The Impact of Positive vs. Negative Online Buzz on Retail Prices

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Hyun S. Shin[1]

Dominique M. Hanssens[2]

Bharath Gajula[3]

Abstract

Online buzz or electronic word-of-mouth (e-WOM) has become more influential on customer decision-making due to increasing product complexity and product availability over the internet. Moreover, e-WOM spreads rapidly among customers and can be accessed anytime and anywhere, which further increases its significance. These e-WOM conversations describe products in a positive, negative or neutral way, but we do not know if and how such customer perceptions influence important business outcomes such as retail prices.

This paper examines the effect of e-WOM on the prices of digital music players. Using a cutting-edge web crawling technique, we obtain the relevant buzz information collected from diverse online documents on a daily basis for two months. In particular, we capture online buzz sentiment, which allows us to investigate the different implications of positive, neutral, and negative online conversations. Econometric time-series modeling reveals that positive online buzz is a leading indicator of price increases, and vice versa. Furthermore, the effect of online buzz sentiment on prices is moderated by purchase involvement: negative online buzz leads to price cuts for high-ticket items, whereas positive online buzz enables price increases for low-priced items. These findings establish the influence of online buzz sentiment on e-retailers' pricing power, and suggest that managers should frequently monitor the sentiment of online buzz around their products and respond appropriately by adjusting their prices promptly.

[1]College of Management, Long Island University, NY 11548, hyun.shin@liu.edu.

[2] UCLA Anderson School of Management, Los Angeles, CA 90095, dominique.hanssens@anderson.ucla.edu.

[3] Mango Analytics Inc., CA 94022, bharath@mangoanalytics.com.

"Consumers are highly influenced by the experience of other consumers- far more than they are by marketing professionals." By John Lazarchic, Petco Vice President of e-Commerce

1. Introduction

It is widely accepted that quality is a principal driver of the success of new products (Tellis and Johnson 2007). Quality often refers to the actual performance or technical superiority of a product, which can be quantified as a function of the value of key attributes (e.g., the size, weight, and battery time of MP3 players). These attributes may interact with each other, and have non-linear, multiplicative effects on the overall perceived quality or value of a product (Meyer and Johnson 1995). Therefore, quality assessment is inherently a complex task for customers.

The complexity of quality assessment for high-tech products rapidly increases as manufacturers keep adding new features or attributes in order to differentiate themselves from their competitors (Barwise 2004). As a result, confused customers experience difficulty in evaluating the overall quality of a product, especially when they compare relatively complex durable goods in a less familiar category (e.g., Smart phones, MP3 players). Accordingly, customers may engage in additional information search (Dowling and Staelin 1994). However, the marginal benefit from acquiring attributes-relevant information provided by manufacturers is limited when it is difficult for customers to anticipate the consequence of these attributes. To make a choice in such an uncertain situation, customers may depend more on the peripheral route (Petty et al. 1983) or heuristic processing (Chaiken 1980). In this situation, *the subjective quality assessment of other fellow customers based on their individual usage experience or perception* may play an important role, which is called word-of-mouth in the marketing literature.

The importance of word-of-mouth or WOM on customer decision making has been emphasized in previous research (e.g., Arndt 1968, Richins 1983). WOM is known to be more

influential than advertising (Berry and Keller 2003), information provided by marketers (Alreck and Settle 1995), and professional advice by experts (Guernsey 2000). For example, more than half of buyers regard customer-generated reviews more valuable than experts' advice (Piller 1999).

More recently, the internet has become a medium through which customer-generated product quality information is spread rapidly among customers. Moreover, digitized customer feedback information, i.e., electronic WOM or e-WOM, can be accessed anytime and anywhere, which further increases its influence among customers (Dellarocas 2003). Researchers suggest that e-WOM has a strong impact on customer behavior (for a review, see Schindler and Bickart 2004). In practice, firms actively participate in distributing e-WOM via the internet. For example, by including customer feedback information in a promotional email, Petco Animal Supplies Inc. achieved a click-through rate five times higher than the usual rate, while Bath & Body Works increased its sales per customer by 11.5% (Wagner 2008).

In addition to personal emailing, e-WOM is distributed through diverse media such as blogs, chat rooms, online customer reviews, and online forums (Schindler and Bickart 2004). Among them, online customer reviews and online forums are regarded as more powerful because of their high referability[4] (Boush and Kahle 2001) and perceived credibility (Bickart and Schindler 2001). For example, 50% of young internet users consult online customer reviews before buying CDs, DVDs, games or movies (Forrester Research 2000). Positive conversations in online forums lead to higher ratings of TV shows aired on major networks (Godes and Mayzlin 2004). Accordingly, online customer reviews and online forums have been studied extensively by researchers in order to analyze the impacts of e-WOM on consumer behavior and

[4] Referability is defined as the degree to which information can be easily accessed by a large number of people (Boush and Kahle 2001).

firm strategy (e.g., Chen and Xie 2005, Zhu and Zhang 2007, Chen and Xie 2008, Dellarocas and Wood 2008).

Online customers can easily collect information from multiple sources or media at the same time because all the information is just a 'click-away'. Due to limits in data collection, however, prior empirical research has emphasized the effect of e-WOM only within a specific medium (e.g., online product reviews at Amazon.com, or online forums in the case of TV shows). This implicitly assumes that communication outside the chosen medium does not matter, or that the digitized online buzz[5] collected within the medium is able to represent the overall e-WOM occurring across online media. Thus, it would be desirable to collect online buzz data from multiple sources for a better representation of e-WOM.

Moreover, the richness of textual information has received very little attention from researchers. Practitioners are already well aware that customers respond to more descriptive, elaborated reviews (Wagner 2008). In addition, customers may react differently to positive vs. negative opinions. Due to the difficulty in data collection, prior research has focused instead on analyzing the impact of e-WOM by using average measures such as online customer product ratings, leaving the qualitative aspect (e.g., how customers perceive or feel about a product) unexplored. This approach, however, is subject to an important limitation. Let's assume that a consumer compares two products, A and B, and that Product A received two "5 out of 5" ratings and two "1 out of 5" scores, while Product B obtained four "3 out of 5" ratings. Even though their average ratings are the same, these products may differ in terms of quality perception and customer response. To address this issue, some researchers used complementary measures such as the dispersion of opinions (Godes and Mayzlin 2004) and the volume of customer reviews (Liu 2006, Duan et al. 2005). However, it is better to extract consumer perceptions about a

[5] In this paper, we use the terms, 'online buzz' and 'e-WOM', interchangeably.

product directly from online texts and examine the impacts of such perceptions on business outcomes.

e-WOM information is particularly relevant for e-retailers as they decide which products to carry, how to price their products, and how to adjust prices in light of the product popularity or customer feedback (Dellarocas 2003). Thus, *collecting qualitative e-WOM data across diverse media and analyzing the response of e-retailers to online buzz* are imperative for modern marketing strategy. In this paper, we examine the effect of e-WOM or online buzz on e-retailers' pricing power. In particular, we use online buzz data on digital music players collected from diverse online documents through a powerful web crawling technique. These data capture the sentiment of online buzz, enabling us to investigate the different implications of positive, neutral, and negative online buzz. Finally, the dataset is collected "live" on a daily basis for two months (June 2nd, 2007~August 1st, 2007), allowing us to analyze daily price adjustments by e-retailers as they experience the consequences of positive vs. negative online buzz. As such, the data provide a unique opportunity to examine the dynamics of product prices and online buzz sentiment. To our knowledge, this paper represents the first attempt at such an analysis in the literature.

