Understanding the confluence of retailer characteristics, market characteristics and online pricing strategies

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Abstract

Theories from Information Systems, Marketing and Economics suggest that product, retailer, and market characteristics jointly serve as determinants of online retailers’ ability to price differentiate. Until now, the empirical research has focused on examining the impact of these determinants in isolation. In this paper, we extend the prior online price dispersion literature by examining the interactions among product, retailer and market characteristics. We construct a multi-level hierarchical linear model to empirically test whether market level characteristics moderate retailer characteristics in explaining price dispersion. Our analysis is based on a dataset of 13,393 price quotes for 1880 best selling products across eight product categories from 194 online retailers. The analysis indicates that service quality has a positive effect on retailer price levels. We observe that the relationship between competitive intensity in a market and retailer price levels is inverted “U” shaped. In contrast, the influence of the interaction between a retailer’s service quality and market level variables on retailer price levels is “U” shaped. These findings together provide the first known empirical evidence for the existence of mixed pricing strategies among online retailers. Contrary to conventional wisdom, we find that retailers providing quality service are able to charge higher prices as the competition increases.

Keywords: Electronic market efficiency; Price dispersion; Retailer service quality; Pricing strategy

1. Introduction

The growth in Internet based retailing3 has been accompanied with equal interest amongst researchers examining the impact of the Internet-enabled business models. Central to online retailing is the informational transparency provided by third-party websites such as Pricescan.com for comparative product prices and number of competitors, and Bizrate.com, which also provides service quality ratings and consumer opinions of retailers. Such transparency, accompanied by ease of search, was predicted to provide gains in informational efficiency and reduce price dispersion in the marketplace [6,7]. It has been suggested that the increased availability of information accompanied with the ease of search will lead to cost transparency [35]. This will allow the consumers to clearly see through not just the prices but also the cost structures of sellers and
suppliers. This, in turn, will lead to substantial erosion in sellers’ ability to price differentiate and extract premiums, and lead to informationally efficient markets.

Yet, empirical evidence from a wide range of product markets and countries indicates that price dispersion is persistent in online markets and that the so-called “law of one price” does not hold [3,5,9,10,11,13,18]. The persistence of the price dispersion implies retailers’ ability to sustain price differentiation even in the face of increased search efficiency and accessibility to a host of other relevant information. The question arises, what are the primary sources of differentiation that influence a retailer’s ability to extract economic rents?

As can be expected with early work in an area, the vast majority of research has focused on isolated aspects of informational transparency and the resulting impact on price dispersion. Studies shedding light on what enables the retailer to price differentiate from its competition (retailer characteristics) have examined retailers’ ability to service differentiate. For instance, in eBay auctions, sellers’ premiums have been found to be increasing in seller reputation, a proxy for service quality offered [4]. Another retailer characteristic considered is the combination of transaction channels offered; for example, pure-play Internet versus brick-and-click retailers [28]. Another recent study in marketing considers market characteristics such as number of competitors, average price and product popularity [27]. It is worth noting that none of the prior studies have examined the interactions between retailer, product and market characteristics towards explaining price dispersion. Given the enhanced product and retailer rating information disseminated by online intermediaries, we wish to study the impact of this information richness on retailers’ pricing strategies. Electronic markets enable volumes and speeds that human middlemen could not accomplish [20]. There has been limited research on the impact of intermediaries, such as price-comparison agents, on price levels and retailer’s strategies. It has been shown analytically that the increasing numbers of price-comparison shoppers pull prices down, and the rate at which prices decrease is shaped by the diffusion curve and brand preference [23]. Given these theoretical expectations of the impact of widespread information availability, we empirically examine when and how in relation to competitive intensity does retailer service quality and choice of transaction channels shape an online retailer’s ability to price differentiate. The key question we address is whether such information, accessible to both consumers and competitors, is being cross-fertilized and acted upon in a significant way.

To summarize, we seek to answer the following questions with regard to a retailer’s ability to price differentiate:

1. What retailer characteristics matter?
2. When, in context of different market conditions, do they matter?
3. How do they enable different degrees of price differentiation?

The rest of the paper is organized as follows. The next section presents the conceptual model for our analysis. It includes five test hypotheses that examine how market and retailer characteristics interact, and in the process determine the scope of price differentiation available to a given retailer. We then describe our data collection from heterogeneous sources to capture the information that is widely available to consumers and retailers alike. We then present a hierarchical multi-level regression model that includes factors at different levels of measurement (product, retailer and market) to capture the richness of the conceptual framework. Subsequently, we report the results of the data analyses and analyze the implications. We conclude by discussing limitations of our study and directions for future research.

2. Conceptual model and hypotheses

Our research simultaneously analyzes the two forces that determine online retailers’ competitive advantage on the sell-side [31]. These are a) buyers’ bargaining power as a result of lowered search cost and access to widely-available information about the retailers and b) competitive intensity, where sellers can easily observe and assess their competition in terms of not only product and price offerings but also measures that were previously unobservable. Such measures include reputation as reflected in service quality and estimated total sales as measurable from traffic to the competitors’ websites. Fig. 1 presents the conceptual model of our study.

The two forces are represented in the conceptual model as Retailer and Market Characteristics. We hypothesize that these forces and the interactions between them determine the scope of price differentiation available to a given retailer. Based on the conceptual model we formalize the hypotheses below. The hypo-
theses are grouped by the nature of effect, namely main and moderating, and level of effect, namely retailer and market factors.

2.1. Main effects: influence of retailer factors

2.1.1. Service quality

Considering the increased transparency in pricing information enabled by the Internet between buyers and sellers, and more importantly, across sellers, service quality provides an avenue for retailers seeking to differentiate [38]. Improved service quality can increase satisfaction, and intent to repurchase with the retailer [39] and the utility of a consumer [36]. These together will lead to lower price sensitivity on the part of the consumer and enable the retailer to price differentiate. For online markets, it has been found that consumers exhibit higher degrees of loyalty to the products that they currently own [25]. Under conditions where there is little scope for product differentiation, the findings can be extended to loyalty of consumers to the retailers. Another study of the online retail market finds that reputation as measured by service quality explains the retailer’s ability to price differentiate, albeit very little [27]. However, their findings are not consistent across different product categories, and only a small proportion of the price premiums is accounted for by online retailer characteristics. Considering the above-mentioned direct and indirect influences of service quality, we hypothesize:

**H₁. (service quality effect)**
The higher the service quality the higher the prices charged.

2.1.2. Channels of transaction(s)

The channel(s) adopted by retailers can influence their pricing owing to 1) brand recognition, and 2) the options available for transacting with the consumer. More brand recognition of the retailer can lead to greater trust with the consumer [1], leading to lower price sensitivity on the consumer’s part.

