How do Different Sources of the Variance of Consumer Ratings Matter?

Completed Research Paper

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Abstract

To examine the effect of the variance of consumer ratings on product pricing and sales we develop a model which considers goods that are characterized by two types of attributes: experience attributes and experience attributes that were transformed in search attributes by consumer ratings that we call informed search attributes. For pure informed search goods, we find that with increasing variance optimal price increases and demand decreases. For pure experience goods, we find that with increasing variance optimal price and demand decrease. For hybrid goods, when there is low total variance and the average rating and total variance are held constant, optimal price and demand increase with increasing relative share of variance caused by informed search attributes. Via this mechanism, risk averse consumers may prefer higher priced goods with a higher variance. In addition, our model provides a theoretical explanation for the empirically observed j-shaped distribution of consumer ratings.

Keywords: Consumer Rating, Variance, Experience Attribute, Informed Search Attribute, E-Commerce

Introduction

When a new product is introduced on the market, potential consumers have uncertainty about the product's attributes, even though knowing these attributes may be important to make a decision on buying or not buying the product (Shapiro 1983). Nelson (1970) was the first to introduce the distinction between search goods and experience goods into the literature. Search goods such as printing paper or blank CDs are solely characterized by search attributes that can be determined by inspection without the necessity of use (Shapiro 1983). Experience goods such as digitalized books, music, or movies are solely characterized by experience attributes that can only be determined through use (Wei and Nault 2013). Nelson (1981) generalized this dichotomous distinction and suggested that most of the products can be described by a collection of search and experience attributes.

In the pre-Internet and pre-Web 2.0 times, experience attributes could not be determined before buying a product and experiencing it. This has fundamentally changed in recent years due to consumer ratings on electronic commerce platforms which are most commonly provided in the form of a star rating system (indicating the valence of the consumer rating) and an optional textual review. Accordingly we consider a consumer rating as a combination of a quantitative rating (e.g. a star rating) and a qualitative rating (e.g. a textual review that explains the star rating). Researchers have referred to such consumer ratings also as electronic word-of-mouth (eWOM) (see, e.g., Dellarocas 2003, Hennig-Thurau et al. 2004, Cheung and Thadani 2012). In particular, consumer ratings offer a form of peer learning among consumers by enabling prospective consumers to learn from other consumers' experiences (Liu et al. 2014). Thereby, they transform many former experience attributes of a product into search attributes (Hong et al. 2012) and thus reduce the uncertainty of consumers (Chen and Xie 2008, Kwark et al. 2014). We denote these attributes as informed search attributes. An example for an informed search attribute is the sound quality of a headphone. Without additional information, assessing this attribute requires listening to the actual device (experience attribute). This can now be inferred from reading other consumer ratings (informed search attribute). Not surprisingly, 90% of purchasing decisions are influenced by consumer ratings (Drewnicki 2013), 64% of consumers prefer sites with consumer ratings when shopping online (Kee 2008) and the most popular feature of Amazon.com is its consumer ratings (New York Times 2004). This makes online consumer ratings one of the main sources to reduce uncertainty for potential consumers.

Not all experience attributes, however, can be transformed into informed search attributes. These are quality attributes that may differ between two instances of the same good. For example, negative textual reviews for specific headphones (Amazon 2015) show that some of the headphones technically fail after a relatively short period of usage. From these reviews, consumers can make some inference, i.e. learn about the probability of failure. What they cannot infer from these reviews is whether their individual headphones will fail. Thus, the failure rate represents an informed search attribute but the failure itself represents an experience attribute that cannot be transformed into a search attribute by consumer ratings.

The three types of attributes we consider in this paper are summarized in Table 1.

Table 1. Different Types of Product Attributes

Attribute	Definition	Example
Search attributes	Attributes that can be determined by consumers through reading the product specifications provided by the manufacturer.	Color of headphones (e.g., using the Pantone Matching System) Noise Cancelling (yes/no)
Informed search attributes	Attributes that can be determined by consumers through consumer ratings.	Sound quality of headphones Failure rate of headphones
Experience attributes	Quality attributes that may differ between two instances of the same good	Technical failure of headphones

Much of the information contained in the textual reviews is summarized in the star rating ranging from one (lowest recommendation) to five (highest recommendation) on most e-commerce websites. A bar chart shows the distribution of the star rating, with the average rating displayed prominently beneath the product name. Consumers can thus see at a glance how other consumers rated the product on average and the extent to which opinions about the product differ (variance).

Among the significant literature that has recently emerged on consumer ratings, several studies find that the absolute number and the average consumer ratings positively affect consumer demand. However, only few studies explicitly analyze the effect of the variance of online consumer ratings on price of the product and demand (Clemons et al. 2006, Hong et al. 2012, Sun 2012) and, to the best of our knowledge, none explicitly considers the potential effect depending on whether the variance is caused mainly by informed search attributes (i.e., the sound quality of headphones) or by experience attributes (i.e., the technical failure of headphones) or by both.

We consider hybrid goods where variance in consumer ratings can be caused by an informed search attribute and an experience attribute in order to answer the following research question: *How does the variance of consumer ratings caused by informed search and experience attributes affect product price and demand?*

To determine the effect of the different sources of variance of consumer ratings on product price and consumer demand we construct an analytical model featuring a monopoly retailer and consumers that differ in taste and risk aversion. We analyze three product types*: pure informed search goods* where the variance of consumer ratings is solely caused by an informed search attribute; *pure experience goods* where the variance of consumer ratings is solely caused by an experience attribute; and *hybrid goods* where the variance of consumer ratings is caused by an informed search and an experience attribute.

Our analysis yields the following main results: First, a higher variance caused by an informed search attribute always signals that a product is liked by some consumers but disliked by others, and results in a higher equilibrium price and lower equilibrium demand. Second, a higher variance caused by an experience attribute signals that there is some risk associated with buying the product resulting in a lower equilibrium price and demand. Third, holding the average rating as well as the total variance of ratings constant and increasing the relative share of variance caused by the informed search attribute leads to an increase in both the equilibrium price and the demand for products with low total variance. Through this mechanism, equilibrium price and demand can increase with an increasing total variance of product ratings. We demonstrate, therefore, how risk averse consumers may prefer a more expensive product with a higher variance of ratings when deciding between two similar products with the same average rating. Finally, our analytical model provides a theoretical foundation for the empirically observed j-shaped distribution (Hu et al. 2007, Hu et al. 2009) of consumer ratings in electronic commerce.

Related Literature

A substantial fraction of the related literature on the effects of consumer ratings on product sales empirically analyzes the effect of *average product ratings* (e.g., Chevalier and Mayzlin 2006, Sun 2012, Li and Hitt 2008, Luca 2011) and the *number of product ratings* (e.g., Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Duan et al. 2008) on sales of products from different product categories. Some authors have found that an increase in the average ratings has a positive effect on the sales of books (Chevalier and Mayzlin 2006, Sun 2012, and Li and Hitt 2008), restaurants (Luca 2011), and movies (Dellarocas et al. 2007), whereas others fail to find such an effect both for books (Chen et al. 2004) and for movies (Duan et al. 2008). For the total number of ratings, Chen et al. (2004), Chevalier and Mayzlin (2006), Duan et al. (2008) and Sun (2012) find a positive effect on sales, whereas Godes and Mayzlin (2003) do not find any such effect. A comprehensive review of research on online consumer ratings can be found in Trenz and Berger (2013).

