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The Impacts of Shopbots on Online Consumer Search*

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ABSTRACT

Online price comparison agents (shopbots) allow consumers to instantaneously receive price and other information from many online retailers. Online consumer clickstream data from ComScore Inc. demonstrate that consumers are increasingly using shopbots to conduct search. This phenomenon raises such questions as "how do shopbots change consumers' search behavior?" and "do they reduce consumers' online search?" Conventional wisdom suggests that consumers are expected to search less because shopbots have displayed prices and other relative information from retailers on the search result page(s). Surprisingly, this study demonstrates the opposite result. That is, consumers are actually visiting more online retailer web sites after using shopbots. This finding suggests that after searching for an item through a shopbot and receiving the price information, consumers will continue to look for detailed information about the online retailers by visiting their web sites. The empirical finding is explained by an analytical model, which shows that on the one hand shopbots reduce the marginal benefit of searching additional online stores; on the other hand they reduce the cost of search. Therefore whether shopbots reduce consumer search depends on the cost of reducing per unit of risk, which is decided by a number of factors, such as marginal search costs, price dispersion and quality differentiation among stores, price and quality correlation, and consumers' relative preference for service quality. The model also gives sufficient and necessary conditions under which shopbots increase consumer surplus.

Key words: Sequential Search; Online Behavior; Shopbots; Internet Retailing; Clickstream Data; Service Quality.

JEL classification numbers: L15, C12, D11, D12, D83.

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1. INTRODUCTION

As online businesses grow, consumers have more choices of stores to shop, which challenges consumers' ability to find the optimal one. Therefore, consumers, who have a specific item to purchase in mind, still have to engage in a great deal of search in order to find a store with appropriate price and satisfactory product and service quality to purchase from. The more searches a consumer conducts, the more ideal combination of price and quality offers she expect to find. However, searching online stores is time-consuming and therefore costly. The existence of search cost has been ascribed as a main reason for price dispersion across Internet retailers (Brynjolfsson and Smith, 2000; Clay, et al. 2001). For example, Hong and Shum (2006) estimated search cost ranging from $1.31 to $29.40 by applying theoretical search models to online price data for several economics and statistics textbooks. Therefore consumers will not sample an infinite number of online stores, for example, with the 1997 – 1998 ComScore data, Johnson et al. (2004) found that consumers search only one or two online stores for a purchase even though hundreds of competing web stores are just "a click away".

The advent of shopbots has made it almost costless for prospective buyers to see the prices of many online sellers. *Shopbots,* also called price comparison engines, are software agents that automatically query a multitude of online vendors to gather and collate product and service information of a specified product. Since it is easier for shopbots to collect and compare price information rather than other attributes like service quality, reliability and so on, shopbots are currently designed primarily to aggregate and display prices from major online retailers (Harrington and Leahey, 2006; Smith, 2002). Shopbot web sites like BizRate.com, Dealtime.com, PriceWatch.com, and BudgetLife.com are used to search for various categories of consumer goods and services, ranging from computer hardware to mortgages. Figure 1 shows a search result page for a 30GB iPod MP3 player at Dealtime.com.

=============INSERT FIGURE 1 ============================

Shopbots adoption has observed a substantial increase from 0.1% in June 1997 to 5.7% in May 2002 (Montgomery, et al. 2004). Our online consumer clickstream data sample over the period of July to

December of 2001 shows that 45.7% of the online computer hardware shoppers and 7% of the online book shoppers visited at least one shopbot of the corresponding category before purchasing. The fast increasing adoption of shopbots raised numerous interesting questions to researchers and practitioners. For example, will the presence of shopbots significantly alter consumer search behavior? Will shopbots reduce consumers search intensity? Will consumers benefit from searching through shopbots?

Before the emergence of shopbots, economic studies such as Stigler (1961), Stahl (1989) and Weitzman (1979) and marketing theories such as Lynch and Ariely (2000), Urbany, et al. (1989) and Zwick et al. (2003) have modeled consumers' search behavior as a compromise of the anticipated price reduction and the additional search cost. In most of the models, consumers were assumed to be searching for price information only and the search products were supposed to be homogenous in all attributes other than price. Ellison and Ellison (2004) supported that assumption by providing some empirical evidence with respect to the dramatically high demand elasticity on the online market for computer hardware.

Built based on the above search models and given the current shopbot design, most analytical studies on shopbots have also assumed that consumers are searching for a perfectly homogeneous product, comparing only prices and will buy from the retailer that offers the lowest price they can find (Smith 2002, Greenwald and Kephart 1999 and Iyer and Pazgal 2003, Chen and Sudhir 2004). If that is the case, then shopbots will ease consumers' effort in searching across many web sites because after observing the pricing information for the searched item at a shopbot website, consumers can click through the link of a retailer on the search page to go directly to its web store to purchase. However, a couple of recent studies (Brynjolfsson and Smith, 2000; Montgomery, et al., 2004; Smith, 2002; Smith and Brynjolfsson, 2001) have found the above assumption does not hold. When using shopbots, consumers consider not only prices, but also such factors as shipping services, return policies, privacy protections, and brand reputation. Most of these attributes are not feasible for shopbots to collect within seconds and display in a tabular format to compare. Thus after obtaining a list of prices from the shopbot web sites, consumers will have to search each individual store for those unlisted attributes. Thus it is unclear whether shopbots reduce consumers' searching intensity or not and what benefits shopbots bring to consumers.

To address the above questions and to formally examine the impact of shopbots on consumer search, this paper builds a richer model on consumers' online search behavior to derive the optimal search strategy and tests it with the ComScore clickstream data. The paper makes three primary contributions: First, it analytically models consumer search behavior incorporating both price dispersion and service quality differentiation; and proposes an optimal search strategy for shopbot users based on the model. Second, it compares consumer search intensity and surplus with and without using shopbots and analytically identifies the conditions under which shopbots can reduce consumer search and increase consumer surplus. Third, we empirically show that contrary to conventional wisdom about shopbots, consumers visit *more* online book and computer stores while searching through shopbots, which implies that consumers do consider reputation, service quality and reliability of stores, and online stores differ significantly with respect to those quality attributes. Taken together, the above contributions shed light on understanding the impact of shopbots on online consumer search, help online retailers choose pricing and quality differentiation strategies to compete in the Internet market with shopbots, and provide suggestions to shopbot managers on how to improve the design of shopbots.

