

Self Selection and Information Role of Online Product Reviews

Xinxin Li • Lorin M. Hitt

The Wharton School, University of Pennsylvania

Introduction

Word of mouth has long been recognized as a major driver of product sales. It can raise consumer awareness, and may be one of the few reliable sources of information about the quality of experience goods. With the development of the Internet, word of mouth has moved beyond small groups and communities, to being freely available through large-scale consumer networks (Avery, Resnick and Zeckhauser 1999). These networks have reinforced the impact of word of mouth to an unprecedented scale, and correspondingly dramatically changed the way consumers shop, enhancing or even supplanting traditional sources of consumer information such as advertising. In a survey of 5,500 web consumers conducted by BizRate, 44% of respondents said they have consulted opinion sites before making a purchase and 59% considered consumer-generated reviews more valuable than expert reviews (Piller 1999). A recent survey of DoubleClick also found that word of mouth plays a very important role in consumer's purchasing process for many types of products and for some goods, such as electronics and home products, product review websites outrank all other media in influencing customer decisions (DoubleClick 2004).

While a large body of work has been focusing on analyzing the efficiency and sufficiency of eBay-like online reputation systems and their design issues (see a comprehensive review in Dellarocas 2003a), there has been very little systematic research on product review websites. Chevalier and Mayzlin (2003) and Godes and Mayzlin (2003) showed in different settings that online consumer reviews can indeed affect product sales, although they did not examine whether consumer reviews can communicate quality information efficiently. The efficacy of consumer-generated product reviews may be limited for at least two reasons. First, firms may manipulate online rating services by paying individuals to provide high ratings, although theoretical results by Dellarocas (2003b) demonstrated that this type of behavior may not reduce their informativeness if producers and consumers behave optimally. Second, even in the settings where product reviews are all truthfully reported, there are still possibilities that the reported ratings are inconsistent with the preferences of the general population. Unlike ratings of seller quality where higher ratings are unambiguously better for all consumers, ratings of products may reflect both consumer taste as well as quality. This may be particularly problematic if the perceptions of product quality of the buyers who post reviews online differ from those of most consumers since the reviews will yield systematic biases even when they are truthful reports of perceived quality. This self-selection problem is particularly serious in early product introduction periods when marginal effect of a single

review is high. In the meanwhile, the fact that potential buyers may not be aware of these biases and thus do not adjust the relevance of different reviews accordingly bears a direct impact on the efficiency of online review systems. This can partially explain why in reality we often observe product ratings declining over time, while a flat or even an increasing trend would be expected if quality information is indeed communicated online efficiently – if consumers have little difference in tastes and preferences or if beneficiaries of online reviews can distinguish the types of reviewers and locate the products that fit them best.

In this study, we will examine the latter issue utilizing ratings and sales data collected from Amazon. We address two major research questions. First, do product ratings change systematically over time? Our hypothesis is that early adopters may have significantly different preferences than later adopters which will create trends in ratings as products diffuse. Second, we consider whether consumers account for these biases in ratings when making product purchase decisions. We use these empirical observations as the foundation for a theoretical model that examines the relationship between consumer behavior and outcomes in markets where online review systems play a significant role. Understanding these issues is important to firms' customer relationship management and product positioning strategies. Realizing the disproportionate impact of early product adopters on market outcomes, firms can respond by altering their marketing strategies, such as pricing and advertising, or product design to encourage consumers likely to yield positive reports to self-select into the market early and increase the average rating when introducing a new product. This is similar to strategies where firms promote their products to individuals who have credibility in certain online forums (Dellarocas, 2003b), although this study would suggest that knowledge of idiosyncratic tastes of these reviewers is as important as broad reach and influence.

Data Collection

A random sample of 2651 hardback books was collected from "Books in Print" covering books published from 2000-2004 that also have reviews on Amazon. Book characteristic information was collected from Amazon including title, author, publisher, publication date, category, publication date for corresponding paperback editions, and all consumer reviews posted on Amazon since a book was published. Every Friday from March to July in 2004 we collected sales-related data for each book from Amazon including sales rank, price, the number of consumers reviews, the average review, and shipping availability. To control for outside competition and promotion, each Friday we also collect prices listed on a price comparison engine (www.pricescan.com) for each book in our sample.

