	O6←O7	S1←S2	S2←S3	S3←S4	T1←T2	T2←T3
	22.30%	20.20%	18.10%	12.00%	9.80%	5.40%	40.80%	39.60%	31.00%	34.90%	28.90%
increased rank of target listing by 2 units	O1←O3	O2←O4	O3←O5	O4←O6	O5←O7		S1←S3	S2←S4		T1←T3	
	56.80%	59.70%	49.80%	42.40%	35.60%		88.20%	74.80%		66.20%	
move from right sponsored to top sponsored section	T1←S1	T2←S1	T3←S1								
	621.90%	376.00%	326.00%								
TRANSACTIONAL ORIENTED (Screen has more transactional than descriptive text)											
	Organic						**Right Sponsored**			**Top Sponsored**	
increased rank of target listing by 1 unit	O1←O2*	O2←O3	O3←O4	O4←O5	O5←O6	O6←O7	S1←S2	S2←S3	S3←S4	T1←T2	T2←T3
	11.70%	9.50%	7.30%	5.90%	4.20%	2.20%	11.30%	13.00%	13.30%	12.90%	13.20%
increased rank of target listing by 2 units	O1←O3	O2←O4	O3←O5	O4←O6	O5←O7		S1←S3	S2←S4		T1←T3	
	21.60%	20.80%	17.60%	15.70%	11.80%		20.00%	24.30%		26.40%	
move from right sponsored to top sponsored section	T1←S1	T2←S1	T3←S1								
	501.00%	276.10%	250.80%								

Note: * O1←O2: percentage difference (changes) of target listing inspection probability when the target listing is moved from 2nd position in Organic (O2) to 1st position in Organic (O1).

Table 8: Simulation Results – Semantic Environment

Increase ATTRIBUTE by 1 unit (Screen is balanced between transactional and descriptive text)											
Prob. change in	change O1	change O2	change O3	change O4	change O5	change O6	change S1	change S2	change S3	change T1	change T2
O1		-12.79%	-8.00%	-6.62%	-5.28%	-3.57%	9.58%	7.54%	6.37%	10.54%	8.91%
O2	-23.42%*	0.00%	-5.73%	-4.52%	-3.78%	-2.99%	5.46%	4.30%	3.60%	7.86%	5.37%
O3	-15.62%	-19.18%	0.00%	-4.11%	-2.92%	-2.31%	3.11%	2.45%	2.05%	4.48%	3.06%
O4	-11.18%	-9.16%	-12.00%	0.00%	-2.44%	-1.92%	1.77%	1.39%	1.17%	2.55%	1.74%
O5	-8.65%	-7.08%	-6.43%	-8.42%	0.00%	-1.71%	1.01%	0.79%	0.66%	1.45%	0.99%
O6	-7.21%	-5.90%	-3.69%	-3.59%	-7.92%	0.00%	0.57%	0.45%	0.38%	0.83%	0.56%
O7	-6.39%	-5.23%	-3.27%	-3.10%	-2.16%	-4.26%	0.33%	0.26%	0.22%	0.47%	0.32%
S1	5.60%	4.24%	4.02%	2.46%	2.16%	2.05%	0.00%	-12.21%	-10.16%	3.33%	4.09%
S2	3.76%	3.52%	3.39%	1.83%	1.61%	1.53%	-18.60%	0.00%	-8.55%	2.48%	3.05%
S3	3.12%	2.63%	2.53%	1.37%	1.20%	1.14%	-15.34%	-14.81%	0.00%	1.85%	2.27%
S4	2.32%	1.96%	1.88%	1.02%	0.89%	0.85%	-12.90%	-10.27%	-12.32%	1.38%	1.70%
T1	7.01%	5.26%	4.43%	4.11%	3.77%	3.13%	10.11%	8.63%	6.39%	0.00%	-14.84%
T2	5.99%	3.99%	2.24%	1.74%	1.50%	1.45%	7.06%	6.48%	5.36%	-22.04%	0.00%
T3	4.79%	2.87%	1.74%	1.30%	1.05%	1.02%	5.85%	4.70%	3.89%	-18.45%	-17.72%

Increase PRICE by 1 unit (Screen is balanced between transactional and descriptive text)											
Prob. change in	change O1	change O2	change O3	change O4	change O5	change O6	change S1	change S2	change S3	change T1	change T2
O1	0.00%	8.77%	6.27%	4.97%	3.14%	1.72%	-8.36%	-8.30%	-7.81%	-9.45%	-7.35%
O2	20.43%†	0.00%	5.16%	3.12%	2.53%	1.08%	-5.90%	-5.00%	-4.45%	-6.52%	-4.03%
O3	12.36%	13.15%	0.00%	2.64%	2.19%	0.84%	-3.36%	-2.85%	-2.53%	-3.71%	-2.30%
O4	9.25%	6.28%	9.40%	0.00%	1.99%	0.70%	-1.91%	-1.62%	-1.44%	-2.11%	-1.31%
O5	7.55%	4.86%	4.47%	5.45%	0.00%	0.62%	-1.09%	-0.92%	-0.82%	-1.20%	-0.74%
O6	6.29%	4.05%	2.89%	2.37%	4.21%	0.00%	-0.62%	-0.53%	-0.47%	-0.69%	-0.42%
O7	5.57%	3.59%	2.56%	1.99%	1.81%	2.26%	-0.35%	-0.30%	-0.27%	-0.39%	-0.24%
S1	-4.88%	-3.19%	-3.03%	-1.38%	-0.82%	-0.60%	0.00%	14.06%	12.56%	-2.71%	-2.75%
S2	-3.64%	-2.38%	-2.56%	-1.03%	-0.67%	-0.45%	20.17%	0.00%	10.57%	-2.02%	-2.05%
S3	-2.71%	-1.78%	-1.91%	-0.77%	-0.50%	-0.33%	16.68%	17.06%	0.00%	-1.51%	-1.53%
S4	-2.02%	-1.33%	-1.42%	-0.57%	-0.37%	-0.25%	13.97%	11.83%	15.24%	-1.12%	-1.14%
T1	-7.42%	-6.21%	-4.59%	-4.45%	-3.34%	-2.40%	-7.08%	-6.20%	-5.14%	0.00%	10.96%
T2	-6.10%	-5.00%	-3.67%	-3.28%	-2.42%	-1.74%	-6.76%	-3.40%	-2.62%	18.20%	0.00%
T3	-4.68%	-4.08%	-2.12%	-2.04%	-1.76%	-1.26%	-6.36%	-1.37%	-0.81%	15.24%	13.85%

Note: * Percentage change of inspection probability of 2nd listing in the organic section (O2), when increasing attribute information by 1 unit in the 1st listing in the organic section (O1).
† Percentage change of inspection probability of listing 2nd listing in the organic section (O2), when increasing price information by 1 unit in the 1st listing in the organic section (O1).
Shaded area is the "block diagonal," which we used to calculate the impact of the listing's change on all other listings in the current section. Please see Web Appendix A for the results of "descriptive-oriented" and "transactional-oriented" screens.

