The Effect of Online Consumer Reviews on New Product Sales

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ABSTRACT: This study examines the effect of online reviews on new product sales for consumer electronics and video games. Analyses of panel data of 332 new products from Amazon.com over nine months reveal that the valence of reviews and the volume of page views have a stronger effect on search products, whereas the volume of reviews is more important for experience products. The results also show that the volume of reviews has a significant effect on new product sales in the early period and such effect decreases over time. Moreover, the percentage of negative reviews has a greater effect than that of positive reviews, confirming the negativity bias. Thus, marketers need to consider the distinctive influences of various aspects of online reviews when launching new products and devising e-marketing strategies.

KEY WORDS AND PHRASES: New product sales, online product reviews, panel data analyses, search vs. experience products, word of mouth.

Since the advent of the Internet, electronic word-of-mouth (eWOM) communication has become a major source of information for consumers planning to purchase new products. In fact, online product review Web sites outrank all other media in influencing customer decisions [14]. User-generated content, especially online product reviews, helps consumers make informed decisions about purchasing new products and has become a major driving force in new product sales, making effective e-marketing a critical success factor for new product launch. An increasing number of studies have found a positive relationship between online consumer reviews and product sales, including books, movies, and video games [9, 19, 45]. To help marketers harness the power of eWOM, researchers have recommended various strategies on how to influence online product reviews, such as identifying the influentials, encouraging advocates, and withholding product information [8, 12]. However, empirical findings about the effects of online reviews on new product sales are not always consistent.

In the online market, three metrics of consumer product reviews have been under close examination: volume, valence, and dispersion. The rationale behind measuring the volume of product reviews is straightforward—discussions about a product in online forums lead to increased awareness among consumers. The valence, that is, the average ratings or the fraction of positive and negative opinions, carries important information about a product's quality and serves as a recommendation for consumers. Existing studies on online WOM have used product ratings as a revenue-forecasting tool for "new products" such as television shows, movies, and books (e.g., [13, 19]). The dispersion, or the spread, of communication measures how fast WOM spreads within and across communities [19].

With these new measurement tools at their disposal, researchers have conducted an increasing number of studies using data from online forums

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and championed eWOM as an important driver of sales of products such as movies, books, television shows, and video games in the online marketplace (e.g., [13, 19, 45]). For instance, the volume of messages on newly released movies has proven to be a good predictor of their box office success [30]. The valence of online ratings posted during a movie's opening weekend often emerges as the most important predictor of its revenue in subsequent weeks [13]. The dispersion of conversation about weekly television shows across Internet communities also appears to have a strong correlation with the viewership of these shows [19].

Despite the evidence of eWOM's influence on consumer purchases, there remain several important empirical and theoretical questions regarding the effect of online reviews on new product sales. First, most studies to date have dealt with information and entertainment products, such as books, movies, and television shows, which are often well promoted prior to their release and attract customer reviews within a short period following their release. While a few studies have included search products that have more technology elements [10, 34], researchers have not examined whether the existing findings apply to the search products or compared the effect of online WOM across product categories. Moreover, the volume and valence of online reviews have received much attention, but how the volume of readings of online reviews or the page views by readers influence the sales of new products also warrants investigation.

Furthermore, some studies followed the online WOM for new products such as movies only for a few weeks or months in the pre- and postrelease period, which does not allow assessment of the effect of online WOM beyond the introduction period. Some of the products used in the previous studies are not new but have existed for some time, such as books. Although the new product diffusion theory suggests that WOM plays a greater role in the growth period than in the introduction stage [4, 39], recent studies indicate that eWOM can affect product sales early in the process [2, 11, 13]. Thus, research on the effect of online product reviews over time is particularly needed. Last, instead of exploring the effects of various metrics of online WOM in a piecemeal fashion, a unified research framework to address these issues simultaneously would be desirable.

We draw from theories of innovation diffusion and consumer learning and propose an integrative framework and a number of testable hypotheses to address the above-mentioned research questions. Using panel data of 332 new products from Amazon.com over a period of nine months, we adopt fixed effects models with lagged variables to assess the effects of the metrics of online reviews on new product sales for both experience and search products. We also examine the page views by the followers, compare the effect of the percentage of positive versus negative reviews, and report several surprising results and novel insights into the role of eWOM in driving new product sales. These findings have meaningful implications for understanding the effect of online WOM on new product sales and for devising e-marketing strategies.