Only few studies have analyzed the effect of the *variance of consumer ratings* on product sales. In an empirical study focusing on the craft beer industry, Clemons et al. (2006) analyze the effect of consumer ratings on product demand in a market with hyperdifferentiation. Hyperdifferentiation describes drastically increased product variety even in very small markets. In such markets, firms are able to offer products which perfectly match the preferences of very small consumer segments. Thus, for products in hyperdifferentiated markets a good average rating is far less important than a small number of very good ratings from consumers with a perfectly matched taste for the product. Further, the authors find that the variance of product ratings is associated with higher growth in sales in hyperdifferentiated markets. Sun (2012) builds a simple game-theoretical model to analyze the informational role of the variance of product ratings on equilibrium product price and consumer demand. Consumers in this model are risk neutral and all products can be described with two variables: Product quality and mismatch costs. Products with a high mismatch cost are products for which only some consumers have a strong liking while others substantially dislike it, whereas products with a low mismatch cost are products which appeal to a broad audience. In Sun's model, a high average rating indicates a high product quality, whereas a high variance of ratings is associated with a high mismatch cost. The variance of ratings can help consumers to figure out whether a product's average rating is low because of its low product quality or because of its high mismatch cost. In case of a low rating due to a high mismatch cost some consumers will still buy the product because they know that the product matches their taste and that they therefore will not incur any mismatch cost. Thus, a higher variance can increase the demand for a product. Sun empirically tests the theoretical predictions from her model using data for books sold on amazon.com and barnesandnobel.com. In line with her theoretical predictions she finds a positive effect of the variance of consumer ratings for books with a low average rating. The first study that considers different sources of the variance of consumer ratings is Hong et al. (2012). Using the dynamics of online consumer rating variance the authors propose an analytical mechanism for classifying products according to whether they have more search attributes or more experience attributes. By providing empirical evidence for the fact that different sources of variance lead do different realizations of variance over time, they build an important foundation for our analysis. Hong et al. (2012), however, do not analyze the relationship between different sources of variance and their effect on product pricing and sales.

Our paper builds on the results from Clemons et al. (2006), Sun (2012), and Hong et al. (2012). Analyzing the effect of variance of consumer ratings on product pricing and consumer demand for products with an informed search attribute and an experience attribute, we explicitly consider whether these different sources of variance differently affect market outcomes. Indeed, our results indicate that the relative proportion of the different sources of variance serves as a valuable indicator for analyzing the effect of consumer ratings on product pricing and on consumer demand.

Notation and Assumptions

Our assumptions appertain to a number of different factors relating to, first, consumer heterogeneity, second, product characteristics and third, consumer ratings. These are presented in turn.

ASSUMPTION 1 **(Consumer Heterogeneity)**. *Consumers differ in their taste and risk aversion, and taste and risk aversion are independent.*

In line with Sun (2012), we assume that consumers are heterogeneous in their taste for specific product aspects. We represent consumer taste by τ which is equally distributed between zero and one, i.e. $\tau \sim U[0,1]$ where zero is a perfectly matched taste. We further assume that consumers are risk averse. This assumption is justified by results from laboratory experiments (e.g., Holt and Laury 2002) as well as from surveys among online shoppers (e.g., Bhatnagar et al. 2000). Intuitively, this risk aversion is not homogeneous among all consumers. We denote increasing consumer risk aversion by the variable θ which is also equally distributed between zero and one, i.e. $\theta \sim U[0,1]$. Accordingly, we have a horizontally differentiated model along the two dimensions *taste* and *risk aversion* of consumers. Formally, consumers' tastes and their risk aversions are represented by a square with edge length 1 (see figure 1) where the line segment [AB] represents consumer taste and the line segment [AC] represents consumer risk aversion. In each period of the game, a unit mass of consumers is uniformly distributed within this square which means that taste and risk aversion are independent. To keep the analysis simple, there is no overlap in consumers across periods (i.e., a consumer is either among first period- or second-period consumers and, thus, consumers may not exhibit strategic behavior). A consumer's taste is equal to her position on the taste-axis and her risk aversion is equal to her position on the risk aversion-axis. For example, a consumer located in A has zero risk aversion and a perfect taste for the product, whereas a consumer located in E is substantially risk averse and has a slightly incongruous taste for the product.

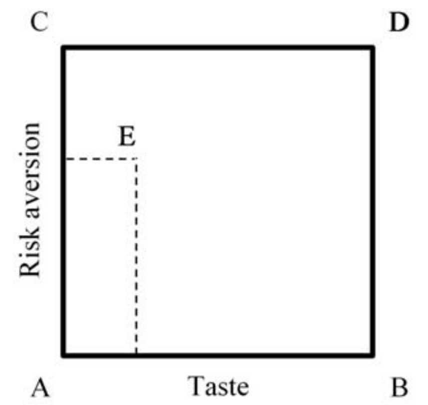

Figure 1. Consumer Taste and Risk Aversion

ASSUMPTION 2 **(Product Characteristics)**. *Each product is characterized by a positive matched quality, positive or zero mismatch costs, and a failure rate between zero and one.*

We denote matched quality as v and assume that $v \in R^+$. *Matched quality* determines how much a consumer enjoys an ideal product (i.e., a product with a perfectly matched taste) that does not fail during its typical period of usage. Product attributes that are related to the matched quality include, for example, plot coherence for novels, distortion and image noise for digital cameras, or computing speed for notebooks. *Mismatch costs* are the same as in Sun (2012) and capture *"aspects of the product that would have an influence on how much consumers would differ in their enjoyment of the product"*. We denote increasing mismatch costs as x and assume that $x \in [0, v]$. Mismatch costs are caused by informed search attributes which are perceived differently among consumers and negatively affect their enjoyment depending on their taste. For example, irrespective of plot coherence, some consumers may love vampire romance stories while others dislike this genre. Products with informed search attributes that cause mismatch costs of close to zero are a perfect fit for all consumers (i.e., typical mass market products) while products with informed search attributes that cause high mismatch costs are a perfect fit for just a small group of people (i.e., typical niche products). In contrast to Sun (2012), we assume mismatch costs to be never higher than the matched quality of a product. Thus, even consumers who maximally dislike all informed search attributes that cause mismatch costs get a positive or zero enjoyment from the product if they were to obtain the product for free. Finally, we consider the technical quality of a product by the product's *failure rate* $f \in [0,1]$ that accounts for the likelihood of technical product failure during the typical time of usage (Bardey 2004). While a product with a failure rate of zero never fails during its typical life expectancy, products with a failure rate of one always fail during this period. Thus, we represent the technical quality of a product by the failure rate which represents an informed search attribute. The actual technical failure of a product instance is Bernoulli distributed and represents an experience attribute. Thus, product instances are vertically differentiated by their technical failure.

In the early launch stage of a product, communicated product specifications from the product manufacturer provides the dominant source of product information (Manchanda et al. 2008). These specifications primarily affect first-period consumer's purchase decision through the elimination of uncertainty about search attributes (Narayanan et al. 2005) and to build expectations about informed search attributes resulting in expected matched quality v_e, expected mismatch costs x_e, and expected failure rate f_e. As we do not consider screening mechanisms or reputational effects of the producer of the product, we do not assume any relationship between v, x, and f.

ASSUMPTION 3. (**Consumer Rating Behavior**). *All first-period consumers publish honest consumer ratings which eliminate uncertainty about informed search attributes of the product.*

Since the 1960s marketing researchers reported that the early adopters of a new product are very keen to talk about the product. For example, Engel et al. (1969) write that *"There seems to be no question that the first users of a new product or service are active in the word-of-mouth channel"*. Consistent with Sun

(2012), we suppose that soon after a product launch all first-period consumers publish a consumer rating. Further, consumer ratings are honest and there is no external manipulation of consumer ratings as discussed in Mayzlin (2006) and Luca (2011). Assumption 3 implies that consumer ratings correspond to the actual utility u derived from its consumption. Consequently, consumer ratings are continuous in our model. The typically provided star rating systems on electronic commerce platforms represent a discretization of our model.

We further assume that uncertainty about informed search attributes can be eliminated through consumer ratings. From a practical perspective, this seems to be a heroic assumption. However, we can make that assumption without loss of generality as long as it can be taken for granted that the uncertainty about informed search attributes are reduced by consumer ratings. Once, a critical mass of consumer ratings are provided on an electronic platform concerning a specific product, this will most likely be the case.

These notations and assumptions are very similar to the model setup of Sun (2012) and overlap with the model assumptions of Kwark et al. (2014). Our model setup is also related to Wattal et al. (2009), who develop a game-theoretic model to examine how information personalization by firms interacts with horizontal and vertical product differentiation. Further, our model is similar in some aspects to Gu and Xie (2012) who examine firms' strategic decisions regarding whether to engage in marketing activities to assist consumers in finding the fit between their personal tastes and products' horizontal attributes. Finally, in terms of the vertical differentiation, our model is similar to (Bardey 2004) who does not treat the quality of the products as a known variable, but interprets the quality issue as a "survival probability" which is equivalent to our "failure rate".

Model Analysis

We consider a two period game with a monopoly retailer and consumers with heterogeneous tastes and risk aversions. The structure of the model is illustrated in Figure 2.

