Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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MANAGEMENT SCIENCE
Vol. 58, No. 4, April 2012, pp. 696–707
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.1110.1458

How Does the Variance of Product Ratings Matter?

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This paper examines the informational role of product ratings. We build a theoretical model in which ratings can help consumers figure out how much they would enjoy the product. In our model, a high average rating indicates a high product quality, whereas a high variance of ratings is associated with a niche product, one that some consumers love and others hate. Based on its informational role, a higher variance would correspond to a higher subsequent demand if and only if the average rating is low. We find empirical evidence that is consistent with the theoretical predictions with book data from Amazon.com and BN.com. A higher standard deviation of ratings on Amazon improves a book's relative sales rank when the average rating is lower than 4.1 stars, which is true for 35% of all the books in our sample.

Key words: information transmission; product ratings; social media; user-generated content
History: Received May 29, 2010; accepted August 23, 2011, by Pradeep Chintagunta, marketing. Published online in *Articles in Advance* December 2, 2011.

1. Introduction

Consumers often seek others' opinions about a product before making a purchase decision. They read magazines such as *Consumer Reports*, browse specialized review websites such as Yelp.com, check consumer ratings posted by previous patrons, and ask their family members and friends for recommendations. According to Kee (2008), 64% of the respondents in Forrester Research's online survey want to see user ratings and reviews on the e-commerce websites they visit, edging out those who want special offers or coupons (61%), personalization (37%), games or quizzes (29%), and videos (44%). According to the same report, 68% of online shoppers check at least four reviews before buying, and almost one quarter of respondents check at least eight reviews.[1]

In response to consumers' desire to read multiple reviews, many leading consumer-review and e-commerce websites, including Yelp.com, Walmart.com and Amazon.com, are making the distribution of ratings salient to consumers by putting up bar charts that demonstrate the percentage of reviews that are associated with each level of ratings.[2] When a bar chart is offered, it often appears in a prominent location on the product's introduction page, over and above any further breakdown of reviews. As evident from the bar charts, reviewers often hold different opinions toward the same product. For example, the book *Breaking Dawn* (part of the *Twilight* series) had received 5,132 Amazon reviews as of May 2, 2010, with an average rating of 3.5 out of 5 stars. All of the three reviews that were considered the most helpful by Amazon visitors featured a one-star rating.[3] Comparing the bar charts for two popular books with similar average ratings, *Breaking Dawn* and *The Lord of the Rings—The Fellowship of the Ring*,[4] one can see that readers clearly disagree about the first book, whereas most readers give the second book high ratings.[5]

Although consumers consistently check out multiple online reviews and can easily observe the differences in the distribution of ratings, prior research (e.g., Chevalier and Mayzlin 2006) has focused on establishing the causal impact of the average rating on sales, and little is known about how the rating distributions would matter.

[1] Branco et al. (2011) study the problem of when a consumer should stop collecting more product information as he tries to make a decision on whether to purchase.

[2] See Sun (2011) for a discussion on how firms would directly disclose information on multiple product attributes. See also Sun and Zhu (2011) for a discussion on how advertising-sponsored business models can use a portion of the ad revenue to induce bloggers to write on popular topics such as the stock market.

[3] See http://www.amazon.com/Breaking-Dawn-Twilight-Saga-Book/dp/031606792X (accessed May 2010).

[4] See http://www.amazon.com/Lord-Rings-Fellowship-Platinum-Extended/dp/B000067DNF (accessed May 2010).

[5] As of May 2, 2010, the rating distribution for *Breaking Dawn* was 2,460 five-star ratings, 673 four-star ratings, 441 three-star ratings, 499 two-star ratings, and 1,059 one-star ratings. The distribution for *Fellowship of the Ring* was 3,292 five-star ratings, 359 four-star ratings, 172 three-star ratings, 124 two-star ratings, and 216 one-star ratings.

Sun et al. (2011) document how users on a large Chinese social network site generally prefer to diverge from the most popular choice even among their friends.

To understand the role of the distribution of ratings, a useful starting point would be to consider the variance of ratings. As a statistical concept, variance is a natural measure to capture the heterogeneity in consumer opinions. From a managerial perspective, variance is also an easy measure to obtain: Market researchers can easily calculate the variance by summarizing online ratings for their products. Given that the variance of ratings is fast and almost costless to obtain, it would be beneficial to the managers if they could understand how the variance informs potential customer' purchase decisions and how to incorporate the measure for better demand forecasts.

Although it would be interesting to study how firms may potentially manipulate online word of mouth (e.g., Mayzlin 2006), we assume truthful ratings and focus our attention on how consumers interpret and make use of the these ratings upon seeing them. In particular, we seek to address three questions. First, what message does a higher variance of product ratings communicate to the consumers? Second, what is the impact of the level of variance on a product's subsequent price, demand, and profit? Third, is there any interaction effect between the average rating and the variance of ratings?

When asked about the role of the variance of ratings, some argue that because consumers are risk averse, inconsistent opinions should have a negative impact on demand; others think that the big differences in ratings might trigger curiosity, which could lead to a higher demand. Although these are interesting arguments, we abstract away from the psychological underpinnings of how consumers would react to risk, and focus on the informative role of the variance.

Our game-theoretical model features one seller and consumers with differentiated tastes. To characterize consumers' taste space, we use a variation of the linear-city model (Hotelling 1929). The product in our model is characterized by two attributes: quality and mismatch cost, which is similar to the "transportation cost" in the Hotelling (1929) model. We use mismatch cost to capture aspects of the product that would have an influence on how much consumers would differ in their enjoyment of the product. A low mismatch cost, for example, suggests that it is easy for all consumers to enjoy the product, regardless of how well their tastes match with the product. In other words, the product is mainstream—it is designed to cater to a broad range of tastes. A high mismatch cost, on the other hand, indicates that a consumer would enjoy the product only if her taste matches well with the product. The product in this case is a niche one: it is designed to cater to only a small group of consumers.

