Working Paper #06-19

October 2006

Search Costs, Demand Structure and Long Tail in Electronic Markets: Theory and Evidence

Anindya Ghose
Stern School of Business, New York University
Bin Gu
McCombs School of Business, University of Texas at Austin

Search Costs, Demand Structure and Long Tail in Electronic Markets: Theory and Evidence[1]

Anindya Ghose
Stern School of Business
New York University
44 West 4th Street, New York, NY-10012
aghose@stern.nyu.edu

Bin Gu
McCombs School of Business
University of Texas at Austin
Austin , TX 78712
Bin.Gu@mccombs.utexas.edu

October 2006

NET Institute Working Paper

[1] Financial support from the NET Institute, www.NETinst.org is gratefully acknowledged.

Abstract

It is well known that the Internet has significantly reduced consumers' search costs online. But relatively little is known about how search costs affect consumer demand structure in online markets. In this paper, we identify the impact of search costs on firm competition and market structure by exploring a unique theoretical insight that search costs create a kink in aggregate demand when firms change prices. The significance of the kink reflects the magnitude of online search costs and the kinked demand function provides information on how search costs affect competition in the online market. Using a dataset collected from Amazon and Barnes & Noble, we find that search costs vary significantly across online retailers. Consumers face low search costs for price information from Amazon.com. It leads to a higher price elasticity when the firm reduces prices than when it increases prices, increasing Amazon's incentive to engage in price competition. On the other hand, consumers face relatively higher search costs for price information from Barnes & Noble. This leads to a lower price elasticity when Barnes & Noble reduces prices than when it increases prices, reducing Barnes & Noble's incentive to engage in price competition. We also find that search costs decrease with the passage of time as the information about price changes dissipates among consumers, leading to increased price elasticity over time. Finally, we highlight that search costs are lower for popular books compared to rare and unpopular books. These findings have implications for the impact of the Internet on the Long Tail phenomenon.

Keywords: Electronic Markets, Search Costs, Kinked Demand Curve, Price Elasticity, Price Competition, Long Tail

1. Introduction

An important advantage that electronic markets posit over physical markets is a reduction in search costs for product-related information. This is especially true for product price information. Unlike in a physical market where consumers need to travel to multiple stores for price comparison, competitors' prices are just a few clicks away in an online market. The emergence of online shopbots such as Froogle, Pricegrabber, Dealtime etc. have further reduced consumer search costs by presenting price information for the same product from multiple online vendors.

The reduction in price search cost has rekindled interests in examining the Law of One Price (Brynjolfsson and Smith 2000). Theoretical research has shown that search costs create imperfect information about firms' prices among consumers, which leads to equilibrium price dispersion in otherwise homogeneous product markets (Stigler 1961, Reinganum 1979, Rob 1985, and Stahl 1989). This provides an intuitive rationale for price dispersion that has been observed in conventional retail markets where consumers must incur the incremental costs of searching for prices at firms' brick-and-mortar stores. As the internet reduces search costs in the online markets, price dispersion is expected to decrease and the Law of One Price is likely to prevail.

Empirical evidence however shows that there is significant price dispersion online. In fact, research has often found a high level of price dispersion across Internet retailers as well as between online and offline channels. For instance, Clay et al. (2002) find a price dispersion of 27 percent for a random selection of hardcover books and 73 percent for paperback bestsellers. Similarly, Brynjolfsson and Smith (2000) find that Internet retailer prices differ by an average of 33 percent for books and 25 percent for CDs. Recent work includes Baye, Morgan and Scholten (2004) who find price dispersion between 3.5% and 22%, depending on the number of online retailers competing in the market. At the same time, a few studies have shown that the Internet has reduced search costs online. Brown and Goolsbee (2002) find that while the use of the Internet is initially associated with an increase in price dispersion of term life insurance premiums, the dispersion decreases as use spreads. Likewise, Morton, et. al. (2001) finds dispersion of car dealer prices decreases with online sales.

This presents an interesting scenario. On the one hand, since the Internet reduces search costs and searching for a better price becomes easier for consumers, conventional wisdom suggests that pricing pressure will increase on firms, thereby significantly reducing price dispersion. On the other hand, mixed empirical evidence on price dispersion shows that search costs are omnipresent in the online world. This calls for a more detailed examination at search costs online and their implications for online retailers. To empirically investigate this issue, our research uses a new approach building on prior theoretical insights that relate the nature of consumer demand structure to the presence of search costs. Moreover, we also empirically validate the related theoretical prediction of how price information diffuses in the market.

A number of empirical studies have tried to quantify search costs both in online and offline settings. Sorensen (2000) finds that patterns in price dispersion across prescription drugs are consistent with the predictions of a search model, as repeatedly purchased prescriptions show lower dispersion and price-cost margins. He estimated that the cost of conducting an exhaustive search is about $15 per consumer by using a structure equation approach (Sorensen 2001). Brynjolfsson, Dick and Smith (2004) take a different approach to estimate search cost as they can directly observe consumer search activity in their shopbot data. They found that the cost of an exhaustive search is about $6.45 per consumer. Hong and Shum (2006) develop a methodology for recovering search cost estimates using only observed price data. Bajari and Hortacsu (2003) quantified the cost of entering into an eBay auction to be $3.20, which includes search costs and other costs related to auction participation. In a related stream of work, Hann and Terweisch (2003) discuss how search costs and other related frictional costs in electronic markets could be substantial. They find the median value of frictional costs ranging from EUR 3.54 for a portable digital music player (MP3) to EUR 6.08 for a personal digital assistant (PDA).

The empirical work on search costs has shown that online search costs, although smaller than search costs in physical markets, are still significant. The presence of such search costs are well known to affect the shape and dynamics of consumer demand and have significant implications for both micro and macro economic equilibrium. However, despite its importance, little empirical evidence exists so far on how search costs actually affect the structure of consumer demand and market competition. The objective of our study is therefore to consider how such search costs affect market competition, and in particular how they influence consumer demand structure faced by online retailers. Moreover, prior search costs literatures usually measure search costs as a consumer characteristic, implicitly assuming that search costs are the same across online retailers. Our study takes a first step to consider how search costs varies across online retailers and how such variations influence consumer demand and market competition for online retailers. The presence of search costs also implies that that it takes time for information about price changes to dissipate among consumers in the market. This indicates that search costs are higher in the short-term. An additional contribution of this study is that we do so with only aggregate level data by exploring a unique insight of Stiglitz (1989) that search costs create a kink in aggregate demand when firms change prices. The significance of the kink reflects the magnitude of online search costs and the kinked demand function provides information on how search costs affect competition in the online market. The use of aggregate retail purchase data enables us to overcome limitations of earlier studies which are based on shopbot users. As shopbot users typically incur lower search costs, it is difficult to interpret the implications from those studies for online markets in general.

Using a dataset on price and demand from Amazon and Barnes and Noble, this paper demonstrates that consumer demand function exhibits a kink, validating Stiglitz (1989). The direction and magnitude of the kink varies significantly across online retailers. Price elasticity is higher for price decrease than for price increases on Amazon, indicating that Amazon's price decrease information is quickly picked up by consumers. This suggests low search costs for Amazon's price information. On the contrary, price elasticity is lower for price decrease than for price increases on

Barnes and Noble, indicating that potential customers are not aware of BN's price decrease information. This suggests high search costs for BN's price information. The combination of the two results implies that, while search costs are ubiquitous in online markets, search costs vary significantly across online retailers. In addition, we find that price elasticity increases during the 4 weeks after price decreases, indicating that price information gradually penetrates the market over time. We also show that search costs are higher for obscure and unpopular books compared to the popular books. The result indicates that less popular books continue to face disadvantages in online markets, suggesting certain limitations on the Long Tail. Further, we also estimate the change in market share due to the presence of search costs, which prevents information about price changes from percolating instantaneously in the market. In this way, our paper also contributes to recent research that demonstrates the price competition between online retailers (Chevalier and Goolsbee 2003). In sum, our paper aims to make the following contributions:

1. We provide the first known empirical analysis of the nature of search cost on consumer demand curve in electronic markets. We show that as predicted by theory, consumer demand is indeed kinked, and this highlights that consumers face positive search costs even in online markets. Unlike prior work, our results use aggregate price and demand data from large online retailers, thus making the result more applicable to the general online markets.
2. We show how search costs vary across online retailers. We find that consumers face low search costs on Amazon, but high search costs on Barnes & Noble. Our finding suggests that consumer search costs are potentially related to differences in retailer characteristics because of which otherwise similar online retailers may impose very different search costs on consumers. The result sheds more light on difference across online retailers and offers new insights into the underlying factors that drive their competitive strategies. Further, we also consider the dynamics of how search costs change over time. We demonstrate that price elasticity after a price decrease increases over time across a period of 4 weeks, suggesting that search costs for price information in

electronic markets do reduce over time. The fact that search costs are dynamic over time has both theoretical and practical implications for online markets, and we discuss them in detail.