Trend in consumer reviews

We start by using Box-Cox transformation to explore if there is any trend in book reviews posted on Amazon over time. The Box-Cox model is established as follows:

$$AvgRating_{it} = \begin{cases} a + b \frac{T^l - 1}{l} + u_i + e_{it} & \text{when } l \neq 0 \\ a + b \cdot \text{Log}[T] + u_i + e_{it} & \text{when } l = 0 \end{cases},$$

where $AvgRating_{it}$ represents the average review for book i at time t , T denotes the time difference (measured as the number of months) between the date the average review was posted and the date the book was released, and u_i stands for the idiosyncratic characteristics of each individual book that keep constant over time. The estimated trend is pictured in Figure 1.

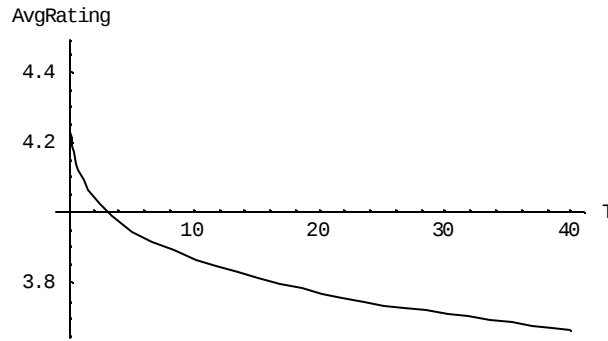


Figure 1

The model shows a significant declining trend in average ratings over time. We also tried other models, including negative exponential model and polynomial regression models. Using J-test, we can not reject the hypothesis that these models are equally good, but the negative exponential model returns the minimum sum of squared residuals. Therefore we'll use the estimates in the negative exponential model for our subsequent analysis – the fitted model is $AvgRating_{it} = 3.90 + 0.45 \cdot \exp[-0.746 \cdot T] + \hat{u}_i + \hat{e}_{it}$.

Impact of consumer reviews on book sales

It has been shown in Chevalier and Mayzlin (2003) that online book ratings do affect book sales. Based on the preceding analysis, book ratings have an obvious trend over time – average ratings decline over time, showing a positive bias in reviews written by early buyers. We will further investigate when consumers compare alternative books, do they notice the timing of the book ratings and adjust the impact of ratings accordingly.

As argued in Chevalier and Mayzlin (2003) and some other studies, sales rank is a log-linear function of book sales with a negative slope. We use $-\text{Log}[\text{SalesRank}]$ as dependent variable and the cross-sectional regression model can be established as follows,

$$-\text{Log}[\text{SalesRank}_i] = b_0 + b_1 \text{AvgRating}_i + g_1 \text{Log}[P_i] + g_2 \text{Log}[\text{NumofReview}_i] + g_3 \text{Log}[P_i^C] + g_4 \text{Promotion}_i + g_5 T + g_6 \text{CategoryDummies}_i + g_7 \text{ShippingDummies}_i + e_i$$

To examine the impact of consumer ratings on book sales, we control other demand-

related factors, including book price offered by Amazon (P_i), the number of reviews posted on Amazon ($NumofReview_i$), outside competitive price (P_i^C), book promotion ($Promotion_i$), book category ($CategoryDummies_i$) and shipping availability ($ShippingDummies_i$)¹. Considering the possibility that sales may naturally decline over time, we also control for how long an individual book has been in market (T).

