Reducing Buyers' Uncertainty About Taste-Related Product Attributes

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Abstract

It is becoming increasingly important for firms to know when to take steps to reduce buyers' uncertainty about their products and services. This article focuses on investments that firms can make to reduce buyers' uncertainty about taste-related product attributes. Using an analytical model, we show that firms should disclose more taste-related information when the customer segment they directly target represents a larger share of the overall market. We proceed to ask if there are practical ways by which managers can decide if such disclosure investments are financially beneficial to their firm, and find that the variance of consumer reviews can guide such decisions. The article's main contribution is to show that firms must consider the variance, but not the mean, of buyer reviews, to determine the need to invest in reducing consumer uncertainty about taste-related attributes. The article's findings are managerially important due to the ubiquity of consumer reviews. They are novel because almost all previous literature views the mean of the review as the key indicator. Finally they are general in their applicability since they are independent of any assumptions about heuristics that buyers may use to ascertain product quality from the reviews of previous buyers.

Keywords

Information dissemination, product ratings, product review variance, consumer uncertainty reduction

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1. Introduction

Today's firms use new technological means to reduce consumers' uncertainty about product characteristics and performance, and doing so may appear to be a strategic necessity [16], since today's consumers are using information to guide purchasing decisions more heavily than ever before. This is true for consumer purchases both online and offline, as evidenced by the increasing percentage of online and offline purchases that are preceded by online search for descriptive product information [1,40]. Not all mechanisms for reducing consumer uncertainty are equally effective, and sometimes the process of reducing uncertainty can be quite expensive; consequently, the question of when to reduce buyers' uncertainty is becoming increasingly important.

Traditionally, firms have had a limited number of options regarding investing in reducing buyers' uncertainty about their offerings. Firms can engage in any or all of the following:

- thorough product testing [22,39] and making the favorable results of the tests easily available
- better organizing and presenting product information, so that consumers become educated about different features and can assess the importance of these features to them [24,31]
- supporting certification intermediaries that act as trusted third parties [2], in providing product samples and free returns
- training their sales force so that it can better communicate the advantage of each product to prospective customers [50].

Other methods, like providing discounts for initial purchase (promotional discounts) and giving away free samples (sampling) have also been used extensively in markets for fast moving consumer goods, where buyers will be expected to make frequent repeat purchases. These are far too expensive to use in markets for expensive technology products and manufactured durable goods, where repeat purchases are unlikely. Sampling is also far too expensive to use in niche markets, where only a tiny fraction of the population provided with samples might be expected to become repeat purchasers.

In recent years, technology has offered firms new ways to increase consumers' knowledge about their offerings. Data analytics allow firms to target even traditional methods to more receptive audiences; for example, Netflix shows different trailers for the same TV-series to different audience segments, based on each segment's viewing preferences [8]. Vendors can now provide interactive applications to help buyers find their perfect product fit. It is now possible to use rich, interactive media [33] to allow buyers to sample products electronically and thus to evaluate the experience of owning the actual product [42]. Sellers can now allow consumers to view a video clip, listen to a snippet of a song, or download the first chapter of a book before making purchase decisions. Indeed, many PC-games feature playable demo versions, while high-end clothing and apparel retailers have begun to offer virtual try-ons and 3D tours of their products. The ability to engage in informative advertising has also been significantly improved with technologies like QR code, which allows vendors to supplement their magazine ads with QR codes that enable readers to explore specific product features using mobile phones and tablets, even while they continue to read their magazine.

Even as firms that wish to reduce buyer uncertainty have more investment options than ever before, these investments are themselves becoming increasingly important. Indeed, a large and continuously growing portion of electronic commerce (e-Commerce) involves active information acquisition on the part of consumers. In 2009 in the USA 10-15% of retail sales that involve the Internet (including Research Online-Purchase Offline, or ROPO) were the direct result of a consumer actively engaging in search for feature information [40]. These sales added up to a $57-67 billion market, about evenly split between online and offline purchases [40]. The number of people who perform such searches before purchasing continues to grow. Accenture reported in 2007 that of consumers they surveyed, more than two thirds explored product features online, and found that this was a rising trend [1]. The e-tailing group [51] reported an increase in the number of people who value retailers' efforts to reducing their uncertainty: the percentage of consumers who think product comparison capabilities are important grew from 67% in 2007 to 70% in 2008, and the percentage of those who appreciate informative product videos climbed from 25% to 31%. Consumers' use of information may or may not result in increased total category sales or to an increase in market size, but failure to provide consumers with precisely the information they want almost certainly represents lost sales for firms that do not learn how to provide information to consumers effectively.

Firms' increasing need to know when to invest and reduce buyer uncertainty is even more pronounced for information about product attributes that are related to differences among consumers' tastes, rather than to differences in product quality. These are product attributes for which consumers do not generally agree on what is better when they try to compare them. Examples of such taste-related attributes abound and are often related to aspects of design, personal preferences, size, etc. Taste-related attributes contrast with attributes that are related to product quality and for which consumers generally agree when they compare them. While consumers may not agree on whether the iPhone design is better than that of a Samsung Android phone, and they may not agree on whether a Belgian strong ale is better than an American double IPA, most generally agree that customer service for an Infiniti FX 37 is better than customer service for the almost identical Nissan Murano.

Taste-related product attributes have always been important, as almost all products and services incorporate them. Today, their relative importance is increasing, for three reasons:

- Increasingly, consumers purchase what they want, rather than what they merely need. This is explained in *Trading Up*, in *The Long Tail* [3], and in numerous references on the shift from merely satisfying basic needs towards self-indulgent delight.
- Increasingly, firms can deliver products tailored at smaller and smaller market niches [46].
- And increasingly, consumers are able to find and use the information they need to guide their purchasing decisions and find their ideal product selections. This is in large measure due to the rising popularity of social commerce platforms [26], and the increased availability of recommendation technologies [44], such as collaborative filtering [6][1].

Indeed, companies like Facebook, Pinterest, and LivingSocial connect like-minded shoppers and encourage consumers to search for products and services based on their own idiosyncratic preferences. At the same time, intelligent shopping recommendations, based on collative filtering techniques, allow people to focus on subjective and idiosyncratic measures of product fit, rather than objective and universal measures of product performance and absolute quality.

Social commerce and recommendation technologies are especially suited to communicate taste-related attributes. The first generation of e-Commerce websites allowed people to sort products based on quality attributes (e.g., sorting of digital cameras based on megapixel count), but could not make intelligent recommendations based on consumers' personal tastes. Yet, while we all prefer more

[1] The complex relationship between taste-based attributes, social networks and informed consumers, and the introduction of increasingly focused niche offerings, was first postulated in [17].

pixels rather than fewer, a greater zoom range rather than a more limited one, and a lighter camera to a bulkier one, we do not all make the same tradeoffs among these attributes when selecting a single camera. Today's social platforms and intelligent online tools support far more sophisticated analyses before making purchasing decisions. Consumers today can choose to "follow" the design-based handbag recommendations of a like-minded shopper in Pinterest, or receive restaurant suggestions when they visit a new country, based solely on their favorite restaurants back home.

In Table 1, we show examples of different information disclosure investments for different products, also highlighting a taste-related attribute for each product.

Insert Table 1 here

In brief, in this paper we find that variance among buyers' reviews for an individual product is a good predictor of the concentration of buyers with preferences for products similar to the product being reviewed. High review variance is an indicator of a low such concentration (wide variation in preferences for the product's combination of taste-based attributes), while low variance is an indicator of a high such concentration (more focused preferences near the product's combination of taste-based attributes – a strong indication that the firm has hit a market *sweet spot* [12]). The latter is itself a good indicator of the high utility to the firm of reducing buyers' uncertainty about the product's taste-based attributes. This result is novel and analogous to what many authors have shown about product quality: Firms should disclose more information about taste attributes when consumers value the firm's specific choices on those attributes, just as they should invest in providing information on their quality, when their quality is high.

The finding makes intuitive sense[2]. High quality appeals to all consumers, and investing in appealing to all consumers by clarifying the product's quality obviously makes sense. Analogously, if the segment that values the firm's choice of taste attributes is large enough, then an investment in clarifying the product's taste-based appeal to that segment likewise is justified. While intuitive, this result is neither obvious nor tautologically true, nor is the implication that review variance can be used to guide investments regarding disclosing taste-related information to consumers.

