

A COMPARISON OF TIME-VARYING ONLINE PRICE AND PRICE DISPERSION BETWEEN MULTICHANNEL AND DOTCOM DVD RETAILERS

XIAOLIN XING, ZHENLIN YANG, AND FANG-FANG TANG

We compare price differences and market dynamics between two types of online retailers: online branches of multichannel retailers (OBMCRs) and pure Internet retailers (Dotcoms), based on a set of panel data collected from the DVD market. We find that (i) OBMCRs charge higher prices than Dotcoms, (ii) prices go up with time for both OBMCRs and Dotcoms, and (iii) prices of Dotcoms go up faster than those of OBMCRs. We also find that price dispersions of OBMCRs and Dotcoms are significantly different and the difference decreases with time. Our results show that although the two types of retailers have different price levels and different price dispersions at the beginning, such differences are getting smaller over time, implying that the two types of retailers will have similar pricing behavior in the long run. However, persistent price dispersion among all retailers exists in the market, even over a long period.

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INTRODUCTION

An explosive growth in online retailing in recent years has triggered an increased research interest in studying online pricing behavior. Early studies in the literature mainly focused on comparing price levels and price dispersions between offline and online competitors, and among online retailers (e.g., Bailey, 1998; Bakos, 1997; Brynjolfsson & Smith, 2000; Clemons, Hann, & Hitt, 2002; Tang & Xing, 2001). As online markets become mature and more data on e-tailing become available, empirical studies have shifted from analyzing cross-sectional data to longitudinally investigating market dynamics in terms of price levels and price dispersions (e.g., Baye, Morgan, & Scholten, 2004a, 2004b; Baylis & Perloff, 2002; Lee & Gosain, 2002; Pan, Shankar, & Ratchford, 2003; Xing, Tang, & Yang, 2004). Since customers can obtain price information in online markets easily and inexpensively, it might be expected that online price dispersion should be small. However, empirical studies have found significant price differences and persistent price dispersions in the Internet markets (e.g., Ancarani & Shankar, 2004; Baye, Morgan, & Scholten, 2003; Chevalier & Goolsbee, 2003; Clay, Krishnan, & Wolff, 2001; Clemons, Hann, & Hitt, 2002; Pan, Ratchford, & Shankar, 2005; Pan, Shankar, & Ratchford, 2003; Smith & Brynjolfsson, 2001; Tang & Xing, 2001). With improved understanding of Internet markets, theoretical researchers in the field have attempted to explore the reasons for price differences and persistent price dispersion among online retailers (e.g., Baye & Morgan, 2001; Cattani, Gilland, & Swaminathan, 2002; Chen & Hitt, 2003; Iyer & Pazgal, 2003; Lal & Sarvary, 1999; Zettelmeyer, 2002).

There are two types of online retailers: pure Internet retailers (hereafter Dotcoms) and online branches of multichannel retailers (hereafter OBMCR). If they have different pricing policies, persistent price differences may exist in online markets. There are strong theoretical reasons that these two types of retailers may have different pricing behaviors: (i) multichannel retailers may wish to coordinate prices across their different channels to prevent destructive competition among themselves, hence they may charge higher prices on the Web than are charged by their online-only competitors; (ii) multichannel retailers may have successfully translated their market power and brand

names from offline to online modes, and they also tend to offer some additional services (such as returns to stores) that can affect prices, thus OBMCRs may charge higher prices than Dotcoms in the intermediate or even in the long term; (iii) price sensitive customers may shop at pure Internet retailers, because they presume that OBMCRs have an inherent cost disadvantage and therefore charge higher prices; and (iv) retailers may employ different pricing strategies, which result in differences in price levels and price dispersions. But it is also possible that competition may drive the prices of OBMCRs and Dotcoms toward the same level in the long run. It is thus of great interest to explore the online market dynamics of prices and to test if prices converge over time on the Internet.

Although some empirical studies have investigated price differences between the two types of online retailers, the analyses are based on cross-sectional data only (e.g., Ancarani & Shankar, 2004; Pan, Shankar, & Ratchford, 2002; Tang & Xing, 2001, 2003; Xing & Tang, 2004). In this study, we use a unique set of panel data, collected in the online DVD market over a span of nearly one year, to examine price trends in the market. Our analyses are made through panel data regression models with error components and serial correlations. Thus, we can not only compare the prices and price dispersions between the two types of online retailers, but also explore the possibility of online price convergence and price dispersion changes in the Internet market for a relatively long term.

Based on our data set, we find that although the online market faces intense competition, prices increase over time.¹ By comparing the pricing behavior between the two types of retailers, we find that Dotcoms offer lower prices than OBMCRs, even in the intermediate term. Although the average prices for both Dotcoms and OBMCRs tend to increase, the prices for Dotcoms increase faster, implying that relative prices between the two types of retailers may

¹In a theoretical study, Inderst (2002) showed how competition could drive up prices. Lal and Sarvary (1999) found that, under some conditions, firms may be able to raise prices and increase profits by using the Internet as a complementary channel of distribution. Schulz (1995) argued that increasing competition may lead to higher prices.

converge in the long run. We also find that the price dispersion among OBMCRs was much bigger than that among Dotcoms at the beginning of the study. However, as time elapses, the price dispersion among Dotcoms becomes bigger. Thus, our results suggest that the two types of retailers may not only charge similar average prices in the long run, but also have similar price dispersions. However, price dispersion among all retailers persists in the market even over a long time period. Such persistent price dispersion may be due to differentiation, consumer search cost, mistakes by consumers, or other factors yet to be identified.

In the next section, we discuss the related theoretical background and empirical findings on price dispersion and price dynamics, and develop our main research questions. Next, we describe our data collection methodology and provide some summary statistics on the price data. Then we introduce our econometric models on market dynamics in pricing, estimate the parametric models, and discuss the empirical results. Finally, we summarize our main results and discuss the possible implications and limitations.

PRICE LEVELS AND PRICE DISPERSION IN THE INTERNET MARKETS

Price Levels in the Internet Markets

A variety of related studies have investigated price levels among different retailer types, but the results so far seem conflicting. For example, Bailey (1998) found that online prices for books, CDs, and computer software were higher than those in conventional stores. Clay, Krishnan, and Wolff (2001) and Clay, Krishnan, Wolff, and Fernandes (2002) compared prices between online and physical stores and found that average prices were similar in both online and offline book markets. But taking sales tax and shipping cost into account, total prices were lower in conventional stores than in online stores. Xing, Tang, and Yang (2004) found that Dotcoms charged higher prices than OBMCRs in the online consumer electronics market.

In contrast, many other studies have found that online retailers tend to charge lower prices than

traditional retailers (e.g., Brynjolfsson & Smith, 2000; Chevalier & Goolsbee, 2003; Clay, Krishnan, & Wolff, 2001; Clemons, Hann, & Hitt, 2002; Smith & Brynjolfsson, 2001). For example, Brynjolfsson and Smith (2000) compared prices of books and CDs sold through the Internet and through conventional channels. They found that online prices were 9–16% lower than in conventional stores.