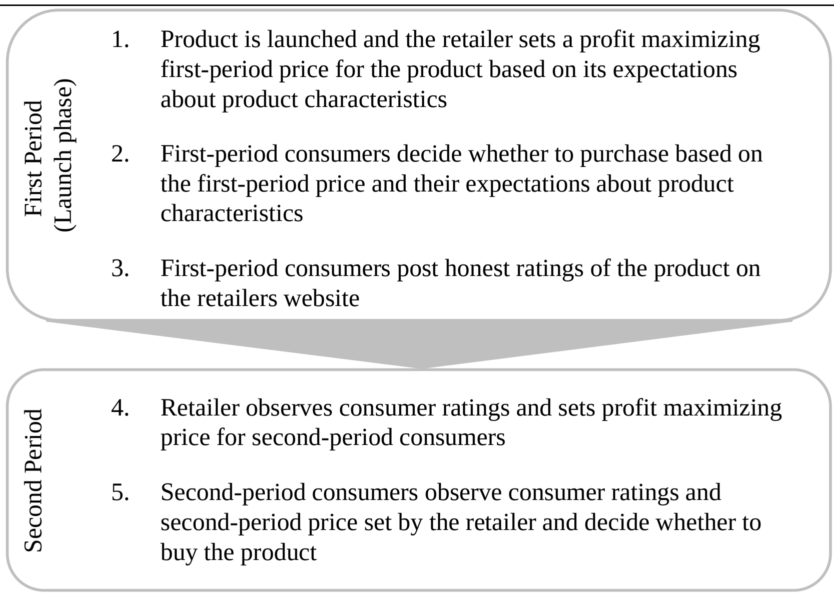

Figure 2. Model Structure

If a consumer with taste τ and risk aversion θ buys the product in the first period at price P_1, then her expected utility is

$$u_1 = (v_e - x_e\tau)(1 - f_e) - P - f_e z\theta. \tag{1}$$

The first part of equation (1) is equal to the expected utility of a risk neutral consumer. The last part of this equation captures a consumer's negative utility caused by risk aversion due to potential product failure. To allow for different absolute levels of consumer risk aversion for different products, we multiply θ by a scaling factor $z \in R^+$. Note that our modelling of consumer risk aversion does not make any assumptions about the specific type of risk aversion. Our only assumption is that consumers do not like the possibility of their product failing. Consumers buy the product if their expected utility from consumption is greater than zero, and do not buy otherwise. Please note the similarities between our model and models with horizontal and vertcial product differentiation (see, e.g., Wattal et al. 2009 , Grilo and Wauthy 2000).

In the first period of the game, a unit mass of first-period consumers enter the market. Each consumer has a maximum demand of one unit of the product and receives a utility of zero when not buying the product. The retailer sets price P_1 based on a profit maximization calculus and consumers decide whether to buy a unit of the product based on their expected utility. For a consumer who buys a product of realized matched quality v_r and with realized mismatch cost x_r, at price P_1 the utility is $v_r - x_r\tau - P_1$ if the product does not fail and $-P_1$ otherwise. After learning the realizations of v_r, x_r, and f_r each consumer publishes an honest rating $v_r - x_r\tau$ for the product if it does not fail or a rating of zero if the product fails. In the second period, a unit mass of second-period consumers enter the market. Second-period consumers and the retailer observe the mean and the variance of the rating distribution. Based on this information, the retailer sets price P_2 based on a profit maximization calculus and second-period consumers decide whether to buy a unit of the product.

In the following, we discuss three types of products: pure informed search goods, pure experience goods and hybrid goods. The failure rate for pure informed search goods is zero. Thus, for these products, consumer valuation is only determined by their expectations on matched quality v_e and mismatch costs x_e. For pure experience goods, the mismatch costs are equal to zero. Accordingly, consumer valuation of these products is determined by their expectations on matched quality v_e and product failure f_e. For hybrid goods, consumer valuation depends on their expectations on all three product attributes: matched quality, mismatch cost, and product failure. Depending on the product type, the expected utility for first-period consumers simplifies to

$$u_1 = \begin{cases} v_e - x_e\tau - P_1 & \text{for informed search goods,} \\ v_e(1-f_e) - P_1 - f_e z\theta & \text{for experience goods,} \\ (v_e - x_e\tau)(1-f_e) - P_1 - f_e z\theta & \text{for hybrid goods.} \end{cases} \quad (2)$$

Pure Informed Search Goods

In a first step we analyze pure informed search goods i.e., products with $f = 0$. For these products, the variance of the rating distribution is solely caused by the informed search attribute. First-period consumers make their purchase decisions based on expected matched quality v_e and expected mismatch costs x_e. After the retailer chooses price P_1, the expected utility of a frist-period consumer is equal to $v_e - x_e\tau - P_1$. Solving $v_e - x_e\tau - P_1 = 0$ for τ yields the taste of the indifferent consumer which we denote with $\tilde{\tau}_1 = \frac{v_e - P_1}{x_e}$. All first-period consumers with $\tau \leq \tilde{\tau}_1$ buy the product, while all consumers with $\tau > \tilde{\tau}_1$ do not. As τ is equally distributed between zero and one and there is a unit mass of potential consumers, first-period demand D_1 is equal to $\tilde{\tau}_1$. Consumers who purchase the product publish an honest product rating based on the realizations of matched quality v_r and mismatch costs x_r. As tastes are uniformly distributed in [0, D_1], ratings are also uniformly distributed between [$v_r - D_1 x_r$, v_r]. Given the uniform distribution of ratings, the average rating M and the variance of ratings V can be computed, respectively, as

$$M = v_r - 0.5 D_1 x_r, \text{ and } V = \frac{D_1^2 x_r{}^2}{12}. \quad (3)$$

By considering the average and the variance of ratings, second-period consumers can derive the product characteristics from the rating distribution. For example, a mediocre average rating and a low variance of ratings refers to a mediocre matched quality and low mismatch costs while a mediocre average rating and a high variance of ratings refers to a higher matched quality and higher mismatch costs. Mathematically, consumers can directly derive v_r and x_r by rearranging (3):

$$v_r = M + \sqrt{3V}, \text{ and } x_r = \frac{\sqrt{12V}}{D_1}. \quad (4)$$

After deriving v_r and x_r, second-period consumer have no uncertainty left in the decision process. By observing the ratings from first-period consumers, they exactly know how much they will enjoy the product. Given this information, the utility of a second-period consumer is given by $u_2 = v_r - x_r\tau - P_2$. Based on u_2 the retailer can derive the taste of the indifferent consumer as a function of the second-period product price P_2: $\tilde{\tau}_2 = (v_r - P_2)/x_r$. As taste is uniformly distributed among consumers, the second-period demand D_2 is also equal to $\tilde{\tau}_2$. Knowing this demand, the retailer can maximize profits by solving: $\max_{P_2} P_2 D_2$. This leads to the following second-period equilibrium levels of price and demand:

$$P_2^* = \frac{v_r}{2}, \text{ and } D_2^* = \frac{v_r}{2x_r}. \quad (5)$$

In terms of M and V equilibrium price and demand can be rewritten as:

$$P_2^* = \frac{M}{2} + \frac{\sqrt{3V}}{2}, \text{ and } D_2^* = \frac{D_1}{4}\left(\frac{M}{\sqrt{3V}} + 1\right). \quad (6)$$

Based on these representations of P_2^* and D_2^*, we present the effects of M and V on equilibrium price and demand for pure informed search goods in the following proposition:

PROPOSITION 1. For pure informed search goods, equilibrium price and demand both increase with the average rating, equilibrium price increases and equilibrium demand decreases with the variance of ratings.

PROOF. Differentiating the equilibrium price and demand for pure informed search goods with respect to M and V gives $\frac{\partial P_2^*}{\partial M} = \frac{1}{2}$, $\frac{\partial P_2^*}{\partial V} = \frac{3}{4\sqrt{3V}}$, $\frac{\partial D_2^*}{\partial M} = \frac{D_1}{4\sqrt{3V}}$, and $\frac{\partial D_2^*}{\partial V} = -\frac{3MD_1}{8(3V)^{\frac{3}{2}}}$. Recall that M, V, and D_1 are positive by definition. Thus, we have $\frac{\partial P_2^*}{\partial M} > 0$, $\frac{\partial P_2^*}{\partial V} > 0$, $\frac{\partial D_2^*}{\partial M} > 0$, and $\frac{\partial D_2^*}{\partial V} < 0$. Q.E.D.