In the next section, we review previous research regarding online retailing and e-WOM. In the third section, we explain the data, model, and empirical results. Finally, we provide a summary of findings and associated managerial implications. We also discuss contributions and limitations of this research and suggest directions for future study.

2. Background

2.1 Price Competition among e-retailers

In the late 1990's, economists expected that the advent of the internet would reduce customer search and entry costs, resulting in intense competition among e-retailers (for a review, see Bakos 2001). Accordingly, they predicted: 1) overall, prices would be lower in the e-Marketplace than in the offline stores, 2) product prices would converge in the e-Marketplace, and 3) e-retailers would charge prices at their marginal costs. However, these predictions of 'frictionless commerce' turned out to be wrong (Ellison and Ellison 2005).

Overall price: Examining 107 book titles, Clay et al. (2002) find that average prices are similar between online and offline stores. They also find that total prices are lower in offline stores when shipping costs and sales taxes are considered.

Price dispersion: Empirical evidence suggests that substantial price dispersion exists online for relatively inexpensive product categories such as books and CDs (Brynjolfsson and Smith 2000, Clay et al. 2002), as well as for relatively expensive ones such as electronics (Baye et al. 2004a). In addition, researchers report that price dispersion increases over time (Chevalier and Goolsbee 2003, Baye et al. 2004a).

Price premium: Contrary to economists' expectations, empirical evidence shows that e-retailers are able to charge price premiums. For example, Amazon.com charges 5% higher prices than BarnesandNobles.com and 11% higher than Borders.com (Clay et al. 2002). Demand at Amazon.com is inelastic (-0.5) while BarnesandNobles.com's demand is highly elastic (-4) (Chevalier and Goolsbee 2003). These findings imply that e-retailers can charge price premiums by differentiating themselves in terms of service quality, brand, and customer trust (Bakos 2001,

Brynjolffson and Smith 2001), and that customers are willing to pay premiums to reduce their perceived risk (Rao and Monroe 1996).

Strategic pricing by e-retailers: Since the menu cost (i.e., the cost of changing prices) is ignorable online, e-retailers are expected to monitor their rivals' prices and adjust their own prices frequently (Bailey 1998), and with smaller increments (Brynjolfsson and Smith 2000). Moreover, e-retailers may adopt a strategic pricing policy, for example they may engage in price promotions only in the short-term to avoid intense price competition. In so doing, they may randomly change prices so that their rivals cannot make systematic predictions (Varian 1980). Empirical evidence indeed confirms that such a 'hit-and-run pricing' and 'pricing randomization' strategy is widely used by e-retailers (Baye et al. 2004b).

In sum, price competition among e-tailers is less uniform than originally predicted, and profit opportunities exist for those who are able to promptly adjust their prices considering the changes in demand and competition. Past research, however, has investigated price competition from a static point of a view, analyzing cross-sectional variation in prices. Even when panel data were used, the data were generally collected over relatively coarse time intervals, such as weekly or monthly data. Accordingly, most previous empirical studies fail to observe such a strategic pricing pattern (Ellison and Ellison 2005).

In the fast-moving internet world, one may obtain more useful insights about the dynamics of price competition by analyzing higher-frequency time-series observations. In this paper, we use such high-frequency time-series data collected on a daily basis, which allows us to track e-retailers' frequent price changes with smaller increments over time. Moreover, online buzz data may help us identify potential drivers of e-retailers' strategic pricing behavior.

2.2 Online Buzz Sentiment and Firm Response

Reputation and e-WOM: Online shoppers are reported to perceive a greater risk (Alba et al. 1997), which can be reduced by considering the reputation of an e-retailer. The role of reputation as an informal enforcement mechanism has been extensively studied in economics (for a review, see MacLeod 2007). Reputation is viewed as an asset, whose value can be destroyed when a firm breaks its promise to deliver high-quality products. However, it is costly for customers to observe the firm's reputation. The word-of-mouth (WOM) mechanism, where information is shared and accumulated among the members of a group may help consumers find better quality products (Ellison and Fudenberg 1995).

WOM can be defined as 'one-to-one and face-to-face exchange of information about a product or service' (Godes et al. 2005). The content of WOM includes product news, experts' advice, and personal experience information (Richins and Root-Shaffer 1988). WOM is regarded as a key to the commercial success of products (for a review, see Schindler and Bickart 2004). The effectiveness of the WOM mechanism, however, depends highly on the patience of members and the quality of information (MacLeod 2007). For example, if members are not patient enough, a firm's incentive to shirk increases. This may occur in short life-cycle situations where the cost of waiting looms larger. Similarly, WOM information flows are likely to be imperfect when the participating group is small.

These problems are largely resolved by the internet. Customers are able to exchange their private information in an efficient way and all the information about products is just a click-away (Dellarocas 2003). Even though product-life cycles are shorter, customers can wait for a few days to observe early adopters' opinions and evaluations posted on the web. Furthermore, group membership is open to the public and most of the information can be acquired at little cost. As a

result, electronic WOM or e-WOM[6] has become more influential on customer decision making, and its impact has been studied extensively in the past few years (e.g., Godes and Mayzlin 2004, Senecal and Nantel 2004, Chevalier and Mayzlin 2006). The limitations of e-WOM include that 1) customers may have little incentive to provide reviews for other customers (Chevalier and Mayzlin 2006), 2) the identity of an online information provider is volatile (Dellarocas 2003), and 3) firms may engage in strategic manipulation to distort e-WOM and to boost sales (Dellarocas 2006).

e-WOM Metrics: It is difficult to observe and measure WOM, because "articulated opinions disappear into thin air" (Dellarocas et al. 2007, p.24). Accordingly, prior research relied on proxy variables. For example, Bass (1969) used aggregate-level sales data to study new-product diffusion, while others obtained a WOM metric from survey data (e.g., Richins 1983, Reingen et al. 1984) and controlled experiments (e.g., Herr et al. 1991). However, this measurement problem has been largely resolved as digitized customer feedback from various sources including blogs, online product comparison sites, online shopping malls, and online forums become available to the public (Dellarocas et al. 2007).

Previous research reports mixed empirical results regarding the effect of e-WOM valence on prices and sales: some find a positive effect (Chevalier and Mayzlin 2006, Dellarocas et al. 2007) while others find no effect (Chen and Wu 2005, Duan et al. 2005). These inconsistent outcomes may be due to the fact that only the aggregate ratings were used as a proxy of e-WOM valence (Chen et al. 2006). To resolve this problem, Chen et al. (2006) investigated qualitative aspects of e-WOM, i.e., the quality of reviews as well as the reputation of reviewers. They find

[6] Following Godes et al. (2005)'s definition on WOM, we define e-WOM as 'many-to-many exchange of information about a product or service via the internet'.

that product reviews rated as 'helpful' by other customers have a stronger positive effect on sales, but that the reputation of reviewers does not.

