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Do Online Reviews Affect Product Sales? The Role of Reviewer Characteristics and Temporal Effects++

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Abstract

Online product reviews provided by consumers who previously purchased products have become a major information source for consumers and marketers regarding product quality. This study extends previous research by conducting a more compelling test of the effect of online reviews on sales. In particular, we consider both quantitative and qualitative aspects of online reviews, such as reviewer quality, reviewer exposure, product coverage, and temporal effects. Using transaction cost economics and uncertainty reduction theories, this study adopts a portfolio approach to assess the effectiveness of the online review market. We show that consumers understand the value difference between favorable news and unfavorable news and respond accordingly. Furthermore, when consumers read online reviews, they pay attention not only to review scores but to other contextual information such as a reviewer's reputation and reviewer exposure. The market responds more favorably to reviews written by reviewers with better reputation and higher exposure. Finally, we demonstrate that the impact of online reviews on sales diminishes over time. This suggests that firms need not provide incentives for customers to write reviews beyond a certain time period after products have been released.

Keywords: Word-of-Mouth, Online Product Reviews, Transaction Cost Economics, Uncertainty Reduction, Efficient Market, Portfolio Analysis

1. Introduction

Word-of-mouth (WOM) communication is considered a valuable marketing resource for consumers and marketers and a reliable and effective metric for measuring customer loyalty with critical implications for a product's success. WOM communication includes all forms of information exchange among consumers regarding the characteristics and usage of particular products, services, or vendors. It is widely considered to be a major driver for the diffusion of new products and services [3, 6, 12].

Online product reviews have become a major informational source for consumers due to the fast spread of WOM[1] communication through the Internet. Reichheld [35] claims that a customer's propensity to recommend a product to others – termed "referral value" – is the most important success measure in business today. Reichheld [35] argues that referral value may predict firm performance even better than traditional measures such as customer satisfaction. Hence, online product reviews have fundamental implications for management activities such as reputation building and customer acquisition.

Previous research has studied the impact of online product reviews on product sales with a variety of regression models [14, 15, 26]. This stream of literature provides useful insights by linking online reviews with sales; most of the studies show a positive correlation between the average review score and product sales. However, one implicit assumption in these studies is that consumers consider only the *scales* of review scores when they make a purchase decision. To the best of our knowledge, none of the previous studies considered other informational aspects of online reviews such as the quality reputation of a reviewer and his or her exposure to the online community (the number of times a reviewer's name is exposed to the public), the information environment or the age of a product. The latter variables are more compelling measurements of the information content of online reviews because they are directly related to the intrinsic quality of the reviews in terms of reliability and trustworthiness. Further, in trying to

[1] Although the phrase "word-of-mouth" generally refers to oral communication, in this paper we are using this term to refer to person-to-person virtual communication.

understand the effectiveness of online reviews, it remains unclear what role time periods play in affecting sales. That is, should firms like Amazon.com encourage buyers to provide reviews for all items or only for newly released items?

This paper extends previous research by linking changes in online review scores to changes in sales while considering other important dimensions of online reviews such as the quality and exposure of a reviewer, the information environment, and the age of a product. We use a "market reaction" lens to assess the effectiveness of online reviews. Treating the online review environment as a "market," we argue that online reviews are like market signals that contain information about the quality of an item. This analogy helps us to use a portfolio methodology, typically used in the finance literature, to assess the effectiveness of the online reviews. We show that consumers use the information embedded in online reviews to reduce the uncertainty involved in purchase decisions, thereby enabling them to choose the item with the lowest transaction cost.

The paper makes three primary contributions to the research literature. First, we show that the online review market behaves as an "efficient market" that understands the value difference between favorable news and unfavorable news and responds accordingly. By demonstrating the effectiveness of the online review market, this research sensitizes managers to the importance of improving the underlying quality of items for sale and investing the necessary effort in managing customer expectations and reactions to products. Second, we show that consumers pay attention to elements other than review scores, such as reviewer quality, reviewer exposure, and product coverage. The market is more responsive to a review written by someone with a better reputation and more exposure, while it responds less to an item that is more extensively covered by reviewers; prior research that ignored these dimensions may potentially overestimate the impact of review scores. Our paper explicitly considers these factors and demonstrates the roles they play. Consequently, it provides a more complete understanding of how online reviews influence the sale of an item. Third, over time, online reviews do not affect sales equally. The relationship between online reviews and sales depends on the "age" of a product; the longer an item has been on the market, the smaller the impact online reviews will have on its sales.

The paper proceeds as follows. Section 2 summarizes the related literature. Section 3 describes the theoretical framework and research hypotheses. Section 4 describes the research setting and methodology. Section 5 provides data analysis and results. Section 6 contains a discussion of the findings, their implications, and some concluding remarks.

2. Literature Review

While word-of-mouth has been studied extensively in the marketing literature, it is only recently that online product reviews have begun to draw the attention of marketing and information systems researchers. We summarize a cross-section of research in Table 1. As stated above, previous studies focus on the quantitative aspects of online reviews by linking the level of online reviews to the level of sales. In this study, we link the change in reviews to the change in sales by considering both quantitative and qualitative aspects of online reviews.

Author(s)	Data sources	Findings
Basuroy, Chatterjee, and Ravid (2003) [4]	200 films released between late 1991 and early 1993 from *Baseline Services* in California and *Variety* magazine	- Both positive and negative reviews are correlated with weekly box office revenues over an eight-week period. However, the impact of negative reviews (but not that of positive reviews) diminishes over time. - Negative reviews hurt more than positive reviews help box office performance, but only in the first week of a film's run.
Liu (2006) [33]	*Yahoo! Movies* website	- WOM information offers significant explanatory power for both aggregate and weekly box office revenue, especially in the early weeks after opening. - However, as measured by the percentages of positive and negative messages, most of this explanatory power comes from the volume of WOM, not its valence.
Godes and Mayzlin (2004) [26]	Viewership data from Nielsen ratings and conversation observed in Usenet newsgroup	The dispersion of conversations about weekly TV shows across Internet communities is positively correlated with the evolution of viewership for these shows.

