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A Study of Price Evolution in Online Toy Market

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Abstract We study and contrast pricing and price evolution of online only (Dotcom) and online branch of multi-channel retailers (OBMCRs) based on two panel data sets collected from online toy markets. Panel data regression analyses reveal several interesting empirical results: over time, OBMCRs and Dotcoms charge similar prices on average but Dotcoms significantly increase their shipping costs that eventually drive the overall average price of Dotcoms higher than that of OBMCRs. Price dispersions of both types of retailers are persistent. The price dispersion of OBMCRs is higher than that of Dotcoms at the beginning and does not change much over time, but the price dispersion of Dotcoms increases significantly over time, indicating that the latter will eventually be higher than the former. Moreover, the OBMCRs charge significantly different prices, but the Dotcoms charge similar prices.

JEL L11, L81, L86
Keywords E-commerce; online pricing strategies; online toy market; price dispersion; pricing trends

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1 Introduction

The rapid development of online retailing has inspired a fast growing research interest in studying the online pricing behaviors (Ancarani and 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 and Smith, 2000), and among online retailers (Tang and 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 and Perloff, 2002; Lee and Gosain, 2002; Baye et al., 2004a, 2004b; Xing et al., 2004, 2006; Gan et al., 2007). Our study adds to the literature a new research on the pricing behavior and dynamics in the online toy market based on two panel data sets collected over the span of three years (from October 2000 to January 2004). To our knowledge, this is the first systematic study of the online toy market from such a perspective.

In Section 2, we discuss the theoretical background related to the current research and propose the research questions relevant to this study. In Section 3, we give a simple description of the data, identify major factors that affect toy prices, and propose a formal econometric model to facilitate the price analysis. In Sections 4 and 5, we present the empirical results derived from the two data sets. In Section 6, we give some concluding remarks.

2 Theoretical Background and Research Questions

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 online retailers of either type since consumers can obtain price information in online markets easily and inexpensively, online price dispersion is expected to be small and that online prices of the two types of retailers could be expected to converge over some time, somehow. 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. Although Bakos' theory is supported by Smith (2001), and Smith and Brynjolfsson (2001), Harrington (2001) disputed Bakos's results by demonstrating the absence of symmetric pure-strategy equilibrium in which consumers search. Since then, mounting empirical evidence points to the existence of persistent pricing differences in online markets (Pan et al., 2004; Xing 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. Previous theoretical research suggested that price dispersion may be results of multiple channel operation (Pan et al., 2003b; Ancarani and Shankar, 2004), retailer heterogeneity (Smith and Brynjolfsson, 2001; Baylis and Perloff, 2002), brand, reputation, and trust (Brynjolfsson and Smith, 2000; Chen and Hitt, 2003), and random pricing strategies (Chen and Hitt, 2003, Ghose et al., 2007).

Indeed several studies have compared price dispersions between the online and offline markets. Numerous studies found offline price dispersion was higher than online price dispersion (Bailey, 1998; Brynjolfsson et al., 2000; Clay et al., 2002; Gan et al., 2007), while others showed the reverse trend was true (Morton et al., 2001; Brown and Goolsbee, 2002; Xing et al., 2004; Xing et al., 2006). Yet Scholten and Smith (2002) found no significant difference in price dispersion between the two markets.

In this study, we use a unique set of panel data to examine trends in toy prices. The data was collected from websites of online toy stores over a period of three years using search engines such as Yahoo! Our analyses are conducted using a panel data regression model, rather than employing cross-sectional data as in most of the earlier studies. Using a panel data regression model allows us to compare prices and price dispersions between the two types of online retailers in addition to exploring the possibility of online price convergence and its changes in price dispersion for a relatively long period of time. The fact that multi-channel retailers may wish to coordinate prices across their channels to prevent destructive competition among themselves can result in different pricing policies adopted by various 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 great interest to explore the dynamics of online pricing and to test if these prices converge over time.

These theoretical considerations lead naturally to the following research questions:

Q_1: Do OBMCRs and Dotcoms charge the same price?

Q_2: Do prices charged by OBMCRs and Dotcoms change over time in the same pattern?

Q_3: Are prices charged by OBMCRs homogeneous among them?