[2] It is in some sense the contrapositive of earlier results by the authors, which stated that when firms are going after very small niches of buyers with very strong preferences, market entry may only be possible if it is not necessary to invest in informing buyers

Finally, and perhaps more importantly, the widespread availability of buyer reviews makes our advice practical and easy to follow, and the result does not depend on any specific assumptions about how the buyer themselves process review information by previous buyers. Indeed, we are able to show that our result is independent of any heuristic that buyers may use to ascertain product quality from the reviews of previous buyers.

The paper is structured as follows. Section 2 reviews the related literature. Section 3 introduces our basic model, which shows that firms should disclose more taste-related information when the customer segment that they directly target represents a larger share of the overall market. Section 4 extends our model and shows that consumer reviews can be used by firms to ascertain the distribution of buyer preferences, so that they can then decide whether or not it should invest to reduce buyer uncertainty. We conclude in Section 5 and present summaries and suggestions for future research.

2. Previous Literature

Despite the emerging importance of taste-related product attributes, previous literature has mostly focused on quality attributes[3]. This made great sense when product design and marketing both focused on designing the best possible products for the widest possible markets, which involved ignoring the subtle differences in preferences that defined individual sub-segments. We will show that the logic for focusing solely on quality is far less compelling sense today.

Jovanovic [32] was among the first of many researchers to study how firms undertake costly investments that reduce consumer uncertainty. He focused solely on firms' investments to reduce consumers' uncertainty about their products' quality; he found that, given the cost of the investment, only firms above a quality threshold should invest in reducing consumer uncertainty. This was an extension of the "quality unraveling argument" [28,29,41], which states that rational buyers should discount the quality of firms who do not make credible investments to try to demonstrate their quality.

[3] This is not surprising. In the world after the industrial revolution, most companies focused on mass market fat spots. Budweiser, Miller, and Coors made very similar beer, targeted at the largest possible audience. Lee, Wrangler, and Levis made very similar jeans, likewise targeted at the largest possible audience. Ford, Chrysler, and General Motors likewise made very similar cars; there were quality differences within companies, such as those between Pontiac and Cadillac, or those between Ford and Lincoln, but firms engaged in the most limited taste-based differentiation. The advent of more flexible manufacturing technologies and better technologies for inventory management and sales forecasting led to greater variation within firms, but it was the very recent advent of social marketing that has enabled the additional focus on taste based attributes. See also [12].

When quality demonstration is costly, the Jovanovic threshold applies. Therefore, as long as the mean of consumer reviews is an indicator of how the product's quality is assessed by consumers, and as long as these reviews are not yet fully employed by all consumers, a firm that enjoys high average consumer reviews should invest in further reducing consumer uncertainty about their quality.

Many articles have demonstrated a relationship between a high average product review and subsequent increases in product sales, for example in movies [19] and books [11]. There is currently some disagreement regarding whether consumer reviews cause or merely predict future sales. For example Duan, Gu, and Whinston [21] were careful to account for the endogenous nature of consumer reviews, since reviews can potentially both influence and be influenced by product sales. The authors' results show that in their studies high average product reviews do not influence future ticket sales for movies aimed at mass audiences, but rather merely predict them, simply because high reviews are the result of higher quality. However, the results of Anderson et al. [4] show that in their studies reviews do directly influence future sales. The authors measured the increase in restaurant traffic that follows increases in the mean of consumer reviews and controlled for quality heterogeneity by focusing on restaurants with nearly identical quality that "appear" to have different reviews simply because of rounding errors. For example the authors focus on the difference in traffic between a three star and a three-and-a-half star restaurant, when the real quality difference between the two is marginal: 3.24/5 versus 3.25/5. Regardless of whether consumer reviews influence future sales or merely predict them, the implication is clear: other things equal, high quality firms should invest in ensuring that their quality becomes known.

More recently, there has been important work on the role of differentiation and idiosyncratic consumer preferences. Clemons, Gao, and Hitt [14] were the first to examine the influence of variance in product reviews and they showed that high product review variance in the craft beer market is subsequently associated with higher growth in product market share. Sun [49] found the same to be true for books, but only if the average product review is sufficiently low. Clemons et al. [17] show that long-tail products asymmetrically benefit from increased information availability and Brynjolfsson et al. [7] confirm that long-tail clothing items asymmetrically benefit by the introduction of technologies that facilitate the consumers' information acquisition process.

Our paper is also related to the marketing literature of consumer reviews and word-of-mouth [27] and especially on the marketing response of the firm to such reviews [9,10]. In a model with many similarities to ours, Kuksov and Xie [34] study firms' incentive to offer frills in a two-period model where the average rating from period one is taken into account by market participants in period 2.

Finally, our paper complements and extends the authors' own prior research in informedness, hyperdifferentiation, and resonance marketing. Clemons et al. have argued that differentiation for very small segments makes sense only when consumers have access to reliable information on product attributes almost effortlessly [14]; Clemons et al. have also argued that firms invest in providing consumers with this information by providing free samples to influential bloggers when segments are quite small, but more direct interventions would make sense for larger segments [15].

Table 2 summarizes and codifies the features of the key relevant literature.

Insert Table 2 here

3. A Model of Taste Information Disclosure

We develop a model of a differentiated market with heterogeneous consumer tastes and consumer uncertainty about taste-related product attributes. We explore a single firm facing a concentrated mass of consumers, i.e., a *sweet spot*. The model can be extended to a market with more than one concentration of preferences, where different firms each cater to a different sweet spot[4]. However, the monopolistic market is easier to analyze and it preserves the driving force behind our main results and all of the intuition. Section 3.2 shows that the change in consumers' expected utility for a product is a function of uncertainty and distance from the product's location, so that our findings and the intuition behind them is directly applicable without modification when firms compete for different sweet spots, and to the case where multiple firms compete for the same sweet spot. We thus view our model as a good representation for the evolution of the craft beer market, the smart phone market, and several other markets built around a collection of sweet spots.

[4] Indeed, this observation is fundamental to our definition of a sweet spot and to resonance marketing. In traditional mass spot marketing, two or more firms compete for consumers in the same fat spot. The competition between Bud Light and Miller Lite, or between the Toyota Corolla and the Nissan Altima are examples of fat spot competition. In contrast, the Chrysler Corvette is unique among high performance American sports cars.

3.1. Model Definition

We model a monopolistic market for a single-purchase good, for which consumers are imperfectly informed before purchase. Consumers will be fully informed after purchase, but will not wish to purchase the good again after they are fully informed. That is, consumers demand one unit of the product and cannot use a first purchase "just to try the product out", and then come back for subsequence purchases of additional units. Thus, our model is best suited for durable goods where the same consumer will not purchase a product frequently. Additionally, it is most applicable where products are frequently updated, revised, and improved, and thus have not been in the market long enough for consumers to know the exact utility that they would receive by purchasing and using each individual product's most recent version. This describes consumer durables better than it describes fast moving consumer goods, and it describes newly introduced product offerings better than it describes mature offerings in well developed markets. It is a bad model for established products like Coke and Pepsi, or Bud Light and Miller Lite. It is intended to model the market for new high-end consumer digital cameras or for the rapidly changing market for craft beers.

In our model a monopolist offers a single product that has known and fixed quality, denoted by v, and a taste-related parameter that is fully defined by the product's location in a circular market of unit size [47]. The production cost is normalized to zero.

Each buyer is completely defined by his most preferred product location; as is typical with Hoteling and Salop models, we assume that all buyers have the same maximum willingness to pay for their idealized products and the same *fit cost*, i.e. the unit discount for distance between their idealized products and the products they are actually considering. We assume without loss of generality that buyers are risk neutral; relaxing this assumption increases the value of reducing consumers' uncertainty, which actually strengthens our findings.

We assume that there are two distinct buyer populations of buyers. The first population is assumed to have most preferred locations for products that are uniformly distributed around the circle. This is a heterogeneous group of buyers who disagree among themselves as to what is the most desirable product. The second population shares the same favorite product location, which we term a *sweet spot*. This is a homogeneous group of buyers who agree on what constitutes an ideal product.

The proportion of buyers that belong to this second group is denoted by s and is not precisely known to the seller, who can observe that there is a "spike" of consumer interest in a certain product location. The seller is certain about the exact location of the spike, but is uncertain about its size. The proportion of buyers who belong to the heterogeneous group is given by 1-s. A schematic representation of the model is given in Figure 1.

