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Authors
Shin, Hyun S
Hanssens, Dominique M
Kim, Kyoo il

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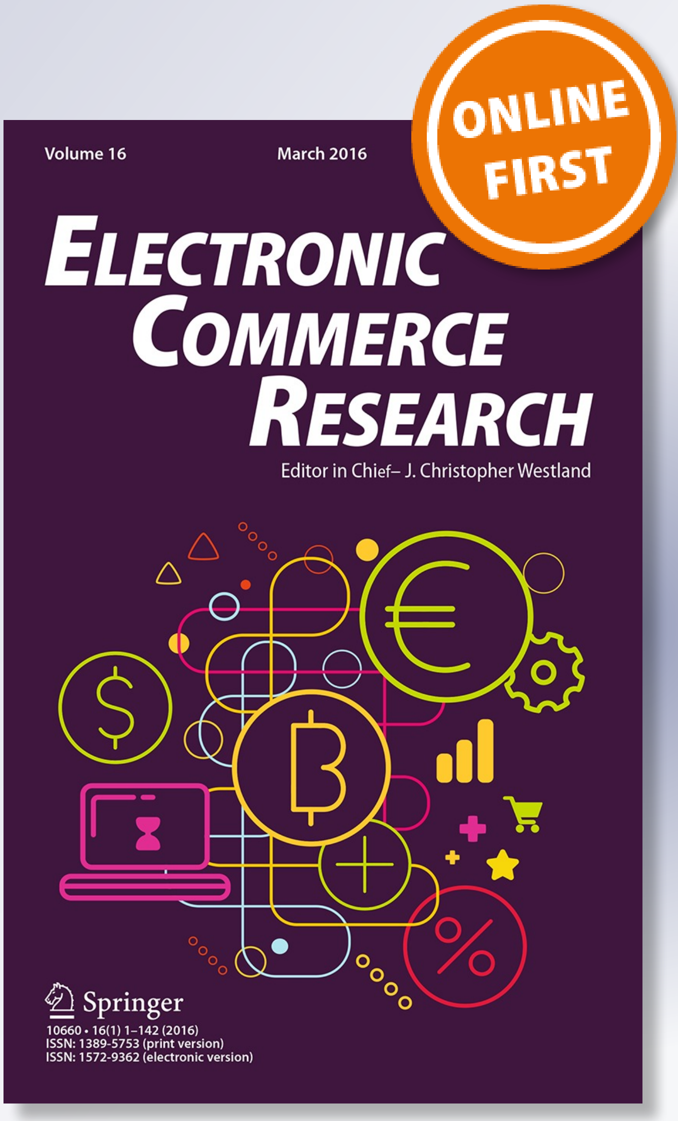

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The role of online buzz for leader versus challenger brands: the case of the MP3 player market

Hyun S. Shin[1] · **Dominique M. Hanssens**[2] · **Kyoo il Kim**[3]

Abstract Online buzz reflects the perceived quality of products in a positive, negative, or neutral way. We have limited understanding of how customers' quality perceptions, often referred to as *e-sentiment*, affect the movement of prices. In this paper, we examine the effect of e-sentiment on the daily price fluctuations of MP3 players by using daily buzz information collected from diverse online documents. Econometric panel data modeling reveals that e-sentiment is a leading indicator of price fluctuations. Furthermore, we find the effect is moderated by the brand's market position: the leading (challenger) brand's price responds more strongly to negative (positive) online buzz. In other words, negative buzz has a greater adverse effect on leading brands, whereas positive buzz has a greater beneficial effect on challenger brands. These findings establish the relevance of e-sentiment information to online price movements and suggest that managers should frequently monitor the online buzz surrounding their products, especially as it relates to their relative perceived quality.

Keywords Online buzz · E-sentiment · Quality perceptions · Price fluctuations · Market position

✉ Kyoo il Kim
kyookim@msu.edu

[1] School of Business, Hanyang University, Seoul, South Korea

[2] UCLA Anderson School of Management, Los Angeles, CA, USA

[3] Department of Economics, Michigan State University, East Lansing, MI, USA

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1 Introduction

It is widely accepted that quality is a principal driver of the success of new products (for a review, see [58]). Quality often refers to the actual performance or technical superiority of a product, which can be specified as a function of the value of key attributes (e.g., the size, weight, and battery time of laptops). These attributes can interact with one another and have non-linear, multiplicative effects on the overall perceived quality or value of a product [45]. Therefore, quality assessment is an inherently complex task for customers.

The complexity of quality assessment for high-tech products rapidly increases as manufacturers add new features or attributes to differentiate themselves from their competitors [7]. As a result, customers experience difficulty in evaluating the overall quality of a product, especially when they compare relatively complex durable goods. Accordingly, customers often engage in additional information searches [26]. However, the marginal benefit from acquiring attribute-relevant information provided by manufacturers is limited if customers cannot easily anticipate the consequences of those 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 experiences or perceptions, which is called word-of-mouth (WOM) in the marketing literature.

Previous studies confirm that WOM affects consumers' decisions [2, 49, 50]. In particular, digitized WOM information, *online buzz*, spreads rapidly through the internet, further increasing its influence on the consumer decision-making process (for a review, see [53]). Accordingly, the role of online buzz has received much attention from researchers [14, 16, 19, 25, 41, 43, 51, 57, 62].

In this paper, we contribute to the literature as follows: First, previous researchers have reported that consumers greatly value descriptive reviews containing detailed information, such as pros, cons, best uses, fit, and rating, and that such reviews lead to strong customer responses [59]. However, the qualitative aspect of online buzz (i.e., how customers perceive or feel about a product) has been less explored.[2] Therefore it would be interesting to extract consumers' quality perceptions about a product directly from online texts and examine the effects of quality perceptions on business outcomes such as prices. For example, investigating how customers' descriptions of a product, such as "cool" or "crap," affect its retail price would provide rich insights to researchers and practitioners.

Previous research has documented several interesting phenomena with respect to price behavior in the presumably frictionless e-marketplace. For example, empirical evidence suggests that online price dispersion does exist [12] and even increases over time [17]. Moreover, e-retailers charge price premiums [20] and frequently

[1] Subjective quality assessment is often called 'quality perceptions,' 'perceived value,' or 'perceived quality' in the marketing literature. Quality perceptions consist of three components: (1) abstract dimensions of intrinsic attributes (e.g., safety, durability), (2) perceived monetary price, and 3) reputation formed through advertising and brand name [61].

[2] A few notable exceptions include [19, 34, 43, 44, 56]. But they collect online buzz data from a single source, such as a movie review site (e.g., Yahoo!Movie) [19, 43], an online forum [34], or a single firm [56].

adjust their prices up or down by small increments [10]. Recently, Schneider and Albers [54] reported that prices continuously drop until about 5 months after the launch of new high-tech products. Surprisingly, they also found that, once stabilized, prices start to fluctuate around that value over time. One interesting question is: what are the factors that drive price fluctuations? In this paper, we examine the effect of online buzz on price fluctuations. Online buzz information is particularly relevant for e-retailers as they decide how to adjust prices in light of customer feedback [22].