Eliashberg and Shugan (1997) [30]	Box office sales data from Baseline, Inc. and Entertainment Data Incorporated (EDI)	Critical reviews correlate with late and cumulative box office receipts but do not have a significant correlation with early box office receipts.
Chevalier and Mayzlin (2006) [15]	Book characteristics and user review data collected from the public web sites of Amazon.com and BarnesandNoble.com	- Reviews are overwhelmingly positive at both sites. - An improvement in a book's reviews leads to an increase in relative sales at that site. - The impact of 1-star reviews is greater than the impact of 5-star reviews.
Clemons, Gao, and Hitt (2006) [19]	Sales data from the craft beer industry and review data from Ratebeer.com	The variance of ratings and the strength of the most positive quartile of reviews play a significant role in determining which new products grow fastest in the marketplace.
Dellarocas, Awad, and Zhang (2004) [21]	User reviews posted on *Yahoo! Movies* website	A newly-derived revenue forecasting model that incorporates the impact of both publicity and word-of-mouth on a movie's revenue trajectory predicts the movie's total revenues accurately.
Duan, Gu, and Whinston (2005) [22]	Variety.com, *Yahoo! Movies* website, and *Box-Office Movies* website	- Box office sales are significantly influenced by the *number* of online postings. - *Ratings* of online user reviews have no significant impact on box office sales.
Chatterjee (2001) [13]	Survey	Consumers who are more familiar with a specific retailer are less likely to be affected by negative reviews of that retailer.
Chen, Wu, and Yoon (2004) [16]	Review and sales data from Amazon.com	More recommendations are associated with higher sales, while consumer ratings are not found to be related to sales.
Chen, Fay, and Wang (2003) [17]	Consumer reviews from Epinions.com, *Consumer Reports,* and *J.D. Power & Associates*	Controlling for price and quality, number of online postings is positively related to automobile sales.
Hu, Pavlou, and Zhang (2006) [28]	A field study and data collected from Amazon.com	The most satisfied and the most disgruntled consumers are the most likely to post reviews. Therefore, the average rating may not be a fair evaluation of the product.

Table 1. A Summary of the Related Literature.

3. Theoretical Background and Development of Hypotheses

Building on earlier work by Nobel prize winner Ronald Coase, Williamson [38] developed the theory of Transaction Cost Economics (TCE). TCE specifies variables (asset specificity, uncertainty, and transaction frequency) that determine why a certain transaction is conducted in a particular form (market, hierarchy, or hybrid) and whether the market or the hierarchy has a lower transaction cost under the two main assumptions of human behavior (bounded rationality and opportunism). Williamson argues that firms will choose a channel that minimizes their total cost, which is comprised of both production and transaction costs. Transaction costs occur because decision makers have limited cognitive processing power and cannot consider all possible scenarios (bounded rationality). Also, people may not be truthful about their intentions all the time and may act in a self-interested manner to take advantage of unforeseen circumstances (opportunism attributable to information asymmetry).

TCE has been successfully used to analyze issues such as internal organization, vertical integration and contracting, resource allocation, outsourcing decisions, etc. In the area of E-commerce, researchers have adopted TCE to explain both firm-level and individual-level issues. For example, Liang and Huang [31] proposed that consumers will choose a channel that has a lower transaction cost in deciding whether to buy from online stores or traditional stores. TCE is also a viable theory for explaining online consumer behavior.

When consumers decide which items to purchase on a given E-commerce website, they must go through a transaction process. It starts with searching for relevant products, followed by comparing prices, evaluating product quality, ordering, delivering, and post-sales services such as customer service and support. Online transactions of experience goods can involve product, process, and psychological uncertainties because the product descriptions might not provide sufficient information and the quality of the product can only be evaluated after trying or inspecting it. Product uncertainty refers to the situation in which consumers find after consuming a product that what they bought is different from what they perceived it to be at the shopping stage. Process uncertainty refers to the case in which consumers purchase products from undesired vendors, while psychological uncertainty refers to all of the emotional costs associated with the uncertainty. Overall, uncertainty refers to the costs associated with unexpected outcomes tied to information asymmetry. Therefore, a higher level of uncertainty implies a higher transaction cost, which will result in lower sales.

The goal of an E-commerce participant is to identify the intrinsic quality of a product based on all available information, and then to purchase the product with the lowest transaction cost or with the lowest uncertainty. To begin, a consumer may or may not possess any prior quality information about the product, and may or may not have previously conducted business with the online vendors involved. In such a scenario, there are both financial and psychological uncertainties associated with the product and the online vendors. According to Uncertainty Reduction Theory [5], whenever consumers lack knowledge of a product or of the outcomes of consuming that product, they will engage in uncertainty reduction efforts to mitigate and eliminate the risk associated with the uncertainty and to maximize the outcome value. Consumers can reduce the quality uncertainty by drilling down to obtain more details about the product's author, publishers, and subject. Consumers can then try to understand the returns policy and product warranty to further reduce uncertainty. For search goods, consumers may stop here because they are already informed about the value of the products. However, for experience goods, product uncertainty may still be high. To reduce this uncertainty, consumers will actively seek other information, such as online reviews written by previous customers. Overall uncertainty reduction theory provides a framework through which we can understand how individuals use different online information, such as online reviews, to: 1) infer product quality; 2) reduce product uncertainty; and 3) make a final purchase decision.

In this study, we investigate how consumers utilize online reviews to reduce the uncertainties associated with online purchases. Figure 1 provides an overview of the key conceptual constructs that we examine in this study. As Figure 1 illustrates, we focus on three sources that may influence a consumer's interpretation of online reviews and subsequent purchase decisions. We discuss each one in detail in the following subsections.

