e-Sentiment as a Leading Indicator of Daily Price Fluctuation: The Case of MP3 Players

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Abstract

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

This paper examines the effect of e-sentiment on the daily price fluctuation of MP3 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 e-sentiment, which allows us to investigate the different implications of positive, neutral, and negative online conversations. Econometric time-series modeling reveals that e-sentiment is a leading indicator of price fluctuation after controlling for the effect of competition. Furthermore, the effect of e-sentiment on price fluctuation is moderated by the customers' expectation level: the effect of negative online buzz is larger for well-known brand items (e.g., Apple products) and high-ticket items for which customers have higher expectations or standards, whereas the effect of positive online buzz is greater for less well-known brand items and low-priced items. These findings establish the relevance of e-sentiment information on online retail price movement, and suggest that managers should frequently monitor the sentiment of online buzz surrounding their products and respond appropriately by promptly adjusting their prices.

Keywords: e-Sentiment, Quality perceptions, Daily price fluctuation, MP3 players

"Consumers are highly influenced by the experience of other consumers- far more than they are by marketing professionals." 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 attribute-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 often rely on *the subjective quality assessment*[1] *of other customers based on their individual usage experience or perception*, which is called word-of-mouth or WOM in the marketing literature.

The importance of WOM on customer decision making (e.g., Arndt 1968, Richins 1983) and firm performance (e.g., Luo 2007, 2008) has been emphasized in previous research. WOM is known to be more influential than advertising (Berry and Keller 2003), information provided by marketers (Alreck and

[1] 'Subjective quality assessment' is often referred to as 'quality perceptions,' 'perceived value,' or 'perceived quality' in the marketing literature. Quality perceptions consist of three components including 1) abstract dimensions of intrinsic attributes (e.g., safety, durability), 2) perceived monetary price, and 3) reputation formed through advertising and brand name (Zeithaml 1988).

Settle 1995), and professional advice by experts (Guernsey 2000). For example, more than half of buyers regard customer-generated reviews as more valuable than experts' advice (Piller 1999).

More recently, the internet has become a medium through which customer-generated product quality information spreads rapidly among customers. Moreover, digitized customer feedback information, i.e., electronic WOM or e-WOM, can be accessed anytime and anywhere (Dellarocas 2003), which further increases its influence among customers (for a review, see Schindler and Bickart 2004). In practice, firms actively participate in distributing online buzz[2] 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, online buzz is distributed through diverse contexts 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[3] (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), while positive conversation in online forums leads 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 online buzz on consumer behavior and 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 because all the information is just a 'click away.' Due to limits in data collection, however, prior empirical research has investigated the effect of e-WOM only within a specific source (e.g., online product reviews at Amazon.com, or online

[2] We use online buzz and e-WOM interchangeably.
[3] Referability is defined as the degree to which information can be easily accessed by a large number of people (Boush and Kahle 2001).

forums in the case of TV shows). 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 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 (i.e., how customers perceive or feel about a product) unexplored. This approach, however, is subject to a 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 be perceived differently in terms of quality, yielding different customer responses. To address this issue, some researchers employed 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 product directly from online texts and examine the impact of such quality perceptions on business outcomes such as retail prices. For example, investigating how customers' descriptions of a product, such as "awesome" or "poor," affect its retail price over time would provide richer insights to researchers and practitioners.

Previous research has documented several counter-intuitive phenomena with respect to the behavior of prices in the presumably 'frictionless' e-marketplace. For example, empirical evidences suggest that online price dispersion does exist (e.g., Brynjolfsson and Smith 2000) and even increases over time (e.g., Chevalier and Goolsbee 2003). Moreover, e-retailers are reported to charge price premiums (e.g., Clay et al. 2002) and to frequently adjust their prices, up or down, by small increments (e.g., Baye et al. 2004b). Recently, Schneider and Albers (2008) have reported that minimum prices, i.e., the lowest available prices for a certain period, continuously drop until about 5 months from the launch of new high-tech products. Surprisingly, they have also found that once the minimum prices become stabilized, prices begin to fluctuate around that value over time. The question is: which factors drive prices to move around a certain value after a certain time period has passed?

In this paper, we examine the effect of online buzz on the fluctuation of minimum prices. Online buzz information is particularly relevant for e-retailers as they decide how to adjust prices in light of customer feedback (Dellarocas 2003). Thus, *collecting qualitative online buzz data across diverse sources and analyzing the response of e-retailers to online buzz* are imperative for modern marketing strategy. In particular, we use online buzz data on MP3 players collected from diverse online documents through a powerful web crawling technique. These data capture the sentiment of online buzz (i.e., e-sentiment) enabling us to investigate the different implications of positive and negative online buzz. Finally, the dataset is collected "live" on a daily basis for two months (June 2, 2007~August 1, 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 between product price fluctuation and e-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 retail prices and e-sentiment analysis. 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 Behavior of Online Retail Prices

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 level: 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 actually 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).

As such, there is not much difference between online and offline with respect to overall price level, price dispersion, and price premium. One interesting difference, however, is that online retail prices change more frequently than offline prices.

Price fluctuation: While some e-retailers like Amazon.com are able to charge price premiums, others with low service quality and/or unknown brand name may be involved in intense price competition. Since the consumer search cost is low and the menu cost (i.e., the cost of changing prices) is ignorable online, those undifferentiated e-retailers are expected to monitor their rivals' prices and adjust their own prices frequently (Bakos 1997, Bailey 1998), and in 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 (Shilony 1979). In so doing, they may randomly change prices so that their rivals cannot make systematic predictions (Varian 1980). Empirical evidence indeed confirms that e-retailers widely utilize such 'hit-and-run pricing' and 'pricing randomization' strategies (Baye et al. 2004b).