As one can imagine, both product attributes, quality and mismatch cost, affect ratings. Consumers who arrive late at the market can therefore infer the two product attributes from earlier ratings. A high average rating in our model communicates to the consumers that the product has high quality, which increases subsequent price, demand, and profit. The role of the average rating in our paper is hence consistent with prior literature (e.g., Chevalier and Mayzlin 2006). A high variance, on the other hand, is a double-edged sword: it communicates to consumers that the product has both a high quality and a high mismatch cost. Upon seeing a high variance, consumers infer that the product is a niche one that some people love and others hate.

Given the message contained in the variance of ratings, how does a higher variance relate to equilibrium price, demand, and profit? Interestingly, the answer depends on the level of the average rating. When the average rating is high, perceived quality is already above a certain threshold. In this case, most consumers are interested in the product. As a result, the dominant effect of a higher variance is to drive away marginal consumers. When the average rating is low, on the other hand, few consumers are interested in the product. A higher variance then helps the seller to secure demand from well-matched consumers. Putting these two scenarios together, we find that equilibrium demand will increase with the variance of product ratings if and only if the average rating is low, which is a key result of our model. In an extension, we give early consumers the option to defer their purchase decisions until after they have read the product ratings, and find a similar role of variance.

We provide empirical evidence in the context of online book sales that is consistent with our theoretical predictions. For a random set of bestselling books, we collect from Amazon.com and BN.com[6] the consumer ratings, price, sales rank, and shipping information for each book. We then employ a difference-in-differences (DID) approach to identify the causal effect of product ratings. Consistent with previous empirical research on product ratings (e.g., Chevalier and Mayzlin 2006), we find that a higher average rating on Amazon always increases book sales. As an important new insight consistent with our theoretical framework, we also find that a higher standard deviation of ratings on Amazon increases a book's relative sales if and only if the average rating is lower than approximately 4.1 stars, which is true for 35% of all the books in our sample.

Our findings provide important managerial implications and suggest that managers should realize the important role of the rating distribution. They should keep in mind that a product with a low average rating may still turn out to be profitable if the variance

[6] The URL is the same as http://www.barnesandnoble.com.

of ratings is sufficiently high. The seller of such a niche product should therefore make sure that consumers can easily observe the high variance of ratings and provide detailed product information that further facilitates the matching between consumers and the product. A truthful high variance of ratings coupled with detailed product information can help a seller to skim the market by selling to the best matched consumers at a premium price. A mainstream-product seller, on the other hand, should make sure that consumers can easily observe the low variance of ratings and limit the disclosure of detailed product information that may drive away marginal consumers. The low variance would then lead to purchases from consumers with a wide range of tastes, and the seller can profit from selling across the board.

Our paper fits into the marketing literature of consumer reviews and, more generally, user-generated content. In the theoretical literature, Chen and Xie (2005, 2008) study whether firms should allow consumer reviews to be posted on their sites, and how they should adjust their marketing strategies accordingly. Mayzlin (2006) examines firms' incentives to post fake reviews and finds that even with fake reviews, consumers will still be able to extract some information on product quality in equilibrium. Bhardwaj et al. (2008) look at how the choice between seller-initiated and consumer-initiated information revelation affects the equilibrium level of product quality. In a different context, Kuksov and Xie (2010) study firms' incentive to offer frills in a two-period model where the average rating can help late consumers infer early consumers' utility.[7] Most theoretical research to date focuses on how firms react to the possibility of showing consumer reviews as a new information revelation mechanism.

In the empirical and experimental literature, the most closely related paper is Chevalier and Mayzlin (2006). They were the first to use a difference-in-differences approach to identify the causal effect of online consumer ratings on sales. The focus of their paper is the average rating, and they also found that the impact of a one-star rating is greater than that of a five-star rating. To expand our understanding beyond how the first moment of the rating distribution matters, we examine the average rating as well as the variance of ratings, and particularly their interaction.

There is a small literature that directly studies the distribution of ratings. Meyer (1981) shows that consumers discount the average critic rating to adjust for critic disagreement. Martin et al. (2007), in contrast, survey individuals choosing between two movies with pregiven ratings and find that consumers prefer the high-variance movie. Along the same lines, Clemons et al. (2006) find that beer brands with higher variances of ratings grow fastest in terms of sales. West and Broniarczyk (1998) also consider how others' opinions influence consumers' evaluations of product attributes. They examine consumer attitudes toward critic consensus and find experimental evidence that is consistent with the current paper: a higher variance increases purchase likelihood if and only if the average rating is below an aspiration level. The major difference between the paper by West and Broniarczyk (1998) and the current paper is that they ground their study in the prospect theory framework (Kahneman and Tversky 1979), focusing on how consumers respond to uncertainty (Jaccard and Wood 1988) and how their risk attitudes are reference dependent, whereas we model risk-neutral consumers making inferences on the underlying product characteristics through product ratings. Finally, Zhang (2006) finds that the variance of movie reviews does not play a significant role in determining box-office revenues altogether. (Interested readers can see Table 1 for a summary of theoretical and empirical studies of consumer reviews.)

Unlike previous studies, we allow the variance of product ratings to capture the extent to which consumers differ from each other in their enjoyment of a particular product and attribute this difference to the underlying product characteristics. By exploring the interaction of the variance of ratings and the average rating, we are able to provide a theoretical model that reconciles the mixed evidence on the role of the variance. To our best knowledge, we also provide the first empirical demonstration of how the interaction of the variance of ratings and the average rating is a significant determinant of product sales.

The rest of the paper is organized as follows. Section 2 presents our theoretical framework in which consumers learn about product characteristics from earlier ratings. We also discuss in this section the possibility of consumers' choosing to defer their purchase until after seeing the ratings. Section 3 presents empirical evidence on the role of the variance of ratings using data from Amazon.com and BN.com. Section 4 concludes.