Insert Figure 1 about here

3.1 The Information Content of Online Reviews

Extending the market metaphor to online reviews, we suggest that when consumers purchase experience goods such as music CDs through the Internet, they first form a quality evaluation based on the combination of product information, their own personal tastes, and recommendations from friends or relatives. Due to the nature of experience goods, they will read reviews written by previous customers to help determine the value and quality of a product and to reduce the uncertainty associated with consuming that product. Reduced uncertainty should result in decreased transaction costs. Out of all the products that meet a consumer's requirements, the consumer will then select the one with lowest transaction cost.

Online reviews written by previous customers provide information about an item's perceived value. These reviews are helpful for making purchase decisions because they provide new customers with indirect experiences and help prospective customers reduce the uncertainties involved in inferring product quality. Product quality, which is the aggregate of all consumers' perceived values, reflects a product's intrinsic value.

In this paper, we use the term *favorable news* if a newly released review for any single item is better than its prior average (prior consensus reviews). On the other hand, if the newly released review is worse than the prior average for that product, we call it *unfavorable news*. Both types of news can change consumers' expectations about product quality. Favorable news may convert a consumer from "not buying" to "buying" because it reduces the quality uncertainty and, hence, the total transaction cost for a new customer. On the other hand, unfavorable news may convert a consumer from a potential "buying" consumer to a "not buying" one. In other words, favorable news and unfavorable news contain different information about product quality.

Hypothesis 1: Products with favorable reviews enjoy better sales than products with unfavorable reviews.

In this study, we investigate whether the marginal change in sales associated with the favorable news group exceeds that of the unfavorable news group. This is a more conservative test than testing the impact of each group of news on sales separately, in that the former method controls for the potential differences in risk-return relations for items included in our study. By controlling for the unobserved heterogeneity of items, we can ensure that our results are less likely to be distorted by sample selection bias.

3.2 The Role of Reviewer Quality

When consumers read online reviews, they will not limit themselves to the numerical scores alone. Consumers are likely to pay attention to reviewer credibility as well. To some degree, online reviews are not verifiable and may not be objective and credible to potential customers. Consumer reviews are user-generated and they measure product quality and valuation from a user's perspective [34]. Review scores are based more on reviewers' own experiences rather than on underlying characteristics of the product. In such cases, the reviews should have limited influence on other consumers' evaluations because consumers might think the reviewers have not provided unbiased quality assessments for the product. In other words, not all reviews have the same influence on consumers and consumers might selectively pay attention to the reviews written by reviewers with better quality reputations because such reviews are more trustworthy and reliable.

Trust can be defined as the expectation that an engaging partner will forgo short-term outcomes obtained through opportunistic behavior even when there is uncertainty about long-term benefits [11]. Chiles and McMackin [18] examined ways to incorporate trust and reputation into TCE. The honoring of moral obligations generates trust, and trust leads to the constraining of opportunistic behavior by way of reputation [18]. An entity builds its reputation by consistently engaging in trustworthy behavior. Trust reflects all of the historical trustworthy behaviors exerted by the entity and is a strong signal of reliability to third parties, no matter whether they have or have not conducted transactions with the entity before [18].

Without trust, information-exchanging parties need to constantly monitor the information being provided to guard against opportunistic behavior. Trust alleviates the monitoring and safeguarding costs associated with a contract because each party believes that the other party will act in a proper way to generate long-term benefits. Reputation about such trustworthiness decreases the cost of finding a contract partner [18]. Trust and reputation will thus lead to reduced behavioral uncertainty and decreased transaction costs because trust in a contractual relationship can result in more accurate and timely exchange of information and greater influence on the information receiver.

In an online review environment, there is enormous information asymmetry between online reviewers and new customers. Consumers may be inclined to give more weight to reviews written by reviewers with higher quality reputations because they perceive these reviews to be more credible and trustworthy. Reviewers with better reputations will help decrease a product's quality uncertainty because: 1) the market has previously found that these reviewers have the necessary expertise to assess product quality; and 2) they are less likely to engage in opportunistic behavior such as accepting payment from vendors for writing fake reviews that simply promote product sales. Thus, consumers might ignore the reviews written by lower quality reviewers because consumers perceive that the background and motivation of these reviewers prevents them from writing high quality reviews.

Hypothesis 2: The difference in sales between favorable news and unfavorable news is significantly different from zero for reviews written by higher quality reviewers, but not for reviews written by lower quality reviewers.

3.3 The Role of Reviewer Exposure

To some degree, reviews written by consumers on E-commerce websites are similar to reports written by analysts about market securities. The former expresses a reviewer's evaluation of product quality, the latter reveals an analyst's assessment of a company's valuation. In the finance literature, analyst quality is measured in two ways: analyst reputation [7, 20, 25, 34] and analyst exposure to the community [8]. Analysts' reputation and exposure affect both the information content of the signals they send to the market and the efficiency of the price discovery process for a market security.

Prior studies show that superior analysts elicit stronger market responses for their forecast revisions because their reputations affect the way that market participants perceive those forecast revisions [37]. In the analyst forecast literature, Bonner, Hugon, and Walther [8] documented that market participants react more strongly to forecast revisions issued by celebrity analysts (i.e., analysts with greater media exposure). Following Boorstin [9], they defined a celebrity as a famous person who is known for his name recall instead of performance-related qualities.

Conceptually, exposure is different from quality reputation. Exposure here refers to media exposure of a reviewer in the online review community. It can be measured by how many times a reviewer writes reviews on an online community website. In addition to being influenced by higher quality reviewers, consumers may pay more attention to higher exposure reviewers for reasons similar to those outlined above. Because consumers might ignore the reviews issued by reviewers with lower exposure, favorable (unfavorable) news written by such reviewers might not change the uncertainties associated with the consumption of a product or consumers' transaction costs for buying such products. Thus, favorable news might not solicit a different market response from unfavorable news if written by low-exposure reviewers.

Hypothesis 3: The difference in sales between favorable news and unfavorable news is significantly different from zero for reviews written by higher exposure reviewers, but not for reviews written by lower exposure reviewers.

