THE IMPACT OF THE VARIANCE OF ONLINE CONSUMER RATINGS ON PRICING AND DEMAND – AN ANALYTICAL MODEL

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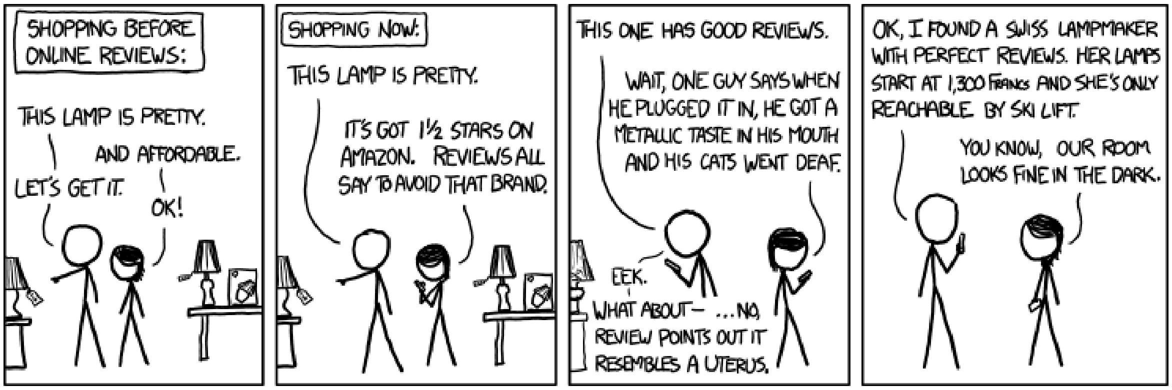
Abstract

It is well known that consumer ratings play a major role in the purchase decisions of online shoppers. To examine the effect of the variance of these ratings on future product pricing and sales we propose an analytical model which considers products where the variance of consumer ratings results from two types of product attributes: observational search attributes and experience attributes. We find that if a higher variance is caused by an observational search attribute it results in a higher equilibrium price and lower equilibrium demand, whereas if it is caused by an experience attribute the result is a lower equilibrium price and demand. Interestingly, when the average rating as well as the total variance of ratings are held constant and the relative share of variance caused by the observational search attribute is increased, we observe a rise in both the equilibrium price *and* the demand for products with low total variance. Via this mechanism, and depending on the composition of the variance of consumer ratings, it is possible for the equilibrium price and demand to increase with increasing total variance of product ratings. In other words we are able to demonstrate that, when faced with a choice between two similar products with the same average rating, risk-averse consumers may prefer a more expensive product with a higher variance of ratings. Moreover, our analytical model provides a theoretical foundation for the empirically observed j-shaped distribution of consumer ratings in electronic commerce.

Keywords: Product Rating Distribution, User Generated Content, Electronic Word-of-Mouth, Analytical Model.

1. Introduction



Source: http://www.xkcd.com/1036

According to Amazon.com its consumer reviews are the most popular feature of the company (New York Times 2004), contributing to its current success in electronic commerce. These reviews are most commonly provided in the form of a star rating system and an optional text review enabling prospective consumers to learn from other consumers' experiences. Amongst other things, online reviews offer a form of peer learning among consumers. Thereby, they transform many former experience attributes of a product into search attributes (Hong et al. 2012), and thus reduce the information asymmetries between consumers, retailers, and product manufacturers.[1,2] For example, while previously, assessing the sound quality of a laptop would have required listening to the actual device (experience attribute), this can now be inferred simply from reading other consumer reviews (observational search attribute). Not surprisingly, then, 64% of respondents in Forrester Research's online survey prefer sites with consumer reviews when shopping online (Kee 2008). This makes online consumer reviews one of the main sources of information for online shoppers. Not all experience attributes, however, can be turned into observational search attributes. For example, negative textual consumer reviews for a Cordless Kettle[3] show that the issue most commonly complained about concerns the failure of the automatic shut-off, a fault that developed, in some cases, even after a relatively short period of usage. From these reviews, consumers can learn that the failure of the automatic shut-off presents a common problem for this kettle and make some inference about the likelihood of the occurrence of this event. What they cannot infer from these reviews, however, whether their individual kettle will develop this fault.

[1] Hong et al. (2012) provide an excellent review of the literature on search and experience attributes.
[2] These attributes are called observational search attributes throughout the paper.
[3] http://www.amazon.com/Aroma-AWK-115S-X-Press-2-Liter-Cordless/product-reviews/B000KDVTJI/

Much of the information contained in the textual consumer reviews is summarized in the star rating ranging from one (lowest recommendation) to five (highest recommendation) on most e-commerce websites.[4] 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. Among the significant literature that has recently emerged on the effects of these different aspects of the distribution of consumer reviews on consumer demand, several studies find that the absolute number and the average consumer ratings positively affect consumer demand. However, to our knowledge, only few studies explicitly analyze the effect of the variance of online consumer ratings on demand (e.g., Clemons et al. 2006, Sun 2012) and none explicitly consider the potential effect in a differentiated way, that is, depending on whether the variance is caused mainly by observational search attributes (i.e., the sound quality in our example) or by experience attributes (i.e., a common technical fault in the kettle).

In our paper we consider products where variance in consumer ratings can be caused by an observational search attribute and an experience attribute in order to answer the following research question: *How does the variance of consumer ratings affect product price and demand if this variance is caused by observational search and experience attributes?*

To determine the effect of the different sources of variance of product ratings on product price and consumer demand we construct an analytical model featuring a monopoly retailer and risk averse consumers. We analyze our model for three product types: pure observational search products where the variance of consumer ratings is solely caused by an observational search attribute; pure experience products where the variance of consumer ratings is solely caused by an experience attribute; and observational search and experience products where the variance of consumer ratings is caused by an observational search and an experience attribute.

