

# **Impact of Positive vs. Negative e-Sentiment on Daily Market Value of High-Tech Products**

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## **ABSTRACT**

Online buzz describes the overall value and experience of products in a positive or negative way, but we do not know if and how such consumers' verbal description shared online, often referred to as "e-sentiment," influence the products' market value. We investigate the relationship between e-sentiment and the market price of a product in a high-technology category, MP3 players. We build on a hedonic pricing model, dealing with time-varying omitted variables problem. Econometric modeling reveals that negative e-sentiment has a stronger impact on products' daily price than positive e-sentiment. Furthermore, the effect is moderated by customers' expectation level: negative online buzz has a stronger adverse impact for higher-priced items and well-known brand items, and positive online buzz has a greater beneficial effect on lower-priced items and lesser-known brand items. Our findings suggest that 1) a customer's willingness-to-pay is influenced by online postings generated by other fellow customers; and that 2) a firm should monitor and manage e-sentiment surrounding high-tech products since today's online buzz is a signal of potential profit-margin changes tomorrow.

*Keywords: online buzz; e-sentiment; daily market prices; customers' expectation level*

## INTRODUCTION

*“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*

The role of reputation as an informal enforcement mechanism has been extensively studied in prior research (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), giving the firm an incentive to keep its promise.

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 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 evaluation spreads rapidly among customers. Moreover, digitized customer feedback information, i.e., electronic WOM or e-WOM, can be accessed anytime and anywhere through diverse contexts such as blogs, websites, and online forums, which further increases its influence among fellow customers (Dellarocas 2003; Schindler and Bickart 2004). Accordingly, the impacts of e-WOM on consumer behavior and firm performance have been extensively studied (e.g., Chen and Xie 2005, 2008; Chevalier and Mayzlin 2006; Dellarocas and Wood 2008; Godes and

Mayzlin 2004; Liu 2006; Senecal and Nantel 2004; Trusov, Bucklin, and Pauwels 2009; Zhu and Zhang 2010). However, prior research tends to focus on the quantitative aspect of e-WOM (e.g., average product rating, # of referrals), leaving the qualitative aspect (i.e., how customers describe the overall value and experience about a product) less explored.<sup>1</sup> In addition, prior research has paid less attention on the role of online buzz in high-tech product markets, where the online buzz should have a stronger impact on business outcomes such as market prices of high-tech products due to the inherent complexity of product assessment.

Furthermore, prior research tends to examine price movement from a static point of a view, analyzing cross-sectional variation in prices. Even when time series or 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 examine dynamic price movement (Ellison and Ellison 2005). In the fast-moving internet world, however, one may obtain more useful insights about a role of online buzz by analyzing higher-frequency time-series observations. For example, a consumer posted on an online bike forum that the Kryptonite bike lock can be easily opened with a Big Pen on September 12, 2004. Three days later, about 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 fully captured by analyzing weekly or monthly data.

To fill the gap, we investigate how customers' positive vs. negative opinions or descriptions of a high-tech product (such as "awesome" or "poor") affect its daily market value (i.e., market

price) differently. In so doing, we use data on MP3 players collected “live” from World Wide Web on a daily basis for two months (June 2, 2007~August 1, 2007), allowing us to examine *the relationship between online buzz around a product and its market value* in a timely manner.

To analyze such relationship using daily online buzz data, two methodological issues arise. First, it is almost impossible for researchers to directly observe other key drivers of a product’s market value such as sales and off-line buzz around the product (e.g., personal communication between friends/family members), which should be correlated with online buzz (e.g., Horvath et al. 2005). If we assume that those unobservable factors (to researchers) that influence market value of products are time-invariant, we can still obtain unbiased estimates of the effects of online buzz variables on prices through a fixed-effects modeling approach. Such assumption can be restrictive, however, because reputations or popularities of products evolve over time, especially in high-tech product markets. Further, daily sales data is hard to obtain, and thus, researchers may rely on a proxy such as sales rank. Even though sales rank information is known to approximate actual sales to some extent (e.g., Godes and Mayzlin 2004), still it is an imperfect measure. Thus, omitting time-varying unobservable factors such as off-line buzz and actual sales may lead to biased estimation, which is one of the key concerns for econometric data analysis in e-WOM literature. Second, it is difficult for researchers to collect online buzz data which represents all online buzz available in the cyberspace. Moreover, online buzz data is subject to certain limitations including volatile identity of online information provider (Dellarocas 2003) and the possibility of firms’ strategic manipulation (Dellarocas 2006). Thus, how to deal with measurement error problem is another challenge for e-WOM researchers.

To address these issues, we build on a hedonic regression approach developed by Bajari, Cooley, Kim and Timmins (2011). By explicitly modeling the evolution of time-varying omitted

variables and estimating the model with GMM (Generalized Method of Moments), their empirical strategy allows us to recover hedonic prices or implicit value of online buzz when the time-varying omitted variables are potentially correlated with online buzz. We show that our approach can provide consistent estimation of the online buzz effects on market value of products while conventional fixed-effects modeling approach can produce misleading results. In addition, we develop an extended empirical model that can account for potential measurement error and show the estimation results of this alternative model for an expository purpose. Thus, our study contributes to e-WOM literature by providing a new solution to key methodological issues in analyzing daily online buzz data.

Our empirical findings suggest that online buzz around a product affects its market value, while negative buzz shows stronger impact than positive buzz. Furthermore, the effect is moderated by customers' expectation level: negative online buzz has a stronger adverse impact for the higher-priced items and the well-known brand items, while positive online buzz has a greater beneficial effect on the lower-priced items and the lesser-known brand items. To our knowledge, this paper represents the first attempt at such an analysis in the literature, which would provide richer insights to researchers and practitioners.

In the next section, we conduct a literature review. Then we explain model and data, and present empirical results. Next, we provide a summary of findings and associated managerial implications. Finally, we discuss contributions and limitations of this research and suggest directions for future study.

## **LITERATURE REVIEW**

### ***Behavior of Online Market 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 (Bakos 2001).

Accordingly, they predicted: 1) product prices would converge in the e-marketplace, and 2) e-retailers would charge prices at their marginal costs. Previous research, however, has documented several counter-intuitive phenomena with respect to the behavior of online prices (Ellison and Ellison 2005). For example, empirical evidences suggest that online price dispersion does exist (Pan, Ratchford and Shankar 2004) and even increases over time (Chevalier and Goolsbee 2003; Baye, Morgan and Scholten 2004a). Moreover, e-retailers with differentiated services and/or better reputations (e.g., Amazon.com) are reported to charge price premiums for the same product (Chevalier and Goolsbee 2003). These findings suggest that online customers are willing to pay premiums to reduce their perceived risk (Rao and Monroe 1996), implying that online buzz may affect the market value of products.