INSERT FIGURE 1 HERE

Although the firm is initially uncertain about the exact size of s, it has a prior estimate $h_S(s)$ that is uniform in $[s_1, s_2]$. After the firm commits to a product design, and after initial consumer reactions are assessed, the firm is assumed to receive a signal about the true size of s, which allows it to update its priors. Its updated estimate of s is now s', where $s' = s + \varepsilon$, with ε distributed uniformly in a small interval $[-\delta, \delta]$[5]. Note that the size of the interval $[-\delta, \delta]$ is a measure of how uncertain the firm is about s, after having received the signal that allows it to update its priors to s'.

Indeed, for many products we do actually observe both a relatively flat distribution of consumer preferences over the product space and a large spike at one or more specific product locations. For example in the product space of digital cameras there is a strong spike in the product location associated with Nikon D800, a highly popular "prosumer" camera. One possible explanation for the existence of such concentrations of buyer preferences is that different consumers have different levels of engagement and interest in a product category. Those consumers who care most about a product are more likely to have had experience with similar products in the past, to engage in active search for product information, to seek expert's opinions on the web and to participate in online forum discussions as readers or contributors. It is also likely that these consumers have discovered that not all product locations are equally attractive to them or equally useful to them, and that some are particularly well suited to their expected needs, or are more convenient for them, or offer them a better overall balance of features. This knowledge may not necessarily be shared among other groups of consumers whose tastes are more heterogeneous, and indeed it may not be useful to consumers whose preferences are divergent from those of consumers within this group.

[5] For simplicity we omit the analysis of the cases where s' is restricted to be farther than δ from the edges of the $[s_1, s_2]$ interval, and consider only the cases where $s' + \delta < s_2$ and $s' - \delta > s_1$.

When the buyer consumes a product he receives utility:

$$u(x) = v - p - x \tag{1}$$

where $u(x)$ is the buyer utility, v is product quality for the buyer's ideal product, p is the product price, and x is the distance between the buyer's ideal product location and the actual location of the product purchased. Also note that we are normalizing the cost per unit of distance to 1, without loss of generality; it is customary in Hoteling and Salop models to assume that all consumers have the same unit fit cost, and we are simply setting it to 1.

In our model we explicitly acknowledge that buyers may be imperfectly informed about the product. This modeling of uncertainty was not present in the initial models of Hoteling and Salop, but was introduced in early work by Clemons et al. [17,12]. Obviously, even without the firm's efforts to reduce consumers' uncertainty about a product's exact location, consumers may already know much about the product; they may have previous experience with other products by the same vendor, or with previous versions of the same product. Additionally, they could be accessing information provided by third party information sources, such as online expert reviews, or reviews from other consumer. However, we accept that even after the buyer receives third-party information, there is still some residual uncertainty. The firm can choose to reduce this uncertainty through investments to make the product's position exactly known, or the firm can choose to forego those investments.

A firm with a product in a given location d has two choices regarding a potential investment to resolve consumers' uncertainty about its product. First, it can choose to invest in reducing consumer uncertainty by incurring a one-time fixed investment with cost c. In that case, all buyers in the market learn the product's exact location and do so prior to making their purchase decisions. Alternatively, the firm can choose to forgo this investment, in which case each buyer receives an imperfect signal of the firm's product's actual location. This signal is equal to $d + \varphi$, with φ distributed uniformly in $[-\alpha, a]$. We assume that the distribution of φ is known to buyers; thus if the firm does not choose to invest in reducing buyers' uncertainty, a buyer who observes a signal that the product is located at z knows that in reality the firm's product's true location could range from $z - a$ to $z + a$. We allow for different buyers to receive different signals, i.e., the realization of φ is allowed to differ for different buyers. Note that in this formulation, the size of the interval $[-\alpha, a]$ represents the residual uncertainty that buyers have about the product, after accessing all other information available to them. It is up to the firm to decide whether or not to invest in reducing this residual product uncertainty; we have assumed that making these investments would reduce a to zero.[6] Of course, in practice, zero uncertainty is never exactly obtainable. We should instead consider that uncertainty becomes zero "for all practical purposes". Also note that, on average, consumers are not biased about the product's location: an unbiased poll of the consumers would reveal that the product's true location is d, even if individual consumers have incorrect expectations about the product's most likely location.

A buyer from the homogeneous group of size s, who observes a product location that is x units away from his ideal, will purchase the firm's product with probability $g(\cdot)$ that increases in the expected utility of the buyer. For convenience we will assume that g is linear and satisfies $g(0) = 0$ and $g(K) = 1$. In other words, buyers will never buy a product from which they receive zero or negative utility and they will always buy a product for which their expected utility is K, where $K > v$. [7] For simplicity, we further assume that the heterogeneous group of buyers of size $1 - s$ will always buy the product with certainty if expected utility is positive and will never buy the product otherwise. We can show that this assumption does not qualitatively change our results, but it greatly simplifies the mathematical analysis, compared to the case where both groups of buyers, even those less informed about the product category, exhibit probabilistic demand. [8]

The firm must decide on product placement, pricing, and information disclosure. Product placement is related to product design, and for most product categories this is the decision that takes the longest to alter, since it requires redesigning the product and reconfiguring its production, sales,

[6] In practice zero uncertainty is never exactly obtainable. We should instead consider that uncertainty becomes zero "for all practical purposes".

[7] Since v is the maximum utility that a buyer can have, in our model the homogeneous buyers will never buy the product with certainty. The requirement $K > v$ simply reduces the number of cases that we must consider without changing our results.

[8] This formulation usually appears in other authors' works by accepting that there exists an external substitute of some given utility, and that consumer choice is stochastic and includes a non-deterministic error term. A good explanation is provided in Li et al. [35]. The different treatment of the two buyer groups is thus consistent with our view of the homogeneous group of buyers as more informed consumers, who are more likely to be aware of alternatives. If L is the utility of the substitute and $E(u(x))$ is the buyer's expected utility, then a popular choice in Economics is for g to be of the form: $g(E(u(x)), L) = exp(E(u(x)))/\left(1 + exp(L) + exp(E(u(x)))\right)$. Our assumption that g is linear is not needed to derive our main result – that firms should disclose more when buyer preferences are more concentrated – but it helps make the entire model analytically tractable.

and support. It is thus natural to assume that placement decisions precede decisions on pricing and information disclosure. However, for new product introductions of durable products – the scenario that is best described by our model – it is not clear if the firm retains flexibility to easily update its price, once the product has been designed and announced to the market. Many firms must commit to a product price during product launch and are not expected to re-price until a new generation of their product comes out, or until some other major event occurs. Examples can be found in electronic and computing products, such tablet computers. In other cases, the firms retain considerable pricing flexibility even after product launch. Examples in the latter category include microwave ovens and plasma TVs, as documented in [5]. While the model's results are qualitatively the same regardless of whether the firm commits on product price before or after the its decision on information disclosure, for simplicity we assume that the firm commits on product price before making investments in information disclosure. We define the game as follows:

- **Stage 1**: The firm chooses its product location and its price and enters the market
- **Nature**: The firm receives a signal s' of the size of s
- **Stage 2**: The firm chooses whether or not to invest in information disclosure

While the entire game is analytically tractable, our primary focus will be the firm's information disclosure investments. Also, to avoid discussing corner solutions, we follow the widely used assumption that the market is never fully covered [49][9].

3.2. Results & Analysis

Theorem 1 (Product Design and Information Disclosure): *The firm chooses to locate its product exactly at the concentration of consumer preferences, and the probability that the firm will invest in information disclosure increases with* s.

The proof, including a graph of the relationship between disclosure probability and the concentration of preferences s, is provided in the Appendix.

The first part of the Theorem is intuitively easy to understand. The firm is indifferent about its placement vis-à-vis the heterogeneous consumer segment, as these buyers are uniformly distributed in

[9] We thus require that the most distant buyer, opposite from the firm's chosen product location, should have negative expected utility given the firm's optimal price p^*: $v - p^* - \frac{1}{2} + \alpha < 0 \rightarrow v < p^* + \frac{1}{2} - \alpha$.

the market space, and from the perspective of the firm all locations are equivalent. However, the firm wants to locate as close as possible to the homogeneous consumer segment of size s, because a close placement would reduce the fit costs for all consumers in this segment, and thus would allow the firm to charge more, or, alternatively, it would allow the firm to increase sales for a fixed price level.

