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A Study of Pricing Evolution in the Online Toy Market

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ABSTRACT

We examine the pricing trends in the online toy markets based on a unique set of panel data collected across three years' span. The analysis was made through panel data regression models with error components and serial correlation, allowing comparisons of prices and price dispersions between the two types of online retailers as well as examinations of dynamics of prices and price dispersions. Our results indicate that both online branch of multi-channel retailers (OBMCRS) and dotcoms charge similar prices on average, and over time their prices move in tandem. Although the OBMCR retailers charge significantly different prices, the dotcoms do charge similar prices. Moreover, both retailer types demonstrate different magnitudes of price dispersion that move at different rates over time. Although the price dispersion of OBMCRS is higher than that of the dotcoms at the beginning, the gap narrows over time.

Keywords: e-commerce, online pricing strategies, online toy market, price dispersion, pricing trends

JEL Classification: L11, L81, L86

INTRODUCTION

The rapid development of online retailing has inspired a fast growing research interest in studying the online pricing behaviors (Ancarani & Shankar, 2004; Pan, *et al.*, 2004; Xing, *et al.*, 2006). Early studies in the literature mainly focused on comparing price levels and price dispersions between offline and online competitors (Bailey, 1998; Brynjolfsson & Smith, 2000), and among online retailers (Tang & Xing, 2001; Clemons, *et al.*, 2002). 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 price levels and price dispersions (Baylis & Perloff, 2002; Lee & Gosain, 2002; Baye, *et al.*, 2004a, 2004b; Xing, *et al.*, 2004, 2006; Gan *et al.*, 2007). This study adds to the literature a new research on the pricing behavior and dynamics in the online toy market, with a data set collected in two sections across three years (from late 2000 to early 2004). To our knowledge, this is the first systematic study of the online toy market from such a perspective.

Theoretical Background, Data Description and Summary Statistics

There are two types of online retailers: pure Internet retailer (hereafter Dotcom) and online branch of multi-channel retailer (hereafter OBMCR). Upon a superficial view that online search costs are in fact similar (basically close to zero) for these online retailers of either type, since consumers can obtain price information in online markets easily and inexpensively, online price dispersion should be small or could be expected to converge over some time, somehow. Indeed, 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. However, by showing the absence of symmetric pure-strategy equilibrium in which consumers search, Harrington (2001)

proved that Bakos's (1997) results either contained mathematical errors or they were based on an unjustifiable assumption (Harrington, 2001). Furthermore, mounting empirical evidence points to the existence of persistent pricing differences in online markets (Pan, *et al.*, 2004; Xing, *et al.*, 2006). Theoretically, Baye and Morgan (2001) and Chen and Hitt (2003) both showed that online price dispersion can be an equilibrium outcome of price competition in the Internet markets. Therefore price dispersion in online markets may be persistent.

In this study, we use a unique set of panel data, collected in the online toy market across three years' span, to examine trends in market prices. Our analyses are made through panel data regression models with error components and serial correlation, rather than mainly based on cross-sectional data in most of the earlier studies. Thus, not only can we compare the prices and price dispersions between the two types of online retailers, we can also explore the possibility of online price convergence and price dispersion changes in the Internet market for a relatively long term. The fact that multi-channel retailers may wish to coordinate prices across their different channels to prevent destructive competition among themselves can result in different pricing policies among different types of online retailers, thus persistent price differences may exist in online markets. But it is also possible that competition may drive the prices of OBMCRs and Dotcoms toward the same level in the long run. Therefore it is of a great interest to explore the dynamics of online pricing and to test if prices converge over time on the Internet.

Our analysis of online toy pricing is carried out based on two data sets. The first data set was collected from October 19, 2000 to April 1, 2001, weekly for 12 weeks. It consists of 8 retailers (4 OBMCRs and 4 Dotcoms) with 42 toy titles (20 best sellers and 22 randomly chosen), which gives a total of $8 \times 42 \times 12 = 4,032$ price observations. The second data set was collected from July 12, 2002 to January 23, 2004 for 35 collections. It covers 4 retailers (due

to data availability) and 53 toy titles, yielding a total of $4 \times 53 \times 35 = 7,420$ price observations. For the second data set, all collections were carried out bi-weekly except for the irregular gap between June 20 – August 22, 2003. We took care to have selected typical toy items of various varieties as representative as possible. Around half of the toy items were selected as an even mix of the top bestsellers among the retailers while the rest were chosen randomly. The selected retailers must meet the criteria of selling a general selection of toys online with their respective prices posted on their website. All raw data and more detailed analysis tables are available upon request. Table 1 and Table 2 present a summary of statistics for the first and second data set, respectively.

