Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix

Yubo Chen

Eller College of Management, University of Arizona, Tucson, Arizona 85721,
yubochen@eller.arizona.edu

Jinhong Xie

Warrington College of Business, University of Florida, Gainesville, Florida 32611,
jinhong.xie@cba.ufl.edu

As a new type of word-of-mouth information, online consumer product review is an emerging market phenomenon that is playing an increasingly important role in consumers' purchase decisions. This paper argues that online consumer review, a type of product information created by users based on personal usage experience, can serve as a new element in the marketing communications mix and work as free "sales assistants" to help consumers identify the products that best match their idiosyncratic usage conditions.

This paper develops a normative model to address several important strategic issues related to consumer reviews. First, we show *when* and *how* the seller should adjust its own marketing communication strategy in response to consumer reviews. Our results reveal that if the review information is sufficiently informative, the two types of product information, i.e., the seller-created product attribute information and buyer-created review information, will interact with each other. For example, when the product cost is low and/or there are sufficient expert (more sophisticated) product users, the two types of information are *complements*, and the seller's best response is to *increase* the amount of product attribute information conveyed via its marketing communications after the reviews become available. However, when the product cost is high and there are sufficient novice (less sophisticated) product users, the two types of information are *substitutes*, and the seller's best response is to *reduce* the amount of product attribute information it offers, even if it is cost-free to provide such information. We also derive precise conditions under which the seller can increase its profit by adopting a proactive strategy, i.e., adjusting its marketing strategies even *before* consumer reviews become available. Second, we identify product/market conditions under which the seller benefits from facilitating such buyer-created information (e.g., by allowing consumers to post user-based product reviews on the seller's website). Finally, we illustrate the importance of the timing of the introduction of consumer reviews available as a strategic variable and show that delaying the availability of consumer reviews for a given product can be beneficial if the number of expert (more sophisticated) product users is relatively large and cost of the product is low.

Key words: online consumer review; word-of-mouth; product review information; marketing communications; social interactions

1. Introduction

The Internet and information technology provide a new opportunity for consumers to share their product evaluations online (Avery et al. 1999). Amazon.com began offering consumers an option to post their comments on products on its website in 1995. Currently, Amazon.com has about 10 million consumer reviews on all its product categories, and these reviews are regarded as one of the most popular and successful features of Amazon (*New York Times* 2004). In recent years, an increasing number of online sellers (e.g., BevMo.com, BN.com, cduniverse.com, circuitcity.com, GameStop.com, computer4sure.com, c-source.com, half.com, goodguys.com, wine.com)

have adopted a similar strategy. These online sellers invite users of their products to post personal product evaluations on the sellers' websites or provide their customers with consumer review information offered by some third-party sources such as Epinions.com. Online consumer reviews are common for many product categories such as books, electronics, games, videos, music, beverages, and wine.

Recent evidence suggests that consumer reviews have become very important for consumer purchase decisions and product sales. A study by Forrester Research finds that half of those who visited the retailer sites with consumer postings reported that consumer reviews are important or extremely important in their

buying decisions (*Los Angeles Times* 1999). Based on the data from Amazon.com and BN.com, Chevalier and Mayzlin (2006) find that online book reviews have a significant impact on book sales. Liu (2006) shows that consumer reviews at the Yahoo Movies website has a significant effect on box office revenue.

However, not all online sellers supply consumer reviews on their websites. For example, Chen and Xie (2004) examine three product categories: MP3 players, PDAs, and video games. They identify a list of 68 online sellers from the referral list of the leading shopping agent mySimon.com in June 18, 2003, and find that 46 out of 68 online sellers did not offer consumer reviews.

Online consumer review is a new product information channel with growing popularity and importance. It has generated considerable attention in practitioners and popular presses. Sellers face various important strategic decisions regarding consumer review information. For example, when consumer reviews appear, should a seller adjust its own communication strategy to best respond to such a consumer-created information channel, and how? Under what conditions does the seller benefit from facilitating the creation and dissemination of such user-based review information by allowing consumers to post their comments on its own website (e.g., Amazon.com)? To better understand the fundamental role of this new information channel in the marketplace and its strategic implications to online marketers, more academic research is urgently needed.

Several recent studies have begun to examine online consumer-created information from the perspective of information credibility. Consumer-created information is likely to be more credible than seller-created information because credibility of information is often positively related to the trustworthiness of the information source (Wilson and Sherrell 1993). Dellarocas (2003) reviews the relationship between online consumer feedback information and an unknown seller's reputation. Mayzlin (2006) studies the credibility of the promotional messages in online chat rooms and the implication of such new information channels on sellers' profitability. Furthermore, some recent studies (Fay and Xie 2008, Xie and Gestner 2007) suggest that consumer-created information allows the seller to implement some marketing strategies that may not be credible otherwise (e.g., probabilistic selling, service cancellation). These studies have advanced our understanding of consumer-created information. An important but underexplored aspect of consumer reviews is their degree of relevance to consumers. We argue that online consumer reviews can be deployed as a new element in the marketing communications mix and work as an online seller's free "sales assistants"

(Wernerfelt 1994a) to help consumers to identify products that best match their needs.

To examine such a matching function of online consumer reviews, we first present an empirical study to illustrate how this emerging information source is different from other types of product information, such as third-party product reviews. We then develop a normative model to address several specific questions regarding a firm's strategic decisions vis-à-vis consumer reviews.

Our empirical study suggests that, different from third-party product reviews that emphasize the performance of a product based on its technical specifications, consumer reviews tend to examine the performance of a product from the perspective of its ability to match the consumers' own usage situations. Our strategic analysis reveals several important findings. First, we show that the two types of information—consumer reviews and seller-created product attribute information—can be *complements* or *substitutes*. Such interaction exists when the review information is sufficiently informative. The direction of the interaction (i.e., complementary or substitutive) is determined by the characteristics of the product and market. When the product cost is low and/or there are sufficient expert (more sophisticated) product users, the two types of product information are *complements*. In this case, the seller should *increase* the amount of its own product attribute information conveyed to potential customers when consumer reviews become available. When the product cost is high and there are sufficient novice (less sophisticated) product users, the two types of product information are *substitutes*. Here, the seller should *decrease* its product attribute information supply when consumer reviews become available. In addition, we show that if the seller can anticipate the availability of consumer reviews, it is possible to adopt a proactive strategy by adjusting its marketing strategies even before consumer reviews become available. Second, our analysis reveals that allowing consumers to post user-based product reviews on the seller's website can increase or decrease profit depending on product/market conditions. We show that it is detrimental to a seller to supply consumer reviews unless such information is sufficiently informative. We also find that supplying online consumer reviews is more likely to be beneficial to the seller when there are sufficient novice consumers (e.g., for technology-intensive products). Finally, our results reveal that if it is possible for the seller to decide when to offer consumer reviews at the individual product level, it may not always be optimal to offer them at a very early stage of new product introduction, even if such reviews are available. Delaying the availability of consumer reviews for a given product can be beneficial if the number of the

expert users is relatively large and cost of the product is low.

From a theoretical perspective, this paper is mostly related to Lewis and Sappington (1994), which proposes a model to show when it is optimal for the seller to provide partial- versus full-attribute information to consumers. In their model, there is only one information channel between the seller and consumers (i.e., from the seller to consumers). Unlike Lewis and Sappington (1994), we allow an additional information channel (i.e., from consumers to consumers), and examine a seller's information decision in a setting of dual channels.

Substantially, this paper augments the traditional marketing communications literature. To date, very few studies have examined a firm's strategic decisions regarding information content for its marketing communications. Wernerfelt (1994b) and Simester (1995) investigate when and how firms should include price information in their advertising. Godes (2003) studies the implications of the value-creating versus persuasive personal selling format. Chen and Xie (2005) examine a firm's advertising format strategy in the presence of third-party product reviews, and find that using review-endorsed advertising (i.e., advertisements containing third-party award logos) to broadcast its success can hurt the winning product of a product review. In this paper, we study a firm's information content strategy by investigating how much and what type of product information a seller should provide to its customers.

The remainder of this paper is organized as follows: Section 2 illustrates the marketing role of online consumer reviews and how they differ from other types of product information; §3 presents our model setup; §4 examines how the seller should best respond to consumer reviews (i.e., the optimal information content decision); §5 studies conditions under which the seller should initiate or facilitate such consumer review information itself (i.e., the optimal consumer review supply decision); and §6 concludes the paper and discusses some strategic implications and directions for future research.

