Nga N. Ho-Dac, Stephen J. Carson, & William L. Moore

The Effects of Positive and Negative Online Customer Reviews: Do Brand Strength and Category Maturity Matter?

Research has shown brand equity to moderate the relationship between online customer reviews (OCRs) and sales in both the emerging Blu-ray and mature DVD player categories. Positive (negative) OCRs increase (decrease) the sales of models of weak brands (i.e., brands without significant positive brand equity). In contrast, OCRs have no significant impact on the sales of the models of strong brands, although these models do receive a significant sales boost from their greater brand equity. Higher sales lead to a larger number of positive OCRs, and increased positive OCRs aid a brand's transition from weak to strong. This creates a positive feedback loop between sales and positive OCRs for models of weak brands that not only helps their sales but also increases overall brand equity, benefiting all models of the brand. In contrast to the view that brands matter less in the presence of OCRs, we find that OCRs matter less in the presence of strong brands. Positive OCRs function differently than marketing communications in that their effect is greater for weak brands.

Keywords: online customer reviews, user-generated content, brand equity, category maturity, word of mouth

Easy access to online customer reviews (OCRs) has led some observers to posit that brand names, as assurances of product quality and performance, will lose much of their importance in the interactive marketing environment (see, e.g., Chen 2001). This line of reasoning suggests that customers will bypass marketer-influenced signals such as brands and instead rely directly on unfiltered word of mouth from other consumers. Because the information contained in OCRs does not originate with the company, it is generally considered highly credible and influential (Bickart and Schindler 2001). Therefore, it is possible that this long-tail perspective will hold and consumers will use OCRs to find desired products irrespective of their brand name. However, the marketing literature offers evidence on the importance of brand equity that suggests it is improbable that brands will lose their value just because consumers have access to OCRs.

In this research, we investigate the effects of brand equity and OCRs on sales response in an online selling environment. Of particular interest is how brand equity moderates the relationship between OCRs and sales—that is, whether OCRs have a greater effect on the models of strong versus weak brands.[1] This issue is not as straightforward as it might seem, because different literature streams suggest different relationships. Brand equity and marketing communications research has found evidence that strong brands have greater advertising elasticities, show better marketing communications effectiveness, and are more protected from negative information (see, e.g., Ahluwalia, Burnkrant, and Unnava 2000; Belch 1981; Dawar and Pillutla 2000; Hoeffler and Keller 2003; Petty and Krosnick 1995; Srivastava and Shocker 1991). If consumers respond to OCRs as they do to advertising, strong brands should benefit more from positive OCRs and be hurt less by negative OCRs.

However, OCRs differ from marketer-sponsored communications in that they are more credible (Cheong and Morrison 2008; Hung and Li 2007). Credibility suggests an active form of processing in which consumers evaluate the reliability of the source and its independence from the interests of the marketer. Viewed through the lens of signaling theory, the key issue is how the OCR-provided signal compares with that of the brand. The brand signaling literature (Erdem and Swait 1998; Montgomery and Wernerfelt 1992) has suggested that both positive and negative OCRs affect weak brands more; positive OCRs provide a degree of credibility that weak brands cannot engender through company-sponsored communications, and negative reviews are evaluated without the compensating signal a strong brand provides.

We also investigate how the effects of OCRs on strong and weak brands change across emerging and mature prod-

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[1]We use the term "strong brand" to refer to brands with significant positive brand equity.

uct categories. On the one hand, mature categories feature large cumulative numbers of OCRs that reduce uncertainty and increase the credibility of the information they contain. Therefore, it is possible that strong brands are less resistant to the influence of OCRs in mature categories. On the other hand, as categories mature, consumers learn more about the performance of brands within the category. Because brands store such information, the category-specific equity of successful brands tends to be stronger in mature categories, adding to the resilience of strong brands relative to OCRs. To examine this issue, we estimate models in both the emerging Blu-ray and mature DVD player categories. With the exception of maturity (at the time of data collection), these categories are similar in terms of the mix of strong and weak brands, the number of models, price, and so on.

The emerging research on online word of mouth (eWOM) has not provided any direct evidence about how brand equity moderates the effect of OCRs or how this relationship changes over time. Much of the literature has used categories such as books, music, video games, and movies, in which many products do not have preexisting brand equity (e.g., Chen, Wu, and Yoon 2004; Chevalier and Mayzlin 2006; Dellarocas, Zhang, and Awad 2007; Karniouchina 2011; Li and Hitt 2008; Liu 2006). These studies also provide similar recommendations for all products in a category without discrimination.

Zhu and Zhang (2010) provide an exception to this practice in their examination of the interaction of OCRs and popularity on the sales of individual video games. They use two definitions of popularity. First, due to the typical precipitous sales decline over time, a game is defined as popular if it has been on the market for less than four months. Second, a popular game is one with higher sales than the mean of all games in a given month. Under both definitions, the authors find that less popular games benefit more from OCRs than do popular games.

In contrast, we examine the interaction between OCRs and brand equity, which we operationalize as the impact on sales of models of a brand that cannot be explained by other factors such as advertising, price, OCRs, competition, merchants, or model-specific effects. Brand equity differs fundamentally from the popularity of an individual model in that it is defined at the level of the product line. This enables us to consider the impact of OCRs not just on a specific model but on *all* models in the product line, because reviews for one model spill over to the brand itself. In addition, whereas other variables (e.g., price, promotions) can influence popularity in the short run, brand equity is defined after accounting for such factors and is therefore relatively robust. This makes it somewhat easier for managers to gauge with foresight when planning, particularly early in the product life cycle.

Importantly, we expect our focus on brand equity to generate novel substantive implications for managers operating in contexts in which preexisting brand equity is relevant—for example, when managing product line extensions within a category, brand extensions from closely related product categories, or model updates. According to the perspective we develop in this research, OCRs can affect even newly introduced models and models with high current or expected sales as long as consumers require reassurance because of a weak existing brand. In contrast, models of strong brands are affected less, even if they are poor individual sellers.

The results of our study indicate that brand equity moderates the relationship between OCRs and sales in both emerging and mature categories. Positive (negative) OCRs increase (decrease) the sales of models of weak brands but do not have a significant effect on the sales of models of strong brands. However, these models do receive a significant sales boost from being part of a strong brand. This is important because positive OCRs for all models or for just the leading model help build the equity of weak brands. Combined with the finding that more sales lead to a larger number of positive (but not negative) OCRs, this creates a positive feedback loop between sales and positive OCRs for models of weak brands. Thus, positive OCRs help models of weak brands penetrate the market while simultaneously increasing the equity of the brand. This loop does not exist for the models of already strong brands, because they do not benefit to the same degree from positive reviews.

More broadly, in contrast to the view that brands matter less in the presence of OCRs, we find that OCRs actually matter less for strong brands. Online customer reviews increase the sales of models of weak brands and help weak brands become strong, but they do not affect brands to the same degree after they become strong. The sales boost that models receive from their association with a strong brand further indicates that brand equity is extremely important, even when the effect of model-level OCRs is controlled. In addition, the findings show that positive OCRs function differently than marketing communications in that their effect is greater for weak brands than for strong brands. Finally, we find weaker effects of negative reviews than positive reviews for both the focal and competing models and observe that the number of both positive and negative OCRs first increases and then decreases over time.

As we anticipated, our results lead to a very different set of managerial implications from Zhu and Zhang (2010). Whereas their results suggest that OCRs are more beneficial for unpopular niche games and for games whose sales have fallen significantly from their peak, ours suggest a clear role for OCRs early in the product life cycle for all models of weak brands. Managers of weak brands should focus on generating positive OCRs for both their direct effect on sales of the model and their indirect effect on building brand equity. These paths give weak brands a way to compete other than through traditional marketing communications.

In contrast to weak brands, additional positive OCRs do not further benefit the models of strong brands. Therefore, managers of these brands should not necessarily follow the same strategy used for weaker brands or even do so to the same degree. Instead, strong brands should pursue actions to build brand equity more directly (e.g., through advertising) rather than focus too narrowly on OCRs. Zhu and Zhang's (2010) results are more appropriate for movies, video games, books, and so on, for which there is not a strong preexisting brand component and sales often peak at the introduction and decline from there. In contrast, our results are more appropriate for products in a branded product line that have more traditional sales trajectories.

The remainder of the article is organized as follows. In the next section, we explore arguments in the brand signaling literature to hypothesize interactions between brand strength and OCRs in predicting sales response. We then describe the data and the empirical model. This is followed by our results and a discussion of implications for theory and practice.

Hypotheses

According to the brand signaling literature, uncertainty about product quality and performance creates risk (Erdem, Swait, and Valenzuela 2006). To cope with this risk, customers rely on signals to indicate product quality and performance when purchasing (Shimp and Bearden 1982). Previous research has shown that marketing-mix elements such as price (Stiglitz 1989; Tellis and Wernerfelt 1987), advertising (Kirmani 1990; Nelson 1974), and warranty (Boulding and Kirmani 1993) serve as credible signals. Scholars have also found brands to be especially strong and effective signals of product quality (Erdem and Swait 1998; Rao, Qu, and Ruekert 1999).

When confronted with reviews written by other users, it is likely that consumers will find such reviews en masse to be a highly credible source of information on product quality and performance. Although some believe OCRs to be more credible than marketing communications (Cheong and Morrison 2008; Hung and Li 2007), it is not clear whether OCRs are more or less credible than brand equity because reviews are written by individual people with incomplete information and varying motivations. What is known is that stronger brands provide more credible signals than weaker brands because they are more susceptible to the loss of established brand equity (Erdem and Swait 1998) and future sales and profit (Wernerfelt 1988). Thus, the OCR signal tends to overshadow the limited brand signal for weak brands, whereas for strong brands, both signals provide a degree of credible information. As a result, positive OCRs should have a larger effect on weak brands, which lack a credible brand signal, than strong brands, which already provide substantial assurance. Positive OCRs create a degree of credibility that weaker brands cannot create on their own.

In addition, signals such as brand equity are important in decision making under uncertainty—that is, in the absence of concrete evidence about product quality (Montgomery and Wernerfelt 1992). Whereas positive reviews for models of strong brands largely reinforce consumer beliefs about these models and do little to reduce uncertainty, positive reviews for models of weak brands not only help these models directly but also reduce the level of uncertainty about them. This tends to decrease the overall level of uncertainty facing consumers in the category, reducing the effect of strong brands and further benefiting weaker brands.