3. Our empirical analysis corroborates anecdotal evidence that popular books have lower search cost compared to less popular and obscure books. The results less popular books continue to face disadvantages in online markets. This may put a limit on the extent of the Long Tail phenomenon. On the flip side, it also suggests that there are opportunities for online retailers to further reduce search costs for less popular books. As is being witnessed in the Long Tail phenomenon, consumer demand for less popular books has been substantial and a reduction in their search costs could further enhance the advantages of online retailers.
4. Finally, we also analyze the effect of search costs on relative market shares of Amazon and Barnes and Noble. We show that compared to Barnes and Noble, Amazon has a stronger incentive to have lower prices for unpopular and rare books since the potential market share gains are larger for Amazon. In contrast, for popular books, Amazon has a mixed incentive.

The rest of the paper is as follows: In Section 2, we present the theoretical framework based on which the empirical estimations are carried out. The data is described in Section 3. Thereafter, we provide the empirical methodology and test our main hypothesis in Section 4. The analysis of the impact of search costs on the demand structure for popular vs. unpopular books along with its impact on relative online market shares of Amazon and Barnes & Noble is presented in Section 5. Section 6 offers concluding remarks with discussion of possible extensions. The tables are in the Appendix.

2. Theory

A well-known feature of search costs in a competitive marketplace is that it creates a kinked demand function (Stiglitz 1989). He suggested that when the underlying consumer demand function is kinked, the demand elasticity for price decreases is different from the demand elasticity for price increases. The significance of the kinkiness is determined by the magnitude of the search cost faced by consumers. When search cost is high, consumers are only aware of the price of the store they visit, but are unaware of the prices for the same product in the retailers they do not visit. So when a retailer increases its price, its own immediate customers (who know about the increase) are induced to search for prices amongst rival retailers and the store loses customers accordingly. But when a retailer decreases its price, then unless it expends resources on advertising, its action induces no new customers to launch a search. Hence, while it will able to keep its existing customers, it does not gain a proportionate number of new customers. This leads to a lower price elasticity for price decreases. Under such circumstances, the gains to lowering prices may be markedly lower than the losses from raising prices.

On the other hand, when search cost is low, a reduction in product price by a retailer has the potential to attract customers from its competitors, but a price increase only affects the firm's current customers. This leads to a higher price elasticity for price decreases.[3] Thus, by studying the characteristics of the consumer demand function, we can infer the level of search costs in online markets. In order to empirically investigate the nature of the demand function, we allow the demand elasticity for price decreases to be different from price increases.

The presence of search costs is well documented in physical market. The literature on the economics of information identifies two types of search costs that influence information search – external and cognitive. External search costs include monetary costs of acquiring information, that is, the opportunity cost of time. On the other hand, cognitive search costs reflect the mental accounting efforts consumers must invest in to direct search enquiries, sort incoming information and integrate it with stored information to form decision evaluations. These costs are generally influenced by consumers' bounded rationality in processing the plethora of incoming information.

Electronic markets reduce monetary costs of acquiring information. However, since information in online environments is highly visual and perceptual, it potentially increases cognitive costs that affect consumers' search for information (Chiang 2006). Furthermore, information search

[3] In such a situation a firm enjoys a discontinuous jump in demand when it succeeds in charging the lowest price because it instantly attracts the price-sensitive "shopper" segment of the market

online is characterized by human-computer interaction requiring consumers to have increased ability and knowledge in acquiring information (Hodkison et al., 2000). As a result, the Internet can impose a certain degree of cognitive cost on consumers that could potentially prevent consumers from searching for more information.[4]

3. Data

We estimate our models using a panel data set compiled from publicly available information about product prices and sales rankings, gathered using automated Java scripts. These scripts access and parse HTML and XML pages downloaded from Amazon.com and Barnes & Noble.com between September 2005 and April 2006. The panel includes daily data over 3210 books across all major book categories. These products include a mix of best sellers, new releases, random selected titles and less popular books selected from the different genres such as fiction, non-fiction, business, textbooks, computer books and so on.

We collect data from both Amazon and Barnes & Noble for the same set of books to control for competition among online retailers. In the context of online book sales, Barnes & Noble and Amazon are the two largest book retailers online, and their pricing policies influence each other. To control for competition from remaining online book retailers and used book markets, we also collected secondary market data that including the number of used copies available for sale and the minimum price of the used books in Amazon's marketplace. We note that Amazon allows small book retailers like Abebooks and Powells to sell books on its marketplace. Thus, our data takes into account some of the competitive influence from other retailers.

Each observation from Amazon contains the date of data collection, the product's list price, its Amazon retail price, its Amazon sales rank (which serves as a proxy for units of demand, as described

[4] Chiang (2006) notes that "in order to search online, consumers must not only be able to locate the websites of interest and move between sites but also to acquire information within the sites. There are several ways to identify the location of websites: (1) via search engine, (2) via manual entry of a URL and (3) via the memory aid of a browser such as bookmarks. Given the vast amount of information available on the Internet, these search techniques will affect consumer information search."

later), the date the product was released into the market, the average customer rating for the product, and the number of reviews based on which the average rating was computed. Each observation from Barnes & Noble contains similar items: the date of data collection, the product's list price, its Barnes & Noble retail price, its Barnes & Noble sales rank (which also serves as a proxy for units of demand, as described later), , the average Barnes & Noble customer rating for the product, and the number of reviews based on which the average rating was computed. The summary statistics of our data are in Table 1. It shows a significant amount of variation in the sample we use, covering a wide range of books with different online prices, sales ranks, secondary market information and release dates.

An interesting aspect of the dataset is the frequency of price changes made by both retailers because this is likely to affect search costs. In our data we find that on an average, Amazon changes a book's price every 151 days and Barnes & Noble change prices every 49 days. Such price rigidity has a similar flavor to the findings of the Bergen, Kauffman and Lee (2005) although in terms of the actual magnitude, they find that price changes on an average every 222 days for Amazon.com and every 56 days for Barnes & Noble.com.

4. Empirical Methodology

In order to test the theoretical predictions, we need to estimate demand. Neither Amazon nor Barnes and Noble report their periodic demand levels. Instead, they reports a sales rank for each product sold on its site, which ranks the demand for a product relative to other products in its category. Thus, the lower the cardinal value of the sales rank, the higher the demand for that particular item. Until recently it was difficult to calculate the price elasticity for products sold on the Internet because, while the price of individual items could be readily observed, the quantity sold was generally unobservable. However, an emerging stream of work has addressed this problem by providing a way to map the observable Amazon.com sales rank to the corresponding number of books sold. In both cases, the authors find a stable relationship between the ordinal sales rank of a book and the cardinal number of sales, using the following Pareto relationship:

$$Quantity = \delta \cdot Rank^{\theta} \tag{1}$$

Chevalier and Goolsbee (2003) estimate the parameters of this equation for books by associating demand data with sales rank on the Wall Street Journal best-seller list, and by independently conducting a purchasing experiment on one book whose actual weekly demand was known to them. Observing the extent to which Amazon sales rank reacted to their purchases, they estimate θ=-0.855. Brynjolfsson, Hu and Smith (2003) provide an alternative estimate of the parameters of equation for books. Using data from a book publisher that maps observed sales rank to the number of copies the publisher sold to Amazon, they estimate $\theta = -0.871$[5] and log[δ] = 10.526[6]. In their study of the impact of used book markets on new book sales, Ghose, Smith and Telang (2006), use $\theta = -0.871$. For our study, we continue to use the same parameter for imputing demand for books.