The paper proceeds as follows: §2 presents the analytical model and proposes the insights from the model results, §3 describes the study's empirical data and introduces the empirical results, and §4 discusses the paper's contributions and implications for theory and practice.

2. CONSUMER ONLINE SEARCH MODELS

Conducting business on the Internet requires very low cost compared with in the traditional physical world, which encourages the entry of e-tailers with varied brand names and service qualities. Those e-tailers with inferior brands or bad reputation for services tend to charge a lower price than those with a respected brand name. Thus, price is not the only factor that consumers care for: consumers are not choosing the e-tailer that offers the lowest price, but actually balancing the price and other quality factors (for example, shipping service, product availability, and retailer reputation) in making their purchase decisions. This section builds theoretical models to derive the consumer optimal search strategies without the presence of shopbot (Section 2.1) and the case with shopbot (Section 2.2).

2.1. Sequential Searching without Shopbots

There are n retailers in this product market. When a consumer searches online without shopbots, she must first discover the identity of a retailer (e.g., its web address) before being able to visit the retailer. A consumer who wants to purchase an item on the Internet searches the retailers' web sites for both pricing and quality information. Assume that By purchasing a product of quality q at price p, a consumer of type θ obtains a utility of

$$u(p,q) = \theta q - p , \tag{1}$$

where θ denotes the quality preference of the consumer. Suppose the constant marginal cost of discovering each online retailer is c_d and the constant marginal cost of sampling a retailer is c_s.

Suppose the price-quality pairs at the online retailers follow a (joint) distribution $F(p,q)$, with density $f(p,q)$. The utility for consumer $\theta(u)$ provided by each retailer thus also follows a distribution, denoted by $H(u)$ (which is essentially the convolution of the marginal distributions of p and q) defined on $(\underline{u},\bar{u})$, say.[1] Therefore, the consumer's sequential search for the price and quality of a retailer reduces to sequential search for its utility only.

It is well known that the consumer will stop search if and only if the expected benefit from continued search does not exceed the expected marginal cost. Suppose the consumer's reservation utility for stopping search is $\hat{u}$. Then $\hat{u}$ is the unique solution to

$$\int_{\hat{u}}^{\bar{u}} (u - \hat{u}) dH(u) = c_d + c_s ,$$

which is equivalent to (after integrating the LHS by parts)

$$\int_{\hat{u}}^{\bar{u}} (1 - H(u)) du = c_d + c_s . \tag{1}$$

[1] Here $\bar{u}$ and $\underline{u}$ may be infinite.

The number of online stores searched before she stops (search depth) in this case N_0 follows Geometric distribution $\Pr(N_0 = n) = H(\hat{u})^{n-1}(1 - H(\hat{u}))$. The mean search depth is thus

$$\begin{aligned} E(N_0) &= [1 - H(\hat{u})] + 2H(\hat{u})[1 - H(\hat{u})] + 3[H(\hat{u})]^2[1 - H(\hat{u})] + ... + n[H(\hat{u})]^{n-1}[1 - H(\hat{u})] \\ &= [1 - H(\hat{u})](1 + 2H(\hat{u}) + 3[H(\hat{u})]^2 + ... + n[H(\hat{u})]^{n-1}) \\ &= [1 - H(\hat{u})]\frac{1}{[1 - H(\hat{u})]^2} \\ &= \frac{1}{[1 - H(\hat{u})]}. \end{aligned} \tag{2}$$

We assume that the price p and the quality q found from one store is independent and identically bivariate normal (BVN) distributed with correlation ρ, that is, $\begin{pmatrix} p \\ q \end{pmatrix} \sim N(\begin{pmatrix} \mu_p \\ \mu_q \end{pmatrix}, \begin{pmatrix} \sigma_p^2 & \sigma_{pq} \\ \sigma_{pq} & \sigma_q^2 \end{pmatrix})$ where $\sigma_{pq} = \rho\sigma_p\sigma_q$.[2] Thus, for a consumer of type θ, the utility from purchasing the item from a store follows normal distribution, that is, $u \sim N(\mu_u, \sigma_u^2)$ where $\mu_u = E(u) = \theta\mu_q - \mu_p$, and $\sigma_u^2 = Var(u) = \theta^2\sigma_q^2 + \sigma_p^2 - 2\theta\sigma_{pq}$. Given this distribution, Equation (1) can be transformed to

$$\int_{\frac{\hat{u}-\mu_u}{\sigma_u}}^{\infty} (1 - \Phi(z)dz = \frac{c_d + c_s}{\sigma_u}. \tag{3}$$

Let $g(x) = \int_x^{\infty} (1 - \Phi(z)dz$, then the stopping utility $\hat{u}$ can be solved by

$$\hat{u} = \mu_u + \sigma_u g^{-1}(\frac{c_d + c_s}{\sigma_u}), \tag{4}$$

and the probability density of search depth is

$$\Pr(N_0 = n) = \Phi(g^{-1}(\frac{c_d + c_s}{\sigma_u}))^{n-1}(1 - \Phi(g^{-1}(\frac{c_d + c_s}{\sigma_u}))). \tag{5}$$

$$E(N_0) = \Phi(g^{-1}(\frac{c_d + c_s}{\sigma_u})) \tag{6}$$

[2] This assumption significantly simplifies the solution to the problem, while we need to assume that the majority of the random variables take a positive value.

The above results suggest that the ratio of marginal cost of search and standard deviation of utility $\frac{c_d + c_s}{\sigma_u}$, which is a measure of the uncertainty of search, influences the expected gain from search as well as search depth. We, hence, extract this important indicator and name it "*cost of risk*" in search. The lower the cost of risk, the higher the expected search depth and reservation utility of search are.

2.2. Searching with shopbots

We now examine sequential search at a shopbot. Shopbots allow consumers to search the web for a fully specified product and then to tabulate the sites where the product can be bought with their prices. When the consumer types the product name into the shopbot, the shopbot will return a list of retailers and their prices. In general the qualities of the retailers are not directly revealed by the shopbot, as discovering quality information often requires the consumer to visit and explore each retailer's website. Some shopbots may provide some quality information such as the availability, shipping cost and/or tax of the searched item. Some recent studies, (Harrington and Leahey, 2006; Smith, 2002), however, still show that the current design of shopbots does not provide enough quality information to consumers.