The intuition behind the second part of the Theorem has been previously intuitively explored in [12] and is related to how buyers at different distances from the firm's product are affected by product uncertainty. Buyers whose ideal product location is some distance away from the product do not necessarily discount a product for which they experience a fixed level of uncertainty; in contrast buyers whose ideal product location is much closer almost always discount for the same fixed level of uncertainty [17]. For example, in Figure 2, Buyer B's expected distance from the product is independent of the size of the uncertainty interval, as long as the mid-point of the interval remains fixed. Intuitively, larger uncertainty worsens the worst-case scenario for the buyer (the product may turn out to be located at the far end of the uncertainty interval) but it also improves the best-case scenario for the buyer (the product may turn out to be located at the closer end of the uncertainty interval). On average this buyer would not be affected by changes in the size of the uncertainty interval, and would not necessarily pay less for the product under uncertainty.

INSERT FIGURE 2 HERE

This contrasts sharply with the case of a buyer who already knows that the product is likely to be very close to his ideal location. In Figure 2, Buyer A, who is located inside the product's uncertainty interval, will only perceive a loss in expected utility from increased uncertainty. For this buyer, more uncertainty worsens the worst-case scenario for the buyer but does not improve the best-case scenario, which is that the product truly is located at his exact ideal location. Even in the absence of any risk aversion this buyer would perceive lower expected utility as a result of uncertainty, and thus this buyer would be willing to pay less for the product under uncertainty.

Consequently, while a firm might wish to invest to reduce the uncertainty for Buyer A, it would not benefit from reducing uncertainty for Buyer B. Thus, it should be expected intuitively that the higher the fraction of the buyer population whose ideal products are very close to the firm's actual product location, the higher the incentive for the firm to invest and reduce uncertainty; these investments reduce uncertainty for the entire buyer population, and the higher the fraction of this population that would buy the product as a result, the greater the incentive to make these investments.

4. Using Consumer Reviews

4.1. Consumer Reviews as Potential Signals of Buyer Homogeneity

We have shown that if firms can target their product offerings to locations in the product space with concentrated consumer preferences, they may then use various signals to gauge the size of such buyer concentrations and decide on subsequent investments that are designed to reduce buyer uncertainty. Reactions of early users, *beta-testers*, and product experts can often be good indicators that a product has indeed hit a popular sweet spot, but it is often hard to untangle whether a positive reaction comes from consumers' favorable reactions to the product's quality or from consumers' reactions to the product's perfect fit with their preferences. In the first case it the firm should stress the product's high quality if it makes any investments in reducing consumers' uncertainty, while in the second case the firm should stress reducing uncertainty about the product's exact location in its attribute space.

It would be extremely beneficial if the ubiquitous star-reviews system could be used as the aforementioned signal. If so, the discussion above would indicate that firms would probably need both the mean and the variance of buyer reviews. To test this idea, let us consider how the concentration s would affect the mean and variance of buyer reviews, if a representative sample of those buyers who experienced the product, submitted their reviews. We employ a standard literature assumption that buyers publish a rating $r(x) = v - x$ that includes both the product quality component v, and the distance of the product from their ideal location preference [49].

We can show the following Theorem:

Theorem 2 (Information Contained in Buyer Reviews): *The mean of buyer reviews increases with s. The variance of buyer reviews decreases with s, for $s > K/(K+1)$.*

The proof is provided in the Appendix. The intuition behind Theorem 2 is better understood by employing Figure 3, which depicts the impact of s on the mean and variance of product reviews. On the left graph of Figure 3, we see that the mean review always increases with s, ranging from

$(p+v)/2$ for $s=0$, to v for $s=1$. This is expected because, as we increase s, we are, in effect, replacing buyers who review the product and assign the value $v-x$, where x is their distance to the product, with buyers who review the product with value v. For $s=0$ the market is composed only of the heterogeneous buyer population. These buyers form a uniform density from distance zero all the way to distance $v-p-\alpha$ where their density starts to drop until it reaches $v-p+\alpha$, where it becomes zero (that is the location of the most distant consumer who will actually buy the product). The average fit cost (or distance penalty) of these buyers is thus $(v-p)/2$ and the average review score is $v-\frac{v-p}{2}=\frac{v+p}{2}$. For $s=1$ the market is composed only of the homogeneous buyer population who all rate the product at the perfect score v.

INSERT FIGURE 3 HERE

On the right graph of Figure 3, we see that as we increase s from zero, review variance initially increases by up to 25%. This is expected because, as we initially increase s, we are adding buyers who rate the product at v, and thus differ from the "average buyer" who rates the product lower at $(v+p)/2$. However, as more such buyers enter the market, the average review increases (as shown on the left graph), so that by the point at which $s=K/(K+1)$ these new buyers are closer to the mean than the "average buyers" whose number decreases as $1-s$ decreases. Thus, after a small initial increase in variance, the buyers that enter the market as we increase s contribute to the buyer reviews being increasingly homogeneous as well as increasingly favorable, so that review variance reduces. Review variance reaches zero in the extreme case where $s=1$, because in this case the entire market is concentrated, with all consumers preferring products at the same location in the product attribute space. Also note that only if $s>4K/(4K+1)$ is the relationship between variance and s one to one. For any $s<4K/(4K+1)$, for a given variance of reviews there are two potential concentration values s that can produce this same variance.

There is some empirical evidence that is consistent with our findings, including **Theorem 2**. Hu et al. [30] found that, after correcting for quality, music sampling leads to a subsequent increase in sales of the CD when the review variance for the CD is low, i.e., when there is an indication that a large group of listeners likes this music. Finally, our own empirical findings indicate that vendors whose offerings' initial reviews suggest that the products are close to market sweet spots are more likely to invest in reducing consumers' uncertainty. More specifically, PC-game developers that offer games with low review variance are more likely to develop a playable demo version of their game. These empirical results are preliminary and have not yet been published.

4.2. Definition of Expanded Game

Theorem 2 is important because it shows that numerically expressed product reviews include information about the concentration of buyer preferences, even without textual analyses. Theorem 2 thus provides justification for expanding our model so that firms are allowed to use the reviews of initial product buyers to decide whether or not to disclose.

The surprising result, and the topic of this Section, is that consumer reviews can indeed be used to assess the concentration s of buyers' preferences and that, independently of how buyers process other buyers' reviews, firms should pay more attention to review variances than to review means when deciding whether or not to make investments to reduce buyers' uncertainty. The finding is important because the widespread availability of buyer reviews makes it relatively easy for firms to take them into account when deciding information disclosure investments. The finding is also novel, as there is very little published research on the role of variance in predicting behavior when consumers focus on taste-related attributes; we are aware only of our own published research [13,14].

Further, the above results are not obvious or widely understood. The literature has established the predominance of the mean of buyer reviews for the disclosure of quality-related product attributes. This is because a seller can learn what its customers really think about its quality (and consequently whether its quality is worth advertising) by observing the average of the review scores that it receives. Consequently, one might naively expect that the mean of buyer reviews would also drive the disclosure of taste-related attributes. However, in the case of taste-related attributes, the variance of the evaluations is more important than the average. The reason for this is that the mean of buyer reviews is greatly affected by the quality of the product, i.e., by the product's performance on dimensions on which buyers agree on how to compare. The mean of reviews reveals little about whether or not the firm has succeeded to deliver a product that matches the preferences of a large group of consumers on dimensions on which they tend to disagree. The latter piece of information is easier to obtain by observing the variance of reviews that previous customers have published.

The analysis must proceed carefully, because in the presence of product reviews, customer behavior also changes. Indeed, if buyer evaluations are available to firms contemplating disclosure investments, then they are also available to buyers contemplating purchasing decisions. We thus frame the question that is the topic of this Section, as follows:

If consumer reviews are available both to buyers who consider purchasing the product, and to sellers who consider a disclosure investment about the product's taste-related parameters, then can the sellers use the reviews to guide their investment decisions? If so, what is more important, the mean or the variance of the reviews?

To answer this question we set up a two-period game, where Period 1 is very similar to the game we have already solved in Section 3. Specifically, in Period 1, a few early buyers, representative of the overall population, enter the market, and some of those who purchase the product publish a fair and unbiased review[10]. They do so only once, and only after they have experienced the product. The mean and the variance of these reviews become available to the firm. Then, in Period 2, the firm may choose to invest in information disclosure and the rest of the buyers enter the market, observe previous reviews and benefit from any investments the firm may have made in reducing uncertainty, and then make their purchase decisions. This formulation extends the game that we studied in Section 3 by allowing both the firm and the buyers to make use of the reviews that initial buyers post.

