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Positive versus Negative e-Sentiment and the Market Performance of High-Tech Products

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Report Summary

As the “MSI Research Priorities” (2012-2014) note, “Customers are moving and connected more than ever. We need to get a better sense of what is on their minds and what they are doing at the same time.” For instance, consumers can more easily influence one another by actively sharing opinions online, reflecting their perception of and experience with products.

Firms that can extract online consumer feedback faster and fine-tune their offerings based on these insights will enjoy a competitive advantage. However, little is known about how consumers’ sentiments that are shared online (“e-sentiments”) influence products’ market performance and about the comparative impact of e-sentiment (generated by consumers) and traditional marketing actions such as advertising (controlled by marketers).

To address these questions, Hyun Shin, Dominique Hanssens, Kyoo Il Kim, and Jean Choe track online buzz in the DSLR (digital single lens reflex) camera market and analyze its impact on brand sales via econometric modeling. The DSLR category reflects high-involvement consumer decision making in a dynamic environment, i.e., frequent technological innovation and marketing-mix adjustments.

The authors expect that negative e-sentiment will have a stronger impact on products’ market performance than positive e-sentiment. Furthermore, the authors expect that these e-sentiment effects will be moderated by customers’ expectations levels: negative online buzz may have a stronger adverse impact for higher-priced products, while positive online buzz may have a greater beneficial effect on lower-priced products. In addition, the authors expect that the impact of advertising will also be moderated by customers’ expectations levels, similar to that of positive online buzz which conveys favorable information about a product. The effect size of advertising, however, may be smaller than that of positive buzz. The econometric results largely support these hypotheses.

The finding that the business performance impact of positive versus negative online buzz and advertising is moderated by customers’ expectations levels has important managerial implications. Since e-sentiments can be monitored at the weekly or even daily level, managers can install feedback rules in the areas of e-retail pricing and promotion (e.g., adjusting prices as a function of prevailing e-sentiment), product portfolio management (e.g., prioritizing products with more positive e-sentiment), and advertising (e.g., countering negative e-sentiment with advertising messages). This creates an opportunity to adjust marketing investments to rapidly evolving consumer attitudes, i.e., matching supply and demand conditions through better and faster “market sensing.”

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Background

"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. Accordingly, the role of WOM on customer decision making (e.g., Arndt 1968; Richins 1983) and its impact on firm performance (e.g., Luo 2007, 2008) has been emphasized in previous research.

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). 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[1] 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 demand of a product can be affected by online buzz.

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; Sen and Lerman 2007; Senecal and Nantel 2004; Trusov, Bucklin and Pauwels 2009; Zhu and Zhang 2010). However, prior research tends

[1] See http://www.comscore.com/Press_Events/Press_Releases/2007/11/ Online_Consumer_Reviews_Impact_Offline_Purchasing_Behavior

to focus on the quantitative aspect of e-WOM (e.g., average product rating), leaving the qualitative aspect (i.e., how customers describe the overall value and experience about a product) less explored. When customers refer to online reviews, however, they check not only average rating but also textual feedback information (Schindler and Bickart 2004). Practitioners are also 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). Thus, it would be interesting to investigate how positive or negative descriptions about a product, i.e., online buzz valence or e-sentiment, affect its market performance (e.g., sales, market share).

Literature Review

Textual information from online buzz contains consumers' sentiment towards products (e.g., overall value perception and satisfaction with respect to the underlying products). Such e-sentiment information can be used as a useful leading indicator of business outcomes such as sales and market share (Yi, Nasukawa, Bunescu, and Niblack 2003). Yet, the richness of e-sentiment information 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 capture consumer perception about a product directly from online texts and examine its impact on market outcomes such as sales. For example, one can examine how the demand of a product reacts differently to positive vs. negative online conversation.

To address this issue, Liu (2006) 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. In contrast, more recent studies reported that box office ticket sales of movies can be affected by the valence of online buzz information collected from Yahoo Movie (Chintagunta, Gopinath, and Venkataraman 2010) and blog posts (Gopinath, Chintagunta, and Venkataraman 2013).

McAlister, Sonnier and Shively (2012) also examined the impact of positive, negative, and neutral online communications on firm value. They found positive impact on stock returns of neutral buzz volume, but did not find any impact of positive and negative buzz volume. Sonnier, McAlister and Rutz (2011) documented the positive impact on actual product sales of positive and neutral buzz volume and the negative one of negative buzz. However, they used time-series sales data for a single firm, leaving the role of marketing mix variables such as prices and advertising unexplored.

By using data covering 60 products from two categories (digital cameras, camcorders) collected from Amazon.com, Archak, Ghose and Ipeirotis (2011) examined the impact of e-sentiment on the sales rank of products (as a proxy of sales) after controlling for their prices. In particular, they used advanced text mining techniques to capture multi-facets of online buzz; specifically, they could identify meaningful descriptions such as "good picture quality" or "great design," and examined how such descriptions affect the sales rank of products. However, their findings are somewhat mixed; for example, they found negative impact on sales rank of positive descriptions such as "great video quality," "easy-to-use" and "good battery life."

In sum, we are still in short of empirical evidence on whether and how positive/negative e-sentiment affects the market performance of products. To our knowledge, moreover, whether and how differently e-sentiment generated by consumers and advertising efforts controlled by marketers influence the market performance of products has rarely been examined with actual data.[2] This would be another intriguing topic for researchers.

To fill the gap, we investigate how customers' positive vs. negative e-sentiment, coupled with other marketing mix variables such as prices and advertising, affect the market performance of a product. In so doing, we use data on DSLR (Digital Single-Lens Reflex) cameras collected from major online retailers on a weekly basis for 36 weeks (November 2011~August 2012). We choose this category considering that the online buzz likely has a stronger impact on business outcomes of high-tech products due to the customers' high involvement and the inherent complexity of DSLR product assessment.

To analyze such relationship using weekly 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 performance such as off-line buzz around the product (e.g., personal communication between friends/family members), which should be correlated with online buzz (e.g., Horvath, Leeflang, Wieringa and Wittink 2005). If we assume that those unobservable factors (to researchers) that influence market performance of products are time-invariant, we may still obtain unbiased estimates of the effects of online buzz variables on market performance 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. Thus, omitting time-varying unobservable factors such as off-line buzz 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. Accordingly, previous studies tend to collect online buzz data from a single e-retailer such as Amazon.com. Gu, Park and Konana (2012), however, showed that external WOM sources (e.g., CNET, Epinions) have a significant effect on the sales of high-tech products at Amazon.com. Considering this issue, we use online buzz data from multiple sources collected by a renowned social media research company. Yet, our dataset is not free from measurement error problem since it is almost impossible to cover all the buzz information

[2] One notable exception is Gopinath, Chintagunta, and Venkataraman (2013) who examined the impact of blog posts and advertising in the movie business. Yet, they also pointed out that the role of advertising is relatively important in movie business, implying that their findings might be less generalizable in other product markets.

available on the web. Thus, how to deal with measurement error problem inherent in any online buzz data is another challenge for e-WOM researchers.