2. A Model of Product Ratings

The baseline model in this section features a monopoly seller and risk-neutral consumers with heterogeneous tastes. The seller's product has two attributes: quality and mismatch cost.

The higher the product's quality, the more every consumer enjoys the product. Examples of quality-related product attributes abound. Book readers prefer better prose. Movie goers enjoy a better story line.

[7] The rating is either 0 or 1 in their model, so the average rating captures the entire distribution of ratings, which is a key difference from our model.

Table 1 Previous Research on Consumer Reviews

Theoretical studies	
Chen and Xie (2008)	Whether firms should publish consumer reviews
Chen and Xie (2005)	How firms adjust marketing strategies given reviews
Mayzlin (2006) and Dellarocas (2006)	Firms' incentives to post fake consumer reviews
Awad and Etzion (2006)	Firms' incentives to filter consumer reviews
Jiang and Chen (2007)	Firms' incentives to manipulate early period reviews
Empirical studies	
Godes and Mayzlin (2004)	Dispersion of conversations across communities has explanatory power in a model of TV ratings
Godes and Silva (2006)	Product ratings tend to decrease over time
Zhu and Zhang (2010)	Product ratings are more influential for nonsuperstars
Gao et al. (2006)	Online consumer reviews exhibit remarkable community features
Chevalier and Mayzlin (2006)	A higher average rating leads to higher book sales, and impact of one-star reviews is bigger than impact of five-star reviews
Dellarocas et al. (2007)	Total box-office revenue can be predicted from user reviews in the first week of a movie's release
Duan et al. (2008)	Ratings of online user reviews have no significant impact on movies' box office revenues
Liu (2006)	Word of mouth offers significant explanatory power for both aggregate and weekly box office revenue, especially in early weeks after a movie's release
Chintagunta et al. (2010)	It is the valence that seems to matter and not the volume

Digital camera buyers want higher resolution. Car drivers like more safety features. A higher quality simply increases every consumer's willingness to pay for the product.[8]

There are often other aspects of a product over which consumers disagree (Lancaster 1966). For example, consumers may want different colors when it comes to purchasing a car, a piece of clothing, or a digital camera. They may like different categories of books and different genres of movies. We use the second product attribute, mismatch cost, to capture how niche the product is: mismatch cost is high when the product is a niche one and caters to only a small group of consumers.

Formally, think of consumers' taste space as a straight line of length 2 on which the product is located at the midpoint. Consumers are uniformly distributed on the line: A consumer's location represents her ideal product in the taste space. If a consumer with distance x from the product buys the product at price P, her utility is

$$v - t \cdot x - P,$$

where $v > 0$ is the product's quality, and $t > 0$ is the mismatch cost. A consumer buys at most one unit of the product. If she decides not to buy the product, her utility is zero.[9]

[8] See Desai et al. (2010) for an interesting model of digital rights management, in which they show how consumers with different quality sensitivity choose to steal, buy restricted copies, or buy unrestricted copies of music.

[9] For ease in writing, we refer to a consumer as "she" and the seller as "he."

A high mismatch cost suggests that consumers with different tastes derive very different utility from the product; that is, whereas consumers located near the product enjoy the product a lot, consumers further away do not like it at all. Therefore, we call a high t product a "niche product." A low mismatch cost, in contrast, suggests that all consumers derive more or less the same utility from the product. In the extreme case of $t = 0$, all consumers derive the same level of utility from the product. Therefore, we call a low t product a "mainstream product."

To understand the difference between the two product attributes, one can think of books for example. A book with high quality is generally well written and is characterized by features that most readers would enjoy, such as an interesting plot or the use of exquisite language. A book with high mismatch cost, on the other hand, have features that some people love and others hate, such as violent or salacious content.

Although the taste parameter x differs across consumers, quality and mismatch cost are inherent to the product. When facing a new product, a consumer knows her own taste (i.e., her distance from the product), but she may not know the product's quality or mismatch cost. For example, a book reader may have some idea of how much she likes history books in general (her distance), but she does not know exactly how much she would enjoy a particular history book without further information.

With the observation above, we assume that at the beginning of the game, neither the seller nor consumers know the realizations of v and t, whereas the joint probability density distribution $f(v, t)$ is common knowledge.[10] We treat the levels of quality and mismatch cost as exogenously given: The seller is learning the perceptions of his product together with early consumers. It is natural to assume that many new product sellers do not quite understand their consumers, as 95% of new products fail each year (Burkitt and Bruno 2010).

To avoid discussing corner solutions, we assume that the market is never fully covered[11] and normalize the total cost of production to zero. The extensive form of the game is as follows:

Period 1. A unit mass of early consumers enter the market. Their distance from the product x is uniformly distributed in $[0, 1]$. The seller chooses price (P_1), and consumers decide whether to buy a unit of the product. Every consumer who buys the product consumes it and publishes a rating $s(x) = v - t \cdot x$.

Period 2. A unit mass of late consumers enter the market. Their distance from the product is also uniformly distributed in $[0, 1]$. Late consumers and the seller observe first-period demand,[12] the average rating, and the variance of ratings. The seller chooses price (P_2), and each consumer decides whether to buy the product.

Two features of the game are noteworthy. First, we assume that a consumer's rating equals her consumption utility.[13] In particular, when giving ratings, an unsatisfied consumer does not take into account whether it is a low quality or a high mismatch cost that has led to her low utility. We observe many reviews on Amazon that fit this assumption. For example, the book *Because She Can* received a three-star review saying, "if you have a mean female boss then this is a good book to read." The reviewer realizes that some well-matched readers would love the book but nonetheless gives a low rating, suggesting that his mismatch with the book has hindered his enjoyment of the book.[14]

Second, because uniformly distributed consumer tastes would lead to uniformly distributed ratings, the average rating and the variance of ratings in our model perfectly describe the entire rating distribution. Admittedly, ratings are often not uniform, and some capable consumers might be able to process abundant information from a bar chart (e.g., skewness). Because our main goal is to expand our understanding of ratings to include the variance, we leave considerations of higher moments of the rating distribution for future research.