2. Online Consumer Review: An Emerging Source of Product Information

As an emerging source of product information, what fundamental role can online consumer review play in the marketplace? How does online consumer review differ from other product information, such as seller-created product information, traditional word-of-mouth (WOM), and third-party product reviews?

2.1. Online Consumer Review as a New Element in the Marketing Communications Mix

As consumer-created information, online consumer review is likely to be more relevant to consumers than seller-created information. Seller-created product information is more likely to be product oriented, because it often describes product attributes in terms of technical specifications and measures product performance by technical standards. In contrast, the consumer-created product information is, by definition, user oriented. It often describes product attributes in terms of usage situations and measures product performance from a user's perspective (Bickart and Schindler 2001). Consumers have different information-processing capabilities in inferring benefits from product attribute information due to different levels of expertise (Alba and Hutchinson 1987). For this reason, seller-created product information may be more useful to more sophisticated consumers (i.e., experts). Consumer-created product information, however, can help less-sophisticated consumers (i.e., novices) in finding their best-matched products. As a result, consumer reviews can be deployed as a new element in the marketing communications mix and can work as an online seller's free "sales assistants" (Wernerfelt 1994a) to help consumers to identify products that best match their needs.

Consumer reviews are important for unsophisticated consumers (i.e., novices), who may hesitate to purchase if only seller-created product information is available. However, this sales assistant does not come without cost. By allowing consumers to post their own product evaluations, the seller creates a new information channel for consumers, which thereby eliminates the seller's capability to control the supply of product information. In this paper, we study when the seller should facilitate consumer reviews and how it adjusts its own communication strategy in response to consumer review information.

2.2. Online Consumer Review vs. Traditional (Offline) Word-of-Mouth

Online consumer reviews, as consumer-created product information, can be viewed as a special type of WOM (e.g., Godes and Mayzlin 2004). Different from the traditional WOM, the influence of which is typically limited to a local social network (e.g., Brown and Reingen 1987, Biyalogorsky et al. 2001, Shi 2003), the impact of online consumer reviews can reach far beyond the local community, because consumers all over the world can access a review via the Internet. In addition, in general, traditional WOM is not a direct decision variable for the seller. However, the recent development of information technology allows a seller to effectively initiate and broadcast consumer online reviews via its own website. A seller can also

license consumer reviews from intermediaries (such as Epinions.com), and decide when to offer them on its website (e.g., c-source.com). Given the widespread impact of consumer reviews, our paper investigates how firms should adjust their marketing communication strategy to respond to this emerging source of WOM information. Our paper complements WOM literature by also examining the new and potentially powerful opportunity for a seller to help consumers create and disseminate their personal opinions about the seller's products. We look at the benefits and drawbacks of encouraging or discouraging this special type of WOM information and provide insight into firms' decisions on when and how to provide consumer reviews.

2.3. Online Consumer Review vs. Third-Party Product Review

Another information source closely related to online consumer review is product review from third parties (e.g., CNET.com, caranddriver.com, *PC Magazine*, *PC World*). As discussed in Chen and Xie (2005), third-party product reviews provide product information usually based on lab testing or expert evaluations. Third-party product reviews tend to focus on product attribute information (e.g., performance, features, and reliability) because such information is easier to quantify and measure. As a result, third-party review ratings are likely to be correlated with the performance of these attributes. Different from third-party reviews, online consumer reviews are posted by users based on their personal experiences, which can be highly affected by their taste preferences as well as their personal usage situations. For this reason, consumer reviews are more likely to focus on whether and how a product matches a specific individual's preference and usage condition.

To illustrate this difference, we conduct a preliminary empirical study. We chose the digital camera for our study because it is an ideal product category to study online consumer and third-party product reviews, for the following reasons: (1) according to the Consumer Electronic Association's annual ownership study (Raymond 2006), the digital camera has become one of the top five most popular consumer electronic products; and (2) since 2000 the Internet has been the most popular channel for consumers to buy digital cameras (Photo Marketing Association International 2001). We have collected the following data for our empirical study:

(1) *Third-party product review data* from CNET.com, the leading third-party professional review website for consumer technology products. When reviewing digital cameras, a CNET.com editor presents detailed product attribute information, and rates the camera on a scale of 0 through 10 based on his/her evaluations on four key aspects of cameras: features, performance, image quality, and design.

(2) *Consumer review data* from Amazon.com, the pioneer and top provider for online consumer product reviews. When posting reviews for a camera at Amazon.com, consumers are asked to give a star rating (from 1 to 5) and write a paragraph describing their experiences and rationale for their ratings. Based on the different consumer postings, Amazon.com gives an average customer rating for each model.

(3) *Product attribute data* from CNET.com. We collect data on the three most important digital camera attributes suggested by *Consumer Reports*: image resolution (megapixels), optical zoom, and shooting speed.

(4) *Other control variables.* As the control variables, we also collect data on the product launch date from CNET.com and the number of consumer review postings at Amazon.com.

Our sample includes all 120 digital camera models reviewed by CNET.com from June 2004 to September 2005. Table 1 (Part A) presents the descriptive statistics of our samples. As shown in this table, for each model in our sample, the average number of consumer reviews posted at Amazon.com is 23, and the average product length of life (the difference between the product launch date and our data collection date) is 338 days. Among 120 cameras, 90 models have complete data on third-party product review, product attributes, and the two other control variables; and 87 models have complete information on consumer reviews, product attributes, and the other control variables.

Using the CNET.com editor's review ratings and Amazon.com average consumer ratings as the dependent variables, we run two separate regressions to see if the two types of product reviews—third-party review and consumer review—have a similar relationship to product attribute information. As shown in Table 1 (Part B), *F* statistic is significant for the third-party review model but not for the consumer review model. Also, the rating of third-party review is significantly affected by optical zoom and shooting speed,[1] but none of the three product attributes affect the rating of the consumer review. Furthermore, for the 120

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[1] The coefficient of image resolution is not significant. One main reason, as suggested by *Consumer Reports*, is that the image resolution (megapixels) is the major category variable for a digital camera. Therefore, reviewers tend to rate different cameras within a category such as five megapixels instead of comparing a two-megapixel model with a five-megapixel model. The positive coefficient for product life length shows that, given the same attribute level, a model can get higher ratings if it was launched into the market earlier, which is consistent with the fast-evolving characteristic of the technology-driven digital camera market.

Table 1 Third-Party Professional Review vs. Online Consumer Review

A: Descriptive statistics

	N	Min.	Max.	Mean	Std. deviation
Third-party review rating (CNET.com)	120	4.8	8.4	6.8	0.67
Consumer review rating (Amazon.com)	115	3.0	5.0	4.2	0.44
Image resolution (megapixels)	120	1.9	13.5	5.3	1.82
Optical zoom (X)	111	0.0	12.0	4.1	2.62
Shooting speed (fps)	98	0.0	5.0	2.1	0.92
Product life length (days)	120	71.0	739.0	337.9	156.61
No. of Amazon.com consumer postings	120	0.0	134.0	23.2	23.97

B: Regression analysis

Independent variables	Dependent variable: Third-party review rating (CNET.com)		Dependent variable: Consumer review rating (Amazon.com)	
	Standardized coefficient	t statistic	Standardized coefficient	t statistic
Image resolution	0.082	0.831	0.112	0.968
Optical zoom	0.356***	3.770	0.088	0.799
Shooting speed	0.264**	2.669	0.017	0.145
Product life length	0.194*	1.910	−0.089	−0.756
No. of Amazon.com consumer reviews			0.010	0.091
No. of observations	90		87	
R-squared	0.247		0.032	
F-statistic	6.986***		0.747	

Note. The specification also includes an intercept.

   $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

models tested, the correlation between the consumer review ratings and third-party product review ratings is only 0.267 ($p < 0.01$), which suggests that these two types of reviews may not offer the same information.