However, e-retailers 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), and in smaller increments (Brynjolfsson and Smith 2000). Empirical evidence confirms that e-retailers frequently adjust their prices, up or down, by small increments (Baye, Morgan and Scholten 2004b). Accordingly, online market prices fluctuate over time (Schneider and Albers 2008), affecting financial performance of e-retailers. Then, profit opportunities exist for those who are able to figure out in advance the pattern of market price fluctuation. In other words, by identifying a driver of such price fluctuation, e-retailers can predict next-period market price changes and promptly adjust their prices accordingly to realize profit opportunity.

### *e-Sentiment vs. Online Market Price*

According to a survey by Retail Advertising and Marketing Association/BIGresearch (2009), 44% of electronics purchases are affected by online customer reviews. Another survey of over 2000 U.S. internet users conducted by ComScore/Kelsey Group<sup>2</sup> in 2007 reveals that 24% of internet users checked online customer feedback before purchases across diverse service categories such as restaurants, hotels, automotive, and home. Moreover, over 75 % of them reported that the online feedback had a significant impact on their purchase decision. They are also willing to pay at least 20% more for a service rated “excellent/5-star” than for the same service rated “good/4-star,” implying that the value of a product (reflected on its price) can be affected by online buzz.

When customers refer to online reviews, they check not only average rating but also textual feedback information (Schindler and Bickart 2004). Practitioners are aware that customers respond to more descriptive, elaborated reviews (Wagner 2008). In 2005, for instance, a customer who had been frustrated with Dell’s poor customer service wrote about his bad experience on his blog, using expressions such as “Dell sucks” and “a lemon.” From then, thousands of dissatisfied customers joined to spread the bad brand perception and experience about Dell through their blogs, adding textual responses such as “Dude, get an Apple.” As the online buzz spread fast with more than 10,000 daily visits to his blog, Dell finally responded by adding 4,000 service call representatives and improving its training program (Lee 2005; Jarvis 2007). With the help of social media such as blogs and twitters, the power of textual customer feedback is expected to further increase (Hoffman and Novak 2009).

As such, textual information contained in online buzz, i.e., e-sentiment, reflects the underlying product’s overall value perception and satisfaction, and thus, can be used as a useful leading indicator of business outcomes such as declining sales, increasing product returns/service

cancellation, deteriorating brand image, and decreasing value of products. Yet, the richness of e-sentiment has received little attention from empirical researchers. 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. 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 length of customer review (Chevalier and Mayzlin 2006). However, it would be more interesting to extract consumer perceptions about a product directly from online texts and examine its impact on market outcomes such as the behavior of online prices. For example, how would the value or market price of a product reacts differently to positive vs. negative online conversation would be an interesting research question.

## **MODEL**

### ***Estimating Online Buzz Effect in the Presence of Time-Varying Omitted Variables***

In this section, we consider a hedonic pricing model framework in a differentiated products market (Bajari and Benkard 2005) and estimate the implicit prices of online buzz, i.e. the effect of online buzz on the market value of competing products. In a related literature, hedonic regressions have been often used to assess the effect of seller's reputation (positive or negative feedback by buyers) on the market prices in online auctions like eBay, Yahoo! and Amazon (for a review, see Bajari and Hortacsu 2004).

We consider a linear hedonic pricing model of the form:

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

Here  $PRICE_{i,t}$  represents the market price of product  $i$  at time  $t$ ,  $\alpha_i$  denotes the product-specific effect representing time-invariant characteristics (e.g., size, weight, storage capacity of a MP3 player product),  $X_{i,t}$  denotes the vector of e-sentiment variables such as positive buzz ( $POS_{i,t}$ ), negative buzz ( $NEG_{i,t}$ ), and neutral buzz ( $NEUT_{i,t}$ ) where  $k$  denotes the lag lengths for e-sentiment variables.  $VEND_{i,t}$  stands for the number of e-vendors carrying the product  $i$  at time  $t$ . Finally  $\xi_{i,t}$  denotes the time-varying omitted variables (e.g., unobserved reputation or sales) that also determine the price. Thus, Equation (1) describes how price evolves as online buzz, the number of vendors and the omitted variables vary over time.

Our first key assumption is that the unobserved factor  $\xi_{i,t}$  evolves according to a first order Markov process (this can be extended to higher order Markov process):

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

Note that the model (1) and (2) is fundamentally different from a fixed-effects model with an autoregressive error (AR) because in our model  $\xi_{i,t}$  is allowed to be correlated with all other observables in Equation (1) including e-sentiment variables, while a fixed-effects model assumes  $\xi_{i,t}$  is a purely exogenous error. One can naturally expect that the unobserved reputation is correlated with 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 the time  $t-1$  does not help to predict the innovation term  $v_{i,t}$  in (2) at  $t$ , and thus, we have:

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

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

$$(4) \text{PRICE}_{i,t} = (1 - \rho)\alpha_i + \rho\text{PRICE}_{i,t-1} + \sum_{k=1}^K \gamma_k \cdot (X_{i,t-k} - \rho X_{i,t-1-k}) + \beta \cdot (\text{VEND}_{i,t} - \rho\text{VEND}_{i,t-1}) + v_{i,t}.$$

Taking the first-differencing to remove the product fixed-effects, we obtain:

$$(5) \Delta\text{PRICE}_{i,t} = \rho\Delta\text{PRICE}_{i,t-1} + \sum_{k=1}^K \gamma_k \cdot (\Delta X_{i,t-k} - \rho\Delta X_{i,t-1-k}) + \beta \cdot (\Delta\text{VEND}_{i,t} - \rho\Delta\text{VEND}_{i,t-1}) + v_{i,t} - v_{i,t-1}$$

where we define  $\Delta\text{PRICE}_{i,t} = \text{PRICE}_{i,t} - \text{PRICE}_{i,t-1}$  and other differenced variables are similarly defined. Note that in Equation (5),  $v_{i,t}$  can be correlated with observables at t and also  $v_{i,t-1}$  can be correlated with observables at t-1. Therefore we estimate Equation (5) using GMM based on the moment condition that is consistent with our assumption (3) (hereafter we name our estimator as REx-GMM):