Figure 1: Composition of a Typical SERP

(T) – Top Sponsored Ads Section, (S) – Right Sponsored Ads Section, (O) – Organic Results Section.

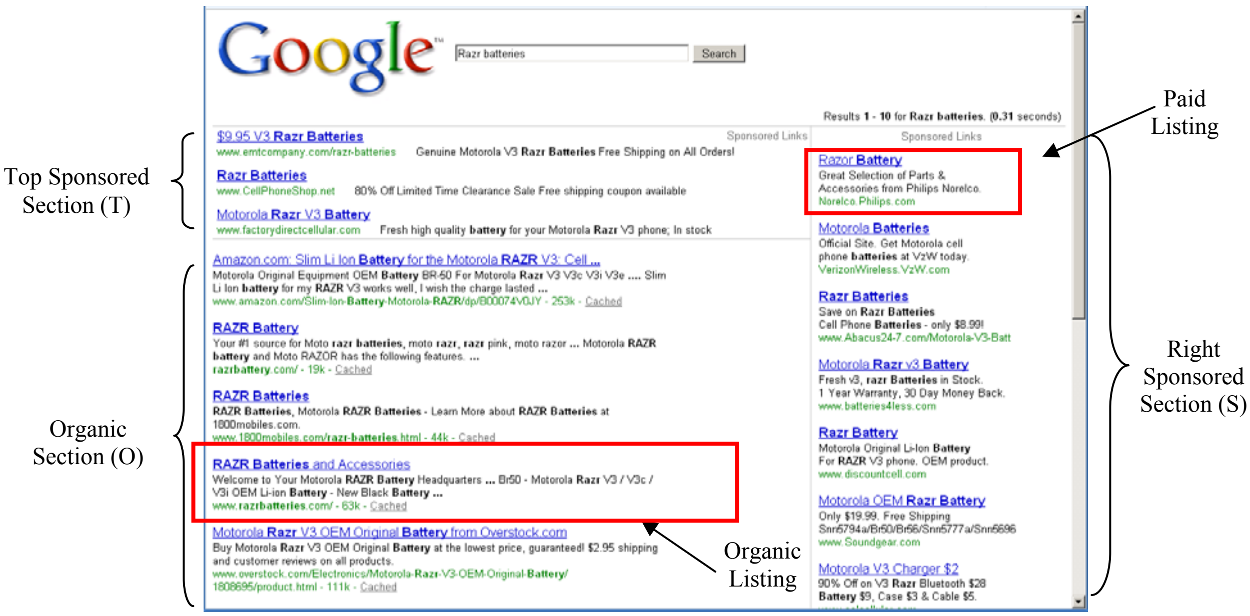


Figure 2: SERP as a Competitive Landscape - Effect of Context

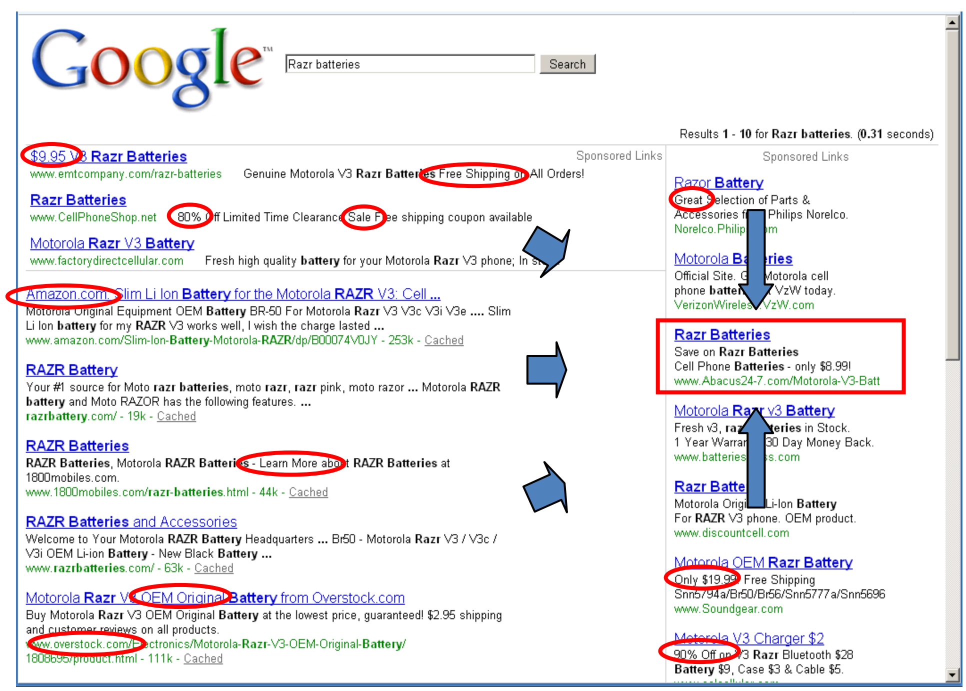
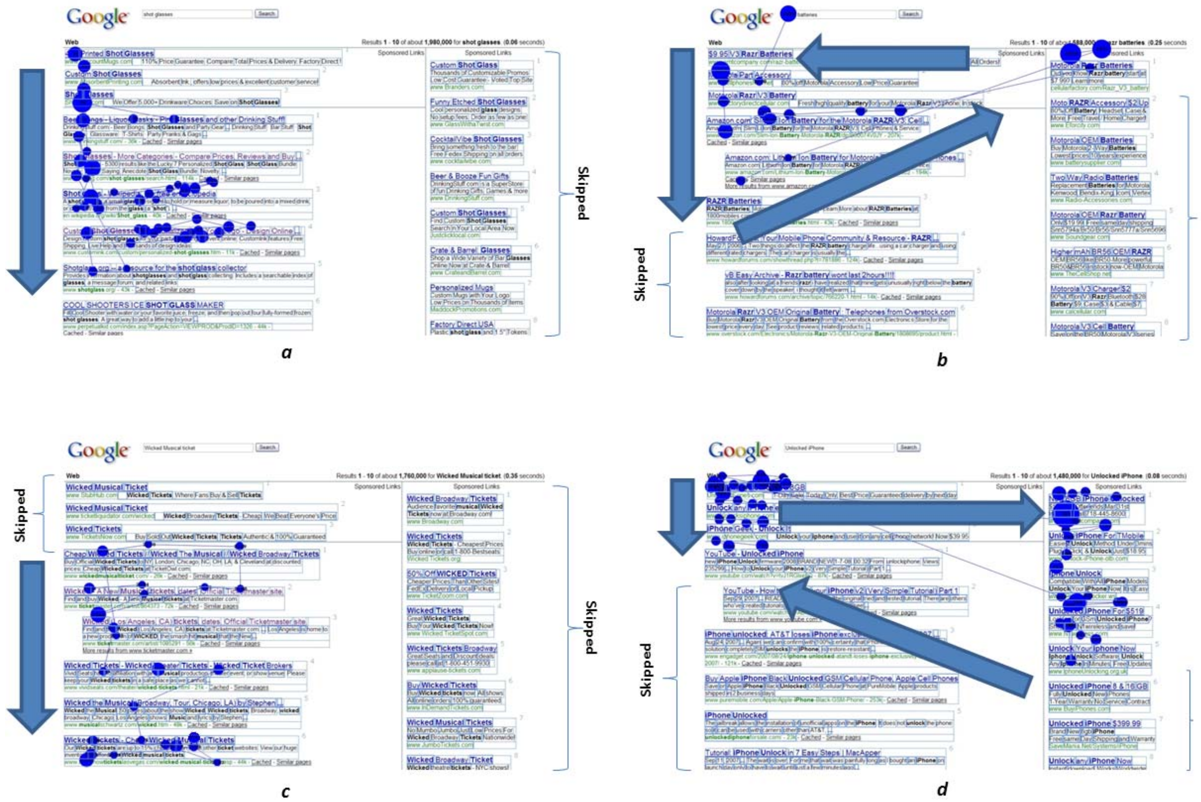