The intuition behind proposition 1 is as follows: First, a higher average rating is a credible signal of overall product quality. Intuitively the retailer charges a higher price and consumers have a higher demand for a product with a higher quality. The findings in the related literature on the impact of average ratings on sales of pure informed search goods are equivocal (see related literature). The first part of proposition 1 represents a theoretical confirmation of the findings of Chevalier and Mayzlin (2006), Sun (2012), Li and Hitt (2008), and Dellarocas et al. (2007) who empirically found a positive impact of average consumer ratings on sales for pure informed search goods (books and movies).

Second, a high variance of product ratings indicates that the mismatch cost of the product is relatively high. This means that consumers with the 'right' taste for the product enjoy the product much more than the average rating would suggest. The retailer charges a higher price to all consumers to skim the higher willingness to pay of consumers with the 'right' taste. This higher price always deters some consumers with an incongruous taste for the product. Figure 3 illustrates the response of second-period price and demand to changes in the average and in the variance of ratings. In contrast to Sun (2012), we do not find that a higher variance of ratings may also increase second-period demand. In Sun's model, a necessary condition for such an effect is that the average rating M is negative. From (3), we know that a negative average rating means that $x_r > 2v_r/D_1$. As D_1 has a maximum of 1 which implies that $x_r > 2v_r$. This would mean that the enjoyment of a consumer with a maximal unmatched taste (i.e., a consumer with $\tau = 1$) is at most $-v_r$ if $P_1 = 0$. As most products will not exhibit such characteristics, our first assumption rules out the possibility of M being negative by assuming $x_r \in [0, v_r]$.

Pure Experience Goods

In a second step, we analyze pure experience goods, i.e., products with $f > 0$ and $x = 0$. For these products, the variance of the rating distribution is caused entirely by the experience attribute. First-period consumers make their purchase decisions based on v_e and f_e, respectively. After the retailer chooses a price P_1, the expected utility of a first-period consumer is $u_1 = v_e(1 - f_e) - P_1 - f_e z\theta$. Solving $v_e(1 - f_e) - P_1 - f_e z\theta = 0$ for θ yields the risk aversion of an indifferent consumer which we denote by $\tilde{\theta}_1 = \frac{v_e(1-f_e)-P_1}{f_e z}$. All first-period consumers with $\theta \le \tilde{\theta}_1$ buy the product, while all consumers with $\theta > \tilde{\theta}_1$ do not. Thus, as θ is equally distributed between zero and one and we have a unit mass of consumers, first-period demand D_1 is equal to the risk aversion of the indifferent consumer. Consumers who purchase the product publish an honest product rating based on the realization of matched quality v_r and whether the purchased product fails. As mismatch costs are zero for pure experience products, consumers publish either a rating of v_r if the product does not fail, or a rating of zero if the product fails. This results in ratings of first-period consumers, where (1 - f_r) percent of the ratings are v_r and f_r percent are zero. For this rating distribution, the average rating M and the variance of ratings V can be computed, respectively, as

$$M = v_r(1 - f_r), \text{ and } V = {v_r}^2 f_r(1 - f_r). \tag{7}$$

As for pure informed search goods, consumers need to consider both the average and the variance of ratings to be able to infer the product characteristics from the rating distribution. For example, a mediocre average rating with no variance suggests that the matched quality of the product is also mediocre while a mediocre rating with high variance shows that the product has a high matched quality but that a substantial fraction of products fail. By considering both the average and the variance of ratings, second-period consumers can unambiguously derive v_r and f_r. Mathematically, later consumers can learn about v_r and f_r by rearranging (7):

$$v_r = M + \frac{V}{M}, \text{ and } f_r = \frac{V}{M^2 + V}. \tag{8}$$

After deriving v_r and f_r, consumers have no uncertainty about the matched quality and the failure rate of the product. However, even after learning about the failure rate, there is still no guarantee that an individual product may not fail. Thus, the expected utility for a second-period consumer is $u_2 = v_r(1 - f_r) - P_2 - zf_r\theta$ where the term $zf_r\theta$ captures consumer risk aversion with regard to product failure. Based on u_r the retailer can derive the risk aversion $\tilde{\theta}_2$ of the indifferent consumer as a function of the second-period product price P_2 : $\tilde{\theta}_2 = (v_r(1 - f_r) - P_2) \,/\, (zf_r)$. Again, second-period demand D_2 is equal to $\tilde{\theta}_2$ and the retailer solves: $\max_{P_2} P_2\, D_2$ resulting in the following second-period equilibrium levels of price and demand:

$$P_2^* = \frac{v_r(1-f_r)}{2}, \text{and } D_2^* = \frac{v_r(1-f_r)}{2f_r z}. \tag{9}$$

In terms of M and V, second-period equilibrium levels of price and demand can be rewritten as:

$$P_2^* = \frac{M}{2}, \text{ and } D_2^* = \frac{M^3}{2Vz} + \frac{M}{2z}. \tag{10}$$

We use these representations of P_2^* and D_2^* to present the effects of M and V on equilibrium price and demand for pure experience goods in the following proposition:

PROPOSITION 2. For pure experience goods, equilibrium price and demand both increase with the average rating, equilibrium price is not affected by the variance of ratings, and equilibrium demand always decreases with an increasing variance of consumer ratings.

PROOF. Differentiating the equilibrium price and demand for pure experience goods with respect to M and V gives $\frac{\partial P_2^*}{\partial M} = \frac{1}{2}$, $\frac{\partial P_2^*}{\partial V} = 0$, $\frac{\partial D_2^*}{\partial M} = \frac{3M^2+V}{2Vz}$, and $\frac{\partial D_2^*}{\partial V} = -\frac{M^3}{2V^2 z}$. As M, V, and z are positive by definition, we have $\frac{\partial P_2^*}{\partial M} > \frac{1}{2}$, $\frac{\partial P_2^*}{\partial V} = 0$, $\frac{\partial D_2^*}{\partial M} > 0$, and $\frac{\partial D_2^*}{\partial V} < 0$. Q.E.D.

As with pure informed search goods, a higher average rating acts as a credible signal of higher expected product quality for consumers and for the retailer, and therefore increases equilibrium price and demand. Regarding the variance of product ratings, we find that it does not affect equilibrium price and always has a negative effect on equilibrium demand. The intuition for this result is as follows: First, given a constant average rating, a higher variance of ratings implies both a higher matched quality and a higher failure rate of the product so that the expected utility of a risk neutral consumer remains constant. Still, as consumers in our model are risk averse, their expected utility decreases with an increasing variance of product ratings. At the same time, the retailer of the product sets the product price as if all consumers were risk neutral because the additional revenue from increased sales to consumers with high risk aversion due to a lower price is always lower than the lost revenue from consumers with a lower risk aversion. Given that the equilibrium price does not depend on the variance of consumer ratings and the expected utility of risk averse consumers decreases with an increasing variance of product ratings, it follows naturally that the equilibrium demand decreases with increasing variance of consumer ratings. Figure 4 illustrates the response of equilibrium price and demand to changes in the variance of product ratings.