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

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

### ***Accounting for Measurement Errors***

As aforementioned, one of possible limitations of e-WOM research is that e-sentiment variables may not represent online reputations about a product, or at most they are noisy measures of such information.<sup>3</sup> Therefore we only assume that e-sentiment variables are proxies for the online

reputation about a product in the hedonic equation. Suppose that e-sentiment variables  $X_{i,t}$  and the “true” online reputations denoted by  $X_{i,t}^*$  are only related as:

$$(7) X_{i,t} = X_{i,t}^* + m_{i,t}$$

with the measurement error  $m_{i,t}$ . Then the true hedonic equation becomes:

$$(1)' PRICE_{i,t} = \alpha_i + \sum_{k=1}^K \gamma_k \cdot X_{i,t-k}^* + \beta \cdot VEND_{i,t} + \zeta_{i,t}$$

and Equation (5) becomes:

$$(5)' \Delta PRICE_{i,t} = \rho \Delta PRICE_{i,t-1} + \sum_{k=1}^K \gamma_k \cdot (\Delta X_{i,t-k} - \rho \Delta X_{i,t-1-k}) + \beta \cdot (\Delta VEND_{i,t} - \rho \Delta VEND_{i,t-1}) + \zeta_{i,t}$$

$$\text{where } \zeta_{i,t} \equiv \Delta v_{i,t} - \sum_{k=1}^K \gamma_k \cdot (\Delta m_{i,t-k} - \rho \Delta m_{i,t-1-k}).$$

Note that in this case the GMM estimation based on Equation (6) is no longer consistent because variables at t-2 can be correlated with  $\Delta m_{i,t-k}$  for  $k \leq 2$  and also be correlated with  $\Delta m_{i,t-1-k}$  for  $k \leq 1$ .

By assuming that the measurement error itself is not serially correlated but is allowed to be correlated with contemporary variables, however, we can consistently estimate Equation (5)' through GMM method using the moment condition based on:

$$(6)' E[\zeta_{i,t} | I_{t-3-K}] = 0$$

Note that none of error terms in  $\zeta_{i,t}$  are correlated with variables in  $I_{t-3-K}$ . Below in our empirical implementation of the model we focus on the specifications with  $K=1$ .

## DATA

### *Industry Background*

For the empirical analysis, MP3 player market is chosen. Initiated in 1998, MP3 player market exhibits several interesting characteristics. First, it is a large and fast-growing market. According to In-Stat market research reports,<sup>4</sup> 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.<sup>5</sup> 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.<sup>6</sup> Since then, Apple has consistently claimed over 70% of total market sales.<sup>7</sup> 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 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 product assessment for purchase decision-making. As the CNET MP3 Player Buying Guide<sup>8</sup> 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 online buzz on price dynamics is likely to be conspicuous because we may observe sufficient variations in our focal variable, i.e., daily market prices. 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 from Top 4 brands were selected based on their popularity. In February 2007, Top 4 brands were: Apple (72.3%), Sandisk (9.7%), Creative Labs (2.7%), and Samsung (2.5%), accounting for 87.2% of the entire retail sales in MP3 player market (Source: NPD Group).<sup>9</sup> In this paper, e-sentiment data is collected for eleven flagship products manufactured by Apple (4), Sandisk (2), Creative Labs (2), and Samsung (3) since they received the most attention from customers. Table 1 presents the description of the products of interest.

===== Insert Table 1 about here =====

*Price:* On a daily basis, market price (**PRICE**) is defined as the average price of each MP3 player product at Amazon.com, the largest online retailer in the U.S. Table 2 summarizes the price histories of the eleven products under study.

===== Insert Table 2 about here =====

To make sure that there is no influence on daily price of time trend and/or seasonality factors such as a "July 4<sup>th</sup> Event," a simple regression analysis is performed. The coefficient estimate for trend is  $-.16$  ( $t\text{-stat} = -.89$ ) while the one for an Independence Day dummy variable (July 2-4) is

6.40 ( $t\text{-stat} = .50$ ). To avoid the possibility of spurious regression results, we also performed Augmented Dickey-Fuller and Phillips-Perron panel unit-root tests on the PRICE variable (Enders 2004). The test results support that the dependent variable, PRICE, is stationary ( $p < .01$ ).

*e-Vendors:* The number of e-vendors (**VEND**) at Amazon.com is obtained on a daily basis (see Table 2). 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.<sup>10</sup> Customers with rational expectations will predict price drop of a product as they expect more vendors to carry the product.<sup>11</sup> Thus, customers' willingness-to-pay will be decreased as VEND increases.

*e-Sentiment:* In this paper, we perform e-sentiment analysis. An "e-sentiment analysis" 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., # of positive vs. negative words) with business outcomes such as prices or sales via econometric analysis (e.g., Nasukawa and Yi 2003; Yi et al. 2003). Through a semantic data mining approach developed by an online marketing research company, e-sentiment data were collected "live" from World Wide Web between June 2, 2007 and August 1, 2007. Specifically, daily online buzz count data were collected from multiple sources including websites (e.g., Amazon, CNET), online forums, and blogs to generate a sentiment factor, i.e., # of positive buzz (POS), # of negative buzz (NEG), and # of neutral buzz (NEUT).

===== Insert Table 3 about here =====

Table 3 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. Both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) panel unit-root tests support that POS, NEG, and NEUT are stationary at a 99% significance level.

## RESULTS

### *Positive vs. Negative e-Sentiment Effects*

Negative product information is often more diagnostic or informative than positive information (Herr, Kardes and Kim 1991). Therefore, negative information is weighed more heavily in consumer judgment and choice decisions. Previous research has shown that negative WOM has a bigger impact than positive WOM (e.g., Arndt 1968; Fiske 1980). In e-commerce settings, negative online buzz is likely to have an even greater effect because customers think negative buzz is more credible (Chevalier and Mayzlin 2006) and more informative (Lucking-Reiley et al. 2007) than positive buzz. Moreover, customers may 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). Considering that 25% of online shoppers are not likely to buy a product with negative reviews (Iverac 2009), some feared companies may moderate customer reviews (Bhatnagar 2006), and even feed bogus reviews (Iverac 2009). This leads to the prevalence of positive reviews, further decreasing the influence of positive buzz. Accordingly, online shoppers may weigh the value of positive vs. negative buzz differently.