To address these issues, we build on a panel regression approach developed by Bajari, Cooley, Kim and Timmins (2012). By explicitly modeling the evolution of time-varying unobservables (i.e., latent goodwill stock due to omitted reputation on products in our model) and estimating the model with GMM (Generalized Method of Moments) method, we recover the impact of online buzz when the time-varying omitted variables are potentially correlated with online buzz. In addition, we develop an extended empirical model that can account for potential measurement error and show the estimation results of this alternative model. Thus, our study contributes to e-WOM literature by providing a new, simple solution to key methodological issues in analyzing online buzz data.

We expect that online buzz around a product will affect its market performance while negative buzz is likely to show stronger impact than positive buzz. Furthermore, we expect that the effect will be moderated by customers' expectation level: negative online buzz may have a stronger adverse impact for the higher-priced items, while positive online buzz may have a greater beneficial effect on the lower-priced items. We also expect that the impact of advertising will be moderated by customers' expectation level, similar to that of positive online buzz which carries favorable information about a product. The effect size of advertising, however, may be smaller than that of positive buzz.

In order to examine the hypotheses, we collect actual sales/prices of multiple products, different from previous studies which tend to use data from a single retailer or manufacturer. In addition, we use actual advertising spending data as well as online buzz data from multiple sources. To our knowledge, this paper represents the first attempt at such analyses in the literature, which would provide richer insights to researchers and practitioners.

Hypotheses Development

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 try to 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.

> *Hypothesis 1: Online buzz around a product will affect its market performance, while negative buzz is likely to show stronger impact than positive buzz.*

Consumers' expectation level as a moderator

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. Customers' expectation can be defined as "a pre-trial belief about a product that serves as a standard or reference point against which product performance is judged (by customers)" (Zeithaml, Berry, and Parasuraman, 1993, p.1). Fiske (1980) argues that negative information about a product may be more influential or diagnostic than positive information when a consumer has a higher expectation level (i.e., "negativity effect"). In contrast, if a customer with a lower expectation level about a product receives positive information, it may dominate negative information in 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).

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,' price tier can be regarded as a signal of product quality (Wolinsky 1983, Milgrom and Roberts 1986). 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. In other words, a single negative buzz may make the customer hesitate to open her wallet when she considers expensive DSLR cameras, leading to a larger negativity effect for higher-priced items. By the same token, a positive buzz may have a larger positivity effect for lower-priced items. One piece of favorable e-sentiment information (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.

Hypothesis 2: Negative online buzz may have a stronger adverse impact for the higher-priced items (negativity effect of e-sentiment), while positive online buzz may have a greater beneficial effect on the lower-priced items (positivity effect of e-sentiment).

Positive online buzz vs. advertising

Note that both advertising and positive buzz convey favorable information to customers. In some sense, positive buzz can be regarded as consumer-initiated, indirect advertising for a product/brand. Thus, it would be interesting to examine whether advertising spending has a similar (or different) effect to that of positive buzz.

Hypothesis 3: Advertising effort may have a greater beneficial effect on the lower-priced items (positivity effect of advertising).

Even though we predict that advertising and positive buzz will show similar effects, some practitioners argue that online buzz would be more influential than advertising (e.g., Berry and Keller 2003). Thus, we will also examine whether the effect size of advertising is smaller than that of positive buzz in DSLR cameras market.

Model & Estimation

Model development

Here we discuss basic ideas of our approach before we introduce more technical terms. Our model and estimation strategy is based on three simple but intuitive assumptions. The first assumption is that market performance of a product is a function of product's observed attributes as well as goodwill stock that consists of firm's advertising and electronic word-of-mouth communications among consumers. We allow this goodwill stock includes an "omitted" factor that is observed to consumers but not by researchers. In many applications it makes sense to believe that consumers have superior information on products of their purchases than researchers.

Our second assumption is that this unobserved factor (to researchers) follows a known time-series process i.e. the unobserved factor evolves over time and its evolution has a systematic component that can be predicted given available information on products.

Our third assumption is that consumers are rational with respect to their predictions on how the unobserved factor evolves over time. In other words consumers do not make systematic errors in their predictions, i.e. on average they do not over-predict nor under-predict. In particular this last assumption allows us to develop econometric conditions that can be used for estimation such as generalized method of moments. Below we develop our model formally.

Let market performance variables such as sales be y_t and goodwill stock of a product (or a brand) be S_t. We model the goodwill stock (or information stock) on the perceived quality of a product is formed from firm's advertising effort and also from electronic word-of-mouth communications among consumers. Here we are interested in measuring how these two different channels affect the goodwill stock evolution as well as market performances.

Let a_t be the advertisement spending. Let positive, negative, and neutral online buzz variables be $c^p{}_t$, $c^n{}_t$, and $c^o{}_t$, respectively. Also let $c_t = [c^p{}_t, c^n{}_t, c^o{}_t]'$ and x_t be other covariates that may affect market performances. Then we jointly model the market performance and evolution of the latent goodwill stock of a product j as

(1) $y_{jt} = \alpha_j + x'_{jt}\beta^x + \log S_{jt} + \varepsilon_{jt}$

(2) $\log S_{jt} = \delta_j \log S_{jt-1} + \gamma^A \log a_{jt-1} + \gamma^{c'} \log \mathrm{c}_{jt-1} + \xi_{jt}$

Here α_j is a product-level fixed effect that can capture persistency in the market performance of a product. In the goodwill stock equation (2), goodwill depreciates over time by δ_j but can be replenished by new advertisement spending or new information arrival through online communications. In the goodwill stock equation, ξ_t can capture other unobserved sources of reputation on products (e.g., off-line buzz, press coverage). Here we assume the goodwill stock follows an autoregressive process of order 1 (i.e., AR(1)) but it can easily extend to a process with more time lags, e.g., AR(2).

In this model we allow a market performance shock ε_t and the error ξ_t in the goodwill stock to be potentially correlated both with the online buzz c_{t-1} and/or advertisement spending a_{t-1}. The endogeneity of a_{t-1} can arise because firms may decide advertising efforts depending on the level of market performance (e.g., sales) and also online sentiments of consumers. In addition, the online buzz c_{t-1} is potentially endogenous due to its measurement error, omitted variables, and possible simultaneity with the goodwill stock.