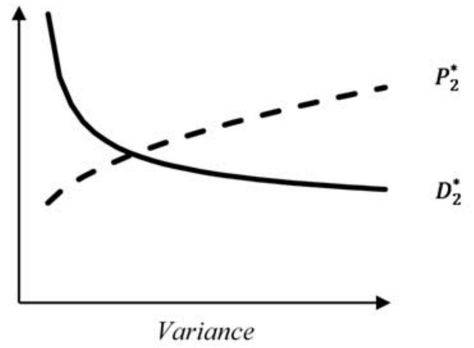

Figure 3. Second-Period Price and Demand for Pure Informed Search Goods

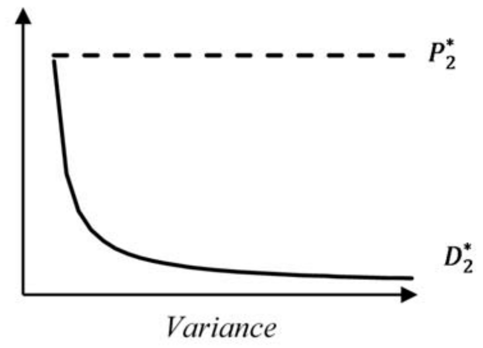

Figure 4. Second-Period Price and Demand for Pure Experience Goods

Hybrid Goods

In a final step, we analyze our model for hybrid goods i.e., products with $f > 0$ and $x > 0$. For these products, the variance of consumer ratings depends on both the informed search and the experience attribute. First-period consumers make their purchase decisions based on v_e, x_e, and f_e, respectively. After the retailer chooses price P_1, the expected utility of a first-period consumer is $u_1 = (v_e - x_e\tau)(1 - f_e) - P_1 - f_e z\theta$. Given u_1 and the independence of taste and risk aversion, we can derive first-period demand D_1. First, we need to derive the taste of an indifferent consumer with zero risk aversion $\tilde{\tau}_1^{\theta=0}$ and the risk aversion of an indifferent consumer given that taste is zero $\tilde{\theta}_1^{\tau=0}$. As taste and risk aversion are independent, first-period demand is equal to the area of the triangle $[\mathrm{A}, \tau_{I,1}^{\theta=0}, r_{I,1}^{\tau=0}]$ (see figure 5 for an example) with $\tilde{\tau}_1^{\theta=0} = (P_1 + v_e(f_e - 1))/(x_e(f_e - 1))$, and $\tilde{\theta}_1^{\tau=0} = (v_e(1 - f_e) - P_1)/zf_e$. Thus, $D_1 = 0.5\tilde{\tau}_1^{\theta=0}\,\tilde{\theta}_1^{\tau=0}$.

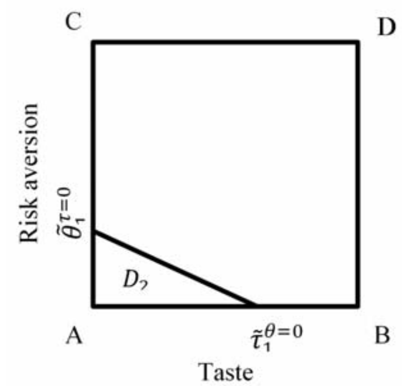

Figure 5. First-Period Demand for Hybrid Goods

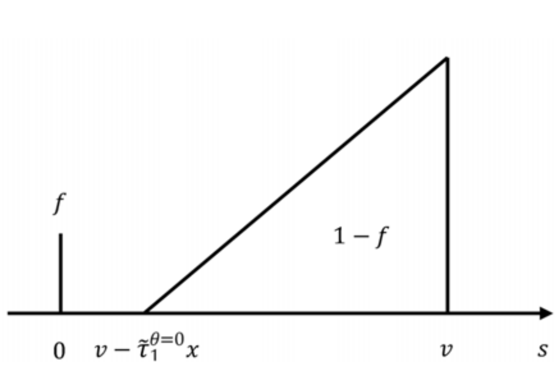

Figure 6. Rating Distribution of Hybrid Goods

Consumers who purchase the product publish an honest product rating based on the realization of matched quality v_r, mismatch costs x_r, and whether the purchased product fails. They publish a rating $r = v_r - x_r\tau$ if the product does not fail and a rating of $r = 0$ if it does. This results in ratings of first-period consumers, where (1 - f_r) percent of the ratings are $v_r - x_r\tau$ and f_r percent are zero. For products which do not fail, ratings are triangularly distributed between $v_r - \tilde{\tau}_1^{\theta=0}x_r$ and v_r with mode at v_r. The explanation for this specific shape of the distribution is as follows: As $\tau = 0$ for consumers who publish a rating of v_r, the maximum risk aversion for these consumers is $\tilde{\theta}_1^{\tau=0}$. For lower ratings the maximum risk aversion and, therefore, the number of consumers who publish a rating also decreases. Thus, the mode of the triangular distribution must be at v_r and the number of ratings strictly decreases with increasing taste. For a rating of $v_r - \tilde{\tau}_1^{\theta=0} x_r$ the maximum risk aversion is zero. Thus, $v_r - \tilde{\tau}_1^{\theta=0} x_r$ is the lower bound of the distribution of ratings for hybrid goods that do not fail. Such a purchasing bias (Chevalier and Mayzlin 2006, Hu et al. 2009) where consumers who are more likely to enjoy a product are also more likely to buy the product has been discussed in several previous studies (e.g., Nagle and Riedl 2014). Figure 6 illustrates the rating distribution for hybrid goods. This distribution has the typical j-shape which has been found for almost all products sold on amazon.com (Hu et al. 2007, Hu et al. 2009).

In contrast to pure informed search goods and pure experience goods, the enjoyment of hybrid goods depends not only on two, but on three product characteristics. Thus, it is not sufficient to consider only the average and the variance of ratings to derive the relevant product characteristics from the rating distribution. For example, based on the average and the variance of the rating distribution alone, consumers cannot distinguish if a mediocre rating and a positive variance is caused by informed search attributes (mismatch costs), experience attribute (product failure), or a combination of the two. However, by decomposing the total variance into (1) variance caused by mismatch costs and (2) variance caused by product failure, consumers and the retailer can distinguish between these cases. Variance caused by mismatch costs, denoted as V_m, can be derived by disregarding all negative ratings which are caused by product failure and computing the variance of the remaining rating distribution, i.e., the triangle on the right in figure 6. As we only have two sources of variance, the variance caused by product failure, denoted as V_f, must be equal to the difference between the total variance and the variance caused by mismatch costs. Mathematically, M, V_m, and V_f can be computed, respectively, as:

$$M = \left(v_r - \frac{\tilde{\tau}_1^{\theta=0} x_r}{3}\right)(1 - f_r),\ V_m = \frac{(\tilde{\tau}_1^{\theta=0})^2 {x_r}^2 (1-f_r)}{18},\ \text{and } V_f = \frac{(1-f_r) f_r (3v_r - \tilde{\tau}_1^{\theta=0} x_r)^2}{9}. \quad (11)$$

Based on M, V_m, and V_f consumers can derive the characteristics of the product. A product with a rating distribution with large M, large V_m, and small V_f suggests that the product has a high matched quality and substantial mismatch costs but only a small failure rate, while a product with large M, small V_m, and large V_f has a high matched quality with a substantial failure rate but only little mismatch costs. Mathematically, consumers can derive v_r, x_r, and f_r for hybrid goods by rearranging (11):

$$v_r = M + \frac{V_f + (2V_m(M^2 + V_f))^{1/2}}{M},\ x_r = \frac{(2V_m(M^2 + V_f))^{3/2}}{M \tilde{\tau}_1^{\theta=0}},\ \text{and } f_r = \frac{V_f}{M^2 + V_f}. \quad (12)$$

After deriving v_r, x_r, and f_r consumers are left with no uncertainty about the product's attributes. They know the exact mismatch costs of the product and, therefore, how well the product fits their tastes. However, even if consumers know the exact failure rate of the product, they cannot know whether their individual product will fail. As with pure experience products, they still need to experience their individual product. Thus, the expected utility for a later consumer is $u_2 = (v_r - x_r \tau)(1 - f_r) - z f_r \theta - P_2$ where the term $z f_r \theta$ still captures the risk associated with product failure. Based on the utility, the retailer can derive second-period demand. As in the first period, second-period demand D_2 is equal to $0.5 \tilde{\tau}_2^{\theta=0} \tilde{\theta}_2^{\tau=0}$. In terms of v_r, x_r, and f_r, second-period demand can be written as:

$$D_2 = \frac{(v_r(1-f_r) - P_2)^2}{2 f_r x_r z (1-f_r)}. \quad (13)$$

Based on second-period demand the retailer solves $\max_{P_2} P_2 D_2$ and second-period equilibrium levels of price and demand can be derived as:

$$P_2^* = \frac{v_r(1-f_r)}{3},\ D_2^* = \frac{2{v_r}^2(1-f_r)}{9 f x_r z}. \quad (14)$$

Using the relationship between v_r, x_r, and f_r and M, V_m, and V_f, equilibrium levels of price and demand can be rewritten as functions of M, V_m, and V_f:

$$P_2^* = \frac{M}{3} + \frac{M\sqrt{2V_m(M^2 + V_f)}}{3(M^2 + V_f)} \text{ and } D_2^* = \frac{M \tilde{\tau}_1^{\theta=0} \sqrt{2(M^2 + V_f)}(\sqrt{2V_m} + \sqrt{M^2 + V_f})^2}{27 V_f \sqrt{V_m} z} \quad (15)$$

Based on these representations of P_2^* and D_2^*, we derive the effects of the average rating, variance caused by mismatch costs, and variance caused by product failure on equilibrium price and demand in the next four propositions.