Further, researchers have become interested in incorporating textual information such as the length of reviews (Godes and Mayzlin 2004, Senecal and Nantel 2004, Chevalier and Mayzlin 2006). However, research that investigates the impact of e-WOM content is still rare (Godes et al. 2005). Recently, Ghose et al. (2006) propose to analyze the impact of qualitative aspects of textual information on price premiums. Specifically, they use a text-mining technique to extract positive and negative e-WOM components (e.g., "great shipping" vs. "never buy here again"), and then measure the monetary value of positive vs. negative word-pairs in an online context. They find that 1) different dimensions of e-WOM influence price premiums differently, 2) a negative reputation hurts more than a positive one on some dimensions but not on others, and 3) prediction accuracy increases about 20% by including textual information. To our knowledge, their work is the first study to combine text-mining, econometric analysis, and predictive modeling. However, they performed a cross-sectional analysis, which provides a static, one-shot description of competition. Time-series or panel-data analysis with long time-series samples is needed to assess the impact of positive vs. negative e-WOM on the dynamics of price competition.

Online Buzz Sentiment Analysis: Previous research has recognized the asymmetric aspects of positive vs. negative WOM. In particular, researchers have paid more attention to understanding the nature and underlying mechanism of negative WOM because 'losses loom larger than gains' (Kahneman and Tversky 1979). Industry experts reportedly disseminate more positive news than negative news (Wojnicki and Godes 2004). In contrast, customers pay more attention to negative WOM, because it may appear more credible (Chevalier and Mayzlin 2006).

For example, over 30% of dissatisfied customers communicate their experience to other customers, spreading negative WOM (Diener and Greyser 1978). As such negative WOM is likely to deteriorate their business performance, firms should develop an appropriate coping strategy. For example, a firm may encourage customer complaints and manage them carefully so that it has a better opportunity to win back a dissatisfied customer (Richins 1983).

Through in-depth interviews, Schindler and Bickart (2004) find that online customers may have a different motivation for information search. Specifically, online shoppers may look for positive information to confirm their previously-made decision, while they may seek out negative information before making a risky and/or important decision. In addition, online shoppers may use textual information such as wording (e.g., inexpressive slang, extreme emotion words) as a cue for the validity of online customer feedback. An "online buzz sentiment analysis" is needed to assess the impact of these behaviors on firm performance, and entails three steps: 1) to identify favorable vs. unfavorable opinions toward specific subjects within large numbers of online documents, 2) to acquire sentiment information (e.g., the number of positive word pairs in a sentence or in a document), and 3) to associate the sentiment information (i.e., positive vs. negative e-WOM) with economic outcomes such as prices, price premiums, and/or sales via econometric analysis (e.g., Nasukawa and Yi 2003, Yi et al. 2003).

Firm Response to Online Buzz: Firms traditionally use various marketing tools such as advertising (Nelson 1974), brand names (Erdem and Swait 1998), slotting allowances (Chu 1992) and higher prices (Rao and Monroe 1988) as signals of unobservable quality (for a review, see Kirmani and Rao 2000). However, in an internet world, customers freely accumulate and share product-quality information and thus resolve any information asymmetry with respect to product quality by themselves via e-WOM. This may change a firm's role from an active one to

a passive one, shifting power from firms to customers. Moreover, e-WOM can provide valuable information to customers as well as to firms. Dellarocas (2003) acknowledges that online buzz can assist a firm in analyzing customer response to its products as well as in evaluating the quality of retailers (e.g., fulfillment of orders). Therefore, how a firm should respond to e-WOM becomes an imperative question for practitioners as well as researchers.

Due to data limitations, previous studies have focused on expert reviews as a proxy for offline WOM. While the impact of expert reviews on the success of products has been studied (e.g., Eliashberg and Shugan 1997, Reddy et al. 1998), firms' response to the reviews has received little attention (Godes et al. 2005) and the relationship between prices and WOM is still ambiguous (Resnick et al. 2002). Recently, Chen and Xie (2005) analyze how expert reviews influence firms' pricing and advertising policy using analytical modeling.

In this paper, we address one such coping strategy, how firms respond to online buzz by adjusting their product prices. We investigate this issue using daily-level time-series data from the digital music device market. In particular, we examine the effect on prices of qualitative textual information, i.e., the sentiment information embedded in the online buzz, from a firm's perspective. Our unique contribution is the quantitative and dynamic assessment of on-line buzz sentiment on business outcomes of competing firms, in this case retail prices.

3. Empirical Analysis

3.1. Data

Industry Background: For the empirical analysis, we choose the Digital Music Player (DMP)[7] industry. A Digital Music Player is a consumer electronics device that is used to store, organize, and play audio files. Initiated in 1998, the DMP market exhibits several interesting characteristics. First, it is a large and fast-growing market. According to In-Stat market research reports[8], the market reached $4.5B in 2005, double the size of the 2003 market, with about one quarter of the U.S. population owning a digital music player in that year.

Second, the market has a typical 'long-tail' shape. The market leader, Apple, has increased its market power in the past five years. Apple's U.S. DMP market share (by unit sales) was 31% in January 2004, then grew to 71% in September 2006.[9] Since then, Apple has consistently claimed over 70% of total market sales.[10] While Apple enjoys the dominant market position, over 40 other manufactures compete for the remaining but still lucrative 30% of the market. Key players include Creative Labs, SanDisk, Samsung, iRiver, Philips, and Nextar.

Third, product life cycles are relatively short in this market. As of April 2008, there were more than 900 SKUs available in the MP3 category at Amazon.com. Considering its relatively short history, such a large number of available options reflects how often new-generation products are introduced in the market.

Lastly, intense competition drives manufacturers to incorporate more features in order to differentiate themselves from competitors. Further, DMP has diverse formats (e.g., AA, AAC, FLAC, MP3, MP3Pro, OGG, WAV, and WMA). Accordingly, the DMP category is notorious

[7] In this paper, we use Digital Music Player (DMP) and MP3 Player interchangeably.
[8] See http://www.instat.com/press.asp?ID=1366&sku=IN0502148ID.
[9] See http://www.iht.com/articles/2006/10/31/bloomberg/sxcreative.php.
[10] See http://apple20.blogs.fortune.cnn.com/2008/01/29/beyond-the-incredible-shrinking-ipod-market.

for its complexity in terms of purchase decision making for customers. As the CNET MP3 Player Buying Guide[11] puts it:

> *Every month, manufactures unleash even more MP3 players to an increasingly confused public. Not only do these devices have widely divergent features, but ongoing format wars mean the MP3 player you choose dictates where you can buy your digital music. These devices are anything but one-size-fits-all.*

These distinctive characteristics provide a unique research opportunity in our context. First, the effect of competition on price dynamics is likely to be conspicuous because we may observe sufficient variations in our focal variables (e.g., prices, the number of e-vendors) on a daily basis. Second, due to the inherent complexity of the DMP products, customers may depend highly on other customers' opinions, and especially, online buzz. As such, the DMP market is an ideal setting to examine our hypotheses.