Research Framework and Hypotheses

Word of Mouth and New Product Diffusion

In the marketplace, WOM forms the basis of interpersonal communications that can significantly influence consumers' product evaluations and purchase decisions. WOM has shown to be more powerful than printed information, because WOM is considered more credible and valuable, especially the text messages prepared for dissemination online [22]. Studies of diffusion of innovations have found that the volume of WOM correlates significantly with consumer behavior and market outcome [3, 36]. Moreover, negative WOM is believed to spread more quickly than positive WOM, thus making "bad news travels faster" a fearful phenomenon to marketers, especially in the online environment. Practitioners often see WOM as a double-edged sword, as informal discussions among consumers can either make or break a product, particularly for new products. Despite its widespread impact, WOM has been considered "the world's most effective, yet least understood marketing strategy" [33, p. 26].

From a theoretical perspective, there is ample support for the effect of WOM on new product sales, even long before the advent of the Internet. The diffusion of innovation literature puts great emphasis on the effect of WOM as a channel of communication, particularly among the early majority and late majority, who tend to follow the innovators and early adopters [39]. In the early stage of a product life cycle (PLC), innovators are mainly affected by mass media, and after using the new products, they pass their opinions to latecomers via WOM channels [4]. Thus, the effect of WOM on new product sales exhibits an inverted U-curve. In studies of innovation diffusion, the coefficient of external influence (mass media) for innovators and that of internal influence (WOM) for imitators are estimated using the density function of time. Aside from surveys and experiments, the effect of WOM on new product sales has largely been inferred from sales data. The Bass model has proved capable of predicting the growth patterns of a wide range of new products and has been widely adopted for sales forecasts of new products across industries [31].

Online WOM is even more influential because of its speed, convenience, wide reach, and the absence of face-to-face human pressure [38]. Moreover, e-commerce operators today can archive WOM interactions from online forums in databases, which lends opportunities to estimate their effects directly and perhaps more accurately. To help marketers benefit from the power of eWOM, researchers have conducted an increasing number of studies that have found a tremendous effect of consumer reviews on product sales [8, 11, 28, 32]. However, because of the different measures and research designs, findings regarding the effects of various metrics of online reviews have not always been consistent. Aside from the volume and valence of reviews, researchers need to pay attention to the influence of product category, the role of followers, and the exact nature of WOM (i.e., positive vs. negative reviews).

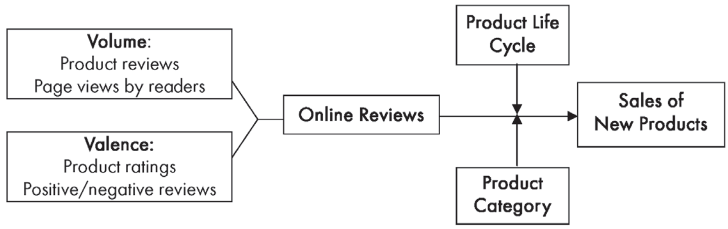

Figure 1. An Integrative Framework on the Effects of Online Reviews on New Product Sales

The lack of theoretical guidance in this area calls for theoretical integration, which can offer a more holistic picture of the process.

An Integrative Model

Given the research questions outlined in the introduction, we propose an integrative framework for the role of online WOM in affecting the sales of new products and address both the important empirical generalizations and theoretical questions (Figure 1). Here we focus on the relationship between online reviews and new product sales. Online WOM in the form of consumer reviews of new products includes two key metrics: (1) volume of reviews and (2) valence of reviews (average rating). In addition, this study also investigates the effect of the page views by readers or followers. Aside from the overall valence of reviews or ratings of new products, we examine the effects of the percentage of positive and negative reviews. Furthermore, product category and PLC serve as the moderating factors for the effect of online reviews. In the following sections, we draw from theories of innovation diffusion and consumer learning to articulate the research questions and propose hypotheses regarding the effects of these factors on new product sales in an online market.

Product Category

Despite the critical role of eWOM in new product diffusion, online reviews may not have similar effects on all products, and there are important contextual variables that moderate the influence of online reviews [45]. Existing studies show that information and entertainment products tend to exhibit a pattern of diffusion that is different from that of durable goods [17]. According to their nature, products can be broadly classified as either search products or experience products, based on the extent to which consumers can evaluate them by specific attributes. Search products, such as electronics, are goods that consumers can evaluate by specific attributes before purchase. Experience products, such as movies and books, require feeling or experiencing, are more difficult to describe using specific attributes, and may render varied experiences across consumers [34, 42]. Researchers have shown that product type affects consumers' search behavior and use of information sources, which in turn influences their choices [27]. Overall, consumers assessing a search product are more likely to use a systematic decision-making process by evaluating the specific attributes of the product, whereas consumers considering an experience product rely more on extrinsic attribute-irrelevant cues, such as the popularity of the product.