Empirical studies on comparing price levels between multichannel retailers and online-only retailers have found that pure Internet retailers charge lower prices than the online branches of multichannel retailers (e.g., Ancarani & Shankar, 2004; Pan, Shankar, & Ratchford, 2002; Tang & Xing, 2001, 2003; Xing & Tang, 2004). Carlton and Chevalier (2001) discussed free-riding problems on the sales and promotional efforts of retailers. They discovered that multichannel retailers might internalize some of the free-riding between online and retail stores and therefore charge higher prices than Dotcoms. Tang and Xing (2001) investigated online prices of DVDs for both multichannel retailers and Dotcoms, and found that, on average, multichannel retailers had higher online prices than Dotcoms. Pan, Shankar, and Ratchford (2002) collected data for eight product categories sold in online markets and found that, after controlling for the effects of other variables, prices at Dotcoms were generally lower than prices at multichannel retailers. Ancarani and Shankar (2004) compared price levels among three types of retailers in Italy during 2002. They found that when posted prices were considered, traditional retailers charged the highest prices, followed by multichannel retailers and online-only retailers.

Dotcoms start their business online directly and may charge lower prices in order to attract customers at first, whereas most multichannel retailers have already established their brand names well and may set higher prices when they go to the Internet. Thus we could expect that these two types of retailers might charge different prices at the early period of online retailing. However, as the Internet markets mature, fierce price competition may result in a similar price level between the two types of retailers.

Therefore our first research question is: Do the two types of retailers charge different prices and maintain the difference, if any, for a relatively long time period?

Price Dispersion in the Internet Markets

Economic theory predicts that, in a competitive market, an identical good has one price at equilibrium.² Online markets are featured by easy access to information, low search costs, weak market power, fierce price competition, and lack of spatial differentiation. Therefore competitiveness in the Internet may result in a relatively small spread between the highest and lowest prices. Thus, we may expect that the price dispersion in online markets should be relatively small and decreasing over time.

However, empirical studies in the literature have shown considerable and persistent price dispersion in online markets. Clemons, Hann, and Hitt (2002) investigated online markets for airline tickets and found that differences in prices across online travel agents were as large as 20%, even after controlling for observable product heterogeneity. Baye, Morgan, and Scholten (2004a) examined online pricing for the best-selling consumer electronics products listed at the price comparison site Shopper.com. They found substantial price dispersions (about 40% in the average range of prices). Even after controlling for shipping costs and firm heterogeneities, they found that prices did not converge, although the average range in prices did fall when the number of competing firms decreased. Lee and Gosain (2002) made a longitudinal price comparison for music CDs between traditional retailers and online retailers. They found that online retailers offered lower prices and the price dispersion was persistent in the Internet market. However, the traditional retailers adopted short-term discount strategies for current-hit albums, and as a result, the prices for current-hit albums in the traditional market were comparable to the prices in the Internet market. Clay, Krishnan, Wolff, and Fernandes (2002) investigated the book market and found that retailers aggressively chose to discount bestsellers, while discounts on random books were typically zero. They also found that relative to random books, the bestsellers had a higher standard deviation as a fraction of average price.

Although persistent price dispersion exists in online markets, empirical studies found that such price

²Rosen (1974) showed that price difference exists among differentiated goods even in a perfectly competitive market.

dispersion was lower across online retailers as compared to conventional retailers or multichannel retailers. Clay, Krishnan, and Wolff (2001) found that in the online book market, although some multichannel retailers set online prices very similar to their Dotcom rivals, others simply charged the same prices as their land-based stores. Thus, there was a substantial price difference among multichannel retailers. Tang and Xing (2001) found that online price dispersion was significantly higher for multichannel retailers than for Dotcoms. Ancarani and Shankar (2004) also found that multichannel retailers had the highest standard deviation in prices, while online-only retailers had the lowest. Pan, Shankar, and Ratchford (2003) found that online price dispersion increased from 2001 to 2003, suggesting that online pricing dispersion is persistent even as Internet markets mature. But, in contrast to Tang and Xing (2001) and Ancarani and Shankar (2004), they found that multichannel retailers on average had lower price dispersion than online-only retailers. Employing comprehensive data collected from BizRate.com, Ratchford, Pan, and Shankar (2003) explored the consumer welfare implications of changes in the structure of e-commerce markets. They found that price dispersion decreased substantially from November 2000 to November 2001, and that measured differences in retailer services bore little relation to their prices.

Varian (1980) argued that if a retailer always charges prices higher than others, consumers will learn from their experience and will not shop from that retailer. Based on the assumption of existence of two groups of consumers (one has high search costs and does not search; the other searches), Varian showed that retailers would adopt a mixed strategy to get business from both groups. According to Varian, retailers strategically vary their prices so that consumers cannot learn from shopping experience whether a store charges the best prices. So price dispersion is temporal in the sense that no retailers consistently charge high or low prices. However, this theoretical conclusion is not corroborated by empirical studies in traditional markets. In Internet markets, Baye, Morgan, and Scholten (2004a) found empirical evidence supporting Varian's theoretical prediction. But Baylis and Perloff (2002) found that high-priced stores remained high priced and low-priced stores remained low priced over long periods. Baye, Morgan, and

Scholten (2004b) found that the difference in prices charged for homogeneous products could not be fully explained by firm heterogeneities, which implies that firms may randomize pricing strategies.

Some theoretical studies in the literature have explored price levels and price dispersions in the Internet markets. Bakos (1997) examined the effects of lower search cost on equilibrium prices and showed that low search cost may drive Internet prices for homogeneous goods toward the Bertrand marginal cost pricing pattern.³ However, Baye and Morgan (2001) and Chen and Hitt (2003) both proved that online price dispersion is an equilibrium outcome of price competition in the Internet markets. Therefore price dispersion in online markets may be persistent.

Lal and Sarvary (1999) classified product attributes into “digital” attributes and “nondigital” attributes, and showed that in some cases, the use of the Internet not only leads to higher prices but also discourages consumers from engaging in search. Zettelmeyer (2002) showed how firms’ pricing strategies may be affected by the size of the Internet, and proved that average prices in the Internet are lower than those in the conventional channel if most consumers can access the electronic channel. Cattani, Gilland, and Swaminathan (2002) explored the issue of coordinating Internet and traditional channels for a monopoly, and found the optimal prices under different degrees of autonomy for the Internet operations. They also showed that it is not always a good strategy to price the Internet channel below the traditional channel.

Responding to these existing empirical studies and theoretical predictions, our second research question is: Is the price dispersion between the two types of online retailers different and if so, will the difference increase or decrease in the long run? The answer to this question, together with the answer to the first question, can show us whether the two types of retailers will have similar pricing behaviors over a long time period.

³Unfortunately, Harrington (2001) found that the two critical results in Bakos (1997)’s paper are either mathematically wrong (Harrington proved that there is no symmetric pure-strategy equilibrium in which consumers search), or based on an implicit assumption that is unreasonable (see Harrington, 2001, p. 1731).

Brand Effect and Price Difference in the Internet Markets

Price differences among retailers may not be explained only by retailers’ service quality. Baylis and Perloff (2002) investigated how Internet prices changed over time and found that online stores charged a wide range of prices for homogeneous products. They also found that “good” firms provided high service and charged relatively low prices, whereas “bad” firms offered low service and charged relatively high prices. Their result is inconsistent with the service-premium hypothesis, which suggests that high-service retailers charge relatively high prices. Pan, Ratchford, and Shankar (2002) found that the proportion of price dispersion explained by service quality was small, and that the stage in product life cycle and popularity of the item did not explain much of the price dispersion. Their findings suggest that online retailers may not always be able to translate superior service attributes into higher prices.