Second, customers can easily access online buzz information through media such as blogs, chat rooms, customer reviews, and forums because all the information is just a click away. However, because of limits in data collection, prior empirical research has investigated the effect of online buzz only within a specific source, such as online product reviews at Amazon.com or online forums about TV shows. Nonetheless, customers likely use information from diverse sources for their decision making. Gu et al. [36], for example, showed that the sales of high-tech products at Amazon.com are affected by customer reviews outside Amazon.com (e.g., CNET, Epinions). Therefore, collecting qualitative online buzz data from across diverse sources and analyzing the response of retail prices to online buzz are imperative for modern marketing strategy. Our research fills the gap by using data from multiple sources to better represent online buzz.

In this study, we use online buzz data on MP3 players collected from diverse online documents by an online marketing research company. These data, obtained through a web crawling technique, enable us to investigate the different implications of positive, negative, and neutral online buzz. The dataset is collected "live" on a daily basis for 2 months (June 2, 2007–August 1, 2007), allowing us to analyze the dynamics between price fluctuations and online buzz.

One important methodological issue arises with this approach. Sales data, which should be one of the main drivers of price fluctuation, are difficult to obtain.[3] Moreover, daily sales data are likely correlated with daily online buzz. Assuming that the (unobservable) daily sales variable is time-invariant, we can use a fixed-effects modeling approach to remove the unobservable from the equation and attain consistent estimates of the effects of online buzz on price fluctuations. However, that assumption can be problematic because the popularity of or demand for new products often evolves over time. Thus, omitting a time-varying unobservable variable such as daily sales could yield biased estimations, which is one of the key concerns in analyzing online buzz data.

To address this issue, we adopt a hedonic regression approach, following Bajari et al. [4]. By explicitly modeling the evolution of time-varying unobservable factor and estimating the model with GMM (Generalized Method of Moments), we can deal with a time-varying omitted variable (daily sales variable in our case) that is potentially correlated with daily online buzz. As such, we contribute to the literature by providing a new solution to a serious methodological challenge in analyzing daily online buzz data.

[3] Accordingly, researchers often rely on a proxy, such as sales rank. Even though sales rank information is known to approximate actual sales to some extent (e.g., [32]), it is still not a perfect measure.

In the next section we review previous research about online retail prices and e-sentiment analysis and develop hypotheses. 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 the contributions and limitations of this research and suggest directions for future study.

2 Background

2.1 The behavior of online retail prices

In the late 1990s, economists expected that the advent of the internet and online shopping would reduce customers' information search costs and retailers' entry costs, resulting in intense competition in the e-marketplace (for a review, see [6]). Accordingly, they predicted: (1) overall, prices would be lower in the e-marketplace than in offline stores, (2) product prices would converge in the e-marketplace, and (3) e-retailers would charge prices at their marginal costs. However, those predictions of 'frictionless commerce' turned out to be wrong [28], as we review below.

2.1.1 Overall price level

Examining 107 book titles, Clay et al. [20] 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 included.

2.1.2 Price dispersion

Empirical evidence suggests that substantial price dispersion exists online for relatively inexpensive product categories such as books and CDs [12, 20], as well as for relatively expensive ones such as electronics [9]. In addition, researchers report that price dispersion increases over time [9, 17].

2.1.3 Price premiums

Contrary to economists' expectations, empirical evidence shows that e-retailers are able to charge price premiums. For example, Amazon.com charges prices that are 5 % higher than those at BarnesandNobles.com and 11 % higher than those at Borders.com [20]. Demand on Amazon.com is inelastic (−0.5), whereas demand on BarnesandNobles.com is highly elastic (−4) [17]. These findings imply that e-retailers can charge price premiums by differentiating themselves in terms of service quality, brand, and customer trust [6, 12], and that customers are willing to pay premiums to reduce their perceived risk [48].

As such, the online and offline retail environments differ little with respect to overall price levels, price dispersion, and price premiums. One interesting difference is that online retail prices change more frequently than offline prices [10, 54].

2.1.4 Price fluctuations

Although some e-retailers, such as Amazon.com, can charge price premiums, others with low service quality or an unknown brand name can be involved in intense price competition. Because the consumer search cost is low and the online menu cost (i.e., the cost of changing prices) is negligible, undifferentiated e-retailers are expected to monitor their rivals' prices and adjust their own prices frequently [6] and in small increments [10, 12].

As a result, prices are likely to fluctuate (i.e., to change frequently in small increments) in the e-marketplace. By examining 38,000 daily online retail price changes for 12 months, Schneider and Albers [54] find that prices drop continuously for about 5 months after the introduction of new high-tech products such as digital cameras and camcorders; after that point, prices become stabilized, fluctuating around approximately 88 % of the initial price.

In sum, price competition among e-retailers is less uniform than originally expected from economic theory, and profit opportunities exist for those who can figure out the pattern of price fluctuations. Past research, however, has investigated price competition from a static point of a view, analyzing cross-sectional variations in prices [28]. Even when panel data were used, the data were generally collected over relatively long time intervals, such as weekly or monthly data. Accordingly, most previous empirical studies have failed to examine the drivers of price fluctuations, as Ellison and Ellison pointed out [28].

In the fast-moving internet world, analyzing high-frequency time-series observations can provide more useful insights about the dynamics of price movement. On September 12, 2004, for example, someone posted on an online bike forum that the Kryptonite bike lock can be easily opened with a Big Pen.[4] 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 *New York Times*. Within 10 days of 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 a fast effect of online buzz on business outcomes cannot be captured by analyzing weekly or monthly data. In this paper, we use data collected daily to track online retail price fluctuations in a timely manner.

2.2 e-Sentiment analysis

WOM can be defined as a "one-to-one and face-to-face exchange of information about a product or service" [33, p. 416]. The power of WOM is vastly increased by the internet. Online customers can exchange their private information in an efficient

[4] http://archive.fortune.com/magazines/fortune/fortune_archive/2005/01/10/8230982/index.htm.

way, and all the information about products is just a click away [22]. Even though product life cycles are shorter than in the past, customers can wait a few days before making a purchase decision to observe early adopters' opinions and evaluations as posted on various sources, such as blogs, online product comparison sites, online shopping malls, and online forums [24]. As a result, online buzz has become more influential, and its effects on customer decision making have been actively studied in the past decade [18, 32, 52, 62].

Researchers became interested in the role of online buzz valence, e.g., how positive or negative buzz affects consumers' purchase decisions differently. Interestingly, previous research reports mixed empirical results regarding the effect of online buzz valence, which could result from the fact that researchers used only aggregate ratings as a proxy of online buzz valence [15]. Indeed, shoppers are often strongly affected by aspects of online texts such as wording (e.g., inexpressive slang, extreme emotion words) [59]. Thus, it would be more informative to capture the valence of online buzz from textual data and then analyze its effects on business [53].

In this regard, an e-sentiment analysis can assess the effect of online buzz information on firm performance through the following three steps: (1) collect favorable and unfavorable opinions toward specific subjects (e.g., brands, products) from large numbers of online texts, (2) measure e-sentiment information (e.g., the number of positive/negative words in an online document), and (3) examine the relation between e-sentiment information and business outcomes using an econometric analysis [46, 60].