We assume that all online retailers in this product market register at the shopbot. Such a consolidating feature of the shopbot spares the consumer the costs of discovering the retailers. The relevant marginal search cost is thus only the cost of sampling each retailer, c_s.[3] Most importantly, because the consumer observes the prices of all retailers before initiating search, her optimal search sequence is no longer random.

After observing a price of the search item *p* offered by a store, consumers can follow the link on the search page to visit the web store for the quality information *q* (Smith and Brynjolfsson, 2001). Specifically, after observing price p_i of firm $i\,(1 \le i \le n)$, the consumer learns the conditional density of firm *i*'s quality:

[3] We ignored the slight difference between the sampling cost when using the shopbot and that when the shopbot is not used in searching.

$$f_{Q|P}(q \mid p_i) = \frac{f(p_i, q)}{\int_{-\infty}^{\infty} f(p_i, q)dq}. \quad (7)$$

and the corresponding conditional probability distribution $F_{Q|P}(q \mid p_i)$. To simplify notation, we let $G_i(q) \equiv F_{Q|P}(q \mid p_i)$.

Therefore, with the list of prices at the shopbot, the consumer faces *n* retailers each with a distinct (conditional) quality distribution $G_i(q)$. She must now decide the order of sampling these retailers, as well as when to terminate search. We first compute the *reservation quality* associated with firm *i*, $\widehat{q_i}$, which is the unique solution to

$$\int_{\widehat{q_i}}^{\infty} \theta(q - \widehat{q_i})dG_i(q) = c_s. \quad (8)$$

The corresponding *reservation utility* of firm *i* ($i \in [1, n]$) is

$$\widehat{u_i} = \theta\widehat{q_i} - p_i. \quad (9)$$

We index the *n* firms in decreasing order of their reservation utilities, i.e., $\widehat{u_{(1)}} \geq \widehat{u_{(2)}} \geq ... \geq \widehat{u_{(n)}}$.

Theorem 1 (Optimal Search Rule at the Shopbot): After observing a price vector $(p_1, ..., p_n)$ at the shopbot, (1) consumer θ will continue to search if and only if $\widehat{u_{(1)}} > 0$; (2) if $\widehat{u_{(1)}} > 0$, then her optimal search sequence is to visit the retailers in decreasing order of their reservation utilities; (3) she stops search as soon as either the maximum realized utility exceeds the highest unsampled reservation utility or all retailers with positive reservation utilities have been sampled.

Suppose that the realized price vector is such that all retailers confer positive reservation utilities for consumer θ (i.e., $\widehat{u_{(n)}} > 0$). We now compute her expected number of searches. According to Theorem 1, she indeed will sample some or all retailers. Search stops after 1 draw if and only if $u_{(1)} \geq \widehat{u_{(2)}}$, which has a probability

$$w_1 \equiv 1 - G_{(1)}(\widehat{q_{(2)}} - \frac{p_{(2)} - p_{(1)}}{\theta}). \quad (10)$$

Search stops after k $(1<k<n)$ draws if and only if $u_{(1)} < \widehat{u_{(2)}}$, $\max(u_{(1)},u_{(2)}) < \widehat{u_{(3)}}$, …, and $\max(u_{(1)},...,u_{(k)}) \geq \widehat{u_{(k+1)}}$. This has a probability

$$\begin{aligned} w_k &\equiv \Pr\{u_{(1)} < \widehat{u_{(2)}}\}...\Pr\{\max(u_{(1)},...,u_{(k-1)}) < \widehat{u_{(k)}}\}\Pr\{\max(u_{(1)},...,u_{(k)}) \geq \widehat{u_{(k+1)}}\} \\ &= [G_{(1)}(\widehat{q_{(2)}} - \frac{p_{(2)}-p_{(1)}}{\theta})]...[G_{(1)}(\widehat{q_{(k)}} - \frac{p_{(k)}-p_{(1)}}{\theta})...G_{(k-1)}(\widehat{q_{(k)}} - \frac{p_{(k)}-p_{(k-1)}}{\theta})]\cdot \\ &[1-G_{(1)}(\widehat{q_{(k+1)}} - \frac{p_{(k+1)}-p_{(1)}}{\theta})...G_{(k)}(\widehat{q_{(k+1)}} - \frac{p_{(k+1)}-p_{(k)}}{\theta})] \\ &= \left(\prod_{i=1}^{k-1}\prod_{j=1}^{i} G_j(\widehat{q_{(i+1)}} - \frac{p_{(i+1)}-p_{(j)}}{\theta})\right)\left(1-\prod_{i=1}^{k} G_i(\widehat{q_{(k+1)}} - \frac{p_{(k+1)}-p_{(i)}}{\theta})\right) \end{aligned} \tag{11}$$

Finally, search stops after n draws if and only if $u_{(1)} < \widehat{u_{(2)}}$, $\max(u_{(1)},u_{(2)}) < \widehat{u_{(3)}}$, …, and $\max(u_{(1)},...,u_{(n-1)}) < \widehat{u_{(n)}}$, which has a probability

$$\begin{aligned} w_n &\equiv \Pr\{u_{(1)} < \widehat{u_{(2)}}\}\Pr\{\max(u_{(1)},u_{(2)}) < \widehat{u_{(3)}}\}...\Pr\{\max(u_{(1)},...,u_{(n-1)}) < \widehat{u_{(n)}}\} \\ &= [G_{(1)}(\widehat{q_{(2)}} - \frac{p_{(2)}-p_{(1)}}{\theta})][G_{(1)}(\widehat{q_{(3)}} - \frac{p_{(3)}-p_{(1)}}{\theta})G_{(2)}(\widehat{q_{(3)}} - \frac{p_{(3)}-p_{(2)}}{\theta})]... \\ &[G_{(1)}(\widehat{q_{(n)}} - \frac{p_{(n)}-p_{(1)}}{\theta})...G_{(n-1)}(\widehat{q_{(n)}} - \frac{p_{(n)}-p_{(n-1)}}{\theta})] \\ &= \prod_{i=1}^{n-1}\prod_{j=1}^{i} G_j(\widehat{q_{(i+1)}} - \frac{p_{(i+1)}-p_{(j)}}{\theta}) \end{aligned} \tag{12}$$

When the consumer observes a price vector $(p_1,..., p_n)$, her expected search depth in this case N_1 is thus

$$E(N_1) = w_1 + 2w_2 + ... + nw_n = \sum_{k=1}^{n} kw_k\ . \tag{13}$$

Assume the BVN distribution of price and quality we made in Section 2.1, the mean and variance of $G_i(q)$ given a price p_i is: $\mu_{q|p_i} = E(q \mid p_i) = \mu_q + \rho\frac{\sigma_q}{\sigma_p}(p_i - \mu_p)$ and $\sigma^2_{q|p_i} = Var(q \mid p_i) = (1-\rho^2)\sigma_q^2$.

