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Context-Dependent Product Evaluations: An Empirical Analysis of Internet Book Reviews

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Abstract

Using book review data on Amazon.com, the authors extend current research into online consumer reviews by empirically investigating the context dependence effect in the review writing process. They find that when product quality remains constant, later reviews tend to differ from previously posted ones, and the difference is moderated by the popularity of the product, the variance of previous reviews, whether later reviews explicitly refer to previous reviews, and the age of the product and the reviews. This phenomenon can be explained by both consumer expectation and self-selection effects in review writing. The implications of this research can help practitioners understand the reviewing process and provide some guidelines for improving the objectivity of online product reviews.

Keywords: Online reviews; Context dependence; Self-selection effect; Expectation effect; Ordered logistic model

Introduction

> "Ok, I liked this book, but I was hoping for more.… I read the previous reviews and couldn't wait to get the book. I was disappointed.… If you like her stuff, read this but don't have high expectations. Maybe that's what ruined it for me."
> —"I expected better," reader, *Dying to Please*

> "The stories shared in this book are interesting and inspiring.... I saw a few negative customer reviews here, all of which completely surprised me. I actually can't fathom how someone who read this book would have such negative reactions!..."
> —"I dissent," reader, *What Should I Do with My Life*

The reader who wrote "I expected better" (whom we refer to as "Jane Disappointed") rated the focal book with a score of 3; its average rating was 4.49. The reader who wrote "I dissent" (whom we call "John Surprised") provided a 5-star rating for a book that averaged 3.12. At Amazon.com, reviews such as these appear often, suggesting that readers such as Jane and John make judgments about the quality of books on the basis of not only their own evaluations but also the views of others. In this paper, we study the context-dependent evaluations of books at Amazon; we define "context" as the external information about a book that a reader obtains before reviewing that book but restrict this context to sources that we can observe, namely, previous evaluations of the book posted online at Amazon.

Various studies and surveys note the rapid increase in the power of such online word of mouth (WOM) in influencing consumer spending. According to a global survey of 26,486 Internet users in 47 markets, the vast majority of respondents (78%) consider recommendations from consumers the most credible form of advertising (Neilson 2007). Similar findings appear in other industrial surveys: 77% of online shoppers use reviews and ratings when purchasing (Jupiter Research 2006), and 83% of respondents polled by Opinion Research Corporation (2008) indicate that online product evaluations and reviews have at least some influence on their purchasing decisions. Another recent survey reveals that 62% of consumers read product reviews

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posted by other consumers on the Internet, and of these respondents, 82% say the reviews directly influence their purchase decisions, and 69% then share those reviews with friends, family, or colleagues, which amplifies the impact (Deloitte 2007). Finally, in a study conducted by ComScore and the Kelsey group, more than 75% of review users in nearly every category report that reviews have significant influences on their purchases, greater than the influence of professional reviews, and that they would pay 20–99% more for a five-star rated product than for a four-star rated product, depending on the product category (ComScore 2007).

As online consumer-generated reviews become increasingly important influences on consumer purchasing, interest in academic research into online WOM continues to grow. The predominant research focus has been on the impact of consumer reviews on product sales (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004), whereas relatively few studies attempt to understand the process by which consumers decide to produce reviews and the aspects that affect these reviews. Yet the influence of previous reviews on a newly posted review may reflect several features. First, previous reviews may influence buyers' expectations before purchase. Because expectations can affect postpurchase satisfaction, and hence the reviews written by buyers (Anderson and Sullivan 1993; Cadotte, Woodruff, and Jenkins 1987; Churchill and Surprenant 1982; Rust et al. 1999; Spreng, MacKenzie, and Olshavsky 1996), previous reviews may indirectly affect the opinions expressed in newly posted reviews. If product quality remains the same, higher expectations tend to breed lower satisfaction. Therefore, the valence of newly posted reviews should be negatively affected by existing reviews, ceteris paribus. Jane Disappointed's review of *Dying to Please* offers a typical example.

Second, existing reviews may attract buyers with different opinions. It takes reviewers time and effort to post reviews, so they write only if the utility of doing so compensates for the costs associated with that time and effort. Such utility may originate from simple altruism (e.g., Dichter 1966; Hennig-Thurau et al. 2004; Sundaram, Mitra, and Webster 1998), such that a reviewer may believe that his or her opinion better reflects the "true" (in his or her own mind, of course) quality of the book, in which case, as an altruist, he or she can draw utility from expressing this true opinion. Publishing a different opinion also can draw attention to the reviewer and enhance self-recognition (Engel, Blackwell, and Miniard 1993). John Surprised's "I dissent" comment about *What Should I Do with My Life* exemplifies such a motive.

With these two context-dependent forces, newly posted reviews by reviewers who use previous reviews as reference points appear more likely to take positions that differ from those expressed by existing reviews. Other reviews may not reference previous reviews at all (i.e., simply express the reviewer's opinion) or be affected by other information sources (e.g., an editorial review in *The New York Times*). With respect to the context we study herein (i.e., reviews posted at Amazon), we consider such reviews independent, in that they are independent of the previous reviews posted on the same web site. Whereas context-susceptible reviewers likely post reviews contradicting existing reviews, independent reviews should not be affected by existing reviews and thus likely be either independent from or, if they are influenced by the same external sources, consistent with those existing reviews. Thus, the existence of both responsive and independent reviews renders the aggregate relationship of previous to newly posted reviews either positive or negative.

