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An Application of a Game-Theory Model Considering Loyal Customers and the Role of Rating Variances in Ebusiness Decision-Making Process

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Keywords

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Customer ratings
Variance
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Abstract.

This study investigates how variance and average rating as a combination factor play different roles in the decision-making process by constructing a game-theory model. Results show that a higher variance is incorporated with low quality in frequently-purchased products and unreliable quality in infrequently-purchased products when average product ratings are high. A higher variance has a stronger influence on consumer demand for frequently-purchased products than on infrequently-purchased products when both products receive similarly high average ratings. There is a counter-effect when both products receive similarly low average ratings. The study demonstrates how consumers are keen to make a risky purchase decision preferring low quality products with a higher variance when making decision on two products that are substitutes for each other with the same average rating. This study will assist managers in developing marketing communication strategies to reduce pre-purchase buyers' feelings of uncertainty.

1. Introduction

This study examines the informational role of the average rating and the variance of the ratings as a combination factor in the decision-making process (DMP) of both seller and consumers by constructing a game-theory model (GTM). The study indicates that the informational role of the effects of the combination of the average rating and the variance (CAV) changes and its influenced by various factors. The factors influencing the role of the CAV have been differentiated in two consequences; a loyal customer's (LC) individual preference effect and a product category effect. The results show that CAV play an important informational role to reduce seller's and consumers' feelings of uncertainty in the DMP when two factors influence the role of the CAV.

Several prior and recent related studies examined the effect of online product ratings. The authors have applied theoretical and empirical analysis of the ratings and sales relationship. Cui, et al. [11] investigated the effect of average rating on video game and found its greater influence on the sales. The positive effect of average rating also found by Luca [30] on restaurant demand. Moe and Trusov [33] analyzed the effect of ratings on beauty products sales. They found the average ratings may impact directly on sales of the product, but the variance is not. However, the most interesting evaluation on rating is by Filieri [17] that the average consumer evaluation of a product's specific characteristics helps to understand the product's quality. Similarly, Clemons, et al. [9] is the first study to investigate the variance of ratings as an information source in the beer industry. The authors show that the variance can be explained as the signals of the different types of needs of customers towards the product. Sun [46] also the first study to investigate the informational role of average rating and variances as a combination factor on consumer demand by building GTM. The author shows that for products with a lower average rating, the variance shows that some consumers are still interested in products although the mismatch cost of the product is higher because consumers know well which product matched their taste. However, in her model, it is not easy to ascertain products' quality with higher variance, because a higher variance may increase or decrease product evaluations only depending on consumers' prior expectation of quality and mismatch cost, which can reduce profits. In addition, she found that a higher variance of ratings increases the demand for books with lower average ratings on amazon.com and barnesandnobel.com. Herrmann, et al. [22] constructed a model that examines the effect of the CAV on product price and consumer demand in a market with hybrid products. In their model, the products characterized by two attributes may cause variances: "a mismatch between consumer taste as an informed search attribute of the product, and the product's failure as experience attributes". The authors found that a higher variance, caused by the informed search attributes, indicates that some of the consumers love the products and others dislike them, resulting in a lower equilibrium demand and a higher equilibrium price. A higher variance caused by the experience attributes suggests an unreliable product, which is associated with a lower equilibrium price and lower equilibrium demand. Thus, the theoretical result of Herrmann, et al. [22] shows that a higher variance has a negative impact on sales. In addition, the authors considered that product experience attributes which are transformed into search attributes, requiring consumers to read all textual reviews. In real online environment, consumers aren't able to read thousands of reviews on the product right from the store, such as Amazon.com, and decide whether a product fits their needs for other product preferences.

The previous studies analyzed a dataset of book, movie, beer, etc., ratings. Those studies assume that the customers' ratings evaluations are depending on their personal taste. However, customers ratings consist of their individual behaviors (see Ganu, et al. [19]), and their satisfaction can be quality- or price-based according to their behaviors which leads loyalty (see Oliver [36]), and also customers' judgement evaluations on post-purchase are differing on the products according to customers buying frequency (see Best and Andreasen [4], Landon Jr [27]). Furthermore, customers with high loyalty are more likely to intend to dissociate the risk from their favorite brands through biased gathered experiential information processing (see Byun, et al. [6]), they tend to leave more reviews (ratings) on the product, and those generated reviews (both positive and negative) are becoming ever more critical to e-commerce. Thus, by the building GTM, this study indicates that the effect of the CAV in the DMP depending on the rater customers' individual behavior (price-loyal customers and quality-loyal customers; PLCs, and QLCs) and its effect varying according to the product categories (frequently-purchased products and infrequently-purchased products; FPPs, and IPPs) in the term of experience products. These types of product's ratings are an excellent way to get information about the product because its ratings reflect the opinions of customers' that have had more experience with a product. It may more effectively play an informational role in the DMP, to determine the majority of the later customers' preferences for the product and their characteristics. That allows consumers based on their preferences to compare themselves with previous customers of the product for deciding how the product would meet their needs without reading textual reviews and use it to determine a product's quality, whether the rating is high or low. Thus, the interaction of the CAV effect could be useful in reducing the risk in both sellers and consumers DMP when they rely on different behavioral LCs' product evaluations ratings. In turn, the sellers and the consumers' reliance strictly depend on the LCs' specific characteristics and product categories, as depicted in Figure 1. Finally, apart from previous studies, this study seeks to understand how the CAV and those ratings given by different behavioral LCs, plays different roles in the DMP, and the process through which this effect changes across product categories. And most important, we conceptualize that in terms of our model composition, the CAV becomes more valuable source of the information for examining the effect of LC ratings on market outcomes.

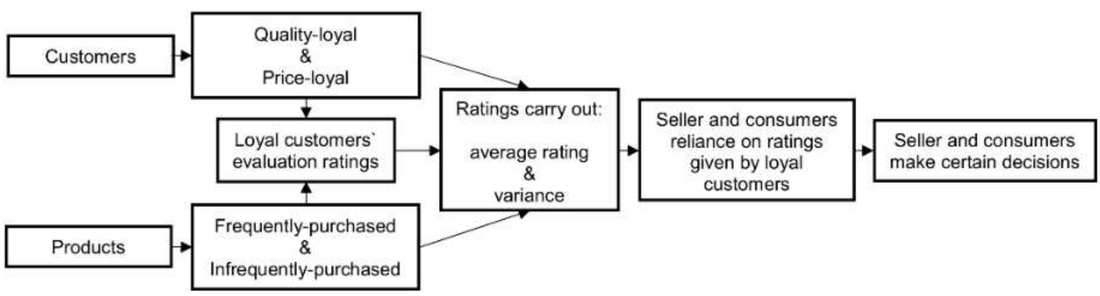


Figure 1: Conceptual framework.