Finally, marketing communications may be more effective for stronger brands because the brand lends a degree of credibility to the advertisement. As we have noted, extending this view to OCRs would suggest that positive OCRs are more effective for strong brands. However, the credibility lent by a strong brand is less necessary for OCR effectiveness because the reviews themselves have inherent credibility. Therefore, the advantage associated with strong brands with respect to marketing communications is unlikely to hold in the context of OCRs. Jointly, these arguments suggest that positive OCRs should benefit weak brands more than strong brands.

> H_1: Positive OCRs have a stronger positive effect on the products of weak brands than those of strong brands.

Negative OCRs should also affect weak brands more than strong brands. The brand equity and marketing communications literature streams have found that strong brands are more protected from negative information (Ahluwalia, Burnkrant, and Unnava 2000; Dawar and Pillutla 2000; Petty and Krosnick 1995; Srivastava and Shocker 1991). Similarly, from a signaling perspective, strong brands possess a highly credible offsetting signal to help overcome and buffer negative reviews. Weak brands, in contrast, lack a compensating signal; thus, negative information affects them to a greater extent.

In the case of negative reviews, the branding/communications perspectives lead to the same prediction as that of the signaling perspective. This is because both negative OCRs and more general types of negative information come from sources independent of the brand. Consequently, both tend to be credible (provided that they do not come from obviously nefarious sources) and require a strong brand to counter their effect.

> H_2: Negative OCRs have a stronger negative effect on the products of weak brands than those of strong brands.

We chose two similar product categories that differ in terms of maturity to examine these relationships across life cycle stages. As a product category matures and the number of cumulative OCRs increases, there will typically be a corresponding reduction in uncertainty in the category as well as an increase in the credibility of the information contained in the reviews. Whereas people may attribute a single review to the idiosyncratic experiences or motivations of the reviewer, large numbers of consistent reviews will be more reliable. In addition, consumers become more knowledgeable posters and consumers of reviews over time. Thus, the credibility and impact of the information contained in OCRs tends to increase as they accumulate, and brands themselves become less influential as uncertainty in the category decreases. Therefore, it is possible that strong brands will not be as resistant to the influence of OCRs in more mature categories.

However, as categories mature, consumers gain additional knowledge about the performance and quality of the brands within the category. This brand equity is in large part category specific because most brands are stronger in some categories than others. For example, Apple is stronger in smartphones than personal computers, and Dodge is stronger in trucks than cars. In an emerging category such as Blu-ray players, initial brand equity will be based on higher-level categories (e.g., consumer electronics) or related product categories (e.g., DVD players) and will be somewhat uncertain. Over time, it will become more concrete and based more on the focal category. Because brands serve as repositories of product information, the category-specific equity associated with successful brands should become stronger as consumers learn more about the performance of the brand in the category. Thus, the relative advantage of strong brands will tend to increase over time, balancing out any potential increase in the credibility of OCRs. This leads us to hypothesize that strong brands will maintain their resistance to the influence of (both positive and negative) OCRs in maturity and that OCRs will affect strong brands no more at maturity than earlier in the life cycle. Therefore, we generalize H_1 and H_2 across categories.

> H_3: The moderating effects of brand equity generalize across both the emerging and mature product categories.

Data, Models, and Estimation

Data

We selected the Blu-ray player category because it was emerging at the time of data collection and seemed to have a variety of strong and weak brands, including those extended from closely related product categories. We selected DVD players as a closely matched mature category with similar numbers of models and brands. We collected data from Amazon.com (Amazon hereinafter), with the exception of advertising data, which we purchased from the Nielsen Company for the same time period. Data collection began shortly after Amazon began selling Blu-ray players.

We collected sales rank, OCRs, price, and other data for all models in the Blu-ray player category weekly for 47 weeks, from November 1, 2008, to September 21, 2009. This sample consists of 2,324 observations in an unbalanced panel structure of 78 individual models and 47 periods. We observed a total of 3,341 OCRs; 791 were posted in or before the first week and an average of 55.4 were posted in each of the following weeks. Although there was considerable fluctuation, the number of additional OCRs decreased by an average of .73 per week. The product selection differed from week to week because some models were introduced or discontinued during the data collection period. We excluded used, refurbished, and bundled models. Of the observations in the sample, 27.19% were models offered by Amazon; the rest were listed on Amazon but sold by other merchants.

We collected data from the DVD player category from November 1, 2008, to June 6, 2009. This sample consists of 1,080 observations in an unbalanced panel structure of 51 models and 32 weeks. We observed a total of 1,664 OCRs; 971 posts were made in or before the first week, and an average of 22.4 were added in each of the following weeks. However, 11 models were added (or returned) to Amazon during the second week, and they accounted for 324 of the 328 reviews that week. After the first two weeks, an average of 13.5 OCRs were posted each week, and there was no significant time trend.

In both categories, price data include the list price plus shipping and handling costs. If more than one merchant sold a single model, we used the lowest price charged for a new model. Following the practice of Amazon, and noting that a three-star rating is below the mean of our data (3.88 for Blu-ray players and 3.62 for DVD players), we classified three-star reviews as negative. Therefore, customer review measures include the number of positive reviews (four or five stars) and the number of negative reviews (one, two, or three stars). We check the robustness of this classification subsequently.

Even though sales data are not accessible, Amazon displays (current) sales ranks for both categories. Therefore, we use the inverse sales rank for each model as an indicator of sales response. Previous research has found that for many product categories, the relationship between sales rank and sales can be described by a Pareto distribution (i.e., the 80/20 rule), which means that the relationship between ln(sales) and ln(sales rank) is approximately linear; that is, $\ln(\text{sales}) \approx a + b \times \ln(\text{sales rank})$. Scholars have found this linear relationship to hold for products such as books, software, yogurt, women's clothing, and electronic products (see, e.g., Brynjolfsson, Hu, and Simester 2011; Brynjolfsson, Hu, and Smith 2003; Ghose and Sundararajan 2006; Goolsbee and Chevalier 2002; Prasso 2011; Rosenthal 2005). Although we did not run a purchasing experiment to verify this assumption in the two categories, the concentration of products by brand (Twice.com 2009) and the concentration of OCRs in the data suggest that it is reasonable to assume a linear relationship.

Assuming that the Pareto relationship holds approximately, the only differences between a linear model using ln(sales) and one using ln(sales rank) are that the estimated coefficients and their standard errors are scaled by a constant and the estimated intercept is shifted by another constant. Neither of these differences changes the signs or significance of our coefficients. We use the negative of ln(sales rank) or ln(1/sales rank) in subsequent equations to make the signs of the coefficients easier to interpret (i.e., positive coefficients indicate a greater sales response).[2]

The Nielsen Company provided weekly advertising expenditures for brands in the Blu-ray and DVD player categories from October 1, 2008, to October 3, 2009. Paid advertisements were placed in newspapers and magazines and on television, radio, and the Internet. Samsung and Toshiba incurred more than 70% of the total $10 million in advertising spending. LG was the only other company to spend more than $500,000. Table 1 presents the descriptive statistics.

[2]The use of ordinal scales with more than four values (e.g., five-point Likert scales) as interval data in regressions does not seem to affect Type I and Type II errors dramatically and is the norm in contemporary social science. The numbers of ordinal values are 72 and 46 in the Blu-ray and DVD data, respectively. Estimating ordinal regressions with 71 and 45 logit (or probit) functions is impractical. Many articles in major journals have set a precedent by analyzing Amazon rank data using regression techniques (e.g., Archak, Ghose, and Ipeirotis 2001; Brynjolfsson, Hu, and Smith 2003; Chevalier and Goolsbee 2003; Chevalier and Mayzlin 2006; Ghose and Sundararajan 2006; Sun 2012).

TABLE 1
Descriptive Statistics

A: Blu-Ray Players					
	Min	**Max**	**M**	**SD**	**Percentage**
Number of models	31	72	53.72	14.00	
Sales rank	1	100	31.91	21.99	
Price	116.06	4,500	535.21	499.26	
Advertising expenditure	0	1,043,881	21,026	108,990	
Offered by Amazon					27.19%
Cumulative number of OCRs	0	450	50.61	81.82	
Average star rating	1	5	3.88	.68	
Cumulative number of positive OCRs	0	377	36.61	62.73	
Cumulative number of negative OCRs	0	117	14.00	24.56	

B: DVD Players					
	Min	**Max**	**M**	**SD**	**Percentage**
Number of models	18	46	35.50	7.85	
Sales rank	1	80	26.41	20.44	
Price	22.48	1,009.98	138.02	104.16	
Advertising expenditure	0	1,043,881	23,493	106,878	
Offered by Amazon					30.37
Cumulative number of OCRs	0	343	38.14	73.85	
Average star rating	1	5	3.62	.86	
Cumulative number of positive OCRs	0	307	28.35	62.72	
Cumulative number of negative OCRs	0	67	9.79	15.72	

Models and Estimation

We estimate a three-equation model in which brand strength is allowed to vary over time and sales and OCRs are endogenous. The first step is to classify brands into strong and weak categories on the basis of their brand equity. Following Sriram, Chintagunta, and Neelamegham (2006) and Sriram, Balachander, and Kalwani (2007), we use sales data on individual models to classify brands as strong or weak in the category. In this regression, the brand-dummy coefficients capture the additional sales impact after the other factors that might influence sales (e.g., advertising, own and competitive OCRs and prices, the total number of models offered, model-specific effects) have been accounted for. Importantly, they capture the impact of a brand on all models in its product line. We use a dynamic specification in which the brand equity regression is reestimated weekly to capture weak brands' growth into strong ones and formerly strong brands' regression to weak brands, consistent with prior research (e.g., Horsky, Misra, and Nelson 2006; Kamakura and Russell 1993).

