Establishing a Framework For Analyzing Market Power in Electronic Commerce: An Empirical Study

Alok Chaturvedi and Subhajyoti Bandyopadhyay
Purdue University
alok, s_bandyopadhyay@mgmt.purdue.edu

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. One of the main reasons why existing research in this area has concentrated on case studies and generalized observations 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. In the process, we develop a framework for measuring market power as applicable to the world of online retailing.

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 [14]). 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). 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. 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 [20]) 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 that attempt to provide some quantitative measures of the aforesaid market power.

There are several reasons for the current state of affairs. First, online retailing is a new phenomenon, modifying the market institution and environment

1 The authors wish to thank Professor Janet Netz of the Economics department at Purdue University and four anonymous referees for their several comments on an earlier version of the paper.
that we identify with traditional retailing. Thus, there has been only a limited rigorous examination of the market processes in an academic sense. Second, while electronic commerce has brought upon us a surfeit of data (e.g., clickstream data 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.

1. 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-merchants 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.

2. Related research

The traditional approach to studying market power in firms 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. 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, [19]).

The new empirical Industrial Organization (NEIO) therefore does not follow the SCP hypothesis. The degree of market power is identified and estimated and the inference of market power is based on the firms’ conduct [2]. 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, 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 [10]).

Our study thus complements these research efforts. We use the “new” data from e-commerce transactions (i.e., the clickstream data), but unlike the researchers mentioned in the last paragraph, we use this data from an industry level perspective to find the relationship between the players’ market power and the various web statistics.

3. Studying the phenomenon of e-mails 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, uniform across products (this requirement is important, since online retailers use 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.

It is in the context of finding new and relevant proxies for market power that we study the phenomenon of e-mails. Recently, there has been a proliferation of Internet-based businesses that have been variously called e-mails or i-mails in the popular business literature. Some of the more prominent examples include ebates.com, dash.com and 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-mails (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.

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. We assume here that the discounts are not affected by the competition among the e-mails, though in real life, there would possibly be some effect of the competition among the various e-mails on the discount levels (however, a cursory analysis of the discount levels across the e-mails show a remarkable similarity of discount levels). The retailers in turn will be willing to subsidize these rewards only if it results in some extra benefit to them.

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-mails (see for example [18], [3], [4] and [21]). We posit that the role of the e-mails 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 [16], for example, fit an S-shaped cubic polynomial to estimate the effect of per capita advertising on sales.

If we assume that the reduction in the total cost (\(C\)) is a function of sales (\(Q\)), it follows that the marginal cost (i.e., \(\frac{dC}{dQ}\)) for the e-tailer should also change.

\[\frac{dC}{dQ}\]

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”.

This therefore results in a change in the producer’s surplus,

\[ PS = \int_0^{q^*} (p - MC) dq = \Pi(q^*) - \Pi(0), \]  

\( p \) being the price of the product, \( MC \) its marginal cost) which is also the change in profits by going from no production to a production level of \( q^* \). (\( \Pi(0) \) is the fixed costs).

There are two possible explanations of the e-mall specific discounts. We argue that a retailer can afford to subsidize the rewards to the final consumers if, and only if, there is a lowering of the marginal costs, which results in 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.

Another possible explanation of the discounts is that the retailers use the e-malls as a method by which they capture the demand of price-sensitive buyers. Thus, in an attempt to capture market share, the retailers are willing to forgo their margins for these price-sensitive consumers.

3.1 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. A better-established retailer might argue that its benefits of going through an e-mail (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. 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-mail indicates the presence of its (larger) market power. The end-consumers of course benefit from this arrangement and continue to buy through the e-mail, since they receive exclusive discounts from the e-mail over and above the lowest prices that they can get from any of the retailers featured at that e-mail.\(^3\) (This is analogous to a store-specific discount for a product that we observe at a retailing store over and above any manufacturer’s rebate or coupons that might be available.)

We visualize this argument by the following schematic:

![Retailer sets discount to consumer](image)

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, mindshare among consumers, etc. have greater market power than smaller, newer firms; the latter thus try to attract a ready cache of customers in the e-

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\(^3\) 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.”
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.

4. 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 \( MP_i \).

\[
MP_i = \frac{1}{\text{Discount}_i}
\]

(1)

\( \text{Discount}_i \) is the discount level for the retailer \( i \) 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.