We solve for the subgame perfect equilibrium of the game. In the first period, there is no information on quality or mismatch cost. Consumers make purchase decisions based on their expectations of v and t, denoted by $E(v)$ and $E(t)$, respectively. Because the joint distribution $f(v, t)$ is common knowledge, $E(v)$ and $E(t)$ are also common knowledge. When the seller chooses price P_1, the indifferent consumer with distance D_1 from the product is given by

$$E(v) - E(t) \cdot D_1 - P_1 = 0. \tag{1}$$

Consumers located with distance $x \in [0, D_1]$ derive higher utility than the indifferent consumer. They would purchase the product, and the first-period demand is D_1.

Now consider the distribution of ratings.[15] The early consumer with $x = 0$ has a perfect match with the product and gives the highest rating, v. Similarly, the marginal consumer with distance D_1 gives the lowest rating, $v - t \cdot D_1$. Although the marginal consumer is indifferent when purchasing the product, her rating can be either positive or negative depending on whether the product exceeds or falls short of her prior expectation.

Ratings are uniformly distributed in $[v - t \cdot D_1, v]$, which suggests that both product attributes play critical roles in the distribution. When product quality v increases, all ratings become higher. When the mismatch cost t increases, two effects occur. First, all ratings become lower as consumers experience a larger utility reduction from their taste mismatch. Second, the difference across ratings becomes larger, which captures the idea that the difference in consumers' utility is larger for niche products.

The average rating and the variance of ratings can be computed, respectively, as

$$M = v - \frac{1}{2} t \cdot D_1 \quad \text{and} \quad V = \frac{1}{12}(t \cdot D_1)^2. \tag{2}$$

These two equations suggest that the average rating and the variance of ratings are not independent. In particular, upon seeing the highest possible average rating, given any D_1, one can infer that the variance of rating is zero. Similarly, upon seeing the lowest possible average rating, one can infer that the mismatch cost, and hence the variance, is the highest possible. Nevertheless, for all other levels of the average rating, the variance is uncertain.

[10] Note that we do not require v and t to be independent.

[11] A sufficient condition for incomplete coverage of the market is $v \in [\underline{v}, \bar{v}]$, $t \in [\underline{t}, \bar{t}]$, and $\bar{v} < \underline{t}$.

[12] For example, consumers can learn prior demand by looking at the product's sales rank on a retailer's website.

[13] Incorporating price into ratings would not affect our analysis as long as all the consumers understand how price enters the rating formula.

[14] Our results would hold, however, even if the reviewers are more lenient toward high mismatch than low quality, that is, changing the rating formula to $s = v - \alpha \cdot tx$, where $0 < \alpha < 1$, would not substantially change the results as long as α is common knowledge.

[15] All analysis remains qualitatively unchanged if the rating score also reflects price: $s(x) = v - t \cdot x - P$.

When consumers observe a relatively low average rating, for example, they make the following inference: The low average may result from either low quality or high mismatch cost. A high variance in this case helps them to figure out that the product has both high quality and a high mismatch cost, and well-matched consumers would actually love it.

Mathematically, the late consumers infer the realizations of v and t by solving (2):

$$v = M + \sqrt{3V} \quad \text{and} \quad t = \frac{2\sqrt{3V}}{D_1}. \tag{3}$$

In sum, a high average rating indicates a high level of quality and suggests that all early consumers enjoy the product to a reasonable degree. A high variance, on the other hand, indicates that early consumers either love or hate the product depending on how well their tastes match with it.

Given Equations (3), there is no uncertainty left regarding the two product attributes in the second period. Late consumers can perfectly infer the product's quality and mismatch cost of the product. In other words, there is complete information in the second period. The game is therefore equivalent to one in which all second-period consumers observe every single rating. Given the uniform distribution of ratings, our game is also equivalent to one in which (1) second-period consumers read only the highest and the lowest ratings, or (2) each second-period consumer reads only one rating, the one from the first-period consumer who has the same taste x. Scenario (1) may be descriptive of consumers who visit review websites with a wide score distribution (e.g., Yahoo! Movies, Metacritics) and read only the most drastic reviews, whereas scenario (2) would hold for consumers that are loyal to certain critics.

Given complete information, the indifferent consumer in the second period is given by $D_2 = (v - P_2)/t$, and hence the seller solves

$$\max_{P_2} P_2 \frac{v - P_2}{t}.$$

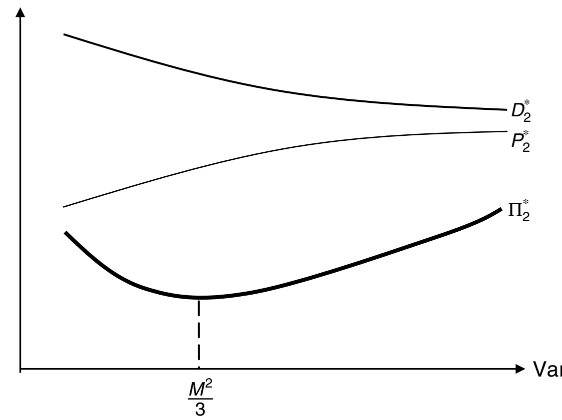
Equilibrium levels of second-period price, demand, and profit can be derived as

$$P_2^* = \frac{v}{2}, \quad D_2^* = \frac{v}{2t}, \quad \text{and} \quad \Pi_2^* = \frac{v^2}{4t}.$$

Based on the correspondence between ratings and the product attributes given in Equations (3), the second-period equilibrium outcomes can be rewritten as

$$P_2^* = \frac{M + \sqrt{3V}}{2}, \quad D_2^* = \frac{D_1}{4}\left(\frac{M}{\sqrt{3V}} + 1\right), \quad \text{and}$$
$$\Pi_2^* = \frac{D_1}{8}\left(\frac{M^2}{\sqrt{3V}} + \sqrt{3V} + 2M\right). \tag{4}$$

Figure 1 **Equilibrium Price, Demand, and Profit in Period 2**



Notes. The average rating is positive in this figure. The horizontal axis is the variance of product ratings in the first period. As the variance of ratings increases, late consumers infer both higher quality and higher mismatch cost. The top, middle, and bottom curves are, respectively, equilibrium levels of demand, price, and profit in the second period.