Specifically, in a model-level regression, we regress $\ln(R_{it})$ on a series of individual brand dummies and control variables as follows:

$$
\begin{aligned}
(1)\quad \ln(R_{it}) = {} & \beta_0 + \sum_{j=1}^{J}\beta_j \ln(R_{i,t-j}) + \beta_{CU}CU_i \ldots + \beta_{YA}YA_i \\
& + \beta_{cPos}\ln(cPos_{it}) + \beta_{cNeg}\ln(cNeg_{it}) \\
& + \beta_{cPos\_n}\ln(cPos\_n_{it}) + \beta_{cNeg\_n}\ln(cNeg\_n_{it}) \\
& + \beta_P \ln(P_{it}) + \beta_{P\_n}\ln(P\_n_{it}) + \beta_{Adv}\ln(Adv_{it}), \\
& + \beta_N \ln(N_t) + \beta_A A_{it} + \mu_i + \varepsilon_{it},
\end{aligned}
$$

where

R_{it} is (1/sales rank) of model i in period t,
$CU_i \ldots YA_i$ are brand dummies indicating the brand of model i (Table 2 lists the brands),
$cPos_{it}$ ($cNeg_{it}$) is the cumulative number of positive (negative) OCRs for model i in period t,
$cPos\_n_{it}$ ($cNeg\_n_{it}$) is the total cumulative number of positive (negative) OCRs for all other models in period t,

TABLE 2
Brands of Blu-ray Players and DVD Players in the Sample

Blu-Ray and DVD Player Brands on Ranking Lists	Interbrand Rank (Out of 100)	Interbrand Value (Millions of Dollars)	BrandZ Technology Rank (Out of 20)	BrandZ Value (Millions of Dollars)
Panasonic	75	4,225		
Philips	42	8,121		
Samsung	19	17,518	17	6,322
Sony	29	11,953	18	6,245

Notes: Blu-ray and DVD player brands that were not on either ranking list: Harman Kardon, LG, Magnavox, Onkyo, Oppo, Pioneer, and Sharp. Brands that produced only Blu-ray players and were not on either ranking list: Curtis Mathes, Denon, Element, Insignia, Marantz, NAD, Sherwood, Sylvania, and Yamaha. Brands that produced only DVD players and were not on either ranking list: Cambridge Audio, Coby, JVC, Memorex, and Toshiba.

P_{it} (P_n_{it}) is the price of model i (the average price of all other models) in period t,

Adv_{it} is the advertising expenditure on the brand associated with model i in period t,

N_t is the total number of models offered by Amazon in period t,

A_{it} is a dummy indicating whether model i was offered by Amazon ($A_{it} = 1$) or by another merchant ($A_{it} = 0$) at time t,

μ_i is the time-invariant, model-specific effect that captures differences such as quality and features (e.g., Internet and Wi-Fi capability) across the models of a brand, and

ε_{it} is an idiosyncratic error.

It is possible that unobserved product characteristics (e.g., product quality) influence both sales and OCRs, so $\ln(cPos_{it})$ and $\ln(cNeg_{it})$ may be correlated with the model-specific effect μ_i. In addition, a shock in sales rank for a model may lead to a change in the cumulative number of OCRs, so $\ln(cPos_{it})$ and $\ln(cNeg_{it})$ may be correlated with ε_{it}.

These two possible endogeneity problems prevent the use of random-effects estimation of Equation 1, which requires the assumption that all explanatory variables are strictly exogenous with respect to the individual effects (Mundlak 1978). Moreover, fixed-effects estimation removes all time-invariant effects, making it impossible to estimate the brand equities. Therefore, we follow an approach suggested by Hausman and Taylor (1981): we use time-demeaned (i.e., mean-centered within model) values of $\ln(cPos_{i,t-1})$ and $\ln(cNeg_{i,t-1})$ as instruments to $\ln(cPos_{it})$ and $\ln(cNeg_{it})$ to estimate Equation 1 with a random-effects estimation method. The time-demeaned values of $\ln(cPos_{i,t-1})$ and $\ln(cNeg_{i,t-1})$ are valid instruments because they are orthogonal to both the model-specific effect μ_i and the idiosyncratic error ε_{it} while being correlated with the associated endogenous variables.

After we have determined the strong brands, we use the following model-level equation to estimate the main and interaction effects of OCRs and brand equity on model sales rank:

$$\begin{aligned}(2)\ \ln(R_{it}) = {} & \beta_0 + \sum_{j=1}^{J}\beta_j \ln(R_{i,t-j}) + \beta_{cPos}\ln(cPos_{it}) \\ & + \beta_{cNeg}\ln(cNeg_{it}) + \beta_B B_{it} + \beta_{BcPos} B_{it} \times \ln(cPos_{it}) \\ & + \beta_{BcNeg} B_{it} \times \ln(cNeg_{it}) + \beta_{cPos\_n}\ln(cPos\_n_{it}) \\ & + \beta_{cNeg\_n}\ln(cNeg\_n_{it}) + \beta_{Adv}\ln(Adv_{it}) + \beta_P \ln(P_{it}) \\ & + \beta_{P\_n}\ln(P\_n_{it}) + \beta_N \ln(N_t) + \beta_A A_{it} + \mu_i + \varepsilon_{it},\end{aligned}$$

where, in addition to the previously defined variables, B_{it} is a strong-brand dummy ($B_{it} = 1$ if the brand of model i is significantly positive at period t, which we estimate from Equation 1 using the data in the first t – 1 periods, and $B_{it} = 0$ otherwise).

As in Equation 1, $\ln(cPos_{it})$ and $\ln(cNeg_{it})$ may be correlated with both μ_i and ε_{it}, so we cannot use random-effects methods. However, unlike Equation 1, we are not interested in time-invariant variables in Equation 2, so we can use an estimation method suggested by Arellano and Bond (1991) that enables us to use more instruments. The first step is to first-difference the model to eliminate all of the model-specific effects, μ_i. Thus, Equation 2 becomes

$$\begin{aligned}(2')\ \Delta\ln(R_{it}) = {} & \sum_{j=1}^{J}\beta_j \Delta\ln(R_{i,t-j}) + \beta_{cPos}\Delta\ln(cPos_{it}) \\ & + \beta_{cNeg}\Delta\ln(cNeg_{it}) + \beta_B \Delta B_{it} \\ & + \beta_{BcPos}\Delta[B_{it} \times \ln(cPos_{it})] \\ & + \beta_{BcNeg}\Delta[B_{it} \times \ln(cNeg_{it})] + \beta_{cPos\_n}\Delta\ln(cPos\_n_{it}) \\ & + \beta_{cNeg\_n}\Delta\ln(cNeg\_n_{it}) + \beta_{Adv}\Delta\ln(Adv_{it}) \\ & + \beta_P\Delta\ln(P_{it}) + \beta_{P\_n}\Delta\ln(P\_n_{it}) + \beta_N\Delta\ln(N_t) \\ & + \beta_A \Delta A_{it} + \Delta\varepsilon_{it}.\end{aligned}$$

Then, we use lags of $\ln(cPos_{it})$, $\ln(cNeg_{it})$, $B_{it} \times \ln(cPos_{it})$, and $B_{it} \times \ln(cNeg_{it})$ up to t – 2 and lags of $\ln(R_{i,t-j})$ up to t – j – 1 as instruments for their first-differences, $\Delta\ln(cPos_{it})$, $\Delta\ln(cNeg_{it})$, $\Delta[B_{it} \times \ln(cPos_{it})]$, $\Delta[B_{it} \times \ln(cNeg_{it})]$, and $\Delta\ln(R_{i,t-j})$, respectively, to perform a generalized method of moments estimation of Equation 2′. These lags are valid instruments because they are uncorrelated with $\Delta\varepsilon_{it}$ while they are correlated with the first-differences of the endogenous variables.

This method yields a consistent estimation of Equation 2. Because the coefficients are the same in Equations 2 and 2′, the first-differencing can be ignored when interpreting the coefficients. Although both first-differencing and a fixed-effects transformation can eliminate the model-specific effects μ_i, we use first-differencing because it involves only data in periods t and t – 1; thus, we can use all data from period 1 up to period t – 2 as instruments. A fixed-effects transformation uses the data from all time periods, so it renders all lags useless as instruments (for mathematical details, see Nickell 1981; Roodman 2006). Specifically, a fixed-effect transformation of $\ln(R_{it})$ (i.e., mean-centering within each model) involves the value of $\ln(R_{it})$ in all periods (in the model mean calculation), which makes the error term correlated with all the lags of $\ln(cPos_{it})$ and $\ln(cNeg_{it})$.

Because research has found that an increase in sales will lead to the posting of more OCRs (Duan, Gu, and Whinston 2008a, b), we use Equations 3 and 4 to examine the effects of sales rank on the number of positive and negative OCRs as follows:

$$\begin{aligned}(3)\quad \ln(Pos_{it}) = {} & \alpha_0 + \sum_{l=1}^{L}\alpha_l \ln(Pos_{i,t-l}) + \alpha_R \ln(R_{it}) + \alpha_B B_{it} \\ & + \alpha_d \ln(d_{it}) + \alpha_{d2}[\ln(d_{it})]^2 + \eta_i + \nu_{it}, \text{ and}\end{aligned}$$

$$\begin{aligned}(4)\quad \ln(Neg_{it}) = {} & \gamma_0 + \sum_{m=1}^{M}\gamma_m \ln(Neg_{i,t-m}) + \gamma_R \ln(R_{it}) \\ & + \gamma_B B_{it} + \gamma_d \ln(d_{it}) + \gamma_{d2}[\ln(d_{it})]^2 + \pi_i + \xi_{it},\end{aligned}$$

where, in addition to the previously defined variables,

Pos_{it} (Neg_{it}) is the number of positive (negative) OCRs generated for model i in period t,

d_{it} is the listed duration of model i on Amazon until period t,

η_i and π_i are time-invariant model-specific effects, and

ν_{it} and ξ_{it} are idiosyncratic errors.

As previously, it is possible that unobserved product characteristics influence both sales and OCRs, so $\ln(R_{it})$ may be correlated with the model-specific effects η_i and π_i. In addition, a shock in the number of positive or negative OCRs may lead to a change in sales rank, so $\ln(R_{it})$ may be correlated with ν_{it} and ξ_{it}. Therefore, we use the same method used to estimate Equation 2 to estimate Equations 3 and 4. The differences are that we use lags of $\ln(R_{it})$ up to $t-2$ and lags of $\ln(Pos_{i,t-l})$ and $\ln(Neg_{i,t-m})$ up to $t-l-1$ and $t-m-1$ as instruments for their first-differences, $\Delta\ln(R_{it})$, $\Delta\ln(Pos_{i,t-l})$, and $\Delta\ln(Neg_{i,t-m})$. We estimate all equations separately in the Blu-ray and DVD player categories in the subsections to follow.