Q_4: Are prices charged by Dotcoms homogeneous among them?

Q_5: Do OBMCRs and Dotcoms have the same magnitude of price dispersions?

Q_6: Do price dispersions of OBMCRs and Dotcoms evolve in the same way?

The unique features of the data sets and the panel data regression approach (described in the next section) will allow us to examine these research questions empirically.

3 Data Description, Factor Identification and Econometric Model

3.1 Data Description

Our analysis of online toy pricing is carried out based on two data sets collected from websites of selected toy retailers. 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 $8\times42\times12$ = 4,032 price observations. Additional information about the data includes the brand name, list price for each title, and the date of collection.

The second data set was collected from July 12, 2002 to January 23, 2004 for 35 collections. Due to the unavailability and inconsistency of data throughout that period of time, it covers only 4 of the original 8 retailers from the first data set. The second data set involve 53 toy titles, yielding a total of 4×53×35 = 7,420 price observations. All collections were carried out bi-weekly except for the irregular gap between June 20–August 22, 2003.[1] Great care was taken to include a variety of typical toy items so as to make our sample 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. In addition to the information on the brand name, list price, and the date of collection from the first data set, this data set also contains the information on the 'availability' of the toy items, which may have an interesting effect on pricing.

The selected retailers must meet the criteria of selling a general selection of toys online with their respective prices posted on the companies' websites. All raw data and more detailed analysis tables are available from the authors upon request. Table 1 and Table 2 present a summary of statistics for the first and second data set, respectively.

Table 1 shows that toy prices vary significantly among the OBMCRs, but only a little among the Dotcoms, irrespective of prices (posted or full) being considered, or what titles (all, best sellers or random) being used. Price dispersion measured by standard deviation or range varies considerably from one retailer to another, in particularly if only the best sellers are involved. Retailers generally price best sellers significantly higher than random titles. The summary statistics do not show significant differences in price or price dispersion between OBMCRs and Dotcoms. Table 2 shows that both the price (posted or full) and price dispersion of the retailer called Smartkids are significantly higher than the other three. While those summary statistics are revealing, a formal investigation on the proposed research problems calls for a proper statistical model which captures all the potential price-affecting variables.

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[1] The irregular gap occurred during the transition period of hiring a new research assistant to collect the data.

Table 1: Statistics Summary for Data Set 1 (Oct. 19, 2000–April 1 2001)
(8 retailers, 42 titles, and 12 time periods)

Posted Price (in US$)									
Retailer	All 42 Titles			20 Best Sellers			22 Random Titles		
	Avg	StDev	Range	Avg	StDev	Range	Avg	StDev	Range
KBKids	19.07	16.83	2.99, 94.99	21.32	14.76	4.99, 79.99	17.03	18.31	2.99, 94.99
Walmart	17.18	16.46	3.94, 98.88	19.09	12.68	3.94, 59.97	15.44	19.12	4.96, 98.88
Kmart	17.85	15.65	3.99, 98.99	18.89	11.08	3.99, 59.99	16.90	18.84	4.99, 98.99
Zany-Brainy	20.92	17.84	4.97, 99.99	23.46	16.39	6.50, 79.99	18.61	18.79	4.97, 99.99
Amazon	18.48	17.02	2.99, 94.99	20.00	14.55	2.99, 74.99	17.09	18.91	4.99, 94.99
EToys	18.74	17.88	4.99, 99.99	21.11	15.85	4.99, 69.99	16.59	19.31	5.00, 99.99
Smarterkids	18.74	18.42	3.34, 99.99	20.84	17.36	3.34, 69.99	16.83	19.17	3.49, 99.99
Nutty-Putty	20.29	18.50	4.99, 99.99	23.19	17.01	4.99, 69.99	17.66	19.42	5.99, 99.99
OBMCR	19.06	17.97	2.99, 99.99	21.28	16.25	3.94, 79.99	17.04	19.18	2.99, 99.99
Dotcom	18.75	16.76	2.99, 99.99	20.69	13.98	2.99, 74.99	16.99	18.78	3.49, 99.99
Overall	18.91	17.37	2.99, 99.99	20.99	15.15	2.99, 79.99	17.02	18.97	2.99, 99.99
Full Price (in US$)									
KBKids	21.07	16.83	4.93, 97.09	23.31	14.76	6.93, 81.93	19.02	18.31	4.93, 97.09
Walmart	19.10	16.46	5.71, 100.85	21.01	12.68	5.71, 61.94	17.36	19.12	6.73, 100.85
Kmart	19.53	15.65	5.67, 100.67	20.57	11.08	5.57, 61.57	18.58	18.84	6.67, 100.67
Zany-Brainy	23.02	17.84	7.07, 102.09	25.56	16.39	8.60, 82.09	20.71	18.79	7.07, 102.09
Amazon	21.26	17.02	5.77, 97.77	22.78	14.55	5.77, 77.77	19.87	18.91	7.77, 97.77
EToys	20.97	17.87	7.12, 102.32	23.34	15.84	7.12, 72.32	18.82	19.31	7.33, 102.32
Smarter-kids	20.74	18.41	5.11, 102.43	22.84	17.35	5.11, 72.43	18.83	19.16	5.11, 72.43
Nutty-Putty	21.89	18.50	6.59, 101.59	24.79	17.01	6.59, 71.59	19.26	19.42	7.59, 101.59
OBMCR	21.21	17.95	4.93, 102.09	23.44	16.22	5.57, 82.09	19.19	19.18	4.93, 100.85
Dotcom	20.68	16.77	5.11,102.32	22.61	14.00	5.11, 77.77	18.92	18.78	5.11, 102.32
Overall	20.95	17.37	4.93, 102.32	23.02	15.15	5.11, 82.09	19.06	18.98	4.93, 102.32