2. Development of Game Theory Model

2.1. Loyal customers' rating behavior

Two important factors, customers' individual behaviors, and involved product category which have been described, influence to change the informational rule of the ratings in the DMP.

2.1.1. The influence of customers' individual behavior

According to Oliver [36]'s loyalty framework, perceivable qualities and features of a certain brand indicate that it is more advantageous and desirable than its other alternatives. Customers with loyalty to a brand have a belief in the highest quality offer from the brand. They only consider the quality of the product they buy repeatedly as very high quality if they satisfy with it (see Dickinson [14]). In this case, their satisfaction spreads into their rating evaluations on the product. However, the studies suggest that customers rating evaluation of the product vary according to their individual behaviors. For example, McAuley, et al. [32] and Engler, et al. [16] found that the words in reviews are describing customers' satisfaction on their individual behaviors. The words such as "quality" or "price" can be used as evaluative criteria of the customers' quality- or price-seeking behaviors (see Bell [3]). Ganu, et al. [19] show that each individual rating given by the customers consists of individual behaviors of them which correspond in the text reviews reported by them. Thus, a strong indication that satisfaction of the LC reflects the rating score baseline. Online ratings can therefore be interpreted as the function of the bias of the LCs' satisfaction with their individual behaviors. Consequently, rating submitter LCs are grouped into two categories according to customers' tendency to customer- and brand-loyalty concepts: price-sensitive LCs, named "price-loyal customer", PLCs and quality-sensitive LCs, named "quality-loyal customers", QLCs. The groups of QLCs and PLCs, are considered to be mutually exclusive.

QLCs' satisfaction judgments respect to the quality feature of the product increase average rates. For example, the quality feature of the laptop, "higher CPU speed", can satisfy all the customers. The variance of the rating given by raters becomes lower because their opinions do not vary about product quality features. Thereby, QLCs' rating judgments carry out with a lower variance and a higher average rating. Their rating judgments carry out with a higher variance and a lower average rating for the low-quality product if their taste match with certain characteristics of it (see Sun [46]).

However, PLCs rating behaviours varies considerably depending on their price-seeking behaviors. Smith and Brynjolfsson [44] show that customers do not always purchase products with the lowest offered price even they are price sensitive. Martins and Monroe [31] assess the transaction utility as reflecting the difference between the equitable price consumers expect to have to pay and the actual market price. Because, buyers absorb the price attribute with respect to the perceived value that may affect the perceived product quality (see Monroe [34], Shirai [43]). Thus, customers will be satisfied if actual performance exceeds or matches expectations, and customers will be dissatisfied if performance fails. This difference may positively affect LC behavior, giving them extra incentives to positively - or negatively - evaluate products which their rating evaluation carry out with a higher or a lower average rating. But the variance of ratings given by PLCs become higher. Because, price sensitivity is an individual difference, and different consumers behave differently when the current price increases or decreases (see Abdullah-Al-Mamun, et al. [1]) which causes considerable differentiated opinions between rater PLCs.

Since consumers use ratings given by prior customers to make informed purchasing decisions (see Lackermair, et al. [26], Von Helversen, et al. [49]), they may somehow incorporate higher risk and uncertainty into their DMP if they do not draw on LCs' ratings as an outcomes of the raters different behaviors, along with as raters satisfaction on product.

2.1.2. Impact of product category involved

Based on classic literature, customers complain more when they consume a product rarely and/or purchase infrequently, and complain less when they consume a product regularly and/or purchase frequently. Dimofte and Yalch [15] hypothesizes that "for infrequent consumers, high advertisement detail will lead to more favorable attitudes in the anticipatory condition; and for frequent consumers, high advertisement detail will lead to more favorable attitudes in the retrospective condition". Because products frequently consumed may actually make buyers more familiar with branded products (see Varela, et al. [47]). The effect of the familiarity presumably makes LCs vary in their rating evaluation. Therefore, we divided branded products into two categories according to LC buying frequency: FPPs and IPPs. The definition of purchasing frequency in this study is the level of experience of the customers on a product according to its category (durable and nondurable goods) that the products purchased frequently (nondurable goods) are known better by customers. Thus, the LCs of the FPP are certainly making a buying decision for the product's new version that they know it will satisfy their total needs; but the LCs of the IPP are not as experienced and are more likely to be disappointed with their choice for product's new version. The ratings of the IPP reflect more disappointed- and different opinions of the LCs. Contrary, opinions are less deferring for FPP. Therefore, the ratings evaluation of the LCs for IPP dramatically vary than FPP.

Further, consumers' motivation for learning about a product from online customer generated reviews can be measured by their participation in the product, and a higher risk connected to their DMP of IPP because information search is higher for IPP than for FPP (see Sarathy and Patro [41]). Which, there are highly consumer sensitivity to mismatch of the products when they make decisions on IPPs (TV sets, bicycles, cameras) than on FPPs (cosmetics, groceries). When consumers do not have enough knowledge of a new product there is a need to seek the information from other sources. They refer to information from other sources like friends, family, and also to the experience of previous customers through their rating evaluations. While the consumers of IPPs are more influenced by negative and positive arguments from early experience customers' ratings than consumers of FPPs (see Park and Lee [38]), they will reduce uncertainty and risk in the DMP if they keep in mind that different behavioral QLCs' and PLCs' product evaluation in ratings considerably vary towards products according to customers buying frequency.

2.1.3. Combination factors in the DMP of consumer

Given the rating distributions, we inferred the rule of ratings given by LCs in the DMP of consumer and likewise inferred combination of other factors that strictly influence the informational rule of the CAV in the consumer decision-making.

2.1.3.1. Evaluating decision-making for frequently-purchased products

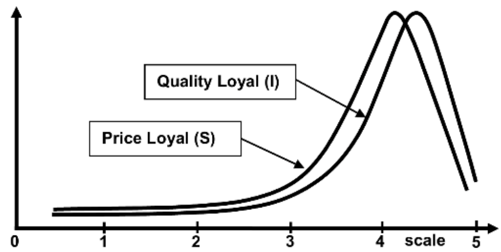


Figure 2: Illustration of the ratings distribution's probability for the customer groups in particular for high-quality FPP.