We use a well-known log-log specification for our demand estimation. The log-log specification has been widely used for estimating demand function and it has the benefits of offering a direct estimation of demand elasticity with the coefficient on the price variable (e.g. Brynjolfsson, Hu and Smith 2003; Ghose, Smith and Telang 2006). Using the relationship in (1), we can then estimate a demand model for a monopolistic online retailer in the following form:

$$\log(Rank_{it}) = \alpha_i + \beta_1 \log\left(P_{A_{it}}\right) + \gamma_i \log\left(T_{it}\right) + \Omega' X_{it} + \varepsilon_{it} \tag{2}$$

where, i and t index product and time. The dependant variable is the log of sales rank of product i at time t. The independent variables are the retailer price at time t (P_{it}) , the number of days since the product was released (T_{it}) and a vector of other control variables (X). X include the log of the lowest used product price for a given product, the consumer rating for the product, the log of the number of reviews, and the log of the number of used products offered for sale. The multiplicative product of coefficient on retailer price β_1 and the Pareto parameter θ represents its price elasticity.

---

[5] Parameter β_2 in their model.
[6] Parameter β_1 in their model.

Stiglitz (1989) suggested that search costs lead to a kinked demand function. When search costs are high, price decrease information disseminates slowly among potential customers, but price increases are immediately observed by current customers. As a result, a firm in a high search costs environment faces lower price elasticity for price decreases than for price increases. This often happens for relatively smaller and lesser known firms whose price information is not well followed by the market. On the other hand, when search costs are low, price decrease information disseminates quickly and attracts not only a firm's own regular customers but its competitors' customer as well. This results in higher price elasticity for price decreases than for price increases. This phenomenon is often observed for market leaders whose price information is well followed by customers and competitors.

Figures 1a and 1b illustrate the two kinked demand functions on a log-log scale plot. In these plots, the slope of the demand function represents demand elasticity. The changes in demand elasticity indicated by prior theory are reflected in the change of slope. Figure 1a shows the high search costs scenario as the demand curve in the figure is steeper for price increases than for price decreases. Figure 1b shows the low search costs scenario. The demand curve is steeper for price decreases, as price decreases attract customers from a firm's competitors while price increases affects only a firm's own customers.

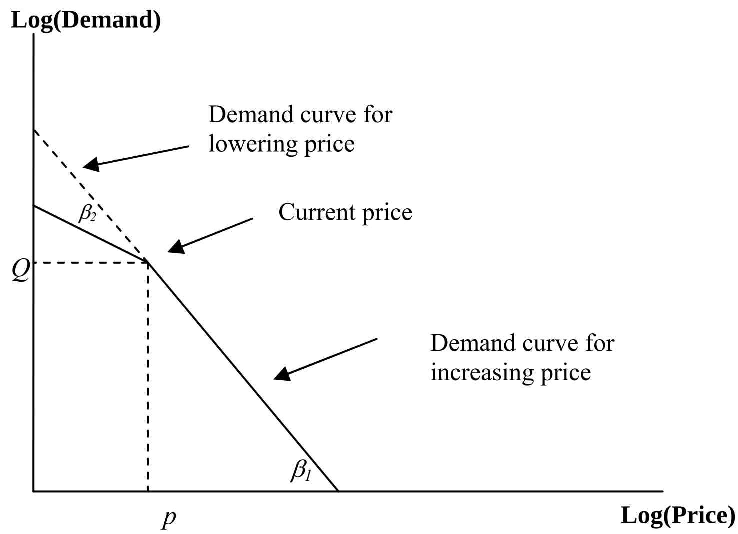

Figure 1a: A Kink in Demand Structure in a High Search Cost Scenario

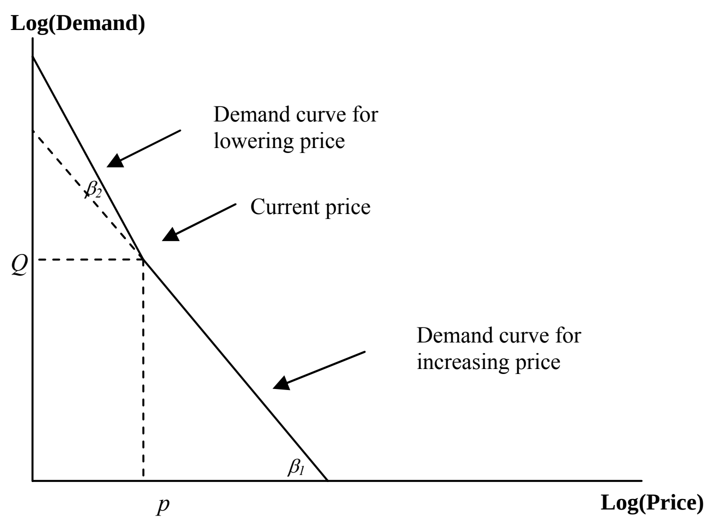

Figure 1b: A Kink in Demand Structure in a Low Search Cost Scenario

We empirically investigate this theory by allowing demand elasticity for price decreases to vary from that for price increases. To do so, we construct a dummy variable *PriceDecrease* which takes the value of 1 if the most recent action on product *i* is a price decrease. We note that the kinkedness happens at the price change point, which indicates that the slope for price decrease from the price change point is different from the slope for price increases from the price change point. Let the price before the most recent price change be $\underline{P}_{it}$. We can then modify equation (2) to the following form to capture the kinkedness in the demand function:

$$log(Rank_{it}) = \beta_0 + \beta_1 log(P_{it}) + \beta_{2j}\left(log(P_{it}) - log(\underline{P}_{it})\right) \times PriceDecrease_{it} + \beta_3 log(T_{it}) + \Omega' X_{it} + \varepsilon_{it} \tag{3}$$

Here β_1 represents demand elasticity for price increases. β_2 denotes the difference between demand elasticity for price decreases and that for price increases. Figures 1a and 1b provide a graphic representation of the two coefficients. A negative value of β_2 implies high search cost wherein demand elasticity for price decreases is smaller than that for price increases. If β_2 is positive, it indicates a low search cost where demand elasticity for price decreases is larger than that for price increases.

The presence of search costs also suggests that it takes time for information on price decreases to spread in the market. To quantify this information diffusion process, we consider how demand elasticity evolves after a price change. We allow demand elasticity to vary from week to week for up to 4 weeks after the initial price decrease.[8] This requires the creation of four weekly dummy variables, denoted by $Week_{ijt}$ to represent the number of weeks after the most recent price decrease. We use the four dummies to extend Equation (3) to capture the changes in price elasticity over time as follows:

$$\log(Rank_{it}) = \beta_0 + \beta_1 \log(P_{it}) + \sum_{j=1,2,3,4} \beta_{2j}\left(\log(P_{it}) - \log(\underline{P}_{it})\right) \times PriceDecrease_{it} \times Week_{ijt} + \beta_3 \log(T_{it}) + \Omega' X_{it} + \varepsilon_{it} \tag{4}$$

Equation (4) presents a kinked demand function for a monopolistic firm whose consumers face positive search costs. In reality, most online retailers operate in a competitive environment. For example, in the book industry, the two largest online retailers are Amazon.com and Barnes & Noble.com. To consider the competitive implications, we extend Equation (4) into two demand

[8] The number of weeks is not very critical towards understanding the result. We are interested in finding out whether search costs decrease with time, and this trend is qualitatively similar across different time periods. We choose 4 weeks because our data reveals that Barnes and Noble responds to a price change on Amazon on an average after 30 days.

equations, one for each retailer. We incorporate both Amazon and Barnes & Noble's prices into the equations to capture the own-price elasticity and the cross-price elasticity. The competition from remaining online retailers is captured by X_{it}, which include book prices from Amazon Marketplace with listings from small online retailers.[9] Chevalier and Goolsbee (2003) show that taking the difference between the demand equations for the two firms enables estimation of relative price elasticity. This leads to the following estimation model:

$$
\begin{aligned}
&\log(Rank_{A_{it}}) - \log(Rank_{B_{it}}) = \\
&\chi_0 + \chi_1 \log\left(P_{A_{it}}\right) + \sum_{j=1}^{4} \chi_{2j}\left(\log\left(P_{A_{it}}\right) - \log\left(\underline{P}_{A_{it}}\right)\right) \times \Pr iceDecrease_{A_{it}} \times Week_{A_{ijt}} + \\
&\chi_3 \log\left(P_{B_{it}}\right) + \sum_{j=1}^{4} \chi_{4j}\left(\log\left(P_{B_{it}}\right) - \log\left(\underline{P}_{B_{it}}\right)\right) \times \Pr iceDecrease_{B_{it}} \times Week_{B_{itj}} + \chi_4 \log\left(T_{it}\right) + \Omega' X_{it} + \varepsilon_{it}
\end{aligned}
$$