Equation (8) can be transformed to

$$\int_{\frac{\widehat{q_i}-\mu_{q|p_i}}{\sigma_{q|p_i}}}^{\infty} (1-\Phi(z))dz = \frac{c_s}{\theta\sigma_{q|p_i}}, \tag{14}$$

and the stopping quality $\widehat{q_i}$ after observing price p_i is given by

$$\widehat{q_i} = \mu_{q|p_i} + \sigma_{q|p_i} g^{-1}(\frac{c_s}{\theta\sigma_{q|p_i}}) . \tag{15}$$

When searching through the shopbot, the reservation utility defined in (9) is therefore expressed as

$$\widehat{u_i} = \theta[\mu_q - \rho\frac{\sigma_q}{\sigma_p}\mu_p + \sqrt{1-\rho^2}\sigma_q g^{-1}(\frac{c_s}{\theta\sqrt{1-\rho^2}\sigma_q})] + (\theta\rho\frac{\sigma_q}{\sigma_p} - 1)p_i . \tag{16}$$

Given the BVN distribution assumption of price and quality of online stores, Theorem 1 implies the optimal search rule when using the shopbot is to (1) when $\rho \le \frac{\sigma_p}{\theta\sigma_q}$, follow an ascending order of the posted prices and stop at the first store with a service quality greater than or equal to the reservation quality given the price; (2) otherwise, follow a descending order of the listing prices.

Note the above optimal search rule is single-directional, that is, consumers search the stores for quality-related information following a uniform order of the listing prices. This result is closely related to the *i.i.d.* distribution of price and quality random variables. If a consumer has a favorable store (non-identical mean) or there are heterogeneous correlations of price and quality across the stores, the optimal search rule can be bi-directional: the consumer searches in a mixed order of increasing and decreasing prices.

Given the BVN assumption about the distribution of price and quality, from Equations of (10) to (12), we have

$$\begin{aligned}
w_1 &\equiv 1 - \Phi(g^{-1}(\frac{c_s}{\theta\sqrt{1-\rho^2}\sigma_q}) - \frac{p_{(2)} - p_{(1)}}{\theta\sqrt{1-\rho^2}\sigma_q}(1 - \theta\rho\frac{\sigma_q}{\sigma_p})) \\
w_k &= \left(\prod_{i=1}^{k-1}\prod_{j=1}^{i}\Phi(g^{-1}(\frac{c_s}{\theta\sqrt{1-\rho^2}\sigma_q}) - \frac{p_{(i+1)} - p_{(j)}}{\theta\sqrt{1-\rho^2}\sigma_q}(1 - \theta\rho\frac{\sigma_q}{\sigma_p}))\right) \cdot \\
&\quad \left(1 - \prod_{i=1}^{k}\Phi(g^{-1}(\frac{c_s}{\theta\sqrt{1-\rho^2}\sigma_q}) - \frac{p_{(k+1)} - p_{(i)}}{\theta\sqrt{1-\rho^2}\sigma_q}(1 - \theta\rho\frac{\sigma_q}{\sigma_p}))\right) \\
w_n &= \prod_{i=1}^{n-1}\prod_{j=1}^{i}\Phi(g^{-1}(\frac{c_s}{\theta\sqrt{1-\rho^2}\sigma_q}) - \frac{p_{(i+1)} - p_{(j)}}{\theta\sqrt{1-\rho^2}\sigma_q}(1 - \theta\rho\frac{\sigma_q}{\sigma_p}))
\end{aligned} \tag{17}$$

Comparing this density function with Equation (5) which is the density of search depth without using shopbots, since $c_s < c_s + c_d$, $\theta\sqrt{1-\rho^2}\sigma_q \le \sigma_u$, and $\frac{p_{(i)} - p_{(j)}}{\theta\sqrt{1-\rho^2}\sigma_q}(1-\theta\rho\frac{\sigma_q}{\sigma_p}) > 0$ for $i > j$, there is no conclusive result regarding the impact of shopbots on the expected search depth. Using the shopbot can potentially increase or decrease consumer search depth:

1) Shopbots reduce the cost of discovering an online retailer. This effect alone will encourage consumers to search more stores.
2) Shopbots provide pricing and some quality information of the stores on the result page, which reduces the variance (uncertainty) of consumer search. This effect alone will give consumers less incentive to search and therefore reduces search depth.
3) Consumers maximize utilities by trading off price and quality. When all the prices are given, consumers, who are searching for information regarding service quality, can rank the stores by their posted prices and search them in an optimal sequential order. The existence of price differentiation discourages consumers' search and reduces search depth.

We then empirically examine the impact of shopbots on consumer search using the ComScore web behavior database.

3. EMPIRICAL EVIDENCE

Information technologies enable in-depth study of consumers' search and purchasing behavior through their web site navigating and purchasing logs tracked using server-side or client-side programs. To verify some of the results from the above theoretical analysis, we employ consumer clickstream data collected by the Internet marketing company ComScore Media Matrix to examine the consumers' online search behavior before making a purchase. The company uses a client-side program installed on the recruited households' home computers to collect detailed website visiting data, transaction data (i.e., records of online purchasing) and demographic data of these households. The ComScore database used in this research captures 100 million website visits and 342,706 transactions conducted by 100,000 households across the United States during a 6-month time period from July 2002 to December 2002 and demographical data of these households.