Table 1
 Statistics summary for data set 1 (Oct. 19, 2000 - April 1 2001) (8 retailers, 42 titles, and 12 time periods)

Posted Price									
Retailer	<u>All 42 Titles</u>			<u>20 Best Sellers</u>			<u>22 Random Titles</u>		
	Avg	StDev	Range	Avg	StDev	Range	Avg	StDev	Range
KBKids	19.07	16.83	92.00	21.32	14.76	75.00	17.03	18.31	92.00
Walmart	17.18	16.46	94.94	19.09	12.68	56.03	15.44	19.12	93.92
Kmart	17.85	15.65	95.00	18.89	11.08	56.00	16.90	18.84	94.00
ZanyBrainy	20.92	17.84	95.02	23.46	16.39	73.49	18.61	18.79	95.02
Amazon	18.48	17.02	92.00	20.00	14.55	72.00	17.09	18.91	90.00
EToys	18.74	17.88	95.00	21.11	15.85	65.00	16.59	19.31	94.99
Smarterkids	18.74	18.42	96.65	20.84	17.36	66.65	16.83	19.17	96.50
Nutty-Putty	20.29	18.50	95.00	23.19	17.01	65.00	17.66	19.42	94.00
OBMCR	19.06	17.97	97.00	21.28	16.25	72.00	17.04	19.18	96.50
Dotcom	18.75	16.76	97.00	20.69	13.98	76.05	16.99	18.78	97.00
Overall	18.91	17.37	97.00	20.99	15.15	77.00	17.02	18.97	97.00
Full Price									
KBKids	21.07	16.83	92.16	23.31	14.76	75.00	19.02	18.31	92.16
Walmart	19.10	16.46	95.14	21.01	12.68	56.23	17.36	19.12	94.12
Kmart	19.53	15.65	95.00	20.57	11.08	56.00	18.58	18.84	94.00
ZanyBrainy	23.02	17.84	95.02	25.56	16.39	73.49	20.71	18.79	95.02
Amazon	21.26	17.02	92.00	22.78	14.55	72.00	19.87	18.91	90.00

EToys	20.97	17.87	95.20	23.34	15.84	65.20	18.82	19.31	94.99
Smarterkids	20.74	18.41	97.32	22.84	17.35	67.32	18.83	19.16	96.50
Nutty-Putty	21.89	18.50	95.00	24.79	17.01	65.00	19.26	19.42	94.00
OBMCR	21.21	17.95	97.32	23.44	16.22	72.66	19.19	19.18	96.50
Dotcom	20.68	16.77	97.16	22.61	14.00	76.42	18.92	18.78	97.16
Overall	20.95	17.37	97.50	23.02	15.15	76.98	19.06	18.98	97.50

Notes: Posted price = Price listed on the website; Full price = Posted price + shipping cost (calculated as the average of various typical purchase baskets). Avg = average; StDev = Standard deviation; Range = Retailer's price range (Maximum price – minimum price).

Table 2

Statistics summary for data set 2 (July 12, 2002 – Jan. 23, 2004) (4 retailers, 53 titles, and 35 time periods)

Retailer	Posted Price			Full Price		
	Avg	StDev	Range	Avg	StDev	Range
Smarterkids	34.07	27.81	132.14	40.81	30.66	148.10
Amazon	26.63	20.04	96.83	32.43	20.48	99.24
Walmart	26.57	20.27	93.01	32.70	20.39	94.73
KBKids	29.91	20.51	97.00	35.73	20.67	104.47
Overall	29.30	22.60	134.74	35.42	23.70	148.29

Notes: Definition: Posted price = Price listed on the website. Full price = Posted price + shipping cost. Avg = average; StDev = Standard deviation; Range = Retailer price range (Maximum price – minimum price).

Tables 3 and 4 present the results from the analysis of variance (ANOVA) for the two data sets to identify factors that control the toy prices, which facilitates the econometric model building. The three main factors are clearly seen to be **title**, **retailer** and **date**.

Table 3

ANOVA for data set 1

Factor	Posted Price			Full Price		
	DF	F Value	Pr > F	DF	F Value	Pr > F
Title	41	10116.8	<.0001	41	10116.8	<.0001
Retailer	7	265.7	<.0001	7	276.6	<.0001
Date	11	12.4	<.0001	11	9.6	<.0001
Title*Retailer	287	42.6	<.0001	287	42.6	<.0001
Title*Date	451	1.1	0.0320	451	1.1	0.0320
Retailer*Date	77	6.1	<.0001	77	5.4	<.0001
R^2	0.9927			0.9927		

Note: DF = Degree of freedom

Table 4
ANOVA for data set 2

Factor	Posted Price			Full Price		
	DF	F Value	Pr > F	DF	F Value	Pr > F
Title	52	3292.46	<.0001	52	3421.53	<.0001
Retailer	3	1187.30	<.0001	3	1370.72	<.0001
Date	34	5.20	<.0001	34	5.00	<.0001
Title*Retailer	156	59.73	<.0001	156	78.14	<.0001
Title*Date	1768	1.19	<.0001	1768	0.99	0.5700
Retailer*Date	102	11.93	<.0001	102	16.94	<.0001
R^2	0.9725			0.9739		