A retailer with multiple channels of interaction with the consumer provides better facilities for picking up and returning products. The cross-channel presence of the retailer can lead to enhanced efficiencies in fulfillment and post-fulfillment aspects of transactions, accompanied with lower perceived risks and enhanced trust for the consumer. This enhanced trust with the retailer drives multi-channel shopping behavior, and lowers the consumers’ price sensitivity [24]. On the other hand, the distribution channels for a pure-play retailer, Internet only, lower the inventory costs. This may potentially be leveraged to price differentiate by cost leadership. Until now, [27] is the only study that has examined retailer channel. Their results indicate that, in equilibrium, a brick-and-mortar retailer provides better service at a higher price in comparison to a
pure-play Internet retailer. We propose our hypotheses for all channels of transactions relative to the pure-play retailer, who we expect to have a greater incentive to price lower.

National brick-and-click retailers should be able charge higher prices due to better brand recognition, greater trust [19] and provision of better facilities related to fulfillment and post-fulfillment transactions. Therefore we hypothesize that,

\( H_{2a}. \) (national channel effect)
National brick-and-click retailers charge higher prices than pure-play retailers.

Local brick-and-click retailers have a provision of better fulfillment and post-fulfillment related provisions and thus should be able to charge higher prices. However, they are also expected to have lower brand recognition, and thus not able to charge the same premiums as retailers with national presence. Typically, these retailers use their online presence to extend their reach and attract additional consumers outside of the geographic reach of their traditional store without incurring significant incremental costs. Since their inventory costs are included within the operating costs of their brick stores, the supplemental cost incurred is limited to the cost of developing and maintaining a website. Given valid expectations for both higher and lower prices for local brick-and-click retailers, we do not specify any directional hypotheses related to their pricing strategy.

Online retailers that provide direct mail catalogs have national brand recognition and have leveraged this brand by establishing an online presence with shared cost for distribution channels [17]. Online retail managers believe that direct mail catalogs allow them to build brand recognition and increase trust among consumers [33]. Their provision for multiple channels of transactions for a consumer enhances the trust in the retailer enabling them to charge higher prices [24]. Hence,

\( H_{2b}. \) (online multi-channel effect)
Online retailers that provide direct mail catalogs charge higher prices than pure-play retailers.

2.1.3. Size of the retailer
The size of a retailer can have a variety of influences on its pricing strategy. Online retailers who have a large number of visitors — a widely used measure of size for an online retailer — can be expected to have high brand recognition. This, in turn, should allow them to charge higher price premiums. However, online retailers that have a large size can also be cost leaders because of economies of scale. They could be using lower prices, disseminated through the infomediary, as a signaling mechanism to both reduce current competition and also deter new entrants. Though we expect the size of a retailer to influence pricing strategies, it is used only as a control variable. No directional hypotheses are made regarding its effect.

2.2. Main effects: influence of market factors

2.2.1. Number of competitors
In a longitudinal study of the online market for books [11], the authors find support for reduced price dispersion due to increased competition. The panel data used [27] also provides empirical support for incrementally smaller price dispersion levels in the number of competitors across the examined product categories. However, it is also worth considering the informational aspects of having increased market competition on consumer search.

In [14], the author suggests that the number of alternative brands of a particular product is a double-edged sword. While on the one hand it increases rivalry and stimulates price competition, on the other hand, beyond a threshold, it causes information overload. This leads to the consumer being poorly informed and thus damps price competition, leaving the consumer vulnerable to exploitation.

In contrast to the suggestion of reduced price differentiation with increased competition, in a segmented market, the prices charged by a retailer can increase with the number of competitors [34]. Using an analytical model [21], it is shown that for an online retailer, participating with an infomediary, it is optimal to increase the price with increased competition. Not surprisingly, an empirical study of the airline industry lends support for an inverse U-shaped relationship between competition and scope of price differentiation, as revealed by the level of price dispersion [26]. Yet, a similar effect has not been established for online retailing. Based on these findings we hypothesize that on average, the prices charged by an online retailer will first increase with the number of competitors, and beyond a certain threshold, an increase in number of competitors will lead to a decrease in the prices charged.

\( H_3. \) (competitive intensity effect)
There is a non-linear relationship between the number of competitors and the prices charged by a retailer.

2.2.2. Price level
The price of a given product captures the perceived risk and measures an important facet of a consumer’s
involvement in a product [16]. For products with higher average price levels, consumers may exhibit increased search efforts due to higher perceived risk levels. Consequently, the retailers may charge lower prices where consumer search is expected to be higher. Interestingly, some empirical evidence indicates the opposite to be true. There is increased price dispersion with increase in price level [32]. This increase in dispersion is a result of the consumers’ willingness to pay higher prices for some retailers who are able to induce trust and hence reduce their perceived risk. Thus, for products with higher average price levels, retailers who are able to foster trust by way of better service quality have more scope for price differentiation and are able to charge relatively higher prices. Owing to the conflicting theories and situational evidence, we do not make any directional expectations about the influence of price level on retailer prices.

2.3. Moderating effects

2.3.1. Interaction of number of competitors and service quality

Cohen [14] puts forth the concept of distortion in information function (hereafter DIF-ness). It measures the amount of information regarding alternatives that are available to the consumer. DIF-ness suggests that until a certain threshold, as the number of choices increase, consumers scan the environment and make the choice that maximizes their utility. Beyond this threshold, any increase in the number of alternatives can lead to consumers using heuristics, such as service quality, to make their choice.

Research in signaling theory suggests that consumers often use price as a proxy for the quality of a product or retailer [22]. Based on these two aspects, we propose that when there are low numbers of competitors in a product market, retailers with quality service can easily differentiate themselves and charge a higher price for their products. With initial increases in the number of competitors, the retailers are forced to lower their prices in order to avoid losing their consumers to competitors. However, when the number of competitors exceeds a certain threshold, a retailer with quality service can again successfully differentiate and charge higher prices. The consumer’s use of heuristics to deal with DIF-ness leads to higher informational rents for ‘good’ retailers as competition increases. To the best of our knowledge, this proposed tension between increasing competitive and informational pressure has never been empirically examined. It leads us to hypothesize that,

**H4. (DIF-ness effect)**

Given quality service there is a U-shaped relationship between the number of competitors and the prices charged by the retailer.

2.3.2. Interaction of average price level and service quality

Cohen [15] suggests that under circumstances where the stakes (price level) are high, the consumers’ selection is based on risk averseness. This leads them to prefer retailers with quality service, who in turn will exploit the consumers’ risk averseness and charge higher prices. As a result, we propose that:

**H5. (stakes effect)**

Given quality service as the average price level increases, there is an increase in the prices charged by the retailer.