We chose to study book and computer hardware categories of goods because 1) they were frequently purchased online --- they were among the top-5 frequently purchased product categories in our database; 2) there are many specialized shopbots for these two categories; 3) they had been studied by previous research (Johnson et al. 2004, Montgomery et al. 2004) so that we can easily compare the difference between research results of this study and previous research results without controlling category-related factors.

For each product category, the corresponding retailer and shopbot websites were chosen according to previous studies, for example, Johnson et al. 2004, Montgomery et al. 2004 and Broida 2005; Internet sources, for example, retailer websites listed by BizRate.com, and shopbot websites from Google Directory of Price Comparison Websites (Google Directory - Home > Consumer Information > Price Comparisons); and websites in each category that appeared in our data sample. We finalized with 24 retailer websites and 21 shopbots in computer hardware and 16 retailer websites and 10 shopbots in the book category.[4] Table 1 lists these retailer websites, the number of visits experienced by each site during the research periods, as well as shopbots for each category.

=============INSERT TABLE 1 ===========================

To examine consumers' search behavior, we need to define search sessions. This paper adopted this monthly-level search session defined in Johnson et al. (2004) which examined households' search behavior using the 1997 ComScore database. That is, a search session is a series of store visits over a span of days, which eventually leads to a purchase. Specifically, they defined a search session covering one calendar month. The key justification of using the monthly-level search session definition in Johnson's study – less than 1% of month-long sessions containing more than one transaction – still holds in the 2002 ComScore database used in our study.

[4] To avoid inflating the number of sites visited during a purchase, we narrowed the web site list to those of specialized retailers in each category and removed those general-purposed retailer web sites such as Yahoo.com and eBay.com.

In the consumer web log data, we queried the number of *unique* retailer websites within a product category visited during a search session leading to a purchase. Combining those search data with the transaction data and household demographic data, we obtained our final data sample for studying the factors affecting consumers' searches that lead to a final purchase. Table 2 (a,b) and Table 3 (a,b) show the descriptive summaries of the variables for book and computer hardware categories respectively in our empirical research. There are 6623 and 2878 households who had made at least one purchase in the book and computer hardware category respectively during the study period. On average, consumers search 2.66 book stores and 3.26 computer hardware stores before making a purchase in the corresponding category. The results have increased dramatically compared with the search depths reported in Johnson et al. (2004). Only 7% of the computer hardware shoppers and 21.7% of the book shoppers are loyal to one retailer website throughout the research period while, in Johnson's study, 70% of the book shoppers were loyal to one retailer website.

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The historical shopbot adoption rates reported by Montgomery, et al. (2004)[5] indicate that shopbots are adopted by consumers at a dramatic speed, increasing from 0.1% to 5.7% over a five-year period. Using the data sample in our study period, we also find that 45.7% of the online computer hardware shoppers and 7% of the online book shoppers visited at least one shopbot of the corresponding category before purchasing. Another interesting finding is that even though the households in our data sample shopped around visiting multiple web retailers, they demonstrated great loyalty to the shopbots they used. One average, those shoppers who used shopbots only visited 1.61 unique computer shopbots and 1.44 unique book shopbots during a search session.

The theoretical comparison of consumer search with and without shopbots gives the conditions under which consumers will search more or less when using shopbots (Section 2.3). Here with the consumer clickstream data, we can test the impact of shopbots on consumer search with the following regression model:

[5] Their shopbot list included Dealtime, Bottomdollar, Pricescan, or MySimon.

$$
\begin{aligned}
N_{ij} = \beta_0 + \beta_1 \ln p_{ij} + \beta_2 \text{Shopbot}_{ij} + \ \beta_3 N_{i,j\text{-}1} \\
+ \beta_4 \text{Connection\_Speed}_i + \beta_5 \text{Household\_Income}_i + \beta_6 \text{Household\_Education}_i \\
+ \beta_7 \text{Household\_Oldest\_Age}_i + \beta_8 \text{Child\_Present}_i + \beta_9 \text{Household\_Size}_i
\end{aligned} \tag{19}
$$

Model (19) is applied to book and computer hardware categories separately. We use a variable $Shopbot_{ij}$ to represent the number of book or computer hardware shopbots consumer i visited to search online book or computer hardware stores before purchasing an item in the same category in search session j. Some other factors are used as control variables: price of the item p_{ij}, last period number of stores searched in the same product category $N_{i,j\text{-}1}$, Internet connection speed $Connection\_Speed_i$ (high-speed Internet-1 or not-0), level of total income of the household (*<15k*-1, *15k-25k*-2, *25k-35k*-3, *35k-50k*-4, *50k-75k*-5, *75k-100k*-6, *>100k*-7) $Household\_Income_i$, the highest education level $Household\_Education_i$ (below high school-0, high school-1, college without a degree-2, associate degree-3, bachelor-4, graduate-5), the oldest age of the household members $Household\_Oldest\_Age_i$, whether there are children in the household $Child\_Present_i$, and number of household members $Household\_Size_i$. The results are provided in Table 4.[6]

For both product categories, we find that households visit more retailer websites after visiting shopbots: on average, they visit 0.86 and 1.86 more retailer websites respectively after visiting one more book and computer hardware shopbot. This result can be explained by the analytical result in Section 2 as shopbots can lower the cost of (reducing each unit of) risk, which has several possible implications: consumers still consider service quality when choosing online stores; there still exists prevalent service quality differentiation on the Internet (Brynjolfsson and Smith, 2000); moreover, the cost of searching an online store following the links given by the shopbot website is significantly low, even when we take into account the search cost per unit of risk.

Empirical results in Table 4 also show that price level, previous search intensity and broadband Internet connection have a positive impact on online store searches for both product categories. They can be explained by the model conclusions in Section 2: more valuable goods tend to have higher price and

[6] Since the Condition Indices (CI) of all the regression models are greater than 25, multi-collinearity does not significantly exist.

quality variances, and broadband Internet connection reduces marginal search cost; and both high product uncertainty and low search cost lead to more stores to search.

We also find that higher income households search fewer book stores but more computer hardware stores before making a purchase in the corresponding category. This is because high-income households tend to have higher preference to quality, and according to results in Section 2.2, optimal search depth increases with quality preference when quality uncertainty is comparable with price dispersion. Thus those high-income households are more sensitive to the higher price and quality variances offered by computer hardware stores than book stores. Younger households are found to search more computer hardware stores is because they are more skillful in navigating the Internet and incur lower search cost.