3.4 The Role of Product Coverage and Age of an Item

Empirical research shows that security price reactions to unanticipated information conveyed to the market by actual earnings and earning forecasts are more substantial for smaller firms because the amount of private pre-disclosure information is an increasing function of firm size [1, 25]. For items with lower product coverage, that is, items with a smaller number of reviewers, there is an often limited amount of quality information about that item other than online reviews written by these reviewers. Therefore, reviewers play a very important role in terms of informing consumers of product quality and reducing uncertainty for such products. Each new reviewer might reveal additional product quality information to a new customer. The incremental impact of the reviews issued by a reviewer will be bigger when an item has fewer pre-existing reviewers that covered it before. After a product receives a critical mass of reviewers, new reviewers generally disseminate only a limited amount of new information. Thus, a new reviewer can not significantly reduce the uncertainty and has little or no impact on the transaction cost associated with buying that product.

One way of characterizing the product information environment is by counting the total number of reviewers that have commented on that product, which is similar to the number of analysts covering a firm. We classify products into two categories: high-coverage products and low-coverage products. High-coverage products are products whose total number of reviewers is above the median of our sample in a given batch; low-coverage products are ones whose total number of reviewers is below the median of our sample in a given batch.

Hypothesis 4: The difference in sales between favorable news and unfavorable news is significantly different from zero for reviews issued about low-coverage products but not for reviews issued about high-coverage products.

Besides product coverage, another factor that may affect the impact of online reviews on sales is the age of the item, that is, how long an item has been selling on the market. Although product coverage is likely to co-vary with the age of an item (a product is likely to have more reviewers if it has been on the market longer), conceptually these are distinct notions. While age refers to the time period an item has been in existence, product coverage refers to the number of reviewers for that item. In the initial phase of a product's introduction, there is a limited number of sources of product quality information. Hence, the market is likely to rely heavily on online reviews for purchase decisions during this time. However, as the market gains experience with the product with the passage of time, consumers can obtain product information from other sources such as recommendations from friends, newspapers, and magazine comments. Therefore, we posit that online reviews will have greater impact in the initial phase of a product lifecycle than in later phases. In other words, the impact of online reviews on sales will decrease with time.

Hypothesis 5: The market's reaction to favorable news and unfavorable news is significantly different from zero ONLY for a newly released product; as the age of a product increases, the difference will fall to zero.

4. Method and Measurement Development

4.1 Data

We collected our data from Amazon.com's Web Service (AWS). These data allow us to examine the effectiveness of online reviews and how consumers react to contextual elements such as reviewer quality, reviewer exposure, product coverage, and the impact of online reviews on sales over time. A panel of books, DVDs, and videos was randomly chosen in July 2005. We used panel data because compared with cross-sectional data, panel data are more suitable for studying the dynamics of adjustments because they control for unobserved heterogeneity [2, 10]. For each item, we collected its price, sales, and review information for several months at approximately three-day intervals. We identified each session by a unique sequence number. Because of some technical glitches in AWS, we had to exclude certain sequences in which only partial data were collected. For example, during several sessions, AWS did not respond to our queries or was offline and we were therefore only able to process partial or no data during these sessions. In total, we obtained 26 batches of review and item-level data.

Table 2 provides summary statistics for our panel data. The data include some very popular books, such as *The World Is Flat: A Brief History of the Twenty-first Century* by Thomas L. Friedman (sales rank fluctuates between No. 1 to No. 7), *Freakonomics: A Rogue Economist Explores the Hidden Side of Everything* by Steven D. Levitt (sales rank fluctuates between No. 3 to No. 11); popular DVDs, such as *The Simpsons* (sales rank fluctuates between 26 to 236) and *Star Wars* (sales rank fluctuates between 27 to 141); and videos, such as *Shall We Dance*, *Cinderella* and *John Wayne: American Hero: The John Wayne Story*. On Amazon.com, consumers can only report an integer product review on a 1-star to 5-star scale, where 1-star = least satisfied and 5-star = most satisfied. The average review scores for books, DVDs, and videos are 3.87, 4.07, and 4.02, respectively. This observation is consistent with Chevalier and Mayzlin's [15] finding that for books in both Amazon.com and BarnesandNoble.com websites, product reviews are overwhelmingly favorable.

Insert Table 2 about here

4.2 The Portfolio Approach

We adopt a portfolio approach to our investigation of whether customers of Amazon.com understand the difference between favorable news and unfavorable news and respond accordingly. The meaning of a portfolio in this context is different from a traditional finance context, where a portfolio represents a basket of securities, typically designed to reduce risk. Here our portfolio comprises products and events (favorable and unfavorable) that share similar characteristics. Our favorable (unfavorable) news group includes events where a newly released review for a product has a higher (lower) score than its previous average review score. Conceptually this is similar to Sloan's [36] study where he tested whether market valuations incorporated fully the information provided by different earnings components. Our method can also be viewed as a variation of matching sample techniques where variables of interest across treatment (in our case favorable news group) and control groups (in our case unfavorable news group) are compared. Matching sample techniques have been widely used across different disciplines including psychology, economics, and management science [23, 27, 29, 32].

We next define how we measure the change in sales, reviewer quality, reviewer exposure, product coverage, and the age of an item.

4.3. Sales Change

There are two types of events of interest in this study: favorable news events and unfavorable news events. A favorable (unfavorable) news event occurs when a newly released review for an item has a higher (lower) score than the previous average review score for that item. We are interested in knowing whether customers at Amazon.com understand the information value difference between favorable news and unfavorable news and respond accordingly by either buying or refusing to buy the product.

Because we can precisely pinpoint the review date of each item, we limit our event window to a starting point (day 0) to estimate the sales change associated with favorable (unfavorable) news. We start at day 0 because it is unlikely that a consumer discloses a review to the Amazon community before it is actually posted online.