Note: DF = Degree of freedom

Econometric Analysis of Toy Prices

Let y_{it} be the price or price dispersion for the i th cross section at t th time period, where subscript i is a combined index for toy titles and retailers when y_{it} represents the price, and a combined index for titles and retailer types when y_{it} represents the price dispersion. The explanatory variables X_k contain the variables that serve for necessary comparisons and the variables that serve for control purposes. To take the advantage of the panel feature of our data, we use the following panel data regression model for our formal analysis

$$y_{it} = \sum_{k=1}^K X_{itk} \beta_k + u_{it}, \quad i = 1, \dots, N; \quad t = 1, \dots, T$$

where N is the number of cross sections, T is the length of the time series for each cross section, and K is the number of exogenous or independent variables. For our first data set, $T = 12$ time periods, and $N = 42$ (number of titles) \times 8 (number of retailers) = 336 cross sections for the analysis of prices, whereas $N = 42$ (number of titles) \times 2 (type of retailers) = 84 cross

sections for the analysis of price dispersion. For our second data set, we have $T = 35$ and $N = 53 \times 4 = 212$ cross sections for the analysis of prices. Since the second data set contains only 4 retailers, analysis of price dispersion is not performed. The specification for the error structure u_{it} is flexible. It can be one and two-way fixed or random effects models, first-order autoregressive model with contemporaneous correlation, or mixed variance component moving average error process. We choose the popular two-way random effects model to analyze our data sets, which accounts for the unobserved cross-sectional-specific effects, the unobserved time-specific effects, and serial correlations (i.e., $u_{it} = \mu_i + \gamma_t + \varepsilon_{it}$). Generalized least squares (GLS) method is followed for model estimation (see, e.g., Baltagi, 2001 and Baltagi and Wu, 1999).

The primary concerns in our analyses are: (1) whether the OBMCRs and Dotcoms charge different prices, (2) whether the price dispersions are different between OBMCRs and Dotcomes, and (3) how the prices and price dispersions move with time.

Empirical results based on the first data set

In order to quantify the effect of retailers, we put retailer dummy in the model so that we can estimate the price difference between the OBMCRs and Dotcoms. To see the price movement over time, two time trend variables are included in the model: T_{OBMCR} , the time trend for the average price of OBMCRs, and T_{Dotcom} , the time trend for the average price of Dotcoms. To control for the toy item effects, we use the variable *ListPrice*. The possible manufacturer effects are also analyzed by classifying the manufacturers into three categories: *FisherPrice*, *Hasbro* and *Others*. It is also important to analyze the relationship between the price level and price dispersion. To this end, a price dispersion variable *SDPrice* is included

in the model, which is defined as the standard deviation of the prices of a given toy title for the retailers of the same type.

The analysis of toy prices based on the first data set is carried out initially using all the price observations, followed by the price observations corresponding to the best sellers, and then the price observations corresponding to the randomly selected titles. The analysis is further classified based on the posted prices and the full prices. In each case, the following four hypotheses are formally tested:

H_1 : OBMCRs and Dotcoms charge the same price,

H_2 : Prices of OBMCRs and Dotcoms change with time in the same manner,

H_3 : All the OBMCR retailers charge the same price,

H_4 : All the Dotcom retailers charge the same price.

Analysis of prices

Tables 5 and 6 summarize respectively the results based on the posted prices and the full prices. From the results, we can see that the test of H_1 is insignificant no matter whether the analysis is carried out based on the posted prices or full prices, or based on all titles, best sellers only, or random titles only. This shows that average prices of OBMCRs and Dotcoms are about the same. The test of hypothesis H_2 is insignificant when the analysis is done based on the posted prices, but significant when the analysis is carried out based on the full prices. The implications of these test results are discussed in details under the “analysis of price trends” section. The test of H_3 is significant in all analyses, showing that the OBMCR retailers have priced significantly differently. In contrast, the Dotcom retailers have charged similar prices as shown by the insignificance of the test of H_4 throughout.