Database Development: For data collection, eleven DMP products were selected based on their popularity as of May 2007. Table 1 presents the description of the products of interest.

Online buzz data were collected "live" between June 2, 2007 and August 1, 2007 (T=61) through a semantic data mining approach developed by Mango Analytics (Mango Analytics Inc. 2004). This novel approach analyzes the patterns of semi-structured data using graph topology and ontology. Ontology is a formal specification of the concepts that exist within a given area of interest and the semantic relationship among those concepts. In a marketing context, ontology is used to identify an industry-specific relationship hierarchy for brands, products, attributes, and features. For example, assume that the web crawler has found the following words on the web: "Apple Corp", "iPod Shuffle", "iPod Nano", "Creative Labs", "2GB storage", "Zen Vision", and

[11] To help 'confused' customers, CNET MP3 Player Buying Guide suggests "10 Key MP3 Play Features" in addition to basic attributes such as sound quality and design. See http://reviews.cnet.com/4520-7964_7-5134106.html.

"Consumer Electronics". Then the ontology-based approach specifies the relationship among the words as follows: 1) "Apple Corp" makes "iPod Nano" and "iPod Shuffle", 2) "iPod Nano" has "2GB storage", 3) "Creative Labs" makes "Zen Vision", 4) "Apple Corp" competes with "Creative Labs", 5) "Apple Corp" and "Creative Labs" belong to "Consumer Electronics" industry. As such, by utilizing keywords/concepts identified by experts, the approach constructs a graph of concepts which helps capture the major underlying themes from the customer's perspective.

ID	Product Name	Brand Name	Storage Capacity	Amazon Launch Date	Amazon Sales Rank*	Amazon Customer Rating	CNET Editor Rating
Helix	Helix (YX-M1Z)	Samsung	1GB	June 2006	#6810	3.7/5 (N=55)	N/A
Nex50	NeXus50	Samsung	1GB	June 2006	#11449	3.4/5 (N=33)	6.7/10
Nex25	NeXus25	Samsung	512MB	June 2006	#5098	4.2/5 (N=21)	6.7/10
Mini	iPod Mini	Apple	4GB	Feb. 2005	#6302	3.9/5 (N=431)	N/A
Nano	iPod Nano	Apple	2GB	Feb. 2006	#435	4.2/5 (N=1355)	8.3/10
Video	iPod Video	Apple	30GB	Sep. 2006	#1221	4.3/5 (N=633)	N/A
Shuffle	iPod Shuffle	Apple	1GB	Sep. 2006	#54	4.4/5 (N=198)	6.7/10
Vision	Zen Vision	Creative Labs	30GB	Dec. 2005	#1299	4.2/5 (N=983)	8.0/10
Sleek	Zen Sleek	Creative Labs	20GB	Jan. 2006	#9756	3.9/5 (N=88)	N/A
E260	Sansa E260	SanDisk	4GB	Apr. 2004	#175	4.1/5 (N=597)	8.0/10
M230	Sansa M230	SanDisk	512MB	May 2006	#312	4.2/5 (N=546)	7.3/10

(*: Rank in the "Electronics" category; "Amazon Sales Rank" and "Amazon Customer Rating" data are obtained as of April 2008.)

Table 1: Description of 11 DMP Products

Based on this approach, the company's algorithm incorporates various functions including a document processor engine, ontology processor, page rank calculator, and web crawler for data acquisition and classification. A unique contribution is that the data mining algorithm is able to capture an aggregate consumer sentiment factor, which is recorded as the number of sentences on each web page that have positive, negative, or neutral sentiment.

Finally, data on retail prices and the number of e-vendors were collected on a daily basis at Amazon.com, the largest online retailer in the U.S., between June 2, 2007 and August 1, 2007 (T=61).[12]

Price: On a daily basis, price (**PRICE)** is defined as the lowest price of each DMP product at Amazon.com. Table 2 summarizes the price histories of the eleven brands under study. Using $140 as a division point, there are three high-price brands (iPod Video, Zen Vision, and iPod Mini) and eight low-priced products. This is representative of the price distribution in the overall market, as about 80% of DMP products available at Amazon.com in April 2008 were priced below $140. Prices do fluctuate over time, with higher variability (coefficient of variation) for the lower-priced items (see Figure 1). In addition, the average coefficient of variation of Apple's four products is 0.03, while that of Creative Lab's two products is 0.10, which illustrates different pricing policies and/or pricing power for different manufacturers.

[12] Note that T=61 for all products except iPod Mini, which was not available at Amazon.com for the first seven days (i.e., June 2-8). Accordingly, there are 54 observations for iPod Mini in our database.

ID	Mean	Median	Min.	Max.	Std. Dev.	Coeff. Variation
Helix	95.9	94.8	65.0	109.0	7.7	0.08
Nex50	45.3	44.4	44.4	54.9	2.4	0.05
Nex25	34.4	34.0	30.0	38.0	2.6	0.08
Mini	180.2	180.0	160.0	200.0	8.6	0.05
Nano	134.4	135.0	125.0	138.5	1.8	0.01
Video	227.3	225.0	220.0	234.9	3.9	0.02
Shuffle	71.9	72.9	64.9	79.0	3.2	0.04
Vision	207.9	210.0	190.0	224.9	12.9	0.06
Sleek	133.2	130.0	106.0	167.0	19.3	0.14
E260	118.0	118.5	110.0	124.9	4.2	0.04
M230	22.5	21.8	19.0	25.5	1.7	0.08

Table 2: Descriptive Statistics on Prices (in $)

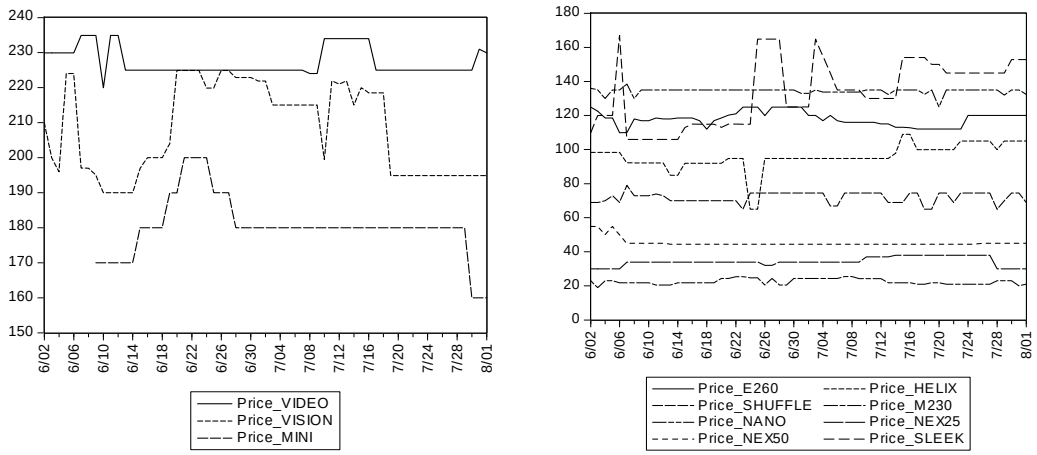

Figure 1: Price Movement over Time (High-ticket vs. Low-ticket Items)

Vendors: As a proxy of competition intensity, the number of e-vendors (**VEND**) at Amazon.com is obtained on a daily basis (see Table 3). For example, the Sansa E260 and Samsung Nexus50 were carried by more than 30 e-vendors, while the Zen Sleek and iPod Mini

were carried by fewer than 10 e-vendors during the data collection period.[13] Interestingly, the number of e-vendors was either stable or declining for most products (see Figure 2).