To estimate this model, we combine (1) and (2) to obtain

$$(3)\quad y_{jt} = (1-\delta_j)\alpha_j + \delta_j y_{jt-1} + \beta^{x'} x_{jt} - \delta_j \beta^{x'} x_{jt-1} + \gamma^A \log a_{jt-1} + \gamma^{c'} \log c_{jt-1} + \varepsilon_{jt} - \delta_j \varepsilon_{jt-1} + \xi_{jt}$$

Removing the fixed effect by taking the first difference, we further obtain

$$(4)\quad \Delta y_{jt} = \delta_j \Delta y_{jt-1} + \beta^{x'} \Delta x_{jt} - \delta_j \beta^{x'} \Delta x_{jt-1} + \gamma^A \Delta \log a_{jt-1} + \gamma^{c'} \Delta \log c_{jt-1} + \Delta\varepsilon_{jt} - \delta_j \Delta\varepsilon_{jt-1} + \Delta\xi_{jt}$$

In this approach our identifying assumption is that although c_{t-1} and a_{t-1} are potentially endogenous, further lagged variables are still exogenous. To formalize this idea, let I_t be the information set available to consumers and firms, which affects their decisions such as purchases, c_{t-1} and a_{t-1}. I_t can include lagged e-sentiment variables, lagged advertising spendings, and other exogenous variables. Therefore we assume $E[\varepsilon_{jt} \mid I_{j,t-1}, x_{jt}] = 0$ and $E[\xi_{jt} \mid I_{j,t-1}, x_{jt}] = 0$. Under these assumptions we have $E[\Delta\varepsilon_{jt} - \delta\Delta\varepsilon_{jt-1} + \Delta\xi_{jt} \mid I_{j,t-3}, x_{jt}, x_{jt-1}, x_{jt-2}] = 0$. This renders us to estimate the model using GMM estimation based on the following moment conditions:

$$(5)\quad E[\Delta y_{jt} - \{\delta_j \Delta y_{jt-1} + \beta^{x'} \Delta x_{jt} - \delta_j \beta^{x'} \Delta x_{jt-1} + \gamma^A \Delta \log a_{jt-1} + \gamma^{c'} \Delta \log c_{jt-1}\} \mid \mathrm{I}_{j,t-3}, x_{jt}, x_{jt-1}, x_{jt-2}] = 0$$

Note that one can construct moment conditions using $I_{j,t-l}$ with $l > 3$ rather than $I_{j,t-3}$ when persistent correlation of observables with shocks and errors are suspected.

Accounting for measurement errors

It is possible that the observed online buzz variables are only noisy measures of online reputations. Suppose that e-sentiment variables c_{jt} are noisy measures of the 'true' online reputations denoted by c^*_{jt} and assume that $\log c_{jt} = \log c^*_{jt} + m_{jt}$ where m_{jt} denotes measurement error. Then the market performance and the goodwill stock equations become

(6) $y_{jt} = \alpha_j + x'_{jt}\beta^x + \log S^*_{jt} + \varepsilon_{jt}$

(7) $\log S^*_{jt} = \delta_j \log S^*_{jt-1} + \gamma^A \log a_{jt-1} + \gamma^{c'} \log c^*_{jt-1} + \xi_{jt}$

Then after substitutions and differencing we obtain

(8) $\Delta y_{jt} = \delta_j \Delta y_{jt-1} + \beta^{x'} \Delta x_{jt} - \delta_j \beta^{x'} \Delta x_{jt-1} + \gamma^A \Delta \log a_{jt-1} + \gamma^{c'} \Delta \log c_{jt-1} + \Delta\varepsilon_{jt} - \delta_j \Delta\varepsilon_{jt-1} + \Delta\xi_{jt} - \Delta m'_{jt-1}\gamma^{c'}$

If we assume $E[m_{jt} \mid I_{j,t-1}] = 0$, we have $E[\Delta m_{jt-1} \mid I_{j,t-3}] = 0$. Then the above equation suggests that the estimation based on the moment condition (5) is also robust to measurement errors.

Data

Industry background

For the empirical analysis, we used weekly sales, prices, advertising, and online buzz data collected from Nov. 27, 2011 to Aug. 4, 2012 (37 weeks) for the DSLR (Digital Single-Lens Reflex) cameras. DSLR market exhibits several interesting characteristics. First, it is a large and fast-growing market. According to NPD research reports, the US DSLR market reached $1.2 billion in 2011. In addition, during the first half of 2012, the market size has increased by 36% versus the same period in 2011. Second, the DSLR market has been dominated by two giants, i.e., Canon and Nikon, and other many small players including Panasonic, Sony, Pentax, and Olympus. According to Bloomberg report (2010), Canon occupied 44.5% of the worldwide DSLR market, while Nikon had 29.8% in 2010. In U.S., the market power of Canon is even stronger. For example, Canon had 50.6% market share while Nikon had 34.4% during the time that our data covers (November 2011~July 2012). During the same period, top 10 DSLR models (6 from Canon, 4 from Nikon) account for 75.5% of the market, showing a typical 'long-tail' shape.[3] While Canon and Nikon enjoy the dominant market position, over 50 other manufacturers compete for the remaining but still lucrative 24.5% of the market. Third, product life cycles are relatively short in this market. As of July 2012, there were more than 200 SKUs available in the DSLR 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, the DSLR category is notorious for its complexity in terms of product assessment for purchase decision-making. For example, consumers who are interested in buying a DSLR camera should consider a number of factors such as lens types/sensor sizes (APS, Four Thirds, Full Frame), megapixels, frames per second, AF speed and tracking, ruggedness, white-balance system, image stabilization, and apochromatic correction. This leads to a situation in which "*digital SLRs generally have a plethora of buttons and dials, which can intimidate some users,"* as the CNET DSLR Buying Guide (2010) puts it.

The aforementioned characteristics offer a unique research opportunity. First, the effect of online buzz on consumer choice dynamics is likely to be conspicuous because we may observe sufficient variations in our focal variable, i.e., weekly market sales. Second, consumers are expected to rely more heavily on online buzz when purchasing high-tech durable products because such products often require high involvement (Gu, Park, and Konana 2012) and entail inherent complexity in product assessment (Shin 2008). Third, by analyzing top 30 products, we can easily cover over 90% of the total market. Additionally, DSLR has little substitution issue with an outside category unlike some other high-tech durables. For instance, compact cameras are increasingly being replaced by alternative products such as smartphones and tablets. As such, the DSLR market is an ideal setting to examine our hypotheses.

Database development

For data collection, 37 DSLR product models from 7 brands were chosen between November 2011 and August 2012. These brands include: Canon, Nikon, Sony, Panasonic, Olympus, Pentax, and Fujifilm, accounting for 96.1% of the entire retail sales in U.S. DSLR market during the data

[3] 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).

period (Source: NPD Group). Table 1 presents the description of the seven brands of interest (see Table 1 following References).