In this paper, we empirically investigate the effects on the prices of product quality perceptions reflected in e-sentiment information using daily-level time-series data from the MP3 player market. Our unique contribution is the quantitative and dynamic assessment of e-sentiment effects on business outcomes, in this case price fluctuations.

2.3 Hypotheses

Economic theory suggests that prices decrease as competition increases, which should hold in an e-marketplace setting. For example, Baye et al. [9] find that the gap between the two lowest prices for a book averages 23 % when only 2 e-retailers compete but falls to 3.5 % when 17 e-retailers carry the title. Accordingly, we expect the price of an MP3 player to 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.

Prior researchers argue that negative product information is perceived as more informative than positive product information [2, 37] because negative attributes are strongly associated with a certain category (e.g., low quality), whereas positive attributes are more ambiguous with respect to category membership [37]. Thus, consumers are likely to regard negative information as more important than positive information in making decisions.

Previous research has shown that negative WOM has a bigger effect than positive WOM (e.g., [2], [30]). In an online business setting, negative buzz might exhibit an even stronger effect than positive buzz [51]. It is well acknowledged that negative online buzz is often regarded as more credible [18] whereas the trustworthiness of positive online buzz is often questioned [22] because consumers are aware that firms can strategically manipulate online buzz to artificially increase sales [23]. Therefore, we expect that the price of a product will respond more strongly to negative buzz than to positive buzz. Therefore, we predict:

Hypothesis 2 (*Negative vs. positive online buzz effect*) The responsiveness of the price to negative online buzz is larger than that to positive online buzz.

Furthermore, the effect of online buzz could be moderated by customers' expectation levels [55]. According to Zeithaml et al. [64], customers' expectations can be defined as their beliefs about a product, which they use as a reference point or standard to assess its performance. Prior studies show that customers' expectations can affect their purchase decisions [11] as well as their level of post-purchase satisfaction because they compare their expectations with the product's actual performance in their evaluation of product quality [63, 64].

Customers' expectations can also affect how they process relevant information. According to Fiske [30], for example, negative product information could have stronger influence than positive information when a consumer has a positive expectation or high standards (negativity effect). Fiske [30] also argues that when positive information is given to a consumer with a negative product expectation, it can dominate the consumer's judgment (positivity effect). The role of customers' expectations as a moderator has been documented by previous marketing studies [27].

In this paper, we focus on the role of market position as a potential driver of customers' expectation levels. Specifically, we expect the price of the market leader's products to be more responsive to negative buzz (negativity effect), whereas we expect the price of challengers' products to be more sensitive to positive buzz (positivity effect). Note that the market leader's products are likely to be associated with higher visibility through advertising and publicity than the challengers' products. Accordingly, a customer is likely to have a higher initial quality expectation of the leader's products, and thus, a single negative online buzz could have a larger negative effect for those items. In our case, the market leader, Apple, is known to enjoy more positive press coverage, which could further boost consumers' baseline expectations. By the same token, one piece of positive online buzz could have a larger positive effect for challenger-brand items. Therefore, we predict:

Hypothesis 3 (*Online buzz effect for leading vs. challenger brand products*) The price of leading (challenger) brand products is more responsive to negative (positive) online buzz.

3 Empirical analysis

3.1 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 was a large and fast-growing market until the late 2000s. According to In-Stat market research reports, the market reached $4.5 billion 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 [13]. The long-tail phenomenon refers to the stylized fact that only a few mainstream products lie at the head of the demand curve, and the majority of the niche products spread out in the thick tail part, mainly due to the virtually unlimited shelf space of e-retailers [62]. In our case, the market leader, Apple, increased its market power from 2004 onward. Apple's U.S. MP3 player market share (by unit sales) was 31 % in January 2004 and grew to 71 % in September 2006. Since then, Apple has consistently claimed more than 70 % of total market sales. Although Apple enjoys the dominant market position, more than 40 other manufacturers—including Creative Labs, SanDisk, and Samsung—compete for the remaining but still lucrative 30 % of the market.

Third, the level of competition in this market is intense. As of April 2008, more than 900 SKUs were 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, resulting in severe competition.

Last, intense competition drives manufacturers to incorporate more features to differentiate themselves from competitors. Furthermore, 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 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.[5]

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 sufficient variations occur daily in our focal variables (e.g., prices, the number of e-vendors). Second, due to the inherent complexity of MP3 players, new customers are likely to depend greatly on previous customers' opinions, and especially on e-sentiment generated by early adopters. Third, it is relatively easy to identify a leader brand versus challenger brands in the MP3 player

[5] 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 (http://reviews.cnet.com/4520-7964_7-5134106.html).

market, unlike in other high-tech markets where leadership shifts occur frequently. As such, the MP3 player market is an excellent setting to examine our hypotheses.

3.2 Data

For data collection, we selected eleven MP3 player products from the top four brands based on their popularity as of May 2007. In February 2007, the top four brands were: Apple (72.3 %), SanDisk (9.7 %), Creative Labs (2.7 %), and Samsung (2.5 %), accounting for 87.2 % of retail sales in the MP3 player market (Source: NPD Group).[6] Data were collected for eleven flagship products manufactured by Apple (4), SanDisk (2), Creative Labs (2), and Samsung (3). Table 1 presents descriptions of the products of interest.

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 ($T = 61$ days).[7]

3.2.1 Price

On a daily basis, price (**PRICE**) is defined as the lowest price or the average price of each MP3 player product at Amazon.com. As shown in Fig. 1, prices are generally stable, fluctuating around a certain level. Considering that all eleven products are well established in the market (ranging from 9 months to 3 years since launch), this pattern is consistent with the finding that prices stabilize about 5 months after launch and that they fluctuate after that point [54].

Both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) panel unit root tests[8] confirm that prices are stable or stationary ($p < 0.01$). To ensure that there is no influence on price movements of either a time trend or a seasonal factor such as a "July 4th Event" simple regression analysis is performed. The coefficient estimate for a time trend is −0.0003 (*t-stats* = −0.05), and that for an Independence Day dummy variable (July 2–4) is −0.09 (*t-stats* = −0.47). This suggests that the effects of the time trend and seasonality on price fluctuations are negligible, and thus, those factors can be omitted from our analysis.

Table 2 summarizes the price histories of the eleven products under study. Our research focus is on price fluctuations, which can be studied by examining price changes (i.e., $\Delta PRICE_t = PRICE_t - PRICE_{t-1}$ at time t). The last three columns of Table 2 present the relevant statistics: 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.

6 http://www.bloomberg.com/apps/news?pid=conewsstory&refer=conews&tkr=AAPL:US&sid=aggTRzHFt1Do.

7 Note that $T = 61$ for all products except the iPod Mini, which was not available at Amazon.com for the first seven days (June 2–8). Accordingly, our database contains 54 observations for the iPod Mini.

8 The ADF and PP panel unit root tests can be used to check whether a focal variable is stationary. If stationary, we can perform a conventional regression analysis. If non-stationary, we can make the variable stationary by differencing. For more details, see Enders [28].