Our analysis yields the following main results: First, a higher variance caused by an observational 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 observational 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

[4] For example, amazon.com and barnesandnoble.com provide such star rating systems.

ratings, but depending on the composition of the variance of consumer 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.

The results presented in this paper have important implications for researchers and practitioners alike, since they suggest that the effects of the variance of consumer ratings on consumer demand and product price heavily depend on its composition, i.e. the relative proportion of variance caused by observational search on the one hand, and by experience attributes on the other. For researchers this composition may be an important additional variable when empirically analyzing the effects of consumer ratings. Retailers may also want to consider the composition of the variance to improve their sales forecasts or to charge higher prices for those products for which a relatively larger share of the variance in product ratings is caused by observational search attributes. Furthermore, they could implement mechanisms to explicitly communicate the source of the variance to enable more customers to consider this important information and, in this way, to further reduce information asymmetries in electronic commerce. 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. This result could serve as a basis for future investigations into these ratings.

Our analysis proceeds as follows. We start by presenting the related literature. Then we define our notation and state our assumptions. Next, we examine the effect of the variance of product ratings if this variance is solely caused by the observational search attribute. We proceed by analyzing this effect for products where the variance is solely caused by the experience attribute. Subsequently we analyze products where the variance can be caused by both the observational search and the experience attribute. We conclude with a summary and managerial implications.

2. Related Literature

A substantial fraction of the related literature on the effects of consumer reviews 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.[5] Some authors have found that an increase in the average ratings has a positive effect on books (Chevalier and Mayzlin 2006, Sun 2012, and Li and Hitt 2008), restaurants (Luca 2011), and movies (Dellarocas et al. 2007), whereas others do not find such an effect both for books (Chen et al. 2004) and for movies (Duan

[5] A comprehensive review of research on online consumer reviews can be found in Trenz and Berger (2013).

et al. 2008). For the total number of reviews, 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.

Only few studies have so far analyzed the effect of the *variance of consumer ratings* on product sales (e.g., Clemons et al. 2006, Sun 2012) and none of these studies have considered the different sources of variance. In an empirical study focusing on the craft beer industry, Clemons et al. (2006) analyze the effect of consumer reviews 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 demand 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. This implies that in such markets variance can play an important positive role on sales. In particular, the authors find that the variance of product ratings is associated with higher growth in sales in hyperdifferentiated markets (Clemons et al. 2006). Sun (2012) builds a simple game-theoretical model to analyze the informational role of the variance of product ratings on 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, 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 product review 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 observational 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 contains valuable information for analyzing the effect of consumer ratings on product pricing and on consumer demand.

3. Notation and Assumptions

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

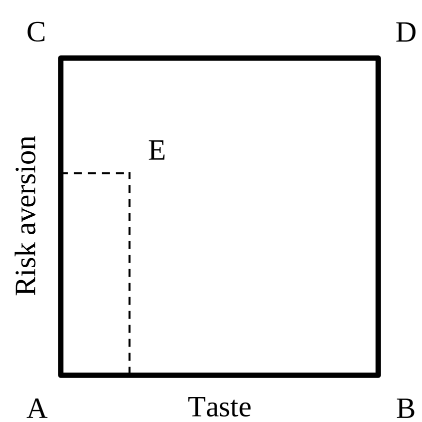
ASSUMPTION 1 **(Product Characteristics)**. *Each product has a positive matched quality, positive or zero mismatch costs, and a failure rate between zero and one.*

We consider a product with three attributes: *Matched quality*, *mismatch costs*, and *failure rate*. We denote matched quality as v and assume that $v > 0$. Matched quality determines how a consumer with a perfectly matched taste enjoys a product that does not fail during its typical period of usage. This enjoyment strictly increases with increasing matched quality. 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 observational search attribute of the product. These 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 mismatch costs as x and assume $0 \leq x \leq v$. Mismatch costs are caused by product characteristics 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 mismatch costs of close to zero are a perfect fit for all consumers (i.e., typical mass market products with universal appeal) while the perceived quality of a product with high mismatch costs heavily depends on consumer taste (i.e., typical niche products which appeal only to a small group of people). We assume that $x \leq v$. This implies that mismatch costs are never higher than the matched quality of a product. Thus, even consumers who maximally dislike all product characteristics 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 *product failure* as experience attribute of the product. A product's failure rate, $f \in [0,1]$ accounts for the likelihood of product failure during the typical time of usage. 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.

ASSUMPTION 2 **(Consumer Characteristics)**. *Consumers are heterogeneous in their tastes and risk aversion and taste and risk aversion are independent.*

In line with Sun (2012), we assume that consumers are heterogeneous in their tastes for specific product aspects. We represent consumer taste by the variable τ which is equally distributed between zero and one. For a consumer with the 'right' taste for a product, i.e. a consumer with $\tau = 0$, mismatch costs do not affect the perceived value of a product, while for consumers with an 'incongruous' taste mismatch costs substantially decrease the perceived value of the product. 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). For example, Bhatnagar et al. find that *"the likelihood of purchasing on the Internet decreases with product and financial risk".* Intuitively, this risk aversion is not homogeneous among all consumers. We denote consumer risk aversion by the variable θ which is also equally distributed between zero and one. Formally, consumer tastes and their risk aversions are represented by a square with edge length 1 (see figure 2) where the line segment [AB] represents consumer taste and the line segment [AC] represents consumer risk aversion. A unit mass of consumers is uniformly distributed within this square which means that taste and risk aversion are independent. 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 3. (**Consumer and Retailer Expectations**). *Neither the consumers nor the retailer know the realizations of but have expectations on matched quality v, mismatch costs x, and failure rate f.*