As suggested by (4), the average rating and the variance of ratings each plays an important informational role in determining the second-period market outcomes, as summarized in the following propositions.

Proposition 1. *Second-period price, demand, and profit all increase with the average rating.*

Existing literature has provided empirical evidence that is consistent with this prediction. Cao and Gruca (2004) and Bruce et al. (2004), for example, find that a seller raises the price when past consumers have high satisfaction. Elberse and Eliashberg (2003) and Chevalier and Mayzlin (2006), on the other hand, find that a higher average rating leads to more sales.

Now we turn to the central proposition of the paper, which examines the impact of the variance of ratings on the equilibrium levels of subsequent market outcomes.

Proposition 2. *In the second period, price increases with the variance of ratings, demand increases with the variance if and only if $M \le 0$, and profit increases with the variance if and only if $M \le \sqrt{3V}$.*[16]

Figure 1 provides an illustration of Proposition 2. The proposition suggests that the seller should charge a high price when the mismatch cost t is high, which is reflected through a high variance of ratings. A high price in this case helps the seller fully exploit well-matched consumers' high willingness to pay. In contrast, equilibrium demand and profit increase with the variance only when the average rating is relatively

[16] Although we find zero to be a threshold in the proposition, one can easily do a linear transformation of ratings to make the threshold positive. Therefore, zero as a threshold should not be taken quantitatively.

low.[17] The intuition is as follows: When the average rating is low, a high variance crucially improves consumers' perception of the product's quality, and hence increases demand and profit. When the average rating is high, consumers are already confident of the product's quality. The dominant effect of a high variance is to signal a high mismatch cost. It therefore drives away marginal consumers and hurts demand and profit.

Given the price and demand patterns, equilibrium profit in the second period turns out to be U-shaped in the variance (see Figure 1), suggesting that profit is the highest when the variance is either extremely low or extremely high. It is noteworthy that Johnson and Myatt (2006) examine demand transformation that results from changes in consumer taste dispersion. In a static model, they also find that firms have preferences for extreme dispersions of consumer tastes, where high dispersion is complemented by niche production, and low dispersion is complemented by mass-market supply. Although the intuition behind our arguments are quite similar, we formulate the problem in the easily testable context of product ratings with the additional focus on how the dispersion of consumer utility, as measured by the variance of ratings, should *interact* with the average rating in affecting subsequent demand.

To complete the characterization of the equilibrium, consider the seller's strategy in the first period. He maximizes the expected total profit:

$$\max_{P_1} P_1 \frac{E(v)-P_1}{E(t)} + E\left(\frac{v^2}{4t}\right).$$

The second term above is determined by the joint distribution $f(v,t)$ and hence independent of P_1. Therefore, equilibrium price, demand, and profit in the first period are

$$P_1^* = \frac{E(v)}{2}, \quad D_1^* = \frac{E(v)}{2E(t)}, \quad \text{and} \quad \Pi_1^* = \frac{E(v)^2}{4E(t)},$$

respectively; that is, the first-period equilibrium outcomes depend on the prior expectations of quality and mismatch cost. When $E(v)/E(t)$ is higher, consumers have a more favorable expectation of the product, and the first-period demand is higher.

An interesting observation one can make is that the equilibrium price is higher in the second period than in the first period if and only if

$$v = M + \sqrt{3V} > E(v);$$

that is, the seller should raise the product's price over time if it receives a favorable average rating and a high variance of ratings. In a different context, Bergemann and Välimäki (2006) examine dynamic price patterns of new experience goods and find a similar result: equilibrium price increases over time for niche products and decreases over time for mass-market products.

2.1. Deferring Purchase Decisions

An important dimension in consumers' use of product ratings is that they can be strategic in the timing of the purchase; that is, whether a consumer purchases the product early or late can be an endogenous decision (e.g., Guo and Villas-Boas 2007). Because a big fraction of online shoppers seek out product ratings and reviews, it is quite conceivable that some consumers choose to defer purchase decisions until after they see the product ratings. Waiting behavior turns out to have interesting consequences. In particular, the impact of the variance of ratings on the second-period price is more negative, as we show below.

Consider two changes to the baseline model. First, consumers in the first period can choose whether or not to defer their purchase decision with a discount factor $\beta \in (0,1)$. If they choose to wait to see the ratings, they are allowed to purchase the product in the second period. Second, late consumers of mass $n > 0$, rather than 1, enter the market in the second period. The indifferent consumer D_1 in the first period is now given by

$$E(v) - E(t)\cdot D_1 - P_1 = \beta \cdot E(\max\{v - t\cdot D_1 - P_2, 0\}).$$

Similar to the baseline model, early consumers with $x \in [0, D_1]$ choose to buy the product, and others choose to wait; that is, consumers who are almost perfectly matched would purchase right away, whereas consumers located further away in the taste space prefer to wait to see the ratings. Intuitively, consumers located further away are more likely to decide not to buy the product when given full information, and hence they are more motivated to wait until the second period.[18]

In the modified game, the formulas of the average rating and the variance of ratings remain the same as in (2) in the baseline model. As before, late consumers observe the average and the variance of ratings and

[17] In an empirical setting, one can often observe and control for the price of a product. The impact of the rating statistics on subsequent demand in this case can be derived by looking at the indifferent consumer: $D_2^* = (v - P_2^*)/t = [(M - P_2^*)/\sqrt{3V} + 1](D_1/2)$. Therefore, the impact of the average rating and the variance of ratings in a context with observable prices remains similar to that in Propositions 1 and 2, except for a different threshold.

