Can Price Dispersion in Online Markets be Explained by Differences in e-Tailer Service Quality?

Xing Pan

Brian T. Ratchford

Venkatesh Shankar*

June 2002

Published in *the* ***Journal of the Academy of Marketing Science***
Special issue "Marketing and Serving Customers through the Internet"

* Xing Pan (*xpan@rhsmith.umd.edu*) is a doctoral candidate, Brian T. Ratchford (*bratchfo@rhsmith.umd.edu*) is the PepsiCo Chaired Professor of Marketing and Venkatesh Shankar (*vshankar@rhsmith.umd.edu*) is Ralph J. Tyser Fellow and Associate Professor of Marketing and Entrepreneurship at the Robert. H. Smith School of Business, University of Maryland, College Park, MD 20742.

We thank the participants at the MSI-JAMS Conference at Miami, three anonymous reviewers and the editors for helpful comments.

Can Price Dispersion in Online Markets be Explained by Differences in e-Tailer Service Quality?

Abstract

It has been hypothesized that the online medium and the Internet lower search costs and that electronic markets are more competitive than conventional markets. This suggests that price dispersion--the distribution of prices of an item indicated by measures such as range and standard deviation—of an item with the same measured characteristics across sellers of the item at a given point in time for identical products sold by e-tailers online (on the Internet) should be smaller than it is offline, but some recent empirical evidence reveals the opposite. A study by Smith et al. (2000) speculates that this is due to heterogeneity among e-tailers in such factors as shopping convenience and consumer awareness. Based on an empirical analysis of 105 e-tailers comprising 6739 price observations for 581 items in eight product categories, we show that online price dispersion is persistent, even after controlling for e-tailer heterogeneity. Our general conclusion is that the proportion of the price dispersion explained by e-tailer characteristics is small. This evidence is contrary to the hypothesis that search costs in online markets are low, or that online markets are highly competitive. The results also show that after controlling for differences in e-tailer service quality, prices at pure play e-tailers are equal to or lower than those at bricks-and-clicks e-tailers for all categories except books and computer software.

Introduction

Despite the meltdown of dot.coms and the economic down turn, sales at U.S. online retailers are growing impressively. Online retail sales for the year 2001 was estimated to be $53 billion (*Comscore* Report 2002). Excluding online travel, e-tail sales in 2001 totaled $33.7 billion, reflecting a growth rate of approximately 20% over the year 2000.

Pricing on the Internet has attracted much research attention (e.g., Bakos 1997; Baye and Morgan 2001; Brynjolfsson and Smith (2000); Clemons, Hann, and Hitt 2002; Degeratu, Rangaswamy, and Wu 2000; Erevelles, Rolland and Srinivasan 2001; Pan, Ratchford, and Shankar 2001; Shankar, Rangaswamy, and Pusateri 2001; Smith, Bailey, and Brynjolfsson 2000; Smith and Brynjolfsson 2001). The themes of much of the research have centered on whether price dispersion or price sensitivity is higher online than it is offline or on the drivers of price dispersion. Price dispersion refers to the distribution of prices of an item with the same measured characteristics across sellers as indicated by measures such as range and standard deviation of prices.

It has been hypothesized that the online medium and the Internet lower search costs, making more price information available to buyers and electronic markets more competitive than conventional markets (Bakos 1997). If electronic markets are highly competitive, we might expect price dispersion to be absent from these markets. This is because price dispersion is thought to be associated with incomplete information (e.g., Carlson and McAfee 1983; Stigler 1961) and buyers with low search costs should not face this in electronic markets.

Contrary to this expectation, however, Bailey (1998), Clemons, et al. (2002), and Brynjolfsson and Smith (2000) have all found that price dispersion in electronic markets is substantial and no narrower than in conventional markets. Their findings cast doubt on the belief that electronic markets are more informationally efficient and competitive than conventional markets. That is, electronic markets offer the right information about prices of competing offerings at low search costs and this should lead to greater price competition in these markets than offline markets. However, these studies did not control for the possibility that the observed price dispersion is due to differences in the services offered by different e-tailers. The purpose of this study is to examine the possibility that observed price dispersion in electronic markets is due to differences in service offerings among e-tailers. If this is the case, then the hypothesis that search costs in electronic markets are low and that these markets are competitive, cannot be rejected. If this is not the case, a major alternative explanation for observed price dispersion in electronic markets will be ruled out and the evidence that these markets are not as informationally efficient or competitive as originally thought will be strengthened.

To test if retailer service quality heterogeneity explains online price dispersion, we empirically analyze data on books, CDs, DVDs, computer software and hardware collected from BizRate.com in November 2000. Our data consist of 6739 price quotes for 581 identical products distributed across eight product categories for 105 e-tailers. For each price quote, we also have data on average consumer ratings of various measures of that e-tailer's service from BizRate.com. Our general strategy is to study how much of the observed price dispersion for each item is explained by these service characteristics and also to examine if prices significantly differ between bricks-and-clicks and pure play

e-tailers. Our general conclusion is that the proportion of the price dispersion explained by heterogeneity in e-tailer services is small and that substantial amounts of price dispersion remain even after correcting for the influence of e-tailer services. This evidence is contrary to the hypothesis that search costs in electronic markets are lower that online markets are highly competitive. The results also show that after controlling for differences in e-tailer service quality, prices at pure play e-tailers are equal to or lower than those at bricks-and-clicks e-tailers for all categories except books and computer software.

In the next section, we formulate economic models of price dispersion based on product differentiation, search costs and incomplete information. These models are the basis for our subsequent empirical analysis. We then describe our data and present our empirical analyses and results. We also discuss our results. We next outline the limitations of our research and directions for future research. Finally, we offer our conclusions in the last section.

Models of Price Dispersion

Much prior research on online price dispersion has been empirical. In contrast, we first propose an analytical model of online price dispersion based primarily on two theories, (1) product differentiation and (2) search costs and incomplete information and follow this model with an empirical analysis.

Price Dispersion due to Product/Service Differentiation

As noted by Betancourt and Gautschi (1993), the value of an item bought from a retailer depends on a variety of distribution services, such as assortment, accessibility, ambiance, availability of information, and assurance of product delivery. These services

provide value either by lowering the cost of acquiring items at retail (Ratchford and Stoops 1988) or by lowering the cost of household production (Betancourt and Gautschi 1993). These services have electronic counterparts such as convenience of finding and navigating the web site, reliability of order fulfillment and convenience of returns, availability of information, and quality of shipping.