Sales. Unit sales (**SALES**) data were purchased from NPD. They were collected on a weekly basis from major U.S. retailers covering both online and offline channels (e.g. Best Buy, Circuit City, Amazon, Buy.com, etc.). The original data set was collected at the product SKU level. Then SKU-level data were aggregated into the product model level. Product model seemed to be the most appropriate unit of analysis as different SKU's within a product model represented variations in colors or lens types and most online mentions were aimed for a model rather than a specific SKU. Among the 149 product models available in the market, top 37 product models (or model, hereafter) were selected based on their popularity (unit market share).

Price. Market price (**PRICE**) data were also obtained from NPD database. PRICE is defined as the average price of each DSLR model, i.e., total $ revenue divided by total unit sales on a weekly basis. Table 2 summarizes the sales and price histories of the 37 models under study (see Table 2 following References).

Advertising. Weekly advertising spending data for the 37 focal models were acquired from A.C. Nielsen (see Table 3 following References). They provided model-level and DSLR category-level advertising spending in dollars across all available advertising channels. As we were interested in the gross spending on advertising, the data for different channels were summed to yield the total advertising spending for each model/category.

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 an advanced data mining approach developed by an online marketing research company, e-sentiment data were collected from World Wide Web. As this buzz data set covers online buzz across a wide range of online media (e.g. blogs, boards, Facebook, Twitter, online groups, videos and images), instead of being restricted to a limited number of sources, it enables us to understand the effect of online buzz in a rather holistic picture. The data not only contained counts for the overall buzz but also had separate counts depending on whether the valence of the message was negative, positive or neutral. Accordingly, we obtain a sentiment factor, i.e., # of positive buzz (POS), # of negative buzz (NEG), and # of neutral buzz (NEUT). Note that we focus on 37 flagship products since they were more likely to have received the most attention from customers.

Table 4 illustrates that two Nikon products (D90 and D3100) and Canon's Mark II generated high levels of positive buzz, while Nikon's D800 and Canon's Rebel T3 and T3i generated high levels of negative buzz. Nikon's D800 and Canon's Mark II received most neutral buzz. Interestingly, the positive buzz counts are 3 to 40 times higher than the negative counts, while the neutral buzz is always more than the positive buzz (see Table 4 following References).

Price tier. To examine whether customers' expectation level moderates the impact of online buzz, we use price tier as a proxy of customers' expectation level (See Table 5 following References). By using the median price of a model, we categorize our data into three groups, i.e., HIGH (median price level > $1,500), MED ($800 < median price level < $1,500), and LOW (median price level < $800). In our dataset, HIGH group represents the top 20% items while LOW group approximately corresponds to the bottom 60% items (see Table 5). This categorization is indeed consistent with a typical DSLR customer segmentation, i.e., entry-level customers, prosumers, and professionals. According to CNET Digital Camera Buying Guide (Goldman and Grunin, 2012), entry level customers are the ones "who want better speed and quality than a compact and prefers shooting using an optical viewfinder… for photographing active kids and pets"; prosumers are "advanced photographers who need speed and quality, want to get artsy, and/or possibly sell their photos"; and professionals are people "who need a reliable, durable, fully configurable and consistent camera that delivers best-quality images and perhaps fast action-shooting level performance." [4] It would be interesting to see how these different types of customer segments respond differently to online buzz as well as marketing mix (advertising and prices).

Results

We estimated our empirical model (as explained in Equation (1) through (5)) by using market share as a market performance measure. As the regressand we used the log difference between

[4] http://reviews.cnet.com/digital-camera-buying-guide/

the market share of each product and the share of outside good. Here the outside good includes all other DSLR models than ones in our data set. If the idiosyncratic demand errors in underlying consumers utility functions - which generate market shares by consumers' choices on alternative products - follow Type I extreme value distributions, then this log difference becomes the mean utility of consumers for each product as in Berry (1994)'s multinomial logit models. One nice feature of the log transformation in this case is that although the mean utility of a product is a function of its own characteristics and goodwill stock only, the demand of a particular product (so its market share) will be a function of characteristics and goodwill stocks of all competing goods due to the consumers' utility maximizing choices over alternative products.

As explanatory variables, we used prices (PRICE), positive/negative/neutral online buzz (POS/NEG/NEUT), and model-level/category-level advertising spending (AD_M/AD_C). We also added ET (elapsed time since launch) to account for a potential time trend in our dependent variable (market share). Note that we took the log of all the explanatory variables. Coupled with our regressand (i.e., the log difference between the market share of each product and the share of outside good), this allows us to obtain scale-free elasticities, which is useful in comparing the responsiveness of market share to our focal covariates. For example, market share elasticities with respect to (positive/negative) e-sentiment can be interpreted as '% change in market share for 1% increase in (positive/negative) e-sentiment.'[5]

Table 6 illustrates the estimation results (See Table 6 following References). When we estimate our empirical model with all 37 DSLR product models, positive buzz has favorable impacts on sales as expected (.18, $p<.05$). In other words, 1% increase in positive e-sentiment leads to .18% increase in market share. However, negative buzz does not show any significant adverse effect on sales, different from our prediction (except high-priced items as we further discuss below). In addition, model-level advertising spending has a significant positive effect while DSLR category-level advertising has a positive but insignificant effect. Interestingly, positive buzz has much stronger impact than advertising, which implies the importance of buzz monitoring.

When we estimate the empirical model across three groups (LOW, MED, HIGH), however, we obtained interesting findings. First, POS (positive buzz) shows significant, positive effects on

[5] Based on the logit model specification we can calculate elasticity with respect to a particular variable as (1 - average share) times the coefficient estimate on that variable.

sales for LOW (.14, p<.01) and MED (.13, p <.05) groups, but has a smaller and insignificant effect for HIGH group. Second, NEG (negative buzz) has a significant, negative effect on sales for HIGH group (-.10, p <.05), but smaller and insignificant effects for LOW and MED groups. Third, NEUT (neutral buzz) has a positive, significant effect for HIGH group (.25, p <.05), but insignificant effects for LOW and MED groups. Fourth, AD (advertising) shows positive effects only for LOW group at both model-level (.02, p <.01) and category-level (.02, p <.01), while no significant effect is found for MED and HIGH groups. This finding imply that novice customers might be more receptive to the information contained in advertising while prosumers and professionals seem not much affected by conventional advertising when they make a purchase decision in the DSLR market. Fifth, PRICE (prices) shows a negative, significant effect for MED group (-.75, p <.01). For HIGH group, however, PRICE has a positive, significant effect (1.19, p <.01). This may be due to a signaling effect ('higher prices signals higher quality') for professional customers who are willing to pay over $1,500 to buy a cutting-edge, seamless DSLR camera. Sixth, positive buzz generally shows a bigger effect than advertising as many practitioners believe. Seventh, ET (elapsed time since launch) shows negative, significant effect for LOW (-1.60, p <.01) and positive, significant effect (1.27, p <.01). One possible explanation is that professional groups may prefer highly reliable products which have lasted the test of time, while beginners tend to prefer newer products if other conditions are the same. Finally, AR term (ρ) represents the depreciation rate of goodwill stock. Interestingly the depreciation rates for LOW group (.66, p <.01) and MED group (.62, p <.01) were higher than that for HIGH group (.48, p <.01). This implies that customers' impressions of past online buzz and advertising may last longer for LOW and MED groups than for HIGH group.