Table 1 Description of MP3 player products

ID	Product name	Brand name	Storage capacity	Amazon launch date
Helix	Helix	Samsung	1 GB	June 2006
Nex50	NeXus50	Samsung	1 GB	June 2006
Nex25	NeXus25	Samsung	512 MB	June 2006
Mini	iPod Mini	Apple	4 GB	Feb. 2005
Nano	iPod Nano	Apple	2 GB	Feb. 2006
Video	iPod Video	Apple	30 GB	Sep. 2006
Shuffle	iPod Shuffle	Apple	1 GB	Sep. 2006
Vision	Zen Vision	Creative Labs	30 GB	Dec. 2005
Sleek	Zen Sleek	Creative Labs	20 GB	Jan. 2006
E260	Sansa E260	SanDisk	4 GB	Apr. 2004
M230	Sansa M230	SanDisk	512 MB	May 2006

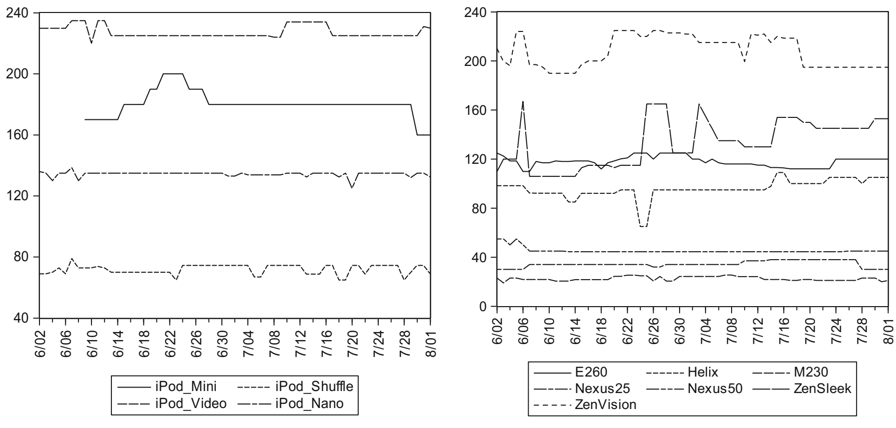

Fig. 1 Price fluctuation over time (daily lowest prices): Apple versus non-Apple products

The column, 'Average of Daily Price Changes,' shows that the averages are close to 0 %, suggesting that the prices fluctuate 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 is small. Using the median as a denominator instead of the mean for the last two columns did not change the results. This pattern of price fluctuation (i.e., frequent price changes with smaller amounts) is consistent with previous research [12]. Interestingly, the average coefficient of variation of Apple's four products is 0.03, whereas that of the other seven products is 0.08, which illustrates different price movement patterns for the leading brand (Apple) vs. those of its challengers.

Table 2 Descriptive statistics on prices (daily lowest prices in $)

ID	Mean	Median	SD	Coeff. variation	# of price changes	Avg. of daily price changes (%)	Avg. of absolute price changes (%)
Helix	95.9	94.8	7.7	.08	13	.12	9.71
Nex50	45.3	44.4	2.4	.05	6	−.36	7.65
Nex25	34.4	34.0	2.6	.08	9	.00	6.47
Mini	180.2	180.0	8.6	.05	13	−.09	2.99
Nano	134.4	135.0	1.8	.01	19	−.04	2.88
Video	227.3	225.0	3.9	.02	9	.00	3.50
Shuffle	71.9	72.9	3.2	.04	22	.00	7.88
Vision	207.9	210.0	12.9	.06	25	−.12	3.99
Sleek	133.2	130.0	19.3	.14	21	.54	12.03
E260	118.0	118.5	4.2	.04	28	−.07	2.50
M230	22.5	21.8	1.7	.08	21	−.15	9.50

3.2.2 e-Vendors

As a proxy of competition intensity, the number of e-vendors (**VEND**) at Amazon.com is obtained on a daily basis (Table 3). For example, the Samsung Nexus50 was carried by more than 30 e-vendors, whereas the Zen Sleek was carried by fewer than 10 e-vendors during the data collection period.[9]

3.2.3 e-Sentiment

Through a web data mining approach, e-sentiment data were collected "live" by a marketing research company between June 2, 2007, and August 1, 2007 ($T = 61$ days). For data collection, a semantic data mining approach was used, which analyzes the patterns of semi-structured data based on ontology. *Ontology* is a formal specification of the semantic relationship among concepts within a specific area of interest that boosts the performance of document classification and feature extraction ([38, 47]). In a marketing context, ontology can be used to identify a market-specific relationship among 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," "2 GB storage," "Zen Vision," and "Consumer Electronics." The ontology-based approach would specify the relationship among the words as follows: (1) "Apple Corp" makes "iPod Nano" and "iPod Shuffle," (2) "iPod Nano" has "2 GB 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.

[9] Note that the iPod Mini was replaced by the iPod Nano in 2006. During the data collection period in 2007, one to two e-vendors carried the iPod Mini at a price approximately 60 % cheaper than the original price.

Table 3 Descriptive statistics on the number of e-vendors

ID	Mean	Median	Min.	Max.	SD	Coeff. variation
Helix	18.8	22	8	28	6.5	.35
Nex50	34.9	35	31	38	2.2	.06
Nex25	26.6	26	24	30	1.5	.06
Mini	1.0	1	0	2	0.5	.50
Nano	18.4	18	15	26	2.5	.14
Video	12.9	13	11	15	1.2	.09
Shuffle	13.9	14	11	18	2.0	.14
Vision	12.2	13	7	16	2.1	.17
Sleek	8.1	8	5	13	2.0	.25
E260	43.8	44	37	51	3.1	.07
M230	33.9	36	24	40	4.7	.14

Thus, by using market-specific keywords/concepts, the approach constructs a hierarchy of concepts that helps capture the major underlying themes from the customer perspective. Based on this approach, data mining algorithms were used to incorporate various functions, including a document processor engine, an ontology processor, a page rank calculator, and a web crawler for data acquisition and classification. The algorithms, coupled with the aforementioned functions, were used to capture an aggregate consumer sentiment factor that is recorded as the number of sentences on each web page that reflect positive (e.g., “cool”), negative (e.g., “disappointing”), or neutral (e.g., “so–so”) sentiments. In so doing, multiple sources, including online product ratings (e.g., Amazon product ratings, Bestbuy.com reviews), online forums (e.g., CNET MP3 Players Forum), and blogs, were used to construct daily online buzz count data based on their sentiment: positive buzz (**POS**), negative buzz (**NEG**), and neutral buzz (**NEUT**).

Table 4 illustrates that three of the four iPod products (Video, Mini, and Shuffle) generated high levels of positive buzz, whereas Creative Lab’s Zen Sleek and Zen Vision generated high levels of neutral buzz. Interestingly, the positive buzz counts are at least ten 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 POS and NEG are stationary variables ($p < 0.01$).