LCs post ratings after they complete a purchase transaction. These ratings and their distribution provide an important resource for later consumers looking to make informed purchase decisions. A higher average rating signals that a product is of high quality, increasing trust in those products (see Sun [46], Flanagin, et al. [18]). A broader ratings distribution (variance) reflects how the majority of customers' opinions honestly differ over the product (see Herrmann, et al. [22]). If product quality W is high H enough to satisfy both customer groups, then PLCs S and QLCs I of the same branded product submit higher ratings. Moreover, customers more familiar with the FPP F know that the product meets their needs and matches their taste, their product opinions differ less. Where customer product opinions differ less, the probability distribution of the ratings given by two separate groups is stated as (see Figure 2):

$$Pr(Z \mid W = H, S, F) = Pr(M = h, V = l) \text{ for } PLCs, \tag{2.1}$$

and

$$Pr(Z \mid W = H, I, F) = Pr(M = h, V = l) \text{ for } QLCs. \tag{2.2}$$

From Eq. (2.1) and (2.2), where M-average rating, V-variance, h-high, and l-low, in the case of existence of two customer groups, the ratings distribution's probability of can be formulated as follows:

$$Pr(Z \mid W{=}H){=}Pr(Z \mid W{=}H, S, F){+}Pr(Z \mid W{=}H, I, F){=}Pr(M{=}h, V{=}l). \tag{2.3}$$

Where $Z = N \cdot S + (1 - N) \cdot I$ is a distribution of ratings for the different customer groups, and $N = S/(S + I)$ is a proportion of customers that $N \in (0, 1)$; Eq. (2.3) and then deriving with respect to the portion of the customer groups which N is approximately equal to zero or one, $N \approx 0$ or $N \approx 1$, we obtain a lower variance and a higher average rating. A higher average rating serves as a reliable signal of a product's quality from the consumers' perspective, showing that product quality is high. A lower variance would simultaneously communicate to consumers that the product's quality is high because both customer groups like it. It also shows that the customers have similar opinions about the product which assert that the average rating is a true indicator of the quality of the product.

Figure 3: Illustration of the ratings distribution's probability for the customer groups in particular for low-quality FPP.

In the case of cosmetics or groceries, for example, which are purchased frequently, customers pay more attention to product quality (see Verbeke and Ward [48], Khraim [25]); assuming that if the product quality W is low L, QLCs I give lower ratings and leave the branded product for its higher-quality competing substitute. The products that meet the needs of PLCs S based on their income level (see Soba and Aydin [45]) may give higher ratings compared to quality to justify the price from their perspective. While price sensitivity varies from customer to customer, the variance of ratings given by PLCs becomes broader, where different income levels further exacerbate the mismatch between the product and customer needs. Then, the probability distribution of the ratings given by two groups is stated as (see Figure 3.):

$$Pr(Z \mid W = L, S, F) = Pr(M = h, V = h) \text{ for } PLCs, \tag{2.4}$$

and

$$Pr(Z \mid W = L, I, F) = Pr(M = l, V = l) \text{ for } QLCs. \tag{2.5}$$

From Eq. (2.4) and (2.5), in the case of existence of two customer groups, the ratings distribution's probability of can be formulated as follows:

$$Pr(Z \mid W{=}L){=}Pr(Z \mid W{=}L, S, F){+}Pr(Z \mid W{=}L, I, F){=}Pr(M{=}l, V{=}l). \tag{2.6}$$

Where $Z = N \cdot S + (1 - N) \cdot I$ is distribution of ratings for the different customer groups, and $N = S/(S + I)$, N is a proportion of customers that $N \in (0, 1)$; Eq. (2.6) and then deriving with respect to the portion of the customer groups which N is approximately equal to zero, $N \approx 0$, we obtain lower variance and a lower average rating. A lower average rating from the consumers' perspective shows that the quality of the product is low and might drive away potential consumers. A lower variance would simultaneously communicate to consumers that the product is of low quality because it has only disappointed QLCs. A lower variance shows that the customers' opinions are the same about the product which it signals that the average rating is a true indicator of the quality.

From Eq. (2.4) and (2.5), in the case of existence of two customer groups, the ratings distribution's probability of can be formulated as follows:

$$Pr(Z \mid W{=}L){=}Pr(Z \mid W{=}L, S, F) + Pr(Z \mid W{=}L, I, F){=}Pr(M{=}l, V{=}h). \tag{2.7}$$

Eq. (2.7) and then deriving with respect to the portion of the customer groups which N is not almost equal to zero, $N \not\approx 0$, we obtain a higher variance and a lower average rating. When the average rating is low, some customers still love the product. A higher variance shows that only a few well-matched QLCs like the product. Also, it shows that the customers' opinions are differ about the product which it signals that the average rating doesn't provide a true information about the product.

From Eq. (2.4) and (2.5), in the case of existence of two customer groups, the ratings distribution's probability of can be formulated as follows:

$$Pr(Z \mid W{=}L){=}Pr(Z \mid W{=}L, S, F) + Pr(Z \mid W{=}L, I, F){=}Pr(M{=}h, V{=}h). \quad (2.8)$$

Eq. (2.8) and then deriving with respect to the portion of the customer groups which N is approximately equal to one, $N \approx 1$, we obtain a higher variance and a higher average rating. A higher average rating attracts more consumers' to the product is of high quality. A higher variance indicates that the product is of low quality, even though it receives a higher average rating, as the product caters only to PLCs. It shows that the customers' opinions are varying about the product which it signals that the average rating is not a true indicator of the quality of the product.

2.1.3.2. Evaluating decision-making for infrequently-purchased products

Investigating LC's post-purchase evaluation of the product, we support the proposition that customer product evaluation in product ratings toward IPPs changes more dramatically than the effects of the FPP. When product quality W is high H, both PLCs S and QLCs I give higher ratings. If product type is infrequently-purchased, unfamiliar QLCs don't know if the product will meet their needs at all when compare to FPP. Thus, the variance of ratings given by QLCs will be narrow but a bit lager than for ratings given for FPP. Consequently, unfamiliar PLCs don't know if the product will meet their needs as equivalent purchases. This unfamiliarity with a product leads to a higher mismatch between the customer and product, and it couples with the price sensitivity of the PLCs to affects their ratings behaviors. Therefore, variance in the rating distribution would be much larger for the PLC group. Thus, the probability distribution of the ratings given by two separate groups for the IPP E is given as (see Figure 4):

$$Pr(Z \mid W = H, S, E) = Pr(M = h, V = h) \text{ for } PLCs, \quad (2.9)$$

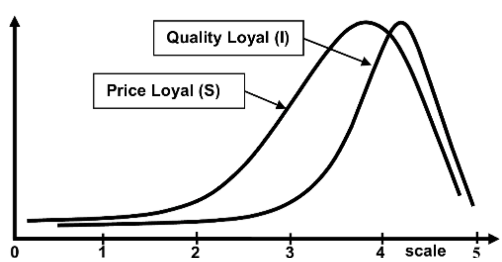


Figure 4: Illustration of the ratings distribution's probability for the customer groups in particular for high-quality IPP.