Discussion

Summary of findings

In order to examine the role of e-sentiment in the e-marketplace, we developed an advanced empirical model, accounting for time-varying omitted variables in the formation of customer goodwill stocks. We estimated the model through GMM method by using online buzz data from DSLR camera market. When we consider all 37 products in our dataset, we found the beneficial impact on market share of positive e-sentiment, but failed to find the impact of negative e-sentiment. So Hypothesis 1 is not supported.

When we take into consideration different customers' expectation level across three price tiers, however, we found that the relation between e-sentiment and market performance is moderated by customers' expectation level. Specifically, the adverse effect of negative buzz on market share is larger than that of positive buzz for the higher-priced items (*negativity effect of e-sentiment*), while the beneficial effect of positive buzz is larger than that of negative buzz for lower-priced and medium-priced items (*positivity effect of e-sentiment*). Further tests show that we can reject the equality and accept a bigger effect of positive buzz (than that of negative buzz) in LOW ($p <.05$) and MED ($p <.05$) groups as well as a bigger effect of negative buzz (than that of positive buzz) in HIGH group ($p <.10$), which is consistent with Hypothesis 2. In addition, the pattern that we observed (i.e., positive buzz shows significant, positive effects only for LOW and MED groups, while negative buzz has a significant, negative effect on sales only for HIGH group) is also consistent with Hypothesis 2.

Consistent with our prediction, advertising exhibits a similar pattern to positive buzz (i.e., a significant, positive effect of advertising only for lower-priced items); yet the size of advertising impact is much smaller than that of positive buzz. Accordingly, Hypothesis 3 is supported.

Interestingly, we do find positive effects of neutral buzz for higher-priced items, implying that positive buzz does not matter too much for professional customers with high level of expectation; but they care more about negative and neutral comments. One possible explanation is that they regard neutral comments as more reliable information (than positive comments) and positively react to neutral buzz when they make purchase decision.

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 present intriguing managerial insights on the impact of e-sentiment. First, a firm competing at the high-end of the price range should closely monitor customer dissatisfaction. 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 for which customers have higher expectations. In contrast, if a firm targets the lower-price tier segment, 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 enhance the market performance of a lower-priced product in the future.

In sum, we show that the business impact of positive vs. negative online buzz and advertising can be moderated by customers' expectations levels. Our findings imply that firms should not rely just on average customer ratings - because things really depend on where their focal product is in the price range, leading to different level of customer expectations. This has immediate relevance for marketing managers, as e-sentiment information can readily be monitored at the weekly or even daily level. Moreover, such e-sentiment information can be used as a useful leading indicator of business outcomes such as declining or mushrooming sales, increasing product returns/service cancellations, deteriorating brand image, and decreasing value of products. Thus managers can install feedback rules for their brands in the areas of e-retail pricing and promotion (e.g. adjusting prices in function of the prevailing e-sentiment), product portfolio management (e.g. prioritizing products with more positive e-sentiment) and advertising (e.g. countering negative e-sentiment with advertising messages). This creates opportunity to adjust marketing investments to rapidly evolving consumer attitudes, i.e. matching of supply and demand conditions through better and faster "market sensing".

We already have evidence of the beneficial financial effects of superior market-sensing capability. For example Zara's and Hot Topic's rapid fashion cycling beats that of traditional clothing retailers such as The Gap and allows them to compete successfully with much larger players in the industry. Similarly, the discipline of "yield management" has improved the performance of the hospitality and airline industry by frequent price adjustments in function of demand evolution for fixed-date events. As such, our study shows the importance of e-sentiment as a barometer for marketing-mix decisions, and thus, marketers should improve their market sensing capability so that they can fine-tune their marketing strategy in response to the evolution of online buzz.

Contributions, limitations, and future research

Our contributions are as follows: First, we have examined the role of e-sentiment information in DSLR camera market, taking advantage of our rich textual dataset collected on weekly basis. In particular, we collected sales and prices data of products covering over 95% of the entire US DSLR market and the associated online buzz data from multiple sources, different from most prior e-WOM studies. We also collected model- and category-level advertising data and compared the impact of online buzz with that of advertising, which has not been addressed in previous e-WOM studies. Second, we have developed an empirical model to analyze the relation between e-sentiment and market performance of products. Different from prior research, our proposed model accounts for the time-evolving nature of omitted variables such as off-line reputation in the customer goodwill stocks, leading to consistent estimation. We have also proposed an alternative approach to address the potential measurement error problem, which would be useful to future e-WOM researchers. Third, we have found an asymmetric impact of positive vs. negative online buzz information, documenting a negativity/positivity effect of e-sentiment. In so doing, we have identified an important moderating factor, i.e., customers' expectation level. In addition, we have examined the role of neutral online buzz and advertising, 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 e-WOM studies. In sum, our findings would provide insights to high-tech firms who face time-intensive online competition.

This study is subject to certain limitations. First, only the impact of e-sentiment on market share is examined. Future research may want to investigate relation between e-sentiment and other dimensions of market performances such as price premium and firm value. Second, by examining other product categories, future study may identify other moderators of e-sentiment effects such as product complexity, the degree of competition, product popularity (Zhu and Zhang 2010), and product types (e.g., hedonic vs. utilitarian products as analyzed in Sen and Lerman 2007).

In spite of these potential short-comings, we believe that this study will provide managers with a useful method to perform e-sentiment analysis and valuable insights to design a better e-marketing strategy for enhancing market performance in high-tech markets.

References

Archak, N., A. Ghose, P.G. Ipeirotis. 2011. Deriving the pricing power of product features by mining consumer reviews. *Management Science* **57**(8) 1485-1509.

Arndt, J. 1968. Word-of-mouth advertising and perceived risk. H. Kassarjian, T. Robertson, eds. *Perspectives in Consumer Behavior*. Scott, Foresman: IL.

