Establishing a Framework For Analyzing Market Power in Electronic Commerce: An Empirical Study\footnote{The authors wish to thank Professor Janet Netz of the Economics department at Purdue University and four anonymous referees for their several comments and suggestions on earlier versions of the paper. Subhajyoti also wishes to thank Sujoy Chakraborty of Purdue University for some of his ideas.}

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Abstract

This research aims to develop some suitable metrics for the measurement of market power in the online retailing business. While it is obvious that market power exists in the online retailing business, especially among the market leaders, the factors that drive that market power have been considerably less analyzed empirically. The main challenge in such research is the lack of data that has been traditionally used to measure market power. On the other hand, the electronic nature of an online transaction makes available “new” clickstream data, in the form of individual and aggregate web statistics. We explain a strategic conduct of an online retailer in terms of its manifestation in the clickstream data. Our results paint an accurate picture of the early online retailing industry, and show that the richness of clickstream data can be used to advantage in empirical research in electronic commerce. In the process, we develop a framework for measuring market power as applicable to the world of online retailing.
1. Introduction

One of the enduring promises of the Internet is its ability to ensure “level playing fields” [7]. Thus, a new firm can attract business as well as an established firm with much higher levels of resources, just by ensuring its product quality, fair price and its presence on the World Wide Web. The early indications did seem to support this opinion. For example, Amazon.com, an Internet-only bookseller established in July 1995, took on the might of well-established national book chains with commanding brand names, and has now taken a stranglehold of the online books market.

Similar stories abound in other markets as well, but in a different manner than previously envisaged. A recent study [1] of the most popular Internet sites show that over 80% of the global Web traffic goes to less than 0.5% of the sites (of an estimated total of over 72 million web hosts [15]). Leading sites in a market segment, like Amazon.com (which holds an estimated 75% of the online book retailing business) command more than half the total business in the category. And finally, as what might be deemed as the unkindest cut of all, there is evidence of large price dispersions among Internet retailers, even in the age of free “shop bots” (Web-based software agents that shop for the lowest prices for a particular product – for some examples of such free applications, look at Fig. 2 in the appendix). Research shows that even for such “low touch”, homogeneous products like books and music compact discs, Internet retailer prices vary by as much as 25% to 33% [6]. Thus, it might seem that while the players might have changed, the game remains the same.

With such commanding shares in the market segments they operate in, it is obvious that the leaders in electronic commerce wield market power. Market power can be thought of as the ability of a player to
enjoy supra-economic profits due to various factors like barriers to entry, business process efficiencies, brand name, patent protections, legislation, etc. (while profits might not be visible for most online firms, it has been often argued that in the early stages, the quest for market share is more important in order to gain first mover advantages that will reap benefits down the line). What is of interest therefore is an investigation into the factors that explain the success of these companies. Results of such an investigation will find a ready audience among practitioners and researchers in this field, as well as regulators who would want to ensure competitive market behavior.

Existing research (for example, see [21]) identifies factors like branding, awareness and trust as some important factors that explain the heterogeneity among Internet retailers. However, there seem to be no analytical models in Industrial Organization that attempt to provide some quantitative measures of the aforesaid market power. Also, while the existing research provides valuable insights in firm strategies and consumer behavior, we felt that it might be interesting if we could look at data across organizations to gain some insight about the entire online retailing industry.

There are several reasons for the current state of affairs. First, online retailing is a new phenomenon, modifying the market institution and environment that we identify with traditional retailing. Thus, while the amount of research in online firm behavior has exploded in the last few years, there still remain a lot of unexplored avenues for research. Second, while electronic commerce has brought upon us a surfeit of data (e.g., clickstream data – which we use in this study – like average time spent by a browser in a certain domain, total number of unique visitors, etc.), it however cannot be readily molded into existing Industrial Organization frameworks for analyzing market power. Third, most of the organizations we would like to study are either privately held or have been public for only a short
period, so that traditional data like costs, revenues, etc. that are used by Industrial Organization
researchers are either not available or do not make sense. Finally, because definitions of key data of
Industrial Organization like revenue are not yet standardized, estimates of aggregate variables like
total profit, total revenue, industry size, etc. vary widely from one source to another.

This study attempts to investigate the reasons behind the existence of market power among online
retailers. As we explain later, existing measures of market power are ill-suited for use in the context
of electronic commerce. We take advantage of the extensive clickstream data (like number of visitors,
time spent by a visitor, number of banner advertisement impressions, and several others) that is
gathered by public and private organizations, and place them in an Industrial Organization
framework. In the process, we intend to identify some metrics that can explain market power in
electronic commerce.

2. Data implications

The empirical study of e-commerce phenomena presents some special challenges. From the
discussion above, it is immediately apparent that due to a lack of “traditional” measures of data,
studying market power in the existing frameworks is a daunting task. For example, given the wide
range of products, and frequent changes of menu prices, measuring price-cost margins for e-retailing
is extremely difficult. Since e-commerce is such a new phenomenon, gathering time series data for
regime analysis (i.e., exploring whether firms behave differently during times of collusion or
competition) is also ruled out. To compound these problems, many of the firms that one wishes to
study have are still privately held, thus limiting the amount of financial information (for extracting costs and prices) that could have been available.

On the other hand, the electronic nature of the transactions makes available a new domain of statistics that were not present before. Statistics like the number of unique web hits, average time spent by a user in a website, click rate of banner advertisements, etc., offer a wealth of information – if they can be channeled in existing economic frameworks, or if they can be meaningfully interpreted in a new framework. The challenge therefore lies therefore in interpreting this wealth of data in the context of market power.

3. Related research

The traditional approach to studying market power in firms empirically is commonly referred to as the Structure-Conduct-Performance paradigm (SCP). The SCP approach, hypothesized by Bain [2], assumes that there is a stable, causal relationship between the structure of an industry, firm conduct and market performance. Since this relationship is assumed stable, a direct relationship between the observable variables, structure and performance, is assumed (conduct is assumed to be more internal to the firm). The typical SCP exercise consists of specifying a measure of market performance and a set of structural variables that are supposed to explain the inter-industry differences in market performance [8]. Since the SCP paradigm assumes that measures of market power can be calculated from available data, accounting data can be used to construct approximations of the Lerner index or economic profits. The SCP paradigm suffers from many criticisms, like endogeneity issues between the structure, conduct and performance variables, problems in measuring economic profitability
(since firms record accounting data) and the inapplicability of the hypothesis in inter-industry studies (see, for example, [20]). However, the essential philosophy of the relationship between structure, conduct and performance, as identified by the SCP paradigm, still holds. More importantly, it introduced something in empirical IO research that has proved to be of tremendous value: use of systematic statistical evidence [5].