As a result, the lowest available prices are likely to fluctuate (i.e., to change frequently with smaller increments over time) in the e-marketplace. By examining 38,000 daily online retail price changes for 12 months, Schneider and Albers (2008) find that minimum prices continuously drop for about 5 months after the introduction of new high-tech products such as digital cameras and camcorders. After that point, minimum prices become stabilized, fluctuating around the value of approximately 88% of the initial price.

In sum, price competition among e-retailers is less uniform than originally expected based on economic theory, and profit opportunities exist for those who are able to figure out the pattern of price fluctuation. In so doing, they can predict next-period price changes and promptly adjust their prices accordingly. 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 basis. 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 movement by analyzing higher-frequency time-series observations. For example, someone posted on an online bike forum that the Kryptonite bike lock can be easily opened with a Big pen on September 12, 2004. Two days later, video clips showing how to open the lock were posted online, and by the following day 900,000 people became aware of the news. The next day the company announced that the story was a rumor. By September 17, however, the story had diffused so widely that it was featured in the NY Times. Within 10 days from the initial posting, 7 million people had become aware of the news. On September 22, the company announced a free product recall, at an estimated cost of $10 million. Such fast impact of online buzz on business outcomes cannot be captured by analyzing weekly or monthly data. In this paper, we use data collected on a daily basis, which allows us to track online retail price fluctuation in a timely manner. Moreover, daily e-sentiment data from multiple sources (e.g., online product reviews, online forums) may help identify potential drivers of such daily fluctuation in prices.

2.2 e-Sentiment Analysis

Reputation and online buzz: Online shoppers are reported to perceive a greater risk (Alba et al. 1997), which can be reduced by considering the reputation of a seller. 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, expert advice, and personal experience information (Richins and Root-Shaffer 1988). The effectiveness of the WOM mechanism, however, depends highly on the quality of information (MacLeod 2007).

The quality of accessible information is vastly improved by the internet. Online 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 these days, 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[4] 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 or online buzz 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

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

strategic manipulation to distort online buzz and to boost sales (Dellarocas 2006). In spite of these weaknesses, online buzz is still regarded as a key to the commercial success of products (for a review, see Schindler and Bickart 2004).

Online buzz 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 largely been 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, which may be due to the fact that only the aggregate ratings were used as a proxy of online buzz valence (Chen et al. 2006). To resolve this problem, Chen et al. (2006) investigated qualitative aspects of online buzz, i.e., the quality of reviews as well as the reputation of reviewers. They find 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 (e.g., Godes and Mayzlin 2004). However, research that investigates the impact of online buzz content is still rare (Godes et al. 2005). Indeed, both practitioners and researchers are aware that online shoppers often rely on online buzz sentiment information such as wording (e.g., inexpressive slang, extreme emotion words) as a cue for the validity of online customer feedback (Schindler and Bickart 2004). An "e-sentiment analysis" is needed to assess the impact of such information 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/negative word pairs in a sentence or in a document), and 3) to associate the sentiment information (i.e., positive vs. negative words) with economic outcomes such as prices, price premiums, and/or sales via econometric analysis (e.g., Nasukawa and Yi 2003, Yi et al. 2003).

Recently, Ghose et al. (2006) propose to analyze the impact of e-sentiment on price premiums. Specifically, they use a text-mining technique to extract positive and negative online buzz components with respect to e-retailers (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 online buzz 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 academic e-sentiment analysis study to combine text-mining, econometric analysis, and predictive modeling. However, their focus is on the effect of e-sentiment around e-retailers on price premium charged by those retailers, while our focus is on the impact of e-sentiment about products on the price fluctuation of those products. Moreover, they performed a cross-sectional analysis, which provides a static, one-shot description of price competition. We perform panel-data analysis with long time-series samples in order to fully assess the impact of positive vs. negative online buzz on the dynamics of price movement.

Firm response to e-sentiment: 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 online buzz. This may change a firm's role from an active one to a passive one, shifting power from firms to customers. Moreover, online buzz 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. Therefore, how a firm responds to positive vs. negative online buzz information 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' responses to the reviews have 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 policies using analytical modeling.

In this paper, we address one such coping strategy, how e-retailers with limited differentiation capabilities respond to product quality perception reflected on e-sentiment information by adjusting their product prices. We empirically investigate this issue using daily-level time-series data from the MP3 players market. Our unique contribution is the quantitative and dynamic assessment of e-sentiment impact on the business outcomes of competing firms, in this case minimum price fluctuation.

3. Empirical Analysis

3.1. Data

Industry Background: For the empirical analysis, we choose the MP3 player market. Initiated in 1998, the MP3 player market exhibits several interesting characteristics. First, it is a large and fast-growing market. According to In-Stat market research reports,[5] the market reached $4.5B in 2005, double the size of the 2003 market, with about one quarter of the U.S. population owning an MP3 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. MP3 player market share (by unit sales) was 31% in January 2004, then grew to 71% in September 2006.[6] Since then, Apple has consistently claimed over 70% of total market sales.[7] While Apple enjoys the dominant market position, over 40 other manufacturers—including Creative Labs, SanDisk, and Samsung—compete for the remaining but still lucrative 30% of the market.