Ba, S. P.A. Pavlou. 2002. Evidence of the effect of trust building technology in electronic markets: Price premium and buyer behavior. *MIS Quarterly* **26**(3) 243-268.

Bajari, P., J. Cooley Fruehwirth, K.I. Kim, C. Timmins. 2012. A rational expectation approach to hedonic regressions with time-varying unobserved product attributes: The price of pollution. *American Economic Review* **102**(5) 1898–1926.

Berry, J., E. Keller. 2003. *The Influentials*. Free Press: NY.

Berry, S. 1994, Estimating discrete choice models of product differentiation, *RAND Journal of Economics*, 25, 242-262.

Bhatnagar, P. Fake reviews on the Web…caveat emptor. *CNNMoney.com* (May 10th, 2006). Downloaded on November 19, 2010 from http://money.cnn.com/2006/05/10/news/companies/bogus_reviews/

Chen, Y., J. Xie. 2005. Third-party product review and firm marketing strategy. *Marketing Science* **24**(2) 218-240.

Chen, Y., J. Xie. 2008. Online consumer review: Word-of-mouth as a new element of marketing communication mix. *Management Science* **54**(3) 477-491.

Chevalier, J.A., D. Mayzlin. 2006. The effect of word-of-mouth on sales: Online book reviews. *Journal of Marketing Research* **43**(3) 345-354.

Chintagunta, P.K., S. Gopinath, S. Venkataraman. 2010. The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science* **29**(5) 944-957.

Dellarocas, C.N. 2003. The digitization of word-of-mouth: Promise and challenges of online reputation mechanisms. *Management Science* **49**(10) 1407-1424.

Dellarocas, C.N. 2006. Strategic manipulation of internet online forums: Implications for consumers and firms. *Management Science* **52**(10) 1577-1593.

Dellarocas, C.N., C.A. Wood. 2008. The sound of silence in online feedback: Estimating trading risks in the presence of reporting bias. *Management Science* **54**(3) 460-476.

East, R., K. Hammond, W. Lomax. 2008. Measuring the impact of positive and negative word of mouth on brand purchase probability. *International Journal of Research in Marketing* **25** 215-224.

Ellison, G., D. Fudenberg. 1995. Word-of-mouth communication and social learning. *Quarterly Journal of Economics* **110** 93-125.

Fiske, S.T. 1980. Attention and weight in person perception: The impact of negative and extreme behavior. *Journal of Personality and Social Psychology* **38**(6) 889-906.

Godes, D., D. Mayzlin. 2004. Using online conversations to study word-of-mouth communication. *Marketing Science* **23**(4) 545-560.

Gopinath, S., P.K. Chintagunta, S. Venkataraman. 2013. Blogs, advertising and local-market movie box-office performance, *Management Science* (Articles in Advance) 1-20.

Gu, B., J. Park, P. Konana. 2012. The impact of external word-of-mouth sources on retailer sales of high-involvement products. *Information Systems Research* **23**(1) 182-196.

Herr, P., F. Kardes, J. Kim. 1991. Effects of word-of-mouth and product attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research* **17** 454-462.

Hoffman, D.L., T.P. Novak. 2009. Flow online: Lessons learned and future prospects. *Journal of Interactive Marketing* **23** 23–34.

Horvath, C.S., P.S.H. Leeflang, J.E. Wieringa, D.R. Wittink. 2005. Competitive reaction- and feedback effects based on VARX models of pooled store data. *International Journal of Research in Marketing* **22**(4) 415-426.

Iverac, M. The upside of bad online customer reviews. *Forbes* (August 4th, 2009). Downloaded on November 19, 2010 from http://www.forbes.com/2009/08/04/bad-customer-reviews-entrepreneurs-management-ebags.html.

Jarvis, J. Dell Learns to Listen. *Business Week* (October 17th, 2007). Downloaded on March 8, 2011 from http://www.businessweek.com/bwdaily/dnflash/content/oct2007/db20071017_277576.htm.

Lee, L. Dell: In the Bloghouse, *Business Week* (August 25th, 2005). Downloaded on March 8, 2011 from http://www.businessweek.com/technology/content/aug2005/tc20050825_2021.htm.

Liu, Y. 2006. Word-of-mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing* **70**(3) 74-89.

Luo, X. 2007. Consumer negative voice and firm-idiosyncratic stock returns. *Journal of Marketing* **71**(3) 75-88.

Luo, X. 2008. Quantifying the long-term impact of negative word-of-mouth on cash flows and stock prices. *Marketing Science* **28**(1) 148-165.

MacLeod, W.B. 2007. Reputations, relationships, and contract enforcement. *Journal of Economic Literature* **45** 595-628.

McAlister, L., G. Sonnier, T. Shively. 2012. The relationship between online chatter and firm value. *Marketing Letters* **23**(1) 1-12.

Milgrom, P., J. Roberts. 1986. Price and advertising signals of product quality. *Journal of Political Economy* **94**(4) 796-821.

Richins, M.L. 1983. Negative word-of-mouth by dissatisfied consumers: A pilot study. *Journal of Marketing* **47** 68-78.

Sen, S., D. Lerman. 2007. Why are you telling me this? An examination into negative consumer reviews on the Web. *Journal of Interactive Marketing* **4** 76-94.

Senecal, S., J. Nantel. 2004. The influence of online product recommendations on consumers' online choices. *Journal of Retailing* **80**(2) 159-169.

Schindler, R.M., B. Bickart. 2004. Published word of mouth: Referable, consumer-generated information on the internet. C. Haugtvedt, K.A, Machleit, R.F. Yalch, eds. *Online Consumer Psychology: Understanding and Influencing Customer Behavior in the Virtual World,* Lawrence Erlbaum Associates. Ch.2. pp. 35-60.

Shin, H. 2008. Strategic and financial implications of new product quality in high-tech industries. UCLA Ph.D. Dissertation.

Sonnier, G.P., L. McAlister, O.J. Rutz. 2011. A dynamic model of the effect of online communications on firm sales. *Marketing Science* **30**(4) 702-716.

Trusov, M., R. Bucklin, K. Pauwels, 2009. Effects of word-of-mouth versus traditional marketing: Findings from an Internet social networking site. *Journal of Marketing* **73**(5) 90-102.

Wagner, M. The power of customer reviews, *internetretailer.com* (February 2008). Downloaded on March 4, 2008 from www.internetretailer.com/printArticle.asp?id=25215.

Wolinsky, A. 1983. Prices as signals of product quality. *Review of Economic Studies* **50**(4) 647-658.

Yi, J., T. Nasukawa, R. Bunescu, W. Niblack. 2003. "Sentiment analyzer: Extracting sentiments about a given topic using natural language processing techniques. *The Third IEEE International Conference on Data Mining*. 427-434 (November).