We empirically examine the impact of previous reviews on the valence of newly posted reviews using 51,854 book reviews contributed by consumers to Amazon.com. Our results suggest that when book quality is held constant, newly posted reviews tend to disagree with existing reviews; this effect is stronger for less popular books, when existing reviews exhibit lower variance, as the number of existing reviews increases, and for the group of reviews that mention previous reviews. These four factors mediate the overall net impact of previous reviews, in that they influence the ratio of responsive to independent reviews and the extent to which responsive reviews are affected by previous reviews.

In turn, this study contributes to emerging online WOM literature by emphasizing the importance of the dynamics of online consumer-generated reviews over time and how existing reviews may influence the reviews that follow. Our findings also shed some light on the particular characteristics of online WOM, in that the opportunity to respond to or interact with previous reviews is possible only for online WOM communication, which is publicly and historically accessible. Understanding the relevance of "context" in the evolution of reviews over time also has important implications for firms that rely on online WOM as an alternative marketing channel to promote their products.

The remainder of this paper is organized as follows: In the next section, we review related literature. We then discuss the theories on which we base our hypotheses. In Model and Results, we present the study data, empirical model, and results. Our Discussion and Conclusion follow.

Related Literature

For years, product diffusion researchers have conceptualized WOM as an important driver of sales (Rogers 1962). Traditional offline WOM, based on social contagion (Foster and Rosenzweig 1995; Reingen et al. 1984), usually occurs between consumers in private, which means it is not observable by researchers. Therefore, early models of WOM often infer WOM interactions (Mahajan and Muller 1979).

The emergence of large-scale online communication networks has provided a channel for consumers to exchange information online beyond traditional social contagion though. Unlike traditional WOM, which usually takes place in small social groups and no longer exists after the conversation ends, online WOM can be accessed by essentially every person on the Internet and persists over time. Conversations can be conducted among many people, mostly anonymous to one another and unlimited by location or time. Conversations also can be documented for public access and shared across web sites. The information exchanged thus can reach an audience of unprecedented size and composition.

Moreover, these documented conversations are publicly accessible over time. On the one hand, this persistency enables consumers to observe and respond to prior WOM, suggesting a potential influence of prior WOM on subsequent WOM. On the other hand, it allows researchers to observe, track, and analyze WOM directly and over time, which has stimulated growing academic research interest in the relationship between WOM and product sales. For example, Chevalier and Mayzlin (2006) demonstrate that the differences between consumer reviews posted on Barnes & Noble's and Amazon.com's web sites relate positively to the differences in book sales through the two sites. Dellarocas, Awad, and Zhang (2007) find that the average rating of online consumer reviews provides a better predictor of future movie revenues than do other measures. In addition to evidence about the effect of the valence of online WOM on sales, studies suggest that alternative measures of Internet WOM may matter. Godes and Mayzlin (2004) find a strong relationship between the popularity of a television show and the "dispersion" of conversations about shows across online consumer communities. Duan, Gu, and Whinston (2008) suggest that the number of online reviews, not the valence, influences box office sales, similar to findings by Liu (2006). Clemons, Gao, and Hitt (2006) find that rating variance and the strength of the most positive quartile of reviews have significant impacts on the growth of craft beers. A few recent studies also examine the mediation effects of other factors, such as reviews written by consumers from the same geographic locations, which have higher impacts on sales (Forman, Ghose, and Wiesenfeld 2008), and the importance of helpfulness ratings for the impact of reviews (Chen, Dhanasobhon, and Smith 2007).

In contrast with the predominant research focus on the correlation between consumer reviews and sales, the process by which consumers decide to produce reviews and the aspects that affect these reviews have been less studied. Because early adopters of products have different preferences, the reviews they provide are not necessarily representative of the market as a whole (Li and Hitt 2008). Therefore, an increase in ratings can increase the dissimilarity of a shopper from the entire set of previous reviewers (Godes and Silva 2006), which leads to more purchase errors and lower ratings. Consumers with polarized opinions are more likely to write reviews (Hu, Pavlou, and Zhang 2007), and reviews can also be affected by the prices paid by the reviewers which may not be observable to the consumers who utilize these reviews to assist their purchase decisions (Li and Hitt 2010). However, none of these studies explicitly examines how the dynamics of reviews over time might depend on prior reviews, which is the focus of this study.

In a recent study, Gao, Gu, and Lin (2006) find that consumer ratings are consistent with previous ratings (measured as the average of all previous ratings) for consumer electronics, when they include both editor reviews and consumer reviews posted on CNet.com. Our findings conflict with their results though; reviewers may tend to disagree with previous ratings, but such disagreement becomes less likely as the portion of responsive reviewers decreases and the popularity of the product increases. This potential mediating effect of reviewer and product heterogeneity may help reconcile the difference between our results and previous findings (Gao, Gu, and Lin 2006). Moe and Trusov (2009) also find that a higher valence of previously posted ratings decreases the likelihood of receiving an additional, moderately positive rating (four-star). Whereas their study concentrates on the influence of previous reviews on the arrival rate of later reviews, prior literature and our own reading of review contents suggest that the rating itself may be affected by previous reviews, which is the focus of this study. Finally, we examine how this effect is mediated by the composition of the reviews (i.e., proportion of independent to responsive reviews) and the extent to which responsive reviews are affected by previous reviews.