In the Amazon market, even when there is no newly released review for a product, the sales of that product still fluctuate. In order to compute the actual marginal change in sales associated with favorable news or unfavorable news, we need to adjust the actual change in sales by a market performance factor and associated risk factors, as is common in portfolio approaches in the finance literature. We, therefore, adopt a variation of the Fama and French [24] model to adjust for the overall performance of the Amazon.com marketplace and for risk factors that might affect the sales of individual items. Fama and French [24] use the average return from a benchmark portfolio, using size (market equity) and book-to-market (the ratio of book equity to market equity) to adjust actual firm returns and produce a measure of abnormal return. In the context of Amazon.com, we believe that each item has some "normal" changes that are driven by the product sub-category and its list price. These are the factors that can explain the cross-sectional variance of expected "normal" sales change. Any extra changes over and above the "normal" changes are classified as "abnormal."

We estimate the average normal change in sales for a benchmark portfolio of products comprising all products within the same product sub-category and with similar Amazon list prices. For product sub-categories, we use the classification scheme provided by Amazon.com. For example, within the book category, sub-categories include history, children, diet, etc. The difference between the change in actual product sales and the change in sales of the benchmark portfolio signifies the abnormal sales related to that event.

We describe below how we estimate the abnormal sales associated with each review event:

1) In step one, we estimate the change in sales by subtracting sales at time *t-1* from sales at time *t* (i.e., actual Sales Change $_t$ = Sales $_t$ – Sales $_{t-1}$).

2) In step two, for every data collection batch, we estimate the average change in normal sales for each benchmark portfolio formed based on product sub-categories and the Amazon.com list price.

3) Finally, we compute the "abnormal" sales at time *t* by subtracting the figure obtained in step two from that in step one (i.e., the Abnormal Sales$_t$ = Actual Sales Change$_t$ – Average Change in Sales for the Benchmark Portfolio $_t$).

Instead of providing the actual sales number, Amazon.com provides the sales rank information of the item. Product sales rank is shown in descending order where 1 represents the best selling product. Consequently, there is a negative correlation between product sales and sales rank. We use SalesRank as a proxy for product sales (with the opposite sign). Henceforth, unless stated differently, whenever we refer to change in sales, it represents an "abnormal" change in sales rank.

4.4 Reviewer Quality

Reviewer quality is measured by the overall quality of the reviews written by reviewers. For each review posted online, Amazon.com also reveals how many customers read it and how many consider it "useful."

To assess the quality of a reviewer, we retrieve all the reviews ever written by that reviewer using AWS. Then, we estimate the mean of the number of "useful" votes divided by the number of total votes of all the reviews ever written by that reviewer.

Based on this measure, we classify a reviewer into a high-quality or low-quality group. High-quality reviewers are those whose average up-to-date quality score is above the median, while the low-quality reviewers are those whose average up-to-date quality score is below the median.

4.5 Reviewer Exposure

To test the conjecture that consumers indeed pay more attention to high-exposure reviewers, one can classify reviewers into two categories – higher exposure and lower exposure. Higher exposure reviewers are those whose up-to-date total number of reviews is above the median for our sample, while the lower exposure category includes those whose total number of reviews is below the median.

Due to limitations in AWS, we could not get reviewer quality and reviewer exposure information for all items. Hence, from the panel data, we select a sample of items for which we are able to get the necessary reviewer quality information. To make sure these items are representative of the original panel data, we compare the means of the average rating, reviewer quality, reviewer exposure, and product coverage for this group to those of the panel data. Our analysis shows that there is no significant difference between these two groups.[2]

4.6 Product Coverage

Product coverage measures the total number of consumers that have reviewed a product. A high-coverage (low-coverage) product is a product whose total number of reviewers is above (below) the median of our sample.

4.7 Age of an item

[2] We also evaluate hypothesis 1 using all of the panel data as well as the sub-sample. These analyses yield consistent results, as we discuss later.

To examine the dynamics of review scores, we first define a concept of "age" for an item, which is the number of days between the publishing date of an item and our data collection date. Then for each item, we divide all the available reviews into three stages of equal duration based on the age of the item. Stage 1 is the earliest stage starting right after an item is released to the Amazon market; while stage 3 is the most recent period. We choose the relative age instead of absolute age because each item sold on Amazon has its own release date and, therefore, its own absolute age. This absolute age varies from several months to several years with a very large variance. Thus, it is difficult to compare the review scores based on an absolute age of an item. Since we are interested in the temporal properties of online reviews, using the relative age of the item allows us to pool items with different absolute ages together under the assumption that reviews of different items have similar trends over each stage.

5. Results

5.1 Results: Are Changes in Online Reviews Associated with Changes in Sales?

We find support for hypothesis 1, which argues that sales respond differently to "favorable" versus "unfavorable" reviews. Panel A of Table 3 presents the results of our analysis of differences in abnormal changes in sales rank when we pool books, DVDs, and videos together. The change in the mean sales rank for unfavorable news exceeds that of favorable news by 1196.4 (*p*-value = 0.06).[3]

Insert Table 3 about here

Panel B of Table 3 presents the results for different product categories. For books, the difference in mean abnormal sales for favorable news events and unfavorable news events is insignificant (difference in sales rank = 3810, *p*-value = n.s.). However, for DVDs, unfavorable news increases the sales rank of an item by 165.37, while favorable news decreases the sales rank by 195.70. The difference in sales rank associated with unfavorable news and favorable news is 361 (*p*-value = 0.035). For videos,

[3] Recall that we use sales rank to approximate sales. Sales rank is a function of actual sales so that an increase in sales rank is associated with decreasing sales.

unfavorable news increases the sales rank by 301.05, while favorable news decreases the sales rank by 236.60. Similarly, for videos, the difference in sales rank of 537 between those items that have received unfavorable versus favorable news is statistically significant (p-value = 0.015).

As a way to assess the robustness of our results, we also estimate the difference between unfavorable and favorable news using Wilcoxon Z-statistics[4]. The results based on splitting our sample at the median are consistent with results obtained using means. Overall, except for the book category, the sales of the unfavorable news group decreased, while sales of the favorable news group increased. In addition, the difference in sales between the favorable and unfavorable news groups is significantly different from zero, consistent with hypothesis 1.