and

$$Pr(Z \mid W = H, I, E) = Pr(M = h, V = l) \text{ for } QLCs. \tag{2.10}$$

From Eq. (2.9) and (2.10), in the case of existence of two customer groups, the ratings distribution's probability of can be formulated as follows:

$$Pr(Z \mid W{=}H){=}Pr(Z \mid W{=}H, S, E){+}Pr(Z \mid W{=}H, I, E){=}Pr(M{=}h, V{=}l). \tag{2.11}$$

Where $Z = N \cdot S + (1 - N) \cdot I$ is distribution of ratings for the different customer groups, and $N = S/(S + I)$ is a proportion of customers that $N \in (0, 1)$; Eq. (2.11) and then deriving with respect to the portion of the customer groups which N is approximately equal to zero, $N \approx 0$, we obtain a lower variance and a higher average rating. While a higher average rating provides information about a high-quality of the product, a lower variance would simultaneously communicate to consumers that the quality of the product is high because QLCs are satisfied with it. Thus, a lower variance shows that the average rating is a true quality indicator of the product.

From Eq. (2.9) and (2.10), in the case of existence of two customer groups, the ratings distribution's probability of can be formulated as follows:

$$Pr(Z \mid W{=}H){=}Pr(Z|W{=}H, S, E){+}Pr(Z \mid W{=}H, I, E){=}Pr(M{=}h, V{=}h). \tag{2.12}$$

Eq. (2.12) and then deriving with respect to the portion of the customer groups which N is approximately equal to one, $N \approx 1$, we obtain a higher variance and a higher average rating. Although a higher average rating attracts a consumer's attention to a high-quality product, a higher variance communicates to consumers that product quality is unreliable, since the product has only PLCs. Because the variance of the ratings distribution become dramatically larger for IPP when compare it FPPs. This means that there are definitely-differing opinions on the product even the majority of the customers are PLCs. On the other hand, potential consumers can't turn to some form of internal and other external information sources. Because of newly released products that consumers and also others do not have direct experience related to the product. Consumers can't decide whether it will satisfy their expectations or not when they looking products at the point of the quality-base, price-base and its reliability as discussed in related studies [37, 40]. On the other hand, a higher variance shows that the average rating is not a true quality indicator of the product.

The more interesting point is the case of low L quality W of the product, where both PLCs S and QLCs I submit lower ratings. The variance of ratings of PLCs becomes dramatically larger because price fairness affects their satisfaction level differently. When customer opinions differ more about the product, the probability distribution of the ratings given by two separate groups is stated as (see Figure 5);

$$Pr(Z \mid W = L, S, E) = Pr(M = l, V = h) \text{ for } PLCs, \tag{2.13}$$

and

$$Pr(Z \mid W = L, I, E) = Pr(M = l, V = l) \text{ for } QLCs. \tag{2.14}$$

Figure 5: Illustration of the ratings distribution's probability for the customer groups in particular for low-quality IPP.

From Eq. (2.13) and (2.14), in the case of existence of two customer groups, the ratings distribution's probability of can be formulated as follows:

$$Pr(Z \mid W{=}L){=}Pr(Z \mid W{=}L, S, E){+}Pr(Z \mid W{=}L, I, E){=}Pr(M{=}l, V{=}h). \quad (2.15)$$

Where $Z = N \cdot S + (1 - N) \cdot I$ is distribution of ratings for the different customer groups, and $N = S/(S + I)$ is a proportion of customers that $N \in (0, 1)$; Eq. (2.15) and then deriving with respect to the portion of the customer groups which $0.5 < N < 1$, $N \neq 1$, we obtain a higher variance and a lower average rating. A lower average rating from the consumers' perspective shows that the quality of the product is low, and might avoids potential consumers to shop. A higher variance shows that the customers' opinions are more differentiated on the product, and signals that the average rating doesn't provide a true information about the product because product has only disappointed PLCs and a few well-matched QLCs.

From Eq. (2.13) and (2.14), in the case of existence of two customer groups, the ratings distribution's probability of can be formulated as follows:

$$Pr(Z \mid W{=}L){=}Pr(Z \mid W{=}L, S, E) + Pr(Z \mid W{=}L, I, E){=}Pr(M{=}l, V{=}l). \quad (2.16)$$

Eq. (2.16) and then deriving with respect to the portion of the customer groups which N is approximately equal to zero, $N \approx 0$, we obtain a lower variance and a lower average rating. A lower average rating causes of marginal consumers avoiding product. A lower variance shows that the quality of the product is low, because it has only disappointed QLCs. It shows that the customers' opinions are the same about the product which it signals that the average rating provides a true information the product.

2.2. The seller's price strategy and quality decision

We investigate seller's product pricing strategy and quality decisions by considering a two-period GTM featuring seller and customers heterogeneous in their tastes. The model concentrated on quality and mismatch cost attributes of product. We take a higher quality product that all customers like and denote quality by v. The quality-related attributes are additional characteristics of the product, such as the high-resolution of digital cameras. From a consumer's perspective, these attributes are what define the product's quality. The mismatch costs are described as in Sun [46] and capture "aspects of the product that would have an influence on how much consumers would differ in their enjoyment of the product". Customers perceive mismatch cost differently; based on customers' taste, it negatively affects their satisfaction. Some of the customers may enjoy camera's different design. They have individual needs and tastes. Even though they agree on a product's overall quality attributes, they may all give only a one-star rating out of five star that covers all measurements conceptually. Customer reviews on Amazon are good examples of quality and mismatch costs: "this DVD+RW is best to use in DVD recorder, because it is cheaper and better"; another customer wrote, "this DVD+RW doesn't burn at top speed correctly as some older versions, but it is still the best cheaper disc for recording screens in HD format"; and one other customer submit, "this PC with Q4OS is best for those whose majors are engineering" The mismatch costs, it is denoted by and we assume that $t \in [0, 1]$.

We also consider heterogeneity in both PLCs (see Wei and Li [50]) and QLCs (see Ramachandran and Balasubramanian [39]) tastes in relation to a product's attribute as in Sun [46] and represent it by z, which is distributed uniformly between zero and one, $z \in [0, 1]$ where customers are uniformly located on line as in Hotelling's location model (see Hotelling [24]). Customers at near-zero have products perfectly matched to their taste. If customers with distance z from the product buy the branded product at a price P, then their utility is:

$$U = v - t \cdot z - P. \tag{2.17}$$

A lower mismatch cost in using Eq. (2.17) shows that customers with different tastes could obtain the same or higher utility from consumption in the extreme case of $t = 0$; that is, customers enjoy the product more while they are located near the product. A higher mismatch cost shows that customers with different tastes could obtain different utility from consumption, which the product with higher mismatch cost only meets the distinct needs of a small group of customers.