PROPOSITION 3. For hybrid goods, equilibrium price and demand increase with the average rating.

PROOF. Differentiating and rearranging equilibrium price and demand for hybrid goods with respect to M yields $\frac{\partial P_2^*}{\partial M} = (\sqrt{2V_m}V_f) \,/\, (3(M^2 + V_f)^{3/2}) + 1/3$, and $\frac{\partial D_2^*}{\partial M} = (d\tilde{\tau}_1^{\theta=0}/27V_f z)(\sqrt{2(M^2 + V_f)/V_m} + 2)(V_f + 4M^2 + \sqrt{2V_t(M^2 + V_f)} + M^2\sqrt{(2V_m)/(M^2 + V_f)})$. As M, V_m, V_f, $\tilde{\tau}_1^{\theta=0}$, and z are positive by definition, we have $\frac{\partial P_2^*}{\partial M} > 0$, and $\frac{\partial D_2^*}{\partial M} > 0$. Q.E.D.

As for pure informed search and pure experience goods the average rating acts as a credible signal of expected product quality for consumers and for the retailer. Therefore, equilibrium price and demand both increase with the average rating. Proposition 3 represents a theoretical confirmation of the empirical findings of Luca (2011) who found that the average rating of restaurants increases sales. A restaurant is a typical example of a hybrid good as consumer ratings on the restaurant's atmosphere, service and food reduce the uncertainty of consumers. However, the service and food quality may differ between two visits of the same restaurant.

PROPOSITION 4. For hybrid goods, equilibrium price increases, and equilibrium demand decreases with increasing variance caused by mismatch costs.

PROOF. Differentiating the equilibrium price and demand with respect to V_m yields $\frac{\partial P_2^*}{\partial V_m} = \sqrt{2}M/(6(V_m(M^2 + V_f))^{1/2})$, and $\frac{\partial D_2^*}{\partial V_m} = -(M\tilde{\tau}_1^{\theta=0}(2V_m(M^2 + V_f))^{1/2}(M^2 + V_f - 2V_m))/(54V_f V_m^2 z)$. As M, V_m, and V_f are positive by definition, we have $\frac{\partial P_2^*}{\partial V_m} > 0$. The sign of $\frac{\partial D_2^*}{\partial V_m}$ solely depends on $(M^2 + V_f - 2V_m)$ which is positive if $V_m > \frac{M^2}{2} + \frac{V_f}{2}$. From assumption 1 we have $x \le v$. Rewriting this inequality in terms of M, V_f, and V_m and simplifying leads to: $V_m < \frac{{\tilde{\tau}_1^{\theta=0}}^2(M^2 + V_f)}{2(\tilde{\tau}_1^{\theta=0} - 3)^2}$. As $\tilde{\tau}_1^{\theta=0} \in [0,1]$ this contradicts $V_m > \frac{M^2}{2} + \frac{V_f}{2}$. Thus, $\frac{\partial D_2^*}{\partial V_m} < 0$. Q.E.D.

As for pure informed search goods, a high variance of product ratings caused by mismatch costs indicates that the mismatch costs of the product are relatively high. Again, this means that consumers with the right taste for the product enjoy the product more than the average rating would suggest. Thus, the retailer charges a higher price to all consumers to skim the higher willingness to pay of consumers with the 'right' taste. The decrease in equilibrium demand with increasing V_m is attributable to the increasing equilibrium price. This price always deters some consumers with an incongruous taste for the product and, therefore, always results in a decreasing equilibrium demand. Figure 7 illustrates the relationship between, on the one hand, equilibrium price and demand, and on the other, the variance caused by mismatch costs.

PROPOSITION 5. For hybrid goods, the equilibrium price decreases with increasing variance caused by product failure. Equilibrium demand decreases with increasing variance caused by product failure if the variance caused by product failure is sufficiently low. Equilibrium demand increases in variance caused by product failure if the variance caused by product failure is sufficiently high and the variance caused by mismatch costs is sufficiently low.

PROOF. Differentiating equilibrium demand and price with respect to V_f gives $\frac{\partial D_2^*}{\partial V_f} = -\frac{\tilde{\tau}_1^{\theta=0}(8M^3V_m + \sqrt{(2M^2V_m)((M^2 + V_f)^{-1})}(2M^4 - V_f^2 + 2V_fV_m + M^2V_f + 4M^2V_m))}{54V_f^2V_m z}$ and $\frac{\partial P_2^*}{\partial V_f} = -\frac{M^2V_m}{3(M^2 + V_f)^2\sqrt{(2M^2V_m)(M^2 + V_f)^{-1}}}$. As M, V_m, and V_f are positive by definition, we have $\frac{\partial P_2^*}{\partial V_f} < 0$. The sign of $\frac{\partial D_2^*}{\partial V_f}$ depends on the sign of the term in parenthesis. If this term is positive, we have $\frac{\partial D_2^*}{\partial V_f} < 0$ and $\frac{\partial D_2^*}{\partial V_f} > 0$ if it is negative. A necessary condition that the term could be negative is that $V_f > 2M^2$ as $(2M^4 - V_f^2 + 2V_fV_m + M^2V_f + 4M^2V_m)$ is always positive if

$V_f < 2M^2$. Assuming that $V_f > 2M^2$ and solving $8M^3V_m + ((2M^2V_m)/(M^2 + V_f))^{1/2}(2M^4 - V_f^2 + 2V_fV_m + M^2V_f + 4M^2V_m) = 0$ for V_m gives $V_m = ((M^2 + V_f)(-2M^2 + V_f)^2)/(2(2M^2 + V_f)^2)$. As $8M^3V_m + ((2M^2V_m)/(M^2 + V_f))^{1/2}(2M^4 - V_f^2 + 2V_fV_m + M^2V_f + 4M^2V_m)$ is strictly increasing in V_m, we have $\frac{\partial D_2^*}{\partial V_f} > 0$ if $V_f > 2M^2$ and $V_m < ((M^2 + V_f)(-2M^2 + V_f)^2)/(2(2M^2 + V_f)^2)$. Q.E.D.

As for pure experience goods, a higher variance of product ratings caused by product failure indicates a higher failure rate of the product and the retailer sets the equilibrium product price as if all consumers were risk neutral. However, due to the positive mismatch costs and differently from pure experience products, the utility of a risk neutral consumer is slightly decreasing with increasing V_f. Thus, the equilibrium price always decreases if V_f increases. Increasing V_f always leads to a decrease in equilibrium demand if $V_f < 2M^2$. As a higher variance caused by product failure is associated with a higher failure rate of the product, consumers are risk averse, and the product is priced as if consumers were risk neutral, which is intuitive. If $V_f > 2M^2$, increasing V_f leads to an increase in equilibrium demand if $V_m < (4M^6 - 3M^2 V_f^2 + V_f^3)/(8M^4 + 8M^2 V_f + 2V_f^2)$. This counterintuitive finding is attributable to the necessary increase in v, x and f caused by the increased variance due to product failure. Ceteris paribus, increasing V_f is associated with an increasing failure rate, and, due to the constant average rating, an increasing matched quality of the product. At the same time, a higher failure rate of the product implies that only a smaller fraction of all sold products do not fail and, therefore, can cause variance due to consumer taste. Thus, increasing V_f is also associated with an increase in x. This combination in connection with a decreasing price may, in very few situations, lead to an increase of equilibrium demand. We note that for ratings in a typical 5 star rating system with a rating of one indicating the worst and a rating of five indicating the best possible quality, it is never possible that $V_f > 2M^2$. Figure 8 illustrates the relationship between equilibrium price and demand and variance caused by product failure for a product with $V_f \leq 2M^2$.