Figure 3: Inspection Patterns



Note: (a) sequential evaluation from a top sponsored section to an organic section; (b) start with an organic section and then move to sponsored results; (c) an organic section only; (d) sponsored section only.

Figure 4: Illustration of Information Search on SERP

Note: arrows illustrate the scan path.

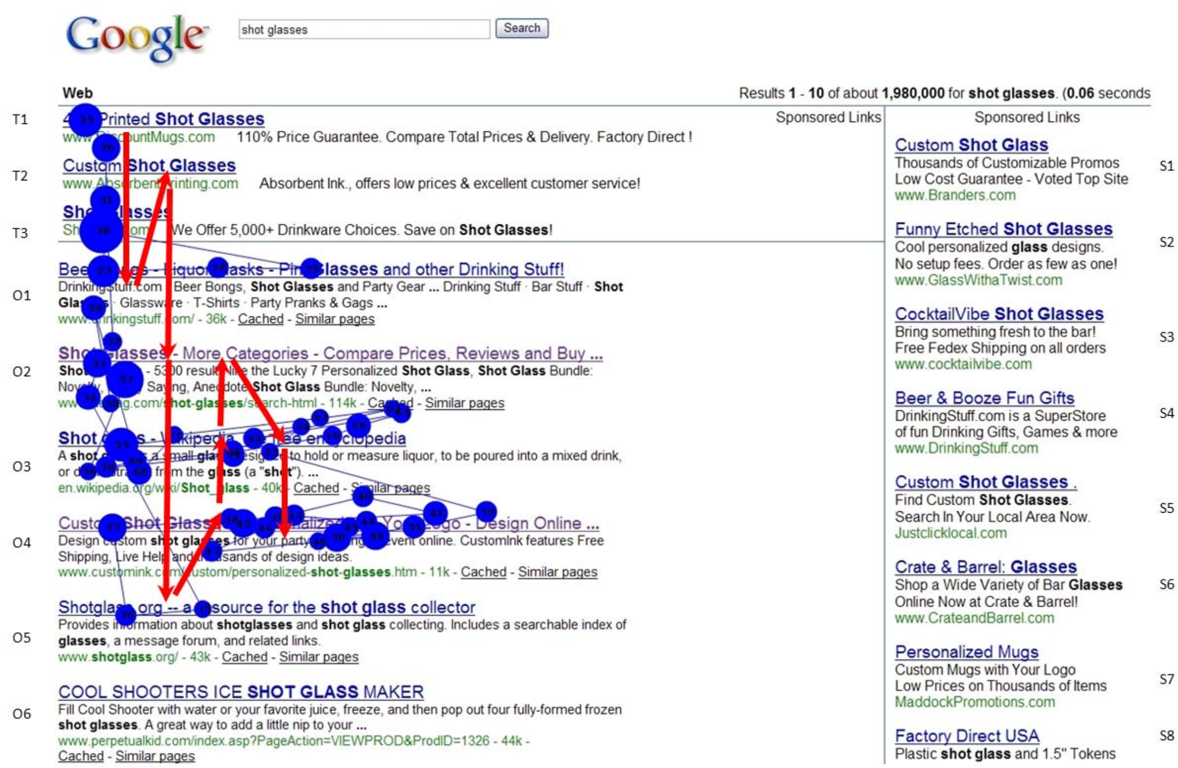


Figure 5: Conceptual Framework for an Information Search Process

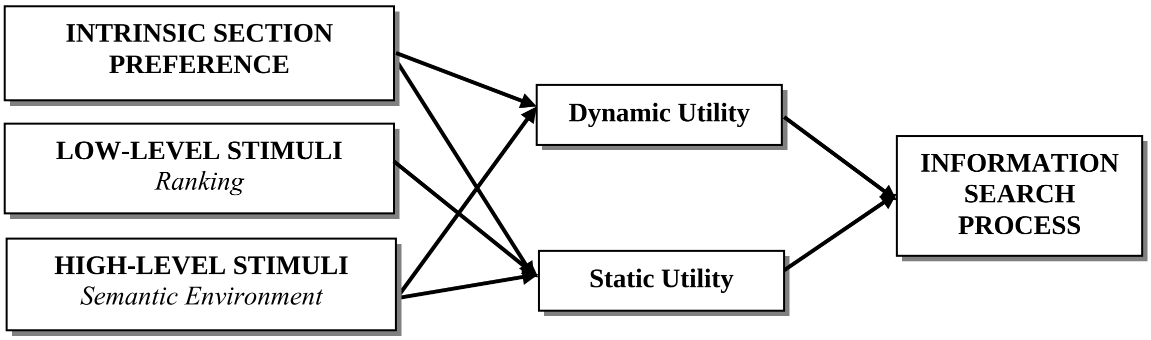


Figure 6: Semantic Hierarchy

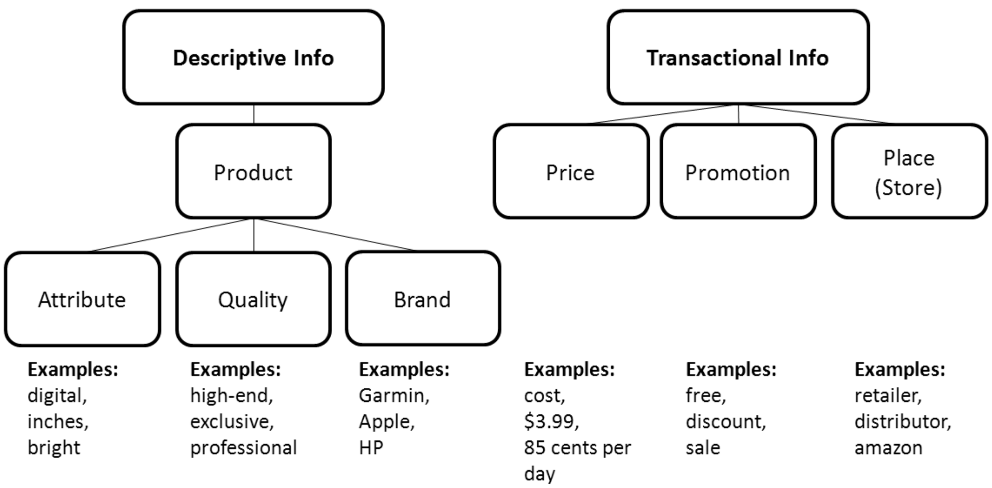


Figure 7: SERP Parsing

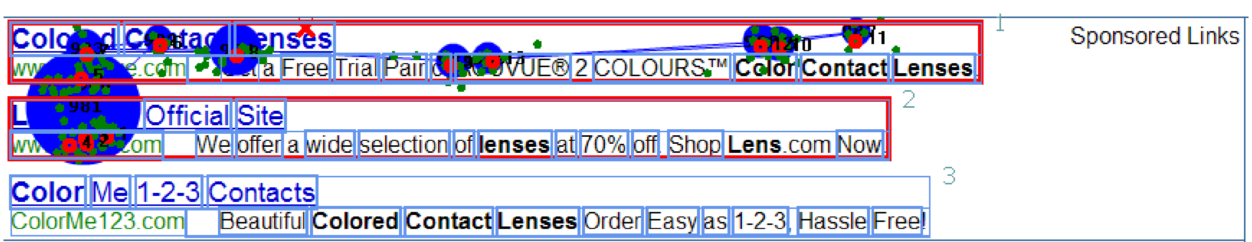
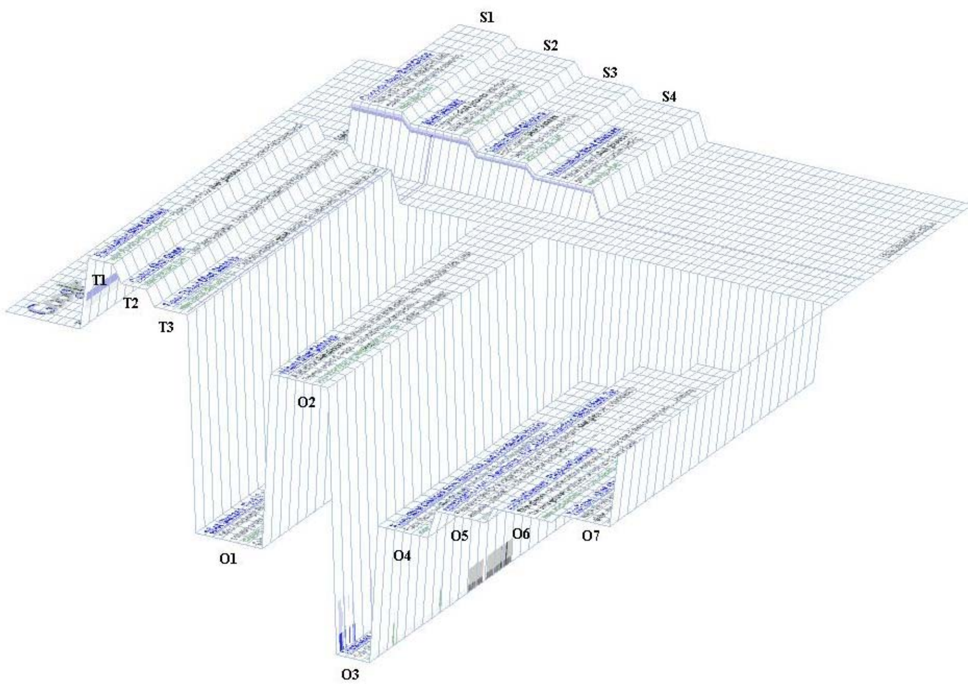