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 in (minimum price, maximum 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 (in US$)			Full Price (in US$)		
	Avg	StDev	Range	Avg	StDev	Range
Smarterkids	34.07	27.81	5.59, 137.73	40.81	30.66	7.58, 155.68
Amazon	26.63	20.04	5.29, 102.12	32.43	20.48	8.99, 108.23
Walmart	26.57	20.27	6.95, 99.96	32.70	20.39	11.47, 106.20
KBKids	29.91	20.51	2.99, 99.99	35.73	20.67	7.39, 111.86
Overall	29.30	22.60	2.99, 137.73	35.42	23.70	7.39, 155.68

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

3.2 Factor identification

In order to examine the research questions listed previously in Section 2 using a panel data regression model, we need to identify the explanatory variables representing the potential factors that control the online toy prices. Apparently, the price of a toy varies across titles and retailers, and from one time period to another. This motivates us to run an analysis of variance (ANOVA) model for each of the two data sets with *Posted Price* or *Full Price* (posted price plus shipping cost) as the response and *title*, *retailer* and *date* as the three factors. The results are summarized in Tables 3 and 4. From the results we see that the three main effects and their two-way interactions together account for more than 99% of the total price variations for data set 1, and more than 97% for data set 2. Thus, our formal price analysis can be carried out using explanatory variables designed based on these three factors.

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

Having identified the three major factors affecting toy prices, our next questions are: how to quantity those factor effects, and what is the suitable econometric model we can base on so as to formally address the research questions proposed in Section 2? We first describe a general model in the following subsection, and subsequently in Sections 4 and 5, we apply it to the actual data upon which detailed definitions of the corresponding explanatory variables are given.

3.3 Econometric Models

Based on the nature of our data sets, we use a panel data regression model in this paper. 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. Let $\{ X_k , k = 1, . . . , K\}$ be the explanatory variable containing the variables that serve for necessary comparisons and the variables that serve for control purposes. The model takes the general form

$$y_{it} = \beta_0 + \sum_{k=1}^{K} X_{itk}\beta_k + u_{it}, \quad i = 1,\cdots,N; \;\; t = 1,\cdots,T \,, \tag{1}$$

where $u_{it} = \mu_i + \gamma_t + \varepsilon_{it}$, representing a two-way error components model with μ_i accounting for the unobservable cross-sectional effects that is not included in the model, γ_t capturing the unobservable time effects that is not included in the model,[2] and ε_{it} denoting the remainder stochastic disturbance. *N* is the number of cross sections (title and retailer combinations, or title and retailer-type combinations), *T* is the length of the time series for each cross section, *K* is the number of the explanatory variables, and the *β's* are the regression coefficients.