We further relax previous assumptions by accepting that in addition to s (the amount by which buyer preferences are concentrated at some point of the circle) not being known beforehand, the firm and the buyers also do not know exactly how much the buyers value the firm's level of quality v, before consuming it. Relaxing this assumption is important because it leads us to the conclusion that

[10] These assumptions may be violated in practice. The average consumer review is known to be biased, as consumers who are strongly positive about the product are more likely to review it, followed by consumers with strongly negative opinions, and comparatively fewer reviews coming from buyers with average opinions [43]. Further it has been shown that early in a products' life reviews tend to be more positive than the reviews that come later [37], and that buyers are more likely to review products of low and high popularity, rather than those of average popularity [18]. There are methods that correct these biases [43]. Finally, the average consumer is also known to be affected by product price when reviewing products [36], but this bias would merely affect the magnitude of coefficient of the mean of the reviews and would not qualitatively affect our results. Known biases that affect the impact of reviews to other consumers [25,23] are outside the scope of our model.

the mean of buyer reviews primarily captures information about the true value of v, and provides less information about the true size of preferences concentration s. This increases the importance of the variance as an estimator for s.

The timing of the game is as follows:

PERIOD 1:

Available information:

- s is uniform in $[s_1, s_2]$
- v is uniform in $[v_1, v_2]$ with expectation β

Players' moves:

1. The Firm chooses location and price and enters the market
2. A fraction $r \ll 1$ of buyers enter the market and those who buy the product publish a rating.

PERIOD 2:

Available information:

- the mean and variance of the reviews from Period 1
- the firm's updated beliefs on s and v

Players' moves:

3. The firm decides whether or not to disclose its exact location on the product attribute circle
4. The remaining $1 - r$ of buyers enter the market and make their purchase decisions

4.3. Game Solution

We are primarily interested on the firm's Period 2 decision to disclose. Instead of covering all possible firm strategies in Period 2, we will only explore those that are consistent with the firm having located its product exactly at the concentration of consumer preferences in Period 1. In Lemma 2 in the Appendix, we show for the base model that the firm will always choose this location, and it is straightforward to extend the result for the two-period model, as well. Furthermore, in order to understand how the firm uses the mean and variance of buyer reviews, we must first understand what information is contained within these two measures. This information depends on how buyers in Period 1 review the firm's product, which in turn depends on which buyers purchase the product, and what utility they receive from its consumption.

In Period 1, buyers from the heterogeneous group buy the product if the expected utility is positive and buyers from the homogeneous group buy the product with a probability that increases with the expected product utility. It is easy to show that if we substitute the firm's quality level v with its expected value β, buyer purchase decisions are the same as in the case we studied in Section 3. Buyer reviews reflect how buyers actually experience product quality v and how far the product's location really is from their ideal; reviews are based on consumers' realized rather than expected utilities. Given firm price p we can calculate the mean and variance of the reviews as follows:

$$mean = \frac{s \cdot g(\beta - p)}{s \cdot g(\beta - p) + 2(1-s)D} \cdot v + \frac{2(1-s)D}{s \cdot g(\beta - p) + 2(1-s)D}\left(v - \frac{D}{2}\right) \tag{2}$$

and

$$var = \frac{s \cdot g(\beta - p)}{s \cdot g(\beta - p) + 2(1-s)D} \cdot (v - mean)^2 + \frac{2(1-s)D}{s \cdot g(\beta - p) + 2(1-s)D} \int_0^D \frac{1}{D}(v - x - mean)^2 dx \tag{3}$$

Where β is the a-priori expected value of v, and D is the demand of the heterogeneous group on one side of the firm which can be shown to be $D = \beta - p$.

The above expressions simplify to:

$$mean = \frac{K(1-s)(p + 2v - \beta) + s \cdot v}{2K(1-s) + s} \tag{4}$$

and

$$var = \frac{K(K(1-s) + 2s)(1-s)(p-\beta)^2}{3(2K(1-s) + s)^2} \tag{5}$$

Note that the mean of reviews includes information both on how buyers perceive the firm's quality v, and on how concentrated buyer preferences are, s. In contrast, the variance of reviews includes only information about s.

As can be seen in Figure 4, if review variance does not exceed $(\beta - p)^2/12$, then variance information uniquely determines s. In that case, knowing s, review mean information suffices to also ascertain v. However, if review variance exceeds $(\beta - p)^2/12$, then variance information gives rise to two possible values for s and consequently two possible values for v.[11]

[11] As can be seen in Figure 4, the two potential values for s can be substantially different (var_B is associated with both s_{B1} and s_{B2}), giving rise to substantially different values for v. If the firm has independent information on v and can rule out one of the two values, then it can exactly determine both v and s. One such case could emerge if the prior $[s_1, s_2]$ about s excludes one of the two values. In fact, it is easy to extend the

INSERT FIGURE 4 HERE

Buyers care about product quality v because it determines their utility – see Equation (1) – which determines whether or not they purchase the firm's product. A fully rational buyer who has the means and the time required to perform the necessary computations would want to know both the mean and the variance of product reviews. Depending on whether or not the observed review variance exceeds $(\beta - p)^2/12$, the buyer may either exactly determine product quality v, or obtain two possible values for v, based on which they can calculate expected product quality, given their priors. A buyer who does not have the means or time to perform the above computation may use some other heuristic to derive an estimate for v. Surprisingly, as we show below, the seller's decision to disclose does not depend on the mean of the reviews, but instead it depends on the variance of the reviews in a manner that is independent of how buyers estimate v, or more generally, independent of what conclusions buyers draw from observing previous buyers' reviews.

If review variance is less than $(\beta - p)^2/12$, the firm can exactly derive s (and hence also v) and it will disclose if the profit under disclosure $p \cdot (s \cdot g(v - p) + 2(1 - s)D) - c$ exceeds the profit when the firm does not disclose $p \cdot (s \cdot g(v - p - 2\alpha/3) + 2(1 - s)D)$. Taking the difference of the two expressions yields the maximum disclosure cost that the seller would incur:

$$c < \frac{2p \cdot s \cdot \alpha}{3K} \tag{6}$$

In this case, the firm does not care about the mean of buyer reviews and the incentive to disclose increases with s, and thus decreases with review variance. For example in Figure 4, as var_A increases, s_A decreases. Also, note that no matter how buyers estimate v from the reviews, taking the difference removes it from Equation (6).

If review variance is greater than $(\beta - p)^2/12$, the firm calculates that there are two values s_1 and s_2 for s that are consistent with the observed review variance. If the firm has uniform priors for v and s, as we assumed, then it is easy to show that the firm should assign equal probabilities to s_1 and s_2. If the firm discloses, expected profit is

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model and allow firms to use additional information that may have on v and s. We expand on this point below, and explain that such extensions do not qualitatively change our results and managerial recommendations.

$$\frac{1}{2}p(s_1 \cdot g(\beta - p) + 2(1 - s_1)D) + \frac{1}{2}p(s_2 \cdot g(\beta - p) + 2(1 - s_2)D) - c$$

and if the firm does not disclose, expected profit is

$$\frac{1}{2}\left(s_1 \cdot g\left(\beta - p - \frac{2\alpha}{3}\right) + 2(1 - s_1)D\right) + \frac{1}{2}\left(s_2 \cdot g\left(\beta - p - \frac{2\alpha}{3}\right) + 2(1 - s_2)D\right).$$

where, again, β is the a-priori expected value of v, and $D = \beta - p$. Taking the difference, we find the maximum disclosure cost that the seller would incur:

$$c < \frac{p(s_1+s_2)\alpha}{3K}. \tag{7}$$

Similarly to the previous case, the firm does not care about how buyers estimate v from previous reviews when deciding on whether or not it should disclose information about its product's position in the attribute space. We can also accommodate non-uniform priors for v and s, in which case the firm would assign different probabilities o_1 and o_2 (depending on the priors) to s_1 and s_2, changing the above formula to $c < \frac{2p(o_1 s_1+o_2 s_2)\alpha}{3K}$. The incentive to disclose increases with the average of s_1 and s_2 (or with $o_1 s_1 + o_2 s_2$ in the case of arbitrary priors). However, as we can see on the left side of Figure 4, as var_B increases, the average of s_{B1} and s_{B2} does not change considerably and as can be seen on the right side of the figure, it may increase or it may decrease. We have thus shown the following:

Theorem 3 (Disclosure Driven by Consumer Reviews): *Let the incentives for the firm to disclose be measured by the disclosure investment cost that the firm is willing to incur. Then, independently of how buyers estimate firm quality v from previous reviews:*

- *The incentive for the firm to disclose taste-related information is independent of the mean of buyer reviews,*
- *If review variance is less than $(\beta - p)^2/12$, the incentive for the firm to disclose increases as review variance decreases*
- *If review variance exceeds $(\beta - p)^2/12$, the incentive for the firm to disclose falls discontinuously and can increase or decrease as review variance decreases*

On the right graph of Figure 4, we plot the firm's disclosure incentive (the cost that the firm would be willing to incur to disclose its exact product position) as a function of the variance of buyer reviews. When review variance is below $(\beta - p)^2/12$ the disclosure incentive decreases with variance. At that threshold the incentive to disclose drops discontinuously, as a second –very low– buyer concentration is now also consistent with the observed variance, and the incentive is proportional to the average of the two potential buyer concentrations. Above $(\beta - p)^2/12$, we see that the disclosure incentive can increase or decrease with review variance.