Retailers’ reputation and brand loyalty may contribute to considerable price differences in online markets. According to search theory, the low cost of online searching should result in low price dispersion in the Internet markets (e.g., Carlson & McAfee, 1983; Nelson, 1970; Pratt, Wise, & Zeckhauser, 1979; Stigler, 1961). However, empirical studies have revealed that although online search cost is low, many consumers may not be engaging in search (e.g., Clay, Krishnan, & Wolff, 2001). Reichheld and Scheffer (2000) found that online shoppers were most likely to shop on a Web site that they knew and trusted. Ward and Lee (2000) examined whether consumers used brands as sources of information when shopping online. They found that recent adopters of the Internet would be less proficient at searching and would rely more on brands. Dana (2001) argued that firms’ reputation for availability may increase demand, and showed that firms would use higher prices to signal higher availability. Thus, firms holding greater inventory may charge higher prices than others. Smith and Brynjolfsson (2001) empirically analyzed online consumer behavior, and found that in the Internet bookselling markets, heavily branded retailers held a significant price advantage over generic retailers.

Thus, our third research question is: Does brand name make differences in price levels among

individual retailers? If brand name does matter, we can expect that price dispersion will persist in the online markets over a long time period.

DATA AND SUMMARY STATISTICS

Data Collection

The first step in our data collection was to select the DVD retailers and DVD titles. First, six top Dotcoms selling a general selection of titles were selected following the store ratings by BizRate.com and DVD Talk Online store listing (www.dvdtalk.com), and five top OBMCRs were selected according to the ratings by BizRate.com and the authoritative rankings in Darnay and Piwowarski (1999) on the conventional stores in the category of record and prerecorded tapes. Together, the market share of these retailers is substantial, insuring that their pricing behavior represents the online DVD market.

Next, a total of 51 DVD titles were selected, of which 26 titles were an even mix of the bestsellers from Borders and Amazon, and 25 were chosen randomly.⁴ The reason for such a combination is that the bestsellers occupy a substantial market share in the DVD market and fierce competition in the bestsellers' segment may result in different pricing behavior among retailers. The random titles were compiled by randomly selecting pages from an English dictionary and finding a title starting with the words on the page. We refer to the first category of titles as "popular" and the second as "random." Further, during the data collection process, we took care to make sure that the version and other features were exactly the same for a given title across retailers and over time.

We commenced our data collection on July 5, 2000 and ceased on June 26, 2001. We first collected data every five days for the first eight collections, and then almost twice a month for the next 20 collections. The short interval at the beginning reflected our intention to capture price changes, which was later extended to

about two weeks when it was realized that the prices did not change that often. With 28 collections over almost a one-year span, we obtained 15,708 price observations in total.

Summary Statistics

Table 1 summarizes the averages and standard deviations of the posted prices by retailers and retailer types. From Table 1, we can see that the posted prices do differ across individual retailers and between two types of retailers. Djangos (an OBMCR) prices the highest and BuyCom (a Dotcom) the lowest, with a difference of \$5.05, or 26.3% relative to the average price of BuyCom. The average price of OBMCRs is \$1.74 (or 8.5%) higher than that of Dotcoms. Further, a high average price tends to be associated with a high standard deviation of prices. Similar numbers and patterns are observed when either only popular titles or only random titles are involved in the calculations.⁵

More details about the market dynamics of price and price dispersion can be seen in Figures 1 and 2. The plots reveal some rather insightful information which determines our model formulations. Figure 1 gives plots of average prices and their standard deviations versus the collection time (measured in days from the date of first data collection), categorized first by title type (to give different plots) and then by retailer type (to give different lines in the same plot), allowing easy visual comparison between OBMCR and Dotcom retailers; Figure 2 plots the within title and within retailer price dispersions, which "decomposes" the total price dispersion presented in plots b, d, and f of Figure 1. The within title price dispersion (WTPD) is defined as the standard deviation of all prices from the retailers of the same type, for a given title and at a given time point of data collection. The within retailer price dispersion (WRPD) is defined as the standard deviation of prices of all DVD titles from the same retailer at a given point of data collection time.

⁴Our original goal was 50 titles in total. Initially, we selected 64 titles (32 bestsellers and 32 random titles) and 12 retailers. After removing a retailer that stopped selling DVDs online and a few titles that had become unavailable in some stores during the period of the data collection, there were 11 retailers and 51 titles left. The data set is available from the authors upon request.

⁵We also calculated the per item shipping cost based on their shipping cost tariff table for various baskets of typical purchases, and found that there is no significant difference in shipping costs between the two types of retailers. So we focused our analysis on the posted prices in the following analysis, omitting further consideration of shipping costs in analyzing pricing behaviors of the types of retailers.

TABLE 1

Averages and Standard Deviations of Prices by Retailers

RETAILER	ALL TITLES			POPULAR TITLES		RANDOM TITLES	
	AVE	STDEV	OBS.	AVE	STDEV	AVE	STDEV
Borders	22.95	4.44	1428	22.57	4.01	23.34	4.81
Musicland	21.01	4.00	1428	20.64	3.98	21.39	3.99
TransWorld	22.04	3.54	1428	21.70	3.59	22.40	3.45
Tower	21.15	4.19	1428	20.76	4.06	21.54	4.29
Djangos	24.27	4.22	1428	24.44	4.08	24.09	4.36
Amazon	21.51	3.90	1428	21.05	3.72	21.99	4.02
Bigstar	22.12	3.71	1428	22.04	3.51	22.21	3.91
BuyCom	19.22	3.36	1428	19.30	3.33	19.13	3.39
DVDempire	19.90	3.58	1428	20.04	3.64	19.75	3.52
DVDplanet	19.50	3.30	1428	19.65	3.28	19.34	3.31
Express	20.99	3.69	1428	20.47	3.40	21.53	3.90
<i>OBMCR</i>	22.28	4.27	7140	22.02	4.19	22.55	4.33
Dotcom	20.54	3.75	8568	20.42	3.60	20.66	3.90
Overall	21.41	4.11	15,708	21.22	3.99	21.61	4.23

Note. The first five retailers are OBMCRs and the last six Dotcoms.