Because these services add value or provide utility to the consumer, we can write the utility of any item bought from a given retailer or e-tailer as $U(x, s_1,\ldots,s_k)$, where x refers to a vector of attributes of the good and s_i refers to utility-providing service feature i. Rosen (1974) shows that, if consumers are perfectly informed, the textbook model of perfect competition can be extended to the case where consumers have different valuations of the various attributes $x, s_1,\ldots,s_k$ and producers have different costs of supplying $x, s_1,\ldots,s_k$.[1] If we assume that producers and consumers act independently about how much to buy and how much to sell, then the key outcome of all of the independent decisions of producers and consumers is a functional relationship between prices and attributes of the form:

$$p_j = p(x, s_{1j},\ldots, s_{kj}), \tag{1}$$

where P_j refers to the price of the e-tailer or retailer j. The relationship in Equation 1 is often called the hedonic price function. If all attributes are measured correctly, the correct functional form is chosen, and if information is perfect, Rosen's model predicts an exact functional relationship between the prices of different retailers or e-tailers for a given item and the services that they provide with the item. Thus, price dispersion in this model is completely explained by differences in service offerings. Moreover, the model predicts

that services that are positively valued will have positive signs in the hedonic relationship.[2]

In practice, however, measurement errors and omitted attributes are likely to keep the estimated relationship between prices and service levels for a given item across e-tailers from being perfect. However, given a reasonably complete list of attributes, we should expect a high R-squared value and small standard error from estimates of Equation 1 if the status of information availability in a market is perfect or close to it.

Price Dispersion due to Search Costs and Incomplete Information

The explanation of price dispersion as due to incomplete information has a long tradition and dates back to the classic study by Stigler (1961). Subsequent studies have modeled price dispersion as an equilibrium outcome when some consumers find it too costly to locate the lowest price offered in a market (Burdett and Judd 1983; Burdett and Coles 1997; Carlson and McAfee 1983; Salop and Stiglitz 1982;). Among these studies, the Carlson and McAfee (1983) model is perhaps the most insightful and easy to calibrate empirically (see Dahlby and West 1986 for an empirical application). Carlson and McAfee define a search as inspection of one alternative, and assume that consumers search sequentially until the marginal cost of an additional search is more than the marginal gain. If there is a distribution of search costs across consumers and if sellers also have different costs, Carlson and McAfee show that price dispersion will be an equilibrium outcome. Price dispersion will increase if the highest search cost increases and if the distribution of search costs across consumers becomes more dispersed.[3] The other studies of equilibrium price dispersion listed above obtain qualitatively similar

results in which price dispersion results from differences in buyer search costs and the consequent differences in incentives to locate the lowest price.

Price Dispersion due to Other Explanations

A number of other explanations of price dispersion that rest on differences in information across consumers have been advanced. One explanation is staggered price setting due to menu costs (Fishman 1992), which would not lead to sales at different prices unless consumers do not find it feasible to locate the lowest price. Another explanation is price discrimination, which involves charging different prices to customers with different degrees of information (Clemons, Hann, and Hill 2002). Yet another explanation is inertial brand loyalty resulting from lags in awareness (Wernerfelt 1991). In sum, a variety of models postulate that price dispersion results from differences in information across consumers that occur when search costs are high.

Testing the Explanations

Combining the two theories of price dispersion, we can write the price of an item sold by e-tailer j as

$$p_j = p\left(x, s_{1j}, ..., s_{kj}\right) + e_j + v_j, \tag{2}$$

where e_j is unmeasured service attributes that are specific to e-tailer j, v_j is idiosyncratic differences in price charged by j due to differences in cost or pricing policy, and the mean values of e and v are assumed to be 0. In a world with perfect information, v_j must be zero because consumers would buy only at the lowest price for their preferred level of service, forcing all e-tailers to charge the same price.

If one can measure all the relevant service attributes and capture the functional form of the relationship between prices and attributes we can make $e_j \to 0$.

Thus, if we denote the estimated price in a regression of price on service attributes as $\hat{p}_j = \hat{p}(x, s_{1j}, ..., s_{kj})$, we can define the *quality-adjusted* price as:

(3) $$p_j - \hat{p}_j \approx \hat{v}_j,$$

Computing the variance of $\hat{v}_j$, $V(\hat{v}_j)$, across the sample of *j* e-tailers would provide a measure of pure price dispersion net of the effects of service quality. If v_j and $p(x, s_{1j}, ..., s_{kj})$ are independent, $\hat{v}_j$ will be an unbiased estimate of v_j and $V(\hat{v}_j)$ will be an unbiased estimate of price dispersion. If they are not independent, the regression of prices on service attributes will explain some of the variance of v_j, leading $V(\hat{v}_j)$ to underestimate the true price dispersion. Thus, $V(\hat{v}_j)$ will be a conservative estimate of price dispersion after controlling for the effects of service quality. If this is found to be large after controlling for the effects of retail services on prices, one can conclude that imperfect information must be present in the corresponding market.

Empirical Analysis

Data

The data for this study are primarily drawn from BizRate.com, one of the well-known price comparison web sites. BizRate.com surveys e-tailers' customers and asks them to evaluate the e-tailers' services. It also searches and updates the product, price, and deal information for a large number of e-tailers daily. We intentionally focus on identical products or items to avoid the potential problem of unmeasured product heterogeneity. Such products are found in the following categories: books, CDs, DVDs, computer software and hardware, and consumer electronics. For example, the Toshiba Satellite 2775XDVD laptop computer with the part number of PS277U-6M9J0K and

features of PIII 650 MHz processor, 64 MB memory, 12 GB hard disk, 8x DVD, 56 Kbps modem, and 14.1" TFT screen sold by any e-tailer is the same. We collected 6739 price quotes for 581 identical products from 105 e-tailers during November 2000. Summary statistics of the data appear in Table 1. The data show that the mean price ranges from $13.48 for CDs to $2441.66 for laptop computers. The standard deviation of price ranges from a low of $2.71 (CDs) to a high of $1079.86 (desktop computers).

(Table 1 about here)

BizRate.com also surveys e-tailers' customers and asks them to evaluate the e-tailers' services. The survey results are published on BizRate.com's web site, so we can use them to measure evaluations of the service of individual e-tailers. Ten aspects of e-tailers' services are evaluated using a ten-point scale and an overall measure of the average of the ten measures is also provided. The ten measures of retail services are explained in Table 2. The ratings of the retailers on service attributes by Bizrate.com are widely used in online markets. For example, shopper.com, shopping.com, and price.com, all cite BizRate.com's ratings. In addition, many e-tailers who are BizRate.com's certified sellers, also indicate this on their own websites (e.g., CircuitCity.com, Mercata.com, Motorola, CD Universe, Euclid Computers). This reflects the acceptance of BizRate.com as an authority on e-tailer evaluation. Thus, e-tailer service ratings from BizRate.com have a high degree of credibility. We also collected information on the type of e-tailer (pure play versus bricks-and-clicks), whether the item was popular, and the stage in product life cycle of each item to be used as additional factors in the hedonic price regression.

(Table 2 about here)

Factor Analysis of e-Tailer Services

An analysis of the data indicated that the 10 measures of e-tailer services are not independent. To examine the redundancy in these measures, we subjected them to a factor analysis. The results of the factor analysis of the ten measures for 105 e-tailers indicate the existence of five underlying factors, which capture 91.5% of the variance in the original data. These five factors are: reliability of e-tailers, shopping convenience, product information, shipping and handling, and pricing policy. Table 3a provides the rotated component matrix obtained using Equimax rotation[4]. Table 3b shows the eigenvalues and Table 3c provides the communalities associated with the five-factor solution.