Theorem 3 says that the disclosure incentive generally decreases with variance. When variance becomes too high (within 25% of its theoretical maximum) then the disclosure incentive drops even further. In a way, the managerial importance of the discontinuity at point $(\beta - p)^2/12$ is somewhat limited: firms do not care if buyers are aware of it (disclosure incentive is independent of how buyers process review information) and it does not alter the main managerial message that the incentive to disclose critical taste-related information to buyers is higher when review variance is low.[12]

Theorem 3 and Equations (6) and (7), which measure the incentive of the firm to reduce consumer uncertainty, reveal that firms respond differently to product information made available by third parties, compared to information made available in buyer reviews. Third-party information, such as product wikis maintained by aficionados, thorough reviews by product experts, or detailed product walk-throughs in online forums, all reduce product uncertainty for buyers, but carry little information about the distribution of consumer preferences, as such information is – compared to consumer reviews – relatively objective and unaffected by personal preferences [9] (in our model we assumed that initially the firm can only learn the size of the sweet spot, within a range the $[s_1, s_2]$). However, such information may enable the firm to *free ride*, i.e. to forgo information investments. This can be seen in Equations (6) and (7), where by decreasing α, the measure of residual product uncertainty, the firm only discloses if the disclosure cost is low. Intuitively, the firm has less to lose by not disclosing, if consumers already know much about its product from third-party sources. On the other hand, reviews by consumers that are expressed in a simple numerical score, collectively carry a lot more information about the distribution of consumer preferences [9] and the firm responds to them based on what the reviews reveal about the concentration of buyer preferences, as Theorem 3 explains.

[12] While we focus on the mean and variance of consumer reviews, we should also point out the number of reviews should also affect firms' incentives to invest. In our model, the market size is normalized to be of size one, but, in general, a larger number of reviews would be associated with more buyers in the market (perhaps with a mass-market product). Since in our model the disclosure cost is fixed, it would mean that the incentive for the firm to disclose would also increase on the number of reviews that it receives, in a given period of time.

4.4. Discussion and Limitations

We have shown that the variance of buyer reviews can help a firm decide whether or not to invest and reduce buyer uncertainty about its product's taste-related attributes. We also showed that a firm cannot use the mean of buyer reviews for this purpose, although the mean of reviews is widely accepted to inform *quality* disclosure decisions. Thus, review variance is to taste-related product attributes what review mean is to quality-related attributes: an indicator of the value that the firm can obtain from advertising that discloses critical information to consumers. Products with low review variance from initial buyers are likely to be close to concentrated sweet spots in the product space, so that the firm should actively inform consumers about its product's taste-related attributes.

Before a firm makes an investment decision based on the variance of buyer reviews, the firm should consider potential limitations to our work, which we discuss in the context of an example:

> *A project management application for smartphones organizes information in a way that is optimal to keep track of a small number of complex projects, but that is less suitable for the management of many disconnected simpler tasks — a design choice that is obviously taste-related. The firm decided to target its application for start-up founders on-the-go and it mainly advertises through online media that are popular with this market segment. The firm observes a low variance in the online reviews that its software receives, and wishes to decide if it should divert scarce resources to produce detailed videos that depict how its product manages different use cases.*

The first limitation of using review variances to guide disclosure decisions is caused by the fact that an investment that reduces buyer uncertainty about taste-related attributes is also likely to convey information about quality-related attributes. Therefore, the developer's videos are also likely to reveal information about quality aspects of the product, such as the designers' attention to typography and usability, or the degree of integration with popular cloud-based services. The developer must thus also pay attention to the mean of the reviews as well as the variance when planning a strategy for information disclosure. Reviews with a low mean can indicate that the product has a quality problem, and the firm should first improve quality before attempting to encourage adoption. A very low mean and a very low variance together may suggest that everyone agrees that the product is simply bad.

Disclosing information about quality can kill the product's chances in the market, as buyers form negative opinions that are likely to persist, even if the developer improves the software in the future. So with low review mean, even if variance is also very low, the developer should not invest in information disclosure. This is compatible with the intuition in [14] where variance was considered important, but the article's heuristic was to focus on the strength of the top decile of reviews.

Additionally, if the reviews include consumer comments, then the developer of the product management application should actually read the reviews! Regardless of what the review variance is, if the reviews consistently express surprise at how well the product fits the needs of start-up firms, then either (i) the product's attributes are not yet well understood by its target market or (ii) the product itself is not well known. Either would suggest a greater need for advertising. The recommendation that decision makers should actually read their firm's reviews was convincingly made by Pavlou and Dimoka [45].

Finally, our model only considers single-purchases of a durable product with a fixed design. At least two other cases are worth studying:

- Expensive fast moving consumer goods may rely more on trial as a mechanism for providing consumers with information on taste-based attributes. If the consumer is only going to buy one camera every five years, then it needs to be the right camera the first time. If the same consumer is going to drink four beers a week, or more than 1,000 beers in the same five year period, there are more than 1,000 opportunities to sample a new beer without making a year-year commitment. Intuitively, it would appear that the importance of unambiguously reducing consumer uncertainty should be reduced. However, the problem may be more complex. For example, a recent article by Li et al. [38] found that, for repeat purchase products, online reviews may encourage switching and lead to increased price competition.
- Many digital products are sold with subscriptions, or can offered online via Software as a Service; in these cases, customers have the option to stay with the product and continue to pay for it, or to switch to another product after they have experience with the first product. This is an intermediate case. Switching is still possible, as with the beer example, but switching is certainly not free if files will need to be converted to new formats for new

software, or if a large number of users will need to be retrained. The role of review variance in this context is not immediately clear, especially when many reviews describe previous versions of a product which may keep improving over time, as is the usual case with software, among other product categories.

In summary, it is in the context of a single-purchase product and especially a new market introduction, that our model is most useful, and within this context:

- The low variance of product reviews is a more useful indicator of the need to disclose taste-related product attributes, than the mean of product reviews. We believe that it is most useful when variance is very low and co-occurs with a high review mean. This combination strongly supports the decision to reduce consumers' uncertainty by disclosing information about taste-related product attributes.
- Low variance alone is less useful when the mean of reviews is also very low, suggesting widespread agreement that product quality is low. In that case, disclosure investments may in fact reveal low product quality to consumers and destroy the product's future prospects. In a different context, Abraham Lincoln said, "Better to remain silent and be thought a fool than to speak out and remove all doubt".
- Any additional information, such as the content of buyer comments, that helps explain the source of variance in a product's reviews, should also be considered, since the concentration of buyer preferences is never the sole driver of variance in reviews.

5. Conclusions and Future Work

This article showed that firms should account for the heterogeneity or homogeneity of consumer preferences when making investments that are designed to reduce consumers' uncertainty about their products. If a firm believes that its product is offered in a sweet spot — in a part of the product space with a large concentration of buyers with the same preferences — then investments in information disclosure are highly desirable. We also explained that a firm whose product receives buyer reviews with low variance should view this as a signal that it has hit a sweet spot in the product attribute space, and that it is likely to benefit greatly from investing in information disclosure about to its taste-related attributes. We showed that the mean of buyer reviews is not as informative as the variance, because it mostly caries information about the product's quality attributes rather than information about its position in the attribute space. The ubiquity of buyer reviews today and consumers' growing reliance upon acquiring information before purchase make our recommendations easy to follow, and managerially important. Finally, our results' applicability is further improved by the fact that they are independent of the way by which consumers estimate product quality from previous buyers' reviews.