ID	Mean	Median	Min.	Max.	Std. Dev.	Coeff. Variation
Helix	18.8	22	8	28	6.5	0.35
Nex50	34.9	35	31	38	2.2	0.06
Nex25	26.6	26	24	30	1.5	0.06
Mini	1.0	1	0	2	0.5	0.50
Nano	18.4	18	15	26	2.5	0.14
Video	12.9	13	11	15	1.2	0.09
Shuffle	13.9	14	11	18	2.0	0.14
Vision	12.2	13	7	16	2.1	0.17
Sleek	8.1	8	5	13	2.0	0.25
E260	43.8	44	37	51	3.1	0.07
M230	33.9	36	24	40	4.7	0.14

Table 3: Descriptive Statistics on the Number of e-Vendors

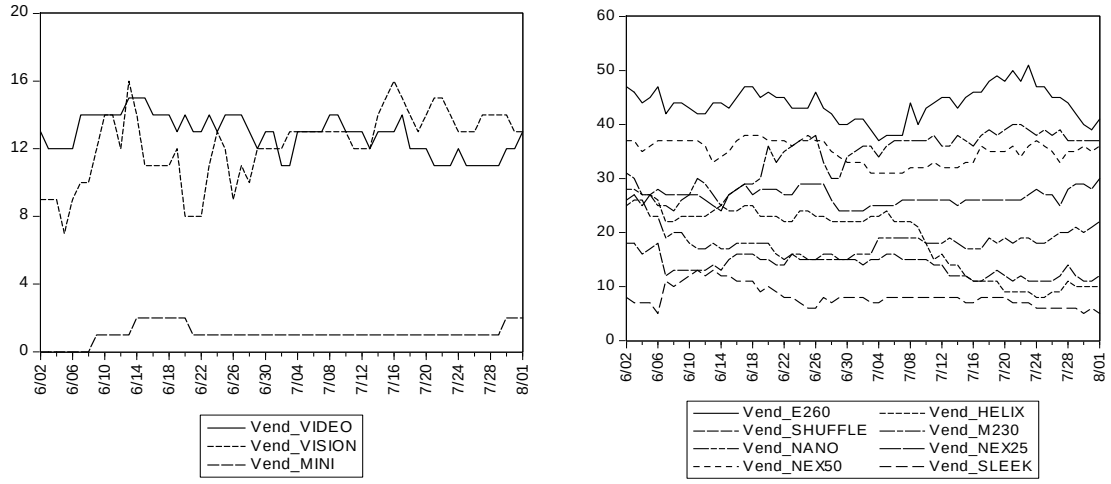

Figure 2: Number of Vendors over Time (High-ticket vs. Low-ticket Items)

Online Buzz: Daily online buzz data were collected based on the sentiment factor, i.e., positive buzz (**POS**), negative buzz (**NEG**), and neutral buzz (**NEUT**). Table 4 illustrates that three iPod products (Video, Mini, and Shuffle) generated high level of positive buzz, while

[13] Note that the iPod Mini was replaced by the iPod Nano in 2006. During the data collection period in 2007, 1-2 e-vendors decided to carry the iPod Mini at an approximately 60% cheaper price compared to original price.

Creative Lab's Zen Sleek and Zen Vision generated a high level of neutral buzz. Interestingly, the positive buzz counts are at least 10 times higher than the negative counts, with the exception of the Samsung Helix.

ID	POSITIVE (POS)		NEGATIVE (NEG)		NEUTRAL (NEUT)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Helix	23.1	7.3	7.2	2.0	8.5	5.6
Nex50	9.0	2.7	0	0	15.8	2.8
Nex25	4.9	2.3	0.2	0.5	21.6	5.7
Mini	144.4	32.8	12.7	2.2	57.9	7.0
Nano	36.6	8.9	2.2	2.0	13.7	4.2
Video	226.4	52.8	18.5	2.9	81.0	11.0
Shuffle	145.6	15.8	12.6	3.7	38.4	10.7
Vision	30.5	8.9	3.1	2.0	186.5	19.5
Sleek	42.9	6.2	1.4	2.2	99.4	14.0
E260	147.7	23.9	9.4	1.3	62.0	24.2
M230	70.0	15.9	4.8	1.5	7.3	3.7

Table 4: Descriptive Statistics on Online Buzz Sentiment

ID	TOTBUZZ		POSR		NEGR	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Helix	38.8	12.2	0.60	0.07	0.20	0.05
Nex50	24.8	5.1	0.36	0.05	0	0
Nex25	26.7	7.1	0.18	0.08	0.01	0.02
Mini	215.0	37.7	0.67	0.04	0.06	0.01
Nano	52.4	12.5	0.70	0.05	0.04	0.03
Video	327.6	61.0	0.69	0.04	0.06	0.01
Shuffle	196.6	25.4	0.74	0.03	0.06	0.01
Vision	220.1	20.8	0.14	0.04	0.01	0.01
Sleek	143.7	17.8	0.30	0.03	0.01	0.01
E260	219.1	29.3	0.68	0.09	0.04	0.01
M230	82.0	16.6	0.85	0.06	0.06	0.02

Table 5: Descriptive Statistics on total and relative buzz sentiment (TOTBUZZ, POSR, NEGR)

The total buzz count (**TOTBUZZ**) is computed as the sum of POS, NEG, and NEUT, which varies greatly across the eleven products (Table 5). The positive buzz rate (**POSR**) is computed by dividing POS by TOTBUZZ while the negative buzz rate (**NEGR**) is obtained by

dividing NEG by TOTBUZZ. These relative sentiment values also vary significantly across the eleven competing products, with positive sentiments always dominating negative. Figure 3 and 4 show that both POSR and NEGR are relatively stable over time, though some gradually increase or decrease.