3. Data collection

For the purpose of this study, we are interested in obtaining price quotes and service quality ratings for

Table 1
Operationalization of constructs

<table>
<thead>
<tr>
<th>Construct</th>
<th>Data collected for operationalization</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service quality</td>
<td>Survey ratings obtained by Bizrate from online consumers. Survey is conducted on a 10-point scale (1=Poor, 10=Outstanding) measuring: On Time Delivery, Consumer Support, Product Met Expectations and Shop Again.</td>
<td>Bizrate.com</td>
</tr>
<tr>
<td>Transactional channels</td>
<td>Dummy coded variables for characterizing the channels through which the retailer offers the products. The channels are first classified as one of the following: pure-play (online only), national chain with online presence, and local store(s) with online presence. In addition, we also distinguish retailers that offer mail-order catalog.</td>
<td>Manual inspection and verification</td>
</tr>
<tr>
<td>Size</td>
<td>Rank of retailers based on number of unique visitors to the online store.</td>
<td>Alexa.com</td>
</tr>
<tr>
<td>Competitive intensity</td>
<td>Number of retailers offering an identical product and with service quality ratings available from BizRate.</td>
<td>Bizrate.com</td>
</tr>
<tr>
<td>Consumer involvement</td>
<td>Average posted-price for a product.</td>
<td>Bizrate.com</td>
</tr>
</tbody>
</table>
Table 2
Bias reduction reduces analyzable data

<table>
<thead>
<tr>
<th>Product category</th>
<th># Collected</th>
<th># Analyzed</th>
<th># Retailers</th>
<th># Analyzed</th>
<th># Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Books</td>
<td>5750</td>
<td>2752</td>
<td>19</td>
<td>9</td>
<td>685</td>
</tr>
<tr>
<td>Camcorder</td>
<td>1386</td>
<td>882</td>
<td>86</td>
<td>57</td>
<td>57</td>
</tr>
<tr>
<td>DVD</td>
<td>9242</td>
<td>5738</td>
<td>30</td>
<td>15</td>
<td>799</td>
</tr>
<tr>
<td>DVD player</td>
<td>547</td>
<td>446</td>
<td>66</td>
<td>51</td>
<td>40</td>
</tr>
<tr>
<td>PDA</td>
<td>568</td>
<td>479</td>
<td>77</td>
<td>57</td>
<td>32</td>
</tr>
<tr>
<td>Printer</td>
<td>1087</td>
<td>906</td>
<td>75</td>
<td>54</td>
<td>36</td>
</tr>
<tr>
<td>Scanner</td>
<td>708</td>
<td>574</td>
<td>77</td>
<td>53</td>
<td>31</td>
</tr>
<tr>
<td>Video games</td>
<td>2921</td>
<td>1616</td>
<td>74</td>
<td>42</td>
<td>200</td>
</tr>
<tr>
<td>Totals</td>
<td>22,209</td>
<td>13,393</td>
<td>504</td>
<td>338</td>
<td>1880</td>
</tr>
</tbody>
</table>

eight different product categories, one of which is books. We describe these categories in detail later in this section. While several websites, such as fatwallet.com and resellerratings.com, offer retailer ratings in addition to price quotes, Bizrate.com is the only site that follows up with a comprehensive surveying technique in conjunction with retailers. Further, because of its wide coverage in the eight product categories of interest, we obtain our price and service quality data from Bizrate.com. In accordance with the established literature, and to compare our results with other studies, we choose product categories such that our sample includes homogenous products with a range of average price levels. The choice of homogenous products ensures that product differentiation is not a source of variation in prices. In addition, using Bizrate’s consumer guide feature, we ensured that at least 20 different products were offered in each of the eight categories indicating substantial penetration of these categories among Internet-enabled retailers. In order to have some minimum competitive intensity, we ensured that there were at least seven or more retailer price quotes for each product. Based on these criteria, we obtained eight product categories — books, camcorders, DVDs, DVD players, PDAs, printers, scanners and video games. Table 1 provides the summary information about the data collected for operationalizing the constructs of our conceptual model presented earlier in Fig. 1.

For each retailer, we collected service quality ratings and competitive intensity information from Bizrate.com. We also collected information about the size of the retailer, measured in terms of number of unique visitors to the retailer’s website, from Alexa.com. The transaction channel(s) provided by the retailer were coded similar to [36]. In order to classify a retailer by transaction channels, the retailer’s website was inspected to obtain the presence, location and geographical spread of physical store(s). If physical stores were present, and located in more than one state, the retailer was classified as National Brick-and-Click. Retailers with a more localized presence, with physical store locations within one state, were classified as Local Brick-and-Click. If no physical stores were present, the retailer was classified as Pure-Click. If the retailer offered mail-order catalog services they were additionally classified as a Catalog Provider. In rare cases where enough information was not available from the website, we searched for news articles regarding the retailer. If that failed to be informative, we established telephonic contact with the retailer to obtain the requisite information.

3.1. Bias reduction
A closer look into the price quotes revealed that the available posted-prices are for products in varying condition — new, refurbished, or used. Each posted-price contains information regarding condition of the item being offered for sale. Such price quotes would introduce product heterogeneity bias into the data. In order to eliminate this potential bias, we ensured that only items listed as new were included in our data.

While pursuing the transaction channel classification, we checked to see whether a particular retailer primarily sold refurbished items. Such retailers tend not to list the condition of the item as “refurb” in price search engines. For example, for retailers such as refurbddepot.com and overstock.com, an overwhelming number of items listed as “new” on Bizrate.com were found to be “repackaged” and “reconditioned” on the retailer’s websites. These retailers’ websites explicitly mention that they primarily deal with liquidated and refurbished merchandise under the “About Us” pages. These retailers were additionally also classified as Refurb Discounters. The presence of refurbishers is a significant source of bias in the price information. It would almost certainly contribute to increasing price dispersion, as ceteris paribus, refurbishers can be expected to price lower. Yet, to the best of our knowledge, no prior study has explicitly accounted for their presence in the data.

Overall, we collected 22,209 price quotes, for 1880 products from 233 retailers. For our data analysis we only used prices quoted for items in “New” condition, by retailers other than refurb/discouners, and excluded retailers with missing service quality ratings.\(^5\) The exclusion of retailers without service ratings is

\(^5\) To publish any ratings information on a retailer, Bizrate requires a minimum of 30 customer surveys over a period of last ninety days. The published ratings are computed over a rolling window of 90 days.
methodologically necessary because service rating is the independent variable in our analysis. Table 2 shows the impact of the bias reduction on the size of the dataset suitable for analysis.

In order to assess the qualitative impact of the bias reduction process, we investigated the dispersion in prices between the collected data and the analyzed data. While we did not find any significant difference, we believe that the elimination of bias gives more reliable and credible parameter estimates of our model. We next describe the calibration of our price and service quality index and subsequently present our model.

3.2. Calculation of price index

Fig. 2 provides a snapshot of the information Bizrate.com offers to consumers searching for prices and retailer service quality measures of a given product. One of the objectives of our study is to measure the influence of the effect of service quality on retailer prices. However, in order to account for differences in price levels across different products within a category, we compute a price index relative to the minimum price charged by a retailer for a product. The price index is calculated as the percentage difference between the price charged by a retailer and the minimum price offered for the product in the market.

3.3. Measuring service quality

As is evident in Fig. 2, four retailer service quality measures are immediately visible to shoppers using Bizrate. These are — Would Shop Again, On Time Delivery, Consumer Support and Product Met Expectations. The measure of service quality needs to reflect the ability of a given retailer to service differentiate at the level of the product market. However, the service quality rating available from Bizrate is unique to the retailer at the market level. Hence, similar to the price index, a relative scaled index was computed for the four items representing retailer service quality. The intuition for using relative service quality, in a given product market, was to capture the retailer’s differentiation from the competitors based on service quality which, in turn, determines the retailer’s ability to price differentiate.