Table 5
Analysis of posted prices based on data set 1

Variable	All Titles		Best Sellers		Random Titles				
	Par. Est.	<i>p</i> -value	Par. Est.	<i>p</i> -value	Par. Est.	<i>p</i> -value			
Intercept	1.6647	0.0284	2.9964	0.0141	-0.7582	0.3270			
KBKids	-1.1557	0.1827	-1.2372	0.3489	-0.7727	0.4011			
Walmart	-3.0518	0.0004	-3.4716	0.0086	-2.3612	0.0103			
KMart	-2.3811	0.0061	-3.6681	0.0055	-0.9022	0.3269			
ZanyBrainy	0.6926	0.4245	0.9048	0.4933	0.8087	0.3795			
Amazon	-1.8177	0.0346	-3.1931	0.0148	-0.5674	0.5326			
etoys	-1.5522	0.0712	-2.0771	0.1127	-1.0750	0.2372			
Smarterkids	-1.5535	0.0710	-2.3477	0.0731	-0.8314	0.3605			
T _{OBMCR}	-0.0406	0.0020	-0.0287	0.1062	-0.0299	0.1418			
T _{Dotcom}	-0.0332	0.0148	0.0129	0.5025	-0.0413	0.0444			
Fisher	0.3315	0.5280	0.6963	0.3743	0.2861	0.6172			
Hasbro	-0.3205	0.5663	-0.0890	0.9218	-0.8123	0.1492			
SDPrice	-0.3137	<.0001	-0.6339	<.0001	-0.1605	<.0001			
ListPrice	0.8761	<.0001	0.8198	<.0001	0.9523	<.0001			
BestSeller	-1.3209	0.0029							
R^2 $N \times T$	0.6004 336×12		0.5276 160×12		0.7575 176×12				
Testing Hypotheses	DF	χ^2 -Stat	<i>p</i> -value	DF	χ^2 -Stat	<i>p</i> -value	DF	χ^2 -Stat	<i>p</i> -value
H_1	1	0.30	0.5839	1	0.00	0.9571	1	0.16	0.6892
H_2	1	0.19	0.6629	1	2.65	0.1035	1	0.27	0.6033
H_3	3	21.93	0.0001	3	16.23	0.0010	3	12.18	0.0068
H_4	3	5.58	0.1339	3	6.45	0.0917	3	1.56	0.6685

Note: To avoid dummy variable trap, the retailer dummy Nutty-Putty is omitted, so that the prices of other retailers are compared with the price of Nutty-Putty. The manufacturer dummy “Others” is also omitted. The GLS method is used.

Table 6
Analysis of full prices based on data set 1

Variable	All Titles		Best Sellers		Random Titles	
	Par. Est.	<i>p</i> -value	Par. Est.	<i>p</i> -value	Par. Est.	<i>p</i> -value
Intercept	1.1643	0.1137	2.6491	0.0319	-0.8263	0.2401
KBKids	-0.0776	0.9256	-0.6094	0.6429	0.3783	0.6495
Walmart	-2.0471	0.0138	-2.9171	0.0265	-1.2835	0.1232
KMart	-1.6164	0.0519	-3.3535	0.0108	-0.0645	0.9382
ZanyBrainy	1.8774	0.0240	1.6393	0.2123	2.0664	0.0131
Amazon	-0.6377	0.4392	-2.0131	0.1224	0.6126	0.4558
etoys	-0.9222	0.2633	-1.4471	0.2667	-0.4450	0.5880

Smarterkids	-1.1568	0.1606	-1.9510	0.1343	-0.4348	0.5966			
T _{OBMCR}	-0.0329	0.0030	-0.0289	0.0989	-0.0395	0.0051			
T _{Dotcom}	0.0233	0.0447	0.0340	0.0737	0.0085	0.5563			
Fisher	0.1533	0.7606	0.7419	0.3414	-0.1053	0.8385			
Hasbro	-0.2859	0.5935	-0.0260	0.9770	-0.4929	0.3328			
SDPrice	-0.6872	<.0001	-0.6465	<.0001	-0.7168	<.0001			
ListPrice	0.8890	<.0001	0.8243	<.0001	0.9591	<.0001			
BestSeller	-0.6389	0.1327							
R^2 $N \times T$	0.6361 336×12		0.5301 160×12		0.8006 176×12				
Testing Hypotheses	DF	χ^2 -Stat	p -value	DF	χ^2 -Stat	p -value	DF	χ^2 -Stat	p -value
H_1	1	0.25	0.6167	1	0.00	0.9496	1	0.62	0.4303
H_2	1	12.41	0.0004	1	6.19	0.0129	1	5.64	0.0177
H_3	3	27.87	0.0001	3	18.81	0.0003	3	17.10	0.0007
H_4	3	2.22	0.5306	3	3.09	0.3761	3	2.22	0.5306

Note: To avoid dummy variable trap, the retailer dummy Nutty-Putty is omitted, so that the prices of other retailers are compared with the price of Nutty-Putty. The manufacturer dummy “Others” is also omitted. The GLS method is used.

Analysis of price trends

Some detailed comments on the time trends are as follows. Although the test of H_2 is insignificant from the analysis based on the posted prices, the coefficients of the two time-trend variables are significantly smaller than zero based on the analysis using all 42 titles. This means that average prices of OBMCRs and Dotcoms do change (reduce) with time in the same manner, so that their prices are kept at a similar level during the period of study. However, when the test is carried out based on the full prices, it becomes highly significant. In particular, the average full price of OBMCRs decreases significantly with time, but the average full price of Dotcoms increases significantly with time. The implication of this is that the Dotcoms have significantly increased their shipping cost over time. Further implication of this is that although the OBMCRs charge slightly higher than Dotcoms at the beginning of our study (shown by the coefficients of the retailer dummies), the gap may further diminish if the prices keep moving in this direction. To illustrate this idea, we calculate an estimate of

the difference in average prices of OBMCRs and Dotcoms in the beginning and ending periods, and they are shown to be \$0.2037 and \$0.1077, respectively.