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

[5] See http://www.instat.com/press.asp?ID=1366&sku=IN0502148ID.
[6] See http://www.iht.com/articles/2006/10/31/bloomberg/sxcreative.php.
[7] See http://apple20.blogs.fortune.cnn.com/2008/01/29/beyond-the-incredible-shrinking-ipod-market.

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, digital songs are recorded in diverse formats (e.g., AA, AAC, FLAC, MP3, MP3Pro, OGG, WAV, and WMA). Accordingly, the MP3 player category is notorious for its complexity in terms of purchase decision-making. As the CNET MP3 Player Buying Guide[8] puts it:

> *Every month, manufacturers 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 and short product life cycle of the MP3 player products, new customers are likely to depend greatly on previous customers' opinions, and especially on e-sentiment generated by early adopters. Third, by analyzing Apple's key products, we can easily cover about 70% of the total market. As such, the MP3 player market is an ideal setting to examine our hypotheses.

Database Development: For data collection, eleven MP3 player products were selected based on their popularity as of May 2007. Table 1 presents the description of the products of interest.

Through a semantic data mining approach developed and patented by a private company, e-sentiment data were collected "live" between June 2, 2007 and August 1, 2007 (T=61). 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

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[8] To help 'confused' customers, the 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.

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 "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," and 5) "Apple Corp" and "Creative Labs" belong to the "Consumer Electronics" industry. As such, by utilizing keywords/concepts identified by industry/market 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
Helix	Helix	Samsung	1GB	June 2006	#6810	3.7/5 (N=55)
Nex50	NeXus50	Samsung	1GB	June 2006	#11449	3.4/5 (N=33)
Nex25	NeXus25	Samsung	512MB	June 2006	#5098	4.2/5 (N=21)
Mini	iPod Mini	Apple	4GB	Feb. 2005	#6302	3.9/5 (N=431)
Nano	iPod Nano	Apple	2GB	Feb. 2006	#435	4.2/5 (N=1355)
Video	iPod Video	Apple	30GB	Sep. 2006	#1221	4.3/5 (N=633)
Shuffle	iPod Shuffle	Apple	1GB	Sep. 2006	#54	4.4/5 (N=198)
Vision	Zen Vision	Creative Labs	30GB	Dec. 2005	#1299	4.2/5 (N=983)
Sleek	Zen Sleek	Creative Labs	20GB	Jan. 2006	#9756	3.9/5 (N=88)
E260	Sansa E260	SanDisk	4GB	Apr. 2004	#175	4.1/5 (N=597)
M230	Sansa M230	SanDisk	512MB	May 2006	#312	4.2/5 (N=546)

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

Table 1: Description of 11 MP3 Player Products

Based on this approach, the company's data mining 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 (e.g., "cool"), negative (e.g., "disappointing"), or neutral (e.g., "so-so") 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).[9]

Price: On a daily basis, price (**PRICE)** is defined as the minimum or the lowest price of each MP3 player product at Amazon.com. As shown in Figure 1, minimum prices are stable, fluctuating around a certain level. Considering that all 11 products are rather old ones in the market (9 months~3 years since the launch), this pattern is consistent with the finding that minimum prices are stabilized after about 5 months since the introduction and that they fluctuate after that point (Schneider and Albers 2008).

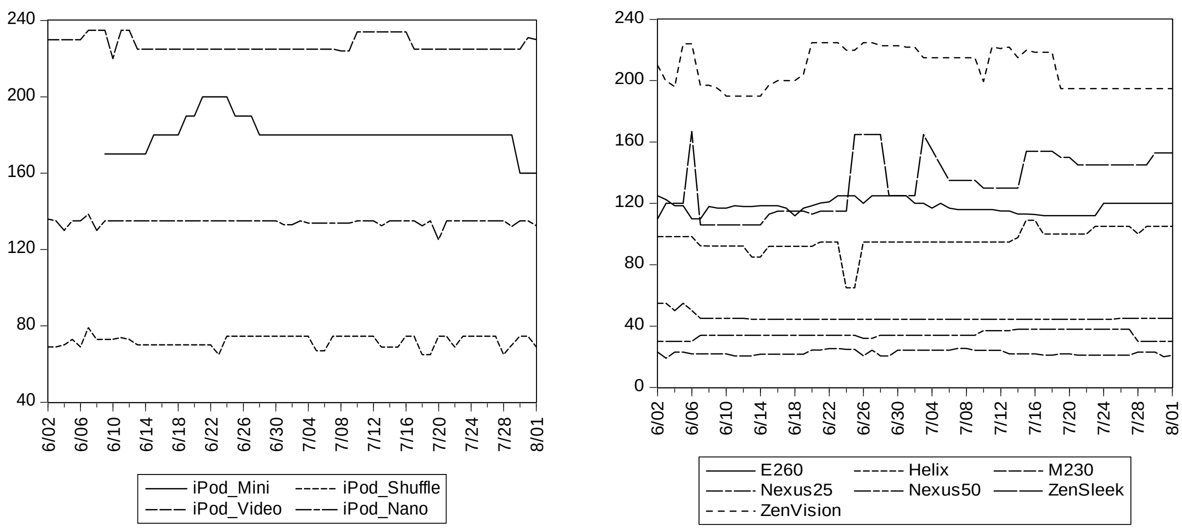

Figure 1: Price Fluctuation over Time (Apple vs. Non-Apple Products)

Both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) panel unit root tests confirm that prices are stable or stationary at the 99% significance level. To make sure that there is no influence on price movement of time trend and/or seasonality factor such as a "July 4th Event," simple regression analysis is performed. The coefficient estimate for trend is -0.0003 (*t-stat* = -0.05) while the one for Independence Day dummy variable (July 2-4) is -0.09 (*t-stat* = -0.47).