In the early launch stage of a product, marketing communication from the product manufacturer provides the dominant source of product information (Manchanda et al. 2008) and this communication primarily affects consumer choice through the reduction of uncertainty about product attributes (Narayanan et al. 2005). Based on this communication, both the consumers and the retailer expect some realizations of v, x, and f. We denote these expectations with $E(v), E(x)$, and $E(f)$. As we do not consider screening mechanisms or reputational effects of the producer of the product, we do not assume any relationship between $E(v), E(x), E(f)$ and v, x, and f.

ASSUMPTION 4. (**Consumer Rating Behavior**). *All launch consumers publish an honest rating for the product.*

From as early as the 1960s marketing researchers reported that the early consumers 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 assume that all launch consumers publish a product rating. We further assume that consumer ratings are honest and that there is no external manipulation of consumer reviews as discussed in Mayzlin (2006) and Luca (2014). This assumption implies that consumer ratings correspond to the actual utility derived from its consumption.

4. Model Analysis

We consider a two period game with a monopoly retailer and consumers with heterogeneous tastes and risk aversions. If a consumer with taste τ and risk aversion θ buys the product at price P her expected utility $E(u)$ is:

$$E(u) = (E(v) - E(x)\tau)(1 - E(f)) - P - (E(f))z\theta. \tag{1}$$

The first part of equation (1) is equal to the expected utility of a risk neutral consumer. The second 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 $z > 0$.[6] Consumers buy the product if their expected utility from consumption is greater than zero, and do not buy otherwise.

[6] 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.

In the first period of the game, a unit mass of early 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 and consumers decide whether to buy a unit of the product based on their expected utility. For a consumer who buys a product of matched quality v, with mismatch cost x and failure rate f, at price P_1 the utility is $v - x\tau - P_1$ if the product does not fail and $-P_1$ otherwise. After learning the realizations of v, x, and f, each consumer publishes an honest rating r for the product. In the second period, a unit mass of late consumers enter the market. Late consumers and the retailer observe the mean and the variance of the rating distribution. Based on this information, the retailer sets price P_2 and late consumers decide whether to buy a unit of the product.

In the following, we discuss three types of product: pure observational search products, pure experience products and observational search and experience products. The failure rate for pure observational search products is zero. Thus, for these products, consumer valuation is only determined by matched quality v and mismatch costs x. For pure experience products, the mismatch costs are equal to zero. Accordingly, consumer valuation of these products is determined by matched quality and product failure. For observational search and experience products, consumer valuation depends on all three product attributes: matched quality, mismatch cost, and product failure. Depending on the product type, the expected utility simplifies to:

$$E(u) = \begin{cases} E(v) - E(x)\tau - P & \text{for observational search products,} \\ E(v)(1 - E(f)) - P - E(f)z\theta & \text{for experience products,} \\ (E(v) - E(x)\tau)(1 - E(f)) - P - E(f)z\theta & \text{for observational search and experience products.} \end{cases} \tag{2}$$

4.1. Pure Observational Search Products

In a first step we analyze pure observational search products i.e., products with $f = 0$. For these products, the whole variance of the rating distribution is caused by the observational search attribute. First period consumers make their purchase decisions based on their expectations of v and x which are denoted by $E(v)$ and $E(x)$ respectively. After the retailer chooses price P_1, the expected utility of an early consumer is equal to $E(v) - E(x)\tau - P_1$. Solving $E(v) - E(x)\tau - P_1 = 0$ for τ yields the taste of the indifferent consumer which we denote with $\tilde{\tau}_1$. All early consumers with $\tau \leq \tilde{\tau}_1$ buy the product, while all consumers with $\tau > \tilde{\tau}_1$ do not buy the product. 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 the taste of the indifferent consumer. Consumers who purchase the product publish an honest product rating. As tastes are uniformly distributed in $[0, D_1]$, ratings are also uniformly distributed between $[v - D_1 x, v]$. Given the uniform distribution of ratings, the average rating M, and the variance of ratings V can be computed, respectively, as

$$M = v - 0.5D_1x, \text{ and } V = \frac{D_1^2x^2}{12}.^{7} \quad (3)$$

By considering the average and the variance of ratings, 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 the realizations of v and x by rearranging (3):

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

After deriving the realizations of v and x, late 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 for a late consumer simplifies to $u = v - x\tau - P_2$. Based on u the retailer can derive the taste of the indifferent consumer as a function of the second period product price P_2: $\tilde{\tau}_2 = (v - P_2)/x$. 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:

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

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

$$P_2^* = \frac{M}{2} + \frac{\sqrt{3V}}{2}, \text{ and } D_2^* = \frac{\mathrm{D}_1}{4}\left(\frac{\mathrm{M}}{\sqrt{3\mathrm{V}}} + 1\right). \quad (6)$$

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 observational search products in the following proposition:

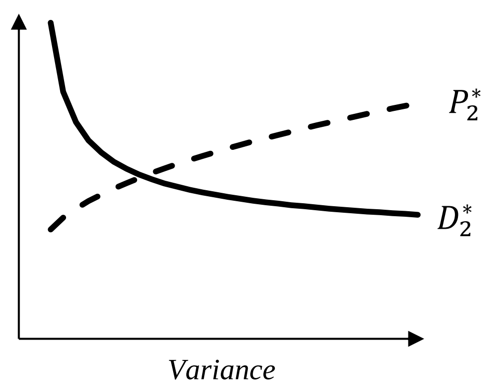
PROPOSITION 1. For pure observational search products, equilibrium price and demand both increase with the average rating, equilibrium price increases and equilibrium demand decreases with the variance of ratings.