The new empirical Industrial Organization (NEIO) therefore does not follow the SCP hypothesis. While using the basic structure of the SCP paradigm (use of empirical analysis for understanding and interpreting market power), it admits that inter-industry differences are too large to be incorporated in a cross-sectional study of market power. It has also been argued that accounting data that has been used in research is not appropriate, as the economic marginal cost (MC) cannot be directly or straightforwardly observed. The degree of market power is therefore estimated and the inference of market power is based on the firms’ conduct [5]. NEIO studies differ in homogeneous product industries and differentiated products industries – in the former, a conduct parameter of the firm under study is estimated, while the latter simply assumes or imposes upon a conduct that is analyzed in the market power framework.

While there has been no research of analyzing clickstream data in the context of market power from an *industrial organization viewpoint*, a lot of work has been done in the area of using such data to gain e-commerce intelligence for making strategic e-marketing decisions (see for example, Gomory et al [11]). The data has also been used in marketing (see for example [14], for analyzing consumer behavior) and finance (in relating stock prices to website visits, for example [10]).
Our study thus complements these research efforts. We use the “new” data from e-commerce transactions (i.e., the clickstream data) and put them in an IO perspective. We identify several variables that can be treated as estimates for performance, and use them to explain the strategy adopted by early online retailers (i.e., the conduct).

Our analysis has also gained from existing research in economics, MIS, marketing and finance, which we felt would be more appropriate to cite throughout the course of this paper.

4. Studying the phenomenon of e-malls to estimate market power

Online retailers would obviously fall under the category of differentiated products industry for the purpose of classifying in a NEIO framework. With that in mind, it becomes necessary to find a suitable conduct of these firms that can be used as evidence of the market power that is being hypothesized. It is necessary that this conduct be directly observable, is uniform across products (this requirement is important, since online retailers are increasingly using dynamic pricing strategies across products and customers), and is demonstrated by all the firms under study. Given the extreme heterogeneity of the online retailing firms, this becomes a challenge.

Having stated that, the early days of online retailing provides very “homogeneous” data from the empirical IO point of view. If we consider the period when our data was collected (February 2000), most of the offline retailers were yet to flex their influence in the online world, which essentially meant that totally new players, with no prior exposure to the industry and no existing brand names, came in to conquer the brave new world. The lack of established norms of doing business meant that
most of the players followed similar strategies – regardless of the products being sold. These “strategies” were (and are) often nothing more than what another online retailer had tried, or what an industry observer thought to be a good idea. Thus, the entire online retailing industry could be considered to be one entity, as far as their strategies of success or dominance was concerned. We therefore felt that considering cross-sectional data would not be that much of a deterrence as it will (probably) be when strategies become more differentiated, and existing offline retailers with brand names establish their presence in the offline world also.

Consider now the set of strategies that a retailer can employ in order to capture a certain percentage of the total market (in terms of revenues) he operates in. Depending on its brand identity, a retailer can focus more on existing customers or on acquiring new customers.

*Existing customers*: If existing customers continue to be loyal, there is a lesser requirement for getting new customers that involves high customer acquisition costs. Getting new customers is always important, but the requirement is less pronounced if one meets the revenue quotas from the existing customer base. For the cash-strapped online businesses, this issue thus assumes great importance.

*New customers*: For new businesses that are yet to develop their brand identities, new customers are the primary sources of revenue. These customers can be enticed to visit their store through various marketing and promotional tactics. For example, one common strategy is to place attractive promotions in banner advertisements on popular sites. The underlying strategy is to attract customers through attractive promotions, and then hope to capture their attention beyond the first visit. This strategy is common in the offline world – new stores signal their arrival with attractive discounts and
promotions to drive initial traffic; also, first-time buyers in many grocery chains have noticed the disproportionate amount of in-store coupons that are printed out at the cash register that identifies them as new buyers from their credit card information.

**Acquiring customers in the online world**

Customers can be acquired in several ways. One popular strategy is to drive up the website’s unique audience. It seems reasonable to assume that part of the unique audience – who might have been driven to the website due to online advertisements (in fact, the data that we used for our analysis shows a very high correlation between unique audience and the number of banner advertisements) or offline advertising (e.g., Super Bowl ads) – will go on to buy merchandise from the store. In fact, unique audience can be thought to be a somewhat crude proxy for the cumulative effect of all offline behavior – after all, any offline strategy that is somewhat successful has to at least drive audience to the site. Established brand names are expected to attract more of the audiences who are new to online shopping, since it is expected that they would have heard of lesser number of retailers than experienced shoppers, and also would trust their initial shopping experiences with established retailers.

Another strategy that has been extensively used by online retailers is to entice first-time users with very attractive promotions. These promotions mostly appear in banner advertisements that appear throughout the web. The underlying idea is again to entice the surfer to buy something from the site based on the sheer attractiveness of the offer, and then hope to recoup the initial investments through her repeated visits.
A third popular strategy has been to get customers from customer aggregator sites or e-malls, by targeting them with special promotions. We discuss the phenomenon of e-malls in detail in the next paragraph. It is apparent that these various strategies are geared towards attracting various classes of shoppers. Depending on the relative success of their customer acquisition strategies, retailers are expected to emphasize one over the other. Our model is based on the relative use of these strategies.

**E-malls:** Recently, there has been a proliferation of Internet-based businesses that have been variously called e-malls or i-malls in the popular business literature. Some of the more prominent examples include [ebates.com](http://ebates.com), [dash.com](http://dash.com) and [MyPoints.com](http://mypoints.com). The modus operandi of these businesses is essentially as follows: these businesses act as a portal to other Web-based retailers in various popular categories like books, music, etc., with whom they have arrangements to offer exclusive discounts (or points-based loyalty “rewards”) to its subscribers. Once a consumer becomes a subscriber to these e-malls (subscription is free, often accompanied by sharing of some basic demographic information), she gets discounts in the various stores with whom the particular e-mail has an arrangement with, by following hyperlinks on the Web-site. Discounts vary from category to category, and even from store to store within a category. However, the discount does not vary from product to product within a retailing site, suggesting that the discount value is a firm-level (as opposed to being a product-level) variable, and is part of the firm’s overall pricing strategy. Fig. 3 in the appendix shows a typical opening page view of [ebates.com](http://ebates.com).