Results

Brand Classification and Dynamics

In both categories, we first estimated Equation 1 with Samsung as the base (i.e., reference) brand. (In 2009, Samsung was listed in Interbrand's [2009] "Best Global Brands" list and BrandZ's [2009] top-ranking technology brand list; see Table 2.) To reestimate Equation 1, we then set the brands that had significant negative intercepts as the base/reference brands. We coded brands with significant positive intercepts in the reestimated model as strong brands. We used the first 14 weeks as a calibration period. Recognizing that brand strength is dynamic, we updated these brand classifications weekly on the basis of t – 1 weeks of data (e.g., we use data from week 1 to week 14 to estimate brand strength in week 15).

In the Blu-ray category, Sony and Samsung were classified as strong brands for the entire period. Panasonic and LG were initially classified as weak brands, but each grew its brand equity within the category over time. Panasonic became a strong brand in week 15 and LG did so in week 26. Oppo did not enter the market until week 38, but it became a strong brand in week 40. None of the strong brands reverted to being a weak brand over time.

In the more established context of the DVD category, LG, Oppo, Panasonic, Philips, Pioneer, Samsung, and Toshiba were strong brands from the beginning of our data window. Sony was not a strong brand initially; however, after launching several new models in weeks 22 and 23, it achieved strong brand status in week 28. None of the strong brands reverted to being a weak brand over time.

The Effect of OCRs on Brand Equity

Several brands made the transition from weak to strong, so we examined the impact that cumulative OCRs had on this transition. Because only one brand made the transition in the DVD player category, we restrict our attention to the Blu-ray category.

Figure 1 shows the cumulative number of positive OCRs generated for the leading model of each of the ten brands of Blu-ray players that began as weak brands and had one or more models on the market for our entire data collection period. Models of Panasonic and LG, which became strong brands, generated many more positive OCRs (and proportionally fewer negative OCRs) than their competitors. The flattening of the curves for these two brands indicates that most of the OCRs were generated within the first 20–30 weeks. Figure 2 expands this finding to show the total cumulative number of positive OCRs for each brand across all models. Here, the curves for these two brands continue to rise, indicating that as new Panasonic and LG models were introduced, they also generated positive OCRs. Finally, a comparison of the two figures illustrates that one model generated most of LG's OCRs in the first 20 weeks, but more than one Panasonic model generated a substantial number of OCRs.

To observe how Panasonic and LG differed from the other eight brands, we estimated a proportional hazard function on the probability that brand k became a strong brand in period t given that it was not a strong brand previously, at the brand level on these ten brands:

$$h_k(t, X_{k,t}) = h_0(t)e^{X_{kt}\Phi + \tau_k}, \quad (5)$$

where

$h_0(t)$ is the baseline hazard rate;

X_{kt} is a vector of independent variables for brand k {1, ..., 10} in period t {1, ..., 47};

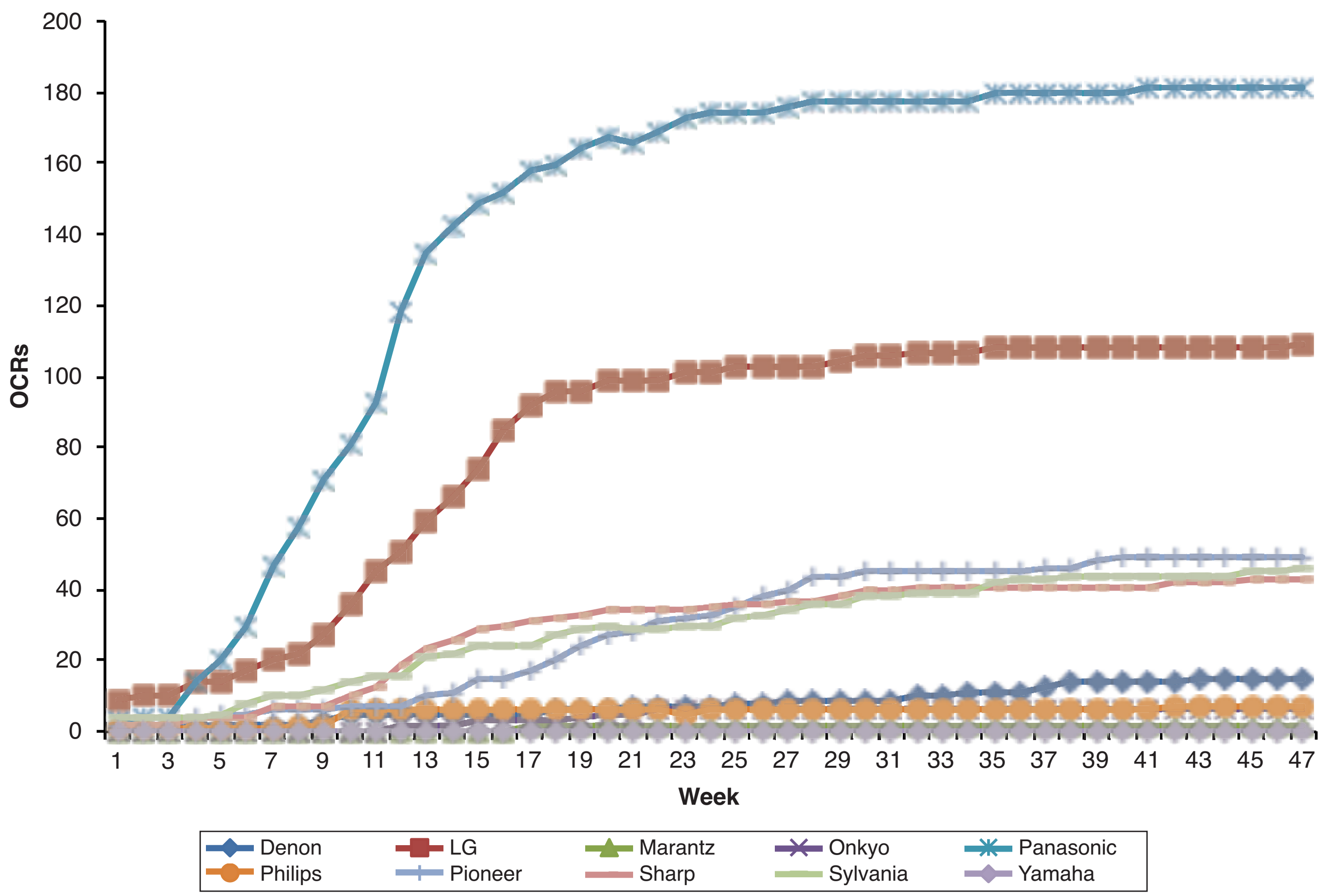
Φ is a vector of estimated coefficients; and

τ_k is the time-invariant, brand-specific effect that represents the combined effect of all omitted brand-specific covariates.

Because only two brands became strong during this period, we focus on a parsimonious model with four independent variables: cumulative numbers of positive and negative OCRs for the brand, advertising expenditures, and the number of models in the product line of the brand. Again, we face potential complexities in that the cumulative numbers of positive and negative OCRs can be endogenous in two ways. First, a change in brand strength may lead to a change in OCRs. Second, OCRs might be correlated with τ_k. We address the first issue by using lags of the cumulative numbers of positive and negative OCRs to instrument for them. For the second issue, estimations of Equation 5 with and without τ_k yielded the same results, indicating that we could eliminate τ_k so the correlation between τ_k and OCRs is not a concern.

The results indicate that a brand's transition from weak to strong is highly related to the cumulative number of positive OCRs but not related to the cumulative number of negative OCRs, advertising expenditures, or the number of models the brand sells (see Table 3). We also estimated Equation 5 on the basis of the cumulative number of positive and negative OCRs for only the leading model of each brand (which is not confounded by the number of models the brand sells). This analysis also indicated that brand strength was significantly related to the cumulative number

FIGURE 1
Cumulative Number of Positive OCRs for the Leading Model of Each Brand



of positive OCRs but not to the cumulative number of negative OCRs, advertising expenditures, or the length of the product line.

The Moderating Effect of Brand Equity

After determining the strong brands each week, we estimated Equations 2, 3, and 4. We determined the appropriate number of lags using the method suggested by Arellano and Bond (1991). In both categories, tests (see Table 4) indicated that the instruments are valid and the estimations do not suffer from serial correlation problems.[3]

Blu-ray players. Table 5, Panel A, presents results for Blu-ray players with and without the brand interactions. The first column in Table 5, Panel A, shows the elasticities of cumulative positive and negative OCRs on sales rank for all models (i.e., both strong and weak brands). The sales rank elasticity with respect to the cumulative number of positive OCRs (.568) is significant, but the sales rank elasticity with respect to the cumulative number of negative OCRs (–.327) is not significant.

In the second column of Table 5, Panel A, the main effects give the elasticities of cumulative positive and negative OCRs for the models of weak brands. The cumulative number of positive and negative OCRs for the models of weak brands have significant elasticities (1.091 and –.579, respectively) on their sales ranks. The interactions indicate significant differences between the elasticities for the models of strong and weak brands for both cumulative positive and negative OCRs (–1.154 and .902). The elasticities of cumulative positive and negative OCRs for the models of strong brands are the sums of the main effects and interactions (–.063 and .323); neither of these elasticities are significant (*p*-values of .870 and .367, respectively).[4] However, the models of strong brands receive a substantial sales

[3]The Arellano–Bond (1991) tests for second-order serial correlation in the first differences $\Delta\varepsilon_{it}$, $\Delta\nu_{it}$, and $\Delta\xi_{it}$ are insignificant, indicating no evidence of first-order serial correlation in ε_{it}, ν_{it}, and ξ_{it}. The Sargan (1958) tests for overidentifying restrictions are insignificant, so we cannot reject the joint validity of the instrument sets we used to estimate Equations 2, 3, and 4. The difference-in-Sargan tests of exogeneity of the instrument subsets used to estimate the three equations are also insignificant, indicating that all instrument subsets are exogenous.

[4]To calculate significance, we reversed the coding of the brand dummy variable from identifying strong brands to identifying weak brands. Under this formulation, the main effect coefficients give the impact of cumulative OCRs on models of strong brands. Neither was significant.