4. Discussion and Conclusion

Consumers' online search, especially the changes in consumer search behaviors due to the emergence of shopbots, has received relatively less attention than searching in the traditional non-electronic market. However, due to the fast growing of e-commerce and online search technologies, both business and practitioners have realized the increasing importance of understanding consumers' search behavior on the Internet.

4.1 Key Findings

Shopbots were initially expected to drive all consumers to the lowest priced retailer and therefore increase the pressure on retailers' sales margins. However, in this study, shopbot users are found not to be completely satisfied with the price information provided on the shopbot search result pages. Instead, they search more retailer web sites than other Internet customers do before making a purchase. Those consumers are not choosing a retailer that offers the lowest price, but actually balancing the price and other critical quality factors, for example, product availability, shipping services, retailer brand names and reputation, in making their purchase decisions. Based on that empirical evidence, we have built a richer model of consumers' online search, incorporating multiple search factors to derive the optimal search strategy.

The theoretical conclusions in this paper suggests that consumers' search intensity depends on their cost of risk, which is the ratio of marginal search cost and the standard deviation of the utility from searching and purchasing. Therefore lower search cost and higher price and quality uncertainties induce consumers to search more online retailers.

When consumers search online stores without a shopbot, they incur the risks from both price and quality uncertainties. A shopbot brings queried price information and web addresses to the search result page, which decreases both the uncertainty from price variation and marginal search cost. Therefore whether shopbots will reduce the number of stores to search depends on the remaining uncertainty in quality dispersion and the degree of search cost reduction. Given the optimal level of search without using shopbots, consumers are better off with the usage of shopbots when the degree of search cost reduction relative to variance reduction is large enough.

Our consumer clickstream data suggest that shopbot adoption has increased at a dramatic speed, and shopbot users have demonstrated great loyalty to a particular shopbot but are less loyal to retailers than that reported in Johnson et al. (2004). Our empirical results show consumers search additional book and computer hardware retailers even when they use shopbots for a purchase, which implies that

1. Consumers put a significant weight on service quality attributes when they evaluate the retailers in purchase decision, which mitigates their price sensitivity.
2. There are still significant variations in service quality among the book and computer hardware retailers
3. The reduction in search cost provided by shopbots encourages consumers to visit each individual retailer for more information.

The above results have important implications to consumers, online retailers, shopbot designers as well as academic researchers.

4.2 Managerial Implications

Implication for Consumers

Balancing the tradeoff of cost and expected gains from search, consumers will choose an optimal number of stores to sample before making a purchase decision. Consumers gain from search by reducing the risks in prices and quality of stores at a cost. The higher the variance of consumers' value in search due to price dispersion or quality differentiation, the higher the marginal value consumers will receive from sampling *n* number of stores and the greater number of stores they will search. Besides, when search cost becomes lower, for example, adopting broadband Internet connection, improving web site navigating skills, consumers are expected to search more intensively. Thus, consumers' optimal search depth depends on the cost of reducing each unit of risk.

When price dispersion is high, for example, computers usually have a higher price variance than books, shopbots will be more attractive to consumers because they can help consumers obtain the prices of retailers within seconds. Nonetheless, shopbots may not necessarily reduce consumers' search depth. Since online retailers were found to avoid fierce price competition by differentiating in quality attributes, and stores with lower service level or inferior brand names tend to charge a lower price, consumers who use shopbots may still need to look further at each individual online store's detailed service level and policy, and they may end up with engaging a more intensive search.

Shopbots reduces both consumers' search cost and uncertainty of search. Therefore consumers need to evaluate both in order to decide whether to use a shopbot. They will benefit from using a shopbot when degree of search cost reduction is large, quality differentiation is small, or price-quality correlation is large.

Implication for Retailers

Shopbots have been regarded as a threat to retailer profits. This study shows that shopbots do reduce the cost and risks in searching. However, the lower cost of risk reduction provided by shopbots encourages consumers to investigate more stores rather than stop searching and choose the lowest priced one. Thus shopbots do not necessarily discourage consumer search and result in retailers' fierce price competition.

Empirical evidence in this study suggests that consumers care more about quality attributes than simply price when choosing a store to purchase. Therefore, rather than competing by cutting profit margins, retailers can invest in improving service quality, building up reputation and advertising to promote brand names to attract consumers and to avoid head-to-head price competition. As a result, more than the mixed pricing strategies proposed by Baye and Morgan (2001), Iyer and Pazgal (2003) and Greenwald and Kephart (1999), a mixed strategy with both price and quality differentiation is expected to be optimal for online retailers.

Implication for Shopbot Designers

Most shopbots earn revenue from advertising fees and commissions. Advertising revenue depends on the number of viewers visiting the shopbot website, and these commissions depend on the participation and sales of the retailers through the shopbot website. To maximize shopbot profits, they should balance the attraction of users and participation of retailers. To attract users, shopbots should strive to reduce search cost by developing better algorithms for quick and accurate responses. To ease consumer search, shopbots can display more quality attributes in addition to prices and organize them in an efficient way. However, too many attributes will increase the delay of searching and the cognitive cost of the consumers (Montgomery et al. 2004), and they will prevent consumers' click-through to more websites for more information and therefore discouraging the retailers' participation. As a result, shopbot designers should choose an appropriate number of product attributes to display.

Shopbots can also rank the search results by other attributes than price. For example, many shopbots have adopted a fee-for-placement strategy, which allows a retailer to be ranked higher in the search list at a cost. This strategy increases shopbots' revenue and reduces the tension in price competition. Similar to this, shopbots can also use a combination of price, shipping and other quantitative quality measures to rank retailers. It will ease consumer search and mitigate price competition.

Implication for Academic Researchers

The contributions to academic research are threefold

1. This study extends the traditional search model into a two-attribute search model and discusses the impact of the correlation of the two attributes on search results. Empirical evidence that consumers are not only searching for prices but also for service quality attributes have been reported in Brynjolfsson and Smith (2000), Montgomery, et al. (2004), and Smith and Brynjolfsson (2001), but so far there has not been a model formally investigating this phenomenon. This paper fills in the gap by presenting a multi-attribute search model and deriving the optimal search strategies.