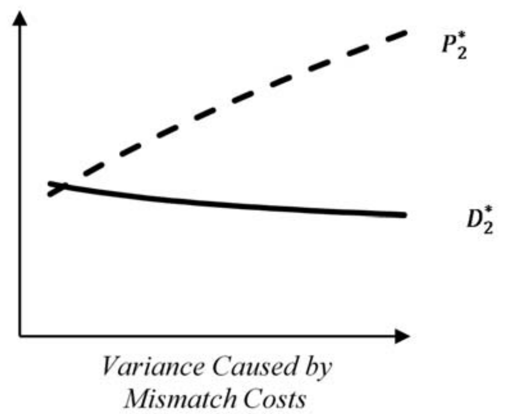

Figure 7. Equilibrium Price and Demand for Hybrid Goods – Mismatch Costs

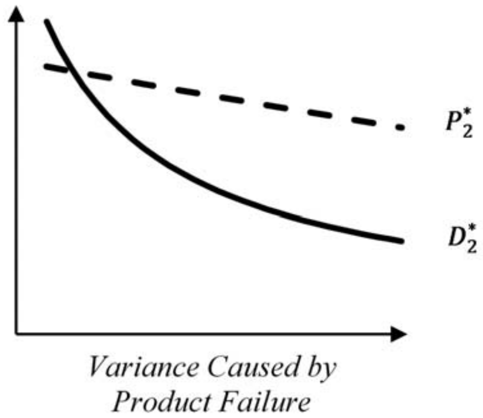

Figure 8. Equilibrium Price and Demand for Hybrid Goods – Product Failure

PROPOSITION 6. For hybrid goods, holding the total variance constant, equilibrium price always increases (decreases) with an increasing relative share of variance caused by mismatch costs (product failure). Equilibrium demand increases (decreases) with an increasing share of variance caused by mismatch costs (product failure) if $V < \underline{V}$ and decreases (increases) with an increasing share of variance caused by mismatch costs (product failure) if $V > \overline{V}$.[1] If $\underline{V} \leq V \leq \overline{V}$ second-period demand increases (decreases) with increasing share of variance caused by mismatch costs (product failure) if this variance exceeds threshold V_T.

PROOF. To analyze the effect of the relative share of V_f (which is equivalent to the effect of the relative share of V_m), we need to substitute V_m by $V - V_f$ in (15). Differentiating the resulting equilibrium price and demand with respect to V_f and rearranging terms it gives $\frac{\partial P_2^*}{\partial V_f} = -\frac{\sqrt{2}M^2(M^2+V)}{6(M^2+V_f)^2\sqrt{(M^2(V-V_f))(M^2+V_f)^{-1}}}$, and $\frac{\partial D_2^*}{\partial V_f} = \frac{\sqrt{2}M\tilde{\tau}_1^{r=0}}{54V_f^2 z\sqrt{(V-V_f)^3(M^2+V_f)^{-1}}}((M^2V_f + V_f^2 + \frac{2V_f(V-V_f)^2}{M^2+V_f}) - (V-V_f)(4(V - V_f) + 2M^2 + 4M^2\sqrt{2\frac{V-V_f}{M^2+V_f}} + V_f))$. As V_f is by definition always smaller than V, we have $\frac{\partial P_2^*}{\partial V_f} < 0$ and, vice versa, $\frac{\partial P_2^*}{\partial V_m} > 0$. As $\frac{\sqrt{2}M\tilde{\tau}_1^{r=0}}{54V_f^2 z\sqrt{(V-V_f)^3(M^2+V_f)^{-1}}}$ is always positive, the sign of $\frac{\partial D_2^*(M,V,V_f,\tilde{\tau}_1^{\theta=0},z)}{\partial V_f}$ depends only on the term:

$$(M^2V_f + V_f^2 + \frac{2V_f(V-V_f)^2}{M^2+V_f}) - (V-V_f)(4(V - V_f) + 2M^2 + 4M^2\sqrt{2\frac{V-V_f}{M^2+V_f}} + V_f) \tag{16}$$

which is strictly increasing in V_f for $V_f \in [0, V]$ and strictly decreasing in V. From our assumptions that $x < v$ and $\tilde{\tau}_1^{\theta=0} < 1$ we get $V - \frac{\tilde{\tau}_1^{\theta=0^2}(M^2+V)}{3(\tilde{\tau}_1^{\theta=0^2} - 4\tilde{\tau}_1^{\theta=0} + 6)} < V_f < \frac{(4V - 2M^2)\tilde{\tau}_1^{\theta=0^2} - 36V\tilde{\tau}_1^{\theta=0} + 81V}{6\tilde{\tau}_1^{\theta=0^2} - 36\tilde{\tau}_1^{\theta=0} + 81}$. Inserting the upper bound of V_f into (16) and solving (16) $= 0$ for V gives $V = \underline{V}$. Thus, if $V < \underline{V}$, we have $\frac{\partial D_2^*}{\partial V_f} < 0$ and, vice versa $\frac{\partial D_2^*}{\partial V_m} > 0$. Inserting the lower bound of V_f into (16) and solving (16) $= 0$ for V gives $\overline{V}$. Thus, if $V > \overline{V}$, we have $\frac{\partial D_2^*}{\partial V_f} > 0$, and, vice versa $\frac{\partial D_2^*}{\partial V_m} < 0$. If $V \geq \underline{V}$ and $V \leq \overline{V}$, the sign of (16) depends on the specific value of V_f. As (16) is strictly increasing with increasing V_f, and (16) is neither always positive nor always negative there is some threshold V_T where $\frac{\partial D_2^*}{\partial V_f} < 0$, and $\frac{\partial D_2^*}{\partial V_m} > 0$ if $V_f < V_T$ and $\frac{\partial D_2^*}{\partial V_f} > 0$, and $\frac{\partial D_2^*}{\partial V_m} < 0$ if $V_f > V_T$. Q.E.D.

The intuition for this result is as follows: A larger relative share of variance caused by the informed search attribute is necessarily associated with a smaller relative share of variance caused by product failure. Holding the total variance constant, this means that the variance caused by mismatch costs increases and the variance caused by product failure decreases by the same amount. Again, the increased variance caused by mismatch costs indicates that some consumers value the product even more than the average rating would suggest. Based on this information, the retailer increases the product price to take advantage of these consumers' higher willingness to pay. At the same time, the decreased V_f indicates both a lower matched quality and a lower failure rate of the product. This leads to a further increase of the equilibrium price as the utility of a risk neutral consumer increases with decreasing V_f for hybrid goods.

Holding the average rating constant, a lower matched quality and a lower failure rate of the product makes the product more attractive to risk averse consumers. This increase overcompensates for the decrease in second-period equilibrium demand due to the increased product price discussed in the paragraph above if $V < \underline{V}$ or $V \geq \underline{V}$ and $V_f < V_T$. If $V > \overline{V}$ or $V \geq \underline{V}$ and $V_f > V_T$, the positive effect of the lower failure rate on equilibrium demand is smaller than the negative effect caused by the price increase due to the higher share

[1] $\underline{V} = \frac{2M^2(\tilde{\tau}_1^{\theta=0})^2(4\tilde{\tau}_1^{\theta=0} - 27)}{(2\tilde{\tau}_1^{\theta=0} - 9)^2(4\tilde{\tau}_1^{\theta=0} - 9)}$ and $\overline{V} = \frac{M^2\tilde{\tau}_1^{\theta=0^2}(\tilde{\tau}_1^{\theta=0} - 9/2)}{(2\tilde{\tau}_1^{\theta=0} - 3)(\tilde{\tau}_1^{\theta=0} - 3)^2}$.

of V_m. Thus, in these cases, the total effect of an increasing share of V_m on equilibrium demand is negative. Figure 9 illustrates the response of equilibrium price and demand to changes in the composition of the variance of consumer ratings for $V < \underline{V}$ in (a), $\underline{V} \leq V \leq \overline{V}$ in (b) and $V > \overline{V}$ in (c).