===== Insert Table 4 about here =====

To examine the impact of positive vs. negative e-sentiment on product prices, we estimated Equation (5) using REx-GMM with AR(1) specification. Below we use the specification with  $K=1$  in our empirical implementation of the model. Table 4 displays that the magnitude of the

negative buzz effect (about -.22) is much larger than that of the positive one (about .01). However, such simple comparison of coefficient estimates can be misleading, and thus, scale-free elasticities are computed to compare the responsiveness of market prices to positive vs. negative e-sentiment. In a hedonic regression setting, *price elasticities with respect to e-sentiment can be interpreted as ‘% change in consumers’ willingness-to-pay extra \$\$ for 1% increase in (positive/negative) e-sentiment.’* Table 4 again illustrates that 1% increase in positive (negative) e-sentiment leads to .007% increase (.117% decrease) in market value. Consistent with our prediction, the impact of negative buzz is much bigger (more than ten times) than that of positive buzz. Note that Liu (2006) analyzed the impact of textual e-WOM information but do not find any effect of positive/negative buzz. Thus, our finding contributes to the e-WOM literature by documenting asymmetric impact of positive vs. negative e-sentiment information. Table 4 also show that the sign of VEND is negative as expected (-.927), implying that customers with rational expectation would expect price drop of a product as the number of vendors carrying the product increase. Positive autocorrelation ( $\rho = .550$ ) reflects the degree of inertia in daily market prices, implying that prices tend to be persistent over time.

#### ***Consumers’ Expectation Level as a Moderating Variable***

Prior research reports that the effect of WOM is moderated by factors such as involvement. For example, Ba and Pavlou (2002) show that the impact of seller ratings on prices is larger for relatively expensive (i.e., high-involvement) product categories such as camcorders and digital cameras. However, whether the effect of positive vs. negative buzz would be moderated within a product category is uncertain.

Within a product category, the effect of e-sentiment may be moderated by the customers’ expectation level. 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 a negative expectation about a product receives positive information, it may dominate her judgment and choice decisions (i.e., “positivity effect”). Such effect of consumer expectation has been empirically supported in prior research (for a review, see East, Hammond and Lomax 2008).

*Consumers’ expectation levels and price tier:* In this paper, we use price tier as a proxy of consumers’ expectation level, given that rational customers expect to ‘get what they pay for.’ Specifically, a customer is likely to have a higher pre-purchase expectation on higher-priced items, and thus, the effect of the negative online buzz would be stronger for higher-priced items than for lower-priced items. In other words, a single negative buzz may make the customer hesitate to open her wallet when she considers expensive MP3 players, leading to a larger negativity effect for higher-priced items. By the same token, one piece of positive e-sentiment may have a larger positivity effect for lower-priced items than for higher-priced items. One piece of favorable buzz (e.g., light weight, longer battery life) may help the customers justify their decision of buying a cheap product, who expect that there should be a number of negative issues about the product.

To address this issue, we estimated Equation (5) separately for the three price tiers in the market. Specifically, HIGH (high-priced items) includes the top 3 items in terms of prices: iPod Mini, iPod Video, and Zen Vision (mean/median price level: over \$180). LOW (low-priced items) includes the bottom 3 items: Sansa M230, Samsung Nexus25, and Samsung Nexus 50 (mean/median price level: less than \$100). MED (medium-priced items) includes the remaining 5 items: iPod Nano, iPod Shuffle, Sansa E260, Samsung Helix, and Zen Sleek (mean/median price level: \$100-180). Figure 1 illustrates the movement of average market prices of the three

price tiers. One can observe that market prices are stable, fluctuating around a certain level. Such frequent price changes with a smaller amount are reported in previous research (e.g., Brynjolfsson and Smith 2000; Schneider and Albers 2008).

===== Insert Figure 1 about here =====

Table 4 illustrates that higher-priced items are more sensitive to negative buzz than lower-priced items: HIGH ( $|-0.344|$ ) > MED ( $|-0.238|$ ) > LOW ( $|-0.158|$ ). The comparison of price elasticities with respect to e-sentiment also yields the same pattern: HIGH ( $|-0.195|$ ) > MED ( $|-0.121|$ ) > LOW ( $|-0.065|$ ). Thus, our result suggests that the “negativity effect” exists in the e-marketplace.

Table 4 also illustrates that lower-priced items are more sensitive to positive buzz than higher-priced items: HIGH ( $0.010$ ) < MED ( $0.023$ ). The comparison of price elasticities also show the same pattern (HIGH ( $0.006$ ) < MED ( $0.012$ )), where the effect of positive buzz on MED items’ prices is twice bigger than on HIGH items’ prices. However, we do not find such relation when we consider LOW group items (coefficient estimate =  $0.003$ , elasticity =  $0.001$ ). This might be due to relatively small number of positive buzz for Nex50 (mean: 8.6) and Nex25 (mean: 5.0), as shown in Table 3. Table 3 also shows that there were more neutral buzz for Nex50 (mean: 15.4) and Nex25 (mean: 21.8). This is indeed consistent with significant positive effect of neutral buzz for LOW group items ( $0.030$ ,  $p < 0.01$ ), which is ten times bigger than that of positive buzz ( $0.003$ ,  $p < 0.01$ ). This implies that customers who buy low-end MP3 players (less than \$100) regard neutral information as more diagnostic for their decision making.

*Consumers’ expectation levels and brand position:* In addition, we examine the moderating role of brand position, which may also impact customers’ expectation level. Specifically, the leading-brand’s products are likely to be associated with higher visibility through advertising and

publicity. In our case, Apple, the leading-brand, has consistently claimed over 70% market share and enjoyed more positive press coverage, which may further boost consumers' baseline expectations. Then the effect of negative buzz is likely to be larger for the leading-brand's products, while the effect of positive buzz is likely to be larger for the following-brands' products.

To investigate such possibility, we estimated Equation (5) 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. Table 4 illustrates that the coefficient estimate of negative buzz on LB's prices ( $|-0.362|$ ) is smaller in magnitude than on FB products ( $|-0.377|$ ). Comparing the price elasticities with respect to negative buzz, however, we find LB's market value is more sensitive to negative buzz than FB's market value is: LB ( $|-0.278|$ ) > FB ( $|-0.127|$ ). In addition, the effect of positive buzz on FB items' prices is bigger than that on LB items' prices: LB ( $0.008$ ) < FB ( $0.023$ ). Comparison of price elasticities with respect to positive buzz yields the same pattern: LB ( $0.006$ ) < FB ( $0.008$ ).

Altogether, our findings show that both "negativity effect" and "positivity effect" with respect to e-sentiment exist in the e-marketplace.