Using estimates from the negative exponential model, average rating can be considered as the sum of a population average, $3.90 + \hat{u}_i + \hat{e}_{it}$, denoted as $\bar{R}_i$ which represents underlying quality of book i , plus a time varying component, $0.45 \exp[-0.746 \cdot T]$, denoted as R_T which stands for review bias at time T . If we replace $AvgRating_i$ with the value estimated from the negative exponential model, the regression model is changed to

$$- \text{Log}[SalesRank_i] = b_0 + b_{11}\bar{R}_i + b_{12}R_T + g_1\text{Log}[P_i] + g_2\text{Log}[NumofReview_i] + g_3\text{Log}[P_i^C] + g_4Promotion_i + g_5T + g_6CategoryDummies_i + g_7ShippingDummies_i + e_i$$

If the consumers notice the bias in early periods and fully account for it, the time variant component R_T should have no impact on consumer purchase decision and therefore β_{12} should be zero.

We use the book sales data collected on March 19th to fit the model (results are similar if other time periods are used). All estimates are significant and have the right sign. With other demand-related factors controlled for, the time variant component R_T has a significant impact on book sales when consumers compare different books at the same time period, which leads to the conclusion that consumers did not fully account for the positive bias of early raters. Using a time series model to study how the impact of consumer reviews on an individual book evolves over time, the same conclusion is supported.

Theory Model and Implications

The empirical investigation demonstrates the potential bias in consumer reviews in early product introduction periods and empirically verifies that buyers generally do not fully account for this bias when they examine online reviews. We now utilize these observations to motivate a theoretical model that examines how these biased reviews can impact market outcomes.

Consider a market for an experience good where in each period a group of consumers comes into the market and makes a decision on whether to purchase (at most) one unit of the product. An individual consumer's preferences over the product can be characterized

¹ P_i^C is measured as the minimum price listed on Pricescan.com for book i ; $Promotion_i$ is defined as $(List\ Price - Second\ Maximum\ price\ listed\ on\ Pricescan.com) / List\ Price$ for book i .

by two components (x_i, q_i) . The element x_i is known by each consumer before purchasing and represents the consumer's preference over product characteristics that can be inspected before purchase. The element q_i measures the quality of the product for consumer i – each consumer may perceive quality of the same product differently. Consumers only learn q_i after buying the product, and their demand is determined by x_i and their expected quality q^e which can be affected by online review systems. In each period, consumers who bought the product post their (truthful) product reviews online that are available to all future buyers. Because of consumers' idiosyncratic tastes over quality, the reported review may not be an unbiased indicator of product quality. If q_i is unrelated to consumer characteristics then this simply introduces noise in the reported rating since ex-post some consumers may be more or less satisfied than they expected. However, if x_i and q_i are correlated, such as when early buyers are product aficionados who are likely to value the product highly, reviews can become systematically biased, which in turn affects the demand for the product and the types of consumers that purchase the product in future periods.

Our findings suggest the significance of product design and early period product promotion – carefully targeting the potential buyers who may self-select into the market early and also favor your products or incorporating the requirements of early adopters into production is strategically important. McFadden and Train (1996) argued that learning from other consumers may hurt niche products. This study shows that even for a potentially popular product, failure to catering to the preferences of early buyers thus generating unfavorable word-of-mouth in early periods may also hurt.

References

- Avery, C., Resnick, P. and Zeckhauser, R. "The Market for Evaluations," *The American Economic Review* (89:3), 1999, pp. 564-584.
- Chevalier, J. and Mayzlin, D. "The Effect of Word of Mouth on Sales: Online Book Reviews," Working Paper, Yale School of Management, 2003.
- Dellarocas, C. "The Digitization of Word-of-Mouth: Promise and Challenges of Online Reputation Mechanisms," *Management Science* (49:10), 2003a, pp. 1407-1424.
- Dellarocas, C. "The Impact of Online Opinion forums on Competition and Marketing Strategies," Working Paper, MIT-Sloan, 2003b.
- DoubleClick "DoubleClick's Touchpoints II: The Changing Purchase Process," March, 2004.
- Godes, D. and Mayzlin, D. "Using Online Conversations to Study Word of Mouth Communication," Working Paper, Yale School of Management, 2003.
- McFadden, D. and Train, K. E. "Consumers' Evaluation of New Products: Learning from Self and Others," *Journal of Political Economy* (104:4), 1996, pp. 683-703.
- Piller, C. "Everyone Is A Critic in Cyberspace," *Los Angeles Times*, December 3, 1999