The parameter z that varies across different customers (hence the term *vary utility*), so different customer tastes vary toward the product. Customers know their taste as well as their closeness with the product, however they don't know quality and mismatch cost. For example, LCs know how much they like Computer (their closeness to the product), but they don't know the quality of the current version (quality attribute) and how much they will satisfy with Q4OS-based PC (mismatch cost) without further information.

The noteworthy feature of the model is the assumption that customers place more weight on mismatch cost and quality in the DMP, and the ratings reflect their consumption utility. Including price into customer ratings would not influence the analysis as long as all decisions-makers appreciate including method of the price in ratings formula in the term of our model's composition. For example, "this DVD+RW $\cdots$ the best cheaper disc for whoever records screens in HD format"- PLC's lower rating evaluation of IPP, "I love iPhone, however its expensive, its price justified by its good camera"- PLC's higher rating evaluation of IPP, "this PC with Q4OS is best for those whose majors are engineering"- QLC's lower rating evaluation of IPP, "although this face mask high priced, its absolute best face masks for both oily and dry skins" - PLC's higher rating evaluation of FPP, "these sports shoes with leather processing often have a fit price, but are not suitable for long runs" - PLC's lower rating evaluation of FPP, "I would like to continue to use this brand's lotion if they provide it for dry skins" - QLC's lower rating evaluation of FPP. The textual reviews above indicate that the product with higher mismatch still matches the needs of some customers, although it got lower ratings. It also shows that price does not play a key role in evaluating product ratings, even for PLCs. Therefore, excluding price from consumers utility only when we write it as a function of their ratings which not affect our analysis.

When the new version of the branded product comes onto the market, there is no available customer usage information on the characteristics of the product. Both seller and LCs don't know the realizations of the quality and the mismatch cost. The LCs buy the products if their expected utility $E(U)$ based on experience is greater than experienced utility U_0 derived from the previous product version, or do not buy otherwise. Beginning with the first period of the game, each of the LCs has maximum demand for one unit of the product and he(she) receives a utility of zero when not buying the product. The seller decides on the price and LCs consider whether to choose for a unit of the product based on their expected utility, which is built according to their experience. Throughout an evaluation of a product, customers submit a rating of true utility $U = v - tz$ after experiencing expected utility $E(U)$. Thus, during the second period, later consumers come to market. Later consumers and the sellers together observe the ratings' distribution that was submitted by early LCs. This assumes that customers provide a honest rating for branded products without external manipulation of customer reviews as discussed in Li and Hitt [28] and Nevskaya [35], and the ratings are submitted by LCs who have purchased the product before, as discussed in Anderson and Simester [2]. Thus, later consumers can easily decide how the product will meet their wants and needs by observing early LCs' ratings. Then, the seller can update the offered price P_2 on the basis of information gathered from the market. Figure 6 shows the structure of the model.

Beginning with the first period, LCs without knowing information about the quality and mismatch cost of the product, make purchase decisions in respect to their expected utility $E(U) = v - tz$ according to expectations of v and t that denoted as $E(v)$ and $E(t)$, (see the outcomes for the first period in Appendix 1), which is expected utility regarding

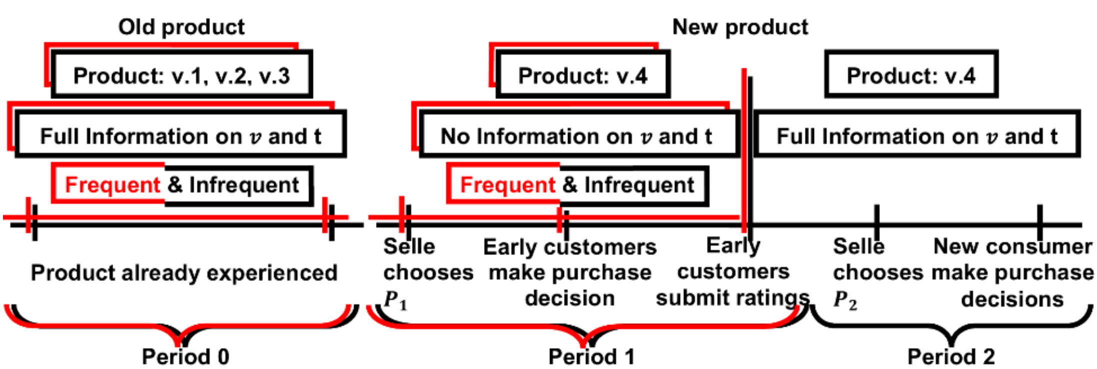


Figure 6: The structure of two-period model.

a particular product depending upon experienced utility $U_0 = v_0 - t_0 z$ derived from the product's previous version. A sufficient condition is $z \sim F(z)$, $Pr(Z \leq z) = F(z) = z$, $F(z) \in \{0, 1\}$, $U \in (0, 1)$ that produce the event.

When the transaction is complete, if the expected utility of LCs based on experience is lower than real utility, $v - tz \geq E(U)$, the LC is satisfied with product. Given the probability that is $Pr(Z \leq v - tz) = F(v - tz)$, the customers' satisfaction ratings equal to $G_1(v - tz)$. If the expected utility of LCs based on experience is higher than real utility, $v - tz < E(U)$, then the customer is dissatisfied or less satisfied. Given the probability that is $Pr(Z \leq v - tz) = 1 - F(v - tz)$, customers have a dissatisfied rating equal to $G_2(v - tz)$. Therefore, the expected rating equals:

$$E(R) = [F(v - tz)] \cdot [G_1(v - tz)] + [1 - F(v - tz)] \cdot [G_1(v - tz)]. \tag{2.18}$$

The importance of our model assumption is that the information derived from ratings is influenced by multiple factors. We include two commonly known parameters $\alpha > 0$ and $\beta > 0$ customers' utility function: $U(z) = v - (t \cdot z^{\beta})^{\alpha} - P$. $\alpha > 1$ product type is IPP; $\alpha < 1$ product type is a FPP, $\beta > 1$ customers are PLCs, $\beta < 1$ customers are QLCs. Also known that the product rating trends are almost linear in real world situations; customer ratings still equal $v - t \cdot z$. The ratings are assumed to be equal utility in our model. The linear ratings reflect the nonlinear consumption utility when we include α and β parameters, as a result, we get the consumption utility, $v - (tz^{\beta})^{\alpha}$ and change more dramatically than rating (see Figure 7 in Appendix 2). Therefore, we exclude α and β parameters when we determine the outcomes of the second period as a function of the ratings. While the main purpose explores in-depth how ratings affect consumers' DMP, we will also see how α and β affect the impact of ratings.