[18] Theoretically, the seller can charge an extremely high first-period price so that all early consumers choose to wait. If he does this, however, there would be no ratings from early consumers, and hence no way for late consumers to learn about how great the product is. We assume that if the first-period price is so high that there is no purchase in the first period, all consumers in the second period believe that the product has the lowest possible quality and highest possible mismatch cost.

have complete information on the product attributes. The second-period demand D_2 is now given by

$$D_2 = n \cdot \frac{v - P_2}{t} + \max\left\{0, \frac{v - P_2}{t} - D_1\right\},$$

where the first term on the right-hand side is demand from late consumers, and the second term is demand from early consumers who choose to wait. If the second term is zero, second-period equilibrium outcomes are proportional to those in the baseline model, and the impact of M and V are simply multiplied by n.

The seller in the second period chooses P_2 to maximize $P_2 \cdot D_2$. To solve this maximization problem, one simply needs to compare the highest possible profit when the seller serves only the late consumers with that when the seller serves both late consumers and early consumers. Based on this comparison, one of the following two equilibrium prices will emerge in the second period. First, $P_2^* = v/2$. In this case, no early consumer purchases in the second period, and the equilibrium outcomes are proportional to those in the baseline model. Second, $P_2^* = \frac{1}{2}(v - (t \cdot D_1)/(n+1)) = \frac{1}{2}(M + ((n-1)/(n+1))\sqrt{3V})$. In this case, some early consumers purchase the product in the second period. The equilibrium demand becomes $D_2^* = \frac{1}{2}[v(n+1)/t - D_1] = [(n+1)(M/4\sqrt{3V} + \frac{1}{4}) - \frac{1}{2}]D_1$,[19] and the equilibrium profit in the second period is $\Pi_2^* = ((n+1)/4t)(v - (t \cdot D_1)/(n+1))^2 = ((n+1)D_1)/8\sqrt{3V}(M + ((n-1)/(n+1))\sqrt{3V})^2$.

Based on these equilibrium outcomes, we can make the following observations. First, as in the baseline-model, equilibrium demand in the second period always increases with the average rating. Second, equilibrium demand increases with the variance of ratings if and only if $M \leq 0$. Therefore, the interaction effect of the variance of ratings and the average rating continue to hold when early consumers are given the option to defer their purchase decisions. Third, a higher variance increases second-period price if and only if $n > 1$. The intuition for this result is as follows. When $n > 1$, many consumers come to the market late and the second-period demand comes mostly from late consumers. Variance of product ratings in this case has a similar impact to that in the baseline model. When $n < 1$, early consumers who choose to wait form a big portion of the second-period demand. These consumers are located further away from the product and react more negatively to the variance than the typical late consumer. As a result, the equilibrium price in the second period decreases, rather than increases, with the variance of ratings. When $n = 1$, the two pricing incentives associated with a high variance, exploiting well-matched late consumers and trying to keep mismatched early consumers, balance each other out. The variance hence does not affect the second-period price. Finally, second-period profit still always increases with the average rating, but the condition under which the profit increases with the variance is quite different from before. In general, a high variance is more likely to be profitable for the seller when most consumers can observe some product ratings when they first come across the product. When $n \leq 1$, most second-period demand comes from the early consumers that are sensitive to mismatch, and hence the profit decreases with the variance. When $n > 1$, profit increases with the variance if and only if $\sqrt{3V} > ((n+1)/(n-1))M$. In this case, most second-period patrons are late consumers, and the impact of ratings on profit is similar to that in the baseline model.

[19] If price is controlled for, demand can be written as $D_2^* = (n+1)((v - P_2^*)/t) - D_1 = [(n+1)/2((M - P_2^*)/\sqrt{3V} + 1) - 1] \cdot D_1$, which always increases with the average rating M, but increases with the variance of ratings V if and only if $M \leq P_2^*$.

3. Evidence from Online Book Retailers

In this section, we provide empirical evidence that is consistent with our theoretical predictions. In an ideal empirical setting, we would have data on sales and prices over two periods, product ratings from only the initial period, and control variables on product characteristics that the consumers could observe without reading any product ratings. Such variables could include, for example, reputation of the brand, advertising, and promotions.

Our actual data were obtained from two leading booksellers on the Internet: Amazon and Barnes & Noble. There are three reasons for employing the data. First, book ratings are commonly sought after by potential book buyers. Second, the fact that there are two retailers means that we can use a differencing approach to control for unobserved book characteristics that may influence both sales and ratings. Third, the possibility of tracking the two websites over time provides an opportunity to perform a DID analysis to eliminate any potential book-website effects, as discussed by Chevalier and Mayzlin (2006).

To collect data, we first created a list of 3,828 random ISBNs from the bestseller section of Global Books in Print.[20] All of the books in our list were released in 2002–2006. For each book, we recorded the number of reviews, numerical values of its ratings, price, sales rank, availability, and shipping information from Amazon.com and BN.com (henceforth, BN).

There were 892 books with complete data in January 2009. To use the DID approach, in May 2009

[20] See http://www.GlobalBooksinPrint.com.

Table 2 **Summary Statistics of Books**

Variable	Website	January 2009 Mean	January 2009 Std. dev.	May 2009 Mean	May 2009 Std. dev.
Sales rank	Amazon	201,696	307,726	267,085	350,943
	BN	113,952	146,965	130,309	163,633
Price	Amazon	12.3	6.7	12.6	6.8
	BN	15.2	9.1	14.8	8.8
Number of reviews	Amazon	110.1	134.5	101.2	140.5
	BN	29.2	53.1	30.5	55.0
Average rating	Amazon	3.6	0.6	4.2	0.5
	BN	4.4	0.6	4.4	0.6
Std. dev. of ratings	Amazon	1.4	0.3	1.0	0.4
	BN	0.7	0.6	0.7	0.5

Note. Observations: 667.

we collected a second round of data including the same information for every book.[21] As a result of the changes in Amazon's and BN's selections of book offerings, we have a total of 667 books available for the DID analysis, with summary statistics presented in Table 2.