From the results in Table 5, it is interesting to note that the variable *SDPrice* is highly significant in all the analyses and its estimated coefficient has a negative sign. This shows that the price level and the price dispersion are negatively correlated – a lower price level is associated with a higher price dispersion. Finally, as expected, for the price analysis to be done in a rigorous manner, it is rather important to control the title effect. To achieve this end, we use the *ListPrice* variable to control this effect, and the result is highly significant. We have also used title dummies (41 of them for the analysis using all the 42 titles) to control this effect and it gives a similar set of estimates. Clearly, if the two methods give similar estimation results, the use of a single *ListPrice* variable (in place of 41 dummy variables) is preferred. Another advantage of using a single *ListPrice* is that it allows testing of other effects in the form of dummy variables such as the manufacturer effects (*FisherPrice* and *Hashbro*), and the effect for the title type (*BestSeller*). The *BestSeller* effect is significant in the analysis we perform on posted prices. This shows that as compared to random titles, bestsellers tend to be associated with lower posted prices. The manufacturer effect is insignificant through out all the analyses.

Analysis of price dispersion

The results for the analysis of price dispersion are summarized in Table 7 using posted prices and Table 8 using full prices. Here the price dispersion is defined as the standard deviation of prices of a given item for a given retailer type. In this case, we concentrate on testing the following two hypotheses:

H_1 : OBMCRs and Dotcoms have the same magnitude of price dispersions,

H_2 : Price dispersions of OBMCRs and Dotcoms change with time in the same way.

From the results shown in Table 7, we can see that both hypotheses are highly significant in all the analyses, no matter whether it is based on the posted prices or full prices, or using all titles, or based on best sellers or random titles only. This means that OBMCRs and Dotcoms have different magnitudes of price dispersions, and that their price dispersions move with time at different rates.

Some details are as follows. From the coefficient of the retailer type dummy *OBMCR*, we see that it is significantly larger than zero, showing that the price dispersion of the OBMCRs is significantly larger than that of Dotcoms at the beginning period. Very interestingly, however, we observe from the coefficients of the two time-trend variables that this gap in price dispersion diminishes over time. To illustrate this conclusion, using the results from Table 7 with all titles, the estimated difference in price dispersions between OBMCR and Dotcom is \$1.1367 at the beginning period, and \$-0.0313 at the ending period. A similar pair of numbers based on full price show \$1.1647 and \$0.0637, respectively. We also see that bestsellers demonstrate a larger dispersion in both posted and full prices than random titles.

Table 7
Analysis of posted price dispersion based on data set 1

Variable	All Titles		Best Sellers		Random Titles				
	Par. Est.	<i>p</i> -value	Par. Est.	<i>p</i> -value	Par. Est.	<i>p</i> -value			
Intercept	-0.6508	0.0968	-1.4307	0.0157	0.4754	0.1503			
OBMCR	1.2535	0.0009	1.4443	0.0136	1.0800	0.0030			
T_{OBMCR}	0.0189	0.3789	0.0478	0.0618	-0.0070	0.7627			
T_{Dotcom}	0.1357	<.0001	0.1824	<.0001	0.0936	<.0001			
ListPrice	0.0735	<.0001	0.1191	<.0001	0.0330	0.0001			
BestSeller	0.7678	0.0350							
R^2 $N \times T$	0.1163 84×12		0.1949 40×12		0.0696 44×12				
Testing Hypotheses	DF	χ^2 -Stat	<i>p</i> -value	DF	χ^2 -Stat	<i>p</i> -value	DF	χ^2 -Stat	<i>p</i> -value
H_1	1	11.05	0.0009	1	6.13	0.0133	1	8.88	0.0029
H_2	1	42.32	<.0001	1	25.49	<.0001	1	17.58	<.0001

Table 8

Analysis of full price dispersion based on data set 1

Variable	All Titles			Best Sellers			Random Titles		
	Par. Est.	p -value		Par. Est.	p -value		Par. Est.	p -value	
Intercept	-0.6451	0.1057		-1.6380	0.0066		0.6348	0.0578	
OBMCR	1.2748	0.0006		1.5557	0.0067		1.0194	0.0040	
T_{OBMCR}	0.0124	0.5697		0.0425	0.0956		-0.0141	0.5513	
T_{Dotcom}	0.1225	<.0001		0.1732	<.0001		0.0773	0.0011	
ListPrice	0.0716	<.0001		0.1181	<.0001		0.0306	0.0002	
BestSeller	0.7337	0.0408							
R^2 $N \times T$	0.1095 84×12			0.1929 40×12			0.0594 44×12		
Testing Hypotheses	DF	χ^2 -Stat	p -value	DF	χ^2 -Stat	p -value	DF	χ^2 -Stat	p -value
H_1	1	11.79	0.0006	1	7.42	0.0065	1	8.34	0.0039
H_2	1	39.52	<.0001	1	25.74	<.0001	1	15.05	<.0001