[2] In our context, μi may represent the "hidden" price policies of an individual retailer on a specific item and γt may represent the holiday effects, clearance of sales, etc.

In this paper, μi and γt are treated as random effects that give rise to the popular two-way random effects model3. More specifically, μi's are assumed to be independent and identically distributed (iid), so are the γt's and the εit's; the three error components (μi, γt and εit) are assumed to be independent of each other; and μi's and γt's are uncorrelated with the explanatory variables. We employ the generalized least squares (GLS) method for our model estimation (Baltagi, 2008), and the White's heteroscedasticity-corrected standard error for model inference (White, 1980).

4 Empirical Results Based on the First Data Set

The relatively rich structure of the first data set allows us to conduct a full analysis of price and price dispersion, and to answer the interesting research questions put forth in Section 2. As shown in Section 3.2 through an ANOVA model, the three factors *title*, *retailer*, and *date* and their two-way interactions explain more than 99% of the total price variation~~s~~, hence the construction of the explanatory variables is essentially based on these three factors.

4.1 Analysis of Prices

In order to quantify the effect of retailers, we put retailer dummy variables in the model so that we can estimate the price difference between the OBMCRs and Dotcoms and thus examine the first research question Q_1. For example, the dummy variable *Walmart* takes value 1 if the price observations correspond to the retailer Walmart, and otherwise 0. To see the price movement over time, two time trend variables, T_{OBMCR} and T_{Dotcom} are

[3] Ideally, one should conduct a Hausman test before deciding on using the random effects model rather than the fixed effects model (Hausman, 1978). However, given the nature of the data where many explanatory variables are time invariant and their effects cannot be estimated by the fixed effects method, the Hausman test cannot be applied (see, Wooldrige 2002, p. 286). Those time invariant explanatory variables are rather important in answering the research questions proposed earlier.

created such that T_{OBMCR} takes value $t = 1, \ldots, T$ corresponding to price observations from an OBMCR at time period t, and zero corresponding to price observations from a Dotcom. The time trend T_{Dotcom} is defined in a similar but converse way. Thus, the research question Q_2 can be examined by testing whether the coefficients of the two time trend variables are equal. Q_3 and Q_4 can be examined by testing the equality of the coefficients of either the four OBMCR retailer dummies, or the four Dotcom dummies. 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. Having defined these explanatory variables, the final model for the analysis of prices based on the first data set is defined specifically as follows:

$$\begin{aligned} Price = {} & \beta_0 + \beta_1\, KBKid + \beta_2\, Walmart + \beta_3\, KMart + \beta_4\, ZanyBriany \\ & + \beta_5\, Amazon + \beta_6\, etoys + \beta_7\, Smarterkids + \beta_8\, T_{OBMCR} + \beta_9\, T_{Dotcom} \\ & + \beta_{10}\, Fisher + \beta_{11}\, Hasbro + \beta_{12}\, SDPrice + \beta_{13}\, ListPrice \\ & + \beta_{14}\, BestSeller + errors, \end{aligned} \tag{2}$$

where *Price* may be the *Posted Price* or *Full Price*, and the last variable *BestSeller* is dropped when the analysis is concentrated on the best sellers or on the random titles. The retailer dummy variable *Nutty-Putty* is omitted to avoid the dummy variable trap, and for the same reason the manufacturer or brand dummy *Others* is also omitted.

The analysis of toy prices based on the first data set is carried out initially by fitting Model (2) using all the price observations, followed by the price observations on the best sellers, and then the price observations on the randomly selected titles, first using the *Posted Price* as the response and then the *Full Price*. In each situation, the following four hypotheses are formally tested corresponding to the first four research questions Q_1–Q_4:

H_1: OBMCRs and Dotcoms charge the same price at the beginning of the study[4],

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.