We also realize that product demand is largely determined by its characteristics unobserved by researchers. We therefore leverage our panel data structure to include fixed effect for each book. In addition, we also note that each book has its own demand dynamics. Some books last for months on the best sellers list, while demand for other book saturates rather quickly. To accommodate differences in demand dynamics across books, we allow the coefficient on $\underline{\log(T_{it})}$ to vary from product to product. The final empirical model therefore takes the following form:

$$
\begin{aligned}
&\log(Rank_{A_{it}}) - \log(Rank_{B_{it}}) = \\
&\phi_i + \chi_1 \log\left(P_{A_{it}}\right) + \sum_{j=1}^{4} \chi_{2j}\left(\log\left(P_{A_{it}}\right) - \log\left(\underline{P}_{A_{it}}\right)\right) \times \Pr iceDecrease_{A_{it}} \times Week_{A_{ijt}} + \\
&\chi_3 \log\left(P_{B_{it}}\right) + \sum_{j=1}^{4} \chi_{4j}\left(\log\left(P_{B_{it}}\right) - \log\left(\underline{P}_{B_{it}}\right)\right) \times \Pr iceDecrease_{B_{it}} \times Week_{B_{itj}} + \varphi_i \log\left(T_{it}\right) + \Omega' X_{it} + \varepsilon_{it}
\end{aligned}
\tag{5}
$$

To test the above model, we need to impute product demand from their sales ranks listed on Amazon. The Pareto curve indicates the log of demand is a linear function of the log of Amazon sales rank. We can therefore use *log(Rank$_{it}$)* in place of *log(Demand$_{it}$)* in our log-log model and convert the

[9] A browsing of Amazon Marketplace shows book offers from the following online retailers: A1books.com, Powells.com, eCampus.com and SuperBookDeals.com consisting of both new and used book offers.

coefficients on prices to demand elasticities by multiplying with the appropriate value of the Pareto parameter, θ.[10]

5. Analysis

In this section we present the results of our empirical estimations. Specifically, we focus on the impact of search costs on overall demand structure, on the differences of search costs across retailers, on popular versus obscure books and on market competition between Amazon and Barnes & Noble.

5.1 Search Costs and Demand Structure

The estimates are presented in Table 2. Column 1 presents the result of a base case analysis with consideration of competition between Amazon and Barnes & Noble but without considering the presence of search costs. The parameters of interest have the expected signs. The coefficient on Amazon price is positive, suggesting that price increase leads to increase in Amazon sale rank relative to Barnes & Noble sale rank, i.e. decrease in Amazon relative sales. On the other hand, the coefficient on Barnes & Noble price is negative, indicating that a Barnes & Noble price increase leads to decrease in Amazon sales rank relative to Barnes & Noble sales rank, i.e. an increase in Amazon's relative sales. We also find that the coefficient on number of used books is positive, i.e. an increase in supply of used books on Amazon Marketplace reduces Amazon's new book sales. On the other hand, minimum used product prices have a negative relationship with sales rank suggesting that an increase in used product prices boosts sales of new books on Amazon. Amazon customer rating and number of

[10] Note that because of the structure of this industry, quantity and price are not jointly determined, and thus we do not face the endogeneity concerns that would normally arise in demand regressions. With regard to a retailer's own price, because books are produced in large quantities prior to going to market, the quantity of new books Amazon can sell is predetermined (and virtually infinite) at the time Amazon sets their price.[10] This follows the standard approach taken in the literature for demand estimation of Internet product sales (see for example, Chevalier and Goolsbee 2003, Ghose, Smith and Telang 2006). Moreover, Amazon has publicly claimed that it engages in price experimentations such that the sales ranks movements do not determine changes in price. This is also evident from the fact while we observe multiple changes in the sales rank of a given book on a given date, prices only change once every few days. This further reduces any potential endogeneity concerns.

reviews are also negatively related to sales rank, since an increase in customer ranking or in number of customer reviews potentially leads to higher sales on Amazon.

The regression results can be used to calculate the relative price elasticities of the two online retailers. As we discussed before, the relative price elasticities equals to the products of the coefficients from Table (2) and the Pareto parameter θ. Thus, using relevant values of θ, we see that Amazon's relative price elasticity for books is between -1.49 and -1.89 and Barnes & Noble's relative price elasticity for books is between -1.53 and -1.60. The range of price elasticities for the two firms is in tune with what one would expect. We find that the relative price elasticities for Amazon are both negative and statistically significant, suggesting that, when prices rise at an online bookstore, relative sales ranks at that bookstore become larger, that is, relative sales go down.

Interestingly, we also find that the relative price elasticity for Amazon is very close to the relative price elasticity for Barnes & Noble. This however does not necessarily imply the demand dynamics at Amazon are similar to Barnes & Noble. As noted by Chevalier and Goolsbee (2003), the two retailers may have significant differences in their competitive position even if their relative price elasticities appear to be similar. We also note that the relative price elasticity of Amazon in this sample is between -1.79 and -1.86. This is slightly higher than that obtained in the prior research. Given that our sample has a high proportion of more new releases than the first sample, this is what one would expect. New releases have wider availability on the Internet, thereby leading to reduced market power for Amazon and thus higher relative price elasticities.

Columns 2 and 3 consider the presence of a kink in the demand function. After allowing price elasticity to be different for price increases compared to price decreases, we find that demand functions are indeed kinked for both Amazon and Barnes & Noble. We observe that Amazon's relative price elasticity increases after a price decrease. The increase is gradual over time. Column 3 shows that the increases in price elasticity for the first two weeks are not statistically significant. However, starting in Week 3, the increase becomes statistically significant. Based on the Pareto parameter of -0.871, the relative price elasticity for Amazon increases from -1.86 to -2.15 in Week 3 and -2.21 in

Week 4.[11] This result corresponds to the low search cost scenario in Stieglitz's (1989) theoretical model where a reduction in price produces higher price elasticity as a lower price enables the firm to attract consumers from its competitors. Our results also show that search costs reduce further over time as information disperses among online consumers.

Contrary to the result on Amazon, we find that Barnes & Noble's relative price elasticity decreases after price decrease. Column 3 shows that the decrease in price elasticity is stable over time and statistically significant. Based on the Pareto parameter of -0.871, the relative price elasticity for Barnes & Noble decreases from -1.59 to -0.82 in Week 1 and remains at the same level through the four-week period. This result corresponds to the high search cost scenario in Stiglitz's model where, due to search costs, a large number of potential customers are not aware of price decreases. As a result, price decreases do not lead a significant increase in sales. Our result also reveals that information on Barnes & Noble price decreases are not disseminated to potential customers even with the passing of time.

The results of this study suggest that search costs vary significantly across online retailers. Some online retailers enjoy low search costs where its price information is quickly disseminated to potential customers. Conversely, other online retailers face much higher search costs, and few potential customers are aware of their price information.

To avoid the impact of new book promotion and other site-based marketing activities that potentially affect book demand, we also ran similar regressions limiting our observations to those during the first 90, 180 and more than 180 days of book release. The 180 days cut-off threshold is established based on anecdotal evidence of a survey of marketing activities on Amazon.com which reveals most featured books are taken down within 6 to 7 months after release and that publicity is the

[11] The relative price elasticity is equal to the Pareto parameter (-0.871) times the sum of the coefficient on Amazon price (2.14) and the coefficient on Week 3 after price decrease on Amazon (0.33). Other relative price elasticities are similarly calculated.

most vital within the first six months from its publication date.[12] The qualitative nature of our results was robust to these changes.