3.3 Model specification

In this section, we consider a hedonic pricing model framework in a differentiated products market [3] to estimate the implicit prices of online buzz, i.e., the effect of online buzz on the prices of competing products. In the related literature, hedonic regressions have often been used to assess the effect of a seller’s reputation (positive or negative feedback by buyers) on market prices in online auctions such as eBay, Yahoo!, and Amazon (for a review, see [5]).

Here, we consider a linear hedonic pricing model of the form:

Table 4 Descriptive statistics on e-sentiment

ID	Positive buzz (POS)		Negative buzz (NEG)		Neutral buzz (NEUT)	
	Mean	SD	Mean	SD	Mean	SD
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	.2	.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

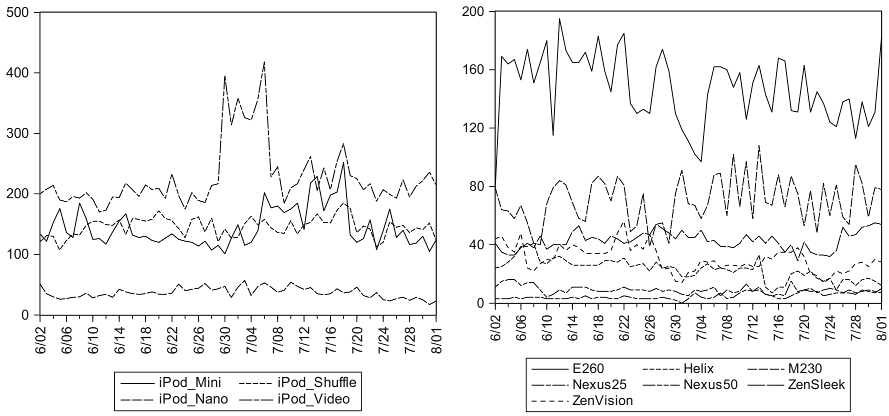

Fig. 2 Positive e-sentiment (POS) over time: Apple versus non-Apple products

$$PRICE_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_k \cdot X_{i,t-k} + \beta \cdot VEND_{i,t} + \xi_{i,t}. \tag{1}$$

$PRICE_{i,t}$ represents the average price of product i at time t, α_i denotes the product-specific effect representing time-invariant characteristics (e.g., size, weight, storage capacity of a MP3 player product), and $X_{i,t}$ denotes the vector of e-sentiment variables, i.e., positive buzz ($POS_{i,t}$), negative buzz ($NEG_{i,t}$), and neutral buzz ($NEUT_{i,t}$), where k denotes the lag lengths for the e-sentiment variables. $VEND_{i,t}$ stands for the number of e-vendors carrying product i at time t. Finally $\xi_{i,t}$ denotes the time-varying omitted variables (i.e., unobserved sales) that also affect the price, while the fixed-effect parameter α_i represents the unobservable, product-specific characteristics (e.g., design appeal) of product i (This fixed-effect term implicitly

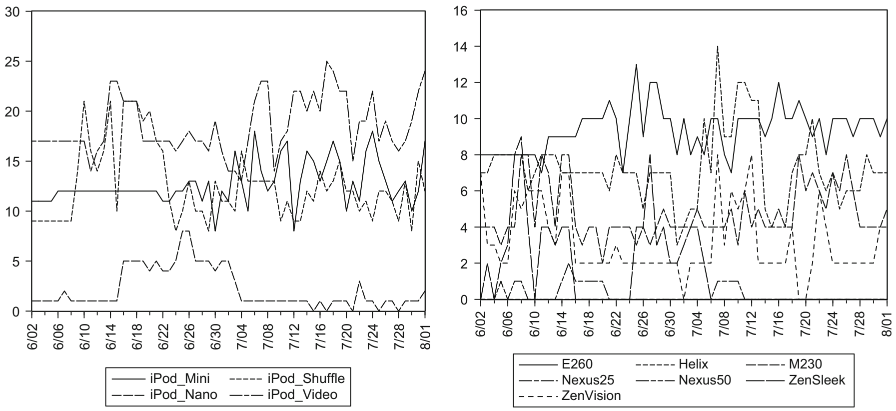

Fig. 3 Negative e-sentiment (NEG) over time: Apple versus non-Apple products

assumes that the product-specific characteristics are time-invariant). Thus, Eq. (1) describes how price evolves as online buzz, the number of vendors, and the omitted variable vary over time.

Our first key assumption is that the unobserved factor $\xi_{i,t}$ evolves according to a first order Markov process:

$$\xi_{i,t} = \rho \xi_{i,t-1} + v_{i,t}. \tag{2}$$

Note that the model in Eqs. (1) and (2) is fundamentally different from a fixed-effects model with an autoregressive error (AR) because $\xi_{i,t}$ is allowed to be correlated with all the observables in Eq. (1), including e-sentiment variables. In contrast, a fixed-effects model assumes $\xi_{i,t}$ to be a purely exogenous error. It is reasonable to expect that unobserved sales will be correlated with the observed e-sentiment variables.

Our second key assumption is that although consumers are uncertain about how $\xi_{i,t}$ evolves in the future, they are rational in the sense that any information I_{t-1} on products available at time t-1 does not help in predicting the innovation term $v_{i,t}$ in Eq. (2) at t, and thus we have:

$$E[v_{i,t}|I_{t-1}] = 0 \tag{3}$$

where I_{t-1} can include lagged prices, lagged e-sentiment variables, and other variables. Therefore, we interpret Eq. (3) as a Rational Expectation (REx) condition. To identify and estimate our parameters of interest, γ_k's (the effects of the online buzz variables on prices), we first combine Eqs. (1) and (2), and obtain:

$$\begin{aligned} PRICE_{i,t} = (1-\rho)\alpha_i + \rho PRICE_{i,t-1} + \sum_{k=1}^{K} \gamma_k \cdot (X_{i,t-k} - \rho X_{i,t-1-k}) + \beta \cdot (VEND_{i,t} \\ - \rho VEND_{i,t-1}) + v_{i,t}. \end{aligned} \tag{4}$$

Then, taking first-difference to remove the product fixed-effects, we obtain:

$$\Delta PRICE_{i,t} = \rho \Delta PRICE_{i,t-1} + \sum_{k=1}^{K} \gamma_k \cdot (\Delta X_{i,t-k} - \rho \Delta X_{i,t-1-k}) + \beta \cdot (\Delta VEND_{i,t} - \rho \Delta VEND_{i,t-1}) + v_{i,t} - v_{i,t-1} \tag{5}$$

where $\Delta PRICE_{i,t} = PRICE_{i,t} - PRICE_{i,t-1}$, and the other differenced variables are similarly defined. Note that $\Delta PRICE_{i,t}$ captures the change in the price of product i from time t-1 to time t, whereas $\Delta VEND_{i,t}$ (= $VEND_{i,t} - VEND_{i,t-1}$) represents the change in the number of e-vendors that carry product i. Thus, Eq. (5) describes price change as an outcome of the change in the *perceived quality* information reflected in online buzz and the change in *competition intensity* captured through the number of e-vendors. Also note that in Eq. (5), $v_{i,t}$ can be correlated with observables at t, and $v_{i,t-1}$ can be correlated with observables at t-1. Finally, the parameter ρ captures price inertia.