### ***Robustness Checks***

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

===== Insert Table 5 about here =====

First, we compare the main results from our model, i.e., REx-GMM with AR(1) specification, with the ones from alternative approaches. Econometric theory suggests that ignoring endogeneity can lead to biased estimates (Greene 2003). Table 5 illustrates that a conventional fixed-effects model that does not account for ‘correlated’ time-varying unobservable factors can yield biased estimates. We find the fixed-effects model yields negative sign for positive e-sentiment for LOW products case while our model estimates positive sign as expected. Even with instruments (IV) for fixing endogeneity, however, a fixed-effects model without AR term produces negative (positive) signs for positive (negative) e-sentiment. As such, ignoring time-varying unobservable factors leads to biased results with unexpected signs. In contrast, our main model, Equation (5) with AR(1) estimated with GMM using the moments specified in Equation (6), accounts for endogeneity and time-varying omitted variables and yields statistically significant coefficient estimates with expected signs for positive e-sentiment, negative e-sentiment, and AR term. Therefore, we conclude that our approach provides the most preferable results.

===== Insert Table 6 about here =====

Second, we compare our main results with the results from REx-GMM with AR(2) specification. Table 6 shows that inclusion of additional autoregressive term in Equation (2) yields similar results. Third, we estimated Equation (5)’ to see the impact of potential measurement errors. Table 6 illustrates that both Measurement Error-robust REx-GMM with AR(1) and Measurement Error-robust REx-GMM with AR(2) specifications produce similar results to the main results, implying that our findings are robust to potential measurement errors.

===== Insert Table 7 about here =====

One notable difference between our main results and the results from Measurement Error-robust REx-GMM specifications is that the absolute value of negative buzz effect for LB is smaller than the value for FB in the former results (LB:  $|-0.362| < \text{FB: } |-0.377|$  in AR(1) case; LB:  $|-0.352| < \text{FB: } |-0.365|$  in AR(2) case), while the relation changes in the latter results (LB:  $|-0.365| > \text{FB: } |-0.318|$  in AR(1) case; LB:  $|-0.367| > \text{FB: } |-0.316|$  in AR(2) case). However, Table 7 shows that when we compare the elasticities from REx-GMM with AR(1)/AR(2) vs. the ones from Measurement Error-robust REx-GMM with AR(1)/AR(2), we can see that the responsiveness of price to negative buzz is bigger for LB ( $|-0.270| \sim |-0.282|$ ) than the one for FB ( $|-0.106| \sim |-0.127|$ ) in both cases. Table 7 also confirms that our main results are similar to the results from other specifications. Therefore, we conclude that our overall results are robust to alternative model specifications as well as measurement errors.

## **DISCUSSION**

### *Summary of Findings*

Online shoppers are reported to perceive a greater risk (Alba et al. 1997), which can be reduced by collecting additional information around 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. Since group membership is open to the public and most of the information can be acquired online at little cost, customer-generated e-sentiments around a product travel fast across online customers, affecting business outcomes.

In order 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 through GMM method by using online buzz data from MP3 player market. To measure the impact of e-sentiment on the market value of products, we computed scale-free

price elasticities with respect to e-sentiment, which is summarized in Table 7. In sum, we find that the impact on market prices of negative e-sentiment is stronger than that of positive one (*positive vs. negative e-sentiment effect*). We also find that the relation between e-sentiment and product value is moderated by customers' expectation level. Specifically, the effect of negative buzz on price changes is larger for the higher-priced items and for the leading-brand items (*negativity effect of e-sentiment*), while the effect of positive buzz is larger for lower-priced items and for the following-brand items (*positivity effect of e-sentiment*). We do find some effects of neutral buzz (in particular for lower-priced items and leading-brand items), but the magnitude of those effects (in terms of elasticity) seem to be ignorable.

### ***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. Our findings provide interesting managerial insights with respect to the impact of e-sentiment. 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. Moreover, the internet allows dissatisfied customers to negatively affect other customers' decisions in a short time span, and eventually, the firm's profitability as well as its firm value (Jarvis 2009). Our findings further suggest that the importance of promptly managing the level of post-purchase dissatisfaction is even greater for managers who sell higher-priced products or leading-brand items for which customers have higher expectations. In contrast, if a firm targets the lower-price tier segment or manages following-brand items, then the firm may want to focus on finding good things to communicate about its product, so that positive internet

buzz develops online. Giving customers delightful news may increase the market value of a lower-priced product or following-brand items, leading to higher profitability in the future.

Second, our data were collected from MP3 player market which exhibits the ‘long-tail’ phenomenon, and thus, our empirical results may have an implication for ‘long-tail’ online markets. 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 (Anderson 2006). 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, Hu and Smith 2006). Because there will be a smaller number of customer reviews for those products, even one negative opinion will loom large (Chen, Dhanasobhon, and Smith 2006, Zhu and Zhang 2010). Our findings from MP3 player market suggest that such impact of a few negative e-sentiments on the value of a niche product will be further amplified when the product targets at customers with higher expectation level. Thus, a manufacturer of niche products may want to manage complaints promptly before they become digitized and spread over the internet, especially when their target customers’ expectation level is high.

### ***Contributions, Limitations, and Future Research***

Our contributions are as follows: First, we have examined the role of e-sentiment information in MP3 player market, taking advantage of our rich textual dataset collected on daily basis. Our findings provide insights to high-tech firms who face time-intensive online competition. Second, we have used an empirical model to analyze the relation between e-sentiment and market prices of products. Different from prior research, our proposed model accounts for the time evolving

nature of omitted variables (e.g., sales, reputation), leading to consistent estimation. Third, we have found intriguing associations between e-sentiments and online prices of products.

Specifically, we find that negative e-sentiment has a stronger impact than positive one. We also identify an important moderating factor, i.e., customers' expectations levels, adding to e-marketing literature a new insight. Indeed, such findings were not likely obtained had we examined more homogeneous, less complex, and cheaper product categories such as books and CDs, which are prevalent in prior studies.