Customers with $z \in [0, 1]$ would purchase the product; whereas, customers located $z = 0$ derive almost the same higher utility. First period customers with a distance D_1 derive lower and different utility. While LCs are indifferent when they are purchasing the product, their ratings can be higher or lower, depending on whether their true utility exceeds or falls below their expected utility or prior experienced utility. True utility based on the realization of v and t, and increasing quality v to fit all customers expectations, results in higher ratings and increasing mismatch cost t makes a larger difference across ratings, meaning that only a small group of distinct customers derive higher utility. Thus, the ratings are thus distributed uniformly in $[0, D_1]$. Therefore, it is possible to calculate the variance of ratings V and the average ratings M as:

$$V = \frac{1}{144}(tD)^2 \quad \text{and} \quad M = v - \frac{3}{4}tD. \tag{2.19}$$

In the next period, via solution (Eq. (2.19)), consumers refer to learn about v and t:

$$v = M + 9\sqrt{V} \quad \text{and} \quad t = \frac{12\sqrt{V}}{D}. \tag{2.20}$$

After the realization of v and t, later consumers have the product's information, leading to a certain purchase decision. The demand for the second period is $D_2 = (v -$

$P_2)^{1/\alpha\beta}/t^{1/\beta}$ and the seller maximizes: $\max_p P_2(v-P_2)^{1/\alpha\beta}/t^{1/\beta}$. Thus, price, demand, and profit are:

$$P_2=\alpha\beta\cdot\frac{v}{1+\alpha\beta},\quad D_2=\frac{1}{t^{\frac{1}{\beta}}}\cdot\left(\frac{v}{1+\alpha\beta}\right)^{\frac{1}{\alpha\beta}} \text{ and } \Pi_2=\alpha\beta\cdot\frac{1}{t^{\frac{1}{\beta}}}\cdot\left(\frac{v}{1+\alpha\beta}\right)^{\frac{1}{\alpha\beta}+1}. \quad (2.21)$$

In respect to M and V in Eq. (2.21), the outcomes can be formulated as:

$$P_2^*=\frac{\alpha\beta}{1+\alpha\beta}\cdot(M+\sqrt{V}),\quad D_2^*=\frac{1}{(1+\alpha\beta)^{\frac{1}{\alpha\beta}}}\cdot(M+9\sqrt{V})^{\frac{1}{\alpha\beta}}\left(\frac{D_1}{12\sqrt{V}}\right)^{\frac{1}{\beta}}$$

and

$$\Pi_2^*=\frac{\alpha\beta}{(1+\alpha\beta)^{\frac{1}{\alpha\beta}+1}}\cdot(M+\sqrt{V})^{\frac{1}{\alpha\beta}+1}\left(\frac{D_1}{12\sqrt{V}}\right)^{\frac{1}{\beta}}. \quad (2.22)$$

Eq. (2.22) presents the effects of M and N on the outcomes; both play an important role for determining outcomes in the second period, as in the following propositions:

Proposition 1: *Price, demand and profit increase with a higher average rating.*

Proof: Differentiating equilibrium outcomes with respect to M gives, $\partial P_2^*/\partial M=\alpha\beta$, $\partial D_2^*/\partial M=(M+9\sqrt{V})^{(1/\alpha\beta)-1}\cdot(D_1/12\sqrt{V})^{1/\beta}$ and $\partial\Pi_2^*/\partial M=(M+9\sqrt{V})^{1/\alpha\beta}\cdot D_1/12\sqrt{V})^{1/\beta}$. Since M, V, and D_1 are positive by definition, thus $\partial P_2^*/\partial M>0$, $\partial D_2^*/\partial M>0$ and $\partial\Pi_2^*/\partial M>0$, mathematical proof is complete.

A higher average rating keeps informed that the product is of high quality which might represent higher satisfaction of the LCs with branded products. Consuegra, et al. [10] found that customers accept higher product prices when the product provides higher satisfaction. Bruce, et al. [5] found that the seller of the product drives up the price if consumers more satisfied. Related works (see Sun [46], Chevalier and Mayzlin [8], Dellarocas [12]) found that the higher sales are linked to the higher average ratings of the product.

Proposition 2: *The price always increases with the variance of the ratings, demand increases with the variance of ratings if and only if $9\sqrt{V}/M>\alpha(1-\alpha)$ and profit increases with the variance if and only if $9\sqrt{V}/M>\alpha/(1-\alpha(1-\beta))$.*

Proof: Differentiating the equilibrium outcomes with respect to V gives $\partial P_2^*/\partial V=9/2\sqrt{V}$, $\partial D_2^*/\partial V=9\sqrt{V}-\alpha(M+9\sqrt{V})$ and $\partial\Pi_2^*/\partial V=9\sqrt{V}(\alpha(\beta-1)+1)-\alpha M$. As M,V,D_1,α and β are positive by definition, thus, $\partial P_2^*/\partial V>0$, $\partial D_2^*/\partial V>0$ and $\partial\Pi_2^*/\partial V>0$ mathematical proof is complete.

According to the main proposition, *In the case of a higher variance & a higher average rating*: for both product categories a higher average rating attracts attentions that product quality is high. However, a higher variance communicates that FPP's quality is low because it has only PLCs. It shows that the average rating is not a true indicator of the quality of the product because the customers' opinions are considerably varying about the product. It indicates that the mismatch cost of the product is comparatively high.

This means that PLCs perceive the most suitable alternative to satisfy their needs depending on their taste. Thus, a higher variance increases equilibrium demand, although the PLCs' consumption utility for the FPP is lower than a higher rating evaluation when rating is high (see Figure 7). Therefore, the seller of the product charges a higher optimal product price to take advantage of the PLCs' and willingness of price-sensitive potential consumers to pay a higher price. The equilibrium profit increases accordingly.

For IPPs, a higher variance attracts attention to the unreliable quality of the product via showing that the majority of the customers are price-loyal. It communicates that the average rating is not providing accurate information about the product. A higher variance decreases equilibrium demand and indicates that the mismatch cost of the product is comparatively high. Therefore, the seller decreases product price to take advantage of the customer's higher willingness to pay with their price-elastic demand. Then, the PLCs' consumption utility for the IPP would be higher than a higher rating evaluation. The equilibrium profit increases while equilibrium demand increases with a lower price.

