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When Biased Ratings Benefit the Consumer— An Economic Analysis of Online Ratings in Markets with Variety-Seeking Consumers

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Abstract:

For the sake of variety, consumers in many markets often choose to consume an unknown, potentially low-quality good over a known, high-quality one. Online ratings, despite their widely recognized importance for assessing the quality of unknown goods, have not yet been studied in the light of such variety-seeking behavior. In particular, it remains unclear how online ratings interact with variety-seeking in terms of market outcomes. This study proposes an analytical model to analyze this interaction, including pricing, profits, and consumer surplus. The main results of the model analysis suggest that for markets where consumers' tendency for variety-seeking is sufficiently strong, the following holds: (1) An increase in online ratings is more profitable for low-quality than for high-quality sellers, and (2) an increase in online ratings leads to an increase in consumer surplus even if ratings overestimate actual quality (i.e., are positively biased). These insights can help not only businesses operating in these markets with managing their online reputation and setting their prices, but also review system designers with de-biasing the ratings published on their system.

Keywords: Online Ratings, Variety-Seeking, Analytical Modeling, Economics of IS

JEL Classification: M15, M31, O32, D43

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1 Introduction

The secret of happiness is variety, but the secret of variety,
like the secret of all spices, is knowing when to use it.
- Daniel Gilbert[2]

Can you imagine eating at the same restaurant every day? Unsurprisingly, consumers repeatedly deviate from their routine by trying out an unknown alternative for a wide range of products and services, just for the sake of variety. Such variety-seeking tendencies (e.g., Kahn 1995) are seen as a main driver of consumer behavior – especially in markets for hedonic goods (e.g., van Trijp et al. 1996). Rather than visiting their favorite restaurant twice in a row, a consumer might choose a different one instead, even if they know that their favorite eatery offers them, by definition, the best experience. Similarly, consumers might switch to a different brand of breakfast cereals even when their favorite brand is available (Che et al. 2007). To satisfy their desire for variety, consumers need to frequently compare the quality of possible alternatives. The consumer in the previous example might prefer to stick to their favorite restaurant as long as they expect the quality offered by the alternative to be too inferior. Online review platforms, like Yelp or TripAdvisor, have become an established way of supporting consumers in the endeavor to assess the uncertain quality of products and services (Wu et al. 2015). Consequently, online reviews, and the ratings provided alongside each review, help consumers to decide when to give in to their intrinsic need for variety (i.e., 'when to use it') and when not to deviate from their habitual choice (i.e., when the alternatives are expected to offer poor quality).

Consumers rely heavily on online ratings (Dellarocas 2003), which are known for their considerable economic impact on consumer choice (Chevalier and Mayzlin 2006). For instance, Luca (2016) found that a half-star increase in a restaurant's average rating on Yelp causes a 5- 9% increase in revenue. Building on this well-established economic relevance of online ratings, prior literature suggests that businesses should dynamically adjust their pricing based on changes in their online ratings (Feng et al. 2019; Li and Hitt 2010). However, not all markets are equal and variety-seeking behavior is heterogenous across different markets (e.g., van Trijp et al. 1996). Since online ratings support

[2] in an interview on NPR (2006)

consumers in their variety-seeking behavior as outlined above, the economic impact of ratings should also differ across markets with different variety-seeking tendencies. By how much a business should increase its prices in response to an increase in their ratings arguably depends on consumers' intrinsic willingness to seek variety relative to their propensity of staying with the business's competitors. Consequently, businesses need to know how to strategically respond to changes in their online ratings while simultaneously considering the strength of variety-seeking behavior exhibited by consumers in the market. This argument extends to online reputation management as well. The amount of time and money a business should optimally invest in efforts intended to generate positive ratings—for instance by replying to negative reviews (Proserpio and Zervas 2017) or giving rebates in exchange for reviews (e.g., Cabral and Li 2015)—should also depend on the variety-seeking tendencies in a specific market. Depending on these tendencies, sellers need to decide whether to prioritize incentivizing their customers to stay loyal (e.g., through loyalty programs, or discounts; Zeithammer and Thomadsen 2013) or build a positive reputation to lure in new customers. This trade-off between customer retention and reputation management is a strategic decision that needs to be investigated. Additionally, understanding the value of online ratings in the light of variety-seeking behavior might also contribute to explaining why some businesses manipulate their reviews, while others do not (Luca and Zervas 2016).