PROOF. Differentiating the equilibrium price and demand for pure observational search products with respect to M and V gives $\frac{\partial P_2^*}{\partial M} = \frac{1}{2}$, $\frac{\partial P_2^*}{\partial V} = \frac{3}{4\sqrt{3\mathrm{V}}}$, $\frac{\partial D_2^*}{\partial M} = \frac{\mathrm{D}_1}{4\sqrt{3\mathrm{V}}}$, and $\frac{\partial D_2^*}{\partial V} = -\frac{3M\mathrm{D}_1}{8(3\mathrm{V})^{3/2}}$. 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.

[7] A detailed derivation of M and V for pure observational search products can be found in the appendix.

The intuition behind proposition 1 is as follows: First, a higher average rating is a credible signal of overall product quality. Thus intuitively the retailer charges a higher price and consumers have a higher demand for a product with a higher quality. 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 2 illustrates the response of second period price and demand to changes in the average and in the variance of ratings.[8]

Figure 2: Second Period Price and Demand for Pure Observational Search Products



4.2. Pure Experience Products

In a second step, we analyze pure experience products, 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 $E(v)$ and $E(f)$, respectively. After the retailer chooses a price P_1, the expected utility of an early consumer is equal to $E(v)(1 - E(f)) - P_1 - E(f)z\theta$. Solving $E(v)(1 - E(f)) - P_1 - E(f)z\theta = 0$ for θ yields the risk aversion of an indifferent consumer which we denote by $\tilde{\theta}_1$. All early consumers with $\theta \leq \tilde{\theta}_1$ buy the product, while all consumers with $\theta > \tilde{\theta}_1$ do not buy the product. 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.

[8] In contrast to Sun (2012), we do not find that a higher variance of ratings may also increase second period demand. In Sun's as well as in our 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 $x > 2v/D_1$. As D_1 has a maximum of 1 which implies that $x > 2v$. This would mean that the enjoyment of a consumer with a maximal unmatched taste (i.e., a consumer with $\tau = 1$) is at most $-v$ if $P_1 = 0$. As we cannot think of any product with such characteristics, our first assumption rules out the possibility of *M* being negative by assuming $0 \leq x \leq v$.

Consumers who purchase the product publish an honest product rating. As mismatch costs are zero for pure experience products, consumers publish either a rating of v if the product does not fail, or a rating of zero if the product fails. This results in $(1-f)$ ratings of v and f ratings of zero. For this rating distribution, the average rating M, and the variance of ratings V can be computed, respectively, as

$$M = v(1-f), \text{ and } V = v^2 f(1-f).^9 \tag{7}$$

As for pure observational search products, 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 and f. Mathematically, late consumers can learn about the realizations of v and f by rearranging (7):

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

After deriving the realizations of v and f, 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 $E(u) = v(1-f) - P_2 - zf\theta$ where the term $zf\theta$ captures consumer risk aversion with regard to product failure. Based on $E(u)$ 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: $\tilde{\theta}_2 = (v(1-f) - P_2)\ /\ (zf)$. 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:

$$P_2^* = \frac{v(1-f)}{2}, \text{and } D_2^* = \frac{v(1-f)}{2fz}. \tag{9}$$

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 products in the following proposition:

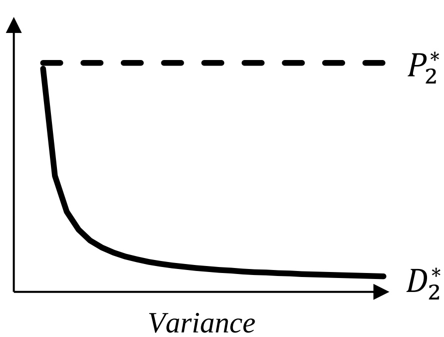
[9] A detailed derivation of M and V for pure experience products can be found in the appendix.

PROPOSITION 2. For pure experience products, 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 products with respect to M and V gives $\frac{\partial P_2^*}{\partial M} = \frac{1}{2}$, $\frac{\partial P_2^*}{\partial V} = 0$, $\frac{\partial D_2^*}{\partial M} = \frac{3\mathrm{M}^2+\mathrm{V}}{2\mathrm{Vz}}$, and $\frac{\partial D_2^*}{\partial V} = -\frac{M^3}{2\mathrm{V}^2 z}$. 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 observational search products, 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 3 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 Experience Products



4.3. Observational Search and Experience Products

In a final step, we analyze our model for observational search and experience products i.e., products with $f > 0$ and $x > 0$. For these products, the variance of consumer ratings depends on both the observational search and the experience attribute. First period consumers make their purchase decisions based on $E(v)$, $E(x)$, and $E(f)$, respectively. After the retailer chooses price P_1, the expected utility of an early consumer is equal to: $E(u) = (E(v) - E(x)\tau)(1 - E(f)) - P_1 - E(f)z\theta$. Given $E(u)$ 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, second period demand is equal to the area of the triangle [A,$\tau_{I,1}^{\theta=0}, r_{I,1}^{\tau=0}$] (see figure 4 for an example) with $\tilde{\tau}_1^{\theta=0} = (P_1 + v(f-1))/(x(f-1))$, and $\tilde{\theta}_1^{\tau=0} = (v(1-f) - P_1)/zf$. Thus, $D_1 = 0.5\tilde{\tau}_1^{\theta=0}\,\tilde{\theta}_1^{\tau=0}$.[10]