What are the sources of revenue for the e-malls? Since these sites give out exclusive discounts to their subscribers (*over and above* whatever discounts that the actual retailer might be offering on a particular product), and they themselves do not produce anything, it is reasonable to assume that the
discounts or “rewards” to the consumers are subsidized by the retailers. This explanation is further strengthened by the fact that the most common source of revenue of many e-commerce sites, banner advertisements, are hardly present in these sites – whatever advertisements do appear, they are of the participating retailers only. Thus, the only plausible source of income for these sites is the retailers themselves.\(^2\) We assume here that the discounts are not affected by the competition among the e-malls, though in real life, there would possibly be some effect of the competition among the various e-malls on the discount levels (however, a cursory analysis of the discount levels across the e-malls show a remarkable similarity of discount levels, indicating that whatever might be the nature of competition among the e-malls, there does not seem to be any differences in their discounting strategies).

E-malls are fast becoming the preferred source for new customers, especially with the newer online retailers. Since these e-malls offer a ready cache of registered users who frequent their sites, retailers target them with exclusive discounts in order to attract these users to their sites.\(^3\) One would not expect established retailers to use this medium as often as the newer retailers, since the former has a larger set of existing customers, and can expect to attract first-time online shoppers more to their websites based on their brand names. Channeling customers through the e-malls means handing out an automatic discount to these buyers (there are effectively two discounts: one for appearing at the e-mail, and the other for appearing to be attractive relative to more established brands of retailers whose discounts are advertised on the same page), as well as perhaps losing out on brand-building

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\(^2\) In fact, the mission statement of ebates.com, the e-mail whose data we use for our analysis, states, “By utilizing the collective buying power of our members, ebates.com is able to pass commission payments we receive from our members in the form of rebates”.

\(^3\) The number of registered visitors runs into a few millions, a large number for an online retailer. It is thus no wonder ebates.com has over 400 retailers advertising on their website.
opportunities (something often observed in discount supermarkets where brand name merchandise is less common) that might have long-term effects.

The traditional roles of intermediaries that have been analyzed in the literature so far (e.g., as timesaving agents between buyers and sellers, value-added resellers, experts, etc.) do not throw light on the role of the e-malls (see for example [3], [4], [19] and [22]). We posit that the role of the e-malls essentially reduces the cost of acquisition of customers (in terms of advertising, promotions, etc.) that is required to result in a given level of sales for the e-tailers. Marketing literature has several established models that relate customer acquisition costs to sales. Rao and Miller [17], for example, fit a (cubic) polynomial to show the relationship between per capita advertising costs and the sales of a product.

Since e-malls offer a ready source of customers, a retailer’s customer acquisition costs gets reduced on one hand, but on the other, he however loses out on the extra discounts that he has to offer at the e-mall. If we assume that the total cost \( C \) is a function of sales \( Q \), (i.e., \( C = C(Q) \)), if there is a change in total costs, it follows that the marginal cost (i.e., \( MC = C'(Q) \)) for the retailer should also change. This therefore results in a change in the producer’s surplus,

\[
PS = \int_{0}^{q^*} [p - MC] dq = \Pi(q^*) - \Pi(0),
\]

(1)

\( p \) being the price of the product, \( MC \) its marginal cost and \( \Pi \) the profit which is also the change in profits by going from no production to a production level of \( q^* \) (\( \Pi(0) \) being the profit at zero production level, i.e., the fixed costs).
There are two possible explanations of the e-mall specific discounts. One argument is that a retailer can afford to subsidize the rewards to the final consumers if there is a higher producer surplus. To illustrate this with an example, let us assume that the producer’s surplus, i.e., the change in profits at production level $q^*$, increases by 10% for a retailer going through a particular e-mall. In this fictitious example, the retailer can then negotiate with the e-mall to distribute 5% of this surplus to the latter, which in turn induces its subscribers to buy from that retailer by giving away 2% of that surplus (and keeping the remaining 3% as its own profits). It is this surplus that appears as the exclusive discounts to the consumer. (The actual change in the producer’s surplus will be the result of an interplay of three variables shown in equation (1): the price $p$ which falls, the quantity produced (and sold) which increases due to the lower price, and the change in the marginal cost $MC$ due to the change in customer acquisition costs)

Another explanation of the discounts is that the retailers use the e-malls as a method by which they capture the demand of a readily available cachet of (possibly price-sensitive) buyers. Thus, in an attempt to capture market share, the retailers are willing to forgo their margins by getting their customers through the e-malls.

The reasons behind an online retailer approaching an e-mail would possibly be a combination of both factors. For more established retailers, e-mail customers, though less profitable, do result in a larger customer base and a method to capture the market of price-sensitive and Internet-savvy customers; while for newer retailers, e-mails are the ready source of customers in order to gain initial market share. With that in mind, let us consider the basic customer acquisition strategy of an online retailer.
Let the total number of customers of the online retailer be $N$. We denote

$$N = N_m + N_{-m}, \quad (2)$$

where $N_m$ signifies the number of customers it attracts from e-malls, and $N_{-m}$ represents the number of customers it attracts from other sources. If the retailer were well established, it would possibly get its majority of customers from other sources, without resorting to attracting audiences by giving special discounts at e-malls. A new retailer, on the other hand, would have to depend more on e-mall audiences in order to get its customers. Thus, depending on a retailer’s success in the use of various strategies for attracting customers, he would use one over the other.

5. **Market power in the e-tailing business**

The issue of interest is the level of discount available at an e-mall in each category. *A priori*, in a competitive market, we would assume that the discount level in a particular category, e.g., books, to be the same regardless of the retailer. However, this is not the case. As real-life examples show, the discounts across the various retailers vary widely, often by wide margins.