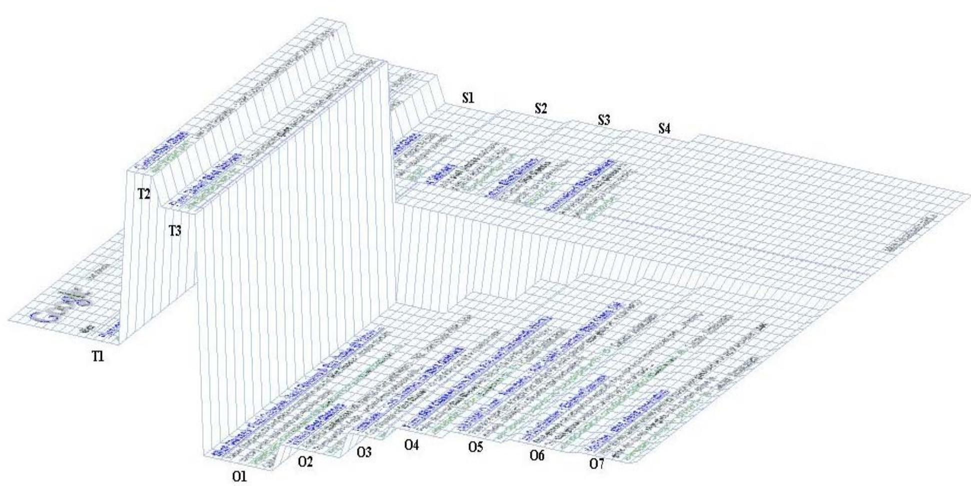
Figure 8a: Area Map of the Impact of the Semantic Environment

For more plots, see Online Appendix B.



Note: when we increase the count of attribute information in the 2nd listing in the organic section (O2), the listing immediately below it (O3) is affected most (the inspection probability decreases by 19.18%); For the other listings within the orgaic section (O), the magnitude of the impact decreases as the distance increases between the listing and the target listing (O2). The inspection probabilities of the listings in the other section (right sponsored S and top sponsored T) increase (see Table 8 for details).

Figure 8b: Area Map of the Impact of the Semantic Environment



Note: when we increase the count of price information in the 1st listing in top sponsored section (T1), the listing immediately below it (T2) is affected most (the inspection probability increases by 18.20%); For the other listings within the top sponsored section (T), the magnitude of the impact decreases as the distance increases between the listing and the target listing (T1). The inspection probabilities of the listings in the other section (organic O and right sponsored S) decrease (see Table 8 for details).

Online Appendix A
Simulation Result – Semantic Impact

Descriptive-Oriented Screen

Increase ATTRIBUTE by 1 unit (Screen has more descriptive than transactional text)											
	change O1	**change O2**	**change O3**	**change O4**	**change O5**	**change O6**	**change S1**	**change S2**	**change S3**	**change T1**	**change T2**
O1	0.00%	-15.01%	-10.33%	-7.47%	-5.59%	-4.08%	9.98%	7.86%	6.68%	10.83%	10.28%
O2	-25.54%	0.00%	-7.05%	-5.00%	-4.43%	-3.60%	5.68%	4.48%	4.12%	8.37%	6.15%
O3	-16.83%	-20.87%	0.00%	-4.39%	-2.96%	-2.66%	3.24%	2.55%	2.25%	5.10%	3.50%
O4	-11.87%	-10.12%	-12.43%	0.00%	-2.46%	-2.12%	2.51%	2.13%	1.90%	2.90%	1.99%
O5	-9.04%	-7.63%	-6.68%	-9.32%	0.00%	-1.82%	1.43%	1.21%	1.08%	1.65%	1.14%
O6	-7.43%	-6.22%	-3.83%	-4.10%	-8.60%	0.00%	0.81%	0.69%	0.62%	0.94%	0.65%
O7	-6.51%	-5.41%	-3.35%	-3.39%	-2.55%	-4.62%	0.46%	0.39%	0.35%	0.74%	0.37%
S1	5.97%	5.18%	4.67%	2.66%	2.40%	2.07%	0.00%	-13.68%	-11.54%	3.79%	4.41%
S2	4.04%	4.23%	3.87%	1.99%	1.79%	1.54%	-19.14%	0.00%	-9.83%	2.83%	3.29%
S3	3.32%	3.15%	2.89%	1.48%	1.34%	1.15%	-16.74%	-15.23%	0.00%	2.11%	2.46%
S4	2.48%	2.35%	2.15%	1.11%	1.00%	0.94%	-13.20%	-12.21%	-13.58%	1.57%	1.83%
T1	8.70%	6.67%	6.00%	4.72%	4.64%	3.19%	10.57%	9.60%	6.94%	0.00%	-16.93%
T2	7.22%	5.29%	3.38%	2.19%	2.13%	1.71%	7.40%	6.75%	5.84%	-23.85%	0.00%
T3	5.68%	4.09%	2.57%	1.62%	1.50%	1.17%	6.09%	4.89%	4.22%	-19.77%	-19.16%