Tables 5 and 6 summarize respectively the results based on the posted prices and the full prices. The reported estimates are the two-way random effect estimates using the method of Fuller and Battese (1974). All the *p*-values are calculated based the White's (1980) heteroscedasticity-corrected standard errors.[5] 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 at the beginning period of our study. The test of hypothesis H_2 is insignificant when the analysis is done based on the posted prices (except for the best sellers where H_2 is significant at only 10% level), but significant when the analysis is carried out based on the full prices. The implications of these test results will be discussed in details under the "analysis of price trends" section. The test of H_3 is highly significant in all analyses, showing that the OBMCR retailers have priced significantly differently. In contrast, the Dotcom retailers have charged quite similar full prices as shown by the insignificance of the test of H_4 in Table 6, and slightly different posted prices for the categories of all titles and best sellers.

4 The formal definition of H_1 is as follows: The average of the coefficients of the four OBMCR dummies equals to the average of the coefficients of the four Dotcom dummies. Other hypotheses are defined similarly.

5 The estimate of the variance component for cross sections is big for all models fitted and Breusch and Pagan (1980) test for cross section random effect is highly significant. However, the estimate of the variance component for the time series is small or close to zero for all models fitted, showing that after controlling for the time trend, the 'left-over' timewise price variation is small.

Table 5: Analysis of Posted Prices Based on Data Set 1

Variable	All Titles Par. Est.	All Titles *p*-value	Best Sellers Par. Est.	Best Sellers *p*-value	Random Titles Par. Est.	Random Titles *p*-value
Intercept	1.6619	0.0137	2.9964	0.0293	-0.7583	0.2352
KBKids	-1.1562	0.1678	-1.2372	0.3599	-0.7727	0.3658
Walmart	-3.0522	<.0001	-3.4716	<.0001	-2.3612	<.0001
Kmart	-2.3816	<.0001	-3.6681	<.0001	-0.9022	0.0773
ZanyBrainy	0.6922	0.2214	0.9048	0.3722	0.8087	0.1559
Amazon	-1.8177	0.0107	-3.1931	0.0120	-0.5674	0.3657
Etoys	-1.5522	0.0349	-2.0771	0.0741	-1.0750	0.1821
Smarterkids	-1.5535	0.1306	-2.3477	0.1001	-0.8314	0.4890
T_{OBMCR}	-0.0406	0.0005	-0.0287	0.0565	-0.0299	0.0814
T_{Dotcom}	-0.0333	0.0856	0.0129	0.5192	-0.0414	0.1299
Fisher	0.3330	0.5257	0.6963	0.4574	0.2861	0.4964
Hasbro	-0.3189	0.5618	-0.0890	0.9230	-0.8123	0.1578
SDPrice	-0.3133	<.0001	-0.6339	<.0001	-0.1605	0.0078
ListPrice	0.8762	<.0001	0.8198	<.0001	0.9523	<.0001
BestSeller	-1.3218	0.0056				
R^2	0.6003		0.5276		0.7575	
$N \times T$	336×12		160×12		176×12	

Testing Hypotheses	All Titles DF	All Titles X^2-Stat	All Titles *p*-value	Best Sellers DF	Best Sellers X^2-Stat	Best Sellers *p*-value	Random Titles DF	Random Titles X^2-Stat	Random Titles *p*-value
H_1	1	0.31	0.5748	1	0.00	0.9568	1	0.16	0.6925
H_2	1	0.16	0.6868	1	2.85	0.0914	1	0.23	0.6300
H_3	3	44.11	<.0001	3	27.44	<.0001	3	30.20	<.0001
H_4	3	9.84	0.0200	3	8.45	0.0375	3	2.34	0.5040

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. For the same reason, the manufacturer dummy *Others* is also omitted. The reported estimates are the two-way random effect estimates using the method of Fuller and Battese (1974). All the *p*-values are calculated based on White's (1980) heteroscedasticity-corrected standard errors.