FIGURE 2
Cumulative Number of Positive OCRs for Each Brand

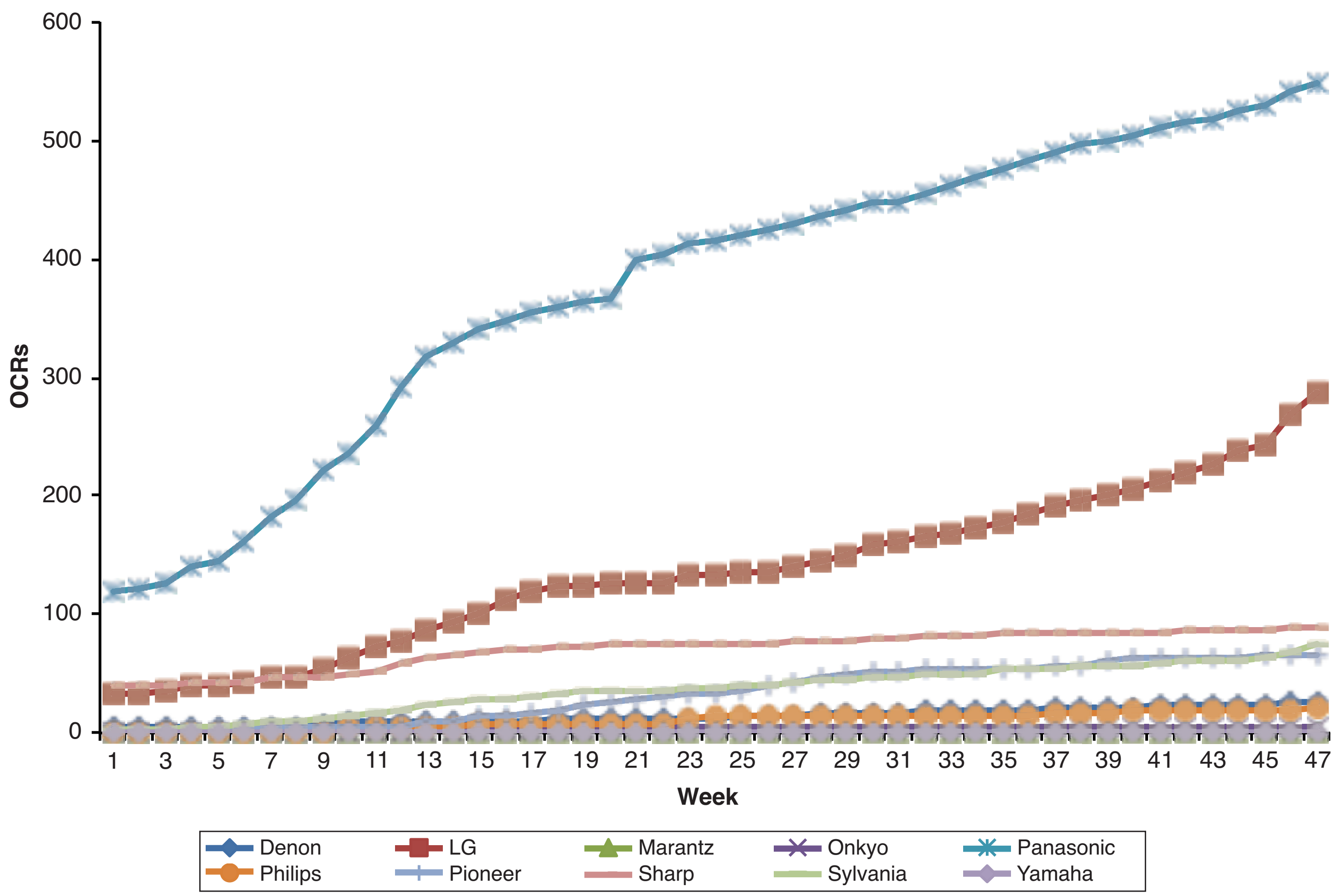


TABLE 3
Effect of Cumulative OCRs on Brand Strength

	All Models		Leading Model	
	Coefficients	***p*-Values**	**Coefficients**	***p*-Values**
Total cumulative number of positive OCRs for the $brand_{kt}$	.018	.006		
Total cumulative number of negative OCRs for the $brand_{kt}$	.011	.813		
Cumulative number of positive OCRs for the leading $model_{kt}$			.055	.012
Cumulative number of negative OCRs for the leading $model_{kt}$			.080	.643
Advertising $expenditure_{kt}$	.000	.940	.000	.962
Number of models in the product line of the $brand_{kt}$	.592	.604	.811	.685

boost from brand equity, as can be observed in the sales multiplier of 2.186 associated with the strong brand dummy. Thus, our results demonstrate that both cumulative positive and negative reviews more strongly affect the models of weak brands, in support of H_1 and H_2 in the Blu-ray player category.

The effects of the other variables are similar in the first and second columns and of the expected signs with or without interactions. The price of model i and the cumulative number of positive reviews for other models are significantly and negatively related to the sales rank of model i. The total number of models offered on Amazon has a marginal negative effect on the sales rank of model i. The price of other models is significantly and positively related to the sales rank of model i. However, a model's being offered by Amazon, advertising expenditures for the brand, and the cumulative number of negative reviews for other models are not significantly related to the sales of model i.

DVD players. Table 5, Panel B, presents results for the DVD player category. In contrast to the Blu-ray analysis, neither cumulative positive nor cumulative negative OCRs are significantly related to sales rank in the first column. Therefore, OCRs seem to have less effect, without considering strong and weak brands.

TABLE 4
Serial Correlation and Instrument Validity Tests

	Arellano–Bond Test		Sargan Test		Difference-in-Sargan Tests
	Z	*p*-Value	χ^2	*p*-Value	*p*-Value Range
Blu-Ray Players					
Equation 2	–.46	.647	4.27	.893	.364–.945
Equation 3	.76	.448	3.06	.216	.216–.216
Equation 4	–.02	.985	4.98	.289	.723–.799
DVD Players					
Equation 2	.89	.375	46.74	.215	.274–.819
Equation 3	–1.24	.216	4.13	.765	.375–.830
Equation 4	–.18	.858	3.15	.369	.139–.638

When we include the interactions with brand strength in the second column of Table 5, Panel B, the cumulative number of positive and negative OCRs for the models of weak brands again have significant elasticities (1.192 and –.972) on their sales ranks. There are significant interactions between brand strength and cumulative positive OCRs (–1.274) as well as cumulative negative OCRs (1.018).[5] Summing the main effects and interactions, we observe that neither cumulative positive nor negative OCRs have a significant elasticity with the sales ranks of models of strong brands (*p*-values of .545 and .704, respectively). However, the sales multiplier associated with the strong brand dummy variable of .718 again indicates a substantial benefit to models of these brands. Therefore, we find support for H_1 and H_2 in the DVD player category and, thus, the generalizability of the results as per H_3. Online customer reviews seem to matter roughly equally, and brand equity exhibits moderating effects of approximately the same magnitude.

In the first column of Table 5, Panel B, the only other variable significantly related to sales rank (in addition to lagged sales rank) is own model price. In the second column, the number of cumulative positive OCRs for other models is also significantly and negatively related to sales of the focal model, whereas cumulative negative OCRs for other models are insignificant. Advertising expenditures are controlled but insignificant. This may be explained in part by the relatively infrequent nature of category-specific advertising we observed in both categories.

The Role of Brand Equity and Sales in OCR Generation

With regard to the factors associated with the generation of positive and negative OCRs, Table 6 presents estimates for Equations 3 and 4 for both Blu-ray (Panel A) and DVD players (Panel B). Sales rank significantly and positively predicts the number of positive OCRs, but the effect of sales rank on the number of negative OCRs is insignificant. In addition, the effects of listed duration on the number of both positive and negative OCRs are positive, but the effects of its quadratic term are negative. This means that the longer a model has been listed on Amazon, the more (both positive and negative) OCRs are posted for it; however, after a peak (in all regressions, this peak occurs less than three weeks after introduction), it receives fewer OCRs. Therefore, both positive and negative reviews increase and then decrease over time, but greater sales tend to generate only additional positive reviews. Thus, there is no penalty in terms of more negative reviews being generated for more popular models. Finally, the models of strong brands do not generate more OCRs, either positive or negative, after the effect of sales is controlled. Models of strong brands might be expected to attract more attention and generate greater customer involvement, both of which would result in more OCRs, but this is not the case.

Robustness Check

Our main analysis is based on the number of positive and negative OCRs, for which we classify four- and five-star reviews as positive and one-, two-, and three-star reviews as negative, following Amazon's practice. Because there is uncertainty regarding how three-star reviews should be classified, we keep the same definition of positive reviews and classify reviews with one or two stars as negative to check the robustness of the analysis to this classification.

The first column of Table 7 repeats the second column of Table 5 for ease of comparison. The second column of Table 7 contains the coefficients when we exclude the OCRs with three stars. There is no meaningful change from the first column in terms of control variables, so they do not appear in Table 7. The primary change is that all of the cumulative OCRs and interaction coefficients (except the cumulative positive OCR coefficient for Blu-ray players) are larger in absolute value due to the larger difference between positive and negative OCRs. The interpretations are similar; therefore, we conclude that our results are robust to a different classification of positive and negative reviews.

Comparison with Volume and Valence Approach

Previous studies have found a significant positive relationship between the number of OCRs and sales (e.g., Chen, Wu, and Yoon 2004; Chevalier and Mayzlin 2006; Dellaro-

[5]The *p*-value of .053 is marginally significant. However, we use two-tailed confidence intervals despite the a priori directional hypotheses. A formally correct one-tailed test is significant at $p \leq .05$. Moreover, we produced a lower *p*-value in our robustness check in which we counted four- and five-star reviews as positive and considered only one- and two-star reviews as negative ($p = .043$, two-tail), which gives us confidence in the result.