5.2 Search Costs and Product Popularity

Since the inception of online retailing in the mid-to-late 1990s, product assortments on the web have increasingly become broader and deeper. Internet retailers have nearly unlimited "virtual inventory" through centralized warehouses and drop shipping agreements with distributors (Mendelson and Meza 2002). This enables them to offer convenient access to a larger selection of products than brick-and-mortar retailers. For example, small stores stock approximately 20,000 unique titles, and large independent booksellers stock approximately 40,000 unique titles (Brynjolfsson, Hu and Smith 2003). Large differences in product variety are also seen in music, movies, and consumer electronics products. Even Wal-Mart Supercenters, which can be up to 230,000 square feet in size, only carry one-sixth of the number of SKUs that are carried by Walmart.com (Owen 2002). As an example of how the Internet is increasing orders for many titles not previously stocked in brick-and mortar stores, the MIT Press reported 12 percent annual increases in sales of backlist books (Postrel 2004). 30-40 % of Amazon book sales are represented by titles that wouldn't normally be found in brick-and-mortar stores (Brynjolffson, Hu and Smith 2003).

Prior work has argued that the Internet reduces search costs for rare and relatively unpopular books because online consumers are easily able to locate, evaluate, order, and receive millions of books that are not available on the shelves of local bookstores (Brynjolffson, Hu and Smith 2003). However, it is not clear to what extent that the internet has leveled the playing ground for the two kinds of books. Popular books are still more likely to be advertised and prominently featured by bookstores. This is evident in both online and offline stores. For example, Amazon always features the most popular books on its bookstore homepage. It also has pages dedicated to NY Times best

[12] Florez, Jessica. 2005. Seven Vital Book Promotion Tips. (www. spotlightpublicity.com)

sellers and other best selling book lists. These actions reduce search costs for price information of popular books more than that for the less popular books.

Moreover price changes on popular books by one retailer are more likely to be matched by its competitor, leading to a faster dissemination of price change information and lower search costs on consumers. As an example, while it takes Amazon on average 74 days to response to Barnes & Noble price changes, if we separate books by their popularity, our data show that it takes Amazon an average of 55 days to respond to changes in prices for the top 20,000 books, 58 days to respond to changes in prices for the top 40,000 books and 65 days to respond to changes in prices for the top 100,000 books. On the other hand for unpopular books Amazon takes much longer to respond to changes in price by Barnes & Noble. For example, for books with sales rank higher than 100,000 Amazon responds to a price change after 90 days.[13]

In order to understand how search costs vary between popular books versus less popular books, we conduct a similar analysis as before but on a selected sample. Specifically, we split the sample by sales rank into two sub-samples. In keeping with the findings of prior work, we use 20,000 and 40,000 as the median sales rank cut-off for denoting books that are relatively popular and are more likely to be stocked by offline retailers such as discount stores and specialty bookstores. Our results are consistent across different specifications and are reported in Tables 3 and 4. As a robustness check, we also used a median sales rank of 20,000 or 40000 as cut-off at Barnes and Noble. The results were qualitatively similar. Results using a median sales rank of 100,000 across both Amazon and Barnes and Noble are also very similar. These robustness checks are omitted for brevity.

Our results reveal that the search costs for unpopular books are much higher than popular books. For unpopular books with median Amazon sales rank of more than 40,000 (Table 3, Column 2), Amazon's relative price elasticity decreases slightly after a price decrease. However, for popular books with a median Amazon sales rank of less than 40,000 (Table 4, Column 2), relative price

[13] Interestingly BN's response to price changes on Amazon seems independent of a book's popularity. For the same cut-off ranges of top 20,000, top 40000, top 100000 and books with sales ranks greater than 100,000 the BN response time to a price change by Amazon consistently varies in a narrow range between 30 and 35 days.

elasticity increases dramatically after a price decrease. This suggests information about price decreases in popular books is quickly disseminated among potential customers, but similar information for unpopular books does not spread as fast. We observe the same phenomenon for Barnes & Noble. We find that Barnes & Noble's relative price elasticity decreases significantly after a price decrease for unpopular books, but only decreases slightly for popular books. The results indicate a high level of search costs for unpopular books on Barnes & Noble.com, but only moderate level of search costs for popular books. The difference in search costs between popular books and less popular books suggests that the Internet has not entirely removed the inherent disadvantages faced by less popular books. This imposes a limit on the extent of Long Tail phenomenon observed in the online book markets. This result also suggests that we may see more Long Tail phenomenon if the retailers are able to further reduce the search costs for less popular books to bring them in line with their popular books.

5.3 Search Cost and Market Competition

The presence of search cost has a direct impact on competition between Amazon and Barnes & Noble by influencing their incentives to change prices. To illustrate the implication of search costs on market competition, we need to consider how price changes affect the market shares of the two retailers in the online world. However, one weakness of sales rank data is that it provides only information with regard to sales within sites but not across sites. To alleviate the problem, we calculate the relative market shares of Amazon and Barnes & Noble using actual sales data from their respective 2005 annual reports. Amazon's annual report shows that its total sales of media products are $3 billion, while Barnes & Noble notes that its online division has total sales of $0.44 billion.[14] This suggests the relative online market share between Amazon and Barnes & Noble is about 6.82:1. We use this ratio as a reference case for our illustration of the impact of price changes on market competition.

[14] Ideally, we would like to obtain relative market shares of Amazon and Barnes & Noble in the online book retailing market. However, after extensive research, we are unable to obtain such information. We therefore use the market share of media products (including books, CDs, and DVDs) as a proxy.

Using a Pareto parameter of -0.871 and results from Column 3 in Table 2, we find that a 1% increase in Amazon price leads to a 1.86% decrease in Amazon's relative sales, thereby reducing its relative market share from 6.82:1 to 6.69:1. Similarly, a 1% price increase in Barnes & Noble price leads to a 1.59% decrease in Barnes & Noble relative sales, thereby increasing Amazon's relative market share from 6.82:1 to 6.93:1. The result indicates that despite the significant difference in online market shares, the two online book retailers have about the same magnitude of impact on the market shares for price increases. The impacts of price decreases, however, are significantly different. The same table indicates that a 1% price decrease in Amazon price leads to a 2.13% increases in Amazon relative market share in the 4th week after the price reduction. But a 1% decrease in Barnes & Noble price leads to only 0.80% increase in Barnes & Noble's relative market share in the same week. Therefore, the impact of price decreases on Amazon's market share is about 2.5 times the impact of price decreases on Barnes & Noble market share. The results indicate that Amazon could benefit substantially more from price decreases than Barnes & Noble due to the relatively lower search cost of price information incurred by consumers. As a result, Amazon has more incentives to reduce prices than Barnes & Noble does and in equilibrium, Amazon is likely to charge lower prices than Barnes & Noble. This intuition is validated in Table 1a which shows that the average Amazon price is $19.41, much lower than the average Barnes & Noble price of $23.35.

A closer look at the competition between Amazon and Barnes & Noble shows the impact of search costs on market share also varies from popular books to unpopular books. The results from Column 1 in Table 3 show that price increases in Amazon have a larger impact on relative market share for unpopular books than price increases in Barnes & Noble. A 1% increase in Amazon price leads to a 2.30% decrease in Amazon's sales, thus reducing its relative market share from 6.82:1 to 6.66:1. But a 1% increase in Barnes & Noble price leads to only a 1.14% decrease in Barnes & Noble sales, thereby increasing Amazon's relative market share to 6.90%. The asymmetry between the two online book retailers indicates that Amazon has a lower incentive to increase prices on unpopular books compared to Barnes & Noble. The results from Table 3 also show that the magnitude of impact of Amazon price decreases on unpopular books are about the same as that of its price increases. A 1% decrease in Amazon price leads to a 2.15% increase in Amazon sales, increasing its relative market share from 6.82:1 to 6.96:1. On the other hand, the impact of Barnes & Noble price decreases on its market share is very different from that of its price increases. A 1% decrease in Barnes & Noble prices leads to a mere 0.16% increase in Barnes & Noble relative sales, barely increasing its relative market share. This indicates that price decreases have little value for Barnes & Noble, but a much higher value for Amazon.

In sum, the combination of the impact of price increases and price decreases across the two online book retailers indicates that Amazon has a strong incentive to reduce prices on unpopular books, but Barnes & Noble has little incentive to do so. Consequently, Amazon is more likely to have lower prices for unpopular books. This suggests that Amazon is in a better position to encourage sales of obscure and rare books and take advantage of the emerging Long Tail. On the other hand, it also reveals that Long Tail results based on Amazon sales data may not be representative of the online book retailing industry in general, since Amazon appears to enjoy a significantly lower search costs for its less popular books than most of its competitors.