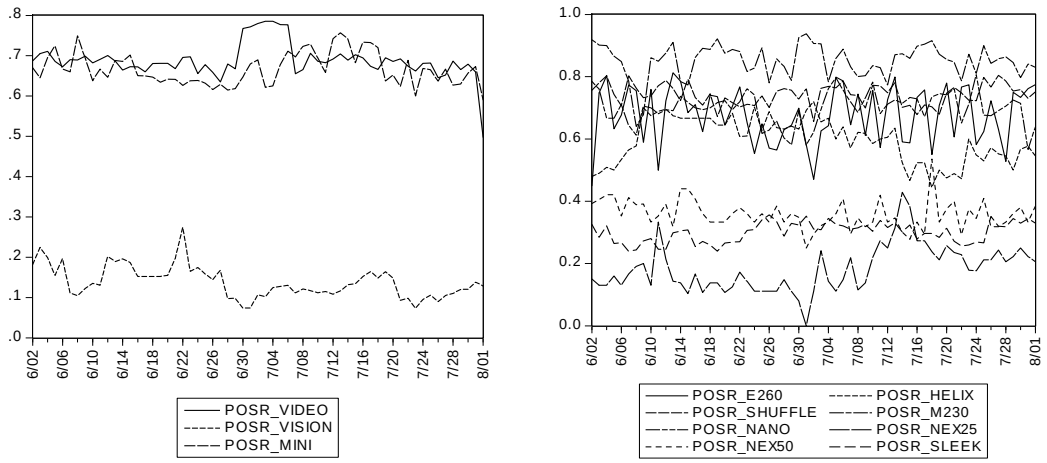

Figure 3: POSR over Time (High-ticket vs. Low-ticket Items)

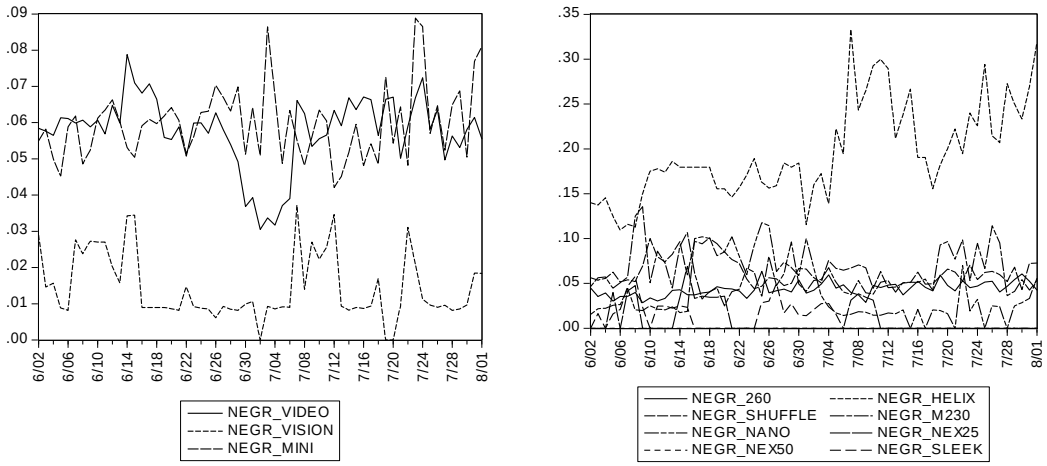

Figure 4: NEGR over Time (High-ticket vs. Low-ticket Items)

3.2. Hypotheses and Model

Hypotheses Development: Economic theory suggests that prices decrease as competition increases, which should hold in an e-marketplace setting. For example, Baye et al. (2004a) find that the gap between the two lowest prices of a book title averages 23% when only 2 online retailers compete, but falls to 3.5% when 17 online retailers carry the title. Accordingly, we expect the price of a DMP product will decrease as more e-vendors carry the product. Thus we postulate:

HYPOTHESIS 1 (Competition Effect): *As the number of e-vendors carrying a product increases, the price of the product decreases.*

Second, previous research suggests that the volume of e-WOM has a positive effect on the price of a product (Liu 2006, Duan et al. 2005, Dellarocas et al. 2007). Thus we postulate:

HYPOTHESIS 2 (Online Buzz Demand Effect): *As the total online buzz count for a product increases, the price of the product increases.*

Third, prior studies suggest that positive WOM increases pricing power (e.g., Kalyanam and McIntyre 2001, Melnik and Alm 2002), while negative WOM decreases pricing power (e.g., Lucking-Reiley et al. 2000). Through cross-sectional analysis, Ghose et al. (2006) also find that positive (negative) e-WOM has a positive (negative) effect on pricing power. Accordingly, we expect that positive (negative) online buzz will lead firms to raise (lower) the price of a product. Thus we postulate:

HYPOTHESIS 3 (Online Buzz Sentiment Effect)

HYPOTHESIS 3.1 (Positive Online Buzz Effect): *As the positive online buzz count for a product increases, the price of the product increases.*

HYPOTHESIS 3.2 (Negative Online Buzz Effect): *As the negative online buzz count for a product increases, the price of the product decreases.*

Fourth, the effect of online buzz may be moderated by purchase involvement (Ba and Pavlou 2002, Pavlou et al. 2007). Purchase involvement refers to the customer's perceived relevance of the focal purchase (Zaichkowsky 1985); it is higher for products with important consequences to the customer (e.g., cars, houses, medicines) and for expensive products (e.g., electronics). Prior research reports that the effect of e-WOM on prices is larger for high-involvement products (Ba and Pavlou 2002), and that perceived risk plays a more important role for high-involvement online purchases (Pavlou et al. 2007). However, whether the effect of positive vs. negative e-WOM would be moderated by purchase involvement has yet to be explored.

In this paper, we focus on the moderating role of the relative price level of a product. Assume that an online shopper is considering two DMP products, one high-ticket item and one low-ticket item. Also assume there are only two online customer reviews available for each product at that time; one is positive, while the other is negative for both products. In this situation, prospect theory (Kahneman and Tversky 1979) predicts that the effect of the negative review would be stronger for the high-priced item than for the low-priced item. This is because the customer has a higher initial quality expectation (i.e., higher reference point) of the former, and thus the single negative e-WOM may have a larger negative effect for the high-priced item than for the low-priced item. By the same token, one piece of positive WOM may have a larger

positive effect for the low-ticket item given that customers expect to 'get what they pay for' (i.e., lower reference point).

HYPOTHESIS 4 (Asymmetric Effect of Online Buzz): The effect of online buzz on prices is asymmetric for high-ticket items vs. low-ticket items.