One can see from the table that a book on BN typically has a higher price, fewer ratings, a higher average rating, and a lower standard deviation of ratings than it does on Amazon. The books in our sample generally become less popular during our data collection period (January–May 2009), as the average sales rank increases on both Amazon and BN. Although both websites are known to constantly adjusted the prices of their books, the average prices remain largely the same during the five months, with a slight decrease on Amazon and a slight increase on BN.

Table 2 also shows another interesting trend: While a book on average earns 1.3 more reviews on BN during the five months, the average number of reviews on Amazon goes down, possibly because of pruning.[22] Moreover, whereas the average rating on BN remains largely the same, the average rating on Amazon increases significantly, suggesting that the pruning tends to concentrate on reviews with low ratings.

Because previous research repeatedly demonstrates the positive effect of a higher average rating, we focus on examining the role of the standard deviation of ratings. Based on our theoretical framework, we formulate the following hypothesis.

Hypothesis 1. *A higher standard deviation of ratings for a book leads to higher sales if and only if the average rating is low.*

We adopt a DID estimation approach from Chevalier and Mayzlin (2006). Denote Amazon variables by superscript A and BN variables by superscript B, and use subscript i as an index for books. The underlying data generating process is assumed to be

$$A0: \quad \log(Rank_{it}^J) = \mu_i^J + v_i + X \times \Gamma^J + \Omega_i^J \times \Upsilon^J + \xi_{it}^J, \quad J \in \{A, B\}.$$

Consistent with previous studies (e.g., Chevalier and Mayzlin 2006, Brynjolfsson et al. 2003), we use log sales rank on the left-hand side as a linear proxy for log sales. If log sales quantity were used directly as the dependent variable, the estimated coefficients would be scaled by a constant. Brynjolfsson et al. (2003), for example, find a scaling coefficient of −0.871 using sales quantity and rank data from Amazon.[23]

On the right-hand side, μ_i^J is an unobservable book-site effect that captures any possible interaction between characteristics of book i and preferences of consumers on site J. For example, compared with BN users, Amazon users may like to buy computer books more and also give them higher ratings. If this is the case, μ_i^A would be positive for the computer books. The second term, v_i, is a book-level fixed effect that captures certain aspects of book i that can directly influence sales, such as the reputation of the author and the publishing company, newspaper reviews of the book, author events, and other forms of advertising. Vector X contains rating variables from both Amazon and BN. In our specification, a book's ratings on Amazon can affect its sales ranks on both Amazon and BN. Similarly, its ratings on BN can also affect its sales ranks on both sites. Control variables in Ω are price, log number of reviews, and shipping dummies. Finally, ξ_{it}^J is a normally distributed random error.

To control for book-level fixed effects and book-site effects, we take the difference of $A0$ across the two sites and across time:

$$\begin{aligned}\Delta[\log(Rank_i^A) - \log(Rank_i^B)] &= \gamma_1^A \cdot \Delta M_i^A - \gamma_1^B \cdot \Delta M_i^B + \gamma_2^A \cdot \Delta SD_i^A - \gamma_2^B \cdot \Delta SD_i^B \\ &\quad + \gamma_3^A \cdot \Delta(M_i^A \cdot SD_i^A) - \gamma_3^B \cdot \Delta(M_i^B \cdot SD_i^B) \\ &\quad + \Delta\Omega_i^A \times \Upsilon^A - \Delta\Omega_i^B \times \Upsilon^B + \epsilon_i, \qquad (5)\end{aligned}$$

where M_i^J and SD_i^J denote, respectively, the average and standard deviation of ratings of book i on site J, $J \in \{A, B\}$. Given the fact that sales rank is negatively correlated with sales, Hypothesis 1 would be confirmed if $\gamma_2^J < 0$ and $\gamma_3^J > 0$. As proposed by Zhu and Zhang (2010), the sales of a popular product may

[21] BN, in general, ships faster than Amazon.

[22] Chevalier and Mayzlin (2006) find the same pattern.

[23] The specification they use is $\log(quantity) = \beta_1 + \beta_2 \cdot \log(rank) + \epsilon$, and the intercept β_1 is estimated to be 10.526.

Table 3 The Effect of Five-Month Changes in Ratings on Changes in Sales

	(1)	(2)	(3)
Amazon $\Delta\ln$(*price*)	1.521***	1.507***	1.552***
	(0.201)	(0.286)	(0.200)
BN $\Delta\ln$(*price*)	−1.917***	−2.050***	−1.876***
	(0.584)	(0.758)	(0.583)
Amazon $\Delta\ln$(*no. of reviews*)	−0.835***	−0.858***	−0.847***
	(0.092)	(0.105)	(0.094)
BN $\Delta\ln$(*no. of reviews*)	0.522***	0.465**	0.560***
	(0.194)	(0.224)	(0.214)
Amazon Δ*average rating*	−0.196***	0.103	−1.014***
	(0.067)	(0.254)	(0.366)
BN Δ*average rating*	−0.415	0.240	0.633
	(0.397)	(0.872)	(0.917)
Amazon Δ*std. dev. of ratings*		0.485	−2.562***
		(0.395)	(0.873)
BN Δ*std. dev. of ratings*		0.540	3.786
		(0.568)	(2.426)
Amazon Δ(*average rating* $\times$ *std. dev.*)			0.627***
			(0.167)
BN Δ(*average rating* $\times$ *std. dev.*)			−0.753
			(0.521)
Shipping dummies	Yes	Yes	Yes
Observations	667	667	667
Adjusted R^2	0.174	0.175	0.192