TABLE 5
Effects of Cumulative OCRs and Brand Strength on Sales

A: Blu-Ray Players

	Estimation of Equation 2 Without Interactions		Full Estimation of Equation 2	
ln(1/Rank$_{it}$)	**Coefficients**	***p*-Values**	**Coefficients**	***p*-Values**
ln(1/Rank$_{i, t-1}$)	.371	.000	.236	.010
ln(1/Rank$_{i, t-2}$)	.092	.027	.053	.201
ln(Cumulative number of positive OCRs$_{it}$)	.568	.051	1.091	.000
ln(Cumulative number of negative OCRs$_{it}$)	–.327	.176	–.579	.010
Strong brand$_{it}$	–.014	.917	2.186	.017
Strong brand$_{it}$ × ln(Cumulative number of positive OCRs$_{it}$)			–1.154	.011
Strong brand$_{it}$ × ln(Cumulative number of negative OCRs$_{it}$)			.902	.015
ln(Cumulative number of positive OCRs for others$_{it}$)	–1.016	.011	–1.230	.001
ln(Cumulative number of negative OCRs for others$_{it}$)	.499	.187	.486	.191
ln(Advertising expenditure$_{it}$)	–.002	.471	–.002	.412
ln(Price$_{it}$)	–.183	.004	–.195	.002
ln(Average price of others$_{it}$)	.427	.036	.408	.040
ln(Total number of models$_{t}$)	–.263	.229	–.385	.076
Offered by Amazon$_{it}$	.013	.677	.021	.497

B: DVD Players

	Estimation of Equation 2 Without Interactions		Full Estimation of Equation 2	
ln(1/Rank$_{it}$)	**Coefficients**	***p*-Values**	**Coefficients**	***p*-Values**
ln(1/Rank$_{i, t-1}$)	.869	.000	.726	.000
ln(1/Rank$_{i, t-2}$)	–.014	.889	.101	.217
ln(1/Rank$_{i, t-3}$)	.048	.430	.078	.127
ln(Cumulative number of positive OCRs$_{it}$)	.125	.128	1.192	.001
ln(Cumulative number of negative OCRs$_{it}$)	–.130	.114	–.972	.038
Strong brand$_{it}$	.052	.392	.718	.047
Strong brand$_{it}$ × ln(Cumulative number of positive OCRs$_{it}$)			–1.274	.005
Strong brand$_{it}$ × ln(Cumulative number of negative OCRs$_{it}$)			1.018	.053
ln(Cumulative number of positive OCRs for others$_{it}$)	–.105	.472	–.411	.053
ln(Cumulative number of negative OCRs for others$_{it}$)	.054	.856	.152	.577
ln(Advertising expenditure$_{it}$)	–.001	.766	–.002	.635
ln(Price$_{it}$)	–.170	.006	–.217	.000
ln(Average price of others$_{it}$)	–.056	.841	–.220	.400
ln(Total number of models$_{t}$)	–.009	.971	.169	.502
Offered by Amazon$_{it}$	.047	.360	.033	.482

cas, Zhang, and Awad 2007; Li and Hitt 2008; Liu 2006). However, the relationship between the valence of OCRs (average customer rating) and sales is mixed. Whereas some studies have shown that the valence of customer reviews affects sales positively (e.g., Chevalier and Mayzlin 2006; Dellarocas, Zhang, and Awad 2007; Karniouchina 2011; Li and Hitt 2008), others have found an insignificant relationship (e.g., Chen, Wu, and Yoon 2004; Duan, Gu, and Whinston 2008a, b; Liu 2006). Duan, Gu, and Whinston attribute the result to controlling endogeneity. If one takes the position that positive reviews help sales, whereas negative reviews hurt them, it may be better to estimate these two effects separately than to estimate the effect of their sum and average. Therefore, we compare our approach with the volume and valence approach.

The third column of Table 7 replaces cumulative positive and negative OCRs with cumulative total OCRs and valance. As with the second column, most of the control variables retain the same size, sign, and significance as those in the first column, so they do not appear in Table 7. Turning to the key comparison, in Column 3, the cumulative total number of OCRs is significantly related to sales, but the coefficient is smaller than the coefficient of cumulative positive OCRs in the first column. Therefore, it is possible that the effect of cumulative total OCRs is a compromise between the positive effect of cumulative positive OCRs and the negative effect of cumulative negative OCRs. Note that both Blu-ray and DVD players have many more positive OCRs than negative OCRs, so the cumulative total OCRs have a positive effect overall.

The coefficient of the interaction between cumulative total OCRs and brand strength is significantly negative, indicating that the products of strong brands benefit less from cumulative total OCRs, which is consistent with our theory. An estimation with reverse brand coding shows that cumulative total OCRs have no significant effect on sales of

TABLE 6
Effects of Sales and Brand Strength on OCR Generation

A: Blu-Ray Players

	ln(Number of Positive OCRs$_{it}$)		ln(Number of Negative OCRs$_{it}$)	
	Coefficients	*p*-Values	Coefficients	*p*-Values
ln(Number of positive OCRs$_{i,t-1}$)	.186	.002		
ln(Number of positive OCRs$_{i,t-2}$)	.230	.000		
ln(Number of positive OCRs$_{i,t-3}$)	.154	.003		
ln(Number of negative OCRs$_{i,t-1}$)			–.086	.803
ln(Number of negative OCRs$_{i,t-2}$)			–.042	.915
ln(Number of negative OCRs$_{i,t-3}$)			–.039	.913
ln(1/Rank$_{it}$)	.251	.040	–.153	.530
Strong brand$_{it}$	–.020	.762	.250	.442
ln(Duration$_{it}$)	2.511	.000	1.270	.037
[ln(Duration$_{it}$)]^2	–.453	.000	–.248	.052

B: DVD Players

	ln(Number of Positive OCRs$_{it}$)		ln(Number of Negative OCRs$_{it}$)	
	Coefficients	*p*-Values	Coefficients	*p*-Values
ln(Number of positive OCRs$_{i,t-1}$)	–.248	.000		
ln(Number of positive OCRs$_{i,t-2}$)	–.221	.031		
ln(Number of negative OCRs$_{i,t-1}$)			–.021	.682
ln(Number of negative OCRs$_{i,t-2}$)			–.052	.452
ln(1/Rank$_{it}$)	.208	.008	.102	.284
Strong brand$_{it}$	–.027	.699	–.002	.985
ln(Duration$_{it}$)	.341	.065	.363	.003
[ln(Duration$_{it}$)]^2	–.062	.077	–.068	.012

the models of strong brands (*p*-values are .380 and .131 for Blu-ray and DVD players, respectively). Meanwhile, the coefficients of both valence and its interaction with brand strength are insignificant. Thus, we observe a pattern in which only volume (not valence) matters, as in the aforementioned studies. Because the volume and valence approach provides fewer insights than ours, it may be better for both researchers and managers to account for positive OCRs and negative OCRs separately.

Discussion

Summary of Findings and Theoretical Implications

In this study, we provide evidence across two product categories that brand equity moderates the relationship between OCRs and sales. In both categories, cumulative positive OCRs increase and cumulative negative OCRs decrease the sales of models of weak brands. In contrast, neither cumulative positive nor cumulative negative OCRs have a significant effect on the sales of models of strong brands. However, these models do receive a significant sales boost from being part of a strong brand; therefore, their resistance to positive OCRs does not disadvantage them. In addition, they are protected to a degree from negative OCRs. In the reverse direction, greater sales lead to more positive OCRs but are not significantly related to the number of negative OCRs. We find a decline in the number of positive and negative OCRs that customers post over time, although the relationship is curvilinear in that OCRs increase for the first three weeks and then decrease.

The results of the hazard model for the Blu-ray category show that cumulative positive OCRs help build the equity of weak brands regardless of whether the OCRs pertain to all models in the product line or only the leading model. Notably, cumulative negative reviews do not significantly influence this transition in brand strength, which indicates that their effects are largely constrained to the individual model itself. Therefore, weak brands do not seem to be held back by cumulative negative reviews so much as they are helped by cumulative positive reviews. Combined with the finding that sales generate more positive than negative OCRs, this creates a positive feedback loop for the models of a weak brand: sales lead to positive OCRs and greater brand equity, which loops back to positively affect sales for all of the models of that brand.

In contrast to the speculation that brands will matter less as OCRs become more readily available, we find that OCRs matter less for strong brands. In essence, brand equity tends to affect OCRs more than the other way around. Much like the importance of brands in the face of stronger, more concentrated retailers and their private labels (the last purported "brand killer"), brands continue to be a critical factor for companies competing in an online environment. The results also suggest that corporate brand equity may not be a good indicator of strength in a specific category. For example, Philips has the third-largest corporate brand value in the Interbrand ranking, after only Samsung and Sony, but in the

TABLE 7
Effects of Cumulative OCRs (Different Measures) and Brand Strength on Sales

A: Blu-Ray Players

$\ln(1/\text{Rank}_{it})$	Equation 2 Positive OCRs: Four or Five Stars; Negative OCRs: One, Two, or Three Stars		Equation 2 Positive OCRs: Four or Five Stars; Negative OCRs: One or Two stars		Equation 2 Total OCRs and Valence	
	Coefficients	*p*-Values	Coefficients	*p*-Values	Coefficients	*p*-Values
ln(Cumulative number of positive OCRs_{it})	1.091	.000	1.034	.001		
ln(Cumulative number of negative OCRs_{it})	–.579	.010	–.635	.013		
Strong brand_{it} × ln(Cumulative number of positive OCRs_{it})	–1.154	.011	–1.488	.047		
Strong brand_{it} × ln(Cumulative number of negative OCRs_{it})	.902	.015	1.357	.046		
ln(Cumulative number of total OCRs_{it})					.723	.007
ln(Cumulative valance_{it})					1.646	.694
Strong brand_{it} × ln(Cumulative number of total OCRs_{it})					–.966	.031
Strong brand_{it} × ln(Cumulative valence_{it})					–1.448	.627

B: DVD Players

$\ln(1/\text{Rank}_{it})$	Equation 2 Positive OCRs: Four or Five Stars; Negative OCRs: One, Two, or Three Stars		Equation 2 Positive OCRs: Four or Five Stars; Negative OCRs: One or Two stars		Equation 2 Total OCRs and Valence	
	Coefficients	*p*-Values	Coefficients	*p*-Values	Coefficients	*p*-Values
ln(Cumulative number of positive OCRs_{it})	1.192	.001	1.384	.003		
ln(Cumulative number of negative OCRs_{it})	–.972	.038	–1.769	.033		
Strong brand_{it} × ln(Cumulative number of positive OCRs_{it})	–1.274	.005	–1.511	.008		
Strong brand_{it} × ln(Cumulative number of negative OCRs_{it})	1.018	.053	1.949	.043		
ln(Cumulative number of total OCRs_{it})					1.080	.016
ln(Cumulative valance_{it})					1.040	.597
Strong brand_{it} × ln(Cumulative number of total OCRs_{it})					–1.223	.011
Strong brand_{it} × ln(Cumulative valence_{it})					1.255	.591

Blu-ray disc player category, its brand equity is lower than that of LG, Panasonic, and Oppo.