Therefore we estimate Eq. (5) using GMM based on the moment condition that is consistent with our assumption expressed as Eq. (3) (hereafter we name our estimator REx-GMM):

$$E[\Delta v_{i,t} | I_{t-2}] = 0. \tag{6}$$

The first-difference approach in Eq. (5) removes the influence of other product-specific, time-invariant factors. We assume that the product-specific characteristics such as storage capacity (e.g., 4 GB), durability, weight, and size of MP3 players are time-invariant, which is a reasonable assumption for daily data collected over a relatively short time span (i.e., 2 months).

To prevent the possibility of spurious regression results, we performed Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) panel unit-root tests on the ΔPRICE variable [29]. The test results suggest that the dependent variable, ΔPRICE, is stationary ($p < 0.01$). For estimation, we chose the specification with $K = 1$ in our empirical implementation of the model.[10]

3.4 Results

3.4.1 Competition and e-sentiment effects

To examine Hypotheses 1 and 2, we estimated Eq. (5) with the three e-sentiment variables, POS, NEG, and NEUT.

Table 5 (Columns 2, 3, and 4) shows that the sign of VEND is statistically significant and negative as expected (−.927), suggesting that higher competition is associated with lower prices. This result is consistent with Hypothesis 1, implying that rational customers would expect a product's price to drop as the number of

[10] For a specification with $K = 2$ and above, we found that either the estimation does not converge or the coefficients of additional lag terms are statistically insignificant. Accordingly, we conclude that $K = 1$ is the best specification, even aside from the parsimony issue.

Table 5 Effects of competition and e-sentiment: REx-GMM with AR(1) specification

Dependent variable: *price*$_t$	All items	Leading versus challenger-brand items	
Coefficient estimates	All	Leading brand (LB)	Challenger brand (CB)
POS_{t-1}	.013***	.008**	.023***
	[7.10]	[2.01]	[4.62]
NEG_{t-1}	−.224***	−.362***	−.377***
	[−3.67]	[−7.56]	[−2.86]
$NEUT_{t-1}$	−.004	.045***	−.004
	[−.54]	[3.15]	[−.35]
$VEND_t$	−.927***	−.647***	−1.705***
	[−2.65]	[−4.94]	[−3.84]
AR term (ρ)	.550***	.550***	.325***
	[20.05]	[17.48]	[7.36]
# of observations	616	221	395
# of cross−sections	11	4	7
R^2	.985	.981	.880
Price elasticities w.r.t. e-*Sentiment*	All	Leading brand (LB)	Challenger brand (CB)
POS_{t-1}	.014**	.008*	.018***
	[2.44]	[1.71]	[2.79]
NEG_{t-1}	−.025**	−.031***	−.022*
	[−2.50]	[−6.29]	[−1.79]
$NEUT_{t-1}$	.004	.015***	−.002
	[.67]	[2.85]	[−.31]

t-Statistics are in parentheses. t-statistics reported here are calculated using Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors based on the Bartlett kernel with 10 lags. Price elasticities in the table are calculated as the average of each individual product's price elasticity

*** $p < .01$, ** $p < .05$, * $p < .10$

vendors carrying the product increases. Positive autocorrelation ($\rho = .550$) reflects the degree of inertia in daily prices.

Table 5 (Column 2) also shows that the magnitude of the NEG coefficient (about -.224) is much larger than that of POS (about .013). However, such a simple comparison of coefficient estimates can be misleading, and thus, we compute scale-free elasticities to compare the responsiveness of prices to positive and negative e-sentiments.[11] In a hedonic regression setting, *price elasticity with respect to e-sentiment can be interpreted as the percent change in consumers' willingness-to-pay, given a one percent increase in (positive/negative) e-sentiment.*

Table 5 (Column 2) illustrates that a 1 % increase in positive (negative) e-sentiment leads to a .014 % increase (.025 % decrease) in price. Consistent with

[11] Price elasticity reported in the table is calculated as the average of each individual product's price elasticity, which is calculated by multiplying the estimated coefficient of the e-sentiment variable by the average value of the variable divided by the average value of price in the sample.

our prediction, the responsiveness of price to negative buzz is much larger (about two times) than that to positive buzz (t-stat = 3.06, $p < 0.01$, one-sided test), supporting Hypothesis 2. This contrasts with Liu [42], who analyzed the effect of textual e-WOM information but did not find any effect of positive/negative buzz. Our finding shows that it is important to recognize the asymmetric effects of positive versus negative e-sentiment information.

3.4.2 Asymmetric effects of e-sentiment for leading versus challenger-brand items

We consider the moderating role of brand position, which could also affect customers' expectations. Specifically, the leading-brand's products are likely to have higher visibility through advertising and publicity, as stated in Hypothesis 3. In our case, Apple, the leading-brand, has consistently claimed more than 70 % market share and enjoyed positive press coverage, which could further boost consumers' baseline expectations. In that situation, the effect of negative buzz is likely to be larger for the leading-brand's products, whereas the effect of positive buzz is likely to be larger for the following-brands' products.

To investigate this scenario, we estimated Eq. (5) separately for the leading-brand (LB) products (Apple iPod family: Video, Mini, Nano, Shuffle) and the challenger-brand (CB) products (the remaining 7 items). Table 5 (Columns 3 and 4) shows that the coefficient estimate of negative buzz on LB item prices ($|-.362|$) is slightly smaller in magnitude than that on CB items' prices ($|-.377|$). Comparing the price elasticities with respect to negative buzz, however, we find that the LB items' prices are more sensitive to negative buzz than the CB items' prices: LB ($|-.031|$) > CB ($|-.022|$) (t-stat = 1.86, $p < 0.05$, one-sided test).

In addition, the coefficient estimate of positive buzz on CB items' prices is bigger than that on LB items' prices: LB (.008) < CB (.023). A comparison of price elasticity with respect to positive buzz yields the same pattern: LB (.008) < CB (.018) (t-stat = 2.82, $p < 0.01$, one-sided test). These results support Hypothesis 3, implying that prices of the leading-brand products respond to e-sentiment differently than do those of the challenger-brand products. Taken together, our findings show that both the negativity effect and the positivity effect exist in the e-marketplace with respect to e-sentiment.

3.4.3 Robustness checks

Overall, our findings are consistent with the theoretical predictions in that (1) negative e-sentiment is more influential than positive e-sentiment, and (2) the effect of e-sentiment on the price of a product is moderated by the brand's market position. To evaluate the robustness of our findings, we perform additional analyses.