There are many possible extensions for this line of research. An interesting extension would be to use information about the structure of the product space, embedded within consumer reviews, to inform not only information investment decisions, but also decisions regarding how many products to offer and also if some of these products should allow for customizations that would cover a range, rather than a spot in the product space [20]. The prospect of studying the actual disclosures more closely is also appealing. Ideally we would like to be able to also prescribe the kind of disclosure investment that would be more appropriate for each firm, given the structure of published consumer reviews.

Detailed empirical and experimental investigation is also required to verify the applicability of the article's theoretical recommendations. Investments could be observed in any of the forms that we discussed (from playable game demos of computer games, to the use of technology-enabled informative advertising) and causally linked to the mean and especially the variance of consumer ratings. Our own preliminary results in the PC-game market appear highly promising.

We believe that the line of research that uses higher moments of the ratings distribution to improve managerial decisions will prove to be highly fruitful. Learning to interpret as much as possible of the information embedded in buyer reviews will help firms to improve their decisions regarding investment in reducing consumer uncertainty, as this article has argued. It should also improve decisions on other competitive actions such as potential product line extension opportunities, product customization strategies, and prospects for price discrimination. Consequently, the firms that do a better job than their competitors in extracting useful and actionable information from higher moments of consumer reviews will gain a competitive edge.

The information in buyer review should be used far more fully than it is today, and requires far more analysis than has been completed to date. Indeed, it is still very much an open research question as to what information is encoded in the mean, variance, skewness and curtosis of the distribution of buyer reviews, and under what conditions.

The increasing availability of ratings information, combined with the increased importance of the kind of managerial decisions that ratings information can potentially support, virtually guarantee that these questions will continue to attract interest among members of our research community.

Appendix

Summary of Notations

s:	Proportion of buyers that share a unique ideal location in the product space. The
s':	In the base model, s' is the firm's estimate for s after it enters the market: $s' = s + \varepsilon$, with ε uniformly distributed in $[-\delta, \delta]$
v:	Product quality (i.e., the perception of product quality by the buyers)
p:	Product price
$u(x)$:	Buyer utility $u(x) = v - p - x$, where x is the distance between the buyer's ideal product location and the actual location of the product purchased
d:	Firm's actual product location. If the firm does not disclose its location, each buyer receives a signal $z = d + \varphi$ about d, with φ uniformly distributed in $[-a, a]$
α:	A measure of uncertainty about d
$g(\cdot)$:	Probability that a buyer in the homogenous segment will purchase the product, as a function of expected utility. The function is linear with $g(0) = 0$ and $g(K) = 1$
K:	Constants that controls the steepness of the demand function $g(\cdot)$
$r(x)$:	Buyer's rating for the product. $r(x) = v - x$, where x is the distance used in $u(x)$
β:	The prior that buyers and the firm have about v
D:	The demand of the heterogeneous group on one side of the firm which can be shown to be $D = v - p$ in the base model, and $D = \beta - p$ in the two-period model

Lemma 1: *Given product price p, the demand generated by the heterogeneous group of buyers is given by:* $2(1-s)(v-p)$

Proof: Due to symmetry, it suffices to show that the demand generated by the heterogeneous group of buyers on one side of the seller is given by $(1-s)(v-p)$. The distance x_1 from the product of the furthermost consumer that will purchase the product with certainty is given by $v - p - a - x_1 = 0 \leftrightarrow$

$x_1 = v - p - a$. This is because at this location, even the buyer who, due to uncertainty, has the most pessimistic view possible about the product, would still gain positive utility from purchasing it. It is easy to show that beyond distance x_1 the probability that buyers will purchase the product decreases linearly until it reaches zero at distance x_2. The distance x_2 is the distance from the product of the furthermost buyer who has a nonzero probability of purchasing the product. This distance is given by $v - p + a - x_2 = 0 \leftrightarrow x_2 = v - p + a$. This is because at this location, even the buyer who, due to uncertainty, has the most optimistic view possible about the product, would still gain no utility from purchasing it. Thus, the demand generated on one side is given by $(1-s)\left(v - p - a + \int_0^{2a} \frac{x}{2a} dx\right) = (1-s)(v-p)$.

Lemma 2: *For a fixed price p, the firm will always expect to earn greater profit when it exactly targets the concentration of buyer preferences*

Proof: The heterogeneous group of buyers is uniformly distributed around the circle and, due to symmetry, will always generate the same demand for a fixed price, regardless of the product's position. Thus, it suffices to show that for a fixed price p the homogeneous group of size s will generate greater demand when it is exactly targeted with the product offering. This is equivalent to showing that when the product exactly targets the homogeneous buyers, their fit costs are minimized.

We will use the fact that if a buyer receives a signal z' for the location of the product, then it should assign a uniform probability to the real z being any point in the $[z' - a, z' + a]$ range. The proof follows exactly the logic of presented below as part of the proof of Theorem 1.

Next we calculate the expected fit cost of a buyer who believes that the firm is likely to be located in a range $[z' - a, z' + a]$ with equal probability, and whose own ideal product is at distance $x < a$ from z'. This fit cost is given by $\varphi(x) = \int_0^{a-x} \frac{y}{2a} dy + \int_0^{a+x} \frac{y}{2a} dy = \frac{a^2+x^2}{2a}$.

Finally, the expected fit cost for a buyer from the homogeneous group when the firm is offering a product that is y units away from their ideal location, is given by: $\frac{a-y}{2a} \int_0^{a-y} \frac{\varphi(x)}{a-y} dx + \frac{a}{2a} \int_0^{a} \frac{\varphi(x)}{a} dx + \frac{y}{2a}\left(a + \frac{y}{2}\right) = \frac{8a^3+6ay^2-y^3}{12a^2}$ which is easy to show that it is increasing in x, if $x < a$. The minimum fit cost is thus obtained at $x = 0$ and is given by $2a/3$. Finally, if $x > a$ then it is easy to show that the expected fit cost is always greater than a. Thus, exactly as we claimed, the firm minimizes the fit costs of the homogeneous group when $x = 0$, i.e., when it exactly targets their product at them.

Proof of Theorem 1: Making use of Lemmata 1 and 2, we prove Theorem 1. We first prove that the probability that the firm will invest in information disclosure increases with s. We begin by showing that if a firm receives signal s' for the size of s, then it should assign a uniform probability to the real s being any point in the $[s' - \delta,\ s' + \delta]$ range.

From Bayes Theorem: $h_S(s|S' = s') = h_{S'}(s'|S = s) \cdot h_S(s)/h_{S'}(s')$. But it is the case that $h_{S'}(s') = \int_{s'-\delta}^{s'-\delta} h_S(x) \cdot h_{S'}(s'|S = x)dx$. Note that $h_S(x)$ is the same everywhere, so we can set it to the constant $h_S(s)$. Also note that $h_{S'}(s'|S = x) = 1/2\delta$. Thus, we get simply $h_{S'}(s') = h_S(s) \rightarrow h_S(s|S' = s') = h_{S'}(s'|S = s)$, so that s can equiprobably be any point in the $[s' - \delta,\ s' + \delta]$ range.

When the firm decides on disclosure, price p has already been decided in the previous stage. Thus, using Lemma 1, the firm expected profit if it decides to disclose is given by:

$$E(\Pi_{disclosure}) = -c + \int_{s'-\delta}^{s'+\delta} \frac{1}{2\delta} p(x \cdot g(v - p) + 2(1 - x)(v - p))dx \tag{8}$$

and if it decides not to disclose:

$$E(\Pi_{Nondisclosure}) = \int_{s'-\delta}^{s'+\delta} \frac{1}{2\delta} p(x \cdot g(v - p - 2a/3) + 2(1 - x)(v - p))dx \tag{9}$$

with $2a/3$ the expected fit cost of buyers in the homogenous segment, as was derived in Lemma 1.