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6 We define product market as the retailers offering a particular product. In this study we use product market interchangeably with market (as indicated in Fig. 1).
Specifically, the relative measure is computed as the percentage difference in service quality for a retailer to the minimum service quality among the retailers offering that product.

Our preliminary analysis indicated that a very high and significant correlation exists between the four relative service quality indices. To avoid multicollinearity in the analysis and achieve variable reduction, we factor analyzed the service quality indices. The results of the principal component factor analysis are shown in Table 3.

A single factor solution (shown in Table 3) of the items explains approximately 93% of the variance with similar loadings for each of the indices. We use the factor score computed using the scoring coefficients as a composite measure of the service quality of the retailer at the market level. The composite measure was then used to calculate the relative index of service quality of a retailer in each product market.

3.4. Market description

The descriptive statistics for the variables used in our analyses are shown in Table 4. We see from Table 4 that the mean of number of retailers in individual product markets is lesser for books, DVDs, and video games as compared to other product categories. In addition, the market for books (26%), and video games (93%) is more price dispersed than other product categories (camcorders = 12%, DVD players = 17%, PDAs = 14%, scanners = 19%, DVDs = 14%). The observed price dispersion levels (provided by the standard deviation of the price index measures) are comparable to those reported by Pan et al. [27].

Regarding service quality measures, we observe that, on an average, retailers providing camcorders have a higher service quality rating than the retailers in other product categories. Finally, while the number of retailers offering books, DVDs, and video games is lower, we observe that these retailers are on average substantially larger than the retailers in other product categories. In the next section we present our modeling framework.

4. Hierarchical linear model

The purpose of our study is to examine in a single framework the influence of retailer characteristics, namely service quality and channels of transaction; market characteristics, namely competitive intensity and average price levels, and interactions among these factors on retailer pricing strategies in electronic markets. Two unique characteristics of our data need to be considered before choosing an appropriate model. First, the variables used to test our hypotheses correspond to different levels of aggregation. Specifically, retailer characteristics are measured for each retailer and market characteristics are measured for each product. Second, we are interested in evaluating the interactions across variables at these two levels of aggregation. Hence, we use a hierarchical linear regression modeling (HLM) framework to test our hypotheses [8]. In HLM, a linear regression model is specified at the lowest level of aggregation (Level 1). The intercept and slope coefficients for the model at Level 1 are modeled as a function of the variables at the next level of aggregation, Level 2.

In our study, we are interested in explaining variation in prices charged by different retailers for a particular product. The prices charged by the retailer can be a function of (1) the various characteristics unique to each retailer such as service quality, the channels of transaction that are available to the retailer, and the reach of the retailer, (2) the various characteristics unique to each product market such as number of competitors and average price levels, and (3) the interactions across the retailer and market characteristics. The retailer prices and characteristics that we are interested in are at the lowest level of aggregation and hence form the basis for the Level 1 regression model. The intercept and slope coefficients of the Level 1 model (the retailer level) are modeled as a function of the market characteristics — the Level 2 variables. The basic framework for our model can be represented as,

\[
PIND_{ij} = f(\text{retailer characteristics}_{ij}, \beta_j) + r_{ij}
\]

Where,

\[
PIND_{ij} \quad \text{Price index of retailer } i \text{ in product market } j, \text{ and } \\
\beta_j \quad \text{the vector of coefficients specific to product market } j.
\]

---

Table 3

<table>
<thead>
<tr>
<th>Variable/measure</th>
<th>Factor loading</th>
<th>Scoring coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shop again</td>
<td>0.98</td>
<td>0.27</td>
</tr>
<tr>
<td>On-time delivery</td>
<td>0.94</td>
<td>0.26</td>
</tr>
<tr>
<td>Consumer support</td>
<td>0.85</td>
<td>0.25</td>
</tr>
<tr>
<td>Product met expectations</td>
<td>0.90</td>
<td>0.26</td>
</tr>
</tbody>
</table>

We also investigated the Scree plot and found that a single factor solution was sufficient (Eigen value for the second factor was only 0.23). Thus, we use the composite factor score of the four items as a measure of service quality in our analyses.
The coefficient vector $\beta_j$ is then modeled as a function of the various market characteristics as:

$$
\beta_j = f(\text{market characteristics}_j, \gamma) + u_j 
$$

where,

$$
\gamma \quad \text{the vector of coefficients.}
$$

Note that, $r_{ij}$ are the residuals at the retailer level and $u_j$ are the residuals at the product ID level. $r_{ij}$ is a homoscedastic error term with mean 0 and variance $\sigma_r^2$ and $u_j$ is a random parameter with mean 0 and variance $\sigma^2_{uj}$ and measures the deviation of product market $j$ from the mean. A Full Information Maximum Likelihood (FIML) methodology is used to estimate the parameters $\gamma$, $\beta_j$, $u_j$ with an iterative algorithm (details on the estimation are provided by Raudenbush and Bryk [40]). Estimates based on FIML have certain desirable properties — 1) the estimates are consistent, i.e., they are very near the true parameter with high probability for large datasets, 2) they are asymptotically efficient for large datasets and the maximum likelihood estimators are approximately unbiased with minimum variance ([8], p. 52). We obtained very similar results using restricted maximum likelihood (RML), the other alternative estimation technique for large datasets. For simplicity sake, we report only the FIML estimates. The $\beta_j$s are termed as the random parameters, and the $\gamma$s are termed as the fixed parameters.

4.1. Analysis of pricing strategies

In addition to testing our hypotheses, we are also interested in evaluating how much variance in retailer pricing strategies is explained by the factors proposed in our study. We hence estimate two separate models — the Null Model and the Full Model. In the Null Model, the price index of a retailer is specified as a function of only an intercept term and is given by;

$$
PIND_{ij} = \beta_0j + r_{ij} 
$$

Table 4
Summary statistics indicate market differences in books, DVDs and video games and the other product categories