Notes. For a variable x, $\Delta x = x_{\text{May 2009}} - x_{\text{Jan 2009}}$. The dependent variable in all three specifications is Δ\{ln(*Amazon sales rank*) − ln(*BN sales rank*)\}.
$^{**}p < 0.05$; $^{***}p < 0.01$.

react less to online consumer ratings as other sources of information become abundant. If this is true in our context, we would expect the error term in (5) to be heteroscedastic, because its variance increases with a book's popularity. A White test confirms heteroscedasticity ($p < 0.01$), and we use a two-step feasible weighted least squares estimation approach (Greene 1999), with each book's number of reviews on Amazon and BN in January and May 2009 as predictors for the variance of errors in the first stage.[24]

Table 3 presents our estimation results. To highlight the importance of the standard deviation of ratings and how it interacts with the average rating in affecting demand, we compare three specifications. In the first specification, the rating variables include only the average rating. In the second one, we also include the standard deviation of ratings. In the third specification, we further add the interaction of the average rating and the standard deviation of ratings. In all the three specifications, a lower price and a higher number of reviews lead to higher sales. Regarding the role of consumer ratings, we make the following observations. First, a higher average rating on Amazon increases the book's relative sales on Amazon in columns (1) and (3), which is consistent with our baseline model and the previous literature (Chevalier and Mayzlin 2006). BN average rating is not significant, which might be due to the fact that BN ratings remain largely unchanged during our data collection period (see Table 2).

Second, column (3) suggests that a higher standard deviation of Amazon ratings leads to relative higher sales if and only if the average rating on Amazon is low, confirming Hypothesis 1. The three coefficients on Amazon's rating variables are all significant with $p < 0.01$. Based on these estimates, a higher standard deviation of Amazon ratings increases the book's relative sales when the average Amazon rating is lower than 4.1 stars, which is true for 35% of all the books in our sample. Meanwhile, a higher average rating on Amazon increases the book's relative sales when the standard deviation is lower than 1.6 stars, which is true for almost all (96%) of the books.

Notably, if a researcher ignores the interaction and uses the specification in column (2), he may reach an imprecise conclusion that neither the average rating nor the standard deviation of ratings affect a book's relative sales rank. Comparing across the three columns, one can see that incorporating the interaction term significantly changes the coefficients of the rating variables, while increasing the adjusted R^2 value. At the same time, incorporating the interaction term does not have a big impact on the estimated effect of nonrating variables such as price and the number of reviews. This suggests that the explanatory power of the interaction term comes within the ratings, as suggested by our theory, rather than potential correlation between the interaction term and nonrating variables.

Overall, the empirical evidence we find is consistent with the hypothesis that a higher standard deviation of ratings on Amazon improves the book's relative sales on Amazon when the average rating is low, and hurts its relative sales when the average rating is high.

4. Concluding Remarks

In this paper, we examine the informational role of the distribution of product ratings by focusing on the variance of ratings. We find that the interaction of the average rating and the standard deviation of ratings plays a significant role on subsequent market outcomes. For a product with a low average rating, a higher variance of ratings communicates to potential buyers that well-matched consumers would love

[24] To be more exact, our weights are obtained by regressing the squared error terms on the numbers of book ratings in January and May 2009 on Amazon and BN. Our results are robust to alternative choices of the weight. In particular, a prespecified weight that equals the inverse of the total number of ratings across the two websites yields similar results.

the product, which in turn increases demand. For a product with a high average rating, a higher variance of ratings drives away marginal consumers and reduces demand. We provide empirical evidence with data from two leading Internet book retailers, Amazon and Barnes & Nobel, that is consistent with our theoretical predictions.

Two directions of future research are promising. First, this paper opens up the possibility for managers to use the variance of ratings as an additional measure in demand forecasts. The measure can be particularly useful in a competitive environment. Consider a motion-picture studio trying to determine a movie's release date. The studio may try to forecast the opening box-office revenue by mapping the locations of its own movie and the competing movies into consumers' taste space by solving for quality and mismatch cost from the distribution of prerelease critic ratings.

Second, there are many other aspects of consumer reviews that are worth exploring. For example, some websites offer multidimensional ratings. It is remarkable, for example, that Best Buy (bestbuy.com) not only asks consumers to rate its products along multiple dimensions, but also caters the set of dimensions to the product category. For a global positioning system, consumers need to rate the product along four dimensions: value for price, durability, ease of use, and features. For a TV, the dimensions become picture quality, sound quality, and features. It would be interesting to study the matching between the dimensions and the product category, as well as to measure the different weights that consumers put on these dimensions. Specialized consumer-review websites such as Yelp.com also publish the time trend of consumer ratings. It would also be interesting to examine how such trends influence consumers' decisions to purchase a particular service.[25]

Acknowledgments

The author thanks department editor Pradeep Chintagunta, the associate editor, and three anonymous referees at *Management Science* for their thoughtful suggestions. She is deeply indebted to Albert Ma, Jacob Glazer, Marc Rysman, and Juanjuan Zhang for their advice on this paper. For helpful conversations, the author is also grateful to J. Miguel Villas-Boas, David Godes, Wesley Hartmann, Jim Lattin, Tilman Börgers, Philip Choné, Iván Fernández-Val, Chunyu Ho, Panle Jia Barwick, Ginger Jin, Xiaofeng Li, Barton Lipman, Michael Manove, Preston McAfee, Dilip Mookherjee, In-Uck Park, Larry Samuelson, Jean Tirole, Ram Rao, Al Roth, Michael Zhang, Dazhuang Zhu, Xiaomei Zhu, Feng Zhu, and seminar participants at Boston University economics workshops, Summer Institute of Competitive Strategy, Stanford Graduate School of Business, Harvard Business School, UT Dallas, UC Davis, HEC Paris, and Singapore Management University.

[25] See Yoganarasimhan (2010) for an interesting discussion on how the network structure among YouTube users affects the diffusion of videos. See also Zhang and Zhu (2011) for a study on how audience size would affect the incentives for users to generate content.

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