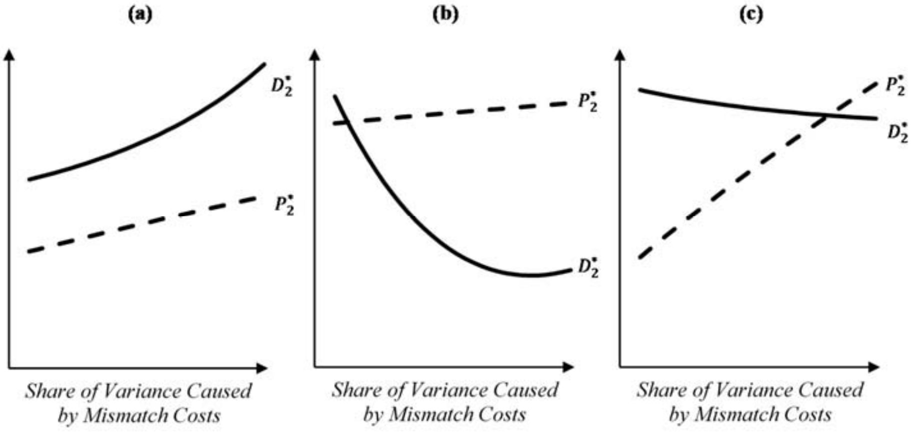

Figure 9. Equilibrium Price and Demand for Hybrid Goods

Through the mechanism described in proposition 6, equilibrium price and demand can increase with increasing total variance of product ratings. The shaded area in Figure 10 illustrates equilibrium demand for a product with an average rating of 4, $\tilde{\tau}_1^{\theta=0} = 1$, a total variance of ratings between one and two, and varying relative shares of variance caused by mismatch costs and product failure. Note that, ceteris paribus, an increasing relative share of variance caused by mismatch costs always leads to an increase in equilibrium demand as for this combination of M, $\tilde{\tau}_1^{\theta=0}$, and V, $V < \underline{V}$. Thus, the lower bound of the shaded area represents equilibrium demand for products with the lowest possible relative share of V_m while the upper bound represents equilibrium demand for products with the highest possible relative share of V_m. The point marked with A represents a product with a total variance of 1.1 with approximately 70% of this variance caused by mismatch costs and 30% by product failure. This combination results in an equilibrium price and demand of respectively 1.75 and 0.18. As equilibrium demand is increasing from bottom to top and the total variance is increasing from left to right, equilibrium demand for all products at the top right of A is higher than the demand for A even if the variance of ratings for these products is also higher than the variance of A. The solid black line in figure 10 represents all products with the same equilibrium price compared to the product marked in A ($P_2^* = 1.75$). Because the relative share of variance caused by mismatch costs increases from bottom to top, equilibrium price also increases in this line. Compared to the equilibrium price of A this results in higher prices for all products above the solid line. Thus, holding the average rating constant and increasing the total variance of ratings, we find higher equilibrium prices and higher equilibrium demand for products at the top right of A. Comparing the worst possible composition of variance, i.e., the lowest possible share of V_m, for a product with a total variance of one (the product marked with B ($D_2^* = 0.17$, $P_2^* = 1.71$)) with the best possible composition of variance, i.e., the highest possible share of V_m, for a product with a total variance of two (marked with C ($D_2^* = 0.34$, $P_2^* = 1.98$)) shows that the product with twice the variance is 15% more expensive, and equilibrium demand doubles. This comparison illustrates that the effect of the variance of product ratings on product prices and sales substantially depends on the source of this variance.

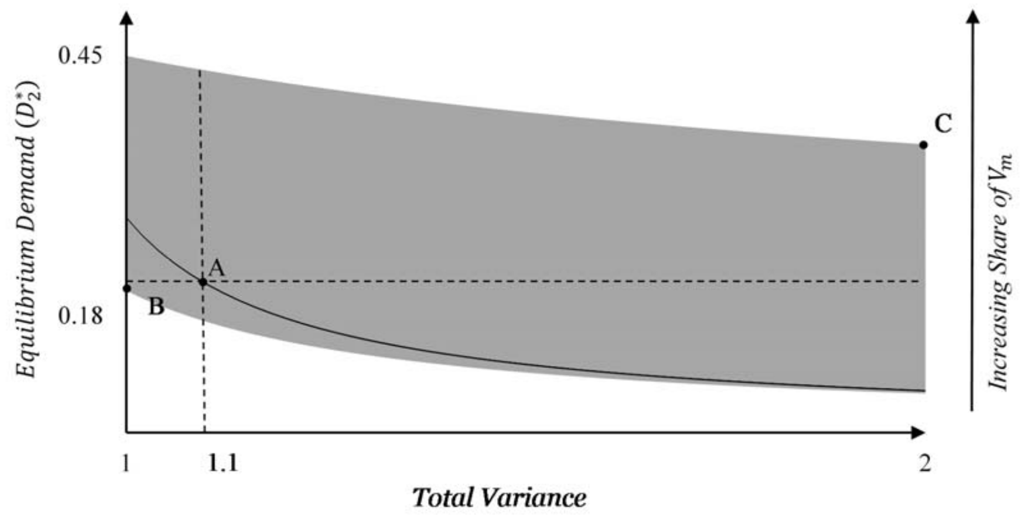

Figure 10. Equilibrium Demand for Products with Different Variance Compositions

Conclusion

The opportunity for online shopping significantly changed the way people purchase goods. Rating systems which enable consumers to observe the distribution of star ratings awarded by other consumers has contributed to this change. Naturally, a significant literature emerged which seeks to understand the effects of different aspects of these rating systems – such as number, average or variance – on product prices and consumer demand. Previous literature which analyzed the role of the variance of consumer ratings concentrated on ratings for products where the variance can be caused solely by informed search attributes. However, a high variance of consumer ratings may not be solely driven by such attributes but may also depend on experience attributes. Our work makes a first contribution towards filling this gap in the literature.

We propose an analytical model where two product attributes may cause the variance of consumer ratings: a mismatch between consumer taste and the informed search attribute of a product, and the product's failure as experience attribute. We find that a higher variance caused by the informed search attribute indicates that a product is liked by some consumers and disliked by others, resulting in a higher equilibrium price and lower equilibrium demand. A higher variance caused by the experience attribute suggests an unreliable product and is therefore associated with a lower equilibrium price and lower equilibrium demand. Interestingly, holding the average rating as well as the total variance of ratings constant while increasing the share of the variance caused by the informed search attribute increases equilibrium prices and the demand for products with low variance. Thus counterintuitively, equilibrium price and demand are capable of increasing concomitant with a rise in the total variance of product ratings. Given the same average rating for two similar products, consumers may prefer the more expensive product with the higher total variance of ratings. Thus, our results suggest that considering informed search attributes and experience attributes as different sources of the variance of consumer ratings may be an important additional factor when assessing the effect of consumer ratings on product pricing and consumer demand. In addition to this result, our analytical model provides a theoretical foundation for the typically observed j-shaped distribution of consumer ratings in electronic commerce.

Our findings have important managerial implications: First, if retailers were to consider the composition of the variance of consumer's ratings they could improve their sales forecasts and increase profits by adjusting their stocks accordingly or by charging higher prices for those products for which a relatively larger share of the variance is caused by mismatch costs. Second, they could implement mechanisms to explicitly communicate information about the composition of the variance in order to enable more customers to consider this important information in their decision making, which would further reduce information asymmetries in electronic commerce. Today, consumers can only indirectly infer this information by analyzing specific characteristics of the ratings distribution, i.e., a peak in 1-star ratings or by reading through the textual consumer reviews for a specific product. As a first step to making this information directly available, retailers may provide additional information on the percentage of the most negative consumer ratings caused by product failure. Retailers could collect this information by asking each consumer posting a negative rating whether it is based on product failure or on other taste specific factors.

As with all research, the current study has limitations that present opportunities for future research. First, in our model the two consumer groups (first-period and second-period) are assumed to be distinct. Hence, consumers cannot exhibit strategic behavior. In reality, however, consumers may consider the timing of the purchase and, hence, the timing of the consumers purchase decision can be endogenized (e.g., Guo and Villas-Boas 2007, Sun 2012). Sun (2012) finds qualitatively the same results in the extension of her baseline model considering strategic behavior of consumers, but it remains to be analyzed whether this also holds for the model proposed in this article. Second, our results suggest that consumers and retailers would benefit from having information about the composition of the variance of product ratings, i.e. which proportion of the variance is caused by mismatch costs and which by product failure, although, this information is sometimes revealed by the textual reviews. However, products sometimes have too many consumer reviews that consumers and retailers have the ability to read all of them. To solve this issue, researchers should develop text mining approaches or semantic techniques (e.g., as in Archak et al. 2011) that can be used to identify the shares of variance caused by informed search and experience attributes. Finally, our model generates testable predictions regarding the effect of the variance of consumer ratings on product price and consumer demand. The sign of this effect depends to a large degree on the source of this variance. This provides an interesting direction for further research, especially for empirical and experimental investigations into the effects of the variance of consumer ratings which consider the different sources of variance, i.e. informed search and experience attributes.

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