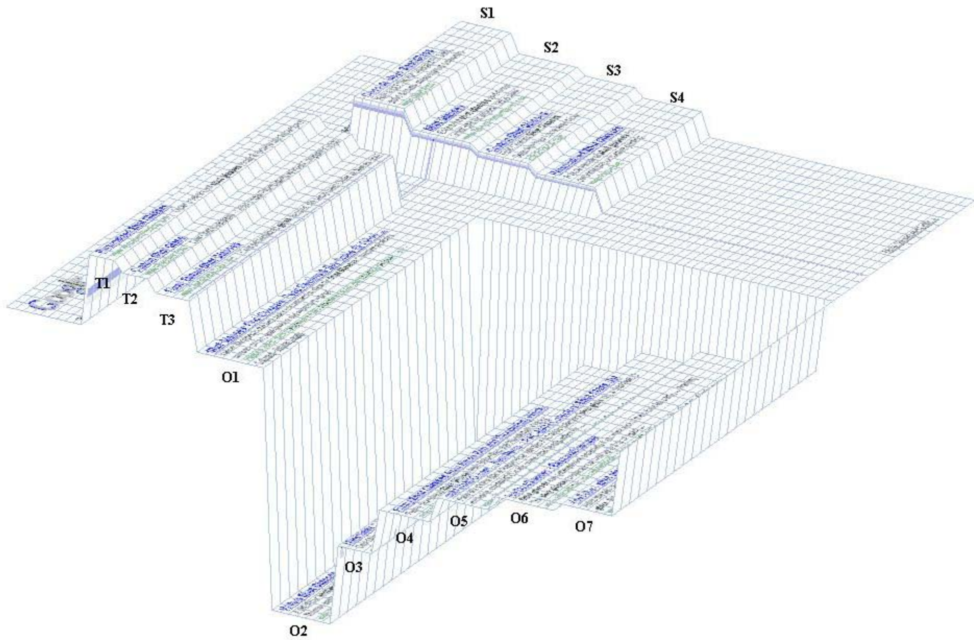
Increase PRICE by 1 unit (Screen has more descriptive than transactional text)											
	change O1	**change O2**	**change O3**	**change O4**	**change O5**	**change O6**	**change S1**	**change S2**	**change S3**	**change T1**	**change T2**
O1	0.00%	8.07%	5.98%	3.89%	2.67%	1.48%	-7.83%	-7.77%	-6.82%	-8.89%	-6.80%
O2	18.82%	0.00%	4.59%	2.51%	1.59%	1.00%	-5.60%	-4.69%	-3.93%	-5.87%	-3.48%
O3	11.44%	10.90%	0.00%	2.29%	1.31%	0.68%	-3.19%	-2.67%	-2.31%	-3.03%	-2.11%
O4	8.73%	4.99%	8.87%	0.00%	1.72%	0.44%	-1.81%	-1.52%	-1.17%	-1.67%	-0.76%
O5	7.25%	4.13%	4.17%	5.34%	0.00%	0.47%	-1.03%	-0.83%	-0.68%	-0.78%	-0.65%
O6	6.12%	3.63%	2.62%	1.72%	3.57%	0.00%	-0.56%	-0.44%	-0.40%	-0.64%	-0.38%
O7	4.60%	3.35%	2.37%	1.62%	1.44%	1.89%	-0.19%	-0.26%	-0.23%	-0.15%	-0.19%
S1	-4.38%	-2.93%	-2.22%	-1.12%	-0.50%	-0.38%	0.00%	13.11%	11.85%	-2.24%	-2.56%
S2	-3.26%	-1.44%	-1.96%	-0.84%	-0.43%	-0.33%	19.36%	0.00%	9.73%	-1.77%	-1.91%
S3	-2.44%	-1.08%	-1.46%	-0.62%	-0.32%	-0.21%	15.94%	16.52%	0.00%	-1.07%	-1.30%
S4	-1.82%	-0.80%	-1.09%	-0.46%	-0.24%	-0.13%	13.57%	10.93%	14.35%	-0.70%	-0.92%
T1	-5.15%	-5.72%	-3.99%	-3.67%	-2.23%	-2.18%	-6.47%	-5.58%	-4.67%	0.00%	9.92%
T2	-4.45%	-4.60%	-2.25%	-2.72%	-1.62%	-0.96%	-6.32%	-2.55%	-2.29%	17.25%	0.00%
T3	-3.49%	-3.79%	-1.09%	-1.63%	-1.17%	-0.70%	-5.83%	-1.04%	-0.56%	14.26%	11.67%

Transactional-Oriented Screen

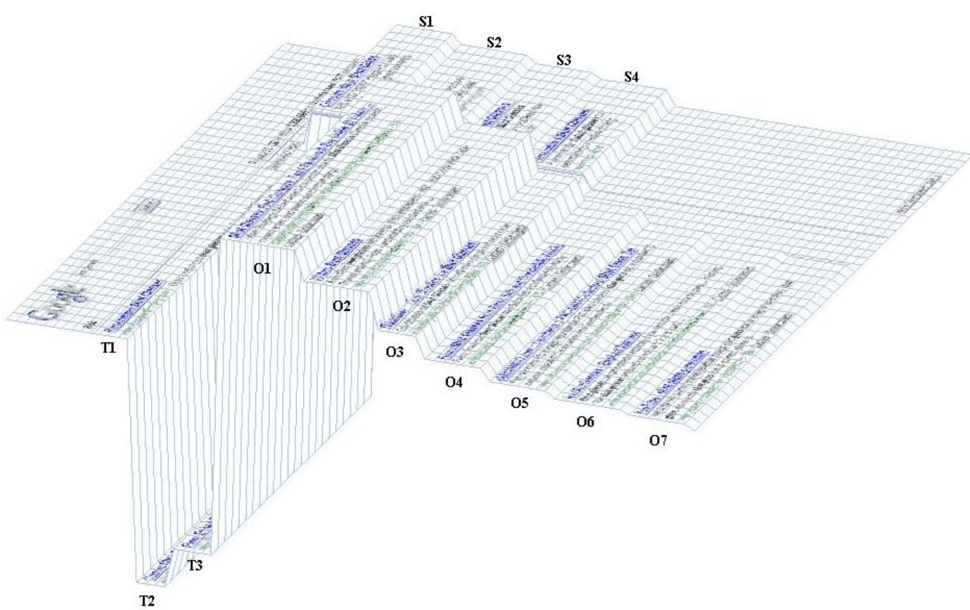
Increase ATTRIBUTE by 1 unit (Screen has more transactional than descriptive text)											
	change O1	**change O2**	**change O3**	**change O4**	**change O5**	**change O6**	**change S1**	**change S2**	**change S3**	**change T1**	**change T2**
O1	0.00%	-11.91%	-7.46%	-6.33%	-4.69%	-3.09%	8.09%	6.55%	4.85%	7.40%	6.96%
O2	-22.75%	0.00%	-5.42%	-3.56%	-3.17%	-2.71%	4.61%	3.73%	2.73%	6.07%	4.26%
O3	-14.84%	-16.32%	0.00%	-3.17%	-2.66%	-2.16%	2.63%	2.13%	1.55%	3.46%	2.42%
O4	-10.36%	-7.53%	-11.00%	0.00%	-2.10%	-1.63%	1.50%	1.21%	0.89%	1.97%	1.38%
O5	-8.23%	-6.16%	-5.86%	-7.62%	0.00%	-1.46%	0.85%	0.69%	0.50%	1.12%	0.79%
O6	-6.74%	-5.38%	-3.37%	-3.02%	-6.50%	0.00%	0.48%	0.39%	0.29%	0.64%	0.45%
O7	-6.29%	-4.93%	-3.09%	-2.90%	-1.89%	-3.84%	0.28%	0.22%	0.16%	0.36%	0.25%
S1	5.29%	2.06%	3.24%	2.00%	1.55%	1.79%	0.00%	-10.44%	-7.46%	2.79%	3.75%
S2	3.53%	1.90%	2.81%	1.49%	1.25%	1.35%	-16.07%	0.00%	-6.53%	2.08%	2.60%
S3	2.94%	1.42%	2.09%	1.11%	0.94%	1.08%	-14.19%	-13.83%	0.00%	1.55%	1.79%
S4	2.20%	1.06%	1.56%	0.83%	0.70%	0.71%	-12.05%	-9.54%	-11.20%	1.16%	1.56%
T1	6.20%	4.63%	3.97%	3.67%	2.84%	2.77%	9.13%	7.50%	4.67%	0.00%	-12.47%
T2	5.40%	3.53%	1.92%	0.03%	1.41%	1.29%	6.35%	5.66%	4.11%	-19.27%	0.00%
T3	4.37%	2.54%	1.50%	0.87%	0.87%	0.84%	5.33%	4.11%	2.98%	-16.44%	-15.47%