(Tables 3a-3c about here)

On-time product delivery, product representation, customer support, and tracking of shipping status load on Factor 1. Since one of the primary concerns of consumers regarding online shopping is the actual receipt of products after making payment (Smith, Bailey, and Brynjolfsson 2000), this factor seems to reflect the *reliability* in fulfillment of the e-tailers. Consumers generally feel confident about buying from e-tailers who have high scores on this factor. Factor 2 is highly related to ease of ordering, product selection, and the e-tailer's web site navigation. These variables reflect the dimension of *shopping convenience*. Factor 3 is highly related to the quantity, quality and relevance of *product information* that the e-tailers provide. Smith, Bailey, and Brynjolfsson (2000) point out that providing product information increases shopping convenience and can be a useful strategic tool for e-tailers to attract web traffic and consequently induce purchase. Brynjolfsson and Smith (2000) also suggest that providing product information may act

as a signal of trust. Factor 4 is highly related to the options and charges of *shipping and handling*. This can be another tool used by e-tailers to attract patronage by matching various consumers' delivery needs. For example, some consumers may seek quick delivery of products, whereas others may prefer to wait if they pay lower shipping and handling charges. It is worth mentioning that it may also help to build up retail store image and create consumer loyalty. For example, Outpost.com offers free overnight delivery for any purchase. Factor 5 is highly related to e-tailers' relative prices, and therefore reflects the *pricing* policy of the e-tailers.

Since the five factors explain a high proportion of the variance in the data, we employ factor scores as our measure of e-tailer services. This eliminates potential collinearity problems from our regressions and therefore greatly facilitates the interpretation of our results. Because our research purpose is to examine the role of e-tailer services in e-tailer prices, we wish to confine our independent variables to specific services offered by e-tailers, dropping the pricing policy factor from our analysis. The four independent variables employed in our analysis, therefore, are factor scores on reliability, shopping convenience, product information, and shipping and handling. These measures are related to the dimensions of retail services specified by Betancourt and Gautschi (1993). Reliability corresponds to Betancourt and Gautschi's assurance of product delivery dimension, shopping convenience is related to their assortment, accessibility and ambiance dimensions, product information is related to their availability of information dimension, and shipping and handling are related to their assurance of product delivery dimension.

To test for the appropriateness of the five-factor solution, we also examined a two-factor solution. The rotated component matrix and the communalites for this two-factor solution appear in Tables 4a and 4b, respectively. The percentage of variance explained by the five factors is high (91.5%), the five-factor solution is more interpretable than the two-factor solution, and we do not lose much information by including all the factors. Therefore, we retain the five-factor solution. We recognize, however, that factors with so few important items are generally unstable.

(Tables 4a-4b about here)

Hedonic Regression Analyses

Using the factor scores described above, we estimated the regressions of prices on service attributes described in Equation 2 for each of the eight product categories. To do so, however, we first had to make the prices across different items in each category comparable. To accomplish that, we created a price index variable for each item, which is defined as observed price divided by the mean price of that item. The price index we use is a relative price measure (the mean for every item is equal to one) and it enables us to eliminate the cross-item differences. However, because the effects of e-tailer characteristics on price may be different for different product categories, we run the hedonic price regression within each product category and compare the results.

Table 5 summarizes the data on the price index $P/\overline{P}$ for each category. The conclusion from the table is that prior to correcting for the influence of service attributes on price, price dispersion in each category is substantial. The standard deviation of $P/\overline{P}$, which is equivalent to the coefficient of variation of price, ranges from a low of .083 for laptop computers to .154 for CD's. The range varies from a low of .777 (consumer

electronics) to a high of 1.377 (software). The range of $P/\overline{P}$ for most categories is greater than one, implying that the range of prices of a given item is likely to exceed the average price. Our main research question is whether this substantial price dispersion can be explained by differences in services offered by e-tailers.

(Table 5 about here)

Because of our normalization of the price of each item by its mean, we estimate a modified version of Equation 2 that has the form:

$$P_j/\overline{P} = a_0 + \sum_i a_i S_{ij} + v'_j, \quad (4)$$

where v' has the same units as $P/\overline{P}$**.** Estimates were obtained using this linear functional form[5] and the Generalized Method of Moments (GMM) method to account for heteroscedasticity.[6]

If differences in e-tailer service quality do not adequately explain online price dispersion, then prior research and real-world evidence suggests that three other factors, namely, the type of e-tailer (pure play vs. bricks-and-clicks), popularity of the product, and stage in the product life cycle of the item studied (introduction/early growth vs. late growth/maturity), on which we have data, might explain online price dispersion. There are differences between pure play and bricks-and-clicks e-tailers that may have different implications for their pricing (Brash, Crawford and Gross 2000). Pure play e-tailers may charge lower than bricks-and-clicks e-tailers because their awareness may be lower and because they may not offer consumers the opportunity to physically inspect, pick-up or return an item. With regard to product popularity, e-tailers may compete more vigorously on more popular items than on less popular items to drive traffic to their web sites, leading to lower price dispersion for more popular items than for less popular items.

Finally, consumers may have more complete information and knowledge on products in the late growth or mature stage than those in the introduction or early growth stage of the product life cycle, so price dispersion for the former products is likely to be lower than that for the latter products. This factor may be viewed as a proxy for the level of market knowledge of the product. The operationalization of the stage in life cycle into growth versus maturity is consistent with prior research (e.g., Shankar, Carpenter, and Krishnamurthi 1999).

To test how much variance may be explained by these three other factors, we perform a stepwise hedonic regression for each category in which each of the three factors is added to the model with e-tailer service attributes, one factor at a time.[7]

Tables 6a-6d summarize the results of the stepwise hedonic price regressions for all the eight product categories. First, we discuss the results of the hedonic regression with e-tailer service quality (Table 6a). All the regressions are significant ($F < 0.001$). However, the adjusted R-squares of these regressions are generally low ranging from 5 percent to 22 percent, except in the CD category that has 43 percent. Among the e-tailer service attributes, provision of product information and shipping and handling service have significant effects on price for all the eight regressions. Reliability in fulfillment and shopping convenience have significant effects on price in five categories. The results suggest that e-tailers do charge different prices according to their service levels as we previously discussed. Thus, a large amount variation in price is captured by the residuals, which suggests that the price dispersion among e-tailers can be explained by their differences in service quality only to a limited extent. The signs of the coefficients of the

service attributes are different in different categories suggesting that e-tailers may not be able to extract price premiums for each service attribute.

(Tables 6a-6d about here)

The effects of e-tailer service attributes on prices are different in different categories. Shopping convenience has a positive and significant effect in four categories, books ($p < 0.01$), desktop computers ($p < 0.01$), PDAs ($p < 0.05$), and computer software ($p < 0.01$). It is, however, negatively associated with price for DVDs ($p < 0.01$). This is because the DVD e-tailers that have easy-to-order and easy- to-navigate web sites and wider product selection also have low prices in our data. This could be because the initial objective of these e-tailers may be to generate volume and market share. Therefore, they could be offering low prices and easy-to-order and easy-to-navigate web sites at the same time.

Reliability is positively associated with price in two categories, CDs ($p < 0.01$) and desktop computers ($p < 0.10$), negatively associated with price in the category of laptop computers ($p < 0.01$), and has insignificant relationship with price in the other five categories, books, DVDs, PDAs, software, and consumer electronics. These results indicate that reliability may not be an adequately strong service attribute to differentiate an e-tailer's prices from those of others. We can only speculate that e-tailers are not vastly different in their fulfillment capabilities, so reliability is not a differentiating factor.