Consumers who buy the product publish a rating $r = v - x\tau$ if the product does not fail and a rating of $r = 0$ if it does. For products which do not fail, ratings are triangularly distributed between $v - \tilde{\tau}_1^{\theta=0}x$ and v with mode at v. The explanation for this specific shape of the distribution is as follows: As $\tau = 0$ for consumers who publish a rating of v, 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 decreases. Thus, the mode of the triangular distribution must be at v and the number of ratings strictly decreases with increasing taste. For a rating of $v - \tilde{\tau}_1^{\theta=0}x$ the maximum risk aversion is zero. Thus, $v - \tilde{\tau}_1^{\theta=0}x$ is the lower bound of the distribution of ratings for observational search and experience products 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 5 illustrates the rating distribution for observational search and experience products. 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 products with pure observational search and pure experience attributes, the enjoyment of observational search and experience products 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

[10] To avoid discussing corner solutions, we assume that $0 < \tilde{\tau}_1^{\theta=0} \leq 1$ and $0 < \tilde{\theta}_1^{\tau=0} \leq 1$.

Figure 4: First Period Demand for Observational Search and Experience Products

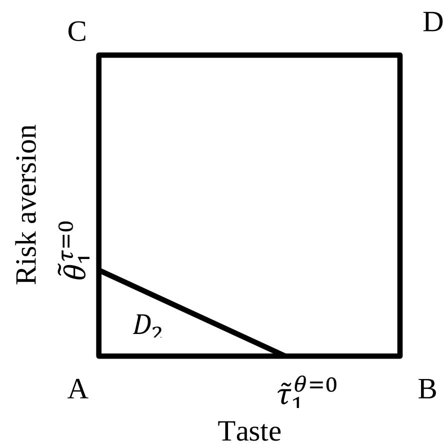
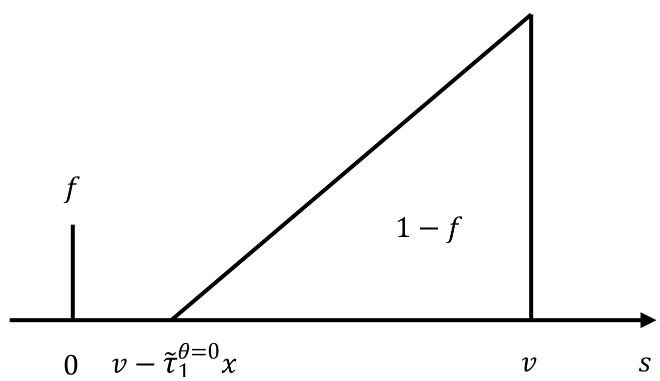


Figure 5: Rating Distribution for Observational Search and Experience Products



positive variance is caused by high mismatch costs, a high failure rate, 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 5. 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:

$$M = (v - \frac{\tilde{\tau}_1^{\theta=0} x}{3})(1-f),\ V_m = \frac{(\tilde{\tau}_1^{\theta=0})^2 x^2 (1-f)}{18},\ and$$
$$V_f = \frac{(1-f) f (3v - \tilde{\tau}_1^{\theta=0} x)^2}{9}. \quad (11)$$

[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 the realizations of v, x, and f for observational search and experience products by rearranging (11):

$$v = M + \frac{V_f + \sqrt{2V_m(M^2 + V_f)}}{M},$$
$$x = \frac{3\sqrt{2V_m(M^2 + V_f)}}{M\tilde{\tau}_1^{\theta=0}},\ \text{and}\ f = \frac{V_f}{M^2 + V_f}. \quad (12)$$

After deriving the realizations of $v, x,$ and f consumers are left with very litte 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 or not 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 $E(u) = (v - x\tau)(1-f) - zf\theta - P_2$ where the term $zf\theta$ still captures the risk associated with product failure. Based on the expected 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, x, and f, second period demand can be written as:

$$D_2 = \frac{(v(1-f) - P_2)^2}{2fxz(1-f)}. \quad (13)$$

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:

$$P_2^* = \frac{v(1-f)}{3},\ D_2^* = \frac{2v^2(1-f)}{9fxz}. \quad (14)$$

[11] A detailed derivation of the derivation of M, V_m, and V_f is provided in the appendix.

Using the relationship between v, x, and f 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:

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

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 observational search and experience products equilibrium price and demand always increase with increasing average rating.

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

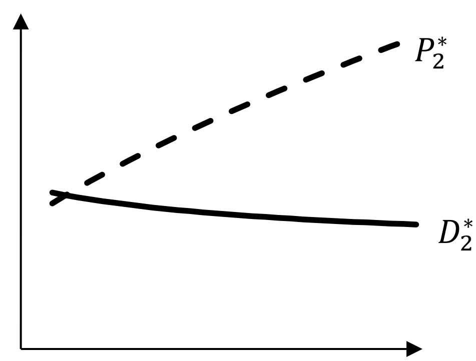
As with pure observational search and pure experience products the average rating acts as a credible signal of expected product quality for consumers and for the retailer. Therefore, equilibrium price and demand both increase with increasing average rating.

PROPOSITION 4. For observational search and experience products, equilibrium price always increases, and equilibrium demand always decreases with increasing variance caused by mismatch costs.