The firm discloses as long as $\Pi_{disclosure} > \Pi_{nondisclosure}$ which yields.

$$s' > \frac{3c \cdot K}{2p \cdot a} \tag{10}$$

INSERT FIGURE 5 HERE

As s increases the probability that the signal $s' = s + \varepsilon$ will exceed $3c \cdot K/(2p \cdot a)$ can only increase. Figure 5 depicts the relationship between disclosure probability and concentration of preferences s, assuming that ε is uniformly distributed in $[-\delta, \delta]$

We now turn to the first stage of the game to show that, as the second part of Theorem 1 claims, the firm will always target its product at the concentration of buyer preferences. Let that location be denoted by P. The second part of Theorem 1 follows from Lemma 2 because a firm can always improve profitability by moving the product at P. For example if a firm is offering a product that is some distance away from P and subsequently maximizes profit by offering price p' then, by Lemma 2, it can increase profitability by offering the product at P and subsequently charging p'. If some other price p'' is optimal for a product at P, then profitability increases even further.

Proof of Theorem 2: The average and variance of buyer reviews depends on product price, since price determines buyer utility and thus determines the mix of buyers that purchase the product.

As Lemma 2 states the firm places its product exactly at the point of concentration of consumer preferences. We can then use Lemma 1 to show that the review mean and variance are given by

$$mean = \frac{s \cdot g(v-p)}{s \cdot g(v-p) + 2(1-s)D} \cdot v + \frac{2(1-s)D}{s \cdot g(v-p) + 2(1-s)D}\left(v - \frac{D}{2}\right) \tag{11}$$

and

$$var = \frac{s \cdot g(v-p)}{s \cdot g(v-p) + 2(1-s)D} \cdot (v - mean)^2 + \frac{2(1-s)D}{s \cdot g(v-p) + 2(1-s)D}\int_0^D \frac{1}{D}(v - x - mean)^2 dx \tag{12}$$

where $D = v - p$.

The first part of Theorem 2 is shown by differentiating Equation (11) with respect to s and also using the fact (proof omitted) that the derivative of the optimal price with respect to v is non-negative. The second part of is shown by differentiating Equation (12) with respect to v, keeping in mind that the firm's chosen price is not affected by the realization of s, which is not known at the pricing stage. It is easy to show that Equation (12) has a maximum at point $K(K+1)$ and that its shape is as shown on the right hand graph of Figure 3.

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FIGURES & TABLES

Product	Example of taste-related attribute	Example of an information disclosure investment
On-demand TV-series	Involved story-line	Analytics-driven customized preview depending on target's preferences in other shows
Music album	Extensive use of syncopated beats	Free sample
Book	Writing style	Free first chapter
PC-game	Shape of learning curve	Downloadable playable demo
Mobile phone	Look and feel of the operating system	HTML-5 page that emulates operating system on other phones
Refrigerator	Placement of deli-bin shelf	Magazine advertisement with QR-code that points to 3D product tour on reader's mobile phone
Prescription glasses	Design	Virtual try-on

Table 1: *Examples of information disclosure investments*

Article	Explores	Implication for disclosure investments
Jovanovic [32]	Quality	Higher quality products should invest more
Chen & Xie [10]	Various parameters	Products facing taste-driven consumers should decrease ad spending in response to reviews
Clemons et al. [17]	Hyperdifferentiation (structure of product space)	Information investments mostly affect buyers for whom the product is "close to ideal"
Clemons et al. [14]	Differentiation (review variance)	Hyperdifferentiated products benefit more from the reduced need to invest in informational campaigns
Chevalier & Mayzlin [11]	Quality (avg. review)	Higher quality products should invest more
Dellarocas et al. [19]	Quality (avg. review)	Higher quality products should invest more
Chen & Xie [9]	Product cost and review informativeness	Low cost products should invest more, especially when there are more expert users
Duan et al. [21]	Quality (avg. review)	Higher quality products should invest more
Brynjolfsson [7]	Long-tail (sales rank)	Long-tail products should invest more
Sun [49]	Differentiation (review variance)	High variance products should invest more iff their quality is low
Anderson & Magruder [4]	Quality (avg. review)	Higher quality products should invest more
Current article	Consumer homogeneity (review variance)	Low variance products should invest more

Table 2: *Key relevant literature*

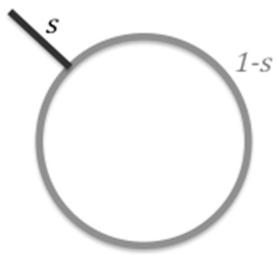

Figure 1: *A circular market where s% of buyers share the same preference*

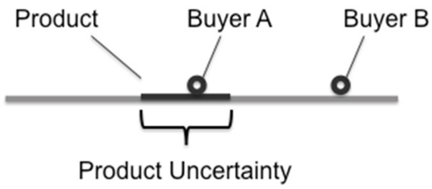

Figure 2: *Two interesting cases: Uncertainty about actual product location spans Buyer A's most preferable product but does not span Buyer B's most preferable product.*

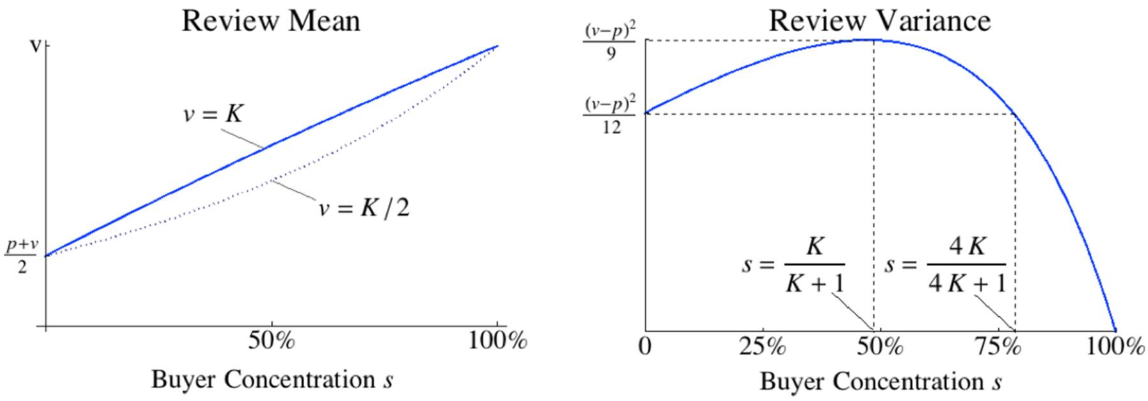

Figure 3: *The impact of buyer concentration on review mean (left) and variance (right).*

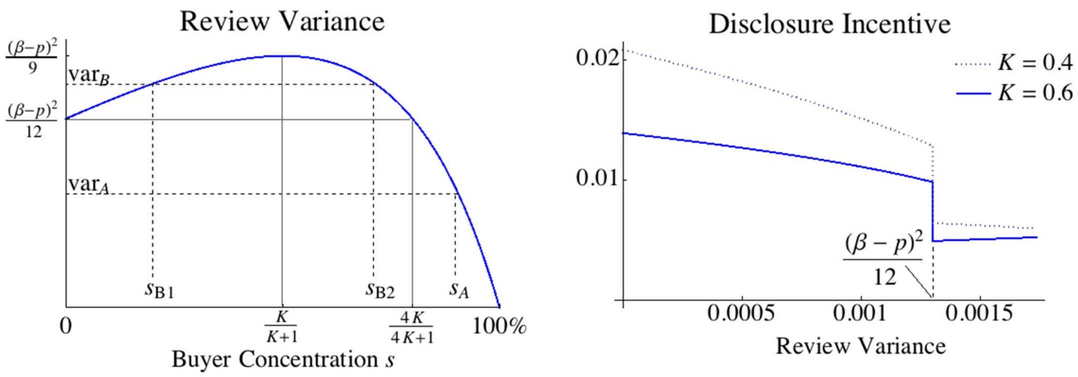

Figure 4: ***Left:*** *Review variance as a function of buyer concentration. The graph is similar to* Figure 3, *where v has been substituted by its expected value β.* ***Right:*** *Disclosure incentive (i.e. maximum disclosure cost that the firm is willing to incur) as a function of review variance for two different values for the demand function parameter K*

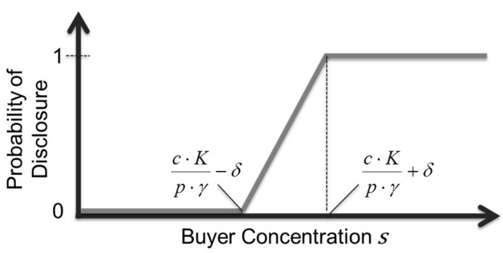

Figure 5: *Probability of information disclosure, as a function of buyer concentration.* $\gamma = 2a/3$