Empirical results based on the second data set

As this data set contains only four retailers, it may not be very meaningful to compare the prices and the price dispersions between the OBMCRs and Dotcoms. Instead, we concentrate on the price differentials among the individual retailers and the price movement with time. To control the potential effect of the single irregular time interval (the two months gap between the 23rd and 24th collections), we put a time dummy T_{24} into the model which takes value 1 if an observation falls into period 24 or later, and otherwise 0. It turns out this effect is not really significant. One interesting aspect of this data is that the information on the *availability* of a given title at a certain time point is available. Its effect is built into the model in the forms of dummy variables where AV = available, OS = out of stock temporarily, and NA = not available. Another interesting aspect of the data is that it covers a much

longer time duration than the first data set (one and half years vs. 12 weeks). The hypotheses H_1 and H_2 in this case have the following meaning:

H_1 : All four retailers charge the same price,

H_2 : Prices of all four retailers change with time in the same manner.

From the results given in Table 9, we see that both hypotheses are strongly rejected, indicating that the average prices of the four retailers are different and that they change with time in different rates and directions. Most of the variables in the table are self explanatory. *Date* is the overall time trend, and $T_{\text{Smarterkids}}$, T_{Amazon} , and T_{Walmart} are the interactions of *Date* with retailer dummies *Smarterkids*, *Amazon*, and *Walmart*.

Some interesting observations are as follows. Based on the posted prices, Smarterkids charges the highest price and its price keeps increasing with time. Based on the full prices, even though the Smarterkids price is the second highest, its price still continues to increase with time. On the other hand, prices charged by Amazon.com tend to decrease over time, this applies to both posted and full prices. Walmart prices the lowest among the four retailers, irrespective of whether the posted or full prices are used. And, its price seems quite stable. This clearly indicates that Walmart is adopting the every-day-low-price pricing strategy (EDLP) since OBMCRS are more likely to offer discounts to clear their inventories given their larger warehouse capacity.

From our general observations, prices are significantly higher when titles are available than when they are shown to be unavailable on the website. Even when the titles are temporarily out of stock, their prices are also significantly higher than when they are unavailable. This is supported by a study (Dana, 2001) that argued some retailers use high prices as a signal for high availability so as to draw customers' traffic. Once again, the price is negatively related to the *SDPrice* variable in a highly significant way, showing that the higher the price

dispersion, the lower the price on average. The use of *ListPrice* variable to control the title effect makes the analyses and comparisons fairer.

Table 9
Analysis of toy prices based on data set 2

Variable	Posted Price		Full Price			
	Par. Est.	<i>p</i> -value	Par. Est.	<i>p</i> -value		
Intercept	5.1295	<.0001	8.0641	<.0001		
Smarterkids	0.3641	0.7354	-0.6769	0.5842		
Amazon	-1.2062	0.2622	-1.9569	0.1133		
Walmart	-3.2863	0.0023	-3.1056	0.0120		
Date	-0.0309	0.0124	-0.0757	<.0001		
T _{Smarterkids}	0.2285	<.0001	0.3372	<.0001		
T _{Amazon}	-0.1212	<.0001	-0.0804	<.0001		
T _{Walmart}	0.0051	0.7081	0.0134	0.3468		
AV	1.2425	<.0001	1.3542	<.0001		
OS	0.6048	0.0039	0.8963	<.0001		
SDPrice	-0.9213	<.0001	-0.9742	<.0001		
T ₂₄	0.1856	0.3188	0.3529	0.0687		
ListPrice	0.8227	<.0001	0.7909	<.0001		
R^2 $N \times T$	0.4457 212×35		0.4106 212×35			
Testing Hypotheses	DF	χ^2 -Stat	<i>p</i> -value	DF	χ^2 -Stat	<i>p</i> -value
H_1	3	14.01	0.0029	3	7.47	0.0587
H_2	3	600.36	<.0001	3	886.20	<.0001

Note: to avoid a dummy variable trap, the retailer dummy KBKids is omitted, so that the prices of other retailers are compared with the price of KBKids. The availability dummy NA is also omitted so that prices corresponding to AV and OS are compared with those associated with NA.