We suggest that these varying (i.e., non-uniform) levels of discounts given by retailers in a particular category of products are a result of the market power that these retailers wield. These discounts are analogous to a store-specific discount that we sometimes observe at a retailing store over and above any manufacturer’s rebate or coupons that might be available. A better-established retailer might argue that its benefits of going through an e-mall (in terms of lower per capita customer acquisition
expenses) might be less than that of a less-established retailer, since more consumers know about the former in the first place. To explain this in another way, a more established retailer would get more of its $N$ customers from $N_m$, as compared to a new retailer, who relies more on $N_m$. Also, a better-established retailer might not want to cultivate less profitable, price-sensitive customers, as opposed to a less-established retailer who wants to gain market share at — literally — any cost. Therefore, we posit that a lower the discount level of a retailer at a particular e-mall indicates the presence of its (larger) market power. The end-consumers of course benefit from this arrangement, since they receive exclusive discounts from the e-mall over and above the lowest prices that is offered by any retailer.\footnote{A published customer comment in one of ebates.com’s newsletters states: “The great thing about ebates.com is that the merchants are as inexpensive as any retail store, plus you get money back. It doesn't take too much to use it, and you don't have to keep track of your account, they do it for you.”}

We visualize this argument by the following schematic:

**Figure 1:** The rationale for discounts at e-malls
It really does not matter whether the visible part of the discount, the part passed on to the end-customers, is a constant fraction of the total discount, since a lesser-established retailer would want to attract customers by maintaining a higher relative discount than a more established retailer.

Thus our hypothesis can be stated as follows: Established firms, with greater brand recognition, unaided or aided recall among consumers, etc. have greater market power than smaller, newer firms; the latter thus try to attract a ready cachet of customers in the e-malls through discount arrangements. These discounts tend to be higher than the discounts of the former, as the latter, in absence of any market power, differentiate themselves through lower prices.

6. The empirical model

From a NEIO framework standpoint, we consider the discount given by a retailer at an e-mall (which is part of a pricing decision) as the observable strategic conduct of the retailer. In order to explain this conduct, we need to specify an econometric relationship between the aforesaid conduct and the various web metrics that plausibly affect this conduct. Ideally, these metrics should be outside the control of the retailer, since otherwise we would run into endogeneity issues.

As a proxy for market power, we use the inverse of the discount provided by an e-tailer in an e-mall. We call this proxy $MP_i$.

$$MP_i = \frac{1}{\text{Discount}} \quad (3)$$
Discount\textsubscript{i} is the discount level for the retailer \textit{i} at an e-mall. The rationale for this formulation is straightforward: the lower the discount, the higher is the value of this proxy for market power. The discount thus is the observable conduct of the firm in the NEIO framework, and is a conduct that can be exercised by all the firms that are being studied. The reason for choosing an inverse relationship is the better fit that was achieved with the given data.

We then try to account for this proxy of market power by using a set of empirically observed metrics. We specify an econometric relationship of the following form:

\[
MP_i = \beta_0 + \beta_1[CLICK_i] + \beta_2[UA_i] + \beta_3[STICK_i] \\
+ \beta_4[GENDER_i] + \beta_5[SOC_i] + \beta_6[TECH_i]
\]  \hspace{1cm} (4)

One issue needs a slight clarification. \(MP_i\) should not be confused as a \textit{measure} of market power; rather, it is a \textit{proxy} of the market power, in the sense that there is a (inverse) relationship between a firm’s market power and \(MP_i\). In other words, \(MP_i\) is not the market power. The above equation (4) explores the relationship between \(MP_i\) and various web statistics, and thus points towards possible metrics that can explain that market power.

Before explaining the basic rationale of the form of the econometric relationship, we explain the various clickstream variables in the right-hand side of the equation. Clickstream data comprises of a large number of variables, a subset of which are considered in the econometric relationship. The variables that appear in equation (4) are essentially the metrics that have been used by industry
observers and analysts in recent times as proxies for performance of online firms. They are explained as under:

- **CLICK** is the “click rate” or the percentage of banner impressions of e-tailer \(i\) which have been clicked upon. It is the fraction of banner advertisements of that retailer that are clicked by online surfers over a period. Since a higher click rate essentially signifies a more “effective” advertisement strategy, we expect a positive correlation between the click rate and market power. We expect that since the customers were attracted by the advertisements to visit the website in the first place, a fraction of them would go on to buy from the website. A higher click rate would thus signify a larger number of people to buy from the website. We did not use the total number of banner advertisements, since it is a variable under direct control of the retailer, and could therefore create endogeneity problems in our model.\(^5\) This results in our first hypothesis:

\[ H_1: \] Higher click rates lead to greater market power

- **UA** is the unique audience at a particular website over a period of time (in our case, one week).

Much of the initial euphoria over Internet stocks have centered around the assumption that larger unique audiences was crucial for the success of online ventures.\(^6\) Baruch and Lev [10], for example, found that the stock prices of public Internet-based firms are very highly correlated to the unique audience. This assumption seems to be questioned in the last few months, and there are

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\(^5\) It also had a very high correlation with the **UA** variable (over 0.9).

\(^6\) Some examples: Last year, a Bear Sterns analyst upgraded **About.com**’s rating when its traffic increased, even though its stock price was unchanged. Also, **VitaminShoppe.com** saw a surge of 59% in its share price in one day in November 1999, when a Media Metrix report showed it to be one of the “top 10 gainers in traffic” among e-commerce sites.
some industry observers who believe that unique audience per se is not a prerequisite for success.\footnote{Wayne Wager, a respected venture capitalist and managing general partner of Encompass Ventures, had the following comment on B2C companies in an online discussion at the Red Herring magazine website, “It’s just that the first wave of them attributed value to things that really didn’t matter, such as eyeballs, stickiness, and unique visitors. It’s like valuing a store based on how many people stop and look in the window, rather than on how many people come in and actually buy something.” [17]} We would therefore want to test our hypothesis

**H2\(0\): Higher unique audience to a website leads to greater market power**

- *STICK* is a measure of the “stickiness” of the Web site of an e-tailer, i.e., the average time spent by a visitor at the Web site. Using a supermarket analogy, the larger time a prospective customer spends at a website, the more is she expected to spend relative to other websites. We expect a positive correlation between the market power and stickiness. Again, this view has been increasingly questioned in recent times (see footnote 5), but we will continue with the conventional wisdom in our hypothesis:

**H3\(0\): Longer time spent by a surfer in the website leads to greater market power**

- *GENDER* is a measure of the audience gender mix: the percentage of the unique audience to a Web site who are women. Several surveys of online shopping habits (see for example [9]) show that most *online* women shoppers (as opposed to the entire women shoppers’ population) prefer lower costs to brand names. Thus, a higher percentage of women at a web site should lead to lower market power. Our next hypothesis therefore is:
**H4**: *A greater percentage of female audience leads to lesser market power*

The next set of variables explores the innovations in retail Web sites that have been thought to help to increase the number of “eyeballs”. We classify these innovations under two headings, sociological factors and technological factors:

- **SOC** is a binary variable, which represents whether or not a certain e-tailer offers “community” features like chat, electronic bulletin boards, or user product surveys. Since sociological factors are expected to make a customer stay longer at a website, making her possibly more loyal to that retailer, presence of sociological features should signify higher market power. \( SOC_i \) equals 1 when such features are present, and is equal to 0 otherwise. Our fifth hypothesis therefore is:

**H5**: *Presence of sociological features lead to greater market power*

- **TECH** is also a binary variable, which represents whether or not a certain e-tailer offers advanced technological features that make it more convenient for a user to navigate through the site than other conventional Web sites. Examples include “one-click” transactions, wish lists that remember items a shopper might have liked during a visit but not bought, a clear and transparent ordering process, automatic e-mail follow-ups on orders, order tracking, price search engines that search for prices on the same product at rival e-tailers to ensure lowest price guarantees, etc. Such features makes shopping easier, and over time a customer is expected to value such comforts and conveniences more over small price variations. Thus, presence of such features should result in greater market power. Again, presence of such features makes \( TECH_i \) equal to 1. Our final hypothesis therefore is:
H66: Presence of technological features lead to greater market power

The last two variables measure intrinsic qualities of a website that are related to the firm’s performance, and are defined subjectively: we made several online shoppers go into each of the websites of the retailers covered in our study and carry out mock exercises (like buying merchandise, searching for product feedback, etc.), and told them to rate the sites in the SOC and TECH categories. We then compared their decisions against the ratings of these retailers at Bizrate.com, a leading online ratings site. In almost all instances, their “average” ratings closely matched those of Bizrate.com.

7. What does the econometric relationship mean?

Our rationale for the form of the econometric relationship shown in equation (3) is as follows: the variables on the right-hand side denote several clickstream variables that can be considered as proxies of a site’s ability to attract customers. Stated in words, equation (3) would translate to: “The ability of an online retailer to attract customers would depend on several factors – (i) the website’s unique audience, since a portion of these “window shoppers” become actual customers; (ii) effectiveness of its promotions, as witnessed by the click rate of its banner advertisements; (iii) the time spent by a prospective shopper at the site; (iv) the site’s ability to attract male or female shoppers as they have different online shopping behavior; and (v) the intrinsic characteristics of the website itself, as captured by the SOC and TECH variables. If these variables are “favorable” overall, the retailer attracts a sizeable number of customers, thereby lessening the need for promoting the site through the
discounts at the e-malls. On the other hand, if the variables are unfavorable (as shown by the number \( N_{m} \), the retailer attracts lesser number of customers, prompting it to resort to heavy discounts at the e-malls.”

It might be clarified that the retailers need not (and perhaps do not) observe all these variables to make their decision – the only signal they need in order to decide on their discounting strategy is the number of customers \( N_{m} \).

The above model presents explanatory variables that do not seem to possess any high degree of multicollinearity, a fact that is verified later. Further, \textit{a priori}, no severe endogeneity issues seem to be present. On estimation using the OLS regression model, the coefficients should provide the degree to which the various regressors affect the index of market power.

8. Data Source

The main source of data used in this study is Nielsen Netratings. Netratings Inc. is a sister concern of Nielsen that deals with Internet media and market research. Since our research proposes to find evidence of market power in various categories of online retailers, one very crucial source of data is their “Top Web Sites by Domain” report, which lets one view unique audience, reach, page views, time spent and other key measures for top domains.

9. Data collection
Our initial access to data was limited to a one-day window for the trial access of the Nielsen Netratings Web site for audience information. We gathered information for over 1000 unique Web sites over the period of one week ending February 26, 2000.\(^8\) This information can be broadly classified under two categories: Web site audience demographics and banner advertisement statistics. We removed the data for the Web sites that were not in the business of online retailing (nearly 850 in number). Then, we combined the various reports and removed those Web sites that did not have all the various categories of information that we were interested in (for example, many sites appeared in the banner advertisement information report, but not in the audience demographics report and vice versa). We combined data of some Web sites that appeared under multiple URLs, but were part of one organization.\(^9\) Finally, we removed two computer resellers whose stated objective is to sell their products at cost (and did not appear at the e-malls) – we felt that their business model was sufficiently different for their data to be considered along with that of other retailers.\(^10\) This left us with a final tally of 23 Web sites\(^11\) for which we had complete data. These Web sites are listed in Table 1. The information about the \(SOC_i\) and \(TECH_i\) variables were gathered from exercises as outlined in the previous section.

For the e-mall discount information, we visited the Web sites of ebates.com, MyPoints.com, dash.com and e-centives.com. The information was collected at the same time when the other Web statistics were gathered. We found a remarkable consistency across the Web sites on the exact amount

\(^8\) Though we had access to data for a week before this date, we reasoned that such data might be unduly influenced by purchases on and before Valentine’s Day on February 14.

\(^9\) For example, the online books retailer Barnes and Noble can be accessed by both the URLs http://www.barnesandnoble.com and http://www.bn.com.

\(^10\) The organizations are Onsale Atcost (now Egghead) and Ecost.

\(^11\) In our initial study, we had 24 data points, but on checking the data for outliers, we discarded one site (ShopNow). We later found out that this site acted as a portal to other e-tailers, and therefore could not actually be considered a candidate for our study.
of discount offered (there were slight differences in just two instances). We finally decided to use the
discount information of ebates.com since this Web site had the maximum number of retailers listed,
and also listed the maximum number of the retailers that we had in our database.

10. Results and implications

The correlation matrix is presented in Table 2. As expected, none of the variables show a high
correlation with one another.