Zeithaml, V.A., L.L. Berry, A. Parasuraman. 1993. The nature and determinants of customer expectations of service. *Journal of Academy of Marketing Science* **21**(1) 1-12.

Zhu, F., X. Zhang. 2010. Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing* **74**(2) 133-148.

TABLE 1

Description of 7 Brands of Interest

Brand	# of Models	Market Share
Canon	8	50.6%
Nikon	10	34.4%
Sony	10	8.1%
Panasonic	4	1.9%
Olympus	3	0.9%
Pentax	1	0.1%
Fujifilm	1	0.1%
Sum	37	96.1%

TABLE 2

Descriptive Statistics on Sales (Unit) and Price ($)

Product	Brand	SALES (Unit)			PRICE ($)		
		Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
EOS 5D Mark II	Canon	426.3	379.0	230.3	2501.3	2459.0	134.0
EOS 60D	Canon	1335.3	1222.0	479.0	1158.6	1159.0	33.0
EOS 7D	Canon	737.5	580.0	365.4	1659.5	1694.1	80.4
EOS Rebel T1i	Canon	35.5	19.0	45.1	481.7	476.8	68.1
EOS Rebel T2i	Canon	3611.5	2982.0	2566.0	629.8	638.9	30.8
EOS Rebel T3	Canon	5334.6	3244.0	6220.1	500.4	502.4	15.0
EOS Rebel T3i	Canon	5054.2	3449.0	3975.0	763.2	766.7	25.2
EOS Rebel T4i	Canon	532.2	205.0	570.1	961.1	940.7	58.0
D3100	Nikon	3195.4	2877.0	1818.5	563.3	549.8	30.2
D3200	Nikon	1245.3	1231.0	431.1	697.4	698.5	2.4
D5100	Nikon	3263.9	3259.0	1105.2	731.0	748.9	64.2
D700	Nikon	62.9	58.0	32.2	2319.9	2202.1	212.9
D7000	Nikon	957.7	994.0	264.7	1357.7	1359.0	41.5
D800	Nikon	549.6	612.0	324.4	2955.1	2991.6	93.7
D800E	Nikon	80.6	70.0	91.5	3298.5	3299.0	2.8
D90	Nikon	217.7	155.0	145.4	989.8	1040.8	120.8
J1	Nikon	1704.4	1174.0	1646.0	569.4	581.1	34.6
V1	Nikon	88.5	74.0	52.0	837.3	846.4	69.2
E-M5	Olympus	141.6	100.0	102.0	1199.0	1208.7	88.8
E-PL3	Olympus	42.2	36.0	23.2	572.4	573.7	75.9
E-PM1	Olympus	182.4	128.0	164.0	432.0	441.1	34.9
DMC-G3	Panasonic	53.5	45.0	40.0	573.6	570.8	26.3
DMC-GF3	Panasonic	475.9	179.0	854.2	423.4	417.8	47.3
DMC-GH2	Panasonic	79.5	69.0	43.8	990.9	1013.7	71.7
DMC-GX1	Panasonic	93.1	79.0	108.1	732.5	720.5	111.9
NEX-5	Sony	372.2	28.0	899.7	435.2	429.3	60.8
NEX-5N	Sony	898.9	920.0	484.7	668.9	680.7	30.6
NEX-7	Sony	176.5	169.0	104.9	1267.7	1286.6	45.8
NEX-C3	Sony	372.3	327.0	427.8	528.0	544.8	44.0
NEX-F3	Sony	303.9	325.5	80.6	590.5	591.8	5.2
SLT-A35	Sony	111.4	76.0	130.5	609.1	603.8	33.0
SLT-A55	Sony	246.2	167.0	283.4	651.5	667.9	112.1
SLT-A57	Sony	371.2	401.5	139.2	748.1	735.8	35.3
SLT-A65	Sony	145.6	152.0	54.9	943.0	949.0	37.5
SLT-A77	Sony	45.9	43.0	22.6	1636.6	1644.7	152.3
K-5	Pentax	18.0	16.0	13.6	1148.7	1149.7	122.6
X-Pro1	Fujifilm	45.2	26.0	95.4	1666.1	1685.8	40.6

TABLE 3

Descriptive Statistics on Advertisement ($K)

Product	Brand	Category Level ($K)			Model Level ($K)		
		Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
EOS 5D Mark II	Canon	1.6	0.1	2.5	20.0	0.0	121.4
EOS 60D	Canon	1.6	0.1	2.5	112.0	0.0	268.7
EOS 7D	Canon	1.6	0.1	2.5	91.0	0.0	245.9
EOS Rebel T1i	Canon	1.6	0.1	2.5	0.0	0.0	0.0
EOS Rebel T2i	Canon	1.6	0.1	2.5	0.0	0.0	0.0
EOS Rebel T3	Canon	1.6	0.1	2.5	0.0	0.0	0.0
EOS Rebel T3i	Canon	1.6	0.1	2.5	646.6	0.0	1161.6
EOS Rebel T4i	Canon	1.6	0.1	2.5	23.6	0.7	87.9
D3100	Nikon	0.0	0.0	0.0	171.3	0.0	352.2
D3200	Nikon	0.0	0.0	0.0	0.0	0.0	0.0
D5100	Nikon	0.0	0.0	0.0	99.7	0.0	238.9
D700	Nikon	0.0	0.0	0.0	0.2	0.0	1.3
D7000	Nikon	0.0	0.0	0.0	0.0	0.0	0.0
D800	Nikon	0.0	0.0	0.0	6.7	0.0	21.7
D800E	Nikon	0.0	0.0	0.0	0.0	0.0	0.0
D90	Nikon	0.0	0.0	0.0	0.0	0.0	0.0
J1	Nikon	0.0	0.0	0.0	614.7	47.0	850.7
V1	Nikon	0.0	0.0	0.0	0.0	0.0	0.0
E-M5	Olympus	142.7	0.2	304.6	0.0	0.0	0.0
E-PL3	Olympus	142.7	0.2	304.6	0.0	0.0	0.0
E-PM1	Olympus	142.7	0.2	304.6	0.5	0.0	0.7
DMC-G3	Panasonic	8.3	0.0	31.9	0.0	0.0	0.0
DMC-GF3	Panasonic	8.3	0.0	31.9	0.0	0.0	0.0
DMC-GH2	Panasonic	8.3	0.0	31.9	0.1	0.0	0.3
DMC-GX1	Panasonic	8.3	0.0	31.9	0.0	0.0	0.0
NEX-5	Sony	23.3	0.0	132.7	11.2	2.2	32.4
NEX-5N	Sony	23.3	0.0	132.7	69.0	5.7	295.9
NEX-7	Sony	23.3	0.0	132.7	8.1	0.0	36.4
NEX-C3	Sony	23.3	0.0	132.7	0.0	0.0	0.0
NEX-F3	Sony	23.3	0.0	132.7	0.0	0.0	0.0
SLT-A35	Sony	23.3	0.0	132.7	0.0	0.0	0.0
SLT-A55	Sony	23.3	0.0	132.7	0.0	0.0	0.0
SLT-A57	Sony	23.3	0.0	132.7	0.0	0.0	0.0
SLT-A65	Sony	23.3	0.0	132.7	0.0	0.0	0.0
SLT-A77	Sony	23.3	0.0	132.7	0.0	0.0	0.0
K-5	Pentax	0.0	0.0	0.0	0.0	0.0	0.0
X-Pro1	Fujifilm	0.0	0.0	0.0	23.6	0.7	87.9