Increase PRICE by 1 unit (Screen has more transactional than descriptive text)											
	change O1	**change O2**	**change O3**	**change O4**	**change O5**	**change O6**	**change S1**	**change S2**	**change S3**	**change T1**	**change T2**
O1	0.00%	9.28%	6.97%	6.34%	3.59%	2.32%	-10.26%	-10.01%	-9.67%	-9.86%	-8.89%
O2	22.29%	0.00%	5.55%	5.22%	2.67%	1.43%	-6.98%	-5.97%	-5.75%	-6.75%	-5.03%
O3	13.85%	14.12%	0.00%	3.84%	2.45%	1.04%	-3.98%	-3.40%	-3.28%	-3.85%	-3.12%
O4	10.53%	7.49%	10.69%	0.00%	2.44%	0.81%	-2.26%	-1.94%	-1.87%	-2.87%	-2.00%
O5	8.06%	5.58%	5.20%	6.34%	0.00%	0.68%	-1.29%	-1.10%	-1.06%	-1.64%	-1.01%
O6	6.30%	4.12%	3.31%	2.59%	5.67%	0.00%	-0.73%	-0.63%	-0.61%	-0.93%	-0.58%
O7	5.99%	3.98%	2.80%	2.11%	2.03%	2.96%	-0.42%	-0.36%	-0.34%	-0.53%	-0.33%
S1	-5.12%	-4.47%	-4.05%	-1.98%	-0.88%	-0.66%	0.00%	17.10%	16.61%	-3.41%	-3.19%
S2	-3.87%	-3.29%	-3.32%	-1.48%	-1.13%	-0.55%	23.15%	0.00%	13.59%	-2.54%	-2.38%
S3	-3.14%	-2.23%	-2.48%	-1.10%	-0.84%	-0.33%	18.15%	18.75%	0.00%	-1.90%	-1.78%
S4	-2.19%	-1.64%	-1.85%	-0.82%	-0.63%	-0.26%	15.07%	13.09%	16.92%	-1.41%	-1.32%
T1	-7.96%	-7.14%	-5.17%	-5.75%	-3.51%	-2.85%	-8.36%	-8.14%	-7.71%	0.00%	13.73%
T2	-6.85%	-5.90%	-4.09%	-4.46%	-3.04%	-2.07%	-7.69%	-4.80%	-4.49%	21.82%	0.00%
T3	-5.23%	-4.51%	-3.02%	-3.62%	-2.65%	-1.50%	-7.03%	-2.39%	-2.16%	17.87%	16.11%

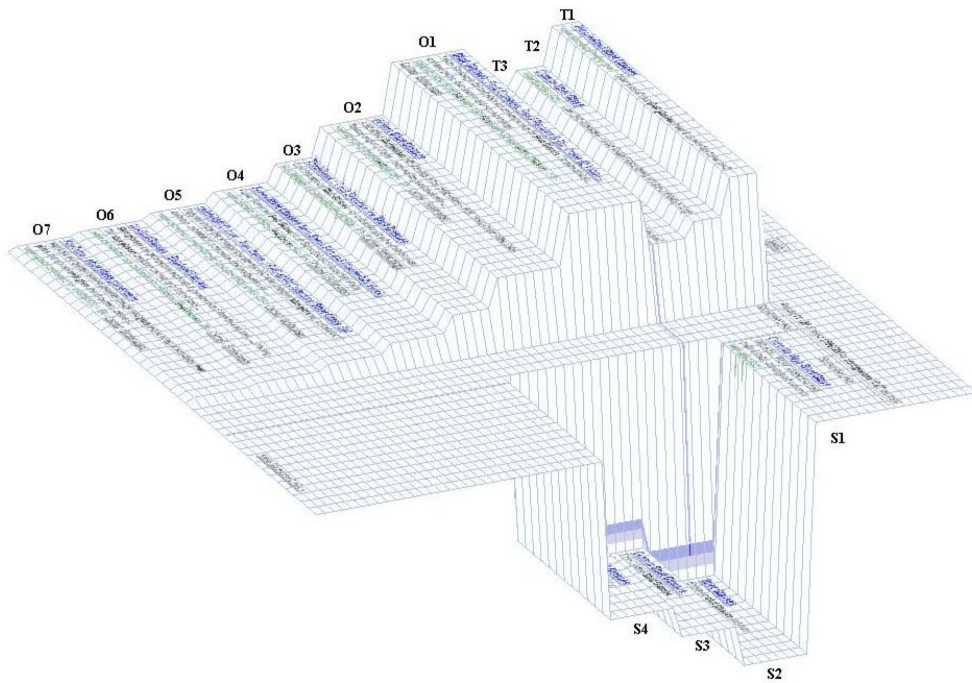
Online Appendix B
Area Map of the Impact of the Semantic Environment