Concluding Remarks

Several studies have been carried out to compare the OBMCRS and dotcoms, with particular emphasis on their price levels, price dispersion, and the frequency of price changes. These studies have been performed on books (Brynjolfsson and Smith, 2000; Clay *et al.*, 2002), CDs (Brynjolfsson and Smith, 2000; Lee and Gosain, 2002), cars (Morton, *et al.*, 2001), DVDs and videos (Tang and Xing, 2001 & 2003), toys (Tang and Gan, 2004), grocery

(Gan *et al.*, 2007), and so on. Our study extends beyond the existing literatures by examining the dynamics of pricing across three years' time span. There are some interesting findings. First, the OBMCRS retailers charge very different prices whereas the dotcoms charge similar prices while both OBMCRS and dotcoms demonstrate different magnitudes of price dispersions. Second, price dispersions move with time at different rates -- specifically, OBMCRS exhibit higher price dispersion than the dotcoms at the beginning period but the gap narrows over time.

The average price levels between the OBMCRS and the dotcoms are found to have no statistically significant difference. This suggests that prices of both types of retailers converge due to reduced search costs among consumers and thus lower information asymmetries. Since the pricing strategies of OBMCRS are influenced by their market power in the bricks-and-mortar market, they are less likely to decrease their online prices as they view their online stores as substitutes and not complements to their bricks-and-mortar stores. Hence, given that smaller dotcoms observe and peg their online posted prices closer to the larger and more reputable OBMCRS in order to remain competitive, there is a lack of significant difference in price levels between the two retailers. In addition, the difference in the magnitudes of price dispersion between the OBMCRS and dotcoms can be explained by the different pricing strategies of the two types of retailers. The smaller price dispersion among the dotcoms suggests that price competition among this type of retailers is relatively more aggressive than within the OBMCRS. The more reputable OBMCRS, on the other hand, often compete on non-price features such as their goodwill and their good customer and delivery services. Some even provide better refund policies such as allowing their online customers to return products to the physical stores. Further, the larger OBMCRS carry with them rich experience of price discrimination from physical market to online market and thus are more adept at it

especially in the Internet age. All these account for the larger price dispersion among the OBMCRS.

From a managerial perspective, our results suggest that there is still room for both types of retailers to differentiate themselves and improve on their profitability using various pricing strategies. One of which is to focus on setting low prices only on certain high volume, high “visibility” products (such as bestsellers) that are critical to signal price image (Cox and Cox, 1990; Nagle and Novak, 1988). When competitors implement price increase on these products, instead of following the price increase, the management could initiate a price cut to strengthen their low price image (Dickson and Urbany, 1994). Another strategy might be the use of promotions. Walters and MacKenzie (1988) found that promotions increase store traffic, resulting in a favorable impact on store sales. The online toy stores can utilize promotions to a greater extent by engaging in aggressive promotions in areas where the customers are less price-sensitive and softer promotions in areas where customers are more price-sensitive (Hoch *et al.*, 1995). This can be carried out at ease on the Internet since online retailers are increasingly more adept at price discrimination in an information age such as today.

Moreover, both types of online retailers can also focus on the frequency of orders and the size of each order. Not only should they cater to customer demands that can be fulfilled effectively, but also that correspond to the bulk of customers’ purchases too. For instance, by providing more product information to customers, it will lead to improved product fit, reduced price sensitivity and hence, higher profit margins (Lynch and Ariely, 2000). In order to retain and further attract online customers, they can focus on other non-price strategies, examples of which are increasing product variety, providing better refund policies such as allowing online customers to return products to the physical stores, improving delivery ser-

vices, ensuring tighter online security, and creating trust to enhance their reputations – some of these can be implemented efficiently with the aid of the information technology. Despite the trusted reputations of OBMCRS and the fact that their financial and operational resources confer advantages upon them in the online market, pure dotcoms can still create niche markets by segmenting their markets and analyzing their customers' needs. It would be interesting to explore how both types of online stores can further obtain alternative sources of advantage through expanding their customer base as well as increasing their profit margins.

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REFERENCES

- Ancarani, F. & Shankar, V. (2004). Price Levels and Price Dispersion Within and Across Multiple Retailer Types: Further Evidence and Extension. *Journal of Academy of Marketing Science*, 32(2), 176-187.
- Bailey, J. P. (1998). Intermediation and Electronic Markets: Aggregation and Pricing in Internet Commerce. Ph.D. thesis, Technology, Management and Policy, Massachusetts Institute of Technology.
- Bakos, Y. (1997). Reducing Buyer Search Costs: Implications for Electronic Marketplaces. *Management Science* 43(12): 1676-92.
- Baltagi, B. H. (2001). *Econometric Analysis of Panel Data*, 2nd Ed. John Wiley & Sons.
- Baltagi, B. H., & Wu, P. X. (1999). Unequally Spaced Panel Data Regressions with AR(1) Disturbances. *Econometric Theory*, 15(6), 814-823.
- Baye, M. and Morgan, J. (2001). Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets. *American Economic Review*, 91 (3), 454-474.
- Baye, M., Morgan, J., & Scholten, P. (2004a). Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site, *Journal of Industrial Economics*, 52(4): 463-496.
- Baye, M., Morgan, J., & Scholten, P. (2004b). Persistent Price Dispersion in Online Markets, in Jansen, D. W. (Ed.), *The New Economy*, the University of Chicago Press, Chicago IL.
- Baylis, K., & Perloff, J.M. (2002). Price Dispersion on the Internet: Good Firms and Bad Firms. *Review of Industrial Organization*, 21(3): 305-324.
- Brynjolfsson, E., & Smith, M.D. (2000). Frictionless commerce? A Comparison of Internet and Conventional Retailers, *Management Science*, 46(4): 563-85.