Theory and Hypotheses

Previous studies classify the motives behind consumers' involvement in traditional offline WOM into four broad categories: (1) releasing the tension caused by consumption experience, (2) enhancing self-image and gaining attention, (3) altruism, and (4) responding to advertisements or other public messages (Dichter 1966; Engel, Blackwell, and Miniard 1993; Sundaram, Mitra, and Webster 1998). These factors remain influential in online WOM (Hennig-Thurau et al. 2004).

Unlike traditional WOM, which usually takes place in small social groups and no longer exists after the conversation ends, online WOM can be accessed by essentially every person on the Internet and persists over time. This persistence enables consumers to observe and respond to existing reviews. Therefore, previously posted reviews form the context for subsequent reviewers, which potentially affects their incentive to post reviews and the tone of those reviews.

Context-dependent choice behavior has been the focus of expansive literature in psychology, marketing, and economics (Swait et al. 2002). Consumers' choices are influenced by the context in which they see the product or choice and the cues in the surrounding context, such as text describing their choices (Tversky and Simonson 1993), cues used in advertisements for the products (Meyers-Levy and Sternthal 1993; Yi 1990), reference prices formed on the basis of information available at the point of purchase or price history (Adaval and Monroe 2002; Briesch et al. 1997), and previously formed product evaluations or examined alternatives (Higgins and Lurie 1983; Kahneman and Miller 1986; Sherman et al. 1978). These previous studies examine how contextual information is encoded and affects consumers' judgment when they purchase products or select among choices; they do not study how consumers' postpurchase evaluations or tendency to share evaluations depend on the context to which they are exposed.

When consumers form their evaluations (which reflect the utility that they receive from consuming the product or their overall satisfaction with the product) or make decisions about sharing evaluations by writing reviews, they are receiving various sources of contextual information. In this study, we define this "context" as the external information sources about a book that a reader obtains before reviewing that book. In particular, we focus on the context that is also observable to researchers, namely, previous evaluations of the book posted at Amazon. Prior literature suggests at least two possible contextual factors of existing reviews may affect a person's product evaluation or motive to post reviews: the expectation effect and the self-selection effect.

Expectation Effect

Studies of consumer satisfaction suggest that consumers' judgments of product or service quality are not necessarily objective; they often depend on the confirmation or disconfirmation of their expectations by the perceived quality of the service or product (Churchill and Surprenant 1982; Oliver 1980; Spreng, MacKenzie, and Olshavsky 1996). According to prospect theory (Kahneman and Tversky 1979), consumer satisfaction and evaluations are context dependent (Anderson and Sullivan 1993). Expectation forms the context that influences consumers' judgments. According to a conceptual framework proposed to explain the causal relationship between expectation and satisfaction (Cadotte, Woodruff, and Jenkins 1987) and a model of the expectation effect using a Bayesian information updating process (Rust et al. 1999), when consumers consider experience products whose quality is uncertain before their usage, existing reviews provide information about postpurchase experience and quality evaluations, which may influence expectations about product quality prior to purchase. At the same quality level, such as for one particular book, high expectations are more likely to lead to negative disconfirmation (disappointment), whereas low expectations may tend to result in positive disconfirmation (positive surprise). Because negative disconfirmation decreases satisfaction but positive disconfirmation increases satisfaction (Anderson and Sullivan 1993), for a given book with an established quality level, high expectations should lower satisfaction and ratings; we anticipate the opposite for lower expectations. Consumers who consult reviews prior to their purchase should be more likely to post reviews that deviate from the existing reviews that helped form their expectations.

Self-selection Effect

Self-selection, a topic for research in education (Willis and Rosen 1979), labor (Magnac 1991), and market competition (Moorthy 1984), also plays an indispensable role in product reviews. A buyer does not have to write an evaluation of each product that he or she purchases; the subgroup of purchasers who decide to write evaluations may not choose to do so randomly. It takes time and effort to write and post reviews, and a buyer only writes reviews if the utility from doing so is greater than the cost incurred. Drawing on the four types of motives for becoming involved in WOM (Dichter 1966; Engel, Blackwell, and Miniard 1993; Hennig-Thurau et al. 2004; Sundaram, Mitra, and Webster 1998), we theorize that the utility of posting a review may originate in simple altruism. An altruist may receive more utility from posting reviews if he or she has distinctive opinions, because fresh perspectives can assist potential buyers in making better informed purchasing decisions and/or correct prevailing "misconceptions" (in the reviewer's mind), which leads to higher overall welfare. In addition, a self-image-minded person may derive utility from differing from existing views, because distinctive opinions can draw attention and thus enhance self-image. A buyer's incentive to engage in WOM then should be higher if his or her evaluation differs from the existing context. These distinctive opinions can be expressed as disagreements with previous reviews on the same features and propositions or perspectives on totally different dimensions not previously discussed. The former types should produce ratings opposite the existing reviews; the latter are likely to assign ratings independent of existing ratings, because they evaluate totally different things. In turn, by combining these two effects and examining the aggregate net effect, we expect to observe that subsequent evaluations that respond to previous reviews disagree with the prevailing opinion.