A closer look at the data finds that although many camera models get low ratings from a third party, they get high ratings from consumers. For instance, Kodak Easy Share Z 740 gets 6.4 out 10 points rated by experts at CNET.com, but gains 4.5 out 5 stars based on more than 100 consumer postings at Amazon.com. Whereas the professional review focuses on its lukewarm performance, most consumer reviews praise how this camera matches their differing usage conditions. For instance, in the Kodak Easy Share Z 740 example, just briefly skimming "the most recent 20 postings" at Amazon.com, we can identify more than 10 different usage situations, varying from outdoor landscape shots, animal and bird shots, kids' sports, New Year's Eve celebrations, long-distance shooting, Christmas gifts, overseas vacation trips, sharing photos with friends, family trips to Disney World, even crime-scene photography. Here are words in some typical consumer reviews: "I was

looking for something that took the picture NOW! As opposed to 3 seconds later. Being a parent, this was very important to me...this camera is a real treasure"; "The 10X zoom makes it easy to see images a long way away. I am able to capture the beauty of deer and other outside landscapes and animals at great quality...." Differently, focusing mainly on the attribute information, a typical paragraph in the third-party review from CNET for the same model is "shutter lag was moderate at 0.7 second under high-contrast lighting but a languorous 1.8 seconds under more challenging low-contrast lighting, even with aid from the focus-assist lamp." Based on this qualitative inquiry, it is clear that consumers evaluate their purchased product based on whether it fits their individual preferences and performs well in their specific situations, which is quite different from third-party reviews provided by professionals emphasizing product technical specifications and performances.

3. Model Setup
In this section we specify key assumptions and setup for our model. Key notations are summarized in the appendix.

3.1. Seller and Consumers
We consider a monopoly seller[2] carrying a multi-attribute product. Let c denote the marginal cost of the product.

We allow consumer heterogeneity in two dimensions: preference and expertise. First, we allow consumers to differ in their preferences toward the seller's product. For a given product, some consumers will find that the product matches their preference better than others. Specifically, consider a product with two attributes, a_1 and a_2. For any given consumer, there is an equal chance that a given attribute matches her preference, which is known to both the seller and buyers. Consumer preferences for the two attributes are independent. For example, a video game often has two key attributes: (1) genre, which specifies the type of the game (i.e., role-playing game or strategy game); and (2) plot difficulty, which indicates the challenge level to the players. Independence in preference implies that a consumer's preference for the type of the game is not necessarily related to her preference for the difficulty of the game

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[2] The seller's monopoly position mainly results from consumers' loyalty and limited search. Recent studies have demonstrated online consumers' loyalty and limited search for online sellers. For example, Johnson et al. (2004) present empirical evidence that consumer online search is very limited during the shopping process. On average, consumers visit 1.2 book sites and 1.3 compact disc sites in each category. The monopoly model can help us understand the fundamental impact of the new information channel, i.e., online consumer review on firm marketing strategies (e.g., Shugan 2002).

(i.e., a role-playing game lover may prefer difficult or easy games). Hence, consumers can be categorized into four types according to their preference-matching situations with the product: fully matched type T_{MM} (matching on both attributes), partially matched types $T_{M\bar{M}}$ and $T_{\bar{M}M}$ (matching on attribute a_1 or a_2), and fully unmatched type $T_{\bar{M}\bar{M}}$ (matching on neither attribute). Let v^F, v^P, v^0 denote consumer valuations for fully matched, partially matched, and fully unmatched consumers when consumers have complete information on product attributes, respectively. When consumers are not fully aware of information on product attributes, they form their valuation based on the expected value. For example, in the case without any product information, all consumers have the same willingness to pay, $\bar{v} = (v^F + 2v^P + v^0)/4$. Without loss of generality, we assume $v^0 = 0$.

Second, we allow consumers to differ in their expertise and knowledge about the product. We consider two consumer segments: an expert segment (E) and a novice segment (N). Let S denote the segment, where $S = E, N$. Alba and Hutchinson (1987, p. 428, Proposition 4.7) argue that, due to their difference in causal inference capability, "experts are more able than novices to infer intended product benefits from technical information and to infer likely technical causes of claimed benefits." This proposition implies that experts are more likely than novices to correctly map their usage situations with the product attributes based on the attribute information offered by the seller. Because consumer-created information is more user oriented than seller-created information, it is likely that all consumers can benefit from such information. Accordingly, we assume that, similar to experts, novices can identify a matching or mismatching product by learning from the experience of existing users through consumer reviews. However, different from experts who can find the matched product solely based on seller-created information, novice consumers are unable to match product attributes with their preferences in the absence of consumer reviews.

To distinguish consumer heterogeneity in the preference and expertise dimensions discussed above, hereafter we refer to consumers with a different preference as a different consumer *type* and consumers with a different expertise level as a different consumer *segment*. As described earlier, there are four types of consumers with different preference-matching situations (i.e., $T = T_{MM}, T_{M\bar{M}}, T_{\bar{M}M}, T_{\bar{M}\bar{M}}$) and two segments of consumers with different expertise levels (i.e., $S = E, N$). The preference dimension and the expertise dimension are orthogonal, i.e., for both expert and novice *segments*, there are four *types* of consumers with different preference-matching situations.

3.2. Information Structure

We allow a two-sided information asymmetry between the seller and consumers. The seller has private product information, but has no information on consumer characteristics. Consumers know their own tastes and expertise levels, but have no information on product attributes.

There are two possible information sources for consumers: (1) seller-created product attribute information, (2) consumer review information (if available). Due to the seller's concern for its reputation, we assume the seller-created product attribute information is accurate and truthful. Without loss of generality, we assume the seller's information supply cost is zero, considering the significantly reduced costs of collecting and distributing information via the Internet (Avery et al. 1999).

The information structure is determined by (1) how much attribute information the seller provides via its own communication to consumers, and (2) whether product reviews created by the current users are available to consumers. We call the former *information content strategy* and the latter *consumer review supply strategy*. The *information content strategy* is completely determined by the seller. Specifically, the seller can choose to adopt a *full-information* strategy (i.e., providing information on both attributes), a *partial-information* strategy (i.e., providing information only on one of the two attributes), or a *no-information* strategy. To focus on more realistic and interesting cases (i.e., *full-* and *partial-information* strategy), we assume that in the absence of consumer review information, the *no-information* strategy cannot be optimal. Specifically, we assume that the seller cannot make a positive profit when refusing to offer any product attribute information to consumers.[3] Let $I = I^F, I^P$ denote the information content decision, where I^F and I^P present the case when the seller adopts *full-* and *partial-information* content strategies, respectively.

Let $P(\theta)$ denote the probability that a consumer's true status is θ for an attribute, where $\theta = M, \bar{M}$ (i.e., the attribute can be either a match or mismatch). In the absence of any information about the attribute, there is an equal chance (i.e., 50%) that the attribute is a match/mismatch for a consumer. Hence, $P(M) = P(\bar{M}) = 1/2$.

Let γ denote the informativeness (accuracy and content) of consumer review information, where $0 \leq \gamma \leq 1$. A higher degree of informativeness is associated with better information such that the consumer review information is perfectly informative when $\gamma = 1$, and completely uninformative when $\gamma = 0$. Let $P(\theta \mid s)$ denote the conditional probability

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[3] This assumption implies that $\bar{v} < c$, where $\bar{v}$ is buyer expected value in the absence of any product information.

that a buyer's true valuation is θ after receiving a signal s from consumer reviews, where $s = m, \bar{m}$ (e.g., the signal can be either a "match" or "mismatch"). Intuitively, $P(\theta \mid s)$ depends on the degree of informativeness of consumer reviews such that consumers are more likely to correctly identify their true status (i.e., match or mismatch with the given attribute) based on consumer reviews when the reviews is more informative. Formally,

$$dP(M \mid m)/d\gamma > 0, \quad dP(\bar{M} \mid \bar{m})/d\gamma > 0,$$
$$dP(\bar{M} \mid m)/d\gamma < 0, \quad dP(M \mid \bar{m})/d\gamma < 0. \quad (1)$$

For mathematical tractability, we adopt the same specification of $P(\theta \mid s)$ suggested in Lewis and Sappington (1994):

$$\begin{cases} P(M \mid m) = P(\bar{M} \mid \bar{m}) = \bar{q}(\gamma) = (1/2 + \gamma/2) \\ P(M \mid \bar{m}) = P(\bar{M} \mid m) = \underline{q}(\gamma) = (1/2 - \gamma/2). \end{cases} \quad (2)$$

This specification satisfies (1) and implies:

(a) When reviews are completely uninformative ($\gamma = 0$), consumers' true status is independent of the signal received from consumer reviews, and such reviews are useless (i.e., $P(M \mid m) = P(M) = 1/2$).