First, we compare the main results from our model, i.e., REx-GMM with the AR(1) specification, with the ones from an alternative approach (Table 6). Econometric theory suggests that ignoring endogeneity can lead to biased estimates ([21, 35]). Even with the instrumental variables (IV) method for fixing endogeneity, however, a fixed-effects model without an AR term that does not account for correlated time-varying unobservable factors produces negative (positive) signs for

Table 6 Comparison of models and estimation methods: all products (# of obs. = 611)

Dependent variable: $PRICE_t$	Fixed-effects without AR	Our model with AR(1)
Estimation method	IV	GMM
Instrument for fixing endogeneity	Used	Used
Time-varying omitted variables	Not considered	Considered
POS_{t-1}	−.005	.013***
	[−.34]	[7.10]
NEG_{t-1}	.067	−.224***
	[.25]	[−3.67]
$NEUT_{t-1}$	−.022	−.004
	[−.78]	[−.54]
$VEND_t$	−1.511**	−.927***
	[−2.01]	[−2.65]
AR term (ρ)	n.a.	.550***
		[20.05]

*** $p < .01$, ** $p < .05$, * $p < .10$

positive (negative) e-sentiment. Thus, ignoring time-varying unobservable factors can yield biased estimates with unexpected signs. In contrast, our main model, Eq. (5) with AR(1) estimated with GMM using the moments specified in Eq. (6), accounts for endogeneity and time-varying omitted variables and yields statistically significant coefficient estimates with the expected signs for positive e-sentiment, negative e-sentiment, and the AR term.

Second, prices can be affected by new-model launches because 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 2 GB) and SanDisk (Sansa View 16 GB, Sansa Shaker 1 GB) (www.smartratings.com). However, Fig. 1 shows that the retail prices of the Samsung and SanDisk products did not exhibit any notable deep-discounts pattern, suggesting that those launches did not affect the prices of the existing models.

3.4.4 Reverse relationship between price and e-sentiments

Finally, the reverse relationship between price and e-sentiment variables could be of interest to researchers and practitioners as well. For each e-sentiment variable we estimate Eq. (5) using GMM by switching the role of price and the e-sentiment variable as the independent and the dependent variables. In our hedonic model framework, price can be interpreted as consumers' implicit evaluation of the product. Therefore, we expect that current price will be positively correlated with current positive online buzz and negatively correlated with current negative online buzz.

Table 7 reports the regression coefficient estimates as well as the estimated elasticities of individual e-sentiment variables with respect to price changes. Overall, the estimation results are consistent with our prediction and are in line with the results from the original hedonic regression (Table 5). In terms of elasticities in Table 7 (Columns 3 and 4) we also find that the positive relationship between price and positive e-sentiment is stronger for the challenger brands' products (LB (.057) < CB (.568)), while the negative relationship between price and negative e-sentiment is slightly larger for the leading brands' products (LB (|−.446|) > CB (|−.425|)).

Overall, the combined results imply that the long-run impact of e-sentiment variations is greater than their short-term effect. For example, a positive e-sentiment movement induces a positive customer evaluation of a product, leading to positive retailer price adjustment. This, in turn, enhances future e-sentiment as the positive price adjustment can be viewed as a signal of quality. The opposite pattern is observed for negative e-sentiment movements. In both cases the magnitude of these effects is moderated by the market position of the affected brand.

4 Discussion

4.1 Summary of findings

To examine the role of e-sentiment in the e-marketplace, we developed an empirical model based on a hedonic pricing approach, accounting for time-varying omitted variables. We estimated the model with GMM by using online buzz data from the MP3 player market. To measure the effect of e-sentiment on the market value of products, we computed scale-free price elasticities with respect to e-sentiment.

Our empirical findings are summarized as follows: (1) as the number of e-vendors carrying a product increases, the price of the product decreases; (2) past negative (positive) buzz leads to a future decrease (increase) in prices, and the responsiveness of the price to negative buzz is larger than that to positive buzz (*positive vs. negative e-sentiment effect*); (3) the responsiveness of price to negative buzz is larger for the leading brand's products (*negativity effect of e-sentiment*), whereas the price response to positive buzz is larger for the challenger brands' products (*positivity effect of e-sentiment*).

4.2 Managerial implications

Online shoppers are reported to perceive a greater risk than in-store shoppers [1], which can be reduced by collecting additional information about a product. Even though product life cycles are short, especially for high-tech products, risk-averse customers can wait for a few days to observe early adopters' opinions and evaluations posted on the web. Because most of the information can be acquired online at little cost, customer-generated e-sentiments about a product travel rapidly among online customers, affecting business outcomes.

Table 7 Reverse regression: e-Sentiment on price: REx-GMM with AR(1) specification

Dependent variable: e-Sentiment	All items	Leading versus challenger-brand items	
Coefficient estimates	ALL	Leading brand (LB)	Challenger brand (CB)
Dependent variable: POS_t			
$PRICE_t$	.183***	.035***	.127*
	[3.83]	[3.76]	[1.88]
AR term (ρ)	.119***	.555***	.159***
	[3.83]	[61.14]	[3.76]
R^2	.51	.85	.73
Dependent variable: NEG_t			
$PRICE_t$	−.024**	−.019***	−.030***
	[−2.17]	[−9.12]	[−3.44]
AR term (ρ)	.078***	.302***	.375***
	[5.49]	[8.33]	[24.39]
R^2	.04	.36	.35
Dependent variable: $NEUT_t$			
$PRICE_t$	.070	.031**	−.047
	[.89]	[2.17]	[−.57]
AR term (ρ)	−.016	.261***	.101***
	[−.67]	[5.79]	[6.15]
R^2	.40	.70	.74
# of observations	616	221	395
# of cross-sections	11	4	7
e-Sentiment elasticities w.r.t. price	All	Leading brand (LB)	Challenger brand (CB)
POS_t	.308***	.057***	.568*
	[3.71]	[2.99]	[1.70]
NEG_t	−.398**	−.446***	−.425***
	[−2.15]	[−6.63]	[−2.84]
$NEUT_t$	.154	.136*	−.155
	[.84]	[1.76]	[−.40]

t-Statistics are in parentheses. t-statistics reported here are calculated using Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors based on the Bartlett kernel with 10 lags. Elasticities in the table are calculated as the average of each individual product's e-sentiment elasticity w.r.t. its own price

*** $p < .01$, ** $p < .05$, * $p < .10$

Our results provide interesting managerial insights with respect to the effect of e-sentiment in long-tail markets, such as the MP3 player market. In such markets, a leading brand does not benefit much from positive customer buzz, but it is vulnerable to negative buzz about its products. Therefore, it should closely observe customers' complaints to protect its profitability [50]. As previously illustrated with the Kryptonite bike lock example, dissatisfied consumers can negatively affect many other fellow consumers' decisions via the internet in very a short time.

Therefore, a prompt response to consumers' dissatisfaction becomes imperative for a leading brand. In contrast, a challenger brand can shift its focus to finding favorable aspects of its product that will generate positive buzz over the internet. By presenting customers with pleasant news, a challenger brand can achieve higher profitability by preventing price erosion.

In practice, managing new products in response to e-sentiment becomes an important task, especially for high-tech firms [40]. Our findings suggest that a careful online reputation management system is warranted for firms to fully enjoy the benefits of their innovation. In so doing, firms need to take their brands' market position into consideration.

4.3 Contributions

Our contributions are as follows: First, we have examined the role of e-sentiment information in the MP3 player market, taking advantage of our rich textual dataset collected on a daily basis. Prior studies tended to focus on cross-sectional variation of prices [28]. However, the internet allows firms to change prices daily or even faster. By using high-frequency time series data, we examined the dynamics between product quality information reflected in e-sentiment and price fluctuations in the highly competitive MP3 player market.