The data was entered into statistical software and the regression results are shown in Table 4. The
data was tested for multicollinearity, and the results are shown in Table 3. The Variation Inflation
Factor (VIF) statistics do not show any causes for concern (since \(1/(1-R^2)\approx 10\), any variables
associated with VIF values exceeding 10 would be considered to be more closely related to the other
independent variables than they are to the dependent variable). The collinearity diagnostics show that
while one of the eigenvalues of correlation matrix of the set of independent variables is close to zero,
the corresponding Condition Index is much lesser than the usual threshold value of 30 to be
considered for multicollinearity issues.

The relatively high \(R^2\) (80%) as well as the adjusted \(R^2\) (66%) shows a good fit (Table 4). The fit is
even more impressive given that the data is cross-sectional, across various types of online retailers.
The \(F\)-value testing for whether all the coefficients are zero is high, rejecting the null hypothesis that
all the coefficients of the independent variables equal zero. In fact, the t-values show that the
coefficients of all the independent variables are estimated to be different from 0 (at 1% significance levels). As we explain below, the data is both statistically significant and economically meaningful.

(In what might be considered an aside, an initial error in our data led us to include data from an online portal along with the other retailers’ data (see Footnote 11 above). Testing for an outlier led us to omit that datapoint, and thereafter, the regression results, which were very insignificant before, became highly significant. The outlier observation made us more comfortable with our decision of considering only retailers as part of our dataset – since data of one non-retailing firm was enough to severely distort the results. It also made us believe more in our hypothesis that retailing firms exhibited similar behavior, which is not replicated among non-retailing firms.)

Before going into the discussion on the coefficients, it needs to be emphasized again that since our market power proxy is an artificially created variable, it is difficult to interpret the values of the coefficients of the independent variables in exact quantitative terms. At most, we can understand the relative importance of the variables, but we would not venture to interpret our results quantitatively beyond such assertions.

As expected, we find that the click rate (CLICK) has a strong effect on our proxy for market power. As opposed to a generic measure of the total number of advertisements, the click rate measures the rate at which banner advertisements get actually clicked upon – i.e., have the desired responses. The message to new media planners seems to be clear enough – bombarding the banner spaces does not work, creating compelling advertisements that elicits a response should be the real goal.
The *GENDER* and *TECH* variables also have the expected signs of their coefficients – as per our reasoning we expect that as the proportion of female audience increases, $MP_i$ should decrease. Also, presence of technological features that make shopping easier should increase $MP_i$.

At first sight, the number of unique visitors ($UA$) to a website apparently does not seem to have any significant effect on $MP_i$. However, running a standardized regression with the data (reducing each variable to zero mean and unit regression prior to running the regression) shows that unique audience is indeed very significant in predicting market power. The results are presented in Table 5. While there have been some emerging views on the lack of relevance of the number of unique visitors [18], at a fundamental level unique audience is important. Since a fraction of the unique audience do go on to buy from a website, unique audience should be a significant variable.

The surprising results are the strong negative coefficients of the *STICK* and *SOC* variables. The data seems to suggest extended periods of visit and presence of “sociological” features actually hinder market power.

The recent reports of the burnouts of several “dot-com”-s put the above findings in proper perspective. As a recent survey of 110,000 adults *who shop online* by the market research firm Harris Interactive shows [13], unaided recall of online merchants remains extremely low, with only the online retailer Amazon.com (at 25%) and the online auctioneer eBay.com (at 17%) having some degree of recall. With most other organizations being hardly ever in the consumers’ minds, the attitude of the average consumer seems to be considering the Internet for primarily bargain-hunting. Consumers are lured into buying from a website primarily from the instant promotions that appear on
banner advertisements (leading to a high *CLICK* or click rate).\textsuperscript{12} Again, consumers might stay on a site for the chats and discussions (thus presence of *SOC* features might lead to a high *STICK*), but when it comes to “voting with their dollars” consumers prefer low prices and a comfortable and transparent shopping process (i.e., presence of *TECH* features) to anything else. Women audiences, who seem to be more “rational” in their decision-making during online shopping than their male counterparts, exacerbate the effect.\textsuperscript{13}

The results, taken as a whole, provide a very accurate picture of the world of online retailing in its early days. It is to be noticed that almost all the players came in without any industry experience, and began their “adventures” in an environment that was new to buyers and sellers alike. The promises of first-mover advantages prompted these retailers to get customers at any cost, often with offers that made no economic sense. Savvy customers took advantage of this naivété – both in terms of the lack of industry and operating environment experience – leading to the cutback in operations or even the end of many online retailing operations. These views are consistent with the online consumer buying behavior that has been recently analyzed in marketing literature [14].

The results show that some strategies of offline retailing can be imported to the online world, while others cannot be – at least in their current form. Reduction of search costs has meant that a consumer can spend all the time in one store, but at the instant of buying – unlike in offline stores – buy the product from a separate store. New software products like “R U Sure” has made it possible for

\textsuperscript{12} A report by the online marketing firm AdRelevance supports this hypothesis – it finds that advertisers are using online ads more for short-term direct marketing (essentially making them instruments for announcing instant promotions) than to create brand awareness [15].

\textsuperscript{13} An article in the *Industry Standard* (July 31, 2000) “Women’s sites shop for profits” talks of sites with highly regarded content (e.g., *iVillage, Women.com*) having failed miserably with their e-tailing efforts.
consumers to not even leave a store in order to search for better prices. Retailers will have to seriously consider the effects of such tools in an online environment, and come up with strategies to combat them. One such strategy that is being increasingly tried by online retailers is dynamic pricing, although it has already faced resistance from online shoppers.\textsuperscript{14} Thus, as Grover and Ramanlal \cite{grover1999} discuss, both buyers and sellers will continue to use sophisticated Information Technology to their advantage, and it is difficult to predict how the market will evolve in this dynamic environment.

The results also confirm our belief that the atomicity of clickstream data captures the richness of information in online transactional behavior. Even with some limitations of our research (which we discuss in the next section), the results paint an accurate picture of the online retailing industry. As explained before, the homogeneity of the strategies in the initial stages of online retailing allowed us to gather data across a cross-section of retailers, but as the strategies become more diverse, and the brand effects of erstwhile offline retailers are felt in the online world, later studies should take cognizance of such effects.