5.2 Results: Role of Reviewer Quality in Sales Change

Because reviewer quality information is not available for the entire panel, we use a sub-sample of the panel data to evaluate hypotheses 2, 3, and 4. We first validate whether the sales change difference between favorable and unfavorable news holds in this reduced sub-sample. Panel A of Table 4 presents the results of our analysis of the differences in sales change between favorable and unfavorable news for the sub-sample panel. As before, the market reacts to favorable and unfavorable news differently; on average, the market responds more favorably to favorable news. The difference in the average change in sales for unfavorable and favorable news events is 6312.7 (p-value < 0.01).

Insert Table 4 about here

Panel B of Table 4 presents the results disaggregated by reviewer quality. We find support for hypothesis 2, which predicts that the impact of reviews on sales between favorable and unfavorable news is different when the reviews were written by higher quality reviewers. We find that for books, DVDs, and videos, the difference in mean sales for the unfavorable and favorable news events is 8950 for the

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[4] The skewness of the change in sales is approximately -0.60; the kurtosis is approximately 7.38, which might also indicate that the data are slightly skewed.

higher quality reviewer group ($p < 0.001$), while the difference is not significantly different from zero (p-value = 0.129) for the lower quality group.[5] This shows that consumers react to favorable and unfavorable news differently when the review is written by a higher quality reviewer, but consumers feel indifferent between favorable and unfavorable news when the review is provided by a reviewer of lower quality.

5.3 Results: The Role of Reviewer Exposure in Changes in Sales

We find support for hypothesis 3, which predicts that consumers will react differently to favorable and unfavorable news depending on whether the review is written by a higher or lower exposure reviewer. Panel C of Table 4 shows that consumers value unfavorable and favorable news differently when the review is written by a higher exposure reviewer (difference = 7712.2, p-value = 0.003), but that difference is only moderate for a lower exposure reviewer (difference = 4876, p-value = 0.075).

5.4 Results: The Role of Product Coverage in Changes in Sales

We present the results for the effect of product coverage in Panel D of Table 4. We find support for hypothesis 4 that predicts that consumers value favorable and unfavorable news differently when the items have lower product coverage. Under a low-coverage scenario, a newly created review is more likely to reveal additional information and change consumers' quality expectations regarding a product. However, when there are many pre-existing online reviewers, a new review, regardless of its favorable or unfavorable content, is unlikely to introduce enough additional information to change consumers' behavior.

Because tabular classifications do not control for other item characteristics and potential interaction effects that can affect expected sales, we specify the following model and estimate the results using multiple regression.

$$\begin{aligned}Sales\_Change &= \alpha_0 + \alpha_1 Signal + \alpha_2 Coverage + \alpha_3 Exposure + \alpha_4 Signal * Coverage \\ &+ \alpha_5 Signal * Exposure + \alpha_6 * Book\_Dummy + \alpha_7 * DVD\_Dummy + \varepsilon_t\end{aligned}$$

[5] The median Z-test results are very similar to the mean difference results.

In this model, the dependent variable is the change in sales. To capture the effect of the level of reviewer quality and the types of reviews (favorable or unfavorable), we define a categorical variable called *Signal* with the following values: +1 represents favorable news written by a high quality reviewer, 0 is a review written by a low-quality reviewer, and -1 represents unfavorable news written by a high quality reviewer. The signal variable represents a qualitative feature of the signal sent to the Amazon.com market by the reviews. To assess the impact of a reviewer's exposure on Amazon.com, we define an indicator variable called *Exposure*. This variable equals 1 if a review is written by a reviewer with more than the median number of exposures, and 0 otherwise. We further include a dummy variable to capture the level of reviewer coverage an item receives (*Coverage*). It equals 1 if an item is followed by more than the median number of reviewers, and 0 otherwise. We also allow for interactions of the signal variable with the exposure and coverage variables by including interaction terms: *Signal x Exposure*, and *Signal x Coverage*. Product category dummies are also included to represent fixed effects due to item-level characteristics.

Table 5 presents the results. The coefficient for *Signal* in this table is negative and statistically significant (coeff. = -3106 , *p*-value = 0.006). This confirms the importance of reviewer quality and the types of reviews as a determinant of abnormal product sales. The interaction between *Signal* and *Reviewer Exposure* is negative and significant, indicating that a review has greater information content if it comes from a high exposure reviewer. In contrast, the coefficient of the interaction between *Signal* and *Product Coverage* is positive and significant, suggesting that the reaction to *Signal* is higher for items with low product coverage. Overall, these results are consistent with the ones reported in Table 4 and lend further credence to those findings. Furthermore, *Coverage* has a direct and indirect (through *Signal*) impact on product sales, while *Exposure* only influences sales through *Signal*.

Insert Table 5 about here

To summarize, the evidence thus far supports the view that reviews written by high quality reviewers, high exposure reviewers, and for products with less reviewer coverage, have a greater impact on sales than reviews written by lower quality reviewers, lower exposure reviewers, or for products with already significant reviewer coverage.

5.5 Results: The Role of Time

In this section, we examine the temporal effects of reviews on sales when a review contains favorable news or unfavorable news (hypothesis 5). Based on the age of an item, for each product category (Books, DVDs, and Videos), we classify favorable and unfavorable news into three sub-groups: early stage, medium stage, and later stage. Then for each sub-group, we compare the mean (median) abnormal difference in sales between the favorable and unfavorable news portfolio. The results are presented in Table 6.

Insert Table 6 about here

Overall, except for books, the abnormal difference in sales between favorable and unfavorable news reviews is significant only for items in the early stages of the product lifecycle. For books, the difference in sales for the unfavorable and favorable news event is significantly different from zero for the medium stage (difference = 8679.8, p-value = 0.045), but not significant for the early stage (difference = 3175.7, p-value = 0.441) and later stage (difference = -1428, p-value = 0.792). For DVDs, the difference in sales between the unfavorable and favorable news portfolio is significantly different from zero for the early stage only (difference = 621.93, p-value = 0.013). Videos behave similarly to DVDs; the difference between the unfavorable and favorable portfolio is significant for early stage only (difference = 839.11, p-value = 0.027).[6]

[6] We also estimate the difference between favorable and unfavorable news using Wilcoxon Z-statistics. The median testing results are consistent with the mean testing results.