Second, we have developed an advanced empirical model to analyze the relation between e-sentiment and product prices. Different from prior research, our model accounts for the time-evolving nature of omitted variables, such as daily sales, leading to a consistent estimation.

Third, we have found intriguing associations between e-sentiments and the online prices of products, providing insights to high-tech firms that face time-intensive online competition. Specifically, we find that negative e-sentiment has a stronger effect than positive e-sentiment. Moreover, we have identified an important moderating factor, brand position, which provides a new insight to the literature. Namely, we show that market position leads to an asymmetric effect of online buzz: leading brands are especially vulnerable to negative buzz, and challenger brands benefit more from positive buzz. Such findings would not have been obtained by examining the more homogeneous and less complex product categories (e.g., books, CDs) commonly used in prior studies.

Broadly speaking, our findings indicate the importance of consumer feedback in determining the success or failure of new products in high-technology sectors [8]. Because customers' feedback in the form of e-sentiment become public quickly and frequently, firms are well advised to become agile and flexible in their marketing, including pricing. Furthermore, our findings suggest that smaller brands that cannot command a price premium can gain a substantial advantage from any positive feedback. This, in turn, can lead to higher profitability for such competitors, which is healthy for the industry and for consumers insofar as they pose a viable threat to the well-established brands. The reverse is true for the leading brands, for which e-sentiment can be dangerous because consumers expect high product performance and customer satisfaction; when those consumer expectations aren't met, such brands suffer negative consequences. Taken together, our findings demonstrate that consumer feedback is becoming a major determinant of market acceptance and business growth in technologically innovative sectors.

4.4 Limitations and future research

This study is subject to certain limitations. First, we obtained our empirical findings from the MP3 player market alone. Even though the MP3 player market provides an ideal setting for this research, as aforementioned, one may raise concerns about the generalizability of the results. Whereas the case study in this paper refers to MP3 players, the metrics, principles and findings are much more general, and our proposed empirical model is applicable to predict or explain the role of online buzz in other product markets.

Second, the data were collected in 2007 and are not very fresh for current IS research. Therefore, future researchers might want to collect more recent data and compare the effects of positive and negative online buzz for different market positions. Summing up the results from diverse markets, like a mosaic, will build a bigger picture of the underlying dynamics between online buzz and price fluctuations.

Third, we examined only the effects of e-sentiment on retail prices. If daily sales quantities were available, we could estimate the demand elasticities of positive versus negative online buzz as well. This would entail simultaneous-equation modeling that reflects the bidirectional relationships between sales, prices, and quality perceptions as reflected in e-sentiment.

Fourth, we used prices only from e-vendors operating on the Amazon platform, leaving out other e-marketplaces that might affect market prices. However, Amazon's annual revenues amounted to $10.7 billion in 2007, and its market cap in 2010 was second only to Walmart among US retailers, ahead of other well-known retailers such as Costco, Best Buy, Target, and Barnes & Nobles. It is also estimated that Amazon's third party sales amounted to $6 billion in 2009, growing 30–35 % annually.[12] Given that our price data were collected from such a large marketplace (comparable to Walmart or Costco in terms of market size and importance) with a number of sub-vendors, our price data are representative. Future researchers could examine and compare other e-marketplaces, which would provide an even deeper understanding of the relation between online buzz and product prices.

Fifth, our empirical model does not consider the effects of e-retailers' differentiation efforts via service quality, brand, and customer trust. With data on the identities of e-retailers, our model could be extended to include e-retailer fixed effects together with product fixed effects, which would enable an examination of the effects of e-retailers' differentiation activities on prices, which is an important area for future research.

Sixth, our analysis, based on a reduced-form modeling approach, is descriptive. Future study could derive the optimal response of firms to e-sentiment via analytical modeling [33]. An excellent example is Li and Hitt [42], who analyzed optimal

[12] See http://onlineprofitable.com/ebay/online-retailing-amazon-vs-ebay-selling-on-amazon-or-selling-on-ebay-which-is-the-best-option-for-online-vendors-part-1.

pricing strategies under uni-dimensional versus multi-dimensional consumer rating systems. Future research could examine whether the optimal response to customer-generated online buzz varies.

Finally, we observed some effects of neutral buzz (positive effects for leading-brand items and negative effects for challenger-brand items), but we do not have a theoretical explanation, which calls for further investigation. In particular, experimental studies could provide a useful theoretical understanding. We leave this task for future researchers.

Just a few years ago, only giants such as Amazon.com and Dell had the financial and technological resources to monitor e-sentiments. For example, through the "Direct2Dell" blog service and "Ideastorm.com," Dell tried to build a direct communication channel with its customers, listening to their feedback and observing their e-sentiment [39]. However, now even small- and mid-sized companies have access to e-sentiment information through outside vendors such as PowerReviews and Bazaarvoice. Accordingly, developing an e-marketing strategy based on e-sentiment analysis becomes imperative [31]. We hope that this study will provide managers with a useful method to perform e-sentiment analysis and design a more effective e-marketing strategy, considering their market positions.

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Hyun S. Shin is Associate Professor at School of Business, Hanyang University (Seoul, South Korea). Prior to joining Hanyang University, he served as Assistant Professor of Marketing at College of Management, Long Island University (New York, USA) and GSIS, Ewha Womans University (Seoul, South Korea). He received B.B.A. (1994) and M.B.A. (1996) from Seoul National University (Seoul,

South Korea), M.S. (2002) in Economics from University of Illinois at Urbana-Champaign, and Ph.D. (2008) in Management (Major: Marketing) from UCLA. His research interests include dynamic interdependence between marketing and innovation, new product development, social innovation, and e-marketing.

Dominique M. Hanssens is the Bud Knapp Professor of Marketing at the UCLA Anderson School of Management. He received B.S. (1974) at the University of Antwerp and M.S./Ph.D. from Purdue University (1976/1977). His research focuses on strategic marketing problems, in particular marketing productivity, to which he applies his expertise in data-analytic methods such as econometrics and time-series analysis. His papers have appeared in the leading journals in marketing, economics and statistics. Six of these articles have won Best Paper awards in Marketing Science (1995, 2001, 2002), Journal of Marketing Research (1999, 2007), and Journal of Marketing (2010), and seven were award finalists. In 2007 he received the Churchill Lifetime Achievement Award of the American Marketing Association, and in 2010 he was elected a Fellow of the INFORMS Society for Marketing Science. He has consulted British Telecom, Disney, Google, Hewlett Packard, Johnson & Johnson, Mattel Toys, Mercedes, Microsoft, Schwab and Wells Fargo, among others.

Kyoo il Kim is Associate Professor of Economics at the Michigan State University. Prior to joining MSU, he served as Assistant Professor at the University of Minnesota-Twin Cities. He received B.A. (1997) and M.A. (2001) from Seoul National University in South Korea and Ph.D. (2006) in Economics from UCLA. He is a micro-econometrician and his research has focused on diverse topics in IO models, including estimation of discrete choice demands, random coefficient models, production functions as well as game theoretic models.