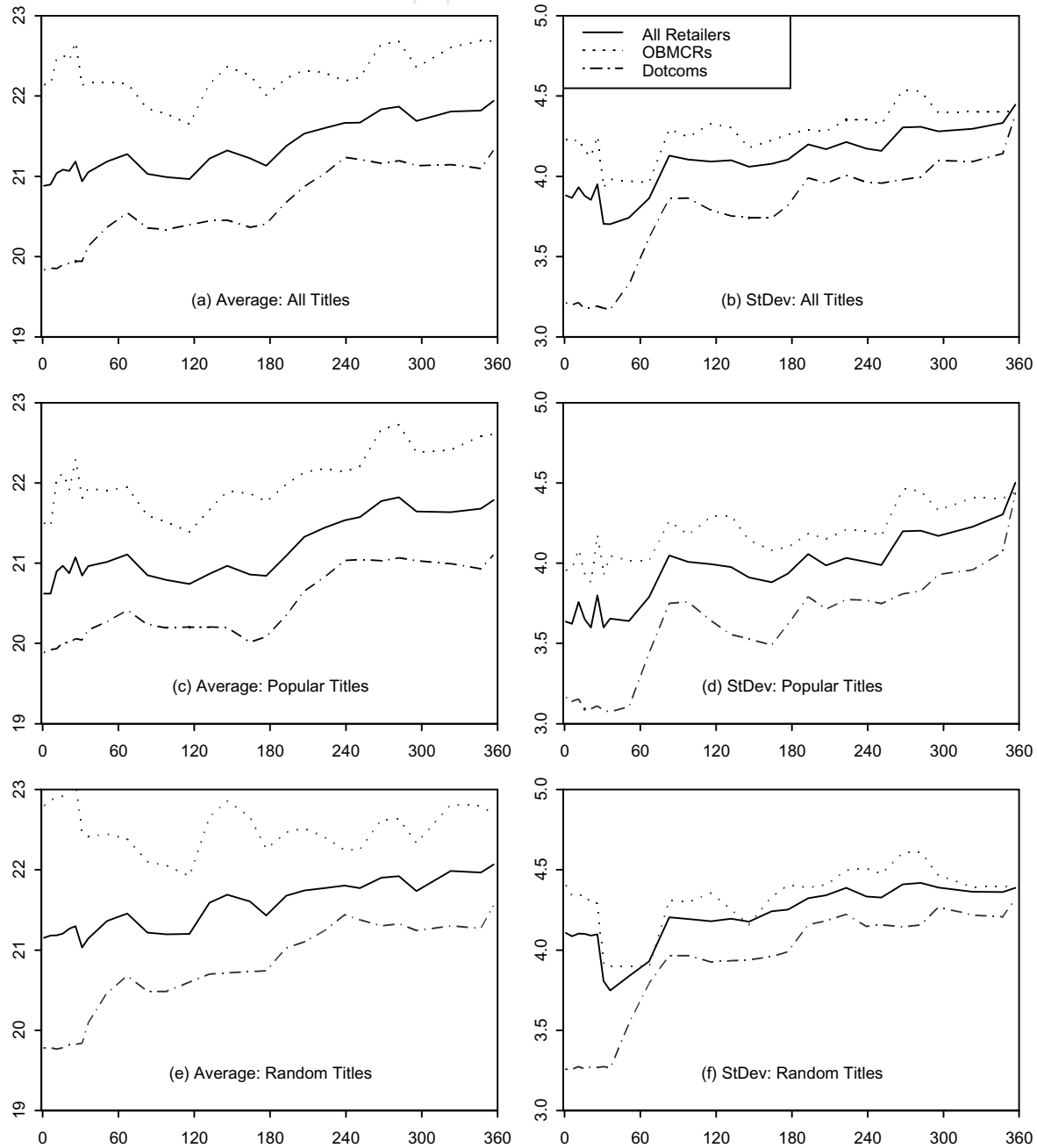
The plots show clearly upward trends of prices and price dispersions over time, in particular for the plots involving the Dotcom retailers. Some interesting phenomena are observed in Figure 1, as follows. At first, Dotcoms have much lower average prices and smaller standard deviations than OBMCRs. However, the differences shrink with time, and by the end of the data collection, there are almost no differences between the standard deviations, and much smaller differences between the average prices.

It is rather striking to see from Figure 2 that once the price dispersions plotted in b, d, and f of Figure 1 are decomposed into within title price dispersion and within retailer price dispersion, the within title price dispersions go down with time for OBMCRs and for all retailers, whereas the within retailer price dispersions go up in all categories with steeper slopes than in the plots for the total price dispersion. This tells us that, when comparing price dispersions and studying the dynamics of price dispersions, one should compare both types of price dispersions. Otherwise, the picture obtained regarding price dispersion and its dynamics will not be complete.

One minor issue is whether we should use dollar price or percentage price as the response variable. Dollar price is the posted price by each retailer at a time point and percentage price equals the dollar price divided by the maximum list price (MLP). A common perception is that one should use percentage prices for comparison to eliminate the effect of changes in the base prices. However, if the MLP enters the model as a controlling variable, it is not critical which should be used as the response variable. Further, if the log price is used as the response variable (as we do in this study), the estimated regression coefficients for the store type and individual store dummies remain the same for dollar price or percentage price, as the MLP does not vary between stores. Another advantage of using the log price as response is that the regression coefficients approximate the percentage changes (after multiplying by 100) with respect to the explanatory variables.

ECONOMETRIC MODELS

We now discuss the econometric models and show how the three important pricing issues raised in the second section can be formulated in the forms of

**FIGURE 1****Plots of Average Prices and Standard Deviation of Prices by Retailer Type**

Note. Plots (a) and (b) are constructed as follows. For each time point, averages and standard deviations of prices for all retailers, for OBMCs, and for Dotcoms are calculated, respectively. The three sets of averages (28 each) are plotted against the 28 time points (1 to 357 days), which give plot (a) after connecting the points and smoothing the lines. Similarly, the three sets of standard deviations are plotted against the time points to give plot (b). Plots (c) and (d) are obtained in a similar way as plots (a) and (b) but involve only the prices of popular titles. Plots (e) and (f) involve only the prices of random titles.