<table>
<thead>
<tr>
<th>Construct</th>
<th>Product category</th>
<th>Camcorder</th>
<th>DVD player</th>
<th>PDA</th>
<th>Printer</th>
<th>Scanner</th>
<th>Books</th>
<th>DVD</th>
<th>Video game</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price index</td>
<td>Mean</td>
<td>0.23</td>
<td>0.27</td>
<td>0.20</td>
<td>0.22</td>
<td>0.25</td>
<td>0.25</td>
<td>0.22</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>Std Dev</td>
<td>0.12</td>
<td>0.17</td>
<td>0.14</td>
<td>0.10</td>
<td>0.19</td>
<td>0.26</td>
<td>0.14</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
<td>0.60</td>
<td>1.33</td>
<td>1.63</td>
<td>1.52</td>
<td>2.26</td>
<td>7.15</td>
<td>3.55</td>
<td>4.46</td>
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<td>Mean</td>
<td>4.19</td>
<td>1.77</td>
<td>1.81</td>
<td>2.82</td>
<td>3.05</td>
<td>2.14</td>
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<td>Std Dev</td>
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<td>-0.09</td>
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<td>1.04</td>
<td>-3.29</td>
<td>-4.32</td>
<td>-1.29</td>
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<td>1.81</td>
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<td>1.91</td>
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<td>4.73</td>
<td>4.60</td>
<td>2004.92</td>
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<td>3.62</td>
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<td>4.67</td>
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<td>354.30</td>
<td>262.01</td>
<td>340.44</td>
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<td>170.03</td>
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<td>-0.34</td>
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<tr>
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<td>11.15</td>
<td>14.97</td>
<td>25.17</td>
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<tr>
<td></td>
<td>Std Dev</td>
<td>9.79</td>
<td>7.59</td>
<td>9.22</td>
<td>9.31</td>
<td>7.97</td>
<td>0.96</td>
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</tr>
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<td>-0.86</td>
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<td>-0.77</td>
<td>-0.83</td>
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</tr>
<tr>
<td></td>
<td>Kurtosis</td>
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<td>2.04</td>
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<td>-1.22</td>
<td>0.58</td>
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<td>Click</td>
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<td>37</td>
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<td>17</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>57</td>
<td>51</td>
<td>57</td>
<td>54</td>
<td>53</td>
<td>9</td>
<td>15</td>
<td>42</td>
</tr>
</tbody>
</table>

Kurtosis measures the fatness of the tails of a probability distribution. A fat-tailed distribution has higher-than-normal chances of a big positive or negative realization. Skewness, of course, measures the fatness of one tail.

8 We also estimated our models using a Restricted Maximum Likelihood (REML) method because when either the number of retailers per product market or the number of total prices per product category is small, the FIML estimates can have smaller standard errors. We did not find any substantive differences in the REML and FIML estimates in our data.
The product market specific intercept $\beta_{0j}$, is then modeled as:

$$\beta_{0j} = \gamma_0 + u_{0j}$$  \hspace{1cm} (4)

Substituting Eq. (4) in Eq. (3), we obtain,

$$\text{PIND}_{ij} = \gamma_0 + u_{0j} + r_{ij}$$  \hspace{1cm} (5)

$\gamma_0$ represents the average price charged by the retailers. The variance of $u_{0j}$ represents an estimate of the unexplained variance in prices at the product market level, and the variance of $r_{ij}$ represents an estimate of the unexplained variance at the retailer level. In the Full Model, the price index of a retailer is specified as a function of the various hypothesized retailer characteristics and product market characteristics and is given by;

$$\text{PIND}_{ij} = \beta_{0j} + \beta_{1j} \cdot \text{Service Quality}$$
$$+ \beta_2 \cdot \text{National Brick} - \text{and} - \text{Click}$$
$$+ \beta_3 \cdot \text{Local Brick} - \text{and} - \text{Click}$$
$$+ \beta_4 \cdot \text{Catalog} + \beta_5 \cdot \text{Size} + r_{ij}$$  \hspace{1cm} (6)

The intercept term, $\beta_{0j}$, is modeled as;

$$\beta_{0j} = \gamma_{00} + \gamma_{01} \cdot \text{# of Competitors}$$
$$+ \gamma_{02} \cdot (\text{# of Competitors})^2$$
$$+ \gamma_{03} \cdot \text{Average Price} + u_{0j}$$  \hspace{1cm} (7a)

and the coefficient of Service Quality, $\beta_{1j}$, is modeled as;

$$\beta_{1j} = \gamma_{10} + \gamma_{11} \cdot \text{# of Competitors}$$
$$+ \gamma_{12} \cdot (\text{of Competitors})^2$$
$$+ \gamma_{13} \cdot \text{Average Price} + u_{1j}$$  \hspace{1cm} (7b)

Substituting Eqs. (7a) and (7b) in Eq. (6) we get,

$$\text{PIND}_{ij} = \gamma_{00} + \gamma_{01} \cdot \text{# of Competitors}$$
$$+ \gamma_{02} \cdot (\text{# of Competitors})^2$$
$$+ \gamma_{03} \cdot \text{Average Price}$$
$$+ \gamma_{10} \cdot \text{Service Quality}$$
$$+ \beta_2 \cdot \text{National Brick} - \text{and} - \text{Click}$$
$$+ \beta_3 \cdot \text{Local Brick} - \text{and} - \text{Click}$$
$$+ \beta_4 \cdot \text{Catalog} + \beta_5 \cdot \text{Size}$$
$$+ \gamma_{11} \cdot \text{# of Competitors} \cdot \text{Service Quality}$$
$$+ \gamma_{12} \cdot (\text{of Competitors})^2 \cdot \text{Service Quality}$$
$$+ \gamma_{13} \cdot \text{Average Price} \cdot \text{Service Quality}$$
$$+ [u_{1j} \cdot \text{Service Quality}] + [u_{0j}] + r_{ij}$$  \hspace{1cm} (8)

The difference in the variance of $u_{0j}$ obtained from the Null Model (Eq. (5)) and the Full Model (Eq. (8)) provides an estimate of the variance explained by the proposed factors at the product market level, and similarly, the difference in the variance of $r_{ij}$ obtained from the Null Model and the Full Model provides an estimate of the variance explained by the proposed factors at the retailer level. The quadratic terms for “# of Competitors” allow us to estimate non-linear relationships. Based on the signs of the coefficients of the linear and the squared terms, we can test if a particular relationship is inverted “U” or “U” shaped. If the linear term is positive and the squared term is negative then the relationship is inverted “U”, and vice versa for “U” shaped relationships.

5. Results and discussion

We first compare the explanatory power of our model of retailer pricing strategies in electronic markets. Subsequently, we report on the role of retailer and market level characteristics, as well as their interactions, in explaining price dispersion. Given the significance of the interaction effects, we round up the discussion by measuring the aggregate effects of service quality and number of competitors.

5.1. Explanation of pricing strategies

Table 5 provides the log-likelihood, and estimates of the variance of the residuals at the product market level, and the retailer level for both the Null Model and the Full Model. For all the eight product categories we see that there is an improvement in the log-likelihood of the Full Model as compared to the Null Model. The likelihood ratio tests indicate that the Full Model explains significantly more variation in price dispersion than the Null Model. The proposed factors, included in the Full Model, seem to explain the pricing strategies adopted by a retailer over and above the intercept term included in the Null Model.