Table 6: Analysis of Full Prices 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	1.1649	0.0996	2.6491	0.0615	-0.8263	0.1978
KBKids	-0.0777	0.9300	-0.6094	0.6513	0.3783	0.6808
Walmart	-2.0471	0.0003	-2.9171	0.0009	-1.2835	0.0330
Kmart	-1.6164	0.0046	-3.3535	0.0002	-0.0645	0.9123
ZanyBrainy	1.8774	0.0035	1.6393	0.1088	2.0664	0.0017
Amazon	-0.6377	0.3996	-2.0131	0.1162	0.6126	0.3561
Etoys	-0.9222	0.2124	-1.4471	0.2001	-0.4450	0.5604
Smarterkids	-1.1568	0.2160	-1.9510	0.1576	-0.4348	0.6651
T_{OBMCR}	-0.0329	0.0006	-0.0289	0.0545	-0.0395	0.0016
T_{Dotcom}	0.0233	0.1544	0.0340	0.0803	0.0085	0.7158
Fisher	0.1531	0.7699	0.7419	0.4281	-0.1053	0.7917
Hasbro	-0.2861	0.5887	-0.0260	0.9773	-0.4929	0.3327
SDPrice	-0.6872	<.0001	-0.6465	<.0001	-0.7168	<.0001
ListPrice	0.8890	<.0001	0.8243	<.0001	0.9591	<.0001
BestSeller	-0.6387	0.1602				
R^2	0.6361		0.5301		0.8006	
$N \times T$	336×12		160×12		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	0.22	0.6393	1	0.00	0.9495	1	0.45	0.5013
H_2	1	9.35	0.0022	1	6.72	0.0095	1	3.16	0.0757
H_3	3	51.34	<.0001	3	30.17	<.0001	3	37.75	<.0001
H_4	3	2.60	0.4573	3	4.16	0.2442	3	2.09	0.5338

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. For the same reason, the manufacturer dummy *Others* is also omitted. The reported estimates are the two-way random effect estimates using the method of Fuller and Battese (1974). All the *p*-values are calculated based on White's (1980) heteroscedasticity-corrected standard errors.

4.2 Analysis of Price Trends

Based on the results of Tables 5 and 6, some detailed analyses on the time trends are as follows. Although the test of H_2 is insignificant from the analysis based on the posted prices (Table 5), the coefficients of the two time-trend variables are both 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 but in the same pattern, so that their prices are kept at a similar level during the period under study. To illustrate, we calculate the estimates of the difference in average prices of OBMCRs and Dotcoms at the beginning and ending periods (based on the coefficients of the 8 retailer dummies and the two time trend variables), and they are shown to be \$0.3273 and \$0.2459, respectively.

However, when the test of H_2 is carried out based on the full prices (Table 6), it becomes very significant. In particular, the average full price of OBMCRs decreases significantly with time, but the average full price of Dotcoms increases significantly with time. This is because 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, the gap diminishes and the OBMCRs will end up charging less than the Dotcomes if prices keep moving in this direction. To show this idea, we calculate the estimates of the difference in average prices of OBMCRs and Dotcoms at the 1st and 12th periods, and they are shown to be \$0.1571 and –\$0.4611, respectively.

From the results in Tables 5 and 6, 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 higher price dispersion. Finally, for the price analysis to be conducted in a rigorous manner, it is 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 involving all the 42 titles) to control this effect and it gives a similar set of estimates. Clearly, if the two methods yield 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 *Hasbro*), 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 throughout all the analyses.

4.3 Analysis of Price Dispersion

The research questions Q_5 and Q_6 can be examined by fitting a similar panel model~~,~~ to the price dispersion, *SDPrice*, which can then be defined based on Model 1 as follows:

$$SDPrice = \beta_0 + \beta_1\ OBMCR + \beta_2\ T_{OBMCR} + \beta_3\ T_{Dotcom} + \beta_4\ ListPrice + \beta_5\ BestSeller + errors \qquad (3)$$

where *OBMCR* is a dummy variable for the retailer type OBMCR, and the last variable *BestSeller* is dropped when the analysis is concentrated on the best sellers or on the random titles.

The results from running Model (3) 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 corresponding to research questions Q_5 and Q_6:

H_5: OBMCRs and Dotcoms have the same magnitude of price dispersions,

H_6: Price dispersions of OBMCRs and Dotcoms change with time in the same way.