Table 2 summarizes the price histories of the eleven products under study. Again, prices do fluctuate over time, with higher variability (coefficient of variation) for the lower-priced items (and *vice versa*). In addition, the average coefficient of variation of Apple's four products is 0.03, while that of other eight

[9] 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.

products is 0.08, which illustrates different price movement patterns for the leading brand (i.e., Apple) vs. others.

ID	Mean	Median	Std. Dev.	Coeff. Variation	# of Price Changes	Avg. of Daily Price Changes	Avg. of Absolute Price Changes
Helix	95.9	94.8	7.7	0.08	13	0.12%	9.71%
Nex50	45.3	44.4	2.4	0.05	6	-0.36%	7.65%
Nex25	34.4	34.0	2.6	0.08	9	0.00%	6.47%
Mini	180.2	180.0	8.6	0.05	13	-0.09%	2.99%
Nano	134.4	135.0	1.8	0.01	19	-0.04%	2.88%
Video	227.3	225.0	3.9	0.02	9	0.00%	3.50%
Shuffle	71.9	72.9	3.2	0.04	22	0.00%	7.88%
Vision	207.9	210.0	12.9	0.06	25	-0.12%	3.99%
Sleek	133.2	130.0	19.3	0.14	21	0.54%	12.03%
E260	118.0	118.5	4.2	0.04	28	-0.07%	2.50%
M230	22.5	21.8	1.7	0.08	21	-0.15%	9.50%

Table 2: Descriptive Statistics on Prices (in $)

Note that we are interested in price fluctuations, which can be studied by examining price changes (i.e., $\Delta PRICE_t = PRICE_t - PRICE_{t-1}$). The last three columns of Table 2 present relevant statistics including the number (frequency) of price changes, average percent of daily price changes with respect to mean prices, and average percent of absolute daily price changes with respect to mean prices, respectively. The column of 'Average of Daily Price Changes' shows that the averages are close to 0%, suggesting that the prices were fluctuating around a certain value. The last column, 'Average of Absolute Price Changes' shows that on average prices go up or down by 2.50-12.03% per change, implying that the magnitude of price changes was incremental. When median is used as a denominator (instead of mean) for the last two columns, the results are not different. This pattern of price fluctuation (i.e., frequent price changes with smaller amount) is consistent with previous research (e.g., Bailey 1998, Brynjolfsson and Smith 2000).

e-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 Samsung Nexus50 was carried by more than 30 e-vendors, while the Zen Sleek was carried by fewer than 10 e-vendors during the data collection period.[10]

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

e-Sentiment: From multiple sources including online product ratings (e.g., Amazon product ratings), online forums, and blogs, daily online buzz count 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 levels of positive buzz, while Creative Lab's Zen Sleek and Zen Vision generated high levels 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.

Figures 2 and 3 show relatively stable patterns of POS and NEG over time. Both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) panel unit root tests confirm that positive buzz (POS) and negative buzz (NEG) are stationary at 99% significance level.

[10] 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.

ID	Positive Buzz (POS)		Negative Buzz (NEG)		Neutral Buzz (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 e-Sentiment

Figure 2: POS over Time (Apple vs. Non-Apple Products)

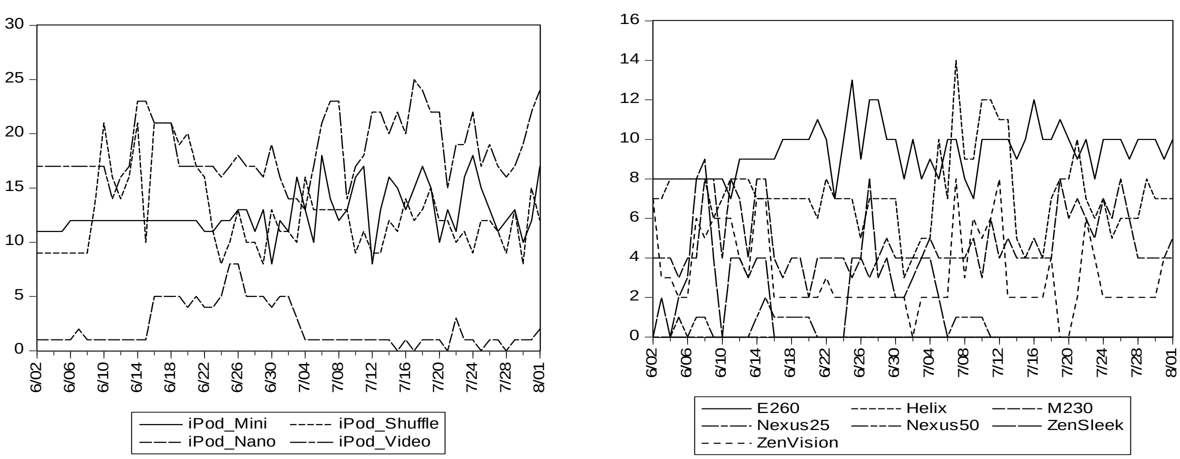

Figure 3: NEG over Time (Apple vs. Non-Apple Products)

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 e-retailers compete, but falls to 3.5% when 17 e-retailers carry the title. Accordingly, we expect the minimum price of an MP3 player 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 minimum price of the product decreases.*