These results are consistent with hypothesis 5. The impact of a review on sales is a decreasing function of age. As time elapses, the difference between the information provided by favorable and unfavorable reviews declines to zero. Consequently, hypothesis 5 is supported.

6. Discussion

6.1 Findings

Our goal in this study is to assess the quantitative and qualitative impact of online reviews on product sales. We want to assess the effectiveness of online reviews and the extent to which sales react to contextual information regarding reviewer quality, reviewer exposure, and product coverage. We use data from a popular online retailer, Amazon.com, to test our hypotheses.

Consistent with our arguments, we find that changes in online reviews are associated with changes in sales. We also find that, besides the quantitative measurement of online reviews (i.e., review scores), consumers pay attention to other qualitative aspects of online reviews such as reviewer quality and reviewer exposure. Furthermore, we find that a consumer's reaction to online reviews is stronger for the items that have less product coverage; that is, new online reviews are more informative when items have fewer pre-existing reviewers. Finally, we find that the review signal moderates the impact of reviewer exposure and product coverage on product sales. Consumers are fully able to appreciate the differential impacts of high-quality signals vs. low-quality signals. Lastly, the impact of online reviews on sales is a decreasing function of the age of the product.

Taken together, our study integrates econometric data with insights from a portfolio approach to reveal how consumers use online review information. Unlike previous studies that focus on linking levels of review scores with levels of product sales, we study how consumers use quantitative and qualitative aspects of online reviews to make purchase decisions. We show that online reviews reduce the uncertainty and decrease the transaction costs of online transactions. In essence, consumers respond through their purchase behavior to quality information embedded in online reviews.

6.2 Implications for Research

The paper has implications for online WOM communication and online consumer behavior, as described below:

6.2.1 Implications for Online WOM Communication

Online WOM communication is becoming a popular informational source for consumers and marketers. As researchers focus on the impact of average online review ratings on consumer relationship management and product success, there is a need to understand how consumers use online reviews, whether they understand the information embedded in reviews, whether they rely on online reviews to make purchase decisions, and under what circumstances a review is likely to impact sales. This paper contributes to this emerging literature by addressing these fundamental but largely neglected questions.

6.2.2 Implications for Online Consumer Behavior and Practice

The econometric results in our study suggest that over time, the impact of online reviews on sales diminishes as consumers begin to receive quality related information from other channels. For the medium and later stages in the life of a product, online reviews may still influence sales, but there is no abnormal sales difference between favorable and unfavorable news except in the case of books. Online retailers, product manufacturers, and companies that specialize in collecting and disseminating product quality information may need to pay more attention to early stage reviews and to find a way to promote favorable reviews at that stage, when consumers pay more attention to online reviews. After this stage, the impact of online reviews on sales begins to decline. Also, online retailers and product manufacturers should encourage and nurture high quality and high exposure reviewers, since the actions of these reviewers have a direct impact on product sales.

6.3 Managerial Implications

Our results suggest that the market for reviews is efficient and that consumers are rational. Over the long run, a strategy of recruiting reviewers to write good reviews of a vendor’s own products and bad reviews of competitors' products is unlikely to succeed. Consumers are able to tell the authenticity of a review and differentiate a good reviewer from a bad reviewer. Firms should identify reviewers with better reputations and higher exposure and try to promote new products to them in the hopes that they will respond with favorable reviews. Those reviewers usually act as early adopters and opinion leaders in the consumer community. Their tastes and judgments will determine which items other consumers are more likely to adopt in the future.

6.4 Limitations and Suggestions for Future Research

This study has several limitations that create interesting opportunities for future research. First, even though our results hold for our sample of DVDs and videos, we did not observe a similar set of results for books. Future research could examine this result by considering heterogeneous properties among different product categories. Second, this paper does not consider the textual content or length of the reviews, factors that may also indicate review quality. Future research could take these factors into consideration in an attempt to document how consumers respond to newly released reviews.

To conclude, online WOM communication in the form of online product reviews has become a major informational source for consumers and marketers. In large part, by linking the average rating of an item to its sales, the literature has assumed that consumers use only quantitative information aspects of online reviews to make purchase decisions. To overcome this problem, this study proposes a portfolio approach to demonstrate that consumers understand and use both the quantitative and qualitative information embedded in online reviews. This study encourages further research in this area as a way to derive deeper insights into the broader implications of online WOM communication.

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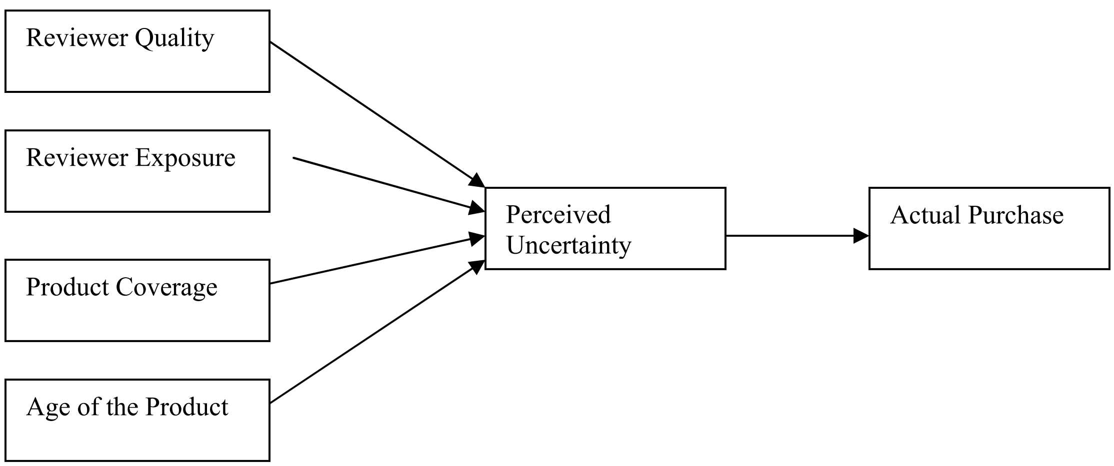
Figure 1: Factors Contributing to Consumers' Reactions to Online Reviews