11. Limitations

There are several limitations to this study that make our observations less robust than we would have liked. Some of the limitations are:

1. We feel that one very important attribute about which we do not have data is the “click-through rate” – the proportion of viewers who click a banner advertisement and actually go on to buy a

\textsuperscript{14} The online magazine E-commerce Times reported pricing variation of the same product for different customers at Amazon.com (http://www.ecommercetimes.com/news/viewpoint2000/view-000918-2.shtml). The company later refunded the difference to customers who paid more, when the pricing strategy was discovered through online bulletin boards.
product. This information is available, but was not accessible to us during the one-day trial access that allowed us to view only one part of the information at the Nielsen Netratings Web site.

2. The number of observations is limited, since the data is available for a single period. We expect to address this issue when we have full and unfettered access to the data. Availability of data over a larger period of time will help us make more robust observations.

3. While the quality of the online data is very rich, we have ignored any offline data – e.g., the effect of offline advertisements by the online firms that might have some explaining power. The UA variable, while managing to capture effects of offline strategies, is a very blunt proxy, since it does not allow us to differentiate effects of various offline strategies. This limitation was not felt so much in this study as the strategy of all the retailers were very similar, but will have to be considered seriously in future studies.

12. Conclusion and future directions of research

One of the aims of this study is to start a discussion towards developing a framework for identifying metrics for measurement of market power in electronic commerce. At this stage, we limited our research to study the world of online retailing. Our basic premise revolved around the fact that it is difficult to develop a suitable measure of market power in the conventional Industrial Organization framework, and therefore we had to look around creatively for observable conduct that indicates market power. We showed that a reasonable proxy for conduct is reasonably explained in terms of several performance-related variables. The choice of the discount at the e-malls is by no means sacrosanct. If we find better measures (or proxies) of market power, the relationship specified in
equation (3) would be suitably modified. Also, for other markets, the explanatory variables would probably differ from those used for the e-tailing scenario.

As markets become more differentiated in the online retailing industry, we will need to take care of new variables and their effects. Some of them are:

- Consideration of offline effects – this will come mostly from current offline retailers as they establish a presence in the online world. With convergence of digital media, these effects will become increasingly complicated.

- As Grover and Ramanlal discuss [12], firms will increasingly use IT to differentiate between products and customers (by using dynamic pricing, for example) in order to extract the consumer surplus. On the other hand, consumers will have increasingly sophisticated tools to reduce search costs and specify product preferences in several dimensions. The effects of such interactions will have to be included in later studies.

We hope that this study would help jumpstart the discussion of IO-related issues in e-commerce, and more generally, induce research in using the rich set of data that capture the details of electronic transactions at a much higher level of atomicity than it was ever possible before.
References


[9] **Cyber Dialogue** survey of online shopping habits reported by The Industry Standard magazine, March 27, 2000, [http://www.thestandard.com/article/display/0,1151,13290,00.html](http://www.thestandard.com/article/display/0,1151,13290,00.html)


[13] **Harris Interactive** poll results reported by The Industry Standard magazine, April 28, 2000, [http://www.thestandard.com/article/display/0,1151,14602,00.html](http://www.thestandard.com/article/display/0,1151,14602,00.html)


## Appendix

<table>
<thead>
<tr>
<th>Retailer</th>
<th>Retailer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-800-Flowers</td>
<td>Garden.com</td>
</tr>
<tr>
<td>800.com</td>
<td>iPrint.com</td>
</tr>
<tr>
<td>Amazon</td>
<td>Living.com</td>
</tr>
<tr>
<td>American Greetings</td>
<td>Mercata.com</td>
</tr>
<tr>
<td>Barnes and Noble</td>
<td>M P 3.com</td>
</tr>
<tr>
<td>Beyond.com</td>
<td>Pets.com</td>
</tr>
<tr>
<td>BigStar</td>
<td>PetsMart</td>
</tr>
<tr>
<td>CDNOW</td>
<td>PlanetRX</td>
</tr>
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<td>Dell</td>
<td>Reel.com</td>
</tr>
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<td>Drugstore.com</td>
<td>ToysRUs</td>
</tr>
<tr>
<td>Etoys</td>
<td>Wrenchead.com</td>
</tr>
<tr>
<td>Gap</td>
<td></td>
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**Table 1**: The e-tailers considered for the study
Table 2: The correlation matrix

<table>
<thead>
<tr>
<th></th>
<th>CLICK</th>
<th>UA</th>
<th>STICK</th>
<th>GENDER</th>
<th>SOC</th>
<th>TECH</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLICK</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UA</td>
<td>-0.08</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>STICK</td>
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<td>0.29</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GENDER</td>
<td>-0.10</td>
<td>0.05</td>
<td>-0.42</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOC</td>
<td>0.24</td>
<td>0.07</td>
<td>-0.24</td>
<td>-0.30</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>TECH</td>
<td>0.19</td>
<td>-0.04</td>
<td>-0.01</td>
<td>0.09</td>
<td>0.42</td>
<td>1.00</td>
</tr>
</tbody>
</table>
## Variance Inflation Factors statistics

| Variable | DF | Parameter Estimate | Standard Error | t-Value | Pr>|t| | Variance Inflation |
|----------|----|-------------------|----------------|---------|-----|-------------------|
| Intercept | 1  | 69.65253          | 15.60426       | 4.46    | 0.0016 | 0                 |
| click    | 1  | 7.91128           | 2.01911        | 3.92    | 0.0035 | 1.30900           |
| ua       | 1  | 0.00000551        | 0.00000114     | 4.83    | 0.0009 | 2.69007           |
| stick    | 1  | -45.37929         | 10.62120       | -4.27   | 0.0021 | 4.22115           |
| gender   | 1  | -32.84109         | 7.72347        | -4.55   | 0.0014 | 4.60360           |
| soc      | 1  | -511.144          | 2.09953        | -3.58   | 0.0060 | 2.56977           |
| tech     | 1  | 6.255850          | 1.72381        | 3.63    | 0.0055 | 1.84782           |