Second, negative product information is often more diagnostic or informative than positive or neutral information (Herr et al. 1991). This is because negative attributes are strongly associated with a certain category (i.e., low quality) while non-negative attributes are more ambiguous with respect to category membership. Therefore, negative information is weighed more heavily in consumer judgment and choice decisions. Moreover, negative information is likely to have an even greater effect in the online setting because online customers may think negative information is more credible (Chevalier and Mayzlin 2006) and suspect the trustworthiness of positive information providers (Dellarocas 2003) since they are aware of the possibility of firms' strategic manipulation of online buzz to boost sales (Dellarocas 2006). Therefore we predict:

HYPOTHESIS 2.1 (Negative vs. Positive Online Buzz Effect): *The magnitude of the negative online buzz effect on price fluctuation will be bigger than that of the positive online buzz effect.*

HYPOTHESIS 2.2 (Negative vs. Non-negative Online Buzz Effect): *The magnitude of the negative online buzz effect on price fluctuation will be bigger than that of the non-negative online buzz effect.*

Third, the effect of e-sentiment may be moderated by the customers' expectation levels. Fiske (1980) argues that negative information about a product may be more influential or diagnostic than positive information when a consumer has higher standards or positive expectation (i.e., "negativity effect"). In contrast, if a customer with negative expectation on a product receives positive information, it may dominate her judgment and choice decisions (i.e., "positivity effect"). The role of consumer expectation as a moderator has been supported in previous marketing research (for a review, see East et al. 2008).

In this paper, we focus on the role of price tier and market position as potential drivers of consumers' expectation levels. Specifically, the effect of the negative review would be stronger for higher-priced items than for lower-priced items. This is because a customer is likely to have a higher initial quality expectation of the former, and thus, a single negative e-sentiment may have a larger negativity effect for those items. By the same token, one piece of positive e-sentiment may have a larger positivity effect for lower-ticket items, given that customers expect to 'get what they pay for.'

HYPOTHESIS 3.1 (Online Buzz Effect for Higher- vs. Lower-Ticket Items): *Higher-ticket (lower-ticket) items are more sensitive to negative (positive) online buzz than to positive (negative) online buzz.*

Moreover, the effect of negative buzz is expected to be larger for the market leader's products, while the effect of positive buzz would be larger for the followers' products. The leader's products are likely to be associated with high visibility through advertising and publicity. In our case, the leader, Apple, is known to enjoy more positive press coverage, which may further boost consumers' baseline expectation.

HYPOTHESIS 3.2 (Online Buzz Effect for Leading vs. Following Brand Products): *Leading (following) brand products are more sensitive to negative (positive) online buzz than to positive (negative) online buzz.*

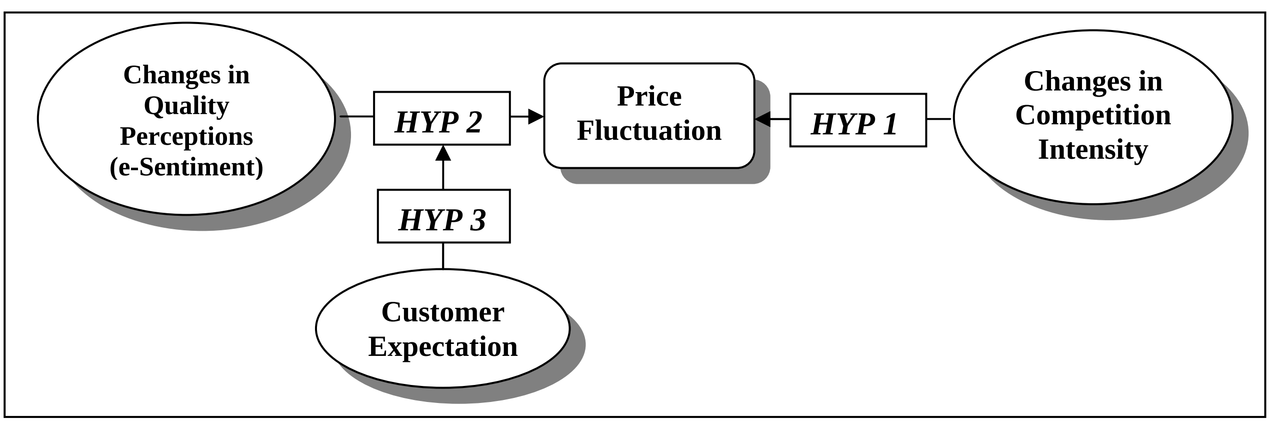

Figure 4: Conceptual Framework

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:

$$\Delta PRICE_{i,t} = \alpha_i + \beta \cdot \Delta VEND_{i,t} + \sum_{k=1}^{K} \gamma_k \cdot \Delta X_{i,t-k} + e_{i,t} \text{ (1)}$$
$$where \;\; e_{i,t} = \rho \cdot e_{i,t-1} + \upsilon_{i,t}, \upsilon_{i,t} \sim N(0, \sigma^2)$$

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. X denotes the vector of e-sentiment variables such as positive buzz ($POS_{i,t}$), negative buzz ($NEG_{i,t}$), and neutral buzz ($NEUT_{i,t}$). Also note that k represents the lag lengths for e-sentiment variables. 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.

Note that $\Delta PRICE_{i,t} = PRICE_{i,t} - PRICE_{i,t-1}$, capturing the change in minimum prices from time t-1 to time t. Thus, Equation (1) describes price change as an outcome of the change in 'perceived quality' information reflected in online buzz and the change in 'competition intensity' captured through the number of e-vendors. Our fixed-effect modeling approach indeed removes the influence of time-invariant, brand-specific factors such as storage capacity (e.g, 4GB), brand name, durability, weight, size, etc.