(b) When reviews are completely informative ($\gamma = 1$), consumers can perfectly identify their true status based on consumer review information (i.e., $P(M \mid m) = P(\bar{M} \mid \bar{m}) = 1$).

(c) When reviews are partially informative ($0 < \gamma < 1$), consumers benefit from consumer review information but are unable to perfectly identify their true status based on it (i.e., $P(M) < P(M \mid m) < 1$, $P(\bar{M}) < P(\bar{M} \mid \bar{m}) < 1, 0 < P(\bar{M} \mid m) < P(\bar{M})$, and $0 < P(M \mid \bar{m}) < P(M)$.[4]

Note that (a)–(c) imply that the buyer revises her expected valuation upward after receiving a "match" signal, but downward after receiving a "mismatch" signal. The more informative the review information, the more the buyer adjusts her valuation based on the consumer reviews.

It is important to notice that although the seller has full control over the information content decision, the availability of consumer reviews may not be completely the seller's decision. For example, even if the seller determines not to offer its users the option to

post their product reviews on its website, some third parties (e.g., consumer social network or infomediary websites) may decide to create such user-generated information for a given product at any time. As a result, some sellers may find themselves facing unexpected consumer reviews (i.e., the case of the seller as an *observer* of online WOM in Godes et al. 2005). In §4.2, we examine this case and show how the seller in this situation can best respond to unexpected consumer reviews by adjusting its own information content strategy once reviews become available. We call this *defensive* response to consumer reviewers. In §4.3, we examine the case where the seller anticipates the availability of consumer reviews (e.g., if the seller allows consumers to post their reviews on its own website), and derive the seller's *proactive* strategy toward consumer reviews.

3.3. Model Timing

We consider two periods, $t = 1, 2$. In each period, one unit of consumers (with different preferences and expertise levels) arrives at the market, makes a purchase decision, and then exits. Let η denote the size of the experts over two periods, and η_t denote the fraction of experts in period t (i.e., $1 - \eta_t$ is the fraction of novice consumers), where $\eta_t = \lambda_t \eta$, $1 \geq \lambda_1 > 0$, $1 \geq \lambda_2 \geq 0$ and $\sum_{t=1}^{2} \lambda_t = 1$.[5] Period 1 arrivals can learn about product attributes only from the seller-created information. Period 2 arrivals can learn about product attributes from an additional information source, consumer review information, if such reviews become available in period 2. In each period t, the seller adjusts its information content strategy I and price P_t to determine which different segments and types of consumers to serve.

4. Information Response to Consumer Reviews

In this section, we examine the seller's best response to consumer reviews. We first derive the seller's optimal strategy in the absence of consumer review in §4.1. We then study the seller's defensive response and proactive response to consumer reviews in §§4.2 and 4.3, respectively.

4.1. Benchmark: In the Absence of Consumer Reviews

We first derive conditions under which it is optimal for the seller to supply partial (full) attribute information to consumers in the absence of consumer reviews.

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[4] As shown in Appendix A.2, the specification in (2) can be derived as a posterior probability by specifying $P(s \mid \theta)$: $P(m \mid M) = P(\bar{m} \mid \bar{M}) = (1/2 + \gamma/2)$ and $P(\bar{m} \mid M) = P(m \mid \bar{M}) = (1/2 - \gamma/2)$, where $P(s \mid \theta)$ is the conditional probability that a buyer obtains a signal s from consumer reviews given that a buyer's true status is θ. Such a specification of $P(s \mid \theta)$ implies that (a) the probability that the buyer gets the correct signal from consumer reviews increases with γ and approaches to 1 when $\gamma = 1$, and (b) the probability that the buyer gets an incorrect signal from consumer reviews decreases with γ and approaches to 0 when $\gamma = 1$.

[5] We assume $\eta_1 > 0$ (a nonzero number of experts arriving in period 1) to ensure the availability of consumer postings.

Partial-Information Strategy. Under this strategy, the seller provides information on only one attribute, for instance a_1. Experts are certain about their match or mismatch on the informed attribute (a_1), but remain uncertain about the uninformed attribute (a_2). Without any information on the uninformed attribute, they perceive an equal probability that the uninformed attribute is a match or mismatch. Hence, the valuation is $(v^P + v^F)/2$ for experts whose taste matches the informed attribute (i.e., $T_{M\bar{M}}$ and T_{MM}) and $(v^P + v^0)/2$ for experts whose taste mismatches the informed attribute (i.e., $T_{\bar{M}M}$ and $T_{\bar{M}\bar{M}}$), respectively. Due to their inability to process the seller-created information, all novice consumers perceive an equal probability to be one of four possible types and their expected valuation is $\bar{v} = (v^F + 2v^P + v^0)/4$. The seller maximizes its profits by setting its price. In order to differentiate the benchmark case from that in the presence of consumer reviews to be examined below, we use a "hat" for all the variables in the former. The optimal profit under the partial-information strategy in the absence of consumer reviews is $\widehat{\Pi}(I^P)^*$.

Full-Information Strategy. Under this strategy, the seller provides information on both product attributes. Expert consumers are fully informed. Their valuations is v^F for fully matched (T_{MM}), v^P for partially matched ($T_{M\bar{M}}$, $T_{\bar{M}M}$), and v^0 for mismatched ($T_{\bar{M}\bar{M}}$) experts, respectively. The expected valuation for novices is $\bar{v}$. The optimal profit under full-information strategy in the absence of consumer reviews is $\widehat{\Pi}(I^F)^*$.

Let $\hat{I}^*$ denote the optimal information content strategy in the absence of consumer reviews. Comparing the profits under the two strategies, partial information and full information, leads to Lemma 1 (see proofs of all lemmas and propositions in the appendix and the online technical appendix, which is provided in the e-companion).[6]

LEMMA 1 (BENCHMARK). *In the absence of consumer reviews, the seller's optimal information content and pricing strategy is*

$$\begin{cases} \textit{offering full information} \\ \quad (\textit{i.e., } \hat{I}^* = I^F),\ P_t^* = v^F & \textit{if } c \geq v^P; \\ \textit{offering partial information} \\ \quad (\textit{i.e., } \hat{I}^* = I^P),\ P_t^* = (v^P + v^F)/2 & \textit{otherwise.} \end{cases}$$

Lemma 1 reveals that, in the absence of consumer reviews, either a full- or a partial-information strategy can be optimal. Note that full information is a

[6] An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal. informs.org/.

margin-driven strategy, because by offering information on both attributes, the seller is able to charge a high price, v^F, to the fully informed/fully matched experts, although other consumers will be priced out of the market at this high price. On the other hand, partial information is a *volume-driven* strategy because when the seller offers information on only one attribute, both fully matched and some partially matched experts (i.e., experts whose preference matches the informed attribute a_1) perceive the same probability to be the fully matched type. The seller can sell to both segments by charging a sufficiently low price, $(v^P + v^F)/2$, to compensate for the consumers' uncertainty. Lemma 1 shows that it is optimal to offer full information and only serve the fully matched experts (i.e., pursue a margin-driven strategy) when the cost is sufficiently high ($c \geq v^P$), but offer partial information and serve more types (i.e., pursue a volume-driven strategy) otherwise.

Lemma 1 is consistent with Lewis and Sappington (1994), although neither the buyer's heterogeneity in expertise nor the availability of consumer review information is considered in their model. In the rest of this section, we examine how the seller should adjust its information content strategy given in Lemma 1 in response to consumer reviews. Then, in the next section, we examine the seller's decision on the supply of consumer reviews—both issues that have not been previously explored.

4.2. The Optimal Defensive Information Response to Consumer Reviews

We now consider the case where the seller faces unexpected reviews, and show how the seller can optimally adjust its own information content strategies in response to consumer reviews. In the presence of consumer reviews, period 1 arrivals learn about the product only from seller-created information, hence, having the same valuation as in the benchmark case. Accordingly, the seller's period 1 strategy is the same as that given in Lemma 1. However, different from the benchmark case, period 2 arrivals can now learn about the product not only from the seller, but also from existing buyers via consumer reviews. Their valuations in period 2 may be different from that in period 1, as shown below.