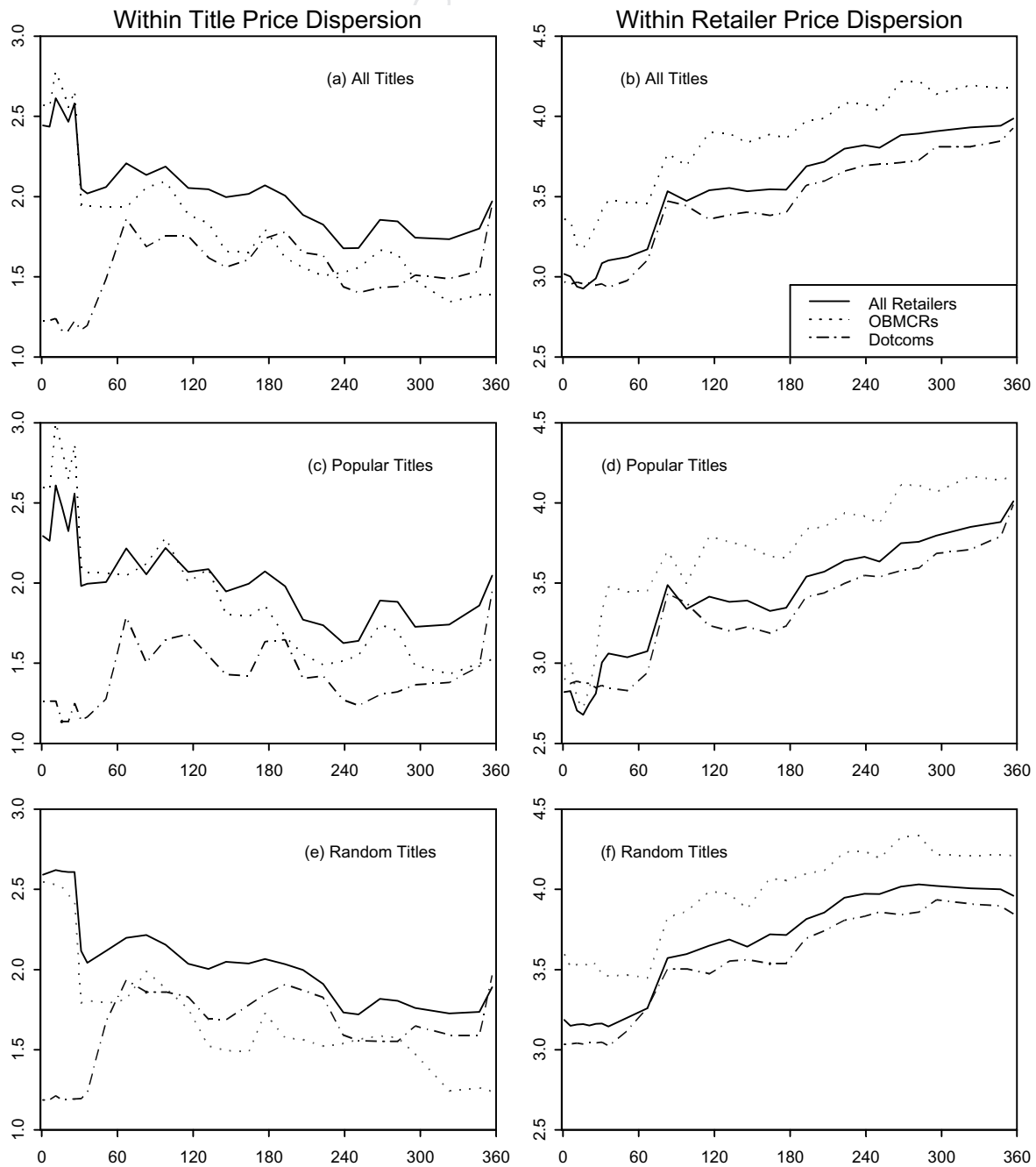


FIGURE 2

Plots of Within Title and Within Retailer Price Dispersions

Note. For prices collected at a given time point, the total sum of squares (SST) is decomposed into sum of squares within title (SSWT) (across retailers for the same title) and sum of squares within retailers (SSWR) (across the titles for the same retailer). The within title price dispersion is defined as square-root of $SSWT/n$, and the within retailer price dispersion is defined as the square root of $SSWR/n$, where n is the total price observations involved. The calculations are done for each of the 28 sets of prices and the 28 "price dispersions" obtained are plotted against 28 time points, which are converted to the plots above by connecting the 28 dots and smoothing the lines.

statistical hypotheses on the model parameters. The rich structure of our data and the flexibility of the panel data regression model make the complicated comparisons of the prices, price dispersions and market dynamics between OBMCRs and Dotcoms possible. In particular, we employ the following error component model with serial correlation:

$$Y_{it} = \sum_{k=1}^K X_{itk} \beta_k + \mu_i + v_{it}, \quad i = 1, \dots, N; t = 1, \dots, T \quad (1)$$

$$v_{it} = \rho v_{i,t-1} + \varepsilon_{it}$$

where the error component μ_i (independent and identically distributed (iid) with mean zero and variance σ_μ^2) captures the unobservable cross-sectional effect, the AR(1) process $v_{it} = \rho v_{i,t-1} + \varepsilon_{it}$ captures the effect of time-wise serial correlation with ε_{it} being iid random variables of mean zero and variance σ_ε^2 , N is the number of cross-sections corresponding to titles and retailers, T is the length of the time series for each cross-section, and K is the number of exogenous or independent variables.⁶ The feasible generalized least squares (FGLS) method is used for estimating the beta coefficients, the best quadratic unbiased (BQU) estimation method is used for estimating σ_μ^2 and σ_ε^2 , and a consistent estimate of ρ is used (see Baltagi, 2001, Sec. 5.2, for details on model specification and estimation). The response variable Y can be log price or log price dispersion. The explanatory variables X_k contain the variables that serve for necessary comparisons and the variables that serve for control purpose. We now give a general description of these variables.

As discussed in the second section, one primary concern (first research question) in this study is to examine whether OBMCRs and Dotcoms have different pricing behaviors. To address this, we design two dummy variables, OBMCR, taking the value 1 if the retailer type is OBMCR and 0 otherwise, and Dotcom, taking value 1 if the retailer type is Dotcom and 0 otherwise. To examine market dynamics of prices and price dispersions, we design two time trend variables: T_M and T_D for OBMCRs and Dotcoms, respectively,

⁶Serial correlation and unobserved cross-sectional random effects are two important features of the panel price data that should be modeled or controlled. A joint test of no random effects and no serial correlation (Baltagi, 2001) is strongly rejected.

defined as the number of days from the first data collection (1, 6, ..., 357) divided by 7. T_M is 0 if Dotcoms are involved and likewise T_D is 0 if OBMCRs are involved.⁷ To test the brand name effect, we introduce the retailer dummies, Retailer_i . As there are intrinsic price differences among different DVDs, it is important to control the effect of this factor so that the analysis corresponding to the store type effect can be meaningful. This effect is modeled by using the maximum list price (MLP).⁸

Model for Analysis of Price Levels

The detailed form of the model in Equation 1 for the analysis of prices and price dynamics is

$$\begin{aligned} \log(\text{Price}) = & \alpha + \theta_1 \text{OBMCR} + \theta_2 \text{Dotcom} + \gamma_1 T_M \\ & + \gamma_2 T_D + \sum_i \phi_i \text{Retailer}_i + \beta \log(\text{MLP}) \\ & + \psi_1 \text{PTitle} + \psi_2 \text{RTitle} + u \end{aligned} \quad (2)$$

where $\theta_1 + \theta_2 = 0$, $\sum_{i=1}^5 \phi_i = 0$, $\sum_{i=6}^{11} \phi_i = 0$, and $\psi_1 + \psi_2 = 0$, the necessary constraints to avoid the dummy variable trap. PTitle and RTitle are dummies for popular titles and random titles, respectively. Thus, a test of the hypothesis

$$H_1: \theta_1 = \theta_2 = 0$$

shows whether or not OBMCRs and Dotcoms charge the same price; a test of hypothesis

$$H_2: \gamma_1 - \gamma_2 = 0$$

shows whether the prices of OBMCRs and Dotcoms change over time, and whether they change toward the same price level; and a test of the hypothesis

$$H_3: \phi_1 = \phi_2 = \dots = \phi_{11} = 0$$

shows whether prices change with retailers.

⁷This partially accounts for the effect of unbalanced duration of data collection. We have further checked this effect by applying the technique given in Baltagi and Wu (1999) and found no significant change in our results.

⁸Each DVD corresponds to one maximum list price value. A less efficient way is to use the title dummies. The results (available from the authors) show no significant changes on key parameter estimates. Furthermore, the use of title dummies prevents an explicit modeling of the effect of popular titles versus random titles.