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 Feasible GLS (FGLS) method to control for cross-sectional heteroskedasticity. We also employed White's period heteroskedasticity-robust standard errors to account for heteroskedasticity across periods. To avoid the possibility of spurious regression results, we performed Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) panel unit-root tests on the ΔPRICE variable (Enders 2004). The test result suggest that the dependent variable, ΔPRICE, is stationary ($p<0.01$).

3.3. Results

Competition and e-Sentiment Effects: To examine HYPOTHESIS 1, 2.1, and 2.2, we estimated Equation (1) with different combinations of e-sentiment variables including POS ('positive'), NEG ('negative'), NEUT ('neutral'), and NONNEG ('non-negative' = POS + NEUT) (see Table 5). Note that *Models 1*, *3*, and *5* use e-sentiment variables with 3 lags, while *Models 2*, *4*, and *6* use ones with 2 lags. The models consistently show that higher competition is associated with lower prices, so we do not reject HYPOTHESIS 1. The first four columns (*Model 1-4*) of Table 5 illustrate that the magnitude of negative buzz effect (about -0.08) is larger than that of the positive one (about zero), supporting HYPOTHESIS 2.1. The last two columns (*Model 5-6*) show that the magnitude of the negative buzz effect (about -0.08) is larger than that of the non-negative one (about zero), supporting HYPOTHESIS 2.2.

	Model 1	***Model 2***	***Model 3***	***Model 4***	***Model 5***	***Model 6***
$\Delta VEND_t$	-0.45**	-0.49***	-0.45**	-0.50***	-0.45**	-0.49***
ΔNEG_{t-1}	-0.08**	-0.08**	-0.08**	-0.08**	-0.08**	-0.08**
ΔNEG_{t-2}	-0.03	-0.04	-0.03	-0.04	-0.02	-0.03
ΔNEG_{t-3}	0.02	NA	0.02	NA	0.01	NA
ΔPOS_{t-1}	0.00	0.00	0.00	0.00	NA	NA
ΔPOS_{t-2}	0.00	0.00	0.00	0.00	NA	NA
ΔPOS_{t-3}	-0.01	NA	-0.01	NA	NA	NA
$\Delta NEUT_{t-1}$	0.00	0.00	NA	NA	NA	NA
$\Delta NEUT_{t-2}$	0.00	0.00	NA	NA	NA	NA
$\Delta NEUT_{t-3}$	0.00	NA	NA	NA	NA	NA
$\Delta NONNEG_{t-1}$	NA	NA	NA	NA	0.00	0.00
$\Delta NONNEG_{t-2}$	NA	NA	NA	NA	0.00	0.00
$\Delta NONNEG_{t-3}$	NA	NA	NA	NA	0.00	NA
AR term (ρ)	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***	-0.18***
# of obs.	612	622	612	622	612	622
# of cross-sections	11	11	11	11	11	11
R^2	0.09	0.10	0.09	0.10	0.09	0.10
F-stat.	2.82***	3.60***	3.36***	4.14***	3.28***	4.11***
Durbin-Watson stat.	1.94	2.03	1.94	2.04	1.94	2.04

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

Table 5: Effects of Competition and e-Sentiment

The Durbin-Watson statistics show that the inclusion of ρ is sufficient to account for residual autocorrelation (i.e., inertia in price changes). Significant F-statistics suggest that fixed-effect specification is preferred to pooled model specification. Note that adding neutral e-sentiment information directly (*Model 1-2*) or indirectly (*Model 5-6*) does not change other parameter estimates, nor does it improve results in terms of R^2 and Durbin-Watson statistics. Moreover, the models with up to 3 lags of e-sentiment variables and those with up to 2 lags do not yield qualitatively different results. Accordingly, *Model 4* is chosen as the best specification in terms of parsimony.

Asymmetric Effect of e-Sentiment for Higher- vs. Lower-Priced Items: To examine HYPOTHESIS 3.1, we estimated Equation (1) separately for the three price tiers in the market. Specifically, HIGH (high-ticket items) includes the top 3 items in terms of prices: iPod Mini, iPod Video, and Zen Vision (mean/median price level: $180-230). LOW (low-ticket items) includes the bottom 3 items: Sansa M230, Samsung Nexus25, and Samsung Nexus 50 (mean/median price level: less than $50). MED (medium-ticket items) includes the remaining 5 items: iPod Nano, iPod Shuffle, Sansa E260, Samsung Helix, and Zen Sleek (mean/median price level: $70-140). In so doing, the specification of *Model 4* is followed (i.e., 2 lags of e-sentiment variables including ΔPOS and ΔNEG) based on the results from Table 5.