The results across both categories show a pattern in which negative reviews tend to be less impactful than positive reviews. That is, the elasticities for cumulative negative reviews are lower than for cumulative positive reviews in both categories, and cumulative negative OCRs for other products are not significantly related to sales of the focal product, whereas cumulative positive reviews for other products are. The lesser effects associated with negative reviews are notable because they contradict perspectives in which losses loom larger than gains (e.g., prospect theory), which should cause consumers to weight negative reviews more heavily because they indicate downside risk. This may be because there are more positive reviews than negative reviews, which could reduce the credibility and influence of the latter.

The effects of product category maturity are complex. On the one hand, the regressions we present in Tables 5 and 6 indicate similar relationships among OCRs, sales, and brand strength across the emerging and mature categories. On the other hand, we observe a much smaller number of OCRs posted each week, a larger number of strong brands, and less movement from weak to strong brands in the mature category. Together, these observations suggest that as a product category matures, there may be less room for new strong brands, and if a brand has not made the move from weak to strong in the first few years of a product category, the chances that it will do so in the future are smaller. However, even in more mature categories, the results show that it is possible for models of new or weak brands to use OCRs to increase sales. Furthermore, in many mature categories, current leading brands are not pioneers or even "fast seconds" but brands that entered the category approximately ten years after the pioneer (Golder and Tellis 1993). Although not all later entrants will become leaders (or strong brands), it does seem that OCRs provide a way for them to accomplish this task.

Finally, the findings suggest that positive OCRs differ from producer-generated marketing communications, the effectiveness of which is boosted by increased brand equity. As we have argued, the greater credibility inherent in OCRs implies that they have less need (than advertising does) of a strong brand to lend credibility. In addition, typical marketing communications are passively received, which gives communications for more familiar brands with established cognitive schemas a better chance of being attended to and remembered. In contrast, people process OCRs more actively, because they must be sought out and read. This active processing may undo the bias in favor of strong brands, especially if the brand strength gives consumers a feeling of confidence about the performance of strong brands so that they attend more to reviews for weaker brands.

Managerial Implications

Most previous studies involving eWOM have found a positive relationship between eWOM and sales. However, this body of research has not studied traditionally branded products. It has implicitly advocated strategies to increase the generation of eWOM for all products (as noted previously, an exception is Zhu and Zhang [2010]). In contrast, our findings suggest very different strategies for the models of strong and weak brands.

Models of weak brands should focus on generating positive OCRs because they benefit sales of that model directly as well as the equity of the brand as a whole. First, in the pursuit of sales, individual models of weak brands benefit from a sizable cumulative positive OCR elasticity. Second, they profit from the positive feedback loop between sales and positive OCRs. Third, the generation of a large number of positive OCRs for one or more models is strongly associated with increased brand equity, which benefits all models in the line, not just the one with increased positive OCRs.

These paths give weaker brands a way to compete other than through traditional marketing communications, which typically favor strong brands. Particularly for weak brands, the results support such current, popular ideas as "flipping the funnel," in which the firm removes marketing dollars from mass media advertising and focuses them on increasing satisfaction, retention, and positive word of mouth, which the firm then uses to drive the acquisition process.

A necessary first step in improving business through OCRs is the development of superior products that capture consumer excitement. Second, online distribution may be easier to acquire than offline distribution, because online distributors such as Amazon are able to carry many more models than even a very large brick-and-mortar store (Brynjolfsson, Hu, and Smith 2003). An additional benefit is that online distribution typically comes with a vehicle for posting reviews. Furthermore, even though both online and offline distributors tend to have Pareto-like concentrations among more popular products, the online channel tends to have a longer tail (Brynjolfsson, Hu, and Simester 2011), which enables models of less well-known brands to capture some initial sales. Then, they can generate more positive OCRs by providing seeds for and facilitating positive OCR generation through actions such as the following:

- Making detailed information about products available and easily accessible. There is anecdotal evidence that customers refer to information from producers in their reviews.
- Establishing brand communities and early adopter clubs. Members of these clubs can buy products with incentives before launch to spark the feedback process. Producers can use positive feedback as seeds and negative feedback to modify their products before launch.
- Providing samples to expert review websites. There is anecdotal evidence that customers refer to expert reviews in their own reviews.
- Sending reminders and incentives to customers to encourage the posting of reviews.

In contrast to weak brands, additional positive OCRs do not further benefit the models of strong brands. Therefore, strong brands should consider actions to build brand equity through advertising and promotions rather than relying too much on OCRs. As we have cautioned, brand equity tends to be category specific, so managers should understand the equity of their brand within a given category, especially when it is new. Although models of a strong brand are not affected by their own OCRs, they are affected by positive OCRs for models of weak brands because these competitors can draw consumers away from them. Therefore, competing with weak brands in the OCR space may not be a winning strategy for strong brands; they may be better off investing in other marketing practices.

A closely related implication is that the role of OCRs is likely to change as the brand evolves over time. Newer, weaker brands should focus on OCRs and the synergistic feedback loop, promoting positive feedback and trying to minimize negative feedback. However, if these brands are able to increase brand equity, additional OCRs become less impactful; therefore, a shift in strategy toward a more balanced approach to marketing and maintaining brand strength may be required. Although controlling negative OCRs may not be as important for stronger brands, they are still well advised to monitor negative OCRs and take corrective actions. At minimum, the cumulative body of negative OCRs will matter if these brands lose their strength over time.

In contrast to Zhu and Zhang's (2010) findings, our results suggest that OCRs are important for models of weak brands even before they are launched and certainly during the first several months of launch. In addition, rather than just being a tool for niche products, OCRs represent a way for a model to help build overall brand equity and benefit all (and future) models under the brand umbrella. This occurs because positive OCRs spill over to the brand itself. For managers of traditionally branded products, attending to existing brand equity is an important part of understanding the influence of OCRs. Brand and product extensions as well as model replacements are situations in which preexisting brand equity will affect consumer processing of OCRs. Strong brands can rely more on traditional marketing strategies for influencing awareness and trial, whereas weaker brands should focus more on facilitating OCRs because they can have a greater impact on the models of these brands.

In addition, we believe it is important for managers to analyze the factors driving the short-term sales of individual models when anticipating the role of OCRs. According to the perspective developed in this research, strong-selling products offered by weak brands may still benefit from positive OCRs, especially if the reason for their popularity is a low price or heavy advertising and promotions, which create a disconnect between sales and the inherent appeal of the brand. Indeed, investing in OCRs for these models may be an especially good strategy because they are already popular despite the weak brand. This may indicate that the product itself is a winner, and its sales can be improved by facilitating the credible reassurance (in the form of OCRs) that the brand does not provide. Positive OCRs generated for the model (which are a function of sales) can then further increase the equity of the brand. In addition, marketers may find that positive OCRs for models that are popular because of price promotions can facilitate higher prices and margins.

Finally, we note a potential implication of the finding that positive reviews for competing products have a negative effect on the sales of a focal product, whereas negative reviews for other products do not. Namely, subterfuge to post negative OCRs as a competitive tactic may not work well and, worse, may trigger a wave of positive OCRs for the competing product from customers who tend to argue for their committed brands (Ahluwalia, Burnkrant, and Unnava 2000). This could result in decreasing sales for the product of the brand responsible for the deception. This is especially likely if marketers of weak brands try to use this tactic against strong brands.

Methodological Implications and Limitations

In this study, we find that it is important to attend to both positive and negative reviews. We observe the same pattern reported in some earlier studies when we use a volume and valence approach, in which valence does not seem to matter. Our study's more fine-grained examination shows that negative reviews hurt sales. It is not only a model's buzz factor that matters.

An explanation for the difficulty encountered in previous volume and valence research is that positive OCRs are generated faster than negative OCRs as a product's sales rank improves, creating the feedback loop for positive OCRs observed in this study. This increases the correlation between the total number and the valence of OCRs as the number of OCRs grows. Coding schemes based on volume and valence may not tease this distinction apart sufficiently. In addition, the effect of cumulative total OCRs on sales may be a compromise between the positive effect of cumulative positive OCRs and the negative effect of cumulative negative OCRs. Thus, we suggest using the number of positive and negative OCRs as distinct variables to reflect consumer generated sentiment accurately.

Moreover, because the effects of OCRs on the sales of models of strong brands differ from those of weak brands, excluding the interactions between brand equity and customer reviews from the equation would bias the results. Therefore, future studies investigating the effects of OCRs on sales in branded categories should consider this factor.

Our treatment of endogeneity is more complete than in most of the extant literature, in which only a few articles address this issue. For example, the difference-in-difference approach in Chevalier and Mayzlin (2006) and Zhu and Zhang (2010) as well as the fixed-effects estimation method in Zhang and Dellarocas (2006) purge the correlation between cumulative OCRs and the individual product-specific effects caused by unobserved factors. The method we use in the current research also remedies the correlation between cumulative OCRs and the idiosyncratic error in Equation 2. Without that extra treatment, Equation 2's results would still be biased. This suggests that similar studies in the future should address both the endogeneity problems.

Sun (2012) posits that OCR variance can affect sales when the average rating is low. Although we do not investigate this issue, it is worthwhile to note that our results seem to be consistent with this finding. A model of a weak brand that received an OCR rating of three stars from each person would be forecast to have lower sales than a model that received half five-star and half one-star reviews.

Our study suffers from several limitations. First, we have not accounted for the effects of expert reviews and customer reviews on other sites. It is possible that expert reviews (e.g., on CNET.com) or OCRs on other sites (e.g., BestBuy.com) also influence sales rank on Amazon. However, the effects of expert reviews are likely to be canceled out in the first-differencing step of our estimation because experts typically post their reviews when a product is launched and are unlikely to change their reviews over time, so they are time invariant. An extension to this research would be to examine the impact of OCRs on other sites.