Hypotheses

Both expectation and self-selection effects imply similar observations with regard to the dynamics of new evaluations. That is, if reviewers consider prior reviews as a reference point, either to form expectations or to build an argument against, subsequently observed evaluations should be more likely to swing in a direction opposite that of previous evaluations. Therefore, we hypothesize:

H1. Newly posted evaluations are more likely to contradict than agree with existing reviews.

In reality, some reviews do not cite previous reviews but instead simply express their own opinions or respond to other information sources. With respect to the context we study herein (reviews posted at Amazon), we call them independent reviews, in that they are not affected by existing reviews on Amazon. We predict they will be either independent from or, if they are affected by the same external sources, consistent with existing reviews.

Furthermore, even reviews that refer to previous reviews may not all disagree, as suggested by the expectation and self-selection effects. Some reviews may comment from totally different perspectives and thus exhibit no relation to previous reviews in terms of the ratings they assign. Finally, some reviewers may show a propensity to agree with the prevailing opinion, which would produce a positive relationship between these reviews and previously posted reviews.

In practice then, both independent reviewers and context-susceptible reviewers exist, and among the context-susceptible reviewers, some behave as suggested by the expectation and self-selection effects, by posting reviews that contradict existing reviews, whereas others do not. The mixture of these different types of reviewers poses a challenge to our efforts to isolate the influence of the two context effects empirically. In this sense, H1 proposes an aggregate net effect, that is, the dominant effect when we allow for different types of reviewers. If the focal reviews mainly are written by buyers who have read previous reviews, whether to form their expectations or to build arguments against, the relationship in H1 should be stronger. If the reviews generally are written independently, the relationship in H1 should be undetectable, and a reverse relationship might even emerge.

Accordingly, we acknowledge the potential influence of the ratio of responsive reviews (written by context-susceptible reviewers) to independent reviews on H1. The higher the ratio, the stronger the effect in H1 should be. In addition, a stronger impact of earlier reviews on responsive reviews should make the effect in H1 stronger. Thus, we develop four additional hypotheses to examine such mediators of the context effect in H1; specifically, in H2, we consider the ratio of responsive reviews to independent reviews, and in H3–H5, we note the impact of earlier reviews on responsive reviews.

First, to examine how the relationship in H1 depends on the ratio of responsive to independent reviews, we adopt a straightforward approach and separate responsive from independent reviews. With this separation, we can determine which group exhibits a greater effect. Responsive reviews (written by context-susceptible reviewers) likely mention previous reviews or reviewers in their content, whereas independent reviews should not. Therefore, we use the presence or absence of mentions of previous reviews or reviewers to distinguish responsive reviews from independent reviews. In turn, we predict stronger context effects among the group of reviews that mention previous reviews.

H2. The effect in H1 is stronger for the group of reviews that mention previous reviews than for the group of reviews that do not mention previous reviews.

Second, the information integration perspective suggests consumers acquire product information from multiple sources to make their purchase decisions. According to a Bayesian information updating perspective (Berger 1993; Gelman et al. 2003; Jackson 1991; Shenoy 1992), the lower the variance of an information source (e.g., previous reviews of a particular book on Amazon.com), the higher is its impact; in addition, more diversified information sources tend to create smaller weights for each source. The first proposition directly implies that the effect described in H1 may be mitigated by variance in the previous ratings. The second proposition suggests that the potential popularity of the product can moderate the effect too. Popular books, such as those that appear on bestseller lists, should receive more attention from various media and experts; in turn, the likelihood of an influence of sources other than reviews on Amazon increases. The impact of previous reviews posted on one particular web site on responsive reviews thus may decrease for popular books, which would mitigate the effect described in H1. Accordingly, we propose:

H3. The effect in H1 is stronger if the variance in existing ratings is smaller.

H4. The effect in H1 is stronger for books that do not appear on publishers' bestseller lists than for books on such lists.

Third, the impact of prior reviews may be mediated by the number of these reviews, because as they increase in number, the expectation and self-selection effects should strengthen, as should the impact of earlier reviews on responsive reviews. Consistent with the argument for Bayesian information updating, when a buyer faces uncertainty about the quality of a product, his or her updated quality expectation reflects a weighted combination of prior expectations and observations of quality evaluations (i.e., reviews the buyer reads before purchasing). The weight of these review observations in an updated expectation should increase as the number of observations increases, such that more existing reviews have a greater effect on the buyer's expectation of book quality, which should enhance the expectation effect.

As the number of reviews increases, the self-selection effect also might grow stronger. An altruistic reviewer obtains utility from adding more information to help others make choices. If a large number of reviews already exist, one more "similar" review should not have much incremental impact on the amount of information available. Therefore, the motivation to post a new review decreases as more reviews appear if the altruistic reviewer agrees with the existing view, though not necessarily if that reviewer disagrees. For a book reader eager to draw attention or build self-image, disagreeing with many people may produce higher self-satisfaction. Therefore, as more reviews appear, the incentive for book readers who disagree with the prevailing opinion to post reviews should be higher. Collectively, these arguments suggest a relatively higher incentive to post reviews when a reviewer disagrees than when he or she agrees with previous reviews as the number of reviews increases. Correspondingly,

H5. The effect in H1 is stronger as the number of existing reviews increases.

Other factors certainly could affect newly posted reviews, but we focus on the context effects associated with self-selection and expectation. To attenuate the influence of the other factors that we do not observe in this study, we use product fixed effects to control for factors that differ across products and that may contribute to differences in reviews.