	HIGH	MED	LOW
$\Delta VEND_t$	-1.38***	-1.10***	-0.09
ΔNEG_{t-1}	-0.17***	-0.08	0.11***
ΔNEG_{t-2}	-0.02	-0.08**	0.01
ΔPOS_{t-1}	0.00	-0.01	0.00
ΔPOS_{t-2}	0.00	0.01	0.01***
AR term (ρ)	-0.12*	-0.21***	-0.09
# of obs.	166	285	171
# of cross-sections	3	5	3
R^2	0.08	0.20	0.03
F-stat.	1.79*	6.85***	0.70
Durbin-Watson stat.	2.10	2.06	1.63

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

Table 6: Asymmetric Effects of e-Sentiment: High- vs. Medium- vs. Low-Priced Items

Table 6 illustrates that the competition effect decreases as average price level goes downs: HIGH (-1.38) < MED (-1.10) < LOW (0.00). In addition, Table 6 shows that higher-priced items are more sensitive to negative buzz: HIGH (-0.17) < MED (-0.08) < LOW (0.11). Moreover, lower-priced items are also more sensitive to positive buzz: HIGH (0.00) = MED (0.00) < LOW (0.01). Overall, these results support HYPOTHESIS 3.1, suggesting that prices of high-priced vs. low-priced products respond differently to e-sentiment. Interestingly, both positive buzz and negative buzz lead to price increase for the LOW group, implying that 'even bad news can be better than no news' for certain items. According to Table 1, Nexus 25 and Nexus 50 receive very little positive and negative buzz. When Equation (1) is re-estimated only for those two products, the 'positive' effect of negative buzz further increases to 0.44 ($p<0.01$), which corroborates the above argument. Note that a poolability test based on F-statistics suggests that the LOW group does not need the fixed-effect specification. However, there was no difference in terms of coefficient estimates when Equation (1) is re-estimated using the pooled model for the LOW group.

Asymmetric Effect of e-Sentiment for Leading- vs. Following-Brand Items: To examine HYPOTHESIS 3.2, we estimated Equation (1) separately for the leading-brand (LB) products (i.e., Apple iPod family: Video, Mini, Nano, Shuffle) vs. the following-brand (FB) products (the remaining 7 items) in the market. Note that Apple has consistently claimed over 70% of market share. Equation (1) is estimated following *Model 4* again (i.e., 2 lags of e-sentiment variables including ΔPOS and ΔNEG).

	LB	**FB**
$\Delta VEND_t$	-1.31***	-0.31**
ΔNEG_{t-1}	-0.10**	-0.03
ΔNEG_{t-2}	-0.05*	-0.01
ΔPOS_{t-1}	0.00	0.00
ΔPOS_{t-2}	0.00	0.01**
AR term (ρ)	-0.20**	-0.10**
# of obs.	223	399
# of cross-sections	4	7
R^2	0.23	0.05
F-stat.	7.13***	1.65*
Durbin-Watson stat.	2.08	1.95

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

Table 7: Asymmetric Effects of e-Sentiment: Leading- vs. Following-Brand Items

Table 7 illustrates that the competition effect is larger for LB items (-1.31) than FB items (-0.31). Table 7 also shows that LB products are more sensitive to negative buzz than FB products: LB (-0.15) < FB (0.00). In addition, FB items are more sensitive to positive buzz: LB (0.00) < FB (0.01). Overall, these results support HYPOTHESIS 3.2, implying that prices of the leading-brand products vs. the following-brand products respond differently to e-sentiment. A poolability test suggests that the fixed-effect model is preferred to the pooled model.

Robustness Checks: Equation (1) may be subject to endogeneity bias because of the potential simultaneous relationship between $\Delta PRICE_{it}$ and $\Delta VEND_{it}$. To address this possibility, we performed a Durbin-Hausman-Wu test. Specifically, we obtained residuals for the potential endogenous variable ($\Delta VEND_{it}$) using the exogenous/predetermined variables ($\Delta POS_{i,t-1}$, $\Delta POS_{i,t-2}$, $\Delta NEG_{i,t-1}$, $\Delta NEG_{i,t-2}$) as well as the instrument variables, i.e., the lagged VEND variables ($VEND_{it-k}$ for k=2,…,K).[11] Then we included residuals from the previous estimation in the main model and checked the t-statistics of coefficients associated with those residuals (for details, see Davidson and MacKinnon 1993).

	ALL	**HIGH**	**MED**	**LOW**	**LB**	**FB**
Coefficient of residual	0.06	0.06	-0.69	0.03	-1.05	0.08
t-stat.	0.22	0.07	-1.14	0.94	-1.64	0.16
ΔNEG_{t-1}	-0.09*	-0.17***	-0.10	0.09***	-0.12**	0.00
ΔNEG_{t-2}	-0.04	-0.02	-0.12***	-0.04***	-0.06**	-0.03
ΔPOS_{t-1}	0.00	0.00	0.00	0.00	0.00	0.00
ΔPOS_{t-2}	0.00	0.00	0.01**	0.00	0.01	0.01***
AR term (ρ)	-0.17***	-0.14**	-0.18**	-0.14	-0.17**	-0.07**
# of obs.	612	164	275	162	208	385
# of cross-sections	11	3	5	3	4	7
Durbin-Watson stat.	1.94	1.90	2.02	2.03	1.83	2.01

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

Table 8: Endogeneity Check (Durbin-Hausman-Wu Test)

Table 8 illustrates that the coefficients of the residual are insignificant even at 90% level, so we conclude that 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 an increase in retail prices. The e-vendor needs to first contact the manufacturer or distributor to reserve inventory before taking orders from customers.[12] On the other hand, when the prevailing price for a product drops, the e-vendor will want to first reduce its inventory by matching the price drop before deciding to stop selling the product. In either case, it will

[11] We begin with k=2 because we assume that the error term follows AR(1) process in Equation (1).
[12] 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.

take several days or even weeks for a price shock to impact the number of e-vendors. Furthermore, e-vendors may have little incentive to take a risk of carrying inventory of a specific product after observing positive price shock, considering that the price of MP3 players changes frequently by small amount as shown in Table 2. In sum, $\Delta VEND$ may be treated as an exogenous variable.