This result is well corroborated by the descriptive statistics in Table 1b which shows that the average price for unpopular books is significantly lower at Amazon than that at Barnes and Noble. The price difference between the two retailers for such books ranges between $3.96 and $ 4.73 which is approximately 25% of the average book price and is thus quite significant. These results are robust to different specifications used for defining unpopular book as shown in Table 1b.

The competitive scenario for popular books is slightly different. Column 1 in Table 4 shows that price increases on popular books have a larger impact for Barnes & Noble than for Amazon. A 1% increase in Barnes & Noble price on popular books reduces Barnes & Noble's relative market share by 2.23%. But a 1% increase in Amazon price on popular books only reduce Amazon's relative market share by 0.77%. This indicates that, unlike unpopular books, Amazon has more incentive to raise prices on popular books than Barnes & Noble. For price decreases, the results indicate that a 1%

decrease in Amazon price on popular books will increase its relative market share by 2.72%, while a 1% decrease in Barnes & Noble price on popular books will increase Barnes & Noble's relative market share by 1.97%. As a result, Amazon has a larger incentive to reduce prices than Barnes & Noble for popular books.

The combination of the impact of price increases versus price decreases shows mixed implication for the competition between Amazon and Barnes & Noble. Not only does Amazon have stronger incentives to increase price than Barnes & Noble but it also has stronger incentives to reduce price than its main rival. The results indicate that price differences between Amazon and Barnes & Noble for popular books are likely to be mixed.

As before, this intuition is well corroborated by the descriptive statistics in Table 1b which shows that the average price for popular books at Amazon could be either higher or lower that at Barnes and Noble. In cases where the BN prices are higher than those at Amazon, the price difference between the two retailers for such books ranges between $0.14 and $ 1.45 which is considerably lower than the range for obscure books. These results are robust to different specifications used for defining popular books as shown in Table 1b.

6. Discussion and Limitations

A fundamental premise of economic theory is that the amount of information search will increase when search costs are reduced. Empirical evidence on consumer behavior with online shopping environments is quite in contrast to theoretical predictions. For example, by examining the shopping patterns of online users over time, Johnson et al. (2004) found that the amount of online search is actually quite limited. On average, households visit only 1.2 book sites, 1.3 CD sites and 1.8 travel sites during a month in each product category. Another study by Jansen et al. (2000) revealed a similar pattern from the analysis of Web queries by Excite users. Most users had only a few queries per search, and 76% of users did not go beyond their first and only query.

This suggests that consumers face search costs even in online markets. But little is known how the search costs affect consumer demand and online retailers' competitive strategies. Our paper aims to empirically test this phenomenon by analyzing the nature of the underlying demand function in electronic markets. Using a dataset from Amazon and Barnes and Noble, we show that consumer search costs vary significantly across online retailers. Consumer price elasticity on Amazon.com is higher for price decreases than for price increases, implying a low level of search cost for Amazon price information. In addition, we find that price elasticity increases during the 4 weeks after price decreases, indicating that Amazon price information gradually penetrates the market over time. On the contrary, we find consumer price elasticity on Barnes & Noble.com is much lower for price decreases than for price increases, suggesting a high level of search cost for Barnes & Noble.com price information. Moreover, the result shows little information dissemination for the 4 weeks after price decreases. The contrast between Amazon and Barnes & Noble indicates that search costs are heavily influenced by online retailers. While we do not have data to reveal the underlying causes of the variations in search costs, one possible explanation is that the presence of search costs leads to consumers searching only on the websites of the largest online retailer (e.g. Amazon) but not on those of the comparatively smaller online retailers. This could lead to a dramatic difference in search costs between the top retailer and the remaining rivals. In this way, our results complement earlier studies that consider search costs as being mainly driven by consumer characteristics. We find that search costs vary significantly across online retailers even for those with similar competitive positions. This calls attention for the need for online retailers to pay more emphasis on search costs incurred by its potential customers and understand its strategic implications.

The Internet is known to facilitate the discovery of lesser known and obscure products. It has been argued that collectively these relatively less popular products could make up a significant portion of sales for online retailers(Anderson 2006). This Long Tail phenomenon makes it critically important that retailers provide active and passive tools to reduce search costs for less known products through both active and passive means (Brynjolfsson, Hu and Smith 2006, Elberse and Oberholzer-Gee 2006).

Our analysis however shows that consumers in electronic markets incur higher search costs on unpopular books than on popular books. This suggests that online retailers are yet to fully recognize the importance the Long Tail phenomenon. Because of higher search costs, potential customers could have a difficult time locating price information for unpopular and rare books. This in turn can lead to fewer sales for such books and a significant reduction in inventory (Cachon, Terswiech and Xu 2006), thereby starting a vicious cycle that leads to fewer and fewer sales. Rather than focusing on promoting popular books which is what brick-mortar bookstores have been doing for years, online bookstores may be better off by reducing search costs for unpopular books to take advantage of the emerging Long Tail. In this context Amazon's efforts to reduce prices for unpopular and rare books, compared to popular books seems like a step in the right direction.

One of our limitations is that we consider the nature of search costs only across online retailers. Our dataset prevents us from considering search costs across price comparison engines or shopping bots which make it possible for consumers to obtain a list of prices for a given product. Since a product search at any one of these sites will return a listing of prices that different merchants charge for the same product, one could argue that the marginal cost of obtaining a price quote is low at these sites. However, since the choices consumer make in a shopbot eventually determines the demand for the enlisted retailer, our results have effectively incorporated the impact of shopbots on overall consumer demand. Another limitation of the paper is that while we show search costs vary significantly across online retailers, we do not have data to pinpoint the exact cause for the phenomenon. It could be due to consumers' preferences for searching only the most well known and branded online retailer, which creates significant variations in the nature of the demand structure across online retailers. Or it could be due to the intrinsic differences in the type of consumers that the different online retailers attract. For example, Amazon may attract more tech-savvy consumers who are better at searching for lower prices, while Barnes & Noble's clientele could be less tech-savvy with less experience in searching online for price information. It is also possible that the recommendation systems and co-purchase networks prevalent on Amazon reduce price search costs for consumers on its website. Hann and Terweisch (2003) discuss how Amazon's One-Click purchase system has reduced the overall cost of purchasing a product from its site compared to its rivals like Barnes & Noble. A deeper exploration of the causes for the variations in search costs across online retailers could be a fruitful area for future research.

References

Anderson, C. 2006. The Long Tail: Why the Future of Business Is Selling Less of More. Hyperion Press, New York, NY.

Bakos, Y. 1997. Reducing Buyer Search Costs: Implications for Electronic Marketplaces. *Management Science* (43:12) , 1676-1692.

Baye, M., J. Morgan, and P. Scholten. 2004. Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site. *Journal of Industrial Economics* 52(4), 2004, 463-496.

Baye, M., R. Gatti., P. Kattuman and J. Morgan. 2005. Estimating Firm-Level Demand at a Price Comparison Site: Accounting for Shoppers and the Number of Competitors. Working paper, Indiana University.

Bergen, M., R. Kauffman and D. Lee. 2005. Beyond the Hype of Frictionless Markets: Evidence of Heterogeneity in Price Rigidity on the Internet. *Journal of Management Information Systems* 22(2): 57 - 89.

Brown, J. R.,A. Goolsbee. 2002. Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry. Journal of Political Economy. 110(2): 481-507.

Brynjolfsson, E., Hu, Y., and Smith, M. 2003. Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety. *Management Science* 49(11), 1580-1596.

Brynjolfsson, E., A. Dick, and M. Smith. 2004. Search and Product Differentiation at an Internet Shopbot", Working Paper, 2004, Carnegie Mellon University.

Brynjolfsson, E., Hu, Y., and M. Smith. 2006. From Niches to Riches: The Anatomy of the Long Tail. *Sloan Management Review*, 47(4) 67-71.

Cachon, G., C. Terwiesch, and Y. Xu. 2006. On the effects of consumer search and firm entry on multiproduct competition. Working Paper, University of Pennsylvania.