For search goods, which are usually evaluated by instrumental evaluative cues (i.e., technical or performance aspects of a product), there is a multitude of information on product attributes, functions, and performance for consumers on online channels. Most important, the evaluation of products by other consumers, that is, their ratings of the products, is prominently displayed. Consumers can easily access such information. Thus, the valence of reviews or the average ratings of products greatly affect consumers' evaluations and purchase decisions for search products. Experience products, in contrast, are typically evaluated by affective evaluative cues (e.g., aesthetic aspects of a product). In the online environment, however, consumers cannot directly feel the products, such as flowers or video games, or experience product attributes. Moreover, evaluations of experience products by consumers tend to be idiosyncratic and less indicative of a product's quality. In such cases, extrinsic cues such as the popularity of a product as indicated by the volume of reviews become more important for consumers. Therefore, even though both the volume and valence of reviews are important factors for new product sales, the extent of their influence tends to be different across the two product categories [24].

> ***Hypothesis 1:*** *The volume of online reviews has a greater impact on sales of experience products than on sales of search products.*

> ***Hypothesis 2:*** *The valence of reviews (ratings) has a greater impact on sales of search products than on sales of experience products.*

Reviews Versus Page Views

In the diffusion literature, early adopters are considered the baseline driving force of the diffusion process, especially in the early introduction period [4, 39]. Studies of social networks and social learning, however, suggest that people's decision to engage in a new behavior depends on the choices of other people, leading to an informational cascade [7]. Thus, recent research has questioned the dominant role of early adopters in the diffusion of new products and highlighted the difficulty in identifying and targeting the early adopters [25]. Some studies of social networks and social contagion have found latecomers to be more influential in the diffusion process. Recent computer simulations by Miller et al. [32] and Watts and Dodds [41] support this view and illustrate that the demand for products evolves partly as a function of interpersonal communication and that social learning processes shape demand for new products. Moreover, they find that large cascades of influence are driven not by influentials or early adopters but by a critical mass of easily influenced latecomers, confirming the threshold model based on social network theory [21] and calling for greater attention to latecomers in the diffusion process.

In online forums, an important indicator of a review's influence is the number of page views by readers or followers which indicates the degree of dispersion of the online reviews and signals the impact of the existing reviews in generating consumer awareness and interest in a product among readers. In the context of e-commerce, online reviews are of limited value unless other people read them and make decisions based on these reviews. Thus, aside from the volume of online reviews, the number of consumer readings or page views of the posted reviews should have a significant effect on new product sales. Following social network theory, a threshold level is reached after a sufficient number of people make a particular choice that is attractive to others [7, 21]. If eWOM is effective in influencing the sales of new products, it is likely that the page views by readers are more important than the reviews themselves. Aside from laboratory findings, stronger evidence is needed to assess the effect of page views on new product sales.

> ***Hypothesis 3***: *The volume of page views by readers has a stronger effect on new product sales than does the volume of reviews.*

Product Life Cycle

The effect of eWOM on new product sales over time has important managerial implications for understanding and influencing online WOM. Although diffusion theory deals with the adoption of innovations in societies at the aggregate product category level, this framework has been implicitly adopted in studies of online reviews [10, 13] and can help analyze the role of eWOM in new product growth. The Bass model posits that in the introduction stage of the PLC, early adopters are affected by external influences, such as mass media. Thus, early adopters dominate the adoption of new products in the initial period of the PLC. In the later growth and maturity periods of the PLC, the adoption of new products accelerates because of the increasing number of followers and latecomers, who are affected by internal influences such as WOM. Thus, WOM plays an increasingly important role in new product adoption during the growth stage of the PLC. If we extend this same thinking to the online environment, we would expect online product reviews to exert minimum effect in the early introductory stage of a new product but greater effect in the growth period of the product, and then to level off thereafter.

However, recent studies suggest that the PLC in the online environment does not necessarily parallel its offline pattern. The escalation in the size of audience and reach is changing the dynamics of many industries in which WOM has traditionally played an important role, especially for new product launches [28]. The entertainment industry has seen rapid spread of online WOM, which is shrinking the life cycle of its products and prompting firms to rethink their pre- and postlaunch marketing strategies. In fact, movies are seeing much more rapid changes in revenues between the opening weekend and the second weekend, suggesting that public opinion is spreading faster and has a greater impact on new product sales [11, 35]. In the connected world of the Internet, product reviews can reach consumers instantaneously. Consumers no longer have to wait for community authorities or their friends to give them advice. Instead, they can access "expert" opinions from other consumers at their fingertips. Recent studies suggest that information cascades can sharpen the takeoff of new products, exaggerate product growth, and reverse sales growth when maturity sets in [7, 15, 20]. While new products may experience explosive growth in the beginning as a result of cascade effects, such effects are not cumulative and tend to dissipate over time. This is true for most new products that are not major innovations and take less time to diffuse through the social networks. Therefore, online WOM in the form of consumer reviews has a greater influence on new product sales early on rather than later in the postlaunch period.