Product information is significantly negatively associated with price in all the categories ($p < 0.01$) except in the cases of laptop computers ($p < 0.01$) and consumer electronics ($p < 0.10$). This finding is somewhat surprising since one would expect e-tailer web sites with deeper product information to offer additional value to visitors or

prospective customers. A closer analysis of the six categories with negative information-price relationship reveals that the e-tailers with deep product information also tend to have low average prices—this finding is consistent with the fact that these e-tailers also practice a volume or traffic generation strategy.

Finally, shipping and handling is significant in all the product categories. In six categories, it is positive—books ($p < 0.01$), desktop computers ($p < 0.05$), laptop computers ($p < 0.01$), PDAs ($p < 0.10$), software ($p < 0.01$), and consumer electronics ($p < 0.01$). In the remaining two categories, however, it is negative—CDs ($p < 0.01$) and DVDs ($p < 0.01$). These results suggest that, generally, e-tailers with superior shipping and handling tend to have higher average prices than other e-tailers.

We now present the results of the hedonic regression models with additional factors. The e-tailer type factor is significant in six of the eight product categories in Table 6b. After controlling for e-tailer service quality, prices at pure play e-tailers are lower than those at bricks-and-clicks e-tailers for CDs ($p < 0.05$), DVDs ($p < 0.05$), desktop computers ($p < 0.01$), and laptop computers ($p < 0.05$). In contrast, prices at pure-play etailers are higher than those at bricks-and-clicks e-tailers for books ($p < 0.01$) and software ($p < 0.01$). One possible reason is that while inspection, pick-up and return are important for categories like desktop and laptop computers (hence higher prices for bricks-and-clicks e-tailers), they may not be very critical for categories like books and software (which can be downloaded). The prices across these two types of e-tailers are not significantly different for PDAs and consumer electronics items. Thus, there does not appear to be a clear-cut pattern of the effect of e-tailer type on prices across categories.

However, in general, it appears that service-quality adjusted prices at pure play e-tailers are equal to or lower than those at bricks-and-clicks e-tailers, as expected.

The effects of product popularity and stage in product life cycle or market knowledge (Tables 6c and 6d, respectively) are insignificant in all the categories except the desktop computer category. In the case of desktop computers, mature/late growth stage products are associated with lower prices, consistent with our expectation. However, more popular products in this category are related to higher prices, contrary to our prediction. The increases in goodness of fit of the stepwise regressions (R^2) are negligible. Overall, these two factors do not explain a significant amount of online price dispersion.

We calculated and compared the price dispersion (measured as both the range and the standard deviation of price) before and after controlling e-tailer service heterogeneity. The results are shown in Table 7. For both the price dispersion measures, range and standard deviation, the dispersion of the service quality-adjusted price is only slightly smaller than the dispersion of the quoted price in most product categories. When the quoted prices are adjusted for service quality differences, the price dispersions are reduced by less than or equal to 20 percent (except in the case of CD with range of price as the measure of dispersion—the reduction is 36 percent). If range of prices is considered as the measure of price dispersion, the dispersion with e-tailer service quality-adjusted price is less than five percent of the dispersion with observed price. In categories such as books, DVDs and laptop computers, the dispersions with and without service quality adjusted price are hardly different. For laptop computers, in particular, there is no change in the price dispersion.

(Table 7 about here)

The findings in Table 7 are consistent with the goodness of fit of the hedonic regression models in different categories. The CD category that has the highest R^2 (43 percent) among all the categories, has the highest reduction in price dispersion when e-tailer service attributes are included in the hedonic regression. On the other hand, the laptop computer category, which has the lowest R^2 (five percent), has no change in price dispersion when e-tailer service attributes are included in the model.

In terms of the reduction in price dispersion due to service-adjusted quality, there are some differences between the two measures used, range and standard deviation. The reduction in price dispersion is higher in standard deviation than in range in four categories, books, DVDs, PDAs, and consumer electronics. However, it is lower in three categories, CDs, desktop computers, and software. In desktop computers and software, the difference is only marginal. These numbers show that the differences in the two measures are not systematic.

Overall, since the variation of the quality-adjusted price (the residual from the hedonic regression) is a conservative measure of the price dispersion, we conclude that the proportion of price dispersion explained by e-tailer service attributes is small and that online price dispersion is persistent even after controlling for e-tailer heterogeneity. Thus, our analysis indicates that electronic markets are far from being informationally efficient during the period of data.

Discussion, Limitations, and Future Research

Discussion

The results offer important insights into the prices of e-tailers. They support the general conclusions from online price dispersion studies (e.g., Baye and Morgan 2001; Brynjolfsson and Smith (2000); Clemons, Hann, and Hitt 2002; Erevelles, Rolland and Srinivasan 2001; Pan, Ratchford, and Shankar 2001; Smith, Bailey, and Brynjolfsson 2000; Smith and Brynjolfsson 2001). More importantly, the results suggest that e-tailer pricing is only partly based on e-tailer service quality. A large proportion of the prices are not explained by these characteristics. E-tailer type (pure play versus bricks-and-clicks) explains some of the online price dispersion, but stage in product life cycle and popularity of the item generally do not explain much of the price dispersion. These results are consistent with the finding that market characteristics such as number of competitors are stronger drivers on online pricing than are e-tailer characteristics (Pan, Ratchford, and Shankar 2001). E-tailers may have to pay more attention to market factors in pricing their products online.

The signs of the coefficients of e-tailer service attributes are mixed, indicating that e-tailers may not always be able to translate superior service attributes into higher prices. This is consistent with the findings of Barsh, Crawford, and Brasso (2000), who studied the margins of a sample of e-tailers of books, drugs, apparel and groceries during the fourth quarter of 1999. They found that most e-tailers lose money on every transaction. For example, although its book sales generate an average of $5 an order, they found that Amazon lost about $7 per order on its non-book sales after taking into account, product, shipping, and fulfillment costs. Sporting goods e-tailers lost an average

of $5 per order while drug e-tailers such as drugstore.com lost about $10 to $15 per order. Therefore, it is unclear if e-tailers may be able to increase their margins through superior service attributes.

Different categories have different effects of service attributes on price and this finding suggests that e-tailers may not want to over-invest in their service attributes without a good understanding of their effects on prices. In general, shipping and handling seems to have a positive effect on price, so e-tailers may like to work on this attribute to mitigate price competition.

The effects of e-tailer service attributes on price do not appear to reveal any pattern across categories. Among the eight categories analyzed, typically, three of them (books, CDs, and DVDs) have low unit prices, PDAs have medium unit prices, and desktop computers, laptop computers, and consumer electronics have high unit prices. From Table 1, the unit price of computer software has the highest range among all the categories. The results of the hedonic regressions, when viewed within each group of product categories (low, medium, and high in terms of unit price), do not reveal a systematic pattern.

Market knowledge of the product or popularity of the item does not seem to have significant effects on e-tailer prices, but prices at pure play e-tailers appear to be equal to or lower than those at bricks-and-clicks e-tailers, after controlling for e-tailer service quality for a majority of the categories, but not all. Pure play e-tailers may charge lower than bricks-and-clicks e-tailers because their awareness may be lower and because they may not offer consumers the opportunity to physically inspect, pick-up or return an item.