2. This study formally models consumer search strategy while using shopbots and theoretically compares the optimal search strategy with the scenario that search without using shopbots. We give analytical conditions under which shopbots can reduce consumer search and increase consumer surplus.

3. It empirically studies the impact of shopbots on consumer search activities with our consumer clickstream data. The empirical finding that consumers are searching more stores while using shopbots sounds surprising according to previous theories, but it can be explained with our theoretical results.

4.3 Limitations and Suggestions for Future Research

First the cost function is assumed to be linear in number of websites searched. In order to make the solution neat and meaningful, we ignored the economy of scale in searching. One way to solve this problem is to assume an exponential term in the number term of the cost function. We believe most of the analytical results will still be qualitatively the same except for the exact forms of the conditions.

Secondly, the consumers are assumed to be risk-neutral. In reality consumers could be either risk-averse or risk-loving. Presumably, risk-averse consumers will spend more effort to search in order to reduce the risk level, while risk-loving consumers will search less. It could be more interesting to discuss them in future research.

Thirdly, we assume that consumers at a shopbot randomly select a store to visit for more service quality and reputation information. By doing that, we ignore that some shopbots can sort the stores by their offering prices in the search result page. Observing the price ranking, consumers can visit the stores from the store with the lowest price and then to the next lowest priced one. We did not model consumers' search behavior that way because 1) consumers were found not to search from the lowest priced store

(Smith and Brynjolfsson 2001); 2) many shopbots are currently replace the price ranking by paid placement, that is, they charge retailers for a fee for a priority placement in the search result list. For example, in the result page in Figure 1, the retailer list returned by DealTime.com for a search of a 30GB iPod MP3 player has a random order of prices charged. Therefore our current assumption about consumer searching on shopbots is valid given empirical evidence about consumer browser at shopbots and the current shopbot design.

Fourthly, the way of dividing consumers search session by monthly web log data is not very rough. Further studies in computer science and marketing are expected to improve on this to get a more accurate estimate about consumer searches.

Overall, this study provides both analytical conclusions and empirical evidence to reveal and predict how shopbots affect consumers' online search. By extending the previous research (Johnson et al. 2004 Montgomery et al. 2004 and Steckel et al. 2005) in the same direction, it derives more managerial insights in understanding consumer online search behaviors through combining research methodologies from economics, marketing and computer science.

Figure 1. An example search page at a shopbot DealTime.com.

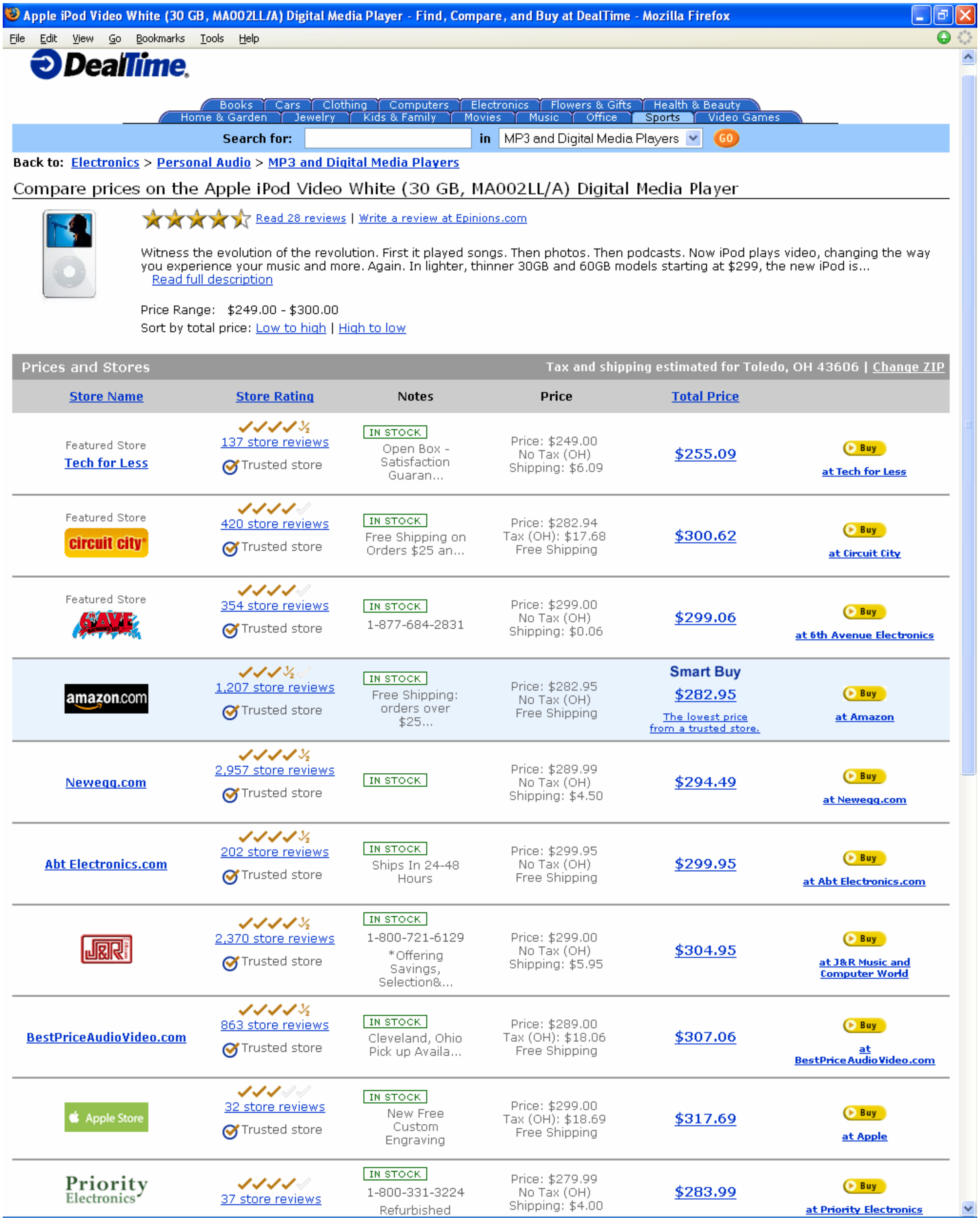

Table 1 Retailer and Shopbot Websites in book and Computer Hardware Categories.