> ***Hypothesis 4:*** *The volume of online reviews has a stronger effect on new product sales in the early period after new product launch than in the post-launch period.*

Percentage of Positive Versus Negative Reviews

Positive reviews by other consumers are indicative of a product's quality and reputation. Negative reviews signal a lack of confidence in the product among the early adopters and dampen new product sales. Thus, aside from the valence of reviews or ratings, the percentage or the relative proportion of positive and negative reviews is another important indicator of the overall sentiment or valence of consumer reviews and can significantly influence consumer perceptions and purchase decisions [30, 32]. In addition to the average rating of products, many e-commerce Web sites display the number or percentage of ratings, for example, the number of stars or thumb-ups and thumb-downs. Amazon.com displays the number of positive and negative reviews as well as bars of different lengths for each category of five ratings, showing clearly the proportion of positive and negative reviews. Obviously, this is an important piece of information for consumers, who can then assess the relative amount of positive and negative reviews that a product attracts.

The literature on impression formation suggests that when comparing negative with positive information, people pay more attention to and place greater weight on negative information during product assessment [18, 40]. Studies of consumer information search also show that when there is a time constraint, people tend to focus more on negative information than positive information [44] and that unfavorable product ratings tend to have a greater impact on purchase intention than favorable product ratings [43]. Overall, negative information has more value to the receiver of WOM communication, and consumers tend to weigh negative information more heavily than positive information in both judgment and decision-making tasks [26].

A widely accepted explanation for the impact of negative WOM is the so-called negativity bias, a psychological tendency for people to give greater diagnostic weight to negative information in making evaluations [23]. This negativity bias can be seen as a function of the individual's social environment, which contains a greater number of positive than negative cues. Thus, negative cues attract more attention and are perceived as counternormative and more often attributed to the stimulus object than are positive cues [26]. Negative information is also more diagnostic than positive information because the influence of negative information assigning a product to a lower-quality class exceeds that of positive information's assigning it to a higher-quality class [1]. Existing studies of eWOM have also reported evidence of the negativity bias, for instance, in the reviews of movies [5]. Thus, the relative amount or the percentage of negative reviews has a greater influence on new product sales than the percentage of positive reviews in the online environment.

> ***Hypothesis 5:*** *The percentage of negative reviews has a greater impact on new product sales than that of positive reviews.*

Methodology

Data Collection

The data for this study were collected from the U.S. Web site of Amazon.com, which sells a variety of consumer products and has been used in a number of studies on B2C e-commerce [2, 30]. Amazon.com serves as a good source of online WOM and new product sales in the e-marketplace for several reasons. First, it is one of the largest and most popular online shopping Web sites, with millions of registered members and also frequented by nonmembers. It requires no membership fee to join. This helps reduce any potential selection bias in the demographic composition of an online forum's members and visitors. Amazon.com is also well known for its extensive customer review system. Anybody—even nonmembers—can post, browse, and comment on a product review and rating. Moreover, the navigational structure of the Web site is well designed, with all of the relevant information (prices and sales rank of products, customer reviews and ratings) conveniently displayed so that finding and collecting it is straightforward, thus reducing possible errors during data collection. "New" products in this study refer to those that are new to the Amazon.com marketplace and its customers and not previously available. On Amazon.com, the release dates of new products are displayed prominently by calendar dates, indicating the first date on which they became available. WOM messages (i.e., reviews and comments) and ratings are archived and indexed by the dates of posting. Thus, it is possible to track the data of new product sales and eWOM on a continuous basis.

Existing studies of online WOM have largely dealt with information or entertainment products such as books, movies, and television programs. These products can be classified as experience products, and their life cycles vary from a short period of concentrated sales since the release date (e.g., movies) to a long time period (television series). Their release dates tend to concentrate on certain periods (e.g., beginning of a new year or in the summer). Since we need to compare two different product categories—search versus experience products—it is important that the data from both product categories come from the same source and largely overlap in time. Thus, we use entertainment video games as the experience products. For search products, we focus on consumer electronics. These two types of products have been used to represent experience versus search products in previous studies [24, 42, 45]. Most important, these two product types are stand-alone categories on Amazon.com, which posts the sales rank data of the products in these categories. This way, the sales rank data are category adjusted.