Supplying Partial Attribute Information ($I = I^P$)

Expert Consumers. In period 2, consumer reviews with informativeness γ become available. Hence, period 2 experts can use the signal from consumer reviews to update their matching probability on the uninformed attribute (a_2). For example, for those experts who have a match with informed attribute (a_1) and receive the match signal on uninformed attribute (a_2), their expected valuation is $\bar{q}(\gamma)v^F + \underline{q}(\gamma)v^P$. Similarly, we can derive the expected

valuations for other types of period 2 experts (see Appendix A.2).

Novice Consumers. In period 2, novice consumers update their valuation based on consumer review information. For example, with the help of consumer review information, the novices who receive the match signals on both attributes have as their expected valuation $\underline{q}(\gamma)\underline{q}(\gamma)v^0 + 2\bar{q}(\gamma)\underline{q}(\gamma)v^P + \bar{q}(\gamma)\bar{q}(\gamma)v^F$. Similarly, we can find the expected valuations for other types of novices (see Appendix A.2).

Given the valuations of different consumer types/segments, the seller sets price P_2 to maximize its profit in period 2, $\Pi_2(I^P)$.

Supplying Full Attribute Information $(I = I^F)$

Expert Consumers. If the seller adopts the full-information strategy, experts in period 2 are fully informed. Their valuation is v^F, v^P, v^0 for types T_{MM}, $T_{\bar{M}M}$ and $T_{M\bar{M}}$, and $T_{\bar{M}\bar{M}}$, respectively.

Novice Consumers. Although the seller provides full information, the expected valuations of novices are the same as in the case where the seller provides partial information, provided that novice consumers are unable to process seller-created information.

Given the valuations of different consumer types/segments, the seller sets price P_2 to maximize its profit in period 2, $\Pi_2(I^F)$.[7]

We now examine WHEN and HOW the seller should vary its own information content strategy in response to consumer reviews. Let I^* denote the optimal information content strategies in the presence of consumer reviews and ΔI denote the difference in the optimal amount of information content with and without consumer reviews, $\Delta I = I^* - \hat{I}^*$. The following proposition states the seller's optimal information response to consumer reviews.

PROPOSITION 1 (DEFENSIVE INFORMATION RESPONSE TO CONSUMER REVIEWS). *Facing unexpected consumer reviews, the seller can improve its profit by adjusting its own information content strategy once reviews become available. Specifically, compared with the case without consumer reviews, in the presence of consumer reviews, it is optimal for the seller to*

(a) *INCREASE attribute information via its own communication if two conditions hold*: (i) *the product cost is low, and* (ii) *either the review informativeness is in a midrange, or the review informativeness is extremely high and there are sufficient expert consumers.*

(b) *DECREASE attribute information via its own communication if three conditions hold*: (i) *the product cost is high,* (ii) *the review informativeness is in a midrange, and* (iii) *there are sufficient novice consumers.*

(c) *MAINTAIN the same level of attribute information, otherwise.*

Mathematically, $\Delta I = I^* - \hat{I}^*$

$$= \begin{cases} I^F - I^P > 0 & \text{if (i) } c < v^P, \text{ (ii) } \gamma \in [\underline{\gamma}, \hat{\gamma}), \text{ or} \\ & \quad \gamma \in [\underline{\gamma}, 1) \text{ and } \eta > \bar{N}; \\ I^P - I^F < 0 & \\ & \text{if (i) } c \geq v^P, \text{ (ii) } \gamma \in [\underline{\gamma}, \gamma''), \text{ (iii) } \eta < \underline{N}; \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

Equation (3) implies that the seller can best respond to the availability of consumer reviews by reversing its information content strategy, i.e., switching from supplying full to partial information or vice versa. This result is intriguing because it implies that the two types of information, consumer created and seller created, can be either *complements* (i.e., consumer reviews increase the seller's incentive to supply attribute information) or *substitutes* (i.e., consumer reviews decrease the seller's incentive to supply attribute information). Proposition 1 reveals that the existence and direction of the interaction are determined by three product/market factors: (1) product cost, (2) informativeness of consumer reviews, and (3) the size of different segments of consumers (experts or novices).

For low-cost products, it is optimal to offer partial information and sell to both fully and some partially matched experts at a lower price in the absence of consumer reviews (see Lemma 1). However, such a volume-driven strategy is no longer optimal when consumers can learn about the product from consumer reviews with sufficient informativeness ($\gamma \in [\underline{\gamma}, \bar{\gamma})$). This is because such review information significantly decreases the valuation of the experts receiving the mismatch signal on the uninformed attribute, even as it also increases the valuation of those experts receiving the match signal on the uninformed attribute. As a result, to maintain such a volume-driven strategy, the seller has to reduce its price greatly. In contrast, switching to a margin-driven (i.e., full-information) strategy, under which the seller sells only to the fully matched experts at a high price, is more profitable. Note that when consumer review information is highly informative ($\gamma \in [\underline{\gamma}, 1)$),[8] the valuation of novices who receive match signals on both attributes increases significantly, so that it becomes profitable to sell to these novice consumers if their segment is sufficiently large. If the novice segment is sufficiently small (or equivalently, the expert

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[7] Theoretically, the seller can also decide to supply no attribute information in the presence of consumer reviews. However, it is straightforward that this strategy is a dominated strategy compared with the partial-information strategy.

[8] When $\gamma = 1$, the seller is indifferent between providing full, partial, or no information given a zero supply cost.

segment is sufficiently large, $\eta > \bar{N}$), switching to the full-information strategy to only serve full-matched experts is more attractive than retaining the partial-information strategy.

For high-cost products, in the absence of consumer reviews, a margin-driven strategy (offering full information and selling only to fully matched experts at a high price) is more profitable than a volume-driven strategy (offering partial information and selling both to fully and some partially matched experts at a low price) (see Lemma 1). However, in the presence of consumer reviews, the volume-driven strategy can be more attractive than the margin-driven strategy. When consumer review information is sufficiently informative ($\gamma \geq \underline{\gamma}$), the valuation of the novices who receive match signals on both attributes increases sufficiently, so that it becomes profitable for the seller to reduce its price to sell to these consumers in addition to the perfectly matched experts if the number of novices is sufficiently high (equivalently, the number of experts is sufficiently small, $\eta < \underline{N}$). As a side benefit of this low-price, volume-driven strategy, the seller can profit from switching to the partial-information strategy by gaining extra demand from some partially matched experts.

Note that switching to the partial-information strategy will not help the seller if the consumer review information is extremely informative ($\gamma > \gamma''$). This is because, under the partial-information strategy, the valuation of expert consumers who receive the mismatch signal on the uninformed attribute is negatively related to the review informativeness (i.e., the more informative the reviews, the more likely for these consumers to realize their mismatch). As a result, when the review informativeness is extremely high ($\gamma > \gamma''$), the valuation of these experts becomes too low to retain the advantage of the partial-information strategy.

4.3. Proactive Response to Online Consumer Reviews

We now examine the case where the seller can proactively respond to consumer reviews. This is possible when the seller anticipates the availability of consumer reviewers in the second period (e.g., if the seller allows consumers to post their reviews on its own website). Different from the last section, where the review informativeness γ is exogenously given, the seller may now influence γ by controlling the number of consumers who purchase in period 1 (e.g., D_1).[9] This is because the number of buyers in

period 1 determines the number of potential reviewers in period 2, which can be positively related to the informativeness of consumer review information, i.e., $\partial\gamma/\partial D_1 > 0$.[10] Note that the seller can control D_1 via its period 1 information content strategy (i.e., the *margin-driven* strategy characterized by offering full-information and high prices or the *volume-driven* strategy characterized by offering partial-information and low prices). Let $\Gamma = \gamma(D_1 = \eta_1)$, which is the level of review informativeness reached under the maximum period 1 demand (i.e., when all period 1 arrivals buy in period 1 under positive prices). We refer Γ to the *review informativeness potential*.

When the seller anticipates the availability of consumer reviews in period 2, the seller can act proactively to adjust its strategies even before reviews become available, which can affect review informativeness. Proposition 2 states when and how the seller can benefit from this proactive strategy.