Model and Results

Data

We collected our data from Amazon.com for books published between January 1, 2000, and February 24, 2004. The sampling methodology for the initial sample appears in the Appendix.[2] For each book, we collected the ISBN, title, author (s), publication date, category, and all the consumer-written

[2] This sampling method is similar to that used in previous studies of online reviews and sales (Chevalier and Mayzlin 2006). As in previous work, our sampling methodology attempts to represent sales in the market for products that are likely to be influenced by online reviews by including both high-sale books (i.e., drawn from bestseller lists) and a sample of other books (i.e., drawn from the broader "in-print" list).

reviews posted on Amazon.com. From this initial sample, we selected books between 20 and 1000 reviews during the first 6 months after their publication, which gives us a meaningful number of observations for each book. We excluded books whose paperback versions were released less than 6 months after the initial hardback publication, to avoid any potential bias introduced by a new form of book packaging. We also excluded books with reviews posted before the publication date or reviews with missing dates. The final data set consists of 858 books and 51,854 reviews, with an average rating of 3.89. We provide the summary statistics of these book reviews in Table 1.

In addition to review data, we collected publishers' weekly bestseller lists released between 2000 and 2004. This supplementary data set enables us to capture the popularity of the books in our sample and categorize the books into popular (on bestseller lists) versus unpopular (not on bestseller lists) books in our analysis.

Empirical Model

The book reviews on Amazon.com employ a five-star system, defined by the company as follows: 1 star = "I hate it," 2 stars = "I don't like it," 3 stars = "It's OK," 4 stars = "I like it," and 5 stars = "I love it." These rating data are ordinal in nature. However, the difference between 4 and 3 is not necessarily equal to the difference between 5 and 4, because negative and positive reviews have different influences on consumer purchase decisions (Chevalier and Mayzlin 2006). Therefore, we use an ordered logistic model (cf., Long 1997), which preserves the order of the rating levels but allows unequal differences between contingent rating levels.

Book i's jth evaluation y_{ij} (= 1, 2, 3, 4, or 5) corresponds to the five-star rating system at Amazon.com. In the ordered logistic model, the utility that reflects the book i's jth evaluation, v_{ij}, can be modeled as

$$\upsilon_{ij} = u_{ij} + \varepsilon_{ij} = \alpha_i + \sum_{k=1}^{K} \beta_k \cdot x_{ijk} + \varepsilon_{ij}, \tag{1}$$

where α_i ($i=1, 2, \ldots, 858$) is the fixed effect for book i, describing the idiosyncratic, constant characteristics of the book. For identification purposes, we use book 1's effect as the base level, such that $\alpha_1=0$. Then, x_{ijk} represent independent variables that capture the factors that determine the utility of the reviewer who writes review j for book i; β_k captures the marginal effect of each factor in the reviewer's utility; and ε_{ij} follows a logistic distribution (Long 1997).

Table 1
Summary Statistics of Book Reviews (for reviews posted within 6 months after release).

	Minimum	Maximum	Mean	Standard Deviation
Number of reviews	20	861	60	78
Average rating	1.38	5.00	3.89	0.63
Review length (characters)	11	8,205	980	885
Percentage of reviews written by reviewers with real name	0%	78%	26%	13%

Let $q_{ij1}, q_{ij2}, q_{ij3}$, and q_{ij4} be the probability that book i is rated 1, less than or equal to 2, less than or equal to 3, and less than or equal to 4, respectively. Following a logistic distribution,

$$q_{ijl} = \frac{\exp(\lambda_l - u_{ij})}{1 + \exp(\lambda_l - u_{ij})}, \forall i, j, l = 1, 2, 3, 4, \tag{2}$$

where λ_1 ($l=1, 2, 3, 4$) are the utility cut-off values for different rating levels. The probability that book i's jth rating is l, $\Pr(y_{ij}=l)$, $l=1, 2, 3, 4, 5$, is therefore:

$$\begin{aligned} \Pr(y_{ij} = 1) &= q_{ij1} \\ \Pr(y_{ij} = l) &= q_{ijl} - q_{ij(l-1)} \qquad l = 2, 3, 4 \\ \Pr(y_{ij} = 5) &= 1 - q_{ij4} \end{aligned} \tag{3}$$

We include the following independent variables x_{ij} ($\forall i, j$) in the ordered logistic model:

$RNAME_{ij}$: a dummy variable capturing whether the reviewer uses his or her real name when writing the review j for book i. We include this variable to capture any potential difference in review writing behavior caused by the revelation of a person's identity.

$RLENGTH_{ij}$: the log of the length of the review j written for book i, measured by the number of words in the review. The length of a review may signal its quality (Forman, Ghose, and Wiesenfeld 2008), such that a long review likely implies greater effort put in by the reviewer compared with a short review. We include this variable to allow for differences in ratings across reviews of different lengths.

$SEQN_{ij}$: the log of the sequential number of reviews j written for book i. The first review would have a value of ln(1), the second review would have a value of ln(2), and so on. We include this variable to control for the differences in reviews of different ordinal numbers, as suggested by previous literature (e.g., Godes and Silva 2006). To allow this effect to vary across books, we interact $SEQN_{ij}$ with book dummy variables in the regression and use the interaction term of $SEQN_{ij}$ with $AVGSCORE_{ij}$ to test H5.