In the case of a higher variance & a lower average rating: a lower average rating drives away attentions for both product categories. A higher variance indicates that FPP's quality is low because the product only has a few well-matched QLCs. It shows that the average rating does not provide true information about the product because customers' opinion are differing on the product. A higher variance decreases demand and indicates that the mismatch cost of the product is comparatively high. That is, some of the QLCs with the right taste actually appreciate the product well beyond the average rating. Because their consumption utility for the FPP is higher than a lower rating evaluation (see Figure 7). The seller keeps the current price of the product and increases profit with the additional unit sales volume of the product through to considering the well-matched QLCs and well-matched potential consumers.

For IPPs, a higher variance attracts attention to the low quality via showing that the vast majority of the products' customers are price-loyal. It communicates that the average rating is not to provide true information. It also indicates that the mismatch cost of the product is high. That is, PLCs that choose products with the right features actually appreciate the product well beyond the average rating, although PLCs' consumption utility for IPPs is lower than a lower rating evaluation. Therefore, the seller sets the lower price to increase PLCs' and price-sensitive potential consumers purchases. Thus, equilibrium demand and profit increases with higher variance.

In the case of a lower variance & a higher average rating: a higher average rating attracts potential consumers' attention. A lower variance signals that the FPP has a higher quality because it shows that both QLC and PLC groups have the highest levels of satisfaction with the product. For IPPs, a lower variance shows that the product has a higher quality, but it only fits QLCs. It communicates that the average rating is a true indicator of the product quality for both product categories, because all the customers have same opinions about the product. Then, both FPPs' and IPPs' sellers charge a higher price accordingly; consumers have higher demand for the product with a higher quality, which leads to higher profit.

In the case of a lower variance & a lower average rating: for both product categories a lower average rating hurts demand. A lower variance signals that both FPPs and IPPs have lower quality because both types of product have only dissatisfied QLCs. It also communicates that the average rating is a true indicator of the quality for both product categories because customers' opinions about the product do not fluctuate considerably over the product. The sellers of those products should extend product attributes because it increases the mismatch cost with the product. The additional product attributes will help reduce customers' heterogeneity in mismatching, which enables more customers to purchase the product (see Liu and Cui [29]). It results in well-matched QLCs and well-matched quality-sensitive potential consumers purchase after attribute extension that increases sellers' total profits.

3. Discussion

The results derived from GTM show that, for both FPPs ($\alpha < 1$) and IPPs ($\alpha > 1$), when products received low- and/or high-average ratings there is an important difference in the DMP for price and demand that exists between two products with similarly low- and/or high-average ratings, and this difference has a greater influence on DMP when the variance is high.

The results also show that CAV has a stronger influence on consumers' decision-making on IPPs ($\alpha > 1$) than FPPs ($\alpha < 1$) when variance is high. It is only when lower-familiarity has a notable impact on consumer product evaluations (see Varela, et al. [47]). Because familiar has a positive influence information diagnosticity about the quality (see Ho-Dac, et al. [23]). Therefore, consumers more trust on familiarity with the product than another source of information (see Grabner-Kräuter and Kaluscha [20], Chen, et al. [7]), such as information derived from the CAV. Moreover, Shen, et al. [42] found that unfamiliarity makes demand more sensitive to price since information on the product is not robust ($\alpha > 1, \beta > 1$). On the other hand, customer satisfaction is directly influenced by the perception of price fairness (see Herrmann, et al. [21]) and this applies to consumers' evaluations of acceptable or justifiable on the price (see Xia, et al. [51]). That is, price positively affects the purchasing behavior, particularly for the group of price-sensitivity consumers. Consequently, consumers become more price-sensitive ($\beta > 1$), and they refer to use the information to drive from the CAV when they are not able to get more information about products where they are not familiar with products (IPPs).

Instead of the above, there is no difference in consumer's decision-making exists between FPPs and IPPs when both variances and average ratings are low. This is in line with Sun [46] reasoning that only when the variance is high then consumers consider whether the product's quality or the product-specific characteristics meet their requirements and needs. Thus, a lower variance plays the confirmatory role for both product types on quality regarding the level of average ratings, and consumers have strong purchase intentions for IPPs compared to FPPs when both variance and average rating are high. The variance becomes the dominant mediator due to lack of familiarity as diagnostic information. However, when the average rating is low, consumers have strong purchase intentions for FPPs, because familiarity is the dominant mediator as a credible information source. Thus, results show that the relationship between average rating, variance, and consumer decision-making is mediated by familiarity with the product.

Consequently, the results show that a higher variance hasn't always had a negative impact on demand for the product with a higher average rating in contrast to Sun [46]. A higher variance increases demand for FPPs and decreases demand for IPPs if and only if the market comprises a particular group of QLCs. This results in sellers' increased total profit on FPPs at a higher price. If the market consists of a group of PLCs then it results in sellers' increased total profit on IPPs' through additional unit sales volume at a lower price. Again, Sun [46] also found that a higher variance has positive impact on demand and profit for the product with a higher average rating, in contrast to Herrmann, et al. [22]. The finding is that a higher variance decreases demand for both product categories if the market consists of a group of quality-seeking customers. If the market consists of a group of price-seeking customers, it results in increased profit through additional unit sales volume of FPPs, and increased profit at a lower price to increase PLCs' purchase intentions for IPPs. As a result, customer characteristics influence potential consumer purchase intention under certain circumstances, as when consumers want to buy unknown or low-quality products at an acceptable price.

Lastly, the CAV always causes an increase in the equilibrium price, regardless of the level of $\alpha > 0$ and $\beta > 0$ when variance is high. For both FPPs and IPPs with a higher average rating, a higher variance suggests that PLCs perceive the most suitable alternative to satisfy their needs and have a higher willingness to pay. For an IPP with a lower average rating, a higher variance suggests that PLCs that find a product with the right features have a higher willingness to pay. Thus, a higher variance gives seller an opportunity to take advantage of that willingness with an optimal higher price, which increases profit while it increases demand.