Models for Analysis of Price Dispersion

Analysis of price dispersion turns out to be a more challenging problem than the analysis of prices. Price dispersion has been measured in various ways in empirical studies, and different measures may result in different conclusions (e.g., Ancarani & Shankar, 2004; Baye, Morgan, & Scholten, 2004a; Brynjolfsson & Smith, 2000; Pan, Ratchford, & Shankar, 2004). It is clear from our second research question that we want to compare price dispersions between OBMCRs and Dotcoms, as well as studying the dynamics of price dispersion over time. To give a complete picture of differences in prices dispersion and its market dynamics, we will compare the price dispersions based on two measures, namely, within title price dispersion (WTPD) and within retailer price dispersion (WRPD). The model in Equation 1, when used for analyzing WTPD, reduces to

$$\begin{aligned} \log(\text{WTPD}) = & \alpha + \theta_1 \text{OBMCR} + \theta_2 \text{Dotcom} + \gamma_1 T_M \\ & + \gamma_2 T_D + \beta \log(\text{MLP}) + \psi_1 \text{PTitle} \\ & + \psi_2 \text{RTitle} + u \end{aligned} \quad (3)$$

where $\theta_1 + \theta_2 = 0$ and $\psi_1 + \psi_2 = 0$. The analysis of price dispersion can be done for all titles together, or separately for popular titles and for random titles. Similarly, tests using the model in Equation 3 on model parameters can be formulated to answer the questions regarding the price dispersions and their dynamics. In particular, to see whether OBMCRs and Dotcoms have the same WTPD, one can test the hypothesis

$$H_1^*: \theta_1 = \theta_2 = 0.$$

To check whether the WTPDs for the two types of retailers change with time in the same manner, one can test the hypothesis

$$H_2^*: \gamma_1 - \gamma_2 = 0$$

For analyzing WRPD, Equation 1 becomes

$$\begin{aligned} \log(\text{WRPD}) = & \alpha + \theta_1 \text{OBMCR} + \theta_2 \text{Dotcom} \\ & + \sum_i \phi_i \text{Retailer}_i + \gamma_1 T_M \\ & + \gamma_2 T_D + u \end{aligned} \quad (4)$$

where $\theta_1 + \theta_2 = 0$, $\sum_{i=1}^5 \phi_i = 0$ and $\sum_{i=6}^{11} \phi_i = 0$. Three hypotheses can be formulated as

$$\begin{aligned} H_1^+ : \theta_1 = \theta_2 = 0, \quad H_2^+ : \gamma_1 - \gamma_2 = 0, \quad \text{and} \\ H_3^+ : \phi_1 = \phi_2 = \dots = \phi_{11} = 0 \end{aligned}$$

and be tested to answer, respectively, the following three questions: (i) Are WRPDs the same for OBMCRs and Dotcoms? (ii) Do WRPDs change over time in the same manner for both types of retailers? (iii) Do WRPDs change with individual retailers?

EMPIRICAL RESULTS

Price and Price Dynamics

Table 2 summarizes the parameter estimates and their z statistics from fitting Equation 2 using all titles, popular titles only, and random titles only. All variables entered in the models are highly significant except Express in the model for popular titles and TransWorld in all three fitted models. This means that the price level for Express is around the average of all Dotcom retailers when only the popular titles are used, and that the price level for TransWorld is around the average of all OBMCR retailers irrespective of whether all titles, only popular titles, or only random titles are used.

Further, all the hypothesis tests (except H_2 for popular titles) are significant. These results allow us to draw qualitative conclusions about the pricing behaviors and to calculate quantitative differences in prices. First, it can be concluded that (i) OBMCRs charge higher prices than Dotcoms (H_1), (ii) the prices go up with time for both OBMCRs and Dotcoms as both time trends have positive and significant coefficients, (iii) the prices at Dotcoms go up faster than those at OBMCRs (H_2), caused mainly by the faster price increase of Dotcoms' random titles, and (iv) individual retailers do charge different prices (H_3).

Quantitatively, the combined analysis shows that in week 1 ($T_M = T_D = 1$) of our study, the average price at OBMCRs is about $100[\exp(.0495 + .00085(-.0495 + .00168)) - 1] = 10.3\%$ higher than the average price at Dotcoms.⁹ This price differential decreases with

⁹Use the method suggested by Halvorsen and Palmquist (1980). The conversion $100[\exp(\beta) - 1]$ gives an approximate percentage change in average original price, where β is the estimated coefficient of the explanatory variable of interest. All calculations are based on this method.

TABLE 2

Analysis of Log Dollar Prices

VARIABLE	ALL TITLES		POPULAR TITLES		RANDOM TITLES	
	PAR.EST.	z-STAT	PAR.EST.	z-STAT	PAR.EST.	z-STAT
OBMCR	0.04950	18.00	0.03814	9.60	0.06162	17.64
Dotcom	-0.04950	-18.00	-0.03814	-9.60	-0.06162	-17.64
Borders	0.03025	4.77	0.02464	2.75	0.03689	4.52
Musicland	-0.06237	-9.83	-0.07076	-7.91	-0.05272	-6.46
TransWorld	-0.00664	-1.05	-0.01065	-1.19	-0.00200	-0.25
Tower	-0.04790	-7.55	-0.05095	-5.70	-0.04737	-5.80
Djangos	0.08666	13.66	0.10772	12.04	0.06520	7.98
Amazon	0.04691	7.24	0.03139	3.44	0.06298	7.56
Bigstar	0.07835	12.10	0.08104	8.88	0.07532	9.04
BuyCom	-0.06373	-9.84	-0.05519	-6.04	-0.07264	-8.72
DVDempire	-0.03150	-4.86	-0.02049	-2.24	-0.04292	-5.15
DVDplanet	-0.04729	-7.30	-0.03596	-3.94	-0.05901	-7.08
Express	0.01726	2.67	-0.00078	-0.09	0.03626	4.35
T_M	0.00085	7.42	0.00120	7.01	0.00045	3.18
T_D	0.00168	16.10	0.00137	8.77	0.00202	15.55
Log(MLP)	0.79311	76.12	0.77051	50.35	0.83966	63.60
PTitle	-0.01459	-6.81				
RTitle	0.01459	6.81				
R^2	0.9350		0.9273		0.9486	
$N \times T$	15708		8008		7700	
H_1		44.25		9.60		17.64
H_2		16.93		0.74		8.15
χ^2 -stat H_3		465.01 ($p < .0001$)		35.81 ($p < .0001$)		42.91 ($p < .0001$)

Notes. Feasible generalized least squares (FGLS) estimates are based on Equation 2, error component model with serial correlation. All statistics are asymptotic. The cutoff values of z-stat are 1.960, 2.576, and 3.291 for 5%, 1%, and 0.1% tests, respectively. For brevity, estimates for intercept and other model parameters are not reported but are available upon request.

time and when $T_M = T_D = 51$ (the ending week of our data collection), OBMCRs charge only 5.8% more than Dotcoms. The same analysis with popular titles shows that OBMCRs charge about 7.9% more at the beginning and 7.0% more at the end; with random titles 12.9% more at the beginning but only 4.4% more at the end. These results suggest that the prices on average will possibly converge over time between the two types of retailers, and the convergence speed may be faster for random titles due to the faster price increase of Dotcoms' random titles.