Since e-tailer service attributes do not explain much of price dispersion, other factors such as online trust and brand may explain price dispersion and allow e-tailers to command price premiums. For example, an e-tailer with a stronger brand name and a more trusted Web site (site that is perceived as more competent, easier to do business with, better protects privacy, and offers better security of transactions) may be able to charge higher prices than one with weaker brand and less trusted site. Studies on online trust (e.g., Shankar, Sultan, Urban, and Bart 2002; Shankar, Urban, and Sultan 2002; Sultan, Urban, Shankar, and Bart 2002; Urban, Qualls, and Sultan 2000) show that trust moderates the effects of web site attributes (such as convenience and product information) on purchase intention and on customer problem resolution. Thus, online trust could be related to prices as well. Managers may want to focus attention on the role of online trust in pricing.

Limitations and Future Research

Our research has some limitations that suggest avenues for future research. First, the net prices of all transactions at an e-tailer web site may not necessarily be at the observed prices. It could be that frequent customers of an e-tailer do not pay the observed prices all the time and only those who buy infrequently pay those prices every time. To explore this issue, individual transaction data are needed. Although such data are beyond the scope of this research, analysis of such data could be a fruitful avenue for future research.

Second, our data were collected during November 2000. Since that period, there has been a shakeout in the e-tailer industry due to the demise of many dot.coms. It would be interesting to test how much of price dispersion is still persistent after market

rationalization. Future research could explore this issue. The work of Ratchford, Pan, and Shankar (2002) is in this direction.

Third, we have not analyzed the profit implications of price dispersion levels, after correcting for e-tailer service levels, for pure play e-tailers and bricks-and-clicks e-tailers. The differences in dispersion levels may have profit implications for different types of e-tailers. Brash, Crawford and Gross (2000) found that the profit margins of bricks-and-clicks e-tailers are better than those for pure play e-tailers. These higher gross margins may make the per-order economics stronger, while lower marketing expenses can create lower fixed costs for bricks-and-clicks e-tailers. According to their estimates, the breakeven point of a multi-channel retailer is typically half the breakeven point of its pure-play counterpart. With adequate number of each type of e-tailers in the data, one can investigate differences in price dispersion levels within each type of e-tailer. Such an analysis will be a valuable addition to online price dispersion literature.

Fourth, cross-category correlation, within a retailer, of e_j and v_j can be included. This could control for complementarity of product lines of a retailer and the resulting one-stop shopping convenience for consumers, which, in turn, may let the retailer charge, a higher price. Fifth, item attributes (such as brand names) and retailer attributes other than service (such as retailer's brand name, retailer size – in terms of total product lines carried, retailer recognition – operationalized as number of years in the e-tailing market) might be included in the model. This could lead to a reduction in the price dispersion.

Conclusion

We proposed an analytical model of price dispersion in online markets based on two theories, product differentiation and search costs and incomplete information. We

tested whether price dispersion in online markets can be explained by differences in service quality of e-tailers. The empirical analysis shows that the proportion of price dispersion explained by heterogeneity in e-tailers is small, and that substantial amounts of price dispersion remain after correcting for the influence of e-tailer services. A portion of the remaining price dispersion is explained by factors such as e-tailer type (pure play versus bricks-and-clicks e-tailer). In other words, online price dispersion is persistent even after controlling for e-tailers' service heterogeneity. Evidence still indicates that electronic markets are not necessarily information-efficient. There are apparently gains associated with search for those who do not already know what the best deal is.

References

Bailey, Joseph. 1998. “Intermediation and Electronic Markets: Aggregation and Pricing in Internet Commerce.” *MIT: Ph.D. Thesis.*

Bakos, Yannis. 1997. “Reducing Buyer Search Costs: Implications for Electronic Marketplaces.” *Management Science* 43 (December): 1676-1692.

Brash, Joanna, Blair Crawford and Chris Grosso. 2000. “How e-Tailing Can Rise from the Ashes.” *McKinsey Quarterly* 3: 98-109.

Baye, Michael R. and John Morgan. 2001. “Price Dispersion in the Lab and on the Internet: Theory and Evidence.” *Working Paper*, Indiana University.

Betancourt, Roger R. and David Gautschi. 1993. “Two Essential Characteristics of Retail Markets and Their Economic Consequences.” *Journal of Economic Behavior & Organization* 21 (August): 277-294.

Brynjolfsson, Erik and Michael Smith. 2000. “Frictionless Commerce? A Comparison of Internet and Conventional Retailers.” *Management Science* 46 (April): 563-585.

Burdett, Kenneth and Kenneth Judd. 1983. “Equilibrium Price Dispersion.” *Econometrica* 51 (July): 955-969.

_____ and Melvyn Coles. 1997. “Steady State Price Distributions in a Noisy Search Equilibrium.” *Journal of Economic Theory* 72 (January): 1-32.

Carlson, John and Preston McAfee. 1983. “Discrete Equilibrium Price Dispersion.” *Journal of Political Economy* 91 (June): 480-493.

Clemons, Eric, Il-Horn Hann, and Lorin Hitt. 2002. “Price Dispersion and Differentiation in Online Travel: An Empirical Investigation.” *Management Science* 48 (4): 534-549.

Comscore Report. 2002. *Online Retail Activity*, Reston, VA.

Dahlby, Bev and Douglas West. 1986. “Price Dispersion in an Automobile Insurance Market.” *Journal of Political Economy* 94 (April): 418-438.

Degeratu, Alex M., Arvind Rangaswamy, and Jinan Wu. 2000. “Consumer Choice Behavior in Online and Traditional Supermarkets: The Effects of Brand Name, Price, and Other Search Attributes.” *International Journal of Research in Marketing* 17 (1): 55-78.

Ehrlich, Isaac and Lawrence Fisher. 1982. “The Derived Demand for Advertising: A Theoretical and Empirical Investigation.” *The American Economic Review* 72 (June): 366-388.

Ellison, Glenn and Sara Fisher Ellison. 2001. “Search, Obfuscation, and Price Elasticities on the Internet.” *Working Paper*, Sloan School of Management, MIT.

Erevelles, S., E. Rolland and S. Srinivasan. 2001. “Are Prices Really Lower on the Internet?: An Analysis of the Vitamin Industry.” *Working Paper*, University of California, Riverside.

Fishman, Arthur. 1992. “Search Technology, Staggered Price-Setting, and Price Dispersion.” *The American Economic Review* 82 (March): 287-298.

Moorthy, Sridhar, Brian T. Ratchford, and Debabrata Talukdar. 1997. “Consumer Information Search Revisited” *Journal of Consumer Research* 23 (March): 263-277.

Pan, Xing, Brian T. Ratchford, and Venkatesh Shankar. 2001. “Why Aren’t the Prices of the Same Item the Same at Me.com and You.com?: Drivers of Price Dispersion Among E-Tailers.” *Working Paper*, University of Maryland, College Park, MD 20742.