We tracked the online consumer reviews, noting the volume, valence (average rating), and page views of the top reviews, the sales rank data, and related information for the new products from these two product categories on a weekly basis for the nine-month period from August 2007 to April 2008, which is sufficient time to examine new product sales for the introductory period of the PLC and beyond. Starting on August 1, 2007, we identified each new product from these two categories on Amazon.com. Based on our comparisons, their release dates more or less coincided with those in the offline market. For this first week and each of the following weeks, we downloaded the home pages of these products and saved them in an archive for data input and verification. Then, all of the relevant data, including the product category, sales rank, number of reviews and page views, average rating, and frequencies of scores, were extracted from these saved Web pages and put into a database. Since the new products were introduced at different times during the nine-month period, we have a maximum of 36 weeks of data only for those new products that were introduced at the beginning, thus resulting in an unbalanced panel data set.

Measures of Variables

Amazon.com does not release the actual sales volume of its products but posts a product's sales rank, which is measured by cumulative sales adjusted by the previous week's sales volume. Like previous studies based on data from Amazon.com (e.g., [9]), we use a transformation of sales ranks of products as a proxy of actual sales. A product's sales rank is inversely related to its sales. Thus, the top-selling product at the site has a sales rank of one, and the slower-moving products are assigned higher sequential ranks. According to Chevalier and Mayzlin [9], the relationship between the sales rank and the actual volume of book sales on Amazon.com can be approximately described by $\ln[Sales] = \beta 0 - \beta 1 * \ln[SalesRank]$. The relationship between $\ln[Sales]$ and $\ln[SalesRank]$ is approximately linear. Thus, in lieu of sales data, log rank is the appropriate dependent variable. Because sales rank is a log-linear function of sales with a negative slope, we use $-\text{Log}[SalesRank]$ as a proxy for sales.

Independent variables include the volume and valence of online consumer reviews. Based on Chevalier and Mayzlin [9], we use the cumulative number of reviews to measure the volume of online reviews. People who have purchased and/or used the products post their reviews and ratings of these products. Following Clemons et al. [10] and Dellarocas et al. [13], we use the average ratings of products, that is, the average number of stars that the reviewers have assigned (on a scale of one to five stars, with five stars being the best), to capture the valence of consumer reviews. According to Amazon.com, one to two stars indicate negative ratings, three stars are neutral, and four to five stars are positive ratings. The frequencies of numeric ratings are also recorded to generate the percentages of positive and negative reviews while excluding the neutral ratings. In addition, Amazon.com posts the most popular reviews on the home page of products. These reviews have been rated as the most helpful, making these reviewers the opinion leaders. The cumulative number of page views of the top reviews by readers is also posted on the home page of a product following these reviews, revealing the dispersion among followers. As for product type, computer/video games represent the experience products and consumer electronics indicate the search goods. Finally, a product's "age" is recorded as the number of weeks since its release date to the end of data collection.

Control variables are product categories and subcategories, list price, price promotion (discount), other stores providing the same products, and free shipping, which may affect the parameter estimates of the independent variables. We include the product subcategories to control for subcategory variations or heterogeneity to minimize any confounding effect. Search products have nine subcategories: cameras, televisions, MP3 players, computers, office electronics, ground positioning systems, equalizers, optics, and electronic accessories. Experience products have ten subcategories from four major manufacturers: (1) Sony: Sony PSP, Playstation 2, Playstation 3; (2) Nintendo: Nintendo DS, Nintendo Wii, Game Boy Advance, GameCube; (3) Microsoft: Xbox, Xbox360; and (4) Apple: Mac Games. We used the list prices to control for price variations among products.

Results

Preliminary Analysis

Over the period of nine months, we collected data on 332 new products, including 131 search products and 201 experience products, and made a total of 7,470 observations. Table 1 provides the summary statistics, including the mean and standard deviation of variables. The sales rank of experience products ranges from 12 to 7,003, and the sales rank of search products ranges from 2 to 64,852. As shown in Figure 2, new product sales in both categories show a downward trend over time. On average, each experience product receives 17 reviews, and each search product receives 5 reviews. Experience products on average attract more page views for their top reviews (42.99), thus having greater dispersion than search products (13.53). The average rating of experience products (3.85) is slightly higher than that of search products (3.72); thus, the overall ratings of both product categories are positive. The percentage of positive reviews for experience products (70.50 percent) is comparable to that for search products (64.10 percent), whereas search products receive a greater percentage of negative reviews (23.40 percent) than experience products do (16.30 percent).

Table 1. Key Descriptive Statistics.