Using the estimated coefficients of the variables OBMCR, Dotcom, T_M and T_D , we could estimate the

time of price convergence. For example, based on all titles (Table 2), setting $.0495 + .00085t_c - (-.0495 + .00168t_c) = 0$, we obtain $t_c = 2(.0495)/(.00168 - .00085) = 119$. This means that if the price trends are kept unchanged, the point of price convergence is estimated to be at the 119th period. However, it would take a much longer time for the prices to converge should the convergence speed become slower as the difference in prices gets smaller.

The coefficient of log(MLP) deserves some further discussion. It represents the price elasticity with respect to the maximum list price. Hence, this coefficient being significantly less than 1 indicates that, for a

certain percentage increase in MLP, there will be a smaller percentage increase in price, which in turn suggests that higher priced titles tend to be discounted more. For example, for Price = 25 and MLP = 35, the discount rate is 28.6%. If MLP increases by 20% to 42, then the corresponding increase in price is estimated to be $20(.79311) = 15.9\%$, which brings the price up to 28.975. The discount rate for the new price is thus 31%.¹⁰

Price Dispersion and Dynamics in Price Dispersion

Tables 3 and 4 summarize the parameter estimates and their z statistics, respectively, from fitting Equations 3 and 4 with only serial correlated errors.¹¹ From the analysis of WTPD (Table 3), one can see that the hypotheses H_1^* and H_2^* are both firmly rejected, and that the coefficients of T_M and T_D are significantly less than or larger than 0. These results suggest that the price dispersions of OBMCRs and Dotcoms are significantly different and the difference

between the price dispersions of the two types of retailers decreases with time. From the estimated coefficients of OBMCR, Dotcom, T_M , and T_D , we calculate that the prices of OBMCRs are about 86.7% more dispersed (within titles) than the prices of Dotcoms in the first week. The same number becomes 104.0% if analysis is based on the popular titles only, and 72.4% if analysis is based on random titles only. However, at the end of the study period, these numbers have become -24.8% , -14.6% , and -40.5% , respectively, that is, the prices of OBMCRs become less dispersed (within titles) than those of Dotcoms. Clearly, this is due to the faster price increase of Dotcoms' random titles than their popular titles, which drives up the Dotcoms' price dispersion.

From the analysis of WRPD (Table 4), we can see that the three hypotheses (except H_2^+ for popular titles) are all rejected at the conventional levels, which implies that the WRPD of OBMCRs is higher than the WRPD of Dotcoms, the difference in WRPD diminishes with time, and the brand name affects the WRPD. Quantitatively, differences in WRPD between OBMCRs and Dotcoms in the first week are 19.6%, 15.1%, and 19.0%, respectively, from the analysis based on all titles, popular titles, and random titles; and in the last week they are 4.7%, 5.9%, and 6.9%, respectively. Among the OBMCRs, Borders has the

¹⁰ We thank an anonymous referee for raising the issues of estimating the point of price convergence and interpreting the coefficient of the log of maximum list price.

¹¹ The random effect is either insignificant or not feasible due to small number of cross-sections.

TABLE 3

Analysis of Within Title Price Dispersion

VARIABLE	ALL TITLES		POPULAR TITLES		RANDOM TITLES	
	PAR. EST.	Z-STAT	PAR. EST.	Z-STAT	PAR. EST.	Z-STAT
OBMCR	0.32140	14.47	0.36496	14.34	0.27859	8.07
Dotcom	-0.32140	-14.47	-0.36496	-14.34	-0.27859	-8.07
MLP	0.02743	8.55	0.02568	7.05	0.02827	5.62
T_M	-0.01241	-11.93	-0.01253	-10.17	-0.01261	-8.10
T_D	0.00579	5.56	0.00487	3.95	0.00625	4.02
PTitle	0.00013	0.02				
RTitle	-0.00013	-0.02				
R^2	0.1608		0.2214		0.1407	
$N \times T$	2856		1456		1400	
H_1^*		14.47		14.34		8.07
H_2^*		12.47		9.99		8.57

Notes. Feasible generalized least squares (FGLS) estimates are based on Equation 3 with serial correlation. All statistics are asymptotic. The cutoff values of z -stat are 1.960, 2.576, and 3.291 for 5%, 1%, and 0.1% tests, respectively. For brevity, estimates for intercept and other model parameters are not reported but are available upon request.

TABLE 4

Analysis of Within Retailer Price Dispersion

VARIABLE	ALL TITLES		POPULAR TITLES		RANDOM TITLES	
	PAR.EST.	z-STAT	PAR.EST.	z-STAT	PAR.EST.	z-STAT
OBMCR	0.09100	8.08	0.07131	4.61	0.08816	6.32
Dotcom	-0.09100	-8.08	-0.07131	-4.61	-0.08816	-6.32
Borders	0.07880	3.66	0.00270	0.09	0.12378	4.46
Musicland	-0.06757	-3.14	-0.07062	-2.40	-0.06780	-2.44
TransWorld	-0.12021	-5.58	-0.06472	-2.20	-0.17748	-6.40
Tower	0.04302	2.00	0.05636	1.92	0.04280	1.54
Djangos	0.06596	3.06	0.07628	2.60	0.07870	2.84
Amazon	0.07497	3.41	0.04646	1.55	0.08760	3.09
Bigstar	0.05712	2.60	0.03491	1.16	0.08278	2.92
BuyCom	-0.07757	-3.53	-0.05417	-1.81	-0.09092	-3.21
DVDempire	0.01505	0.68	0.05719	1.91	-0.01571	-0.55
DVDplanet	-0.07129	-3.24	-0.05168	-1.72	-0.07768	-2.74
Express	0.00172	0.08	-0.03271	-1.09	0.01393	0.49
T_M	0.00391	6.76	0.00528	6.59	0.00371	5.40
T_D	0.00657	12.42	0.00691	9.44	0.00589	9.38
R^2	0.8444		0.6935		0.8542	
$N \times T$	308		308		308	
H_1^+		8.08		4.61		6.32
H_2^+		3.38		1.50		2.33
χ^2 -stat H_3^+	9.89 ($p < .0001$)		3.24 ($p = .0009$)		10.25 ($p < .0001$)	

Notes. Feasible generalized least squares (FGLS) estimates are based on Equation 4 with serial correlation. All statistics are asymptotic. The cutoff values of z-stat are 1.960, 2.576, and 3.291 for 5%, 1%, and 0.1% tests, respectively. For brevity, estimates for intercept and other model parameters are not reported but are available upon request.

highest WRPD (and also has the highest over all retailers), whereas TransWorld has the lowest WRPD; among the Dotcoms, Amazon has the highest WRPD whereas BuyCom has the lowest (and also has the lowest over all retailers). These results indicate that retailers may employ different pricing strategies. Borders, Djangos, and Amazon may have applied the loss leader strategy that results in high WRPDs (some titles being on sale), whereas BuyCom and DVDPlanet may simply have followed the EDLP strategy that results in low WRPDs. Price dispersion is persistent in the market over our sample period.