PROPOSITION 2 (PROACTIVE STRATEGY TOWARDS CONSUMER REVIEWS). *When the seller anticipates the availability of consumer reviewers, it is optimal to*

(a) *Adjust its period 1 strategy (i.e., prices and information content supply) if the review informativeness potential is sufficiently high. Specifically, iff $\Gamma > \bar{\Gamma}$, then compared with Lemma 1, it is optimal to change period 1 strategy by*

$$
\begin{cases}
\textit{decreasing price} & \textit{if } c < v^P, \\
\textit{switching to patial-information strategy} \\
\quad \textit{or remaining with full-information} \\
\quad \textit{strategy but reduce price} & \textit{if } c \geq v^P.
\end{cases}
$$

(b) *Adopt the same period 2 response given in Proposition 1.*

When the seller adopts a proactive response strategy and adjusts its marketing strategy before consumer reviews become available, it will offer a lower price and generates a higher demand in period 1. Although such a response reduces period 1 profits, it can significantly increase period 2 profits because a larger number of buyers in period 1 leads to a higher level of informativeness in the consumer reviews in period 2. Proposition 4 reveals that whether a seller should adopt such proactive strategy depends on the review (WOM) informativeness potential, Γ. When the review

---

[9] An alternative way to model a firm's dynamic behavior is to consider consumers' strategic waiting behavior explicitly and treat λ_t as endogenous. Similar to some previous research (e.g., Lazear 1986, Raju et al. 1990), our model does not explicitly consider such

behavior. An implicit assumption behind this type of model is that the discount rate of early arrivals is very high, which is consistent with the behavior of early consumers in many new product markets (Moore 1991). If the discount rate of early arrivals is very low and reaches zero (λ_t is endogenous), some period 1 experts might wait to buy in period 2. In this case, the required price to induce period 1 purchase would be lower.

[10] We do not specifically model consumer review posting behavior here. Admati and Pfleiderer (2004) have studied consumer posting behavior and review informativeness.

informativeness potential is very high, i.e., $\Gamma > \overline{\Gamma}$, the profit decrease in period 1 from the proactive response can be compensated for by a profit increase in period 2, the proactive response strategy improves seller's profit, and vice versa. Proposition 4 also specifies how a seller responds proactively when $\Gamma > \overline{\Gamma}$. As stated earlier (see Lemma 1), when cost is low ($c < v^P$), the optimal period 1 strategy for a seller is to adopt the volume-driven strategy, under which the seller offers partial information and sells to both fully and partially matched experts at a low price. Proposition 4 shows that when $\Gamma > \overline{\Gamma}$, a seller will adopt a proactive response strategy and deviate from such a strategy by further reducing its price in period 1. When cost is high ($c \geq v^P$), the passive response strategy for the seller is to maintain the margin-driven strategy in period 1 as in the case without consumer reviews, under which the seller offers full information and sells only to fully matched experts at a high price. However, when $\Gamma > \overline{\Gamma}$, the seller will deviate from such a strategy and adopts the volume-driven strategy by either switching to the partial-information strategy or simply further reducing its price.

An important implication of Proposition 2 is that optimal response to consumer reviews may differ depending on the review (WOM) informativeness potential, which largely relies on product characteristics (Bone 1992). A seller acting proactively and intentionally increasing the number of buyers at an early stage of a product's life cycle may NOT be beneficial for ALL products. For instance, vanity products are more likely to generate "buzz" (i.e., the number of review postings), but embarrassing products are less likely to do so; products targeted to younger consumers (e.g., MP3 players) are more likely to generate buzz than products targeted to older consumers (e.g., hearing aids); original products are more likely to increase WOM than less-original products (Moldovan et al. 2006). A proactive response strategy to reviews will improve profit only if the increased demand in the early period can significantly increase the number of review postings, and thus increase the informativeness of consumer reviews in the later period.

5. Decision on Supply of Consumer Reviews

In the last section, we focus on the seller's best information content response to consumer reviews. In this section, we examine another important strategic decision: whether the seller should initiate or facilitate consumer review information itself, such as offering its existing consumers the opportunity to post their product reviews on its own website. We first examine conditions under which such a strategy is beneficial, and then discuss the optimal timing to offer consumer reviews if it is possible to control when consumer reviews become available.

5.1. Supply of Consumer Reviews
To derive the conditions under which it is optimal to offer consumer reviews, we compare the profits in the absence of consumer review information and in the presence of consumer reviews (under the optimal strategic response), $\widehat{\Pi}^*$ and Π^*. Proposition 3 states conditions required for the seller to benefit from supplying consumer reviews.

PROPOSITION 3 (CONSUMER REVIEW SUPPLY DECISION). *The seller will not benefit from offering consumer reviews unless* (i) *the review informativeness potential is sufficiently high* ($\Gamma > \gamma$), *and* (ii) *the size of the expert segment is sufficiently small* ($\eta < \underline{N}'$).

Proposition 3 reveals that the consumer review supply decision depends on two crucial factors: the review informativeness potential and the size of the expert segment. As a new source of product information, consumer review information is a double-edged sword that can benefit or hurt the seller. On the one hand, such information can increase the profit from the novice segment because consumer reviews can serve as a free sales assistant to novice consumers. When the review informativeness potential is sufficiently high ($\Gamma > \gamma$), consumer reviews can significantly increase product valuation for some novices (e.g., those who receive match signals on both attributes). As a result, selling to these consumers is not profitable in the absence of consumer reviews, but can be profitable in their presence. On the other hand, consumer reviews can decrease the profit from the expert segment because such review information takes away the seller's control over the information content available to experts. The seller's decision as to whether or not to provide online consumer reviews depends on the trade-off between its profit gain from novices and loss from experts. When the size of the expert segment is small ($\eta < \underline{N}'$) (e.g., for technology-driven products), the seller will obtain a sufficient profit gain from the novices while incurring very limited profit loss from the experts. As a result, offering consumer reviews is advantageous. However, when the review informativeness potential is extremely small ($\Gamma < \gamma$), or the size of the expert consumer is too large ($\overline{\eta} > \underline{N}'$), the profit gain obtained from the novices segment is insufficient to compensate the profit loss from the expert segment, and the seller can be worse off by offering consumer reviews. This might partially explain why many lesser-known online stores do not offer their shoppers the option to post reviews on their websites. Consumer reviews cannot be very informative unless there is a sufficient number of review postings. For less-popular sellers with a small volume of transac-

tions, it might be difficult to attract sufficient number of review postings on their websites. As suggested by our model, the seller can be worse off from low informative review information. As a result, it can be unprofitable for lesser-known sellers to facilitate such consumer-created information.

5.2. Timing of Offering Consumer Reviews

We have shown that under some conditions (see Proposition 3), the seller benefits from initiating consumer reviews. However, when offering consumer reviews is profitable, is it always optimal to provide such information immediately after product launch? We now address this issue.

To allow for flexibility in timing, we extend our previous two-period model to a three-period model. Let λ_t denote the percentage of experts who enter the market in the beginning of period t, $t = 1, 2, 3$ (i.e., $\sum_{t=1}^{3} \lambda_t = 1$). Without loss of generality, we assume that the review supply cost is zero, and the review informativeness is sufficiently high and reaches its potential in the end of period 1. We examine, if the seller has control over the time to provide consumer reviews at the product level, whether it is best to offer reviews at the beginning of period 2 (i.e., right after the reviews become available) or the beginning of period 3 (i.e., delaying the timing of offering). Proposition 4 provides conditions under which it is profitable to delay the timing of offering consumer reviews.

PROPOSITION 4 (TIMING DECISION ON CONSUMER REVIEW OFFERING). *When consumer reviews improve seller profit, the seller is better off by delaying the timing of offering consumer reviews if $\lambda_2 \geq \underline{\lambda}$ and $c < v^P$.*

Proposition 4 reveals that when the seller benefits from offering consumer reviews, it is not always optimal to provide them as early as they become available. Specifically, for low-cost products ($c < v^P$), if a sufficient percentage of experts enter the market in period 2 ($\lambda_2 \geq \underline{\lambda}$), then it is optimal for the seller to postpone the supply of consumer review information. Because offering consumer reviews weakly decreases the seller's profit from the expert segment but weakly increase its profit from the novice segment, the optimal timing of offering consumer reviews depends on the distribution of expert arrivals. When there are too many experts (or too few novices) in period 2 ($\lambda_2 \geq \underline{\lambda}$), the seller can benefit from delaying the timing of supplying consumer reviews (i.e., offering consumer reviews in period 3 rather than in period 2) because it is more profitable to give up the potential gain from the novices in order to avoid the potential loss from the experts in this period. Finally, delaying supplying consumer reviews can improve profit for low-cost products ($c < v^P$) but not for high-cost products ($c \geq v^P$), because the partial-information (the

full-information) strategy is optimal in the absence of consumer reviews in the former (latter) case and consumer reviews reduce the profit from the expert segment in the former, but not in the latter, case.