Note: Variable definitions are in Sections 4.4, 4.5, 4.6, and 4.7

Table 2: Summary Statistics

Amazon Longitudinal Data (July 2005 – Jan 2006)				
Category	#Reviews	#Amazon Items	#Distinct Items	Avg_Rating
Book	6,759,764	261,187	10,052	3.87
DVD	4,056,340	258,736	9,988	4.07
Video	4,371,833	259,736	10,000	4.02

Table 3: Abnormal Sales Change Difference between Favorable News and Unfavorable News Portfolio

		Abnormal Sales Change associated with unfavorable news (1)	Abnormal Sales Change associated with favorable news (2)	Abnormal Sales Change Difference (unfavorable news - favorable news) (1) - (2)	Wilcoxon Z-statistics (p-value)
Panel A					
Book, DVD, and Video	Mean	1286	89.65	1196.4	-2.940
	N	16256[1]	16226	(0.059)	(0.003)
Panel B					
Book	Mean	4828.4	1017.8	3810.6	1.0173
	N	3742	4000	(0.146)	(0.3090)
DVD	Mean	165.37	-195.7	361.02	-1.9353
	N	6857	6727	(0.035)	(0.053)
Video	Mean	301.05	-236.6	537.62	-2.543
	N	5657	5499	(0.015)	(0.011)

All p-values are based on 2-tailed tests.

[1] Note that the number of items in this table is fewer than reported in Table 2 for longitudinal data because the items that do not have any ratings change associated with them are not relevant for our analysis.

Table 4: Abnormal Sales Change Difference between Favorable and Unfavorable News Portfolios: The Role of Reviewer Quality, Reviewer Exposure, and Product Coverage

	Group		Abnormal Sales Change associated with unfavorable news (1)	Abnormal Sales Change associated with favorable news (2)	Abnormal Sales Change Difference (unfavorable news - favorable news) (1) - (2)	Wilcoxon Z-statistics (p-value)
Panel A						
Book, DVD and Video		Mean	2524.8	-3788	6312.7	-2.3883
		N	1713	1446	(0.001)	(0.017)
Panel B						
Book, DVD and Video	High Quality	Mean	5675.1	-3276	8950.9	-2.3182
		N	796	784	(0.001)	(0.020)
	Low Quality	Mean	-209.9	-4394	4184.5	-1.1946
		N	917	662	(0.129)	(0.232)
Panel C						
Book, DVD and Video	High Exposure	Mean	2555.2	-5157	7712.2	-2.2412
		N	886	732	(0.006)	(0.0250)
	Low Exposure	Mean	2429	-2384	4876	-1.1474
		N	827	714	(0.075)	(0.251)
Panel D						
Book, DVD and Video	High Coverage	Mean	-307.9	-3889	3581.5	0.7563
		N	900	741	(0.120)	(0.449)
	Low Coverage	Mean	5660.6	-3681	9341.7	-3.8836
		N	813	705	(0.002)	(0.000)

Table 5: Regression Results of Impact of Review on Abnormal Sales

		Abnormal Sales
Intercept	α_0	772.42 (0.335)
SIGNAL	α_1	-3106.16*** (0.006)
COVERAGE	α_2	-2026.98** (0.031)
EXPOSURE	α_3	203.76 (0.828)
SIGNAL X COVERAGE	α_4	3696.72*** (0.005)
SIGNAL X EXPOSURE	α_5	-1711.95** (0.02)
N		N=3159 Adj *R-Sq* = 0.0070 F=5.15***

Notes:

1) The variable definitions are in Section 3.4.
2) All of the p-values are based on two-tailed test. * indicates significance at 10%; ** indicates significance at 5%; and *** indicates significance at 1%.
3) The model also includes book and DVD dummies (not shown).
4) The small adjusted R-square is consistent with the abnormal returns in accounting and information systems literature.

Table 6: The Role of Item Age in Abnormal Sales Change Difference between Favorable and Unfavorable News Portfolio

			Abnormal Sales Change associated with unfavorable news (1)	Abnormal Sales Change associated with favorable news (2)	Abnormal Sales Difference (unfavorable news - favorable news) (1) - (2)	Wilcoxon Z-statistics (p-value)
Book	Early Stage	Mean	7371.5	4195.8	3175.7	-0.2602
		N	1633	1733	(0.441)	(0.795)
	Medium Stage	Mean	7955.5	-724.4	8679.8	1.1083
		N	1183	1228	(0.045)	(0.268)
	Later Stage	Mean	-3651	-2224	-1428	1.1085
		N	926	1039	(0.792)	(0.268)
DVD	Early Stage	Mean	373.74	-248.2	621.93	-2.6407
		N	3376	3294	(0.013)	(0.008)
	Medium Stage	Mean	40.93	-170.4	211.32	-0.2262
		N	2097	2035	(0.501)	(0.821)
	Later Stage	Mean	-154.4	-108.7	-45.72	-0.284
		N	1384	1398	(0.896)	(0.775)
Video	Early Stage	Mean	497.53	-341.6	839.11	-3.9013
		N	2685	2347	(0.027)	(0.000)
	Medium Stage	Mean	102.8	-272.6	375.38	-0.6715
		N	1515	1708	(0.323)	(0.502)
	Later Stage	Mean	145.1	-23.32	168.42	1.033
		N	1457	1444	(0.619)	(0.302)

* For Table 6, we use the full sample as in Table 3.