The variance of the residuals in the Full Model is lower than the variance of the residuals in the Null Model. In fact, the variance of the product market level residuals is insignificant in the Full Model for the books, camcorders, DVD players, and printers. This implies that for these

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9 One could expect that using a linear term and quadratic term in an equation could result in multicollinearity. We also estimated the non-linear effect using an exponential conversion of number of competitors in the Full model. We did not observe any substantive changes in the results between the two methods of operationalization. We use the quadratic terms because of the ease of illustration. Also, as will be shown in the Results section, the estimates of the linear and quadratic terms are robust across product categories, leading us to believe that multicollinearity was not an issue in our analyses.
Table 5
Results from estimation of hierarchical linear model

<table>
<thead>
<tr>
<th>Camcorder</th>
<th>DVD player</th>
<th>PDA</th>
<th>Printer</th>
<th>Scanner</th>
<th>Books</th>
<th>DVDs</th>
<th>Video games</th>
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<tr>
<td>Null Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$-2 , LL^2$</td>
<td>$-315$</td>
<td>$43$</td>
<td>$-228$</td>
<td>$-434$</td>
<td>$-52$</td>
<td>$1576$</td>
<td>$-1679$</td>
</tr>
<tr>
<td>Product ID level</td>
<td>$0.01^{***}$</td>
<td>$0.02^{***}$</td>
<td>$0.016^{***}$</td>
<td>$0.008^{***}$</td>
<td>$0.03^{***}$</td>
<td>$0.039^{***}$</td>
<td>$0.018^{***}$</td>
</tr>
<tr>
<td>Retailer level</td>
<td>$0.04^{***}$</td>
<td>$0.047^{***}$</td>
<td>$0.21^{***}$</td>
<td>$0.026^{***}$</td>
<td>$0.038^{***}$</td>
<td>$0.073^{***}$</td>
<td>$0.036^{***}$</td>
</tr>
<tr>
<td>$R^2$</td>
<td>$0.10$</td>
<td>$0.16$</td>
<td>$0.20$</td>
<td>$0.06$</td>
<td>$0.13$</td>
<td>$0.22$</td>
<td>$0.2$</td>
</tr>
</tbody>
</table>

Coefficient estimates

| Intercept | $0.23^{***}$ | $0.27^{***}$ | $0.20^{***}$ | $0.21^{***}$ | $0.24^{***}$ | $0.22^{***}$ | $0.22^{***}$ | $0.49^{***}$ |

Full Model

| $-2 \, LL$ | $-483^{***}$ | $-29.2^{***}$ | $-343^{***}$ | $-546^{***}$ | $-83^{**}$ | $600^{***}$ | $-2473^{***}$ | $3400^{***}$ |
| Product ID level | $4.7E-5$ | $0.007$ | $0.014^{**}$ | $0.004$ | $0.046^{***}$ | $0.058$ | $0.013^{***}$ | $0.74^{***}$ |
| Retailer level | $0.027^{***}$ | $0.045^{***}$ | $0.019^{***}$ | $0.026^{***}$ | $0.038^{***}$ | $0.057^{*}$ | $0.031^{***}$ | $0.40^{***}$ |
| $R^2$ | $0.24$ | $0.24$ | $0.3$ | $0.11$ | $0.21$ | $0.56$ | $0.56$ | $0.45$ |

Coefficient estimates

| Number of Competitors | $0.0041^{**}$ | $0.029^{***}$ | $0.021^{***}$ | $0.017^{***}$ | $0.022^{***}$ | $0.025^{**}$ | $0.04^{***}$ | $-0.12^{*}$ |
| Square of Number of Competitors | $-8.0E$ | $-5.0E$ | $-4.0E$ | $-3.2E$ | $-5.0E$ | $-0.001$ | $-1.8E$ | $0.003^{***}$ |
| Average Price (consumer involvement) | $2.0E-6$ | $2.0E-5$ | $-8.0E-6$ | $-3.0E-6$ | $-5.0E-6$ | $-6.0E-5$ | $-2.0E-5$ | $-9.0E-4$ |

Retailer factors

| Service Quality | $0.058^{***}$ | $0.16^{***}$ | $0.13^{**}$ | $0.19^{***}$ | $0.094^{***}$ | $-0.05$ | $0.038^{*}$ | $-0.11$ |
| National Brick-and-Click | $0.16^{***}$ | $-0.05$ | $0.082^{***}$ | $0.042^{*}$ | $0.08^{**}$ | $0.077^{**}$ | $0.036$ | $-0.033$ |
| Local Brick-and-Click | $0.02$ | $0.03$ | $-0.049^{**}$ | $-0.019$ | $-0.023$ | $0.31^{***}$ | $0.086^{*}$ | $0.024$ |
| Catalog | $0.11^{***}$ | $0.12^{***}$ | $-0.03^{*}$ | $-0.044^{***}$ | $-0.02$ | $0.088^{***}$ | $0.03^{**}$ | $-0.088$ |
| Website Traffic | $36.06^{***}$ | $27.7$ | $5.8^{*}$ | $3.2$ | $2.68$ | $1.95^{***}$ | $2.52^{***}$ | $-10.05^{*}$ |

Interaction effects

| Average Price | $9.14E-6^{***}$ | $1.2E-05$ | $-1.0E-04$ | $-3.0E-04$ | $1.2E-06$ | $1.7E-04$ | $2.4E-3^{***}$ | $-0.0035^{**}$ |
| Service Quality | * | | | | | | | |
| Number of Competitors | $-0.002^{**}$ | $-0.014^{***}$ | $-0.01^{**}$ | $-0.011^{***}$ | $-5.8E-3^{***}$ | $4.9E-3$ | $-0.01^{**}$ | $0.015^{**}$ |
| Service Quality | * | | | | | | | |
| Square of Number of Competitors | $3.0E-5^{**}$ | $2.0E-4^{***}$ | $2.0E-4^{**}$ | $2.0E-4^{***}$ | $1.0E-4^{***}$ | $4.0E-05$ | $4.5E-3^{**}$ | $-4.8E-4^{***}$ |
| Service Quality | * | | | | | | | |

*, **, *** significance level of 0.10, 0.05, and 0.01, respectively.

Comparison of the Full and Null Models is based on the likelihood ratio test.

For six of the eight product categories (DVDs, camcorders, DVD players, PDA, printer, and scanner) we find that the coefficient of number of competitors is positive and significant and the coefficient of the square of the number of competitors is negative and significant. Hence, for the six product categories we observe an inverted “U” shaped relationship between competitive intensity and the product categories, the variables — number of competitors in the product market and average price of the product, are able to explain all the variation in prices attributable to the differences across the various products. For the rest of the product categories, the reduction in variance of the residuals at the product market level ranges from 0% (video games) to 47% (scanner). The reduction in the variance of the retailer level residuals ranges from 4% (DVD players) to 91% (PDAs). Overall, the total reduction in variance, for both the product market level and the retailer level, between the Full Model and the Null Model ranges from 6% (video games) and 85% (PDAs). The $R^2$ values indicate that the explanation of variation in prices ranges for the Full Model ranges from 11% (Printers) to 56% (Books and DVDs). On average, the Full Model provides an improvement in $R^2$ of approximately 15% over the Null Model.

5.2. Influence of market characteristics

5.2.1. Competitive intensity

For six of the eight product categories (DVDs, camcorders, DVD players, PDA, printer, and scanner) we find that the coefficient of number of competitors is positive and significant and the coefficient of the square of the number of competitors is negative and significant. Hence, for the six product categories we observe an inverted “U” shaped relationship between competitive intensity and the
prices charged by a retailer. For video games, the coefficient of number of competitors is negative and partially significant \((-0.12, p<0.10\), whereas the coefficient of the square of number of competitors is positive and significant \((0.003, p<0.01\)). This indicates a “U” shaped relationship between competitive intensity and prices charged by a retailer for video games. However, we do not find support for a non-linear relationship between competitive intensity and prices charged by a retailer for books. For books, we find that the price charged by a retailer increases monotonically as the number of competitors in the market increases.