6. Conclusion, Implications, and Discussions

Recent developments in information technology have significantly increased online sellers' information capacity. In this paper, we investigate an emerging research area: online consumer reviews and their implications on a firm's marketing strategies. Specifically, we study the marketing function of consumer reviews and address three information decisions of an online seller: (1) its best marketing communication response to consumer reviews, (2) its decision to actively facilitate the creation and dissemination of consumer reviews using its website as a medium, and (3) the best timing for supplying consumer reviews.

Compared with seller-created attribute information, consumer reviews are more user oriented and have an advantage in helping consumers to find products matching their preferences. This information is particularly important for unsophisticated consumers (i.e., novices), who will be less likely to buy the seller's product if only seller-created product attribute information is available. However, this sales assistant does not come without cost. By allowing consumers to post their own product evaluations, the seller creates a new information channel for consumers, which eliminates the seller's capability to control the supply of product information (e.g., providing full vs. partial information to consumers). We provide several important strategic implications for online sellers' decisions related to consumer reviews:

• Consumer reviews, as a form of independent product information, may play different marketing roles from that by third-party product reviews. The seller needs to develop a unique strategic response to consumer review information. This research provides some guides for such strategic response.

• The seller's optimal response to consumer reviews may differ for different types of products. The seller would increase the product attribute information in response to consumer reviews for low-cost products, but decrease for high-cost products.

• For "exciting" products (e.g., vanity products, original products) or products targeted to "talkative" segments (e.g., college students), the seller can adopt a proactive response strategy, under which the seller adjusts its marketing strategies even before consumer reviews become available.

• When deciding whether to provide the platform for consumers to post their product reviews on the

seller's website, the seller needs to consider the relative size of expert and novice segments. Offering consumer reviews can benefit products with a sufficient number of novice consumers (e.g., for technology-driven products), but can hurt the seller if the segment of expert consumers is relatively large.

• Less-popular online stores need to be cautious when facing the decision of offering consumers the option to post reviews on their websites. The seller can be hurt by offering such consumer-created information when failing to attract a sufficient number of consumer postings (i.e., failing to ensure a sufficient level of review informativeness). Such sellers may want to consider licensing consumer reviews from well-known third-party sources.

• The timing of the introduction of consumer review information can be an important strategic variable for a seller. When a seller is able to decide such timing at the individual product level, delaying the availability of consumer reviews for a given product can be beneficial if the size of the expert segment is relatively large and cost of the product is low.

Although this research improves our understanding of online consumer review and its implications for firm marketing strategies, many other interesting questions remain unanswered and require further investigation. First, our empirical study is very preliminary. It is a first step to empirically understand the difference between consumer review and third-party professional reviews. To completely study this issue, future research may need to combine the archival statistical data analysis, qualitative netnographic inquiry (Kozinets 2002), and possible experimental testing to provide deeper insights. Second, we study a monopoly model and focus on the matching function of online consumer review. Future research may study some other functions of online consumer reviews and investigate its implications for firm competition. Third, even though the fundamental trade-offs examined in our model apply to both direct-selling manufacturers and distributors, it will be very interesting to study how the decision on supplying consumer reviews and the sellers' best response to consumer reviews differ across different types of sellers (e.g., manufacturers versus retailers). Fourth, future research may study from the perspective of consumer review intermediaries such as Epinons.com, and examine their optimal marketing strategies. Finally, it is important to point out that it is possible for the seller to offer its own product-matching information that mimics consumer reviews. Compared with consumer reviews, the seller-created product-matching information has a cost disadvantage because the seller has to incur the cost of information creation and dissemination. It is expected that such a cost disadvantage increases with

the product-matching complexity. Because consumer reviews are "created by users for users," increasing in the degree of matching complexity implies that the review information will naturally contain more possible usage situations (e.g., see the digital camera examples discussed in §2). An important line of future research will be to empirically investigate firms' consumer review supply decisions and to assess the impact of consumer reviews on a firm's marketing strategy. When testing our model results, the future empirical studies can use the matching complexity between product attribute space and consumer usage condition space as a proxy variable for review informativeness γ.[11]

7. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

Appendix

Summary of Notations

c:	Marginal cost of the seller's product
t:	Time period in the model
γ:	Consumer review informativeness
I:	Product attribute information ($I = I^F, I^P$, I^F: full information; I^P: partial information)
θ:	Consumer true status of attribute matching situation ($\theta = M, \bar{M}$, M: match; $\bar{M}$: mismatch)
s:	The signal from consumer reviews on attribute matching situation ($s = m, \bar{m}$, m: "match," $\bar{m}$: "mismatch")
T:	Consumer type
S:	Consumer segment ($S = E, N$, E: expert; N: novice)
η_t:	Fraction of expert consumers among all consumers in period t
λ_t:	Fraction of experts among all experts in period t
$\bar{v}$:	Consumers' expected valuation in the absence of product information
$V_T^S(I, \gamma)$:	Expected valuation of type T consumers in segment S given attribute information I and review informativeness γ
v^F, v^P:	Consumers' evaluations on their fully and partially matched products separately

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[11] We thank one of the reviewers for this suggestion.

v^0: Consumers' evaluation on their fully unmatched product (v^0 is assumed to 0)

P_t: Seller's price in period t

$\widehat{\Pi}, \widehat{\Pi}_t$: Seller's overall profit and profit in period t in the absence of consumer reviews

Π, Π_t: Seller's overall profit and profit in period t in the presence of consumer reviews

$\widehat{\Pi}^S, \Pi^S$: Seller's profit from segment S in the absence and presence of consumer reviews respectively

A.1. Proof of Lemma 1

In the absence of consumer reviews, when the seller provides full information, the valuations are zero for type $T_{\bar{M}\bar{M}}$, v^P for types $T_{\bar{M}M}$ and $T_{M\bar{M}}$, and v^F for type T_{MM} expert consumers. The seller can charge a premium price v^F to serve only T_{MM} or charge a low price v^P to serve T_{MM}, $T_{\bar{M}M}$, and $T_{M\bar{M}}$. Consistent with Lewis and Sappington (1994), we focus on the case in which the seller charges a premium price with full information, which implies $v^F > 3v^P - 2c$. Notice that for any given consumer, there is an equal chance that a given attribute matches her preference. In other words, each attribute matches the preferences of half the consumers. Hence, the size of each type of consumers is 1/4. Note that the fraction of experts in period t is η_t. In each period t, seller's overall profit (i.e., its profit from the experts) is

$$\widehat{\Pi}_t(I^F)^* = \widehat{\Pi}_t^E(I^F)^* = (v^F - c)\eta_t/4. \tag{4}$$

The seller's overall profit is

$$\widehat{\Pi}(I^F)^* = \widehat{\Pi}^E(I^F)^* = (v^F - c)(\eta_1 + \eta_2)/4 = (v^F - c)\eta/4. \tag{5}$$

When the seller only provides information on one attribute—for instance, a_1—the expected valuation for the product is $(v^P + v^F)/2$ for type $T_{M\bar{M}}$ and T_{MM} experts who have matched tastes in the attribute a_1. For those consumers who have mismatched tastes in the attribute a_1 (type $T_{\bar{M}M}$ and $T_{\bar{M}\bar{M}}$), they have equal probabilities to find match and mismatch in a_2 and have a valuation of v^P and 0 on the

product. Hence, the expected valuation for them is $v^P/2$. This valuation is lower than $\bar{v} = (v^F + 2v^P)/4$ and c. The seller charges a price $P_t = (v^P + v^F)/2$ and gains the demand from type $T_{M\bar{M}}$ and T_{MM} experts. Recalling that η_t is the fraction of the experts among all consumers in period t, the seller's profit in period t is

$$\widehat{\Pi}_t(I^P)^* = \widehat{\Pi}_t^E(I^P)^* = ((v^P + v^F)/2 - c)\eta_t/2. \tag{6}$$

The seller's overall profit is

$$\widehat{\Pi}(I^P)^* = \widehat{\Pi}^E(I^P)^* = ((v^P + v^F)/2 - c)(\eta_1 + \eta_2)/2$$
$$= ((v^P + v^F)/2 - c)\eta/2. \tag{7}$$

Comparing (5) with (7), we find $\widehat{\Pi}(I^F)^* \geq \widehat{\Pi}(I^P)^*$ and $\widehat{\Pi}^* = \widehat{\Pi}(I^F)^*$ iff $c \geq v^P$. $\square$

A.2. Sketchy Proof of Proposition 1

In the presence of consumer reviews, the seller's profit from the experts in period 1 is the same as in period 1 in the absence of consumer reviews, i.e., $\Pi_1^* = \widehat{\Pi}_1^*$.