HYPOTHESIS 4.1 (Online Buzz Effect for High-Ticket Items): *High-ticket items are more sensitive to negative online buzz than to positive online buzz.*

HYPOTHESIS 4.2 (Online Buzz Effect for Low-Ticket Items): *Low-ticket items are more sensitive to positive online buzz than to negative online buzz.*

Empirical Model Specification: To examine the hypotheses, we use an econometric model to estimate the effect of competition and online buzz on the price movement of competing products. Given the available data, the empirical model is specified as a fixed-effect panel response model with an autoregressive residual term as follows:

$$PRICE_{i,t} = \alpha_i + \beta \cdot VEND_{i,t} + \sum_{j=1}^{p} \pi_j \cdot BUZZ_{i,t-j} + \sum_{k=1}^{q} \gamma_k \cdot POSR_{i,t-k} + \sum_{l=1}^{r} \phi_l \cdot NEGR_{i,t-l} + e_{i,t} \quad (1)$$

$$where \quad e_{i,t} = \rho \cdot e_{i,t-1} + \upsilon_{i,t}, \upsilon_{i,t} \sim N(0, \sigma^2)$$

In Equation (1), $PRICE_{i,t}$ represents the price of product i at time t, while $VEND_{i,t}$ stands for the number of e-vendors carrying the product i at time t. The absolute buzz count is $BUZZ_{it}$ and the positive and negative buzz rates are $POSR_{i,t}$ and $NEGR_{i,t}$ for product i at time t. Also note that *p, q,* and *r* represent the lag lengths for $BUZZ_{it}$, $POSR_{it}$, $NEGR_{it}$ variables, respectively. Finally, the parameter ρ captures autocorrelation in the error term (i.e. price inertia), while the fixed-effect parameter α_i represents unobservable, product-specific characteristics (e.g., design appeal) of product i. This fixed-effect approach implicitly assumes that the product-specific

characteristics are time-invariant, which is a reasonable assumption for daily data collected over a relatively short (two months) time span.

Equation (1) can be estimated using a Cochrane-Orcutt data transformation and GLS (Generalized least squares) or NLS (Non-linear least squares) estimation (Greene 2003). In this study, we used the NLS method with White's heteroskedasticy-robust standard errors to control for heteroskedasticity across products. To avoid the possibility of spurious regression results, we performed Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) panel unit-root tests on the PRICE variable (Enders 2004). The test result suggest that the dependent variable, PRICE, is stationary ($p<0.01$).

3.3. Results

Competition and Total Online Buzz Effect: To examine HYPOTHESIS 1 and 2, we estimated Equation (1) using combinations of two variables: the number of e-vendors (VEND) and the total online buzz count (TOTBUZZ). The models show that higher competition is associated with lower prices, but that *total* buzz count does not influence prices (see Table 6).

	Model 1	**Model 2**	**Model 3**
$VEND_t$	-1.23 ***	-	-1.27***
$TOTBUZZ_{t-1}$	-	-0.01	-0.01
$TOTBUZZ_{t-2}$	-	-0.01	-0.01
$TOTBUZZ_{t-3}$	-	-0.01	-0.01
AR term (ρ)	0.74***	0.74***	0.74***
# of obs.	623	623	623
# of cross-sections	11	11	11
AIC	6.18	6.28	6.18
SC	6.28	6.39	6.30
Durbin-Watson Stat.	2.10	2.02	2.00

(***: $p<0.01$, **: $p<0.05$, *: $p<0.10$)

Table 6: Effects of Competition and Total Buzz

In sum, we do not reject HYPOTHESIS 1, but reject HYPOTHESIS 2. The Durbin-Watson statistics show that the inclusion of ρ is sufficient to account for residual autocorrelation in prices.

Competition and Online Buzz Sentiment Effects: To examine HYPOTHESIS 3.1 and 3.2, we estimated Equation (1) with different combinations of POSR and NEGR (see Table 7). We excluded total buzz count because it provided no explanatory power in the previous results. Table 7 illustrates that positive online buzz increases prices (*Model 4*), supporting HYPOTHESIS 3.1. In contrast, negative online buzz decreases prices (*Model 5*), supporting HYPOTHESIS 3.2. By including both POSR and NEGR, however, we find only positive buzz increases prices (*Model 6*). These results control for level of competition and inertia in prices.

	Model 4	**Model 5**	**Model 6**
$VEND_t$	-1.30***	-1.28***	-1.30***
$POSR_{t-1}$	0.53	-	0.24
$POSR_{t-2}$	9.23**	-	8.41*
$POSR_{t-3}$	2.46	-	2.02
$NEGR_{t-1}$	-	-3.09	-2.31
$NEGR_{t-2}$	-	-15.65*	-9.88
$NEGR_{t-3}$	-	-5.81	-3.94
AR term (ρ)	0.74***	0.74***	0.74***
# of obs.	623	623	623
# of cross-sections	11	11	11
AIC	6.18	6.18	6.19
SC	6.30	6.31	6.33
Durbin-Watson Stat.	1.99	1.99	1.98

(***: p<0.01, **: p<0.05, *: p<0.10)

Table 7: Effects of Competition and Positive/Negative Buzz

Asymmetric Effect of Online Buzz Sentiment: To examine HYPOTHESIS 4.1 and 4.2, we estimated Equation (1) separately for the two price tiers in the market. Table 8 illustrates that

negative e-WOM has a negative effect on prices for the high-ticket item group, supporting HYPOTHESIS 4.1. In addition, positive e-WOM has a positive effect on prices for the low-ticket item group, supporting HYPOTHESIS 4.2. As before, competition decreases prices for both groups. Note also that a poolability test across the two groups (Greene 2003) results in an F-statistic = 3.82 ($p<0.05$). This test supports the notion that prices of high-priced vs. low-priced products respond differently to online buzz sentiment.

	High-ticket Item Group	**Low-ticket Item Group**
$VEND_t$	-1.58**	-1.22***
$POSR_{t-1}$	-13.83	2.27
$POSR_{t-2}$	2.73	10.33**
$POSR_{t-3}$	-11.34	3.93
$NEGR_{t-1}$	-68.30**	1.21
$NEGR_{t-2}$	-21.61	-11.96
$NEGR_{t-3}$	-64.43	-2.74
AR term (ρ)	0.85***	0.66***
# of obs.	167	456
# of cross-sections	3	8
AIC	6.08	6.23
SC	6.30	6.38
Durbin-Watson Stat.	2.12	1.91

(***: $p<0.01$, **: $p<0.05$, *: $p<0.10$)

Table 8: Asymmetric Effects of Competition and Positive/Negative Buzz across Groups

Direct vs. Indirect Effects: Conceptually, there may exist two different paths with respect to the online buzz sentiment effect on prices in HYPOTHESIS 3; 1) managers may adjust their retail prices after observing the sentiment of online buzz around their products (*direct effect*), and 2) consumers may change their purchase decisions based on online buzz generated by peer consumers, which will lead to changes in demand of competing products, and accordingly, changes in their prices (*indirect effect*). However, our model cannot separate the direct and indirect effects, because that would require daily demand (sales quantity) data, which

are not available. As a result, we focus on the relationship between online buzz and retail prices using our reduced-form model. Future research may consider acquiring sales quantity data and use a structural model that separates the two paths.

Robustness Checks: Equation (1) may be subject to endogeneity bias because of the potential simultaneous relationship between $PRICE_{it}$ and $VEND_{it}$. To address this possibility, we performed a Durbin-Hausman-Wu test (see Davidson and MacKinnon 1993), the result of which indicated there is no endogeneity bias. This result is intuitive because it takes time for an e-vendor to start carrying a product in response to observing higher retail prices. The vendor needs to first contact the manufacturer or distributor to reserve inventory before taking orders from customers.[14] On the other hand, when the prevailing price for a product drops, the e-vendor will want to first reduce his inventory by matching the price drop before deciding to stop selling the product. In either case, it will take several days or even weeks for a price shock to impact the number of e-vendors. Given our daily observations, VEND may be treated as an exogenous variable.