$DPUB_{ij}$: the log of the number of days since its publication when review j for book i was written. $DPUB_{ij}$ differs from $SEQN_{ij}$, because the tenth review of a book could be written on the first or twentieth day after publication. The correlation between $SEQN_{ij}$ and $DPUB_{ij}$ is only .34, so including both variables in the regression does not raise collinearity concerns. We include this variable to control for the general trend in ratings over time (Li and Hitt 2008), which is unrelated to the valence of previous ratings. To allow this effect to vary across books, we interact $DPUB_{ij}$ with book dummy variables in the regression.

$AVGSCORE_{ij}$: the average of the first, second, …, and (j −1) th ratings for book i, that is, the average of the ratings posted before review j for book i. This variable is defined only for

Table 2
Regression Results.

		Model 1		Model 2		Model 3	
		Estimate	p	Estimate	P	Estimate	p
RNAME				.333 (.021)	<.001	.343 (.021)	<.001
RLENGTH				−.392 (.115)	.001	−.474 (.117)	<.001
DLAG						.057 (.001)	<.001
AVGSCORE						−.681 (.166)	<.001
STDSCORE						.249 (.257)	.334
REF						.012 (.032)	.708
AVGSCORE×STDSCORE						.118 (.065)	.072
AVGSCORE×DLAG						−.013 (.004)	<.001
AVGSCORE×SEQN						−.723 (.045)	<.001
AVGSCORE×REF						−.468 (.040)	<.001
AVGSCORE×PLIST						.666 (.131)	<.001
Cutoff Values	λ_1	−.086 (.306)	.779	−.046 (1.396)	.779	5.300 (1.598)	<.001
	λ_2	.827 (.306)	.007	.922 (1.396)	.007	6.293 (1.598)	<.001
	λ_3	1.469 (.306)	<.001	1.597 (1.396)	<.001	6.987 (1.598)	<.001
	λ_4	2.176 (.306)	<.001	2.331 (1.396)	<.001	7.736 (1.598)	<.001
LL		−66,498		−64,485		−63,653	
AIC		134,719		134,080		132,434	

Notes: Standard errors in parentheses.

$j \geq 2$. We demean this variable in the analysis to improve interpretation. We use this variable to test H1. A negative coefficient would imply the deviation of later reviews from previous reviews—that is, holding book quality constant, a higher-than-average AVGSCORE is likely to be followed by a review with lower rating, and a lower-than-average AVGSCORE is likely to be followed by a review with higher rating.

$STDSCORE_{ij}$: the standard deviation of the first, second, …, and (j −1)th ratings for book i, that is, the standard deviation of the ratings posted before review j for book i. This variable is defined only for $j \geq 2$. We use the interaction of this variable and $AVGSCORE_{ij}$ to test H3.

REF_{ij}: a dummy variable that captures whether review j for book i mentions a previous review. When this variable equals 1, the review considers previous reviews. On the basis of our reading of numerous reviews, we chose the keywords "review" and "reviewer" (both singular and plural forms) as indicators of references to a previous review. This simple algorithm may not perfectly capture every review, but its accuracy is sufficient.[3] As long as the filtering mechanism divides reviews into two groups–one with a significantly higher proportion of independent reviews and one with a significantly higher proportion of responsive reviews–we can use its interaction with $AVGSCORE_{ij}$ to test the mediating effect imposed by the ratio of responsive reviews to independent reviews, as suggested by H2.

$DLAG_{ij}$: the number of days since the j−1th review for book i was posted. This variable controls for the effect of possible "bursts" of reviews, when the rate of arrival of reviews may suddenly increase because of external events, such as media

[3] We randomly selected 100 reviews that mentioned "review" or "reviewer" in the review text (REF = 1) and 100 reviews that did not mention either word (REF = 0) and read them carefully. Of the 100 reviews with REF = 1, 10 reviews either did not talk about previous reviews or responded to reviews outside of Amazon, for an accuracy rate of 90%. Of the 100 reviews with REF = 0, 2 reviews mentioned previous reviews on Amazon without using the word "review" or "reviewer," for an accuracy rate of 98%.

coverage.[4] The interaction of this variable with $AVGSCORE_{ij}$ controls for how the effect described in H1 varies when reviews arrive in groups.

$PLIST_i$: a dummy variable capturing whether the book appeared on a publisher's weekly bestseller list during the 6 months after its publication. We use its interaction term with $AVGSCORE_{ij}$ to test H4.

Because we include book fixed effects to control for the idiosyncratic, constant characteristics of the book, we do not include the book characteristics that are constant over time in the regression. The variance inflation factors of all the independent variables are less than 5, which suggest that multicollinearity is not a concern in this analysis.

Results

We present the results of our ordered logistic models in Table 2, and to demonstrate the significance of the context effect of existing reviews, we consider three models. Model 1 is a null model that contains only the ordered logistic cut-off values and fixed effect estimates (to control for heterogeneity across books); Model 2 adds the review feature variables *RNAME* and *RLENGTH*; and Model 3, or the full model, tests all the hypotheses. Because of the large number of books, we do not report the book-specific fixed-effect coefficients and their interactions with $SEQN_{ij}$ and $DPUB_{ij}$ in Table 2. We use the Akaike information criterion (AIC) to judge the goodness of fit of these models; a smaller AIC value indicates a better fitting model. The full model (Model 3, AIC = 132,434) provides the best fit. We drop the subscripts of the variables in this section to improve readability.