	Mean	SD	Minimum	Maximum
Experience products (n = 201)				
Sales rank*	3,459.06	4,705	12	7,003
Volume of reviews	16.87	34.39	0	278
Valence (average rating: 1–5)	3.85	0.81	1	5
Volume of page views	42.99	76.20	0	548
Percentage of positive reviews**	70.50	27.40	0	100
Percentage of negative reviews**	16.30	23.40	0	100
Search products (n = 131)				
Sales rank*	57,822	45,245	2	64,852
Volume of reviews	4.49	32.46	0	641
Valence (average rating: 1–5)	3.72	1.25	1	5
Volume of page views	13.53	54.44	0	881
Percentage of positive reviews**	64.10	37.70	0	100
Percentage of negative reviews**	23.40	33.10	0	100

* Low sales ranks denote higher sales. ** The percentages of positive reviews and negative reviews do not add up to 100 percent, because the percentage of neutral ratings is not included.

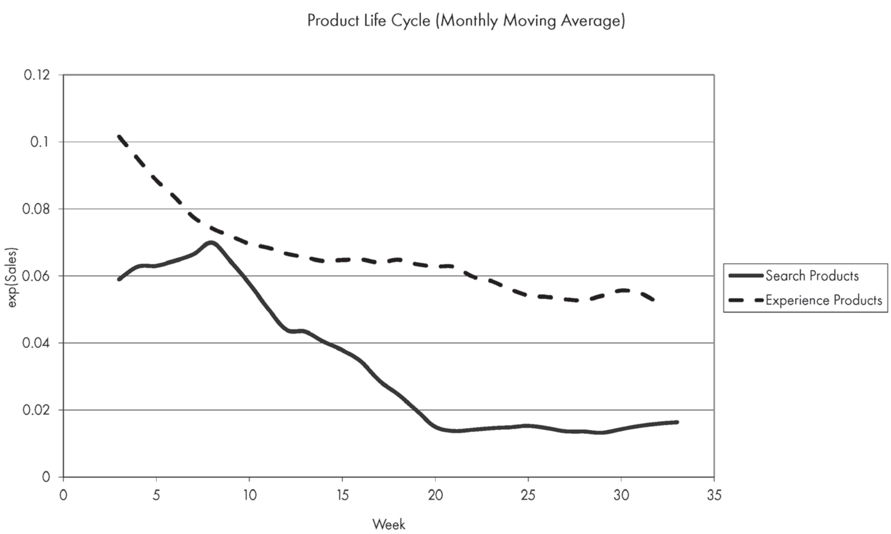

Figure 2. Sales of Experience and Search Products over Time

When examining the effect of online reviews on new product sales, it is necessary to address the potential endogeneity bias among the predictor variables [16, 19]. In the current data set, the dependent variable is a proxy of a product's sales based on the sales rank, which is measured by its cumulative sales adjusted by the sales of the previous week. The volume, valence, and page views of reviews are cumulative, that is, up to date. Thus, the reviews are not necessarily posted during the same week when a product's sales rank is measured. The volume and valence of online reviews measured this way, unlike those of the concurrent periods, are less vulnerable to endogeneity problems. It is unlikely that these measures of online product reviews are systematically related to variations in the periodic shocks of new product sales [6]. However, it is still possible that the metrics of online reviews may be influenced by the sales of new products from previous weeks. Other researchers have adopted the two-stage or three-stage least squares regression methods to handle this problem. In our study, which adopts the fixed effects model, we use the lagged variables of the potentially endogenous variables instead of the original variables in the regression models. Thus, for all the metrics of online reviews such as volume, valence, page views, and percentage of positive versus negative reviews, their lagged variables (for a period of one week) are used in subsequent analyses of the unbalanced panel data.

Panel Data Analysis

Unlike some previous studies that use online reviews as a forecasting tool and adopt time series analyses to examine the changes of their influence over time, we are interested in the long-term effect, that is, the parameter estimates, of online reviews on a new product's sales performance. Thus, we adopt a fixed effects model to generate the coefficients of the lagged predictor variables. To arrive at accurate estimates of the effects of the predictor variables, we include all the necessary control variables as covariates. Variables such as free shipping (Free shipping), prices of products (Price), whether a product is on promotion or not (Promotion), whether the product is available at other stores (Other stores), and product type and subcategories can significantly affect consumer choices; thus, they are controlled for when estimating the effects of other variables. In addition, we also control for the effect of time or trend using week age and week age squared of these products.

Table 2 shows that the models for experience and search products have similar predictive validity (adjusted R^2: 0.660 vs. 0.689). The Chow test of equality indicates that the two regression models are significantly different in terms of their model structures and parameter coefficients ($F = 42.37$, $p \leq 0.001$). Specifically, based on the parameter estimates and the t-test results, the volume of reviews has a stronger positive impact for experience products than for search products (1.042 vs. 0.171, $t = 5.280$, $p \leq 0.001$), thus supporting H1. Meanwhile, the valence of reviews has a greater positive effect on search products than on experience products (0.329 vs. 0.131, $t = 11.072$, $p \leq 0.001$), providing support for H2.