In addition, it is possible that the lagged independent variables, i.e., $POSR_{t-1}$, $POSR_{t-2}$, $POSR_{t-3}$, $NEGR_{t-1}$, $NEGR_{t-2}$, and $NEGR_{t-3}$ are collinear. We verified the 95% confidence ellipses around all parameter pairs and found no evidence of severe collinearity[15].

[14] An alternative is to join the Amazon Associate Program, which allows e-retailers to use inventory managed by Amazon.com. Even in this case, an e-vendor must first apply to the program. If admitted, the vendor has to pay monthly fees as well as a referral fee (about 10% of revenue), which makes this option less attractive.
[15] All econometric analyses were performed in Eviews 6.

4. Discussion

4.1. Summary of Findings

In this paper we estimated various fixed-effect panel regression models on data from eleven leading MDP products. The empirical findings may be summarized as follows (see Table 9): 1) overall, as the number of e-vendors carrying an MDP product increases, the price of the product decreases (*competition effect*); 2) positive (negative) online buzz increases (decreases) prices (*online buzz sentiment effect*); 3) for high-ticket items (low-ticket items), negative (positive) online buzz decreases (increases) prices while positive (negative) buzz does not (*asymmetric online buzz sentiment effect*). Finally, the effects are observed with a one- to two-delay delay, with negative information impacting prices the fastest.

	All 11 items	**High-ticket Item Group**	**Low-ticket Item Group**
$VEND_t$	-1.30***	-1.58**	-1.22***
$POSR_{t-1}$	-	-	-
$POSR_{t-2}$	8.41*	-	10.33**
$POSR_{t-3}$	-	-	-
$NEGR_{t-1}$	-	-68.30**	-
$NEGR_{t-2}$	-	-	-
$NEGR_{t-3}$	-	-	-
AR term (ρ)	0.74***	0.85***	0.66***
# of obs.	623	167	456
# of cross-sections	11	3	8
Sum of Squared Residuals	16654.74	3697.93	12553.24

(***: $p<0.01$, **: $p<0.05$, *: $p<0.10$)

Table 9: Summary of Empirical Results

4.2. Managerial Implications

The advent of the internet challenges the traditional uni-directional model of brand building via advertising, as customers become more sensitive to self-generated product reviews

and e-WOM, which is less controllable by firms. Accordingly, managing brand equity in response to online buzz becomes an important task for firms. Our results, as summarized in Table 9, provide some important managerial insights with respect to the pricing component of the marketing mix.

First, a firm competing at the high end of the price range should closely monitor customer dissatisfaction to protect its profitability. Richins (1983) points out that managing customer complaints is an important task in winning back the customer. However, the internet allows dissatisfied customers to negatively affect other customers' decisions in a short time span. Thus, the importance of managing the level of post-purchase dissatisfaction promptly becomes even more important for high-priced products. In contrast, if a firm targets low-price tier customers who do not have such a high quality expectation, then the firm should focus on finding good things about its product and spreading the positive buzz over the internet. Giving customers delightful news may increase pricing power, leading to higher profitability.

Second, our empirical findings also provide customers with strategic shopping advice. Both positive and negative e-WOM are 1-to-2 day leading indicators of retail price movements. Thus a forward-looking buyer may want to delay the purchase of a high-ticket item that is receiving some negative buzz, in anticipation of a price drop. In contrast, a prospective buyer of an inexpensive product who observes positive online buzz about that product may want to purchase it immediately, before e-retailers respond to the good news by raising the price.

Third, the empirical results have an implication for 'long-tail' markets (e.g., Brynjolfsson et al. 2006). Because e-retailers can stock far more products than typical offline retailers, online product variety grows rapidly; for example, Amazon.com carries over 3 million books while traditional retailers stock 40,000 to 100,000 titles on average (Brynjolfsson et al. 2003, Anderson

2006). The 'long-tail' phenomenon refers to the stylized fact that only a few mainstream products lie at the head of the demand curve while the majority of the niche products spread out in the 'thick' tail part, mainly due to the virtually unlimited shelf space of e-retailers (Zhu and Zhang 2007). These niche products are commercially important in the e-marketplace, for example, 40% of book sales at Amazon.com in 2000 came from 'obscure' book titles that are not even present in conventional bookstores (Brynjolfsson et al. 2006). It is reported that the impact of e-WOM is bigger for products with low popularity and more limited information availability (Chen et al. 2006, Zhu and Zhang 2007). Because there will be a smaller number of customer reviews for those products, even one negative review will loom large. Thus, a producer of niche products should monitor e-WOM carefully and manage complaints promptly before they become digitized and spread over the internet.

As such, online buzz sentiment is valuable information for both customers and companies. In practice, however, customers tend to "sample" online buzz due to their time and cognitive resource constraints. Our analysis also shows that even renowned firms react to online buzz with a time delay. Therefore, there is ample opportunity for marketing information system builders to fill this gap by developing real-time online buzz tracking systems.

4.3. Contributions, Limitations, and Future Research

Practitioners are aware that more descriptive reviews that contain detailed information such as pros, cons, best uses, fit, and rating are valued higher by customers (Wagner 2008). However, previous research has focused on the effect of average ratings on customer behavior, mainly due to data limitations. In this context, Godes et al. (2005) point out that the key issue in e-WOM research is how to process and classify digitized content precisely and meaningfully. In

addition, prior studies tended to focus on cross-sectional variation of prices. However, the internet allows firms to change prices on a daily basis, or even faster. By using long time-series data collected on a daily basis, this paper has examined the pricing dynamics across products in the DMP market and provided insights to firms who face time-intensive online competition.

In addition, data from an advanced text-mining technique allow us to investigate the asymmetric effects of positive and negative e-WOM. In so doing, we have identified an important moderating factor, i.e., purchase involvement. Specifically, we find that positive online buzz matters more for low-ticket items, while negative online buzz does so for high-ticket items. This finding may have a special managerial implication for firms who are competing in the era of the 'long-tail'.

This study is subject to the same limitation that affects all online buzz research, i.e. concerns over data validity and possible strategic manipulation (see Godes et al. 2005, Chevalier and Mayzlin 2006, Dellarocas 2006). However, our use of a sentiment aggregator across multiple websites significantly lessens this concern. Second, we examined only the effects of e-WOM on retail prices. If daily sales quantities are available, we could estimate demand elasticities of positive vs. negative online buzz as well. This would entail simultaneous-equation modeling that reflects the bidirectional relationships between sales, prices and e-WOM. Third, our analysis is descriptive. Future study may derive optimal response of firms to online buzz via analytical modeling (Godes et al. 2005). An excellent example is Chen and Xie (2005), who analyzed optimal response to influential expert ratings. Future research should examine if there are differences in optimal response to customer-generated e-WOM.

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