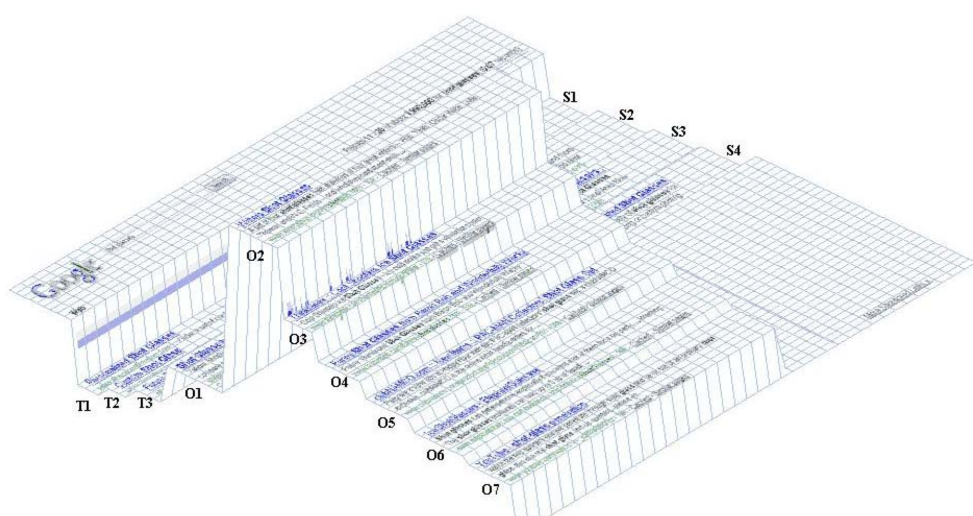
Note: when we increase the count of attribute information in the 1st listing in the organic section (O1), the listing immediately below it (O2) is affected most (the inspection probability decreases by 23.42%). For the other listings within the organic section (O), the magnitude of the impact decreases as the distance increases between the listing and the target listing (O1). The inspection probabilities of the listings in the other section (right sponsored S and top sponsored T) increase.



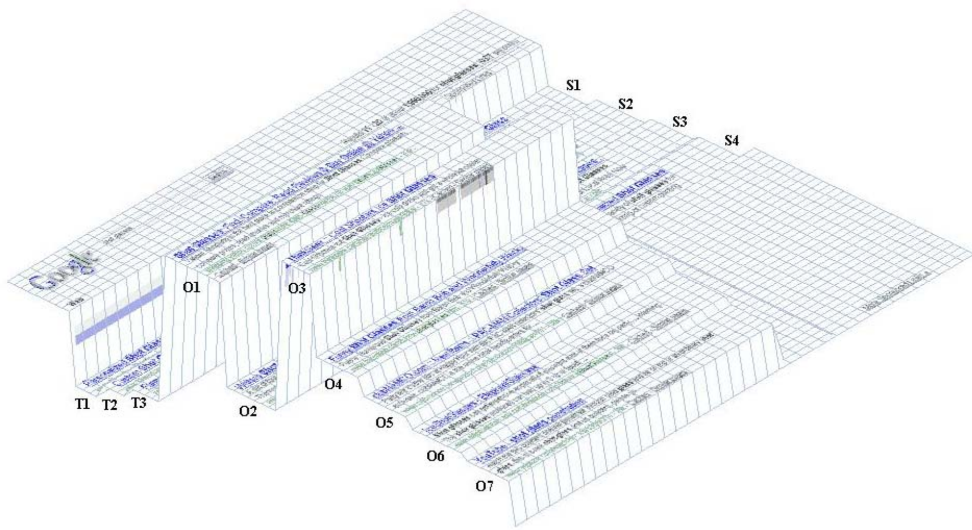
Note: when we increase the count of attribute information in the 1st listing in the top sponsored section (T1), the listing immediately below it (T2) is affected most (the inspection probability decreases by 22.04%); For the other listings within the top sponsored section (T), the magnitude of the impact decreases as the distance increases between the listing and the target listing (T1). The inspection probabilities of the listings in the other section(organic O and right sponsored S) increase.



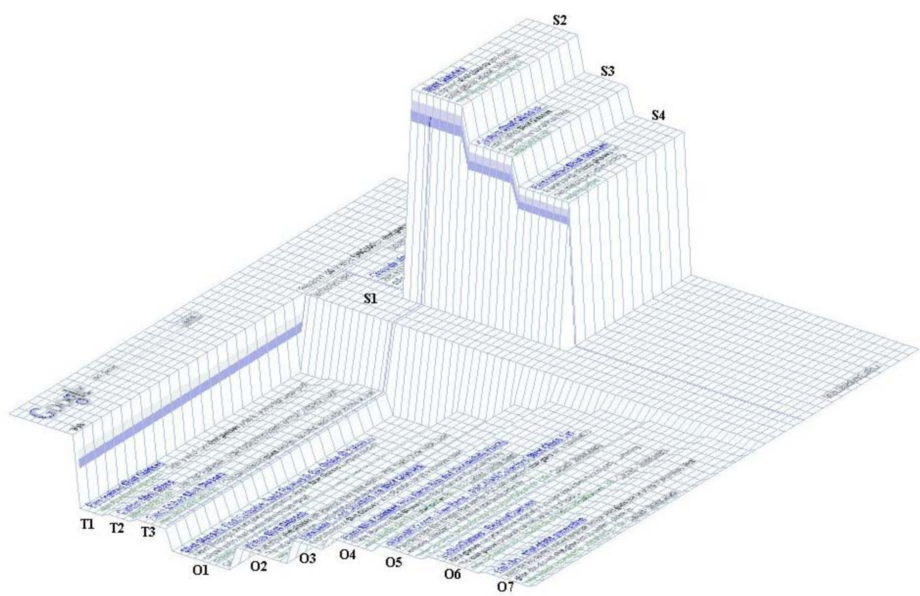
Note: when we increase the count of attribute information in the 1st listing in the right sponsored section (S1), the listing immediately below it (S2) is affected most (the inspection probability decreases by 18.60%); For the other listings within the right sponsored section (S), the magnitude of the impact decreases as the distance increases between the listing and the target listing (S1). The inspection probabilities of the listings in the other section (organic O and top sponsored T) increase.



Note: when we increase the count of price information in the 1st listing in the organic section (O1), the listing immediately below it (O2) is affected most (the inspection probability increases by 20.43%); For the other listings within the organic section (O), the magnitude of the impact decreases as the distance increases between the listing and the target listing (O1). The inspection probabilities of the listings in the other section (right sponsored S and top sponsored T) decrease.



Note: when we increase the count of price information in the 2nd listing in the organic section (O2), the listing immediately below it (O3) is affected most (the inspection probability increases by 13.15%); For the other listings within the organic section (O), the magnitude of the impact decreases as the distance increases between the listing and the target listing (O2). The inspection probabilities of the listings in the other section (right sponsored S and top sponsored T) decrease.



Note: when we increase the count of price information in the 1st listing in the right sponsored section (S1), the listing immediately below it (S2) is affected most (the inspection probability increases by 20.70%); For the other listings within the right sponsored section (S), the magnitude of the impact decreases as the distance increases between the listing and the target listing (S1). The inspection probabilities of the listings in the other section (organic O and top sponsored T) decrease.