Ratchford, Brian T. and Glenn T. Stoops. 1988. “A Model And Measurement Approach For Studying Retail Products.” *Journal of Retailing* 64 (3): 241-263.

_____, Xing Pan, and Venkatesh Shankar. 2002. **“***On the Efficiency of Electronic Markets for Consumers*.” *Working Paper*, University of Maryland, College Park, MD 20742.

Rosen, Sherwin. 1974. “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition.” *The Journal of Political Economy* 82 (1): 34-55.

Salop, Steven and Joseph Stiglitz. 1982. “The Theory of Sales: A Simple Model of Equilibrium Price Dispersion with Identical Agents.” *The American Economic Review* 72 (December): 1121-1130.

Shankar, Venkatesh, Gregory Carpenter, and Lakshman Krishnamurthi. 1999. “The Advantages of Entering in the Growth Stage of the Product Life Cycle: An Empirical Analysis.” *Journal of Marketing Research* 36 (May): 269-276.

_____, Arvind Rangaswamy, and Michael Pusateri. 2001. “The Online Medium and Customer Price Sensitivity.” *Working Paper*, University of Maryland, College Park, MD 20742.

_____, Fareena Sultan, Glen L. Urban, and Iakov Bart. 2002. “The Role of Trust in Online Customer Support.” *Working Paper*, Sloan School of Management, MIT, Cambridge, MA 02142.

_____, Glen L. Urban, and Fareena Sultan. 2002. “Trust and e-Business Strategy.” *Working Paper*, Sloan School of Management, MIT, Cambridge, MA 02142.

Smith, Michael, Joseph Bailey, and Erik Brynjolfsson. 2000. “Understanding Digital Markets: Review and Assessment.” *Erik Brynjolfsson and Brian Kahin, eds, Understanding the Digital Economy.* Cambridge, MA: MIT Press.

_____ and Erik Brynjolfsson. 2001. “Consumer Decision-Making at an Internet Shopbot.” *The Journal of Industrial Economics* 49 (4): 541-558.

Stigler, George. 1961. “The Economics of Information.” *Journal of Political Economy* 69 (June): 213-225.

Sultan, Fareena, Glen L. Urban, Venkatesh Shankar, and Iakov Bart. 2002. “Determinants and Consequences of Trust in e-Business.” *Working Paper*, Sloan School of Management, MIT, Cambridge, MA 02142.

Urban Glen L., Fareena Sultan, and William Qualls. 2000. “Making Trust the Center of Your Internet Strategy.” *Sloan Management Review* Fall (1): 39–48.

Wernerfelt, Birger. 1991. “Brand Loyalty and Market Equilibrium.” *Marketing Science* 10 (Summer): 229-245.

Table 1

Summary Statistics of Price Observations

Category	*Number of Items*	*Number of Obs.*	*Mean($)*	*Std Dev($)*	*Min($)*	*Max($)*
Book	105	1155	20.96	24.10	2.75	212
CD	43	403	13.48	2.71	7.99	23.93
DVD	96	1241	25.00	15.98	4.99	149.98
Desktop	105	976	1215.45	1079.86	208.6	5831
Laptop	78	1073	2441.66	664.48	946.95	4632.99
PDA	37	474	424.17	281.66	16.42	1574
Software	51	668	292.31	664.98	16.39	7752
Electronics	66	749	415.95	445.58	79.99	3999.99
Total	*581*	*6739*	*678.84*	*1026.43*	*2.75*	*7752*

Table 2

Measures and Explanation of e-Tailers' Features by BizRate.com

Measure	*Explanation*
Ease of Ordering	Convenience and speed of ordering
Product Selection	Breadth/Depth of products offered
Product Information	Information quantity, quality and relevance
Price	Prices relative to similar stores
Web Site Navigation and Looks	Layout, links, pictures, images and speed
On-Time Delivery	Expected vs. actual delivery date
Product Representation	Product description/depiction vs. what you received
Level and Quality of Customer Support	Status updates and complaint/question handling
Tracking	Tracking order status
Shipping and Handling	Shipping and handling charges and options

Table 3a

Factor Analysis of e-tailer Services:

Rotated Component Matrix for Five-Factor Solution

	Component				
Variable	*1*	*2*	*3*	*4*	*5*
Ease of Ordering	.057	**.775**	.360	.255	.326
Product Selection	.124	**.757**	.305	.180	.281
Product Information	.121	.232	**.948**	.103	.133
Price	.015	.263	.122	.145	**.940**
Web Site Navigation	.123	**.806**	.189	.203	.380
On-Time Delivery	**.897**	.074	.165	.233	.112
Product Representation	**.811**	.140	.320	.252	.245
Customer Support	**.838**	.128	.216	.386	.056
Tracking	**.868**	.200	.173	.218	.031
Shipping and Handling	.157	.172	.105	**.950**	.168
Factor Name	Reliability	Shopping Convenience	Depth of Information	Shipping and Handling	Pricing Policy

Extraction method: Principal components.
Rotation: Equimax with Kaiser normalization**.**

Table 3b

Eigenvalues and Total Variance Explained for Five-Factor Solution

Factor	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*			*Rotation Sums of Squared Loadings*		
	Total	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*	*Total*	*% of Variance*	*Cumulative %*
1	5.325	53.255	53.255	5.325	53.255	53.255	2.992	29.917	29.917
2	2.042	20.419	73.673	2.042	20.419	73.673	2.058	20.578	50.494
3	.747	7.467	81.141	.747	7.467	81.141	1.388	13.878	64.372
4	.573	5.733	86.874	.573	5.733	86.874	1.388	13.876	78.249
5	.463	4.630	91.504	.463	4.630	91.504	1.326	13.256	91.504
6	.332	3.323	94.828						
7	.196	1.963	96.791						
8	.133	1.327	98.118						
9	.105	1.053	99.171						
10	.083	.829	100.000						

Extraction Method: Principal Component Analysis.

Table 3c

Communalities for Five-Factor Solution

Variable	**Initial**	**Extraction**
Ease of Ordering	1.000	.905
Product Selection	1.000	.782
Product Information	1.000	.994
Price	1.000	.989
Web Site Navigation and Looks	1.000	.886
On-Time Delivery	1.000	.904
Product Representation	1.000	.904
Level and Quality of Customer Support	1.000	.918
Tracking	1.000	.872
Shipping and Handling	1.000	.996

Extraction Method: Principal Component Analysis.

Table 4a

Rotated Component Matrix for Two-Factor Solution

	Component	
Variable	1	2
Ease of Ordering	.177	.916
Product Selection	.206	.823
Product Information	.313	.597
Price	.054	.753
Web Site Navigation	.187	.882
On-Time Delivery	.933	.115
Product Representation	.884	.305
Customer Support	.938	.187
Tracking	.902	.168
Shipping & Handling	.462	.455

Extraction Method: Principal Component Analysis.
Rotation Method: Equamax with Kaiser Normalization.
Rotation converged in 3 iterations.

Table 4b

Communalities for Two-Factor Solution

Variable	**Initial**	**Extraction**
Ease of Ordering	1.000	.871
Product Selection	1.000	.720
Product Information	1.000	.455
Price	1.000	.570
Web Site Navigation and Looks	1.000	.814
On-Time Delivery	1.000	.885
Product Representation	1.000	.875
Level and Quality of Customer Support	1.000	.915
Tracking	1.000	.842
Shipping and Handling	1.000	.421

Extraction Method: Principal Component Analysis.