PROOF. Differentiating the equilibrium price and demand with respect to V_m yields $\frac{\partial P_2^*}{\partial V_m} = \frac{\sqrt{2}M}{6\sqrt{V_m(M^2+V_f)}}$, and $\frac{\partial D_2^*}{\partial V_m} = -\frac{M\tilde{t}_1^{r=0}\sqrt{2V_m(M^2+V_f)}(M^2+V_f-2V_m)}{54V_f V_m^2 z}$. As M, V_m, and V_f are positive by definition $\frac{\partial P_2^*}{\partial V_m} > 0$. 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 $x \leq v$. Rewriting this inequality in terms of M, V_f, and V_m and simplifying leads to: $V_m < \frac{\tilde{\tau}_1^{\theta=0^2}(M^2+V_f)}{2(\tilde{t}_1^{r=0}-3)^2}$. As $\tilde{\tau}_1^{\theta=0} \in [0,1]$ this stands in direct contradiction to $V_m > \frac{M^2}{2} + \frac{V_f}{2}$. Thus, $\frac{\partial D_2^*}{\partial V_m} < 0$. Q.E.D.

As for pure observational search products, 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 much 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 6 illustrates the relationship between, on the one hand, equilibrium price and demand, and on the other, the variance caused by mismatch costs.

Figure 6: Equilibrium Price and Demand for Observational Search and Experience Products



Variance Caused by mismatch costs

PROPOSITION 5. For observational search and experience products the equilibrium price always decreases with increasing variance caused by product failure. Equilibrium demand decreases with increasing variance caused by product failure if $V_f \leq 2M^2$. If $V_f > 2M^2$ and $V_m < \frac{(M^2+V_f)(-2M^2+V_f)^2}{2(2M^2+V_f)^2}$ increasing variance caused by product failure increases equilibrium demand.

PROOF. Differentiating equilibrium price and demand with respect to V_f gives $\frac{\partial P_2^*}{\partial V_f} = -\frac{M^2 V_m}{3(M^2+V_f)^2\sqrt{(2M^2V_m)(M^2+V_f)^{-1}}}$, and

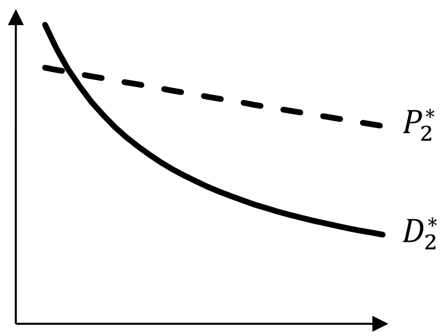
$\frac{\partial D_2^*}{\partial V_f} = -\frac{\tilde{\tau}_1^{\theta=0}(8M^3V_m + \sqrt{(2M^2V_m)(M^2+V_f)^{-1}}(2M^4 - V_f^2 + 2V_fV_m + M^2V_f + 4M^2V_m))}{54V_f^2V_m z}$. As M, V_m, and V_f are positive by definition $\frac{\partial P_2^*}{\partial V_f} < 0$. The sign of $\frac{\partial D_2^*}{\partial V_f}$ depends on the sign of the term in parenthesis. If this term is positive,

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

As for pure experience products, 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 an intuitive result. 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 caused by 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.[12] Figure 7 illustrates the relationship between equilibrium price and demand and variances caused by product failure for a product with $V_f \leq 2M^2$.

[12] For ratings in a typical 5 star rating system with a rating of one indicating the worst and a rating of 5 indicating the best possible quality, it is never possible that $V_f > 2M^2$.

Figure 7: Equilibrium Price and Demand for Observational Search and Experience Products



PROPOSITION 6. For observational search and experience products, 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* $V > \overline{V}$.[13] *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 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

$$\frac{\partial D_2^*}{\partial V_f} = \frac{\sqrt{2}M\tilde{t}_1^{r=0}}{54V_f^2 z\sqrt{(V-V_f)^3(M^2+V_f)^{-1}}}((M^2V_f + V_f^2 + \frac{2V_f(V-V_f)^2}{M^2+V_f}) - (V-V_f)(4(V - V_f) + 2M^2 + 4M^2\sqrt{2\frac{V-V_f}{M^2+V_f}} + V_f)).$$

As V_f is by definition always smaller than V, $\frac{\partial P_2^*}{\partial V_f} < 0$ and, vice versa, $\frac{\partial P_2^*}{\partial V_m} > 0$.

As $\frac{\sqrt{2}M\tilde{t}_1^{r=0}}{54V_f^2 z\sqrt{(V-V_f)^3(M^2+V_f)^{-1}}}$ is always positive, the sign of $\frac{\partial D_2^*}{\partial V_f}$ depends only on the term:

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

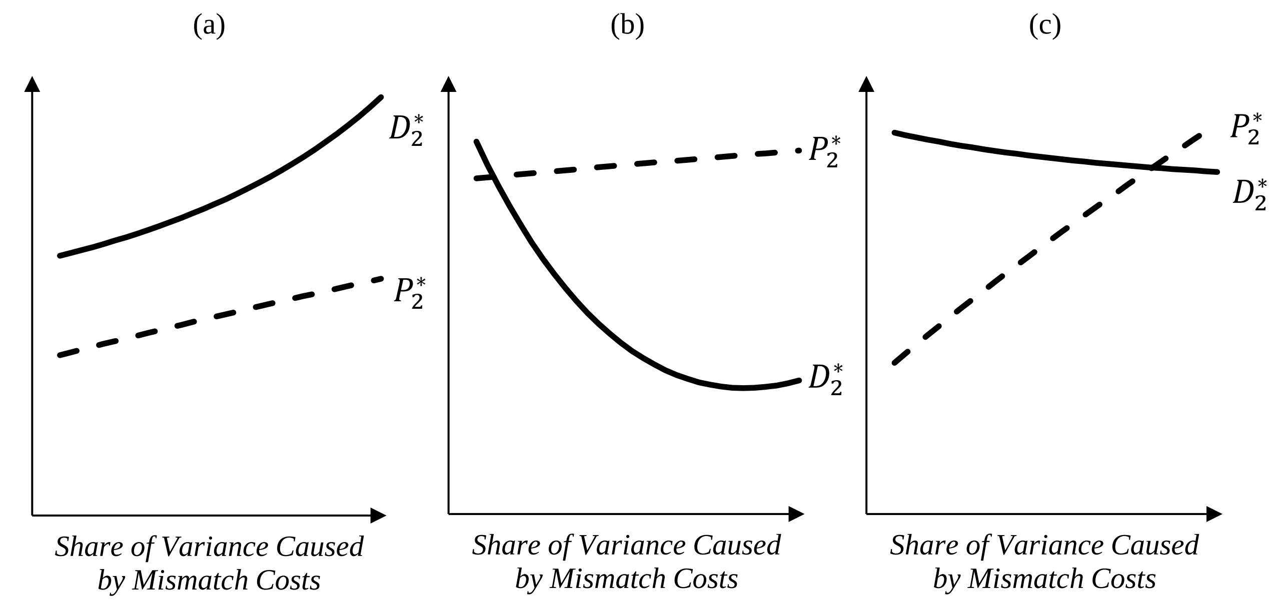
$$((M^2V_f + V_f^2 + \frac{2V_f(V - V_f)^2}{M^2 + V_f}) - (V - V_f)(4(V - V_f) + 2M^2 + 4M^2\sqrt{2\frac{V-V_f}{M^2+V_f}} + V_f)) \quad (16)$$

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 (15) and solving $(15) = 0$ for V gives $V = \underline{V}$. Thus, if $V < \underline{V}$, $\frac{\partial D_2^*}{\partial V_f} < 0$ and, vice versa $\frac{\partial D_2^*}{\partial V_m} > 0$. Inserting the lower bound of V_f into (15) and solving $(15) = 0$ for V gives $\overline{V}$. Thus, if $V > \overline{V}$, $\frac{\partial D_2^*}{\partial V_f} > 0$, and, vice versa $\frac{\partial D_2^*}{\partial V_m} < 0$. If $V \geq \underline{V}$ and $V \leq \overline{V}$, the sign of (15) depends on the specific value of V_f. As (15) is strictly increasing with increasing V_f, and (15) 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 observational 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 like 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 observational search and experience products.

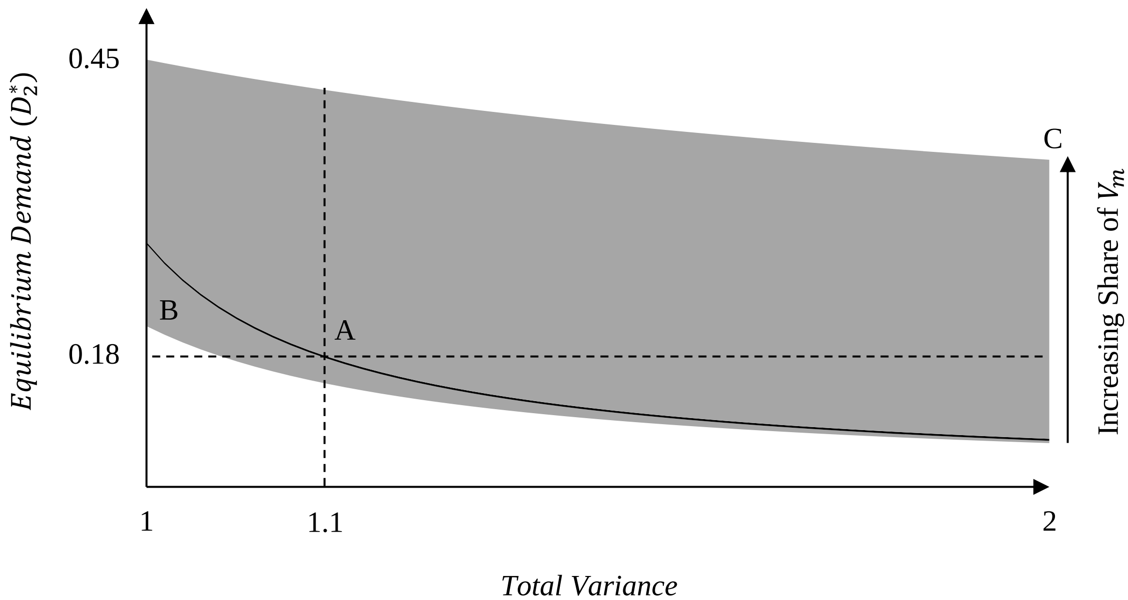
Holding the average rating constant, a lower matched quality and a lower failure rate of the product makes the product more attractive to risk-averse consumers. This increase overcompensates for the decrease in second period equilibrium demand due to the increased product price discussed in the paragraph 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 of V_m. Thus, in these cases, the total effect of an increasing share of V_m on equilibrium demand is negative. Figure 8 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 8: Equilibrium Price and Demand Observational Search and Experience Products



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 9 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 where approximately 70% of the variance are 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 9 represents all products with the same equilibrium price as the product marked in A. 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.

Figure 9: Equilibrium Demand for Products with Different Variance Compositions



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 variance composition, 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.