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:

\[
MP_i = \beta_0 + \beta_1[\text{CLICK}_i] + \beta_2[\text{UA}_i] + \beta_3[\text{STICK}_i] +
\beta_4[\text{GENDER}_i] + \beta_5[\text{SOC}_i] + \beta_6[\text{TECH}_i]
\]

(2)

One issue needs a slight clarification. \( MP_i \) should not
be confused as a measure of market power; rather, it
is a 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 (2) explores the
relationship between \( MP_i \) and various web statistics,
and thus points towards possible metrics that can
explain market power.

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 (2) 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 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.4

- **UA** is the unique audience at a particular web site
over a period of time (in our case, one week). Much
of the initial euphoria over Internet stocks in
recent times have centered around the
assumption that larger unique audiences was
crucial for the success of online ventures.5 This
assumption seems to be questioned in the last few
months, and there seems to be a growing
consensus that unique audience is not a
prerequisite for success.6

- **STICK** is a measure of the “stickiness” of the
Web site of an e-tailer: the average time spent by
a visitor at the Web site. Using a supermarket
analogy, the larger time a prospective customer

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

5 Some examples: Last year, a Bear Sterns analyst
upgraded [About.com](http://www.about.com)'s rating when its traffic increased,
even though its stock price was unchanged. Also,
[VitaminShoppe.com](http://www.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.

6 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]
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 6).

- **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 prefer lower costs to brand names. Thus, a higher percentage of women at a web site should lead to lower market power.

The next set of variables explore 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.

- **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, 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 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.

The last two variables 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](http://www.bizrate.com), a leading online ratings site. In almost all instances, their “average” ratings closely matched those of [Bizrate.com](http://www.bizrate.com).

The above model presents explanatory variables that do not seem to possess any high degree of multicollinearity. Further, *a priori*, no 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.

### 4.1 Data Source

The main source of data used in this study is [Nielsen Netratings](http://www.netratings.com). 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.

### 5. 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.\(^7\) 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. 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

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\(^7\) 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.
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.

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 $MP_i$.

The number of unique visitors ($UA$) to a Web site also does not seem to have any significant effect on $MP_i$. This runs counter to some of the erstwhile beliefs on the measures of online success, but can be interpreted in light of some of the emerging views on the lack of relevance of the number of unique visitors on market power [17]. We will return to these observations in the final parts of this section to get a more global understanding of this phenomenon.

The more 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 [12], mindshare of online merchants remain pitifully low.

For the e-mail 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 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.

6. 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 3. The relatively high $R^2$ (80%) as well as the adjusted $R^2$ (66%) shows a good fit. The fit is even more impressive given that the data is cross-sectional, across various types of online retailers. The $F$-value is high, rejecting the null hypothesis that all the coefficients of the independent variables equal 0. Actually, 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.

8 For example, the online books retailer Barnes and Noble can be accessed by both the URLs http://www.barnesandnoble.com and http://bn.com.
9 The organizations are Onsale Atcost (now Egghead) and Ecost.
10 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.
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). 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]. Thus, consumers might stay on a site for the chats and discussions (thus leading to a high UA or SOC or 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.\footnote{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.}

These results are consistent with similar conclusions that were drawn from online consumer buying behavior in marketing literature [13].

6.1 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 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 in two ways – we have only a limited set of fully available datadoints (23), and secondly, the data is available for a single period. We expect to address this issue when we have full and unfettered access to the data. Of special significance would be data over a larger period of time that can help us make more robust observations.

3. While the quality of the online data is very rich, we have totally ignored any offline data – e.g., the effect of offline advertisements by the online firms that might have some explaining power.

7. 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. The choice of the discount at the e-mails is by no means sacrosanct. If we find better measures (or proxies) of market power, the relationship specified in equation (2) would be suitably modified. Also, for other markets, the explanatory variables would probably differ from those used for the e-tailing scenario. In effect, we wanted to show that the strategic conduct of an online retailer could be explained in terms of the website’s clickstream data, something over which the online retailer has no direct control.

One very interesting extension of this research would be to consider market power implications of dynamic pricing that online retailers frequently employ.

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.
8. References


Appendix

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Table 1: The e-tailers considered for the study

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<th>GENDER</th>
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Table 2: The correlation matrix

Analysis of variance

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<th>Dependent mean</th>
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<td>Root MSE 2.536</td>
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<td>Adjusted R² 0.661</td>
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Parameter Estimates

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<th>Std. error</th>
<th>t-value</th>
<th>Pr &gt;</th>
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Table 4: Regression results