Table 5

Summary Statistics of $P/\overline{P}$

Category	*Standard Deviation**	*Range*	*Minimum*	*Maximum*	*No. of obsns.*
Book	0.150	1.076	0.633	1.709	1155
CD	0.154	1.010	0.585	1.595	403
DVD	0.127	1.094	0.632	1.725	1241
Desktop	0.127	1.197	0.534	1.731	976
Laptop	0.083	0.868	0.542	1.410	1073
PDA	0.118	1.042	0.639	1.681	474
Software	0.117	1.377	0.401	1.778	668
Electronics	0.096	0.777	0.694	1.470	749

* Equivalent to coefficient of variation of price, *P*.

Table 6a

Estimation Results of Stepwise Hedonic Price Regressions

Category	*Book*	*CD*	*DVD*	*Desktop*	*Laptop*	*PDA*	*Software*	*Electronics*
Adjusted R^2	12%	43%	10%	22%	5%	21%	21%	8%
N	1155	403	1241	976	1073	474	668	749
Intercept	**1.005** [a] (0.007)	**0.977** [a] (0.006)	**1.008** [a] (0.003)	**0.982** [a] (0.004)	**1.003** [a] (0.002)	**0.991** [a] (0.004)	**0.983** [a] (0.004)	**0.999** [a] (0.003)
Reliability	-0.011 (0.013)	**0.018** [a] (0.006)	0.003 (0.004)	**0.006** [c] (0.003)	**-0.018** [a] (0.002)	0.008 (0.005)	0.007 (0.007)	-0.003 (0.005)
Convenience	**0.014** [a] (0.003)	0.005 (0.004)	**-0.020** [a] (0.004)	**0.030** [a] (0.006)	-0.001 (0.003)	**0.012** [b] (0.006)	**0.034** [a] (0.007)	0.000 (0.005)
Information	**-0.038** [a] (0.006)	**-0.105** [a] (0.009)	**-0.018** [a] (0.005)	**-0.059** [a] (0.008)	**0.009** [a] (0.003)	**-0.067** [a] (0.012)	**-0.057** [a] (0.014)	**0.011** [c] (0.006)
Shipping	**0.053** [a] (0.008)	**-0.068** [a] (0.011)	**-0.062** [a] (0.007)	**0.007** [b] (0.003)	**0.007** [a] (0.002)	**0.010** [c] (0.005)	**0.018** [a] (0.004)	**0.021** [a] (0.003)

[a] $p < 0.01$; [b] $p < 0.05$; [c] $p < 0.10$.

Standard errors in parentheses. Numbers in bold represent significant estimates.

Table 6b

Estimation Results of Stepwise Hedonic Price Regressions

Category	*Book*	*CD*	*DVD*	*Desktop*	*Laptop*	*PDA*	*Software*	*Electronics*
Adjusted R^2	14%	43%	10%	22%	5%	21%	21%	8%
N	1155	403	1241	976	1073	474	668	749
Intercept	**0.969** [a] (0.007)	**0.999** [a] (0.012)	**1.026** [a] (0.008)	**1.012** [a] (0.011)	**1.022** [a] (0.007)	**1.023** [a] (0.027)	**0.960** [a] (0.008)	**1.016** [a] (0.015)
Reliability	**-0.022** [c] (0.013)	**0.013** [c] (0.006)	0.002 (0.005)	0.005 (0.003)	**-0.018** [a] (0.002)	**0.010** [c] (0.005)	0.007 (0.007)	-0.003 (0.005)
Convenience	**0.017** [a] (0.003)	0.004 (0.004)	**-0.020** [a] (0.004)	**0.030** [a] (0.007)	-0.001 (0.003)	**0.011** [c] (0.006)	**0.035** [a] (0.007)	0.002 (0.005)
Information	**-0.025** [a] (0.006)	**-0.109** [a] (0.009)	**-0.019** [a] (0.004)	**-0.060** [a] (0.008)	**0.009** [b] (0.004)	**-0.067** [a] (0.012)	**-0.056** [a] (0.014)	**0.012** [c] (0.006)
Shipping	**0.047** [a] (0.008)	**-0.061** [a] (0.012)	**-0.059** [a] (0.007)	**0.008** [b] (0.003)	**0.007** [a] (0.002)	**0.010** [c] (0.005)	**0.017** [a] (0.004)	**0.021** [a] (0.003)
e-Tailer Type (Pure e-tailer =1)	**0.058** [a] (0.008)	**-0.031** [b] (0.015)	**-0.023** [b] (0.010)	**-0.031** [a] (0.012)	**-0.020** [b] (0.008)	-0.033 (0.027)	**0.025** [a] (0.009)	-0.018 (0.016)

[a] $p < 0.01$; [b] $p < 0.05$; [c] $p < 0.10$.

Standard errors in parentheses. Numbers in bold represent significant estimates.

Table 6c

Estimation Results of Stepwise Hedonic Price Regressions

Category	*Book*	*CD*	*DVD*	*Desktop*	*Laptop*	*PDA*	*Software*	*Electronics*
Adjusted R^2	14%	43%	10%	22%	5%	21%	21%	8%
N	1155	403	1241	976	1073	474	668	749
Intercept	**0.969** [a] (0.008)	**0.995** [a] (0.013)	**1.025** [a] (0.008)	**1.010** [a] (0.011)	**1.022** [a] (0.007)	**1.024** [a] (0.027)	**0.965** [a] (0.010)	**1.017** [a] (0.016)
Reliability	**-0.022** [c] (0.013)	**0.012** [c] (0.006)	0.002 (0.005)	0.005 (0.003)	**-0.018** [a] (0.002)	**0.010** [c] (0.005)	0.007 (0.007)	-0.003 (0.005)
Convenience	**0.017** [a] (0.003)	0.003 (0.004)	**-0.020** [a] (0.004)	**0.030** [a] (0.007)	-0.001 (0.003)	**0.011** [c] (0.006)	**0.035** [a] (0.007)	0.002 (0.005)
Information	**-0.025** [a] (0.006)	**-0.109** [a] (0.009)	**-0.019** [a] (0.004)	**-0.060** [a] (0.008)	**0.009** [b] (0.004)	**-0.067** [a] (0.012)	**-0.056** [a] (0.014)	**0.012** [b] (0.006)
Shipping	**0.047** [a] (0.008)	**-0.061** [a] (0.012)	**-0.060** [a] (0.007)	**0.008** [b] (0.003)	**0.007** [a] (0.002)	**0.010** [c] (0.005)	**0.017** [a] (0.004)	**0.021** [a] (0.003)
e-Tailer Type (Pure e-tailer =1)	**0.058** [a] (0.008)	**-0.032** [b] (0.015)	**-0.023** [b] (0.010)	**-0.031** [a] (0.012)	**-0.020** [b] (0.008)	-0.033 (0.027)	**0.025** [a] (0.010)	-0.018 (0.016)
Popularity (Popular = 1)	0.001 (0.008)	0.016 (0.013)	0.003 (0.006)	**0.017** [b] (0.007)	-0.001 (0.005)	-0.001 (0.009)	-0.007 (0.008)	-0.004 (0.006)

[a] $p < 0.01$; [b] $p < 0.05$; [c] $p < 0.10$.