5. Conclusion

The opportunity for online shopping significantly changed the way people are purchasing goods. Rating systems which enable consumers to observe the distribution of star ratings awarded by other consumers contributed a lot to this change. Naturally, a significant literature emerged which seeks to understand the effects of different aspects of these ratings systems - such as number, average or variance - on product prices and consumer demand. Surprisingly, 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 observational search attributes. However, a high variance of consumer ratings may not be solely driven by such attributes but may also depend on experience attributes. This paper 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: an observational search and an experience attribute. We find that a higher variance caused by the observational 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 signals 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 observational 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 observational 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 they were to consider the composition of a product's ratings variance retailers could improve their sales forecasts and increase profits by adjusting their stocks accordingly. 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. Moreover, retailers could charge higher prices for those products for which a relatively larger share of the variance of product ratings is caused by mismatch costs. Today, consumers can only indirectly infer this information by analyzing specific characteristics of the rating 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 consumer rating whether it is based on product failure or on other – taste specific – factors.

Our study suggests several directions for future research. First, 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. observational search and experience attributes. Second, our results suggest that consumers too 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. Future research may develop semantic techniques (e.g. as in Archak et al. 2011) to identify the respective shares of variance caused by mismatch costs or by product failure.

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Appendix 1. Derivation of Means and Variances

Pure observational search products: For pure observational search products ratings are uniformly distributed between $[v - D_1x, v]$ and have the following probability density function $f(r) = \frac{1}{D_1x}$. The expected value μ of a continuous random variable is defined as $\int xf(x)dx$. Thus, the average rating can be computed as $\int_{v-D_1}^{v} \frac{1}{D_1x} rdr$. Integrating and rearranging leads to $M = v - 0.5D_1x$. The variance of a continuous random variable is defined as $\int(x-\mu)^2 f(x)dx$. Thus, the variance of ratings can be computed as $\int_{v-D_1}^{v} \frac{1}{D_1x}(r-M)^2 dr$. Integrating and rearranging yields $V = \frac{D_1^2x^2}{12}$.

Pure experience products: As $(1-f)$ consumers publish a rating of v and f consumers publish a rating of 0 consumer rating R is a dichotomous random variable with $P(R=v) = (1-f)$ and $P(R=0) = f$. The expected value of a discrete random variable is defined as $\mu = \sum_{i=1}^{n} p_i x_i$. Thus, for our model $M = (1-f)v$. The variance of a discrete random variable is defined as $\sum_{i=1}^{n} p_i(x_i - \mu)^2$. Thus, for our model, $V = (1-f)(v-M)^2 + f(-M)^2$ which can be rewritten as $V = v^2 f(1-f)$.

Observational search and experience products: Consumers who buy the product publish a rating $r = v - x\tau$ with probability $(1-f)$ and a rating of $r = 0$ with probability f. Thus, the rating distribution for observational search and experience products consists of a continuous part for products that do not fail and a discrete part for products that fail. For products that do not fail ratings are distributed between $v - \tilde{\tau}_1^{\theta=0}x$ and v and have the probability density function $f(r) = (2(1-f)(r - v + \tilde{\tau}_1^{\theta=0}x))/((\tilde{\tau}_1^{\theta=0})^2x^2)$ due to the uniform distribution and independence of τ and θ. Products that fail always receive a rating of zero. Based on these information, the average rating M for observational search and experience products can be computed as $\int_{v-\tilde{\tau}_1^{\theta=0}x}^{v} f(r)\, r\mathrm{d}r + f0$. Integrating and rearranging yields $M = (v - \frac{\tilde{\tau}_1^{\theta=0}x}{3})(1-f)$. Based on the information that $(1-f)$ products do not fail and on the probability density function, the total variance of observational search and experience products can be computed as $\int_{v-\tilde{\tau}_1^{\theta=0}x}^{v} f(r)\,(r-M)^2\mathrm{d}r + f(0-M)^2$. Integrating and rearranging gives $V = \frac{(1-f)(18fv^2 + \tilde{\tau}_1^{\theta=0^2}x^2 + 2\tilde{\tau}_1^{\theta=0^2}fx^2 - 12\tilde{\tau}_1^{\theta=0}fvx)}{18}$. To compute the variance that is solely caused by mismatch costs, we compute the probability density function for the continuous part of the rating distribution assuming that $\int_{v-\tilde{\tau}_1^{\theta=0}x}^{v} f_{m(r)}\,\mathrm{d}r = 1$ which is equivalent to assuming that $f = 0$. The resulting probability density function is $f_m(r) = \frac{2z}{(\tilde{\tau}_1^{\theta=0})^2x^2} - \frac{2(v - \tilde{\tau}_1^{\theta=0}x)}{(\tilde{\tau}_1^{\theta=0})^2x^2}$. The average rating under the assumption that $f = 0$ can be computed as $M_m = \int_{v-\tilde{\tau}_1^{\theta=0}x}^{v} f_{m(r)} r\,\mathrm{d}r$. With this average rating, the variance caused by mismatch costs V_m can be computed as $\int_{v-\tilde{\tau}_1^{\theta=0}x}^{v} f_m(r)(r-M_m)^2\,\mathrm{d}r(1-f)$. Integrating and rearranging yields $V_m = \frac{\tilde{\tau}_1^{\theta=0^2} x^2(1-f)}{18}$. Knowing V and V_m, V_f can be computed as $V - V_m$. Rearranging yields $V_f = \frac{(1-f)f(3v-\tilde{\tau}_1^{\theta=0}x)^2}{18}$.