- Chen, P. Y., & Hitt, L. (2003). Understanding Price Dispersion in Internet-Enabled Markets. Working Paper, The Wharton School of Business, University of Pennsylvania.
- Clay, K., Krishnan, R., & Wolff, E. (2002). Retail Strategies on the Web: Price and Non-price Competition in the Online Book Industry, *Journal of Industrial Economics*, 50 (3): 351-367.
- Clemons, E. K., Hann, I.-H., & Hitt, L. M. (2002). Price Dispersion and Differentiation in Online Travel: An Empirical Investigation. *Management Science*, 48(4): 534-549.
- Cox, A. D., & Cox, D. (1990). Competing on Price: The Role of Retail Price Advertisements in Shaping Store-Price Image. *Journal of Retailing*, 66(4): 428-45.
- Dana, J. D. Jr. (2001). Competition in Price and Availability when Availability is Unobservable. *Rand Journal of Economics*, 32: 497-513.
- Dickson, P. R., & Urbany, J. E. (1994). Retailer Reaction to Competitive Price Changes. *Journal of Retailing*, 70(1): 1-21.
- Gan, L., He, S., Huang, T., & J. Tan (2007). A Comparative Analysis of Online Grocery Pricing in Singapore. *Electronic Commerce Research and Applications* (forthcoming).
- Harrington, J.E., Jr. (2001). Comment on "Reducing Buyer Search Costs: Implications for Electronic Marketplaces". *Management Science*, 47(12): 1727-32.
- Hoch, S. J., Dreze, X., & Purk, M. (1994). The EDLP, Hi-Low and Margin Arithmetic. *Journal of Marketing*, 58(4): 16-27.
- Lee, Z., & Gosain, S. (2002). A Longitudinal price Comparison for Music CDs in Electronics and Brick-and-Mortar Markets: Pricing Strategies in Emergent Electronic Commerce. *Journal of Business Strategies*, 19(1): 55-71.
- Lynch, J. G. Jr., & Ariely, D. (2000). "Wine Online: Search Cost Affect Competition on Price, Quality and Distribution", *Marketing Science*, 19(1), 83-103.

- Morton, F. S., Zettelmeyer, F., & Silva-Risso, J. (2001). Internet Car Retailing, *Journal of Industrial Economics*, 49(4): 501-20.
- Nagle, T. T., & Novak, K. (1988). The Roles of Segmentation and Awareness in Explaining Variations in Price Markups, in DeVinney, T. (Ed.), *Issues in Pricing: Theory and Research*, Lexington Books, Lexington, MA.
- Pan, X., Ratchford, B.T., & Shankar, V. (2004). Price Dispersion on the Internet: A Review and Directions for Future Research, *Journal of Interactive Marketing*, 18(4), 116-135.
- Tang, F.-F., & Gan, L. (2004), Pricing Convergence between Dot.coms and Hybrids: Empirical Evidence from the Online Toy Market, *Journal of Targeting, Measurement and Analysis for Marketing*, 12(4), 340-352.:
- Tang, F.-F., & Xing, X. (2001). Will the Growth of Multi-Channel Retailing Diminish the Pricing Efficiency of the Web? *Journal of Retailing*, 77(3): 319-333.
- Tang, F.-F., & Xing, X. (2003). Pricing Differences between Dotcoms and Multi-Channel Retailers in the Online Video Market, *Journal of the Academy of Business and Economics*, available at http://www.findarticles.com/p/articles/mi_m0OGT/is_1_2/ai_113563641.
- Waters, R., & Mackenzie, S. B. (1998). A Structural Equation Analysis of the Impact of Price Promotions on Store Performance. *Journal of Marketing Research*, 25(1): 51-63.
- Xing, X., Tang, F.-F., & Yang Z. L. (2004). Pricing Dynamics in the Online Consumer Electronics Market. *Journal of Product and Brand Management*, 13(6): 429-441.
- Xing, X., Yang, Z. & Tang, F.-F. (2006). A Comparison of Time-Varying Online Price and Price Dispersion between Multichannel and Dotcom DVD Retailers. *Journal of Interactive Marketing*, 20(2), 3-20.