Moreover, the effect of volume of page views is stronger than that of volume of reviews for search products (0.248 vs. 0.171, $t = 7.99$, $p \leq 0.001$). This is consistent with H2 in that the valence of reviews has a greater effect than the volume of reviews. However, the result is reversed for experience products (1.042 vs. 0.272). Thus, H3 receives only partial support. This is perhaps due to the nature of experience products, for which product popularity as measured by the number of reviews plays a powerful role. Overall, the effect of eWOM metrics varies across the two product categories.

Table 2. A Fixed Effects Model of New Product Sales with Lagged Variables.

Dependent variable: New product sales

Model/fitness	Experience products	Search products	Chow-test/ *t*-test
Adjusted R^2	0.660	0.689	
F-value	342.92	93.23	42.37
Sig. *F*	0.000	0.000	0.000
Control variables			
Free shipping	0.030*	0.176***	7.656***
Price	-0.021†	-0.102**	0.686
Promotion	0.005	0.190***	9.525***
Other stores	-0.043***	-0.072**	2.814**
Week age	–1.150***	-0.380***	0.300
Week age squared	0.759***	0.186*	1.204
eWOM metrics			
Volume of reviews	1.042***	0.171*	5.280***
Valence	0.131***	0.329***	11.072***
Volume of page views	0.272***	0.248**	6.747***
Volume of reviews squared	-0.591***	-0.133†	9.144***

Notes: The results are standardized beta coefficients. † Significant at ≤ 0.1; * significant at ≤ 0.05; ** significant at ≤ 0.01; *** significant at ≤ 0.001.

Table 2 also shows that for both experience and search products, week age has a significant negative effect, and week age squared has a significant positive effect. This suggests that new product sales have a downward slope in the initial period and then rise up again in the later period. The results in Table 2 also indicate that the linear function of the volume of reviews has a positive effect for both product categories ($\beta = 1.042$ for experience products and $\beta = 0.171$ for search products). Thus, the volume of reviews has a positive effect on new product sales in the early period for both product categories. Since the volume of reviews is cumulative, we adopt its quadratic function to examine its effect in the later period. The results indicate that the quadratic function of the volume of reviews has a significant negative effect for both product categories ($\beta = -0.591$ for experience products and $\beta = -0.133$ for search products). These findings provide support for H4: the volume of reviews has a significant positive effect in the beginning period after a new product's launch, and such effect exhibits a downward trend in the later period. This is consistent with recent observations that eWOM has the greatest impact during the early period of a PLC, and such effect decreases over time [2, 13].

Lastly, we use hierarchical regressions to test H5 regarding the effect of the percentage of negative reviews versus that of positive reviews. Table 3 shows that the second regression model is significant (adjusted $R^2 = 0.441$, $F = 323.96$, $p \leq 0.001$). The coefficient of the percentage of negative reviews is -0.187 ($p \leq 0.001$), and the coefficient of the percentage of positive reviews is

Table 3. Regression Results of the Percentage of Positive and Negative Reviews.

Dependent variable: New product sales

Model/fitness	Model 1	Model 2	Model 3 (experience)	Model 4 (search)
Adjusted R^2	0.367	0.441	0.495	0.508
F-value	308.61	323.96	365.27	85.86
Sig. *F*	0.000	0.000	0.000	0.000
Control variables				
Free shipping	0.197***	0.163***	0.311***	0.012
Price	0.068***	-0.014	-0.004	-0.034*
Promotion	0.101***	0.109***	0.343***	0.028*
Other stores	-0.079***	-0.057***	-0.045	-0.081***
Product type (experience)	0.156***	0.109***		
Week age	-0.787***	-0.716***	-0.400***	-0.954***
Week age squared	0.494**	0.438***	0.230*	0.599***
Volume of reviews	0.394***	0.370***	0.064*	0.557***
% of positive reviews		0.104***	0.037	0.057*
% of negative reviews		-0.187***	-0.179***	-0.191***

Notes: The results are standardized coefficients. * Significant at ≤ 0.05; ** significant at ≤ 0.01; *** significant at ≤ 0.001.

0.104 ($p \leq 0.001$); thus, both are significant even after controlling for the effect of the volume of reviews. The *t*-test results suggest that the percentage of negative reviews has a greater effect on new product sales than the percentage of positive reviews ($t = 22.27$, $p \leq 0.001$). Furthermore, we run separate models for the two product categories (Models 3 and 4) and generate results similar to those of the second model. Thus, H5 regarding the negativity bias is supported.