4. Conclusion

The study has examined how CAV plays different positive and/or negative roles in the DMP, depending on the product categories (FPPs and IPPs) and customer characteristics (PLC and QLC), by building a GTM. The results derived from GTM can be highlighted in three important points; (1) CVA contains valuable information for consumers and seller who want to make a decision on a specific product. It indicates a lower quality of FPP and unreliable quality of the IPP when both products receive a higher average rating and a higher variance. It signals low quality of both product categories when they received a lower average rating and a higher variance. In addition, it suggests a higher quality of both product categories with a higher average rating and a lower variance. Also, it signals a lower quality of the products with a lower average rating and a lower variance. (2) CAV has a stronger effect on consumers' demand for FPPs than an IPPs when both products received similarly higher average ratings and a higher variance. It has a stronger effect on consumer demand for IPPs than FPP when both products received similarly lower average ratings and a higher variance. However, CAV did not show any different effect on consumer demand for FPPs compared to an IPP when both products received similarly high- or low-average ratings and a lower variance. (3) CAV has a more efficient effect on price when the average rating of FPPs is high and low for IPPs when variance is high. Through the way of this method, price, demand, and profit increase with an increasing variance in product ratings. Therefore, we demonstrate how consumers are keen to take on a risky purchase decision in preferring a low-quality product with a higher variance when deciding on two products with the similarly average rating that substitute each other. The results show that the CAV is an important additional factor when assessing the effect of the product ratings on market outcomes where LCs are present.

The effect of the CAV applies in respects to practice in the DMP. This study is a preliminary attempt to analyze the effect on demand and price in the consumer's and the seller's DMP in a market of different behavioral QLCs and PLCs. And, the results regarding the product that differentiated according to customers' buying frequency (FPP and IPP) show that the informational role of the CAV had been varied accordingly. The study reveals that the CAV is also useful in providing clear information about different behaviors (quality- and price-seeking) of the customers of the product alongside its quality, and consider what the market demand is for different product categories. Thus, online shopping industry's brand managers seeking to improve their strategy of capturing and keeping customer loyalty, and attracting new consumers should take the concept of the present study into consideration in a profitable way and pay more attention to the different behaviors of the customers, and develop separate marketing strategies to boost consumer demand forecasting for the products by segmenting their overall market based on FPPs and IPPs.

The developed GTM considers the customers' individual preferences and product categories for results. Zhu and Zhang [52] found that the online reviews are more influential when consumers have more experience with Internet. In terms of future research's directions, further study could explore how the informational role of the CAV changes depending on Internet experience of the customers. On the other hand, Dellarocas, et al. [13] different measures of product popularity (hit and niche) influences online consumers' review posting behaviors.

Appendix 1: First period outcomes regarding quality and mismatch cost

In the model, we also consider the seller's strategy for the first period. The seller maximizes expected profit:

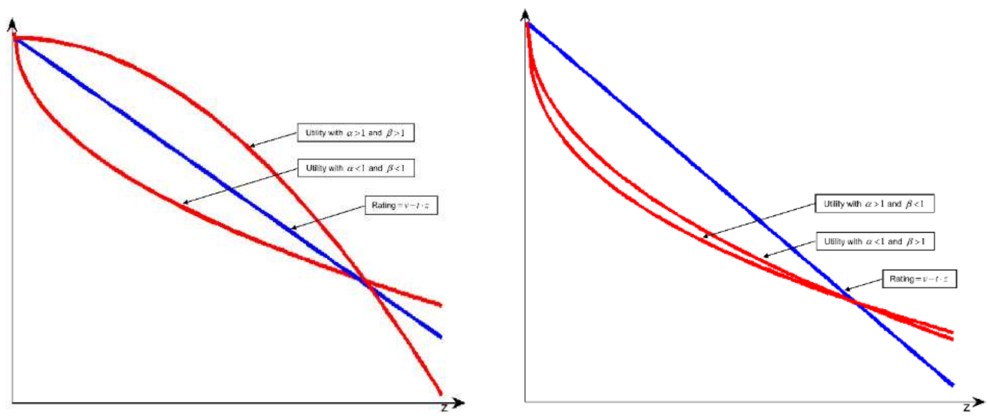
$$\max_{P} P_1 \frac{(E(v)-P_1)^{\frac{1}{\alpha\beta}}}{E(t)^{\frac{1}{\beta}}} + E\Big(\alpha\beta \cdot \frac{1}{t^{\frac{1}{\beta}}} \cdot \Big(\frac{v}{1+\alpha\beta}\Big)^{\frac{1}{\alpha\beta}+1}\Big).$$

Thus, according to the expectations of v and t, and the independence of P given as in the model composition, the equilibrium outcomes of price, demand, and profit in the first period can be formulated as:

$$P_1 = \frac{\alpha\beta \cdot E(v)}{1+\alpha\beta}, \quad D_1 = \frac{\Big(\frac{E(v)}{1+\alpha\beta}\Big)^{\frac{1}{\alpha\beta}}}{E(t)^{\frac{1}{\beta}}}, \text{ and } \Pi_1 = \frac{\alpha\beta}{E(t)^{\frac{1}{\beta}}} \cdot \Big(\frac{E(v)}{1+\alpha\beta}\Big)^{\frac{1+\alpha\beta}{\alpha\beta}}.$$

Consequently, under the assumption that customers make their purchase decisions in terms of the expectations of v and t, both PLCs and QLCs are more positive in their product expectations relative to both IPP and FPP when $E(v)/E(t)$ is higher. Thus, demand for the first period is increased. More interestingly, for both IPP and FPP, the price is higher in the second period if and only if $v = M + 9\sqrt{V} > Ev)$ compared to pierce in the first period. Sellers, in turn, adjust their pricing strategy based on the results of the average rating and the variance of ratings ripples over time.

Appendix 2: Figures



(a) (b)

Figure 7: The difference between "ratings" submitted by customers and customers "consumption utility".

Z is early LCs' distance from the product on the axis. The blue lines in both figures represent the ratings submitted by LCs after consumption, $v - t \cdot z$. The red lines in both figures represent customers' utility, $v - (t \cdot z^{\beta})^{\alpha}$. When $\alpha > 1$ and $\beta > 1$, the product type is an IPP and LCs are highly sensitive to price. We observe that utility line changes more dramatically than the rating: when the rating is high, the consumption's utility is higher than high rating, and when the rating is low, the consumption's utility is lower that low rating. When $\alpha < 1$ and $\beta < 1$, the product type is a FPP and LCs are not sensitive to price: when the rating is high, the consumption's utility is lower than high rating, and when the rating is low, the consumption's utility is higher that low rating. When $\alpha > 1$ and $\beta < 1$, the product type is an IPP and LCs are not sensitive to price: when the rating is high, the consumption's utility is lower than high rating, and when the rating is low, the consumption's utility is higher that low rating. When $\alpha < 1$ and $\beta > 1$, the product type is a FPP and LCs are highly sensitive to price: when the rating is high, the consumption's utility is lower than high rating, and when the rating is low, the consumption's utility is higher that low rating.

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