In period 2, consumer reviews are available. Consumers revise their expected valuations using different posteriors: $P(M \mid m) = P(\bar{M} \mid \bar{m}) = \bar{q}(\gamma) = (1/2 + \gamma/2)$ and $P(M \mid \bar{m}) = P(\bar{M} \mid m) = \underline{q}(\gamma) = (1/2 - \gamma/2)$. These posteriors can in fact be derived using Bayes' Theorem and by assuming $P(M) = P(\bar{M}) = 1/2$, $P(m \mid M) = P(\bar{m} \mid \bar{M}) = (1/2 + \gamma/2)$, and $P(\bar{m} \mid M) = P(m \mid \bar{M}) = (1/2 - \gamma/2)$. Specifically,

$$P(M \mid m) = \frac{P(m \mid M)P(M)}{P(m \mid M)P(M) + P(m \mid \bar{M})P(\bar{M})}$$
$$= \frac{(1/2 + \gamma/2)/2}{(1/2 + \gamma/2)/2 + (1/2 - \gamma/2)/2} = (1/2 + \gamma/2)$$

$$P(\bar{M} \mid m) = \frac{P(m \mid \bar{M})P(\bar{M})}{P(m \mid \bar{M})P(\bar{M}) + P(m \mid M)P(M)}$$
$$= \frac{(1/2 - \gamma/2)/2}{(1/2 - \gamma/2)/2 + (1/2 + \gamma/2)/2} = (1/2 - \gamma/2)$$

Table A1   Novice Consumer Expected Valuations in the Presence of Consumer Reviews

Novice consumer type (T)	Probability that type T novice's true status is θ given the signals obtained form consumer reviews				Consumer expected valuation $V_T^N(\gamma)$
	$\theta = \bar{M}\bar{M}$ ($v = 0$)	$\theta = \bar{M}M$ ($v = v^P$)	$\theta = M\bar{M}$ ($v = v^P$)	$\theta = MM$ ($v = v^F$)	
T_{mm}	$\underline{q}(\gamma)\underline{q}(\gamma)$	$\underline{q}(\gamma)\bar{q}(\gamma)^*$	$\bar{q}(\gamma)\underline{q}(\gamma)$	$\bar{q}(\gamma)\bar{q}(\gamma)$	$(2v^P + v^F)/4 + \gamma v^F/2$ $- \gamma^2(2v^P - v^F)/4$
$T_{m\bar{m}}$	$\underline{q}(\gamma)\bar{q}(\gamma)$	$\underline{q}(\gamma)\underline{q}(\gamma)$	$\bar{q}(\gamma)\bar{q}(\gamma)$	$\bar{q}(\gamma)\underline{q}(\gamma)$	$(2v^P + v^F)/4$ $+ \gamma^2(2v^P - v^F)/4$
$T_{\bar{m}m}$	$\bar{q}(\gamma)\underline{q}(\gamma)$	$\bar{q}(\gamma)\bar{q}(\gamma)$	$\underline{q}(\gamma)\underline{q}(\gamma)$	$\underline{q}(\gamma)\bar{q}(\gamma)$	$(2v^P + v^F)/4$ $+ \gamma^2(2v^P - v^F)/4$
$T_{\bar{m}\bar{m}}$	$\bar{q}(\gamma)\bar{q}(\gamma)$	$\bar{q}(\gamma)\underline{q}(\gamma)$	$\underline{q}(\gamma)\bar{q}(\gamma)$	$\underline{q}(\gamma)\underline{q}(\gamma)$	$(2v^P + v^F)/4 - \gamma v^F/2$ $- \gamma^2(2v^P - v^F)/4$

Notes. If the seller provides full information, in period 2, different from the partial-information content case, consumer reviews have no impact on experts due to their fully realized valuations from full product attribute information. The expected valuations of four types of novices are the same as in the partial information content case. Based on the expected valuations for all types of experts and novices, we can derive seller's profit functions, which vary with c, γ, η_t, and I. By comparing the profits in the presence of full information and in the presence of partial information, we can derive Proposition 1. The detailed derivations are shown in Online Technical Appendix AA.1.

   *$\bar{q}(\gamma) = 1/2 + \gamma/2$, and $\underline{q}(\gamma) = 1/2 - \gamma/2$.

$$P(M \mid \overline{m}) = \frac{P(\overline{m} \mid M)P(M)}{P(\overline{m} \mid M)P(M) + P(\overline{m} \mid \overline{M})P(\overline{M})}$$
$$= \frac{(1/2 - \gamma/2)/2}{(1/2 - \gamma/2)/2 + (1/2 + \gamma/2)/2} = (1/2 - \gamma/2)$$

$$P(\overline{M} \mid \overline{m}) = \frac{P(\overline{m} \mid \overline{M})P(\overline{M})}{P(\overline{m} \mid \overline{M})P(\overline{M}) + P(\overline{m} \mid M)P(M)}$$
$$= \frac{(1/2 + \gamma/2)/2}{(1/2 + \gamma/2)/2 + (1/2 - \gamma/2)/2} = (1/2 + \gamma/2).$$

If the seller only provides information on one attribute—for instance, a_1—then experts know if a_1 is a match from the seller-provided information, and form a probability about whether a_2 is a match based on the signal they obtained from consumer reviews. Thus, experts can be classified into four categories. Let T_{Ms} and $T_{\overline{M}s}$ denote the experts whose preference matches and the experts whose preference mismatches with a_1, respectively. The signal they obtained from consumer review about a_2 is $s = m, \overline{m}$. The expected valuations for four types of experts are

$$V^E_{T_{Mm}}(I^P, \gamma) = v^F \bar{q}(\gamma) + v^P \underline{q}(\gamma) = (v^P + v^F)/2 + \gamma(v^F - v^P)/2,$$

$$V^E_{T_{\overline{M}m}}(I^P, \gamma) = v^P \bar{q}(\gamma) = v^P(1 + \gamma)/2,$$

$$V^E_{T_{M\overline{m}}}(I^P, \gamma) = v^F \underline{q}(\gamma) + v^P \bar{q}(\gamma) = (v^P + v^F)/2 - (v^F - v^P)\gamma/2,$$

and

$$V^E_{T_{\overline{M}, \overline{m}}}(I^P, \gamma) = v^P \underline{q}(\gamma) = v^P(1 - \gamma)/2 < c.$$

When consumer reviews are available, let T_{ss} denote the novices who receive signal s on each attribute, $s = m, \overline{m}$. The novice consumers can be categorized into four types depending on the signals (match versus mismatch) on two attributes they receive from consumer reviews: T_{mm}, $T_{m\overline{m}}$, $T_{\overline{m}m}$, and $T_{\overline{m}\overline{m}}$. As shown in Table A1, we can derive the expected valuations for four types of novices as

$$\begin{bmatrix} V^N_{T_{mm}}(\gamma) \\ V^N_{T_{m\overline{m}}}(\gamma) \\ V^N_{T_{\overline{m}m}}(\gamma) \\ V^N_{T_{\overline{m}\overline{m}}}(\gamma) \end{bmatrix} = \begin{bmatrix} (2v^P + v^F)/4 + \gamma v^F/2 - \gamma^2(2v^P - v^F)/4 \\ (2v^P + v^F)/4 + \gamma^2(2v^P - v^F)/4 \\ (2v^P + v^F)/4 + \gamma^2(2v^P - v^F)/4 \\ (2v^P + v^F)/4 - \gamma v^F/2 - \gamma^2(2v^P - v^F)/4 \end{bmatrix}.$$

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