This study is subject to the same limitations that may affect all online buzz research as well, i.e., concerns over data quality and possible strategic manipulation by firms (Chevalier and Mayzlin 2006; Dellarocas 2006; Godes et al. 2005). In particular, we only used prices from e-vendors operating on the Amazon platform, leaving out other e-marketplaces which might affect market prices. However, Amazon's annual revenues amounted to \$10.7 billion in 2007, and its market cap in 2010 is second only to Walmart among US retailers, ahead of other well-known retailers including Costco, Bestbuy, Target, and Barnes & Nobles. It is also estimated that Amazon's third party sales amounted to \$6 billion in 2009, growing 30-35% annually.<sup>12</sup> 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 is valuable to a certain extent. Future researchers may want to examine and compare other e-marketplaces, which would provide an even deeper understanding of the relation between online buzz and product prices. Second, we examined only the effects of e-sentiment on market prices. If daily sales quantities (or sales rank information) were available, we could have estimated 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 e-sentiments. Third, we have

analyzed only the behavior of market prices, leaving individual e-retailers' pricing strategy unexplored. Dellarocas (2003) argue that online buzz information is particularly relevant for e-retailers as they decide how to adjust prices in light of customer feedback. Thus, future study may derive the optimal strategic response of firms to e-sentiment via analytical modeling (Godes et al. 2005). An excellent example is Li and Hitt (2009), who analyzed the optimal pricing strategies under unidimensional vs. multidimensional consumer rating systems. Future research may examine if there are differences in the optimal response to customer-generated online buzz across different customers' expectation level. Fourth, only the impact of e-sentiment on price level is examined. Future research may want to investigate relation between e-sentiment and other dimensions of prices such as variation in prices and price premium. Fifth, Chen, Fay, and Wang (2011) has recently investigated how product price and quality affect consumers' online buzz generating behavior in terms of the volume and valence of their online postings. Future researchers may want to examine whether and how product price and quality affect the contents of online buzz or e-sentiment. Finally, by examining other product categories, future study may identify other moderators of e-sentiment effects such as product complexity, the number of features, the degree of competition, and product types (e.g., hedonic vs. utilitarian products as analyzed in Sen and Lerman 2007).

Just a few years ago, only giants like Amazon.com and Dell had financial and technological resources to monitor e-sentiments. For example, through "Direct2Dell Blog Service" and "Ideastorm.com," Dell tried to build a direct communication channel with its customers, listening to their voice and observing their e-sentiment (Jarvis 2009). However, now even small- and mid-sized companies have access to e-sentiment information through outside vendors such as PowerReviews and Bazaarvoice. Accordingly, developing e-marketing strategy based on e-

sentiment analysis becomes imperative (Gantenbein 2010). In spite of these potential shortcomings, we believe that this study will provide managers with a useful method to perform e-sentiment analysis and valuable insights to design better e-marketing strategy.

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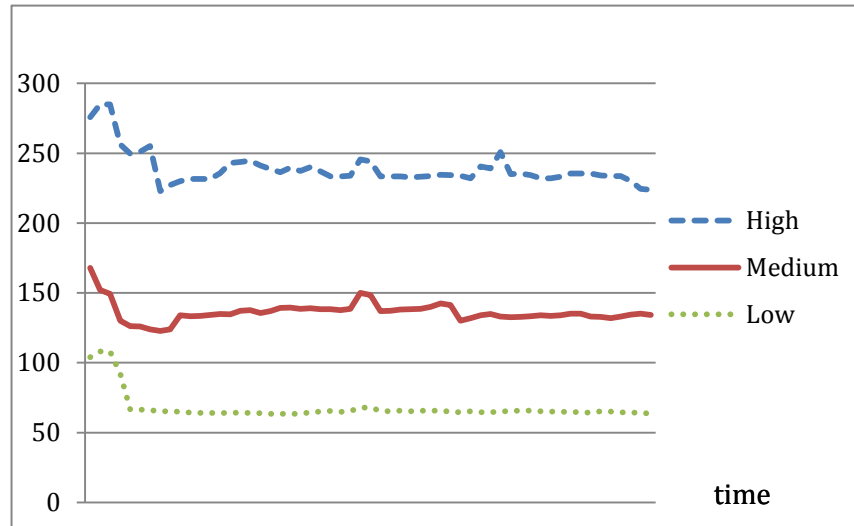
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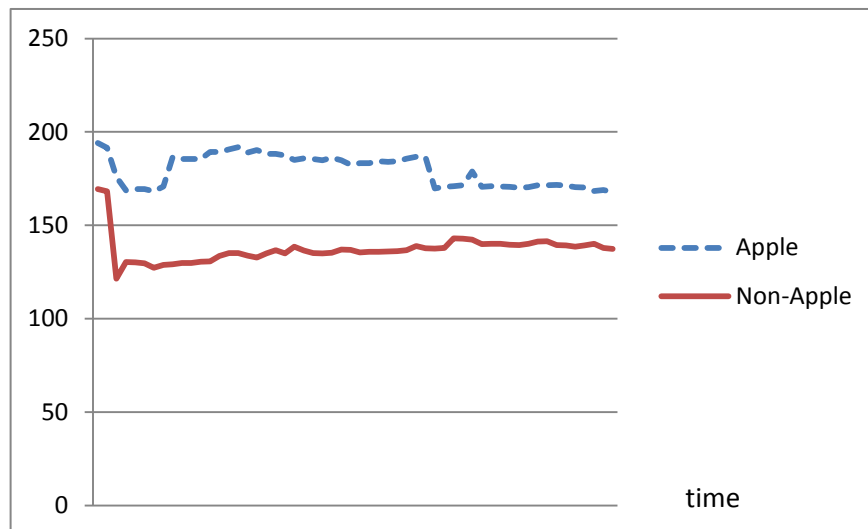
**FIGURES**

**FIGURE 1**

**Market Price of MP3 Players (\$): High/Medium/Low-Priced Items**



**Market Price of MP3 Players (\$): Leading-Brand (Apple) vs. Following-Brand Items**



**TABLES****TABLE 1****Description of 11 MP3 Player Products**

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

Note: "Amazon Sales Rank" is the Amazon's rank in the "Electronics" category; "Amazon Sales Rank" and "Amazon Customer Rating" data are obtained as of April 2008.

TABLE 2

Descriptive Statistics on Prices (PRICE) and the Number of e-Vendors (VEND)

ID	PRICE (\$)			VEND		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
<b>Helix</b>	162.1	153.3	18.2	17.8	22.0	6.3
<b>Nex50</b>	92.0	88.6	13.6	34.8	35.0	2.2
<b>Nex25</b>	73.2	69.8	13.4	26.6	26.0	1.5
<b>Mini</b>	182.2	180.0	7.6	1.2	1.0	0.4
<b>Nano</b>	174.7	171.3	14.4	18.0	18.0	1.8
<b>Video</b>	254.5	252.8	8.3	12.9	13.0	1.2
<b>Shuffle</b>	114.5	112.7	31.0	13.7	14.0	1.8
<b>Vision</b>	275.1	268.4	41.7	12.5	13.0	1.9
<b>Sleek</b>	174.9	178.6	10.0	8.2	8.0	2.1
<b>E260</b>	156.2	153.9	11.3	43.7	44.0	3.1
<b>M230</b>	37.8	37.3	4.1	34.3	36.0	4.6