Brand Loyalty and Pricing Strategy

The results in Table 2 show that H_3 is firmly rejected, i.e., a brand name may have a significant effect on prices. From the coefficients of retailer dummies, we found that Djangos and Borders charge more than the

OBMCR average by, respectively, 9.1% and 3.1%, whereas Musicland, Trans World and Tower charge less than the OBMCR average by, respectively, 6.0%, 0.7%, and 4.7%. The highest priced OBMCR (Djangos) charges about 16.1% more than the lowest priced OBMCR (Musicland). As for the Dotcoms, Amazon, Bigstar, and Express charge more than the Dotcom average by, respectively, 4.8%, 8.2%, and 1.7%, and DVDempire, DVDplanet, and Buy.com charge less than the Dotcom average by, respectively, 3.1%, 4.6%, and 6.2%.

Bigstar.com, who charged the highest price among the Dotcoms, stopped selling DVDs online in July 2001. According to their quarterly report on May 14, 2001, Bigstar.com had "revised its pricing policies during the year 2000 in order to achieve higher gross margins on sales of filmed entertainment products." Relative to the quarter ended March 31, 2000,

Bigstar.com offered smaller discounts. The direct result was a significant decrease in units sold in that quarter. Bigstar.com charged the highest price on average, but lost online customers and soon went out of the business. However, Amazon, the other Dotcom that charged a higher price than many other Dotcoms, started making a profit in the year 2001, which shows that Amazon is comfortably enjoying its brand name. This result is consistent with Smith and Brynjolfsson (2001), who found that Amazon had a \$2.49 price advantage over generic retailers in the online book market.¹²

The impact of brand name on price dispersion was discussed in relation to WRPD, which directly links to the issue of pricing strategies. The results of Table 4 show that the title-to-title price variations are still significantly different from one retailer to another. Therefore, one has reasons to believe that a retailer with a high WRPD may have employed the loss leader strategy, and a retailer with a low WRPD may have used the EDLP strategy, which implies that price dispersion may exist in the market over a long period. The positive trend of WRPD may imply that retailers become more and more aggressive in using the loss leader strategy over time. It may also suggest that retailers become more likely to randomize pricing strategies, as Varian (1980) predicted.

CONCLUDING REMARKS

This study tracks price dynamics in the U.S. online DVD market for about one year and finds that the online branches of multichannel retailers price significantly higher than their online-only counterparts. Furthermore, trend analysis clearly shows that the prices go up with time for both OBMCRs and Dotcoms, with the Dotcom prices going up much faster, implying that the prices on average may converge over time between the two types of retailers.

Our results also show that, although the estimated price dispersion for OBMCRs is about 74% higher

than that for Dotcoms, the difference in price dispersions between the two types of retailers declines over the sample period, consistent with the empirical findings by Pan, Shankar, and Ratchford (2003), who examined price dispersion levels at three discrete points in time. But their data changed in both items and retailers, and, because of the change, they could not compare price levels and changes in price levels between the two types of retailers. Tang and Xing (2001) and Ancarani and Shankar (2004) both found that multichannel retailers had higher average prices and higher standard deviations in prices than Dotcoms. But these two studies used cross-sectional data only, thus did not (and could not) examine the evolution of price levels and price dispersions. Consistent with Lee and Gosain (2002) and Clay, Krishnan, Wolff, and Fernandes (2002), we find that the price dispersion for the popular category is bigger than that for the random category, indicating that the retailers are more likely to adopt the loss leader strategy for the popular DVD items.

We find that overall market prices go up over time, implying that retailers collectively raised their prices during our sample period. This result may reflect the possibility that our sample period may correspond to a tough adjustment period of online retailing.¹³ When there was a shakeout in online retailing in 2000, online retailers faced serious pressure from investors to deliver profits rather than traffic (the number of click times).¹⁴ Changing financial conditions make it more difficult for online retailers to follow a penetration pricing strategy. Online retailers may also realize that competing in prices is not the best strategy for getting profits. They may have changed or given up their lowest price strategy, and started to establish their reputation and charge higher prices.

Our results show that brand name has a significant impact on prices, which is consistent with Brynjolfsson and Smith (2000) and Pan, Ratchford, and Shankar (2002, 2005). But retailers have to firmly establish their reputations before they can

¹² Further analysis can be carried out regarding the price difference between any pair of retailers, not necessarily of the same type. For example, the percentage difference (first week) in price between Djangos (the highest priced OBMCR) and Buy.com (the lowest priced Dotcom) is estimated to be $100[\exp(.0495 + .08666 + 0.00085 - (-.0495 - .06373 + 0.00168)) - 1] = 28.2\%$, indicating that price can vary across the retailers by as much as 28.2%.

¹³ We are grateful to two anonymous referees for raising this point.

¹⁴ Barsh, Crawford, and Grosso (2000) investigated online retailing during the fourth quarter of 1999. They found that most e-tailers lost money on every transaction. Amazon lost about \$7 per order on its non-book sales although its book sales earned about \$5 per order on average, while others experienced even higher losses per order.

enjoy high prices. For example, Bigstar.com charged the highest price on average in our sample, but lost customers and soon exited the market. In contrast, Amazon, the other Dotcom that charged a higher price than many other retailers, started making a profit in the year 2001, which shows that Amazon is comfortably enjoying its brand name. As the Internet markets mature, online retailers may no longer need to compete directly on prices as they have already successfully differentiated themselves. Retailers may also use loyalty programs that make customers less price sensitive, and hence charge higher prices. For example, customers may be asked to open an account for shopping online to reduce their transaction time for future shopping. Our results suggest that, although online markets may be very competitive, retailers still have opportunities to differentiate themselves, and hence charge higher prices and make economic profits.

Although the two types of retailers have different price levels and different price dispersions at the beginning of our study period, our results show that such differences decrease over time, implying that the two types of retailers may have similar pricing behavior in the long run. This is possibly due to the fact that, as the Internet market matures, online shoppers choose retailers more based on their reputations rather than their types, although at the beginning of online retailing, many shoppers might not trust Dotcoms. Thus, regardless of their types, surviving retailers in the Internet market may be forced to choose similar pricing strategies, which would eliminate the difference between the two types of retailers in the long run. Therefore, the persistent price dispersion may not arise only from possible differences in pricing policy between the two types of retailers. Limited search behavior, brand loyalty, advertising, and service quality may all contribute to the persistent price dispersion in the Internet markets. Our results show that retailers do charge different prices. But we have not assessed any embedded effect related to retailer name, such as trust, loyalty, and so on. Future study could test how these factors may influence retailers' pricing strategies.

Our results are based on the data collected in the Internet market from July 2000 to June 2001. One limitation is that some large multichannel DVD sellers, such as Barnes & Noble and Bestbuy were not

included in the data because they neither sold online nor participated in BizRate.com for rating and price comparison. The shopbot participation decision may endogenously affect the retailers' pricing strategies (Baye & Morgan, 2001). Thus, omitting them from the analysis may introduce some bias. Further studies should use data from a more comprehensive set of multichannel retailers. Another limitation of this study is that we investigate price dynamics in the DVD market only. Empirical studies in the literature have found different pricing behaviors in different online markets (see, e.g., Pan, Ratchford, & Shankar, 2004). It is important to assess the online market dynamics in different product categories and to test if the price trends that we find in this study appear also in the Internet markets for other products.

NOTES

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