Chevalier, J., and A. Goolsbee. 2003. Measuring Prices and Price Competition Online: Amazon and Barnes and Noble. *Quantitative Marketing and Economics* 1(2), 2003, 203-222.

Chevalier, J. and D. Mayzlin. 2006. The Effect of Word of Mouth on Sales: Online Book Reviews. forthcoming, *Journal of Marketing Research.*

Chiang, J. P. 2006. Clicking Instead of Walking: Consumers Searching for Information in the Electronic Marketplace. *ASIS Bulletin*, January.

Ellison, G., and Ellison, S. 2004. Search, Obfuscation, and Price Elasticities on the Internet. Working paper, 2005, Massachusetts Institute of Technology.

Elberse, A., and F. Oberholzer-Gee. 2006. Superstars and Underdogs: An Examination of the Long Tail Phenomenon in Video Sales. Harvard Business School Working Paper, No. 07-015.

Ghose, A., M. Smith and R. Telang. 2006. Internet Exchanges for Used Books: An Empirical Analysis of Product Cannibalization and Welfare," *Information Systems Research*, 17(1), 3-19.

Hann, I. and C. Terwiesch. 2003. Measuring the Frictional Costs of Online Transactions: The Case of a Name-Your-Own-Price Channel. *Management Science*, 49(11), 1563 – 1579.

Hodkison, C., Kiel, G., and J. McColl-Kennedy. 2000. Consumer Web search behavior: Diagrammatic illustration of way finding on the Web. *International Journal of Human-Computer Studies*, 52, 805-830.

Hong, H., and M. Shum. 2006. Using price distributions to estimate search costs. Forthcoming, Rand Journal of Economics.

Johnson, E. J., Moe, W., Fader, P., Steven, B., and J. Lohse. 2004. On the Depth and Dynamics of Online Search Behavior. *Management Science*, 50, 299-308.

Lee, D. and R. Kauffman. 2004. Should We Expect Less Price Rigidity In The Digital Economy? *Proceedings of the HICSS.*

Reinganum, J.F. 1979. A Simple Model of Equilibrium Price Dispersion. *Journal of Political Econom*y, 87(4), 851-858.

Sorensen, A.T. 2000. Equilibrium Price Dispersion in Retail Markets for Prescription Drugs. *Journal of Political Economy*, 108, 833-850.

Stiglitz, J.E. 1987. Competition and the Number of Firms in a Market: Are Duopolies More Competitive Than Atomistic Markets? *Journal of Political Economy*, 95(5), 1041-1061.

Stiglitz, J.E, 1989. Imperfect Information in the Product Market. In *Handbook of Industrial Organization* 1. Elsevier Science Publishers. 769-847.

Variable	Observations	Mean	Std Dev.	Min	Max
Amazon Sales Rank	559012	196715.2	319355.5	1	3628125
List Price	557466	25.076	23.51	2.99	299
Amazon Price	555207	19.414	22.092	2	299
Minimum Used Price	532716	14.348	20.695	.01	2069.94
Amazon Rating	433443	4.299	.722	1	5
Amazon_Number_Reviews	433304	24.647	129.069	1	3229
Number of Used	532728	49.66	31.057	1	614
Amazon_Price Decrease	289810	.889	.313	0	1
Amazon Price Change	569459	.025	.158	0	1
Barnes & Noble Sales Rank	457836	99418.74	126015.2	1	724506
Barnes & Noble Price	555852	23.346	22.399	2.99	299
Barnes & Noble Rating	487289	1.665	2.206	0	5
Barnes & Noble_Number_Reviews	182047	11.386	54.571	1	1179
Barnes & Noble_Price Decrease	239830	.151	.358	0	1
Barnes & Noble Price Change	569459	.021	.144	0	1
Days since Release	559012	196715.2	319355.5	1	3628125

Table 1a: Summary Statistics

	Variable	Obs.	Mean	Std Dev.	Min	Max
Amazon Sales Rank >100000	Amazon Price	253380	21.956	26.990	2	299
	Barnes & Noble Price	254883	25.807	26.508	2.99	299
Amazon Sales Rank > 40000	Amazon Price	353576	20.808	25.026	2	299
	Barnes & Noble Price	354901	24.840	24.800	2.99	299
Amazon Sales Rank > 20000	Amazon Price	420774	20.254	23.937	2	299
	Barnes & Noble Price	421895	24.355	23.941	2.99	299
BN Sales Rank >100000	Amazon Price	250301	22.065	25.445	2.38	299
	Barnes & Noble Price	247678	26.772	25.490	2.99	299
BN Sales Rank > 40000	Amazon Price	351499	21.320	24.767	2.38	299
	Barnes & Noble Price	350137	26.096	24.881	2.99	299
BN Sales Rank > 20000	Amazon Price	412639	20.782	24.236	2.38	299
	Barnes & Noble Price	411962	25.409	24.406	2.99	299
Amazon Sales Rank (1-1000)	Amazon Price	13406	16.264	9.253	2.99	162.4
	Barnes & Noble Price	11876	16.405	9.385	2.69	146.16
Amazon Sales Rank (1-10000)	Amazon Price	94455	15.167	12.202	2	162.4
	Barnes & Noble Price	95087	15.327	11.285	2.69	146.16
Amazon Sales Rank (1-20000)	Amazon Price	134431	16.787	14.601	2	299
	Barnes & Noble Price	115315	17.931	14.125	2.69	225
Amazon Sales Rank (1- 40000)	Amazon Price	201625	16.969	15.370	2	299
	Barnes & Noble Price	172080	18.414	14.929	2.69	269.1
BN Sales Rank (1-1000)	Amazon Price	10846	15.267	10.116	2.99	138.13
	Barnes & Noble Price	10882	14.563	9.498	2.69	139.27
BN Sales Rank (1-10000)	Amazon Price	94455	15.167	12.202	2	162.4
	Barnes & Noble Price	95087	15.327	11.285	2.69	146.16
BN Sales Rank (1-20000)	Amazon Price	142565	15.456	13.396	2	162.4
	Barnes & Noble Price	143829	15.693	12.260	2.69	161.77
BN Sales Rank (1- 40000)	Amazon Price	203702	16.126	15.959	2	299
	Barnes & Noble Price	205632	16.796	14.711	2.69	269.1

Table 1b: Summary Statistics for Popular vs. Unpopular books

Independent Variable	(1)	(2)	*(3)*
$Log(P_{Amazon})$	1.71^{***} (0.11)	2.17^{***} (0.14)	2.14^{***} (0.15)
$Log(P_{BN})$	-1.76^{***} (0.10)	-1.84^{***} (0.11)	-1.82^{***} (0.11)
$\Delta Log(_{Amazon})*PriceDecrease_{Amazon}$	0.37^{***} (0.11)		
$\Delta Log(P_{BN})*PriceDecrease_{BN}$	0.74^{***} (0.10)		
$\Delta Log(P_{Amazon})*PriceDecrease_{Amazon}*$ $OneWeek_{Amazon}$		0.08 (0.15)	-0.07 (0.15)
$\Delta Log(P_{Amazon})*PriceDecrease_{Amazon}*$ $TwoWeeks_{Amazon}$		0.28^{*} (0.15)	0.22 (0.15)
$\Delta Log(P_{Amazon})*PriceDecrease_{Amazon}$ $*ThreeWeeks_{Amazon}$		0.38^{**} (0.15)	0.33^{**} (0.15)
$\Delta Log(P_{Amazon})*PriceDecrease_{Amazon}*$ $FourWeeks_{Amazon}$		0.40^{***} (0.12)	0.40^{***} (0.15)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*$ $OneWeek_{BN}$		0.99^{***} (0.12)	0.88^{***} (0.12)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*$ $TwoWeeks_{BN}$		0.88^{***} (0.15)	0.85^{***} (0.15)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*$ $ThreeWeeks_{BN}$		0.89^{***} (0.17)	0.86^{***} (0.17)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*$ $FourWeeks_{BN}$		0.95^{***} (0.14)	0.90^{***} (0.15)
Log(Number of Used)	0.08^{***} (0.01)		0.13^{***} (0.01)
Log (Minm. Used Price)	0.04^{***} (0.01)		0.06^{***} (0.01)
Log(Number of Reviews)	0.06^{**} (0.03)	0.02 (0.04)	0.04 (0.04)
Log(Rating)	-0.27 (0.09)	-0.13 (0.10)	-0.13 (0.11)
No. of Observations	89045	62994	62282
R-square	69%	68%	69%

Table 2: Parameter estimates for search costs in the online book retailing industry. The dependent variable is $\ln(\text{sales rank}_{Amazon})$- $\ln(\text{sales rank}_{BN})$. Standard errors are listed in parenthesis; ***, **, * denote significance at 0.01, 0.05 and 0.10, respectively. All models use product-level fixed effects.