TABLE 3

Descriptive Statistics on e-Sentiment

ID	Positive e-sentiment (POS)		Negative e-sentiment (NEG)		Neutral e-sentiment (NEUT)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
<b>Helix</b>	21.8	6.4	7.2	2.1	6.8	3.0
<b>Nex50</b>	8.6	2.3	0	0	15.4	2.5
<b>Nex25</b>	5.0	2.3	.3	.5	21.8	5.9
<b>Mini</b>	145.0	34.7	12.9	2.3	58.5	7.5
<b>Nano</b>	36.7	8.8	2.3	2.1	13.8	4.3
<b>Video</b>	228.1	54.3	18.6	3.0	81.7	11.1
<b>Shuffle</b>	147.3	14.8	12.8	3.7	39.2	10.6
<b>Vision</b>	29.8	8.7	3.1	2.0	187.5	19.1
<b>Sleek</b>	43.4	6.0	1.5	2.3	100.5	13.6
<b>E260</b>	147.9	22.6	9.5	1.2	61.8	24.1
<b>M230</b>	70.3	16.2	4.8	1.5	7.5	3.7

TABLE 4

## Effects of e-Sentiment: REx-GMM with AR(1) specification

Dependent Variable: $PRICE_t$	All Items	Higher- vs. Lower-Ticket Items			Leading- vs. Following-Brand Items	
		ALL	HIGH	MED	LOW	LB
$POS_{t-1}$	.013*** [7.10]	.010*** [4.17]	.023*** [5.23]	.003*** [2.86]	.008** [2.01]	.023*** [4.62]
$NEG_{t-1}$	-.224*** [-3.67]	-.344*** [-5.93]	-.238** [-2.15]	-.158*** [-9.14]	-.362*** [-7.56]	-.377*** [-2.86]
$NEUT_{t-1}$	-.004 [-.54]	-.012*** [-4.92]	.009 [.81]	.030*** [4.84]	.045*** [3.15]	-.004 [-.35]
$VEND_t$	-.927*** [-2.65]	-1.581*** [-5.49]	-1.977*** [-5.15]	-.114*** [-4.66]	-.647*** [-4.94]	-1.705*** [-3.84]
AR term ( $\rho$ )	.550*** [20.05]	.615*** [14.59]	.580*** [28.02]	.606*** [26.88]	.550*** [17.48]	.325*** [7.36]
# of observations	616	164	281	171	221	395
# of cross-sections	11	3	5	3	4	7
R <sup>2</sup>	.985	.956	.668	.994	.981	.880
<i>Price Elasticities w.r.t. e-Sentiment</i>	<b>ALL</b>	<b>HIGH</b>	<b>MED</b>	<b>LOW</b>	<b>LB</b>	<b>FB</b>
$POS_{t-1}$	.007	.006	.012	.001	.006	.008
$NEG_{t-1}$	-.117	-.195	-.121	-.065	-.278	-.127
$NEUT_{t-1}$	.000	-.001	.000	.001	.003	.000

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

Note: t-statistics are in parentheses. t-statistics reported here are calculated using Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors based on the Barlett kernel with 10 lags.

**TABLE 5**  
**Comparison of Models and Estimation Methods**

Dependent Variable: <i>PRICE<sub>t</sub></i>	Fixed-Effects without AR	Fixed-Effects without AR	Our Model with AR(1)
<b>Estimation Method</b>	<b>OLS</b>	<b>IV</b>	<b>GMM</b>
<b>Instrument for Fixing Endogeneity</b>	<b>Not used</b>	<b>Used</b>	<b>Used</b>
<b>Time-varying Omitted Variables</b>	<b>Not considered</b>	<b>Not considered</b>	<b>Considered</b>
<b>ALL products</b> (# of observations: 616)			
<i>POS<sub>t-1</sub></i>	.011 [.41]	-.005 [-.34]	.013*** [7.10]
<i>NEG<sub>t-1</sub></i>	-.380** [-2.66]	.067 [.25]	-.224*** [-3.67]
<i>NEUT<sub>t-1</sub></i>	.024 [.35]	-.022 [-.78]	-.004 [-.54]
<i>VEND<sub>t</sub></i>	-1.267 [-1.37]	-1.511** [-2.01]	-.927*** [-2.65]
<i>AR term (<math>\rho</math>)</i>	n.a.	n.a.	.550*** [20.05]
<b>LOW products</b> (# of observations: 171)			
<i>POS<sub>t-1</sub></i>	-.015 [-.98]	-.014 [-1.07]	.003*** [2.86]
<i>NEG<sub>t-1</sub></i>	-.074 [-.47]	-.173 [-1.11]	-.158*** [-9.14]
<i>NEUT<sub>t-1</sub></i>	-.039 [-1.11]	.220 [1.44]	.030*** [4.84]
<i>VEND<sub>t</sub></i>	-.281*** [-5.28]	.203 [0.66]	-.114*** [-4.66]
<i>AR term (<math>\rho</math>)</i>	n.a.	n.a.	.606*** [26.88]

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

TABLE 6

Effects of e-Sentiment: REX-GMM with alternative specifications

Dependent Variable: <i>PRICE<sub>t</sub></i>	All Items	Higher- vs. Lower-Ticket Items			Leading- vs. Following-Brand Items	
		HIGH	MED	LOW	LB	FB
<b>REX-GMM with AR(2)</b>	<b>ALL</b>	<b>HIGH</b>	<b>MED</b>	<b>LOW</b>	<b>LB</b>	<b>FB</b>
<i>POS<sub>t-1</sub></i>	.015*** [5.90]	.010*** [3.94]	.037*** [11.24]	.002** [1.98]	.011 [1.55]	.023*** [4.62]
<i>NEG<sub>t-1</sub></i>	-.204*** [-3.04]	-.343*** [-5.81]	-.218** [-2.13]	-.148*** [-6.35]	-.352*** [-6.13]	-.365*** [-2.90]
<i>NEUT<sub>t-1</sub></i>	-.003 [-.43]	-.012*** [-5.55]	.016 [1.81]	.032*** [4.70]	.045** [2.35]	-.003 [-.33]
<b>ME-robust REX-GMM with AR(1)<sup>+</sup></b>	<b>ALL</b>	<b>HIGH</b>	<b>MED</b>	<b>LOW</b>	<b>LB</b>	<b>FB</b>
<i>POS<sub>t-1</sub></i>	.014*** [9.49]	.010*** [4.12]	.027*** [5.45]	.002** [2.28]	.009 [1.59]	.029*** [3.85]
<i>NEG<sub>t-1</sub></i>	-.175*** [-2.89]	-.312*** [-5.23]	-.239** [-2.35]	-.173*** [-9.39]	-.365*** [-4.80]	-.318*** [-2.84]
<i>NEUT<sub>t-1</sub></i>	-.007 [-1.42]	-.015*** [-6.33]	.007 [0.69]	.046*** [7.20]	.037* [1.84]	-.0126 [-1.47]
<b>ME-robust REX-GMM with AR(2)<sup>+</sup></b>	<b>ALL</b>	<b>HIGH</b>	<b>MED</b>	<b>LOW</b>	<b>LB</b>	<b>FB</b>
<i>POS<sub>t-1</sub></i>	.016*** [7.48]	.010*** [3.86]	.042*** [12.00]	.001 [1.33]	.013* [1.65]	.029*** [3.90]
<i>NEG<sub>t-1</sub></i>	-.149** [-2.22]	-.313*** [-5.14]	-.285*** [-3.40]	-.161*** [-5.99]	-.367*** [-5.43]	-.316*** [-2.90]
<i>NEUT<sub>t-1</sub></i>	-.007 [-1.36]	-.015*** [-7.00]	.013 [1.77]	.046*** [6.15]	.037* [1.90]	-.012 [-1.45]