From the results shown in Tables 7 and 8, 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 of our study. 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 disp7ersions between OBMCR and Dotcom is \$1.1367 at the beginning period, and –\$0.1481 at the ending period. A similar pair of numbers based on full price show \$1.1647 and –\$0.0464, respectively. Furthermore, we observe 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.		*p*-value	Par. Est.		*p*-value	Par. Est.		*p*-value
Intercept	-0.6508		0.0582	-1.4307		0.0249	0.4754		0.0819
OBMCR	1.2535		0.0011	1.4443		0.0157	1.0800		0.0047
T_{OBMCR}	0.0189		0.3335	0.0478		0.0347	-0.0070		0.7315
T_{Dotcom}	0.1357		<.0001	0.1824		<.0001	0.0936		0.0025
ListPrice	0.0735		0.0002	0.1191		<.0001	0.0330		0.1163
BestSeller	0.7678		0.0611						
R^2	0.1163			0.1949			0.0696		
$N \times T$	84×12			40×12			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	10.74	0.0010	1	5.88	0.0153	1	8.07	0.0045
H_2	1	36.88	<.0001	1	24.28	<.0001	1	13.73	<.0002

Note: The reported estimates are the two-way random effect estimates using the method of Fuller and Battese (1974). All the *p*-values are calculated based on White's (1980) heteroscedasticity-corrected standard errors.

Table 8: Analysis of Full Price Dispersion Based on Data Set 1

Variable	All Titles Par. Est.	All Titles *p*-value	Best Sellers Par. Est.	Best Sellers *p*-value	Random Titles Par. Est.	Random Titles *p*-value
Intercept	-0.6451	0.0693	-1.6380	0.0107	0.6348	0.0280
OBMCR	1.2748	0.0008	1.5557	0.0080	1.0194	0.0077
T_{OBMCR}	0.0124	0.5384	0.0425	0.0660	-0.0141	0.5014
T_{Dotcom}	0.1225	<.0001	0.1732	<.0001	0.0773	0.0146
ListPrice	0.0716	0.0004	0.1181	<.0001	0.0306	0.1551
BestSeller	0.7337	0.0721				
R^2	0.1095		0.1929		0.0594	
$N \times T$	84×12		40×12		44×12	

Testing Hypotheses	All Titles DF	All Titles χ^2-Stat	All Titles *p*-value	Best Sellers DF	Best Sellers χ^2-Stat	Best Sellers *p*-value	Random Titles DF	Random Titles χ^2-Stat	Random Titles *p*-value
H_1	1	11.24	0.0008	1	7.10	0.0077	1	7.16	0.0074
H_2	1	34.12	<.0001	1	24.42	<.0001	1	11.60	<.0007

Note: The reported estimates are the two-way random effect estimates using the method of Fuller and Battese (1974). All the *p*-values are calculated based on White's (1980) heteroscedasticity-corrected standard errors.

5 Empirical Results Based on the Second Data Set

The second data set contains fewer retailers than the first (4 vs 8), but it contains more titles (53 vs 42) and, more interestingly, it covers a much longer time duration (35 collections bi-weekly vs 12 collections weekly), which allows us to analyze the price evolution more comprehensively. Another interesting aspect of this data is that the information on the *availability* of a given title at a particular point in time is available. The smaller number of retailers in this data set makes comparing prices and price dispersions between OBMCRs and Dotcoms less meaningful. Instead, we concentrate on price differentials among individual retailers and the price movement with time. These studies address issues relating to the first two research questions put forth in Section 2, with the detailed hypotheses of the following forms:

H_1: All four retailers charge the same price,

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

The set of explanatory variables are constructed in a similar manner as in the analysis of the first data set. 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. The effect of the *availability* factor is built into the model in the forms of dummy variables where AV = available, OS = out of stock temporarily, and NA = not available. Four time-trend variables are included in the model: *Date,* $T_{Smarterkids}$, T_{Amazon}, and $T_{Walmart}$, which are, respectively, the overall time trend, and the interactions of *Date* with retailer dummies *Smarterkids*, *Amazon*, and *Walmart*. The final model for the analysis of price for Data Set 2 is defined as follows:

$$\begin{aligned} Price = {} & \beta_0 + \beta_1\, Walmart + \beta_2\, Amazon + \beta_3\, Smarterkids + \beta_4\, Date \\ & + \beta_5\, T_{Smarterkids} + \beta_6\, T_{Amazon} + \beta_7\, T_{Walmart} + \beta_8\, AV + \beta_9\, OS + \beta_{10}\, T_{24} \\ & + \beta_{11}\, SDPrice + \beta_{12}\, ListPrice + errors, \end{aligned} \tag{4}$$

where *Price* may be the *Posted Price* or *Full Price*, and the last variable *BestSeller* is dropped when the analysis is concentrated on the best sellers or on the random titles.