Standard errors in parentheses. Numbers in bold represent significant estimates.

Table 6d

Estimation Results of Stepwise Hedonic Price Regressions

Category	*Book*	*CD*	*DVD*	*Desktop*	*Laptop*	*PDA*	*Software*	*Electronics*
Adjusted R^2	14%	43%	10%	23%	5%	20%	21%	8%
N	1155	403	1241	976	1073	474	668	749
Intercept	**0.967** [a] (0.008)	**1.008** [a] (0.015)	**1.026** [a] (0.009)	**1.028** [a] (0.012)	**1.022** [a] (0.007)	**1.024** [a] (0.027)	**0.966** [a] (0.010)	**1.015** [a] (0.016)
Reliability	**-0.022** [c] (0.013)	**0.012** [c] (0.006)	0.002 (0.005)	0.004 (0.003)	**-0.018** [a] (0.002)	**0.010** [c] (0.005)	0.007 (0.007)	-0.003 (0.005)
Convenience	**0.017** [a] (0.003)	0.003 (0.004)	**-0.020** [a] (0.004)	**0.032** [a] (0.007)	-0.001 (0.003)	**0.011** [c] (0.006)	**0.035** [a] (0.007)	0.001 (0.005)
Information	**-0.025** [a] (0.006)	**-0.110** [a] (0.009)	**-0.019** [a] (0.004)	**-0.063** [a] (0.008)	**0.009** [b] (0.004)	**-0.068** [a] (0.012)	**-0.056** [a] (0.014)	**0.012** [b] (0.006)
Shipping	**0.047** [a] (0.008)	**-0.062** [a] (0.012)	**-0.060** [a] (0.007)	**0.008** [b] (0.003)	**0.007** [a] (0.002)	**0.010** [c] (0.005)	**0.017** [a] (0.004)	**0.021** [a] (0.003)
e-Tailer Type (Pure e-tailer =1)	**0.058** [a] (0.008)	**-0.033** [b] (0.015)	**-0.023** [b] (0.010)	**-0.037** [a] (0.011)	**-0.020** [a] (0.008)	-0.033 (0.027)	**0.025** [a] (0.010)	-0.018 (0.016)
Popular (Popular = 1)	0.001 (0.008)	0.010 (0.013)	0.003 (0.006)	**0.016** [c] (0.009)	-0.001 (0.005)	-0.001 (0.009)	-0.005 (0.008)	-0.005 (0.007)
Stage in PLC (Mature = 1)	0.005 (0.007)	-0.015 (0.012)	-0.001 (0.006)	**-0.026** [a] (0.007)	0.000 (0.006)	-0.002 (0.009)	-0.004 (0.008)	0.005 (0.006)

[a] $p < 0.01$; [b] $p < 0.05$; [c] $p < 0.10$.

Standard errors in parentheses. Numbers in bold represent significant estimates.

Table 7

Price Dispersion Before and After Controlling E-Tailer Service Heterogeneity

Category		*Book*	*CD*	*DVD*	*Desktop*	*Laptop*	*PDA*	*Software*	*Consumer Electronics*
Adjusted R^2		12%	43%	10%	22%	5%	21%	21%	8%
Range	Price	1.08	1.01	1.09	1.20	0.87	1.04	1.38	0.78
	Residual (Service Quality-adjusted Price)	1.04	0.65	1.07	1.00	0.87	1.05	1.13	0.76
	Percentage change	*-4%*	*-36%*	*-2%*	*-17%*	*0%*	*1%*	*-18%*	*-3%*
Std. Dev.	Price	0.15	0.15	0.13	0.13	0.08	0.12	0.12	0.10
	Residual (Service Quality-adjusted Price)	0.14	0.12	0.12	0.11	0.08	0.10	0.10	0.09
	Percentage change	*-7%*	*-20%*	*-8%*	*-15%*	*0%*	*-17%*	*-17%*	*-10%*

About the Authors

Xing Pan is a doctoral candidate in marketing at the Robert. H. Smith School of Business, University of Maryland. His research interests include pricing, electronic commerce, industrial organization, and consumer economics. His dissertation investigates price dispersion and price competition in online retail markets, and wins the Twelfth Annual Doctoral Research Fellowship awarded by the Economic Club of Washington. He has published in the *Advances in Applied Microeconomics* and has presented his several papers at *Marketing Science* conferences and MSI conference.

Brian T. Ratchford holds the Pepsico Chair in Consumer Research at the Robert H. Smith School of Business at the University of Maryland. He holds M.B.A. and Ph.D. degrees from the University of Rochester. His research interests are in economics applied to the study of consumer behavior, information economics, and marketing productivity. He has published over 30 articles in the leading journals in marketing and related fields, including *Journal of Consumer Research, Marketing Science, Management Science, and Journal of Marketing Research*. He is past Editor of *Marketing Science*, and currently on the editorial review boards of *Journal of Consumer Research, Journal of Marketing Research* and *Journal of Retailing*.

Venkatesh (Venky) Shankar is the *Ralph J. Tyser* Fellow and a Professor of Marketing and Entrepreneurship at *the Robert H. Smith School of Business, University of Maryland*. His research interests include e-Business, Competitive Strategy, International Marketing, Pricing, Innovation and Supply Chain Management. His research has been published

journals such as the *Journal of Marketing Research, Marketing Science, Marketing Letters,* and the *Journal of Retailing*. He is an associate editor of *Management Science* and is also on the editorial boards of *Marketing Science, International Journal of Research in Marketing, Journal of Retailing* and the *Journal of the Academy of Marketing Science*. He was a visiting faculty at the Sloan School of Management, MIT last year and has also taught at the *Chinese European International Business School*, Shanghai.

Endnotes

[1] The key assumptions are increasing marginal costs of supplying each element of x and each s_i, and constant or increasing marginal costs of selling more units of each good. The basic results will hold if the latter assumption is violated, but Rosen's elegant modeling framework will no longer hold.

[2] The same result can be derived from models of Ehrlich and Fisher (1982), Ratchford and Stoops (1988), and Betancourt and Gautschi (1993).

[3] A key assumption of Carlson and McAfee (1983) is that the lowest search cost is zero. For example, some consumers know what the best alternative is. While Carlson and McAfee derive their results for a uniform distribution of search costs, their general conclusions should hold for other distributions as well.

[4] We obtained highly consistent results when we did the factor analysis on a subset of randomly selected 60 e-tailers.

[5] A semi-log model provided similar results. We could not use a double-log model because some measures of e-tailer characteristics are factor scores containing negative values.

[6] We tested for heteroscedasticity through the White test and Breusch-Pagan test for all eight regressions.

[7] We also estimated an additional model in which we added dummies for each e-tailer. The coefficients associated with a few of the e-tailer dummies were significant, but those associated with a majority of them were insignificant. We could not, however, meaningfully interpret the significant coefficients. The signs of the parameters associated with the other variables did not change. Therefore, for greater clarity and interpretation, we retain the model without e-tailer dummies.