TABLE 4

Descriptive Statistics on e-Sentiment Variables

Product	Brand	Positive e-sentiment (POS)		Negative e-sentiment (NEG)		Neutral e-sentiment (NEUT)	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
EOS 5D Mark II	**Canon**	134.84	47.53	11.77	4.30	442.70	109.91
EOS 60D	**Canon**	80.44	20.11	2.76	1.05	140.80	28.43
EOS 7D	**Canon**	75.87	22.89	4.37	3.28	166.28	24.58
EOS Rebel T1i	**Canon**	29.20	13.47	2.58	1.50	48.33	19.07
EOS Rebel T2i	**Canon**	70.31	27.10	9.64	5.62	127.18	52.48
EOS Rebel T3	**Canon**	56.71	12.60	14.74	7.28	97.77	24.70
EOS Rebel T3i	**Canon**	72.23	16.95	17.05	8.93	139.32	43.07
EOS Rebel T4i	**Canon**	26.65	23.73	6.92	8.89	43.44	37.69
D3100	**Nikon**	130.77	41.60	5.39	2.44	340.90	100.89
D3200	**Nikon**	33.15	39.02	2.35	5.49	89.31	114.50
D5100	**Nikon**	112.55	26.16	5.40	2.64	305.03	71.06
D700	**Nikon**	93.42	33.66	6.44	3.52	348.79	139.75
D7000	**Nikon**	0.30	0.15	0.03	0.07	5.74	1.20
D800	**Nikon**	94.35	70.64	23.47	24.60	567.06	427.47
D800E	**Nikon**	37.48	26.75	3.32	3.55	106.41	78.99
D90	**Nikon**	154.54	69.76	7.30	3.19	344.01	144.53
J1	**Nikon**	25.50	7.89	1.41	1.34	80.46	23.50
V1	**Nikon**	21.08	5.75	1.88	1.30	91.05	33.00
E-M5	**Olympus**	17.04	9.45	4.15	2.67	154.70	77.99
E-PL3	**Olympus**	9.14	5.46	0.32	0.35	26.44	8.43
E-PM1	**Olympus**	8.10	2.91	0.43	0.39	33.05	10.45
DMC-G3	**Panasonic**	3.91	1.45	0.29	0.60	17.10	8.49
DMC-GF3	**Panasonic**	5.01	2.24	0.42	0.63	31.16	40.79
DMC-GH2	**Panasonic**	13.21	7.05	0.52	0.76	19.44	9.28
DMC-GX1	**Panasonic**	3.76	3.82	0.11	0.19	14.58	13.75
NEX-5	**Sony**	35.32	14.53	1.44	0.93	79.11	24.75
NEX-5N	**Sony**	30.11	11.41	3.03	1.57	125.30	33.85
NEX-7	**Sony**	29.51	11.64	4.67	2.58	151.22	37.24
NEX-C3	**Sony**	3.66	1.77	0.32	0.52	20.42	5.72
NEX-F3	**Sony**	11.39	6.83	0.48	0.42	32.86	23.32
SLT-A35	**Sony**	5.42	2.62	0.70	0.67	15.80	5.81
SLT-A55	**Sony**	16.03	6.97	0.75	0.80	27.47	11.15
SLT-A57	**Sony**	27.06	14.74	0.27	0.51	13.90	9.57
SLT-A65	**Sony**	5.31	2.97	0.65	0.88	15.95	5.90
SLT-A77	**Sony**	5.87	3.27	0.61	0.64	17.18	7.63
K-5	**Pentax**	32.59	10.41	3.42	1.38	164.43	44.85
X-Pro1	**Fujifilm**	21.54	17.63	6.56	5.11	176.40	131.37

TABLE 5

3 Price Tiers: LOW, MED, HIGH

Price Tiers	Model Names
LOW (Median Price < $800)	D3100, D3200, D5100, DMC-G3, DMC-GF3, DMC-GX1, E-PL3, E-PM1, J1, EOS Rebel T1i, EOS Rebel T3i, EOS Rebel T3, EOS Rebel T3i, NEX-5, NEX-5N, NEX-C3, NEX-F3, SLT-A35, SLT-A55, SLT-A57
MED ($800 < Median Price < $1500)	D7000, D90, DMC-GH2, E-M5, EOS 60D, EOS Rebel T4i, K-5, NEX-7, SLT-A65, V1
HIGH ($1500 < Median Price)	D700, D800, D800E, EOS 5D Mark II, EOS 7D, SLT-A77, X-Pro1

TABLE 6

Estimation Results

Dependent Variable: *Market Share$_t$*	All Items	3 Price Tiers		
Coefficient Estimates	**ALL**	**LOW**	**MED**	**HIGH**
POS$_{t-1}$	.182** [.080]	.142*** [.051]	.134** [.064]	.072 [.103]
NEG$_{t-1}$	-.039 [.051]	.017 [.062]	-.043 [.056]	-.100** [.045]
NEUT$_{t-1}$	-.036 [.076]	-.080* [.058]	.097 [.114]	.250** [.101]
AD_M$_{t-1}$	.029*** [.011]	.019*** [.006]	.017 [.023]	-.003 [.008]
AD_C$_{t-1}$	.006 [.017]	.023** [.011]	-.034 [.032]	.003 [.005]
PRICE$_t$	.306 [.834]	-.577 [.818]	-.749*** [.180]	1.195*** [.287]
ET$_t$	.110 [.409]	-1.604*** [.490]	.399 [.520]	1.275*** [.454]
AR term (ρ)	.505*** [.047]	.655*** [.065]	.618*** [.027]	.483*** [.074]
# of observations	1073	608	283	182
# of cross-sections	37	20	10	7
R^2	.888	.900	.842	.559

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

Notes: Standard errors 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 4 lags.