Conclusion and Discussion

Although each of the metrics of online reviews individually affects consumer purchases, their combined impact has a tremendous effect on new product sales. Experience products are more subject to the influence of the volume of reviews, which signals the popularity of a product and an awareness effect from the sheer volume of reviews [15]. Valence, however, has a greater impact on the sales of search products, indicating a stronger persuasive effect of product ratings for more complex products and consumers experiencing a high level of involvement [37]. The effect of the volume of page views by readers is significant for both experience and search products, but the volume of page views exerts a greater influence than the volume of reviews only for search products, suggesting the significant role played by followers or latecomers in this product category. This is similar to the findings from computer simulations [32, 41].

Unlike the proposition of the diffusion model, the effect of eWOM as measured by the volume of reviews has a positive effect in the early period of a PLC, and such effect decreases in the later period, suggesting the significant role played by early reviews [2, 32]. Meanwhile, the percentage of negative reviews has a stronger effect than that of positive reviews, supporting the negativity bias in that negative reviews have a greater effect on consumer decisions. Overall, these metrics of online reviews offer new opportunities to test the effect of eWOM and highlight the need for more theory development and empirical studies. Researchers can incorporate the effects of these eWOM variables to arrive at more accurate parameter estimates and sales forecasts throughout a product's life cycle.

The findings of this study shed some light on the effects of eWOM on new product sales and offer interesting revelations for marketing professionals. While the key metrics of online reviews all significantly affect new product sales, their effects tend to be stronger or weaker depending on the product category, that is, whether it is an experience product or a search product. Clearly, the number of reviews that a product attracts matters, particularly for experience products. Ratings by consumers, however, are more important for search products. Thus, the benefits of satisfied customers as the best advertisement can be amplified many times given the speed and wide reach of online WOM. Quality reviews can help marketers attract a large number of like-minded latecomers and guide them to select the product as their preferred choice early on to create a cascade effect and propel new product growth [28, 32].

Given the effects of the volume of reviews within weeks of a new product's release, marketers need to be vigilant about eWOM early on and encourage quality reviews during the initial launch period. They can adopt proactive strategies, for instance, conducting consumer focus groups or jury panels prior to new product launch to gauge consumer sentiment and the likely nature of consumer WOM and to uncover gaps between new product offerings and consumer perceptions. Marketers may incorporate valuable consumer feedback from these prelaunch activities into the development of new products and formulation of marketing strategies for commercialization. Even though positive consumer reviews can help reduce the uncertainty and risks associated with purchase decisions, it is necessary for marketers to monitor the relative amount of negative reviews given the negativity bias in consumer information search and processing. It is crucial that marketers emphasize the positive aspects of these new products in their promotions and encourage quality and helpful reviews, which a new product needs to attract consumers.

Limitations and Future Directions

The meaningful findings of our study notwithstanding, the study has several limitations that readers need to be aware of. First, we collected data from only one online retailer. Although the data from Amazon.com are reliable and many researchers have used data from this Web site, the results should be validated and compared with data from other sources because e-commerce Web sites may differ in their review and rating systems [29]. Although Amazon.com and this study include "other stores" that may be brick-and-mortar stores, there are no other variables to control for promotion and competition of the same products from offline stores. We do not have an accurate measure for PLCs, which may vary across product categories. While the effects of brand names have been accounted for experience products with the product subcategory variables, there are numerous brands among search products. Thus, we could not fully examine the effect of brand image for search products, although prices of products indirectly reflect product quality and brand image. Future researchers should consider direct measures of brand image when it is feasible. Since many consumers access product reviews at online forums and then make their purchases offline, the effect of eWOM on offline purchases demands greater attention in future research.

The noncumulative data of sales ranks of new products at Amazon.com present a significant challenge to test the effect of online WOM from this Web site. Several researchers have attempted to extract sales volume data for the books category from the sales rankings at Amazon.com by "reverse engineering" [9]. With collaboration from e-commerce operators and actual sales data, researchers may arrive at accurate estimates of the effects of eWOM on the sales of new products. Many online forums let readers comment on the product reviews, for instance, by indicating their perceived helpfulness of these reviews. Future studies might examine the specific features of online product reviews and the reviewers to determine the factors that influence the quality of reviews and attract consumers to new products. Aside from commercial platforms like Amazon.com, social network media such as Facebook and Twitter increasingly present opportunities for studying the effect of eWOM on the adoption of new products by consumers and the process of value co-creation [46]. Other measures of online WOM activities, such as the size of networks and the number of threads in a discussion group, may offer rich insight into consumer interactions and user-generated content and their effects on the diffusion of new products in the e-marketplace.

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