### Collinearity Diagnostics (intercept adjusted)

<table>
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<tr>
<th>Number</th>
<th>Eigenvalue</th>
<th>Condition Index</th>
<th>Proportion of Variation</th>
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<tr>
<td>1</td>
<td>1.81167</td>
<td>1.00000</td>
<td>0.00173</td>
</tr>
<tr>
<td>2</td>
<td>1.43371</td>
<td>1.12411</td>
<td>0.01614</td>
</tr>
<tr>
<td>3</td>
<td>1.16674</td>
<td>1.24610</td>
<td>0.04824</td>
</tr>
<tr>
<td>4</td>
<td>0.89088</td>
<td>1.42603</td>
<td>0.12375</td>
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<tr>
<td>5</td>
<td>0.60904</td>
<td>1.72471</td>
<td>0.2447</td>
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<tr>
<td>6</td>
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<td>4.53867</td>
<td>0.71918</td>
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### Collinearity Diagnostics (intercept adjusted)

<table>
<thead>
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<th>Number</th>
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<td>stick</td>
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<td>gender</td>
<td>0.03518</td>
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<td>soc</td>
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<td>tech</td>
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<td>2</td>
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<td>6</td>
<td>0.42708</td>
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Table 3: VIF statistics and Collinearity Diagnostics
Analysis of variance

<table>
<thead>
<tr>
<th></th>
<th>F-value</th>
<th>Pr &gt; F</th>
<th>Dependent mean</th>
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<tbody>
<tr>
<td></td>
<td>5.87</td>
<td>0.0096</td>
<td>R²</td>
<td>0.797</td>
</tr>
<tr>
<td>Root MSE</td>
<td>2.536</td>
<td></td>
<td>Adjusted R²</td>
<td>0.661</td>
</tr>
</tbody>
</table>

Parameter Estimates

| Variable  | DF | Parameter estimate | Std. error | t-value | Pr > |t| |
|-----------|----|--------------------|------------|---------|------|---|
| Intercept | 1  | 69.65              | 15.60      | 4.46    | 0.0016 |
| CLICK     | 1  | 7.91               | 2.02       | 3.92    | 0.0035 |
| UA        | 1  | 0.00               | 0.00       | 4.83    | 0.0009 |
| STICK     | 1  | -45.38             | 10.62      | -4.27   | 0.0021 |
| GENDER    | 1  | -32.85             | 7.22       | -4.55   | 0.0014 |
| SOC       | 1  | -7.51              | 2.10       | -3.58   | 0.0060 |
| TECH      | 1  | 6.26               | 1.72       | 3.63    | 0.0055 |

Table 4: Regression results
<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Standardized coefficients</th>
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<tbody>
<tr>
<td>CLICK</td>
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<tr>
<td>UA</td>
<td>1.192</td>
</tr>
<tr>
<td>STICK</td>
<td>-1.320</td>
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<tr>
<td>GENDER</td>
<td>-1.300</td>
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<tr>
<td>SOC</td>
<td>-0.862</td>
</tr>
<tr>
<td>TECH</td>
<td>0.742</td>
</tr>
</tbody>
</table>

**Table 5**: Regression results – standardized coefficients
Figure 2(a): Desktop application R’u’sure – stays on top of a page and finds lowest price of item even as the shopper browses on the page.

Figure 2(b): Browser plug-in WhenUShop: informs shopper about retailer information on one page – current promotions, taxes, shipping and return policies, etc.
<table>
<thead>
<tr>
<th>Price</th>
<th>Retailer</th>
<th>Quantity</th>
<th>US Sales Tax</th>
<th>Shipping Costs</th>
<th>Shipping Time</th>
<th>Shipping Service</th>
<th>Delivery Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>US$ 0.00</td>
<td>TheRightBook.com, USA, CA</td>
<td>99%</td>
<td>US$ 0.09</td>
<td>US$ 0.00</td>
<td>n/a</td>
<td>Around</td>
<td>n/a</td>
</tr>
<tr>
<td>US$ 10.60</td>
<td>Walden.com, CAN</td>
<td>10%</td>
<td>US$ 0.99</td>
<td>US$ 0.93</td>
<td>3-7 days</td>
<td>Surface Courier</td>
<td>n/a</td>
</tr>
<tr>
<td>US$ 20.25</td>
<td>Chapters Globe, CAN</td>
<td>11%</td>
<td>US$ 0.99</td>
<td>US$ 7.43</td>
<td>3-5 days</td>
<td>Canada Post</td>
<td>4-6 days</td>
</tr>
<tr>
<td>US$ 21.20</td>
<td>HamiltonBooks.com, USA, VT</td>
<td>60%</td>
<td>US$ 0.99</td>
<td>US$ 8.00</td>
<td>3-12 days</td>
<td>U.S. Postal Service</td>
<td>n/a</td>
</tr>
<tr>
<td>US$ 21.47</td>
<td>TheBookDepot.com, USA, NY, NY</td>
<td>22%</td>
<td>US$ 0.99</td>
<td>US$ 0.35</td>
<td>2-7 days</td>
<td>UPS Regular Mail</td>
<td>n/a</td>
</tr>
<tr>
<td>US$ 21.47</td>
<td>KO Books, USA, MD</td>
<td>22%</td>
<td>US$ 0.99</td>
<td>US$ 0.35</td>
<td>4-6 days</td>
<td>UPS Ground</td>
<td>3-4 days</td>
</tr>
<tr>
<td>US$ 22.10</td>
<td>Bookshare.com, USA, CA</td>
<td>17%</td>
<td>US$ 0.99</td>
<td>US$ 0.00</td>
<td>3-14 days</td>
<td>USPS Parcel Post</td>
<td>6-14 days</td>
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<tr>
<td>US$ 22.15</td>
<td>Borders.com, USA, NV, NV</td>
<td>10%</td>
<td>US$ 0.99</td>
<td>US$ 0.99</td>
<td>3-7 days</td>
<td>Standard</td>
<td>n/a</td>
</tr>
<tr>
<td>US$ 22.15</td>
<td>Amazon.com, USA, WA, WA</td>
<td>20%</td>
<td>US$ 0.99</td>
<td>US$ 1.15</td>
<td>2-7 days</td>
<td>USPS Priority Mail</td>
<td>3-5 days</td>
</tr>
<tr>
<td>US$ 22.15</td>
<td>BookRite.com, USA, CA</td>
<td>10%</td>
<td>US$ 0.99</td>
<td>US$ 0.99</td>
<td>2-7 days</td>
<td>UPS Ground</td>
<td>4-5 days</td>
</tr>
</tbody>
</table>

**Figure 2(c):** Internet application *Dealtime*: Lowest price of book, inclusive of shipping
Figure 3: ebates.com homepage, with discounts at advertised retailers shown