Also note that the coefficients of e-sentiment variables estimated through Durbin-Hausman-Wu test procedure are equivalent to those estimated through the IV/2SLS estimation procedure. The only difference is that the IV/2SLS method yields bigger standard errors due to its well-known inefficiency problem (Greene 2003). Table 8 shows that the estimates of the IV/2SLS method should not be different from the estimates of our FGLS method as presented in Tables 5-7. This result implies that our FGLS method indeed produces consistent estimates with more efficient (i.e., smaller) standard errors.

In addition, it is possible that our independent variables ($\Delta VEND_t$, ΔPOS_{t-1}, ΔPOS_{t-2}, ΔNEG_{t-1}, and ΔNEG_{t-2}) are highly correlated. We computed VIF (Variance Inflation Factor) as shown in Table 9. Given that average VIF is far less than 5 for all six groups, we found no evidence of severe collinearity.

Dependent Variable	**ALL**	**HIGH**	**MED**	**LOW**	**LB**	**FB**
$\Delta VEND_t$	1.00	1.01	1.01	1.05	1.00	1.01
ΔPOS_{t-1}	1.19	1.25	1.25	1.79	1.28	1.23
ΔPOS_{t-2}	1.19	1.25	1.23	1.56	1.28	1.22
ΔNEG_{t-1}	1.23	1.19	1.27	1.25	1.25	1.12
ΔNEG_{t-2}	1.23	1.18	1.25	1.47	1.25	1.12
Avg. VIF	**1.17**	**1.18**	**1.20**	**1.42**	**1.21**	**1.14**

Table 9: Collinearity Check (VIF)

Finally, minimum prices can be affected by new-model launches, as e-retailers have an incentive to remove any excess old-model inventory by deep discounts. We verified that, in our data sample (June 2007 to August 2007), new models were introduced by Samsung (YP-U3 2GB) and Sandisk (Sansa View 16GB, Sansa Shaker 1GB) (www.smartratings.com). However, Figure 1 shows that the retail prices of the Samsung and Sandisk products do not exhibit any notable deep-discounts pattern, suggesting that these launches did not affect the minimum prices of the existing models.

4. Discussion

4.1. Summary of Findings

In this paper we estimated various fixed-effect panel regression models on data from eleven leading MP3 player products. The empirical findings are summarized as follows (see Table 10): Overall, 1) as the number of e-vendors carrying a product increases, the price of the product decreases (*competition effect*); 2) past negative buzz leads to future decrease in prices (*e-sentiment effect*); 3) the effect of negative buzz on price changes is larger for the higher-priced items and for the leader brand's (Apple's) products (*negativity effect of e-sentiment*), and 4) the effect of positive buzz is larger for lower-priced items and for the follower brands' products (*positivity effect of e-sentiment*). Finally, the effects are observed with a one- to two-day delay, with negative sentiment impacting price fluctuation more strongly and quickly than positive buzz.

	ALL	HIGH	MED	LOW	LB	FB
$\Delta VEND_t$	-0.50***	-1.38***	-1.10***	-	-1.31***	-0.31**
ΔNEG_{t-1}	-0.08**	-0.17***	-	0.11***	-0.10**	-
ΔNEG_{t-2}	-	-	-0.08**	-	-0.05*	-
ΔPOS_{t-1}	-	-	-	-	-	-
ΔPOS_{t-2}	-	-	-	0.01***	-	0.01**

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

Table 10: Summary of Empirical Findings

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 other customers' experiences and opinions reflected in e-sentiment, which is less controllable by firms. Accordingly, managing brand equity in response to e-sentiment becomes an important task for firms. Our results, as summarized in Table 10, provide some important managerial insights with respect to the impact of e-sentiment on firms as well as consumers.

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 customers. However, the internet allows dissatisfied customers to negatively affect other customers' decisions in a short time span. Thus, the importance of promptly managing the level of post-purchase dissatisfaction becomes even more important for high-priced products. In contrast, if a firm targets low-price tier customers who do not have such high quality expectations, 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 the price of a product, leading to higher profitability.

Second, our empirical findings also provide customers with strategic shopping advice. Both positive and negative e-sentiments 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 the good news raises 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 online buzz 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 opinion will loom large. Thus, a producer of niche products should manage complaints promptly before they become digitized and spread over the internet.

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 dynamics between product quality information reflected in e-sentiment and price fluctuation in the MP3 player 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 online buzz. In so doing, we have identified an important moderating factor, i.e., customers' expectations about a product. Specifically, we find that positive online buzz matters more for low-ticket items and the follower brands' products, while negative online buzz does so for high-ticket items and the leader brand's products. 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 quality and possible strategic manipulation by firms (Godes et al. 2005, Chevalier and Mayzlin 2006, Dellarocas 2006). Second, we examined only the effects of e-sentiment on retail prices. If daily sales quantities (or sales rank information) were available, we could estimate the 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 quality perceptions (reflected in e-sentiment). Third, our analysis based on the reduced-form modeling approach is descriptive. Future study may derive the optimal response of firms to e-sentiment via analytical modeling (Godes et al. 2005). An excellent example is Chen and Xie (2005), who analyzed the optimal response to influential expert ratings. Future research should examine if there are differences in the optimal response to customer-generated online buzz. Fourth, by examining other product categories, future study may identify other moderators of e-sentiment effects such as product types (e.g., hedonic vs. utilitarian products) (Sen and Lerman 2007).

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