From the results given in Table 9, we see that both hypotheses are strongly rejected, indicating that average prices of the four retailers are different and that they change with time in different rates and directions. The variables and their results presented in the table are mostly self explanatory.

Table 9: Analysis of Toy Prices Based on Data Set 2

Variable	Posted Price		Full Price	
	Par. Est.	*p*-value	Par. Est.	*p*-value
Intercept	5.1295	<.0001	8.0641	<.0001
Smarterkids	0.3641	0.7521	-0.6769	0.6167
Amazon	-1.2062	0.2945	-1.9569	0.1338
Walmart	-3.2863	0.0009	-3.1056	0.0046
Date	-0.0309	0.0193	-0.0758	<.0001
$T_{Smarterkids}$	0.2285	<.0001	0.3372	<.0001
T_{Amazon}	-0.1212	<.0001	-0.0804	<.0001
$T_{Walmart}$	0.0051	0.7332	0.0134	0.3493
AV	1.2425	<.0001	1.3542	<.0001
OS	0.6048	0.0070	0.8963	<.0001
SDPrice	-0.9213	<.0001	-0.9742	<.0001
T_{24}	0.1856	0.2864	0.3529	0.0507
ListPrice	0.8227	<.0001	0.7909	<.0001
R^2	0.4457		0.4106	
$N \times T$	212×35		212×35	

Testing Hypotheses	DF	χ^2-Stat	*p*-value	DF	χ^2-Stat	*p*-value
H_1	3	16.73	0.0008	3	9.02	0.0290
H_2	3	387.80	<.0001	3	579.69	<.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*. The reported estimates are the two-way random effect estimates using the method of Fuller and Battese (1974). All the *p*-values are calculated based on White's (1980) heteroscedasticity-corrected standard errors.

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 price of Smarterkids is the second highest, its price still continues to increase with time. On the other hand, prices charged by Amzon.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.

6 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 (Bailey, 1998; Brynjolfsson and Smith, 2000; Clay et al., 2002), CDs (Bailey, 1998; Brynjolfsson and Smith, 2000; Lee and Gosain, 2002, Pan et al., 2003a), DVDs (Pan et al., 2003a; Ratchford et al., 2003; Xing et al., 2006), videos (Tang and Xing, 2003), electronics (Baye et al., 2004a, 2004b; Xing et al., 2004), cars (Morton et al., 2001), toys (Tang and Gan, 2004), grocery (Scholten and Smith, 2002; Gan et al., 2007), and so on. Based on these literatures and for simplicity, our study uses posted price as well as full prices (i.e., posted price plus shipping cost, similar to price paid at "check out", as though a transaction has taken place) for measuring price dispersion. There have been interesting studies conducted recently based on the use of actual transaction prices to estimate price dispersion (Ghose and Yao, 2011; Sengupta, 2007), such prices can certainly be considered in the extension of our study.

Our present 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 charge very different prices whereas the Dotcoms charge similar prices while both OBMCRs and Dotcoms demonstrate different magnitudes of price dispersions. Second, price dispersions by each retailer type move at different rates with time -- specifically, OBMCRs exhibit higher price dispersion than the Dotcoms at the beginning period but the gap between them narrows over time.

The average price levels between the OBMCRs and the Dotcoms are found to have no statistically significant difference. This is consistent with an earlier study in grocery (Gan, *et. al.*, 2007). It 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 types of 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. Other factors that can contribute towards price differentials and price dispersions between the two types of retailers are greater convenience, wider product selection (Brynjolfsson et al., 2003), and availability from online channels (Ghose et al., 2006; Forman et al., 2009).

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., 1994). 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 corresponds to the bulk of customers' purchases too. For instance, by providing a wider product selection (Forman et al., 2009) as well as 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 services, 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 expand their customer base as well as increase their profit margins by obtaining alternative sources of advantages.

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