\*\*\*p&lt;.01, \*\*p&lt;.05, \*p&lt;.10; +Measurement error-robust REX-GMM.

TABLE 7

## Summary of Price Elasticities with respect to e-Sentiment

Dependent Variable: <i>PRICE<sub>t</sub></i>	All Items	Higher- vs. Lower- Ticket Items			Leading- vs. Following-Brand Items	
		ALL	HIGH	MED	LOW	LB
<b>REx-GMM with AR(1)</b>	<b>ALL</b>	<b>HIGH</b>	<b>MED</b>	<b>LOW</b>	<b>LB</b>	<b>FB</b>
<i>POS<sub>t-1</sub></i>	0.007	0.006	0.012	0.001	0.006	0.008
<i>NEG<sub>t-1</sub></i>	-0.117	-0.195	-0.121	-0.065	-0.278	-0.127
<i>NEUT<sub>t-1</sub></i>	0.000	-0.001	0.000	0.001	0.003	0.000
<b>REx-GMM with AR(2)</b>	<b>ALL</b>	<b>HIGH</b>	<b>MED</b>	<b>LOW</b>	<b>LB</b>	<b>FB</b>
<i>POS<sub>t-1</sub></i>	0.008	0.006	0.019	0.001	0.008	0.008
<i>NEG<sub>t-1</sub></i>	-0.106	-0.194	-0.111	-0.061	-0.270	-0.123
<i>NEUT<sub>t-1</sub></i>	0.000	-0.001	0.001	0.001	0.003	0.000
<b>ME-robust REx-GMM with AR(1)<sup>+</sup></b>	<b>ALL</b>	<b>HIGH</b>	<b>MED</b>	<b>LOW</b>	<b>LB</b>	<b>FB</b>
<i>POS<sub>t-1</sub></i>	0.007	0.006	0.014	0.001	0.007	0.010
<i>NEG<sub>t-1</sub></i>	-0.091	-0.177	-0.121	-0.072	-0.280	-0.107
<i>NEUT<sub>t-1</sub></i>	0.000	-0.001	0.000	0.001	0.002	0.000
<b>ME-robust GMM with AR(2)<sup>+</sup></b>	<b>ALL</b>	<b>HIGH</b>	<b>MED</b>	<b>LOW</b>	<b>LB</b>	<b>FB</b>
<i>POS<sub>t-1</sub></i>	0.008	0.006	0.021	0.000	0.010	0.010
<i>NEG<sub>t-1</sub></i>	-0.078	-0.177	-0.145	-0.067	-0.282	-0.106
<i>NEUT<sub>t-1</sub></i>	0.000	-0.001	0.001	0.001	0.002	0.000

\*\*\*p<.01, \*\*p<.05, \*p<.10; +Measurement error-robust GMM.

## *FOOTNOTES*

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<sup>1</sup> One important exception is Liu (2006) who collected online posts from Yahoo Movie message board and coded the valence of each post as positive, negative, or neutral. But the author did not observe any impact of online buzz valence on his dependent variable, i.e., weekly box office revenue.

<sup>2</sup> See [http://www.comscore.com/Press\\_Events/Press\\_Releases/2007/11/Online\\_Consumer\\_Reviews\\_Impact\\_Offline\\_Purchasing\\_Behavior](http://www.comscore.com/Press_Events/Press_Releases/2007/11/Online_Consumer_Reviews_Impact_Offline_Purchasing_Behavior)

<sup>3</sup> Online customers can easily collect information from multiple sources such as customer reviews, blogs, and online forums 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 forums in the case of TV shows), raising concerns about measurement error problem. In contrast, our dataset contains online buzz information from multiple sources for a better representation of e-WOM. Yet, it is difficult for us to prove that our dataset represents all online buzz available, and thus, our dataset is also subject to measurement errors to certain degree. Moreover, online buzz data has other inherent limitations such as 1) customers may have little incentive to provide reviews for other customers (Chevalier and Mayzlin 2006), 2) the identity of an online information provider is volatile (Dellarocas 2003), and 3) firms may engage in strategic manipulation to distort online buzz and to boost sales (Dellarocas 2006). Such issues also raise a question regarding measurement error problem when we empirically analyze online buzz data.

<sup>4</sup> See <http://www.instat.com/press.asp?ID=1366&sku=IN0502148ID>.

<sup>5</sup> 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 2010).

<sup>6</sup> See <http://www.iht.com/articles/2006/10/31/bloomberg/sxcreative.php>.

<sup>7</sup> See <http://apple20.blogs.fortune.cnn.com/2008/01/29/beyond-the-incredible-shrinking-ipod-market>.

<sup>8</sup> 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](http://reviews.cnet.com/4520-7964_7-5134106.html).

<sup>9</sup> <http://www.bloomberg.com/apps/news?pid=conewsstory&refer=conews&tkr=AAPL:US&sid=aggTRzHFt1Do>.

<sup>10</sup> 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.

<sup>11</sup> Economic theory suggests that prices decrease as competition increases. Baye, Morgan and Scholten (2004a) show that online price competition becomes intense as more e-vendors carry the same product. Yet, VEND can be also positively correlated with unobservable quality. With valid instruments, we expect VEND will have a negative coefficient estimate.

<sup>12</sup> 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>.