The coefficient estimates support our hypotheses. Because we include book fixed effects in the regression, all the following effects refer to situations in which book quality is held constant.

First, *AVGSCORE* is negative and significant (estimate = -0.681, $p<.001$), which indicates that, assuming constant book quality, a higher average previous rating leads to lower subsequent ratings. We are more likely to observe a deviation of opinions from previous reviews, in support of H1. Although reviews that disagree and agree with previous reviews both exist, the main effect (estimate of *AVGSCORE*) reflects an overall aggregate effect. The direction and the magnitude of this effect are mediated by other factors as well. To ensure that this effect is not caused by "regression to the mean" we conducted a simulation by randomizing the sequence of the review scores and re-analyzing the data. We no longer find a negative effect for *AVGSCORE*. This further demonstrates that the actual order in which these reviews are written indeed matters.

Second, the interaction effect $AVGSCORE \times REF$ is negative and significant (estimate = $-.468$, $p<.001$); therefore, given constant book quality, reviews that mention previous reviews or reviewers are more likely to disagree than agree with those previous reviews. This interaction separates the group that contains more context-susceptible reviewers from the group of those who are independent-minded. The finding supports H2, consistent with the idea that reviewers who read previous reviews are more likely to speak up if they have different opinions. The higher the ratio of responsive reviews to independent reviews, the stronger is the negative impact of previous reviews on newly posted reviews.

Third, the interaction effect $AVGSCORE \times STDSCORE$ is positive and moderately significant (estimate = .118, $p=.072$), in support of H3 and consistent with Bayesian information updating theory. Lower variance in the information source increases its impact, and with the negative coefficient of *AVGSCORE*, the positive coefficient of the interaction term verifies a negative mediating effect.

Fourth, the interaction effect $AVGSCORE \times PLIST$ is positive and significant (estimate = .666, $p<.001$), in support of H4; we are more likely to observe diverging opinions for unpopular books than for popular books. This difference may arise because many alternative sources tend to provide information about popular books to potential buyers, so the impact of previous reviews on one particular Web site should be smaller. We also find a negative and significant coefficient for $AVGSCORE \times DLAG$, which suggests that reviews that arrive in groups (smaller *DLAG*) tend to be less susceptible to the context effect hypothesized in H1 than reviews that arrive alone (larger *DLAG*). This finding is consistent with our finding for popular versus unpopular books, because a burst of reviews is less likely to arrive for unpopular books (and as shown previously, diverging opinions are more likely to be observed for unpopular books). Previous studies indicate that the average rating in previous reviews has a positive influence on subsequent reviews (Gao, Gu, and Lin 2006; Godes and Silva 2006), though these works do not distinguish heterogeneous reviewers for popular versus unpopular products, which may explain the difference in our results.

Fifth, the interaction effect $AVGSCORE \times SEQN$ is negative and significant (estimate = $-.723$, $p<.001$), in support of H5. As more reviews get posted, the amount of product information in the market increases, to the extent that it may reduce reviewers' incentive to provide book information, but it does not alter the incentive of reviewers who post in response to existing reviews. This influence augments the self-selection effect. More existing reviews also increase the influence on a potential buyer's expectation of the book quality, so they play a greater role in the review that this buyer may write after purchase, which represents an enhancement of the expectation effect. As a result, with constant book quality, more posted reviews make the context effect more pronounced, with a greater likelihood of opinions that differ from existing reviews.

In summary, our empirical findings support all our hypotheses and show that though both responsive and independent reviews exist, as do reviews that disagree and agree with previous reviews, the aggregate effect maintains that for constant book quality, a higher average in previous ratings is likely to lead to lower subsequent ratings (H1). This effect is mediated by the ratio of responsive reviews to independent reviews (H2) and the strength of previous reviews' influence on those responsive reviews (H3–H5).

[4] We thank an anonymous reviewer for suggesting this variable.

In addition to confirming our five hypotheses, our estimates of two control variables (*RNAME* and *RLENGTH*) reveal some interesting findings. First, reviewers who use their real names in their reviews (tagged "real name" by Amazon.com) are more likely to write positive reviews than are anonymous reviewers (mean estimate $RNAME=.343$, $p<.001$). Higher ratings by those using real names may impose meaningful influences on book sales (Chevalier and Mayzlin 2006). This observation regarding the anonymity effect is consistent with findings in other domains (Hazelwood and Brigham 1998) and has interesting potential implications for the difference between online and offline WOM behavior. In an offline context, WOM usually takes place in a face-to-face environment, and the identities of both the giver and the receiver are well known. Anonymous evaluations are only available online. Thus, online WOM may involve more negative experiences than its offline counterpart. Companies that rely on the Internet as a new media device for promotion should realize that such anonymity can lead to the expression of more negative views. In turn, this finding suggests an interesting question for academics: If online reviews tend to be more negative than real-world communications among consumers, is it possible that extant studies are susceptible to biases, introduced by relying dominantly on Internet reviews instead of counting real-world communications as well? These interesting questions should be examined further in research that includes both online and offline WOM information.