Second, by estimating brand equity from sales data, we introduce measurement error into the second-stage models (Equations 2–4). We believe the dynamic and category-specific nature of the estimates more than makes up for any measurement error; this contrasts with the use of secondary brand rankings, which are themselves subject to measurement error.

Third, advertising is not particularly widespread across brands in these categories. Therefore, although we observe limited effects of advertising on both sales and brand equity, this finding may not hold in other categories. The low advertising by smaller firms may suggest that they understand the limitations of this strategy and are already relying to a degree on OCRs to support their models and brands.

REFERENCES

Ahluwalia, Rohini, Robert E. Burnkrant, and H. Rao Unnava (2000), "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Marketing Research*, 37 (May), 203–214.

Archak, Nikolay, Anindya Ghose, and Panagiotis G. Ipeirotis (2011), "Deriving the Pricing Power of Product Features by Mining Consumer Reviews," *Management Science*, 58 (7), 1485–1509.

Arellano, Manuel and Stephen Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 58 (2), 277–97.

Belch, George E. (1981), "An Examination of Comparative and Noncomparative Television Commercials: The Effects of Claim Variation and Repetition on Cognitive Response and Message Acceptance," *Journal of Marketing Research*, 18 (August), 333–49.

Bickart, Barbara and Robert M. Schindler (2001), "Internet Forums as Influential Sources of Consumer Information," *Journal of Interactive Marketing*, 15 (3), 31–40.

Boulding, William and Amna Kirmani (1993), "A Consumer-Side Experimental Examination of Signaling Theory: Do Consumers Perceive Warranties as Signals of Quality?" *Journal of Consumer Research*, 20 (1), 111–23.

BrandZ (2009), "Top 100 Most Valuable Global Brands 2009," (accessed July 23, 2011), [available at http://www.wpp.com/~/media/SharedWPP/BrandZ/BrandZ%202009%20report.pdf].

Brynjolfsson, Erik, Yu Hu, and Duncan Simester (2011), "Goodbye Pareto Principle, Hello Long Tail: The Effect of Search Costs on the Concentration of Product Sales," *Management Science*, 57 (8), 1371–86.

———, ———, and Michael D. Smith (2003), "Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety," *Management Science*, 49 (11), 540–46.

Chen, Pei-Yu, Shin-Yi Wu, and Jungsun Yoon (2004), "The Impact of Online Recommendations and Consumer Feedback on Sales," in *International Conference on Information Systems 2004 Proceedings*. Washington, DC: Association for Information Systems, 711–24.

Chen, Stephen (2001), "Assessing the Impact of the Internet on Brands," *Journal of Brand Management*, 8 (4), 288–95.

Cheong, Hyuk J. and Margaret A. Morrison (2008), "Consumers' Reliance on Product Information and Recommendations Found in UGC," *Journal of Interactive Advertising*, 8 (2), 1–29.

Chevalier, Judith A. and Austan Goolsbee (2003), "Measuring Prices and Price Competition Online: Amazon.com and Barnes andNoble.com," *Quantitative Marketing and Economics*, 1 (2), 203–222.

——— and ——— (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research*, 43 (August), 345–54.

Dawar, Niraj and Madan M. Pillutla (2000), "Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations," *Journal of Marketing Research*, 37 (May), 215–26.

Dellarocas, Chrysanthos, Xiaoquan Zhang, and Neveen F. Awad (2007), "Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures," *Journal of Interactive Marketing*, 21 (4), 23–45.

Duan, Wenjing, Bin Gu, and Andrew B. Whinston (2008a), "Do Online Reviews Matter? An Empirical Investigation of Panel Data," *Decision Support Systems*, 45 (4), 1007–1016.

———, ———, and ——— (2008b), "The Dynamics of Online Word-of-Mouth and Product Sales: An Empirical Investigation of the Movie Industry," *Journal of Retailing*, 84 (2), 233–42.

Erdem, Tülin and Joffre Swait (1998), "Brand Equity as a Signaling Phenomenon," *Journal of Consumer Psychology*, 7 (2), 131–57.

———, ———, and Ana Valenzuela (2006), "Brands as Signals: A Cross-Country Validation Study," *Journal of Marketing*, 70 (January), 34–49.

Ghose, Anindya and Arun Sundararajan (2006), "Evaluating Pricing Strategy Using e-Commerce Data: Evidence and Estimation Challenges," *Statistical Science*, 27 (6), 995–1011.

Golder, Peter N. and Gerard J. Tellis (1993), "Pioneer Advantage: Marketing Logic or Marketing Legend?" *Journal of Marketing Research*, 30 (May), 158–70.

Goolsbee, Austan and Judith A. Chevalier (2002), "Measuring Prices and Price Competition Online: Amazon and Barnes and Noble," Working Paper No. 02-23, Yale School of Management International Center for Finance.

Hausman, Jerry A. and William E. Taylor (1981), "Panel Data and Unobservable Individual Effects," *Econometrica*, 49 (6), 1377–98.

Hoeffler, Steve and Kevin L. Keller (2003), "The Marketing Advantages of Strong Brands," *Journal of Brand Management*, 10 (6), 421–45.

Horsky, Dan, Sanjog Misra, and Paul Nelson (2006), "Observed and Unobserved Preference Heterogeneity in Brand-Choice Models," *Marketing Science*, 25 (4), 322–35.

Hung, Kineta H. and Stella Y. Li (2007), "The Influence of eWOM on Virtual Consumer Communities: Social Capital, Consumer Learning, and Behavioral Outcomes," *Journal of Advertising Research*, 47 (4), 485–95.

Interbrand (2009), "Best Global Brands 2009," (accessed July 16, 2013), [available at http://www.interbrand.com/de/best-global-brands/previous-years/best-global-brands-2009.aspx]

Kamakura, Wagner and Gary Russell (1993), "Measuring Brand Value with Scanner Data," *International Journal for Research in Marketing*, 10 (1), 9–22.

Karniouchina, Ekaterina V. (2011), "Impact of Star and Movie Buzz on Motion Picture Distribution and Box Office Revenue," *International Journal of Research in Marketing*, 28 (1), 62–74.

Kirmani, Amna (1990), "The Effect of Perceived Advertising Costs on Brand Perceptions," *Journal of Consumer Research*, 17 (2), 160–71.

Li, Xinxin and Lorin M. Hitt (2008), "Self Selection and Information Role of Online Product Reviews," *Information Systems Research*, 19 (4), 456–74.

Liu, Yong (2006), "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing*, 70 (July), 74–89.

Montgomery, Cynthia A. and Berger Wernerfelt (1992), "Risk Reduction and Umbrella Branding," *Journal of Business*, 65 (1), 31–50.

Mundlak, Yair (1978), "On the Pooling of Time Series and Cross Section Data," *Econometrica*, 46 (1), 69–85.

Nelson, Phillip (1974), "Advertising as Information," *Journal of Political Economy*, 82 (4), 729–54.

Nickell, Stephen (1981), "Biases in Dynamic Models with Fixed Effects," *Econometrica*, 49 (6), 1417–26.

Petty, Richard E. and Jon A. Krosnick (1995), *Attitude Strength: Antecedents and Consequences*. Mahwah, NJ: Lawrence Erlbaum Associates.

Prasso, Sheridan (2011), "Chobani: The Unlikely King of Yogurt," *Fortune*, (December 12), (accessed July 16, 2013), [available at http://money.cnn.com/2011/11/29/smallbusiness/chobani_yogurt_hamdi_ulukaya.fortune/index.htm].

Rao, Akshay R., Lu Qu, and Robert W. Ruekert (1999), "Signaling Unobservable Product Quality Through a Brand Ally," *Journal of Marketing Research*, 36 (May), 258–68.

Roodman, David (2006), "How to Do Xtabond2: An Introduction to 'Difference' and 'System' GMM in Stata," Working Paper No. 103, Center for Global Development.

Rosenthal, Morris (2005), "Amazon Sales Ranking and Author Rank: Calculate How Many Books Amazon Sells from Ranks," (accessed July 16, 2013), [available at http://www.fonerbooks.com/surfing.htm].

Sargan, J.D. (1958), "The Estimation of Economic Relationships Using Instrumental Variables," *Econometrica*, 26 (3), 393–415.

Shimp, Terrance A. and William O. Bearden (1982), "The Use of Extrinsic Cues to Facilitate Product Adoption," *Journal of Marketing Research*, 19 (May), 229–40.

Sriram, S., Subramanian Balachander, and Manohar U. Kalwani (2007), "Monitoring the Dynamics of Brand Equity Using Store-Level Data," *Journal of Marketing*, 71 (April), 61–78.

———, Pradeep K. Chintagunta, and Ramya Neelamegham (2006), "Effects of Brand Preference, Product Attributes, and Marketing Mix Variables in Technology Product Markets," *Marketing Science*, 25 (5), 440–56.

Srivastava, Rajendra K. and Allan D. Shocker (1991), "Brand Equity: A Perspective on Its Meaning and Measurement," Report No. 91-124, Marketing Science Institute.

Stiglitz, Joseph (1989), "Imperfect Information in the Product Markets," in *Handbook of Industrial Organization*, Vol. 1, Richard Schmalensee and Robert D. Willing, eds. Amsterdam: Elsevier, 769–847.

Sun, Monic (2012), "How Does the Variance of Product Ratings Matter?" *Management Science*, 58 (4), 696–707.

Tellis, Gerard J. and Birger Wernerfelt (1987), "Competitive Price and Quality Under Asymmetric Information," *Marketing Science*, 6 (3), 240–53.

Twice.com (2009), "Market Share Reports by Category," (July 6), (accessed July 23, 2013), [available at http://www.twice.com/retailing/retailing/market-share-reports-category/22908].

Wernerfelt, Birger (1988), "Umbrella Branding as a Signal of New Product Quality: An Example of Signaling by Posting a Bond," *RAND Journal of Economics*, 19 (3), 458–66.

Zhang, Xiaoquan M. and Chris Dellarocas (2006), "The Lord of the Ratings: How a Movie's Fate Is Influenced by Reviews," in *Proceedings of the 27th International Conference on Information Systems (ICIS)*. Milwaukee: Association for Information Systems.

Zhu, Feng and Xiaoquan (Michael) Zhang (2010), "Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics," *Journal of Marketing*, 74 (March), 133–48.