We believe that the failure to observe a non-linear relationship between competitive intensity and prices for books is because the number of retailers is small (nine) compared to the other product markets. The Summary Statistics in Table 4 indicates that for books, as compared to other product categories, there is insufficient variance in number of competitors and their service quality to find support for a non-linear relationship (number of retailers for DVDs=15, camcorders=57, DVD player=51, PDA=57, printer=54, scanner=53, and video games=42).

5.2.2. Average price

We find that average price level significantly affects the prices charged by a retailer in only two product categories (Scanner and DVD player). For these product categories we find that the prices charged by a retailer decreases in the Scanner case and increases in the DVD player case as the average price level in the product category increases. For the remaining product categories where the effect of average price level though not significant, the sign of the coefficient of average price level indicates consistent directional support for five out of the six product categories (the sign of the coefficient for books, PDA, printer, scanner, and video games is also negative indicating lowered prices as consumer search efforts increase). In summary, for a majority of the product categories our analysis finds directional support that indicates that average price level is inversely related to retailer premiums.

5.3. Influence of retailer characteristics

5.3.1. Service quality

For six of the eight product categories (DVDs, camcorder, DVD player, PDA, printer, and scanner) the coefficient of service quality is positive and statistically significant. The significance supports our hypotheses that retailers who provide better service charge higher prices. Thus service differentiation leads to the ability to price differentiate even in electronic markets.

5.3.2. Channels of transaction

The classification used in our analyses categorizes a retailer into Pure-Play, National Brick-and-Click, Local Brick-and-Click, and Catalog. All the channel classifications are used in the analyses with the exception of Pure-Play, which is used as the base. The coefficients for each of retailer classifications are thus interpreted as the average increase/decrease in the prices that a retailer charges as compared to a pure-play retailer. Overall, we observe that the retailer channel structure has a significant influence on the prices charged by retailers.

Specifically, we find that national brick-and-click retailers charge higher prices than pure-play retailers in five out of eight product categories (books, camcorder, PDA, printer and scanner). The increase in price levels for national brick-and-click retailers as compared to pure-play retailers ranges from 3.6% (DVDs) to 16% (camcorders). We believe that the national brick-and-click retailers are able to charge higher prices because (1) they are able to engender trust among online shoppers given their national presence and brand recognition, and (2) appropriate use of technology enables these retailers to provide shoppers additional convenience in terms of being able to switch channels of transaction from pre-ordering to post-fulfillment, for e.g. options for ordering online and picking up the product and/or returning the product offline in a nearby store. Arguably, such conveniences are part of a higher quality service that a retailer offers and the national retailers are clearly able to charge a premium for these additional services.

The local brick-and-click retailers are observed to be 1) charging higher prices (than pure-play retailers) in two of the eight product categories [books — 31% higher and DVDs — 9% higher], 2) lower prices in one product category (PDAs — 5% lower), and 3) no significant difference in their price levels for the remaining 5 categories.

In summary, we find that (1) for a majority of the product categories analyzed, there is no significant influence of the Local Brick-and-Click channel structure on retailer prices, and (2) the influence of the Local Brick-and-Click channel structure on retailer price levels varies by product category.
Finally, retailers who also provide a mail-order catalog in addition to their website, are found to be charging higher prices for four out of eight product categories (books — 95% higher, DVDs — 3% higher, camcorder — 11% higher, and DVD player — 12% higher). However, for two product categories they charge marginally lower prices than pure-play retailers (PDA — 3% lower, and printer — 4% lower). These results indicate that while providing an additional channel of transaction such as a catalog does influence online retailer pricing strategies, the effect of providing a catalog in addition to a website varies by product category.

5.4. Interaction between market and retailer characteristics

5.4.1. Competitive intensity and service quality

For six of the eight product categories (DVDs, camcorder, DVD players, PDA, printer, and scanner) the coefficient of the interaction between number of competitors and service quality is negative and significant. Also, for these product categories the coefficient of the interaction between the square of number of competitors and service quality is both positive and statistically significant. For these six product categories we find significant support for a “U” shaped relationship between the prices charged by a retailer and the interaction between competitive intensity and service quality. For video games, the coefficient of the interaction between number of competitors and service quality is positive and significant (0.015, \( p < 0.05 \)) and the coefficient of the interaction between the square of number of competitors and service quality is negative and significant (–4.8E–4, \( p < 0.01 \)). In contrast to the other product categories, for video games we observed an inverted “U” shaped relationship between the prices charged by a retailer and the interaction between number of competitors and service quality.

Similar to the main effects of service quality, we do not find any evidence for a relationship between prices charged by a retailer and the interaction between number of competitors and service quality for books. The lack of evidence for any relationship between service quality and price levels charged by a retailer could be attributed to the low variance in service quality across retailers, and the lesser number of retailers in books as compared to the other product categories. It should be noted that [27] did not specify whether they pre-process their data to remove potential biases owing to the presence of refurbishers. In this regard, in our data we do observe significant number of retailers selling used books. There were multiple listings for used books from amazon.com and half.com in the raw data, which were eliminated in the course of pre-processing.

5.4.2. Average price level and service quality

Our analysis indicates a positive relationship between consumer involvement and service quality for DVDs and Camcorder, and a negative relationship for video games. This indicates that depending on the product category, retailers with high service quality can further increase or decrease their price levels as the average price level increases.

5.5. Aggregate effect of service quality and number of competitors

In the presence of significant interaction effects between service quality and number of competitors, it is meaningful to examine the aggregate effects of these factors on prices charged by a retailer. The aggregate effects calculate the rate of change in prices charged by a retailer for a unit change in the number of competitors in a product market and the service quality of a retailer. The aggregate effect needs to be assessed at the mean, one standard deviation above and one standard deviation below the mean of the predictor variables [2]. Evaluating the aggregate effects over the one standard deviation interval allows us to cover a wide range of values observed in our sample. In our study, we are interested in evaluating for a given service quality, how the prices charged by a retailer varies as a function of the number of competitors in the product market. Specifically, based on Eq. (8) the aggregate effects are given by:

\[
\text{Agghs} = \gamma_{00} + \gamma_{00} \times \text{Competitors} \\
+ \gamma_{10} \times \text{Competitors}^2 \\
+ \gamma_{11} \times \text{Service Quality} \\
+ \gamma_{12} \times \text{Service Quality}^2 \\
+ \gamma_{13} \times \text{Service Quality} \times \text{Competitors} \\
+ \gamma_{14} \times \text{Service Quality} \times \text{Competitors}^2
\]

\[
\text{Agghms} = \gamma_{00} + \gamma_{00} \times \text{Competitors} \\
+ \gamma_{10} \times \text{Competitors}^2 \\
+ \gamma_{11} \times \text{Service Quality} \\
+ \gamma_{12} \times \text{Service Quality}^2 \\
+ \gamma_{13} \times \text{Service Quality} \times \text{Competitors} \\
+ \gamma_{14} \times \text{Service Quality} \times \text{Competitors}^2
\]

\[
\frac{\text{Agghs}}{\text{Agghms}} = \frac{1}{\text{Agghms}} \times \frac{\text{Agghs}}{\text{Agghms}}
\]
\[ \text{Aggl} = \gamma_{00} + \gamma_{01} \times (\text{# of Competitors})^2 + \gamma_{10} \times \text{Service Quality} + \gamma_{11} \times [\text{Service Quality}, \text{# of Competitors}] + \gamma_{12} \times [\text{Service Quality}, (\text{# of Competitors})^2] \]