Second, negative reviews are more likely to include more text than are positive reviews (mean coefficient $RLENGTH=-.474$, $p<.001$). Accordingly, negative reviews likely are accompanied by greater detail (possibly to justify the negative evaluation) than are positive reviews, which may amplify the impact of negative reviews.

Discussion and Conclusion

Our findings have important implications for firms that use online WOM as an alternative marketing channel to promote their products. Given the contextual impact of existing reviews on consumers' incentives to post reviews with different sentiments, firms should tailor their approach to influencing consumer reviews for different types of products and in different stages of the product life cycle.

Our results suggest that unpopular products are more susceptible to the context effect exerted by existing reviews. This finding, along with the finding that reviews are likely more influential for unpopular products because of the lack of alternative information sources, suggests the importance of understanding the dynamic process by which existing reviews influence the formation of subsequent reviews for niche products. Inviting independent reviewers to balance the tendency of later reviews to contradict existing favorable reviews might be beneficial. Balancing the display of spotlight reviews on the front page by including diversified opinions, instead of overwhelmingly positive evaluations, also might avoid attracting only criticizers.

Unlike traditional WOM, online WOM persists over time, allowing consumers to observe and respond to existing reviews. Therefore, consumers with different opinions or experiences that disconfirm the expectations formed on the basis of previously posted reviews have opportunities to express their points. Moreover, these consumers usually sense a greater incentive to write reviews, which may increase the probability of more negative WOM online than offline. Our finding that anonymous reviewers tend to write negative reviews, which usually provide greater detail, suggests an even more problematic situation, in that anonymity only prevails online. The impact of online WOM thus appears very different from offline WOM, and firms should adjust their strategies to adapt to this distinction.

The biases we find in Amazon.com's book reviews may have an impact beyond consumers' short-term purchase decisions. For example, with regard to the long-term effect, do consumers realize the existence of such misrepresented opinions online? If consumers find that the reliability or trustworthiness of the reviews leaves much to be desired, they may rely less on these reviews over time for their future purchase decisions. This proposition is consistent with the "influencer" role of movie critics (Eliashberg and Shugan 1997), in the sense that consumers revisit critics whose implied preferences match their own but abandon others.

We provide some insights into the context effect for book reviews, but we cannot claim a complete elaboration of all the nuances of this effect. In the analysis, we do not directly include an autoregressive lagging effect but instead use the average of previous review scores to partially capture such effect. Our approach is subject to the common limitations of secondary data research. Most notably, we do not observe the opinions of reviewers who decide not to post reviews, which means that our analysis is based solely on the outcome of the proposed expectation and/or self-selection effect; we cannot distinguish between them. In addition, we cannot observe alternative information sources, though they also may influence expectations. Our use of presence on bestseller lists as a proxy helps mitigate this problem, but it cannot fully account for all possible alternative information sources.

Thus, our findings raise several interesting questions that deserve further research attention. First, the effects of expectation and self-selection may both influence subsequent reviews. Although distinguishing between these two effects is beyond the possible scope of our investigation using secondary data, it would be interesting to investigate the extent to which they affect the reviewing process. A behavioral study, likely based on controlled experiments, may provide more insights into how WOM or evaluation diffuses and spreads. Sophisticated text mining techniques also could be employed to analyze other behavioral characteristics in the reviewing process, such as propensity to provide distinctive reviews on various dimensions or the desire to herd with the prevailing opinion. Second, if consumers behave strategically, both in interpreting the information in online reviews and when writing reviews (e.g., in response to a book on the best seller list), how does that behavior influence the sales dynamic of products? This question might be answered through analytical and structured empirical analysis. Third, the speed with which online WOM spreads depends on the nature of the products. Reviews of movies tend to start and fade quickly, whereas the process is much slower for books, for example. Might differences in speed change the way context-dependent reviews function?

In conclusion, the implications of our research may help retailers gain a deeper understanding of consumer reviews and improve objectivity in the reviewing process. Academically, we extend extant research on online consumer reviews by investigating the context dependence of subsequent reviews on previously posted reviews. The results suggest that in aggregate, later reviewers tend to differ from earlier reviews, though the effect is mitigated by the popularity of the product, the variance of previous reviews, whether the reviews explicitly refer to previous reviews, and the age of the product or the reviews.

Appendix. Creation of The Initial Sample

Our initial sample of books derives from two sources:

1. A sample of books extracted from *Book In Print*, based on the following criteria:
   - Publication date is between January 2000 and February 2004.
   - Publication language is English.
   - Book edition is hardback.
   - Status is active.
   - For books published before 2004, reviews are available.
2. Hardback books that appeared at least once in *Publisher's Weekly* bestseller lists between January 1, 2000, and February 9, 2004, and were published between January 2000 and February 2004.

We filter this list to ensure a sufficient number of consumer reviews. Thus, we keep only 2,651 books in our final sample, according to the following criteria:

For books published before 2004:

- On average, at least one review is posted on Amazon.com every 10 days, or the total number of reviews posted on Amazon.com is greater than a certain number: 40 for books published in 2000, 30 for books published in 2001, 20 for books published in 2002, and 10 for books published in 2003;
- At least one review is posted on Amazon.com by the end of first month after release.

For books published both before and after 2004:

- Sales rank is smaller (i.e., higher in ranking) than 100,000.

We judge these screening criteria using the pilot data (sales and reviews data), collected from Amazon.com on February 23, 2004.

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