Book			**Computer hardware**		
Retailer Websites	Visits	Shopbots	Retailer Websites	Visits	Shopbots
Amazon.com	16042	a1books.com	Dell.com	5641	dealtime.com
Columbiahouse.com	3942	addall.com	HP.com	1607	bizrate.com
CDnow.com	3023	allbookstores.com	Bestbuy.com	1341	pricegrabber.com
BMGmusic.com	1504	bestbookdeal.com	Officedepot.com	1001	nextag.com
Bestbuy.com	1362	bibliofind.com	Apple.com	796	pricescan.com
MP3.com	1260	bookfinder.com	Tigerdirect.com	728	streetprices.com
Buy.com	678	evenbetter.com	Circuitcity.com	646	calibex.com
CDuniverse.com	560	ISBN.nu	Sears.com	643	ibuyer.net
BN.com	301	kelkoo.co.uk	Compaq.com	422	pricingcentral.com
Fye.com	203	studentmarket.com	CompUSA.com	414	pricewatch.com
Samgoody.com	190		Sonystyle.com	404	thepricesearch.com
Mymusic.com	36		Compgeeks.com	220	productopia.com
CDnowpbc.com	35		IBM.com	201	mysimon.com
Hmv.co.uk	16		Outpost.com	192	gomez.com
CDEurope.com	8		Vikingop.com	192	ciao.co.uk
Musicblvd.com	3		Computers4sure.com	153	comparestoreprices.co.uk
			Digikey.com	137	shopping.com
			Epson.com	137	cairo.com
			PCconnection.com	83	planetonline.com
			Mwave.com	73	pricecomparison.com
			Warehouse.com	73	ucompareit.com
			Insight.com	32	
			Accessmicro.com	29	
			Futureshop.ca	11	

Table 2a. Descriptive Statistics for Book Category

Variables	Mean	N	Std Dev	Maximum	Minimum
N_{ij}	2.66	9380	1.60	14	1
Shopbot	0.07	9380	0.31	4	0
$\log(p_{ij})$	3.41	9380	0.98	6.86	0
$N_{i,j-1}$	0.83	9380	1.58	12	0
Household_income	4.48	9380	1.64	7	1
Connection_speed	0.45	9380	0.50	1	0
Household_Education	3.06	6738	1.38	5	0
Household_oldest_age	6.75	9380	2.61	11	1
Child_present	0.45	9380	0.50	1	0
Household_size	2.99	9380	1.37	6	1

Table 2b. Correlation Matrix for Book Category

	N_{ij}	$\log(p_{ij})$	$N_{i,j-1}$	Shopbot	Household_ Education	Household _Income	Connection _Speed	Child_ Present	Household _Size	Household_ Oldest_Age
N_{ij}	1									
$\log(p_{ij})$	0.027	1								
$N_{i,j-1}$	0.279	-0.004	1							
Shopbot	0.181	0.040	0.057	1						
Household_ Education	-0.040	0.071	-0.005	0.004	1					
Household _Income	-0.013	0.061	-0.002	-0.007	0.212	1				
Connection _Speed	0.054	0.013	0.025	-0.002	0.004	0.028	1			
Child_ Present	0.035	-0.001	-0.007	0.010	-0.040	0.098	0.008	1		
Household _Size	0.043	0.012	-0.0002	0.020	-0.042	0.124	0.025	0.671	1	
Household_ Oldest_Age	0.015	-0.015	0.054	-0.009	0.060	0.119	-0.083	0.003	-0.030	1

Table 3a. Descriptive Statistics for Computer Hardware Category

Variables	Mean	N	Std Dev	Maximum	Minimum
N_{ij}	3.26	3322	1.82	20	1
Shopbot	0.72	3322	1.04	7	0
$\log(p_{ij})$	4.43	3322	1.87	11.05	0
$N_{i,j-1}$	0.38	3322	1.60	17	0
Household_income	4.46	3322	1.66	7	1
Connection_speed	0.48	3322	0.50	1	0
Household_Education	2.85	2420	1.41	5	0
Household_oldest_age	6.82	3322	2.60	11	1
Child_present	0.48	3322	0.50	1	0
Household_size	3.07	3322	0.35	6	1

Table 3b. Correlation Matrix for Computer Hardware Category

	N_{ij}	Shopbot	$\log(p_{ij})$	$N_{i,j-1}$	Household_ Education	Household _Income	Connection _Speed	Household _Size	Household_ Oldest_Age	Child_ Present
N_{ij}	1									
Shopbot	0.389	1								
$\log(p_{ij})$	0.084	0.044	1							
lag_nij	0.236	0.099	-0.041	1						
Hoh_ Education	0.006	0.053	0.017	0.018	1					
Household _income	0.053	0.027	0.115	0.033	0.269	1				
Connection _speed	0.072	0.040	0.047	0.009	0.041	0.053	1			
Household _size	0.027	0.003	0.102	-0.020	0.003	0.131	0.027	1		
Hoh_ Oldest_age	- 0.058	0.013	-0.121	-0.047	0.058	0.074	-0.112	-0.079	1	
Child_ Present	0.040	0.010	0.077	-0.003	-0.001	0.100	0.004	0.665	-0.053	1

Table 4. Regression Results (Dependent Variable: N_{ij})

Independent Variables	Book	Computer Hardware
Shopbot	0.86****	1.85****
	(0.05)	(0.08)
$\log(p_{ij})$	0.04**	0.09****
	(0.01)	(0.02)
$N_{i,j-1}$	0.27****	0.31****
	(0.01)	(0.02)
Connection_Speed	0.15****	0.24***
	(0.03)	(0.08)
Household_Income	-0.02**	0.04*
	(0.01)	(0.02)
Household_Oldest_Age	0.01	-0.04***
	(0.01)	(0.02)
Household_Size	0.04***	-0.01
	(0.01)	(0.04)
Child_Present	0.05	0.15
	(0.04)	(0.11)
Intercept	2.10****	2.83****
	(0.09)	(0.20)
N	9780	3322
R Square	0.111	0.203
Adj. *R* Square	0.110	0.201

**** p value < 0.001, *** p value < 0.01 ** p value < 0.05, * p value < 0.1

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