Independent Variable	**Amazon Salesrank >20000**	**Amazon Salesrank >40000**	**Barnes & Noble Salesrank >20000**	**Barnes & Noble Salesrank >40000**
$Log(P_{Amazon})$	2.64^{***} (0.18)	3.01^{***} (0.2)	3.55^{***} (0.27)	3.21^{***} (0.21)
$Log(P_{BN})$	-1.31^{***} (0.13)	-1.4^{***} (0.14)	-1.77^{***} (0.18)	-1.78^{***} (0.17)
$\Delta Log(P_{Amazon})*PriceDecrease_{AM}*OneWeek_{Amazon}$	-0.23^{**} (0.08)	-0.26^{**} (0.1)	-0.5^{*} (0.27)	-0.48^{**} (0.21)
$\Delta Log(P_{Amazon})*PriceDecrease_{AM}*TwoWeeks_{Amazon}$	-0.15 (0.18)	-0.07 (0.2)	-0.19 (0.26)	-0.35^{*} (0.21)
$\Delta Log(P_{Amazon})*PriceDecrease_{AM}*ThreeWeeks_{Amazon}$	-0.1 (0.18)	0.03 (0.2)	0.04 (0.25)	-0.36^{*} (0.2)
$\Delta Log(P_{Amazon})*PriceDecrease_{AM}*FourWeeks_{Amazon}$	-0.17 (0.15)	0.14 (0.17)	0.18 (0.21)	-0.3^{*} (0.16)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*OneWeek_{BN}$	1.52^{***} (0.14)	1.75^{***} (0.15)	2.48^{***} (0.19)	2.54^{***} (0.18)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*TwoWeeks_{BN}$	1.22^{***} (0.19)	1.3^{***} (0.21)	1.76^{***} (0.28)	2.32^{***} (0.25)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*ThreeWeeks_{BN}$	1.16^{***} (0.21)	1.2^{***} (0.24)	1.43^{***} (0.31)	2.21^{***} (0.29)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*FourWeeks_{BN}$	1.13^{***} (0.17)	1.22^{***} (0.18)	1.64^{***} (0.23)	2.14^{***} (0.22)
Log(Number of Used)	0.24^{***} (0.02)	0.25^{***} (0.02)	0.17^{***} (0.02)	0.28^{***} (0.02)
Log (Minm. Used Price)	0.11^{***} (0.016)	0.12^{***} (0.016)	0.1^{***} (0.02)	0.1^{***} (0.02)
Log(Number of Reviews)	0.16^{***} (0.05)	0.21^{***} (0.06)	0.52^{***} (0.08)	0.24^{***} (0.06)
Log(Rating)	-0.33^{**} (0.13)	-0.4^{**} (0.15)	-0.47^{**} (0.2)	-0.43^{**} (0.17)
No. of Observations	41404	34180	19539	27177
R-square	62%	61%	56%	64%

Table 3: Parameter estimates for books that are relatively unpopular. The dependent variable is ln(sales $rank_{Amazon}$)- ln(sales $rank_{BN}$). Standard errors are listed in parenthesis; ** and * denote significance at 0.01 and 0.05, respectively. All models use product-level fixed effects.

Independent Variable	**Amazon Salesrank < 20000**	**Amazon Salesrank < 40000**	**Barnes & Noble Salesrank < 20000**	**Barnes & Noble Salesrank < 40000**
$Log(P_{Amazon})$	0.88^{***} (0.25)	1.6^{***} (0.17)	0.44^{**} (0.23)	1.37^{***} (0.17)
$Log(P_{BN})$	-2.56^{***} (0.22)	-1.53^{***} (0.15)	-1.48^{***} (0.15)	-1.51^{***} (0.13)
$\Delta Log(P_{Amazon})*PriceDecrease_{AM}*OneWeek_{Amazon}$	0.62^{***} (0.27)	-0.01 (0.18)	1.12^{***} (0.25)	0.38^{**} (0.17)
$\Delta Log(P_{Amazon})*PriceDecrease_{AM}*TwoWeeks_{Amazon}$	1.29^{***} (0.29)	0.29 (0.19)	1.55^{***} (0.25)	0.76^{**} (0.18)
$\Delta Log(P_{Amazon})*PriceDecrease_{AM}*ThreeWeeks_{Amazon}$	1.66^{***} (0.29)	0.42^{**} (0.19)	1.846 (0.29)	0.92^{**} (0.18)
$\Delta Log(P_{Amazon})*PriceDecrease_{AM}*FourWeeks_{Amazon}$	2.24^{***} (0.23)	0.52^{***} (0.16)	1.98^{***} (0.22)	0.95^{***} (0.15)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*OneWeek_{BN}$	-0.46^{**} (0.22)	-0.1 (0.15)	-0.42^{**} (0.16)	0.25^{*} (0.14)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*TwoWeeks_{BN}$	0.22 (0.26)	0.21 (0.18)	-0.25 (0.18)	0.39^{**} (0.17)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*ThreeWeeks_{BN}$	0.3 (0.28)	0.31 (0.2)	-0.22 (0.18)	0.4^{**} (0.19)
$\Delta Log(P_{BN})*PriceDecrease_{BN}*FourWeeks_{BN}$	0.3 (0.25)	0.26 (0.18)	-0.14^{***} (0.05)	0.24 (0.16)
Log(Number of Used)	0.01 (0.01)	0.1^{***} (0.01)	0.05^{***} (0.01)	0.1^{***} (0.01)
Log (Minm. Used Price)	-0.06^{***} (0.01)	0.03^{***} (0.01)	0.001 (0.01)	0.07^{***} (0.01)
Log(Number of Reviews)	-0.26^{***} (0.06)	-0.14^{***} (0.04)	-0.14^{***} (0.05)	0.05 (0.05)
Log(Rating)	0.012 (0.16)	-0.16 (0.13)	0.01 (0.13)	-0.24^{**} (0.11)
No. of Observations	20877	42742	35104	50228
R-square	79%	71%	71%	70%

Table 4: Parameter estimates for books that are relatively popular. The dependent variable is ln(sales $rank_{Amazon}$)- ln(sales $rank_{BN}$). Standard errors are listed in parenthesis; ** and * denote significance at 0.01 and 0.05, respectively. All models use product-level fixed effects.

Sales Rank at Amazon	Variable	Obs.	Mean	Std Dev.	Min	Max
1-1000	Amazon Change	13533	.021	.146	0	1
	Barnes & Noble Change	13533	.115	.319	0	1
1-10000	Amazon Change	84804	.010	.103	0	1
	Barnes & Noble Change	84804	.047	.213	0	1
1-20000	Amazon Change	134960	.009	.096	0	1
	Barnes & Noble Change	134960	.038	.192	0	1
1-40000	Amazon Change	202566	.008	.090	0	1
	Barnes & Noble Change	202566	.032	.177	0	1
1-100000	Amazon Change	303702	.007	.086	0	1
	Barnes & Noble Change	303702	.027	.163	0	1

Table 5: Table shows the descriptive statistics for frequency of price changes

Sales Rank at Barnes & Noble	Variable	Obs.	Mean	Std Dev.	Min	Max
1-1000	Amazon Change	10882	.018	.134	0	1
	Barnes & Noble Change	10882	.142	.349	0	1
1-10000	Amazon Change	95126	.009	.094	0	1
	Barnes & Noble Change	95126	.044	.205	0	1
1-20000	Amazon Change	143887	.008	.090	0	1
	Barnes & Noble Change	143887	.034	.181	0	1
1-40000	Amazon Change	205709	.007	.087	0	1
	Barnes & Noble Change	205709	.038	.192	0	1
1-100000	Amazon Change	308174	.007	.084	0	1
	Barnes & Noble Change	308174	.031	.175	0	1

Table 6: Table shows the descriptive statistics for frequency of price changes