Where,

- \( \text{Aggl} \) aggregate effect for a high service quality rating (i.e., for a service quality rating one standard deviation above the mean service quality)
- \( \text{Agglm} \) aggregate effect for a mean service quality rating (service quality mean)
- \( \text{Aggl} \) aggregate effect for a low service quality rating (i.e., for a service quality rating one standard deviation below the mean service quality)

Eqs. (9a) (9b) (9c) allow us to evaluate how retailers with high, medium or low service quality vary their pricing strategy for a given number of retailers in the product market. In order to visualize how the prices charged by retailers vary as a function of the number of competitors, we present the cumulative effects charts for each product category in Fig. 3. The following interesting observations can be made based on the aggregate effects charts:

- There is an inverted “U” shaped relationship between prices charged by low service quality retailers and the number of competitors in the product market.
- There is a “U” shaped relationship between prices charged by medium and high service quality retailers and the number of competitors in the product market.
- We find that the threshold for number of competitors varies from 10 for printers to 35 for camcorders. Below the threshold, the low service quality retailers raise their prices and beyond the threshold they lower their prices with an increase in the number of competitors. However, the high and medium service quality retailers lower their prices before the threshold, and beyond the threshold they increase their prices with an increase in the number of competitors.
- For DVDs, camcorder, PDA, printer, and scanner the prices charged by low service quality retailers are always below the price charged by medium and high service quality retailers. Similarly, the prices charged by high service quality retailers are higher than prices charged by medium service quality retailers.

6. Conclusions, limitations and future research

Our study contributes to the understanding of the sources of price differentiation among Internet-enabled retailers. We investigate the impact of widespread information availability made possible through IT on pricing strategies of retailers in electronic markets. In this context, we evaluate whether differentiation in service quality and transaction channels affects retailer prices in electronic markets, and if so, how and when in relation to market characteristics does providing quality service and multiple channels of transactions enable online retailers to price differentiate. Examining influences from multiple sources in a unified hierarchical linear modeling framework, we observe that retailers providing medium to high service quality levels can actually benefit from increased competition.

While several prior theoretical studies [6,14] have suggested that increasing competitive intensity in a market can benefit established, branded or high service quality retailers, to the best of our knowledge, ours is the first study to empirically support this claim. The results also support the findings of [4] and [19] that trust with a retailer and the reputation of a retailer are major determinants of premiums in electronic markets. In addition, we also find that market level influences have a significant role in determining a retailer’s ability to charge premiums. For books, camcorders, DVD players, and printers the two market level characteristics, competitive intensity (as measured by number of competitors) and average price level are able to explain all the variation in prices attributable to the differences across the various products.

We find support for our hypotheses that retailers who provide better service quality also charge higher prices. This implies that retailers seem to consider providing better service as a means of differentiation. Our results also show that the influence of service quality on retailer prices varies in a non-linear fashion with the number of competitors in the market. Up to a certain threshold, retailers with low service quality increase their prices as the number of competitors in the market increases. However, beyond the threshold these retailers decrease their prices with increased competition. In contrast, the high and medium service quality retailers decrease their prices with an increase in the number of competitors until a certain threshold, beyond this threshold, these retailers then increase their prices with increased competition. This contradicts the prediction of Porter [31] that increased competition accompanied with enhanced access to competitors’ price information would reduce a retailer’s ability to price differentiate. We conclude that in electronic markets there is room for mixed pricing strategies.
Theoretical expectations based on mixed price strategies suggest that the existence of intermediaries could potentially create at least two consumer segments — the price conscious consumers who use the price scan agents to search for the lowest price for any product and the value conscious consumers who use rating agents such as Bizrate.com as a credible source of retailer reputation and chose the retailers who are good in service quality. Under these circumstances it is optimal for retailers to increase their prices as the number of competitors in the market increases. We also believe that the high and medium service quality retailers are able to charge higher prices when the number of competitors in the market is very high due to the DIF-ness phenomenon [14]. Although consumer search costs are low in online markets, when the number of competitors in the market increases, retailers with good service quality are able to differentiate better because consumers are able to compare the value provided by these retailers relative to the service quality provided by a large number of low service quality retailers.

Our analyses also indicate that retailer channel structure significantly influences the prices charged by the retailers. Importantly, we observe that the national brick-and-click retailers charge higher prices. This is probably due to the trust they engender among online shoppers given their national presence and associated brand recognition, and the increased convenience they provide to consumers. Lastly, we find that while average price level is an important determinant of price dispersion, the relationship between average price level and price levels is not robust across product categories.

Overall, the results imply that due to the ability of online retailers to differentiate based on service quality and the impact of information overload on consumers, the predictions of the electronic market hypothesis (EMH) are not validated in electronic markets for homogenous products. EMH predicts that by reducing coordination costs, information technology (IT) will shift industrial organization from hierarchical to market-based forms of economic activity. In contrast, we find that the market power for the firm is being reinforced by the widespread availability of information regarding prices and service quality in electronic markets. Such information provides retailers an effective and credible source of price differentiation. The emergence of websites such as Bizrate.com provides credible sources of quality information to consumers (especially as competition increases) and also helps retailers that provide quality service to extract higher premiums.

Current price dispersion research is limited by not having access to supply-side cost data. In addition, future research is needed in accounting for revenue measures that take into account where in the price band do actual e-commerce transactions take place. It could be possible that the dispersion among products where transactions are made is different from the dispersion in retailer prices. Another limitation of our work is that we do not consider market factors such as product life cycle. Such a study would imply the necessity of longitudinal data. Also, pricing is one of the many strategic decision criteria that a retailer has to manage in order to optimize profits. For example, a retailer is also interested in building a market share, and in ensuring consumer retention. Future studies should compare the influence of service quality across these different decision criteria and investigate the process through which they lead to optimal profits for retailers. Our results indicate channel choice affects the pricing strategy of the online retailer. In fact we find that retailers providing multiple channels of transaction also charge higher prices. Future research should investigate whether providing multiple channels of transaction also increases the revenues of the retailers, and why providing multiple channels of transaction affects consumer choice.

Given that price dispersion as a metric signals the confluence of consumer search, retailer pricing strategies and informational efficiency of markets, we hope that our integrated approach will be useful to other researchers examining the interactions between these competing forces in electronic markets.

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