The positive relationship between online ratings and economic outcomes has sparked interest in researching the drivers of online ratings. Many studies have identified factors that cause biased ratings, i.e., ratings that deviate from the true underlying quality of a good (e.g., Li and Hitt 2010) or ratings that do not represent an accurate aggregate measure of the population's rating distribution (e.g., Hu et al. 2017). As a result, scholars have analyzed various means to de-bias their ratings, such as fake review filters (e.g., Luca and Zervas 2016) or adjustments to the calculation of the average rating (e.g., Dellarocas 2005). Biases in online ratings have been uncovered in multiple domains ranging from restaurants and hotels rated on Yelp or TripAdvisor (e.g., Huang et al. 2016; Kokkodis and Lappas 2020) to digital cameras rated on Amazon (e.g., Li and Hitt 2010). Even though consumers differ greatly in their variety-seeking behavior across product categories (e.g., van Trijp et al. 1996), the large body of knowledge on online ratings provides little information on how the impact of biases might differ with variety-seeking tendencies. This limits not only the empirical discussion on biased ratings (e.g., Li and

Hitt 2010; Kokkodis and Lappas 2020) but also economic theory on online reviews (e.g., Aperjis and Johari 2010; Kwark et al. 2014) and on variety-seeking (e.g., Zeithammer and Thomadsen 2013). Intuitively, one would argue that review system designers should strive to de-bias ratings because biased ratings always impede consumer decision making. However, given that higher ratings might encourage consumers to indulge their variety-seeking tendencies and affect the pricing decision of competitors, positively biased ratings might ultimately benefit consumer surplus. Therefore, it is essential for review system designers to understand the impact of biased ratings in relation to variety-seeking behavior.

Because the extant literature on the impact of online ratings on market outcomes (i.e., prices, social welfare, etc.) has neglected the role of variety-seeking, both businesses and review system designers are impaired when dealing with online ratings and variety-seeking simultaneously. With this study, we aim to address this knowledge gap by answering the following research question:

How do online ratings affect market outcomes if consumers are variety-seeking?

To answer our research question, we propose an analytical model, which allows us to analyze how businesses should make decisions given that consumers are variety-seeking. We derive suitable model components from previous theoretical work on online reviews (Kwark et al. 2014, 2017; Li et al. 2011; Zimmermann et al. 2018), on the one hand, and variety-seeking behavior (Zeithammer and Thomadsen 2013), on the other. In line with the marketing literature (Kahn 1995), we incorporate variety-seeking behavior into our model from two perspectives, which we term *intrinsic variety-seeking* and *extrinsic variety seeking*. First, we let consumers exhibit intrinsic variety-seeking behavior in our model by actively promoting the switching tendency to unknown alternatives for internal reasons, such as the urge for novelty and curiosity (Berlyne 1970). This means that consumers derive a lower utility from consuming the good of the same seller more than once. Second, we examine how online ratings act as an external factor for variety-seeking, which means that we analyze whether an increase in ratings leads to an increase in observable variety-seeking behavior in a specific market.

With this model setup, we are able to explain how online ratings affect prices, profits, and consumer surplus for different levels of intrinsic variety-seeking. One of our main findings is that, for sufficiently strong (weak) intrinsic variety-seeking, consumer surplus is increasing (decreasing) in seller ratings. Counter to intuition, this is also the case if ratings overestimate (underestimate) a seller's true expected quality. This suggests that biases in online ratings, which have been extensively documented in prior literature (e.g., Hu et al. 2017), are not always detrimental to consumers. Altogether, these results carry valuable managerial implications, as well as are contributing to the extant literature on both online reviews and variety-seeking behavior.

2 Related Literature

While there is empirical evidence on the positive relationship between sales and online ratings (see Babić Rosario et al. 2016 for a review) as well as on strategic price setting based on online ratings (Feng et al. 2019; Li and Hitt 2010), this study is more closely related to studies that analyze the impact of online reviews by developing an analytical model. Amongst these studies, there are those that focus on the review system itself. Li and Hitt (2010) and Jiang and Guo (2015), investigate the influence of design changes (e.g., single- vs. multidimensional rating scale) to the online review system. Sun (2012) Zimmermann et al. (2018) consider the impact of the online rating distribution's variance on consumer decision making and firm's pricing. Li et al. (2011) investigate online reviews in repeat purchase markets with switching costs. This setting is similar to ours, but Li et al. (2011) focus on the overall informativeness of online reviews and not on the magnitude of numerical ratings. Moreover, their model does not capture variety-seeking behavior. All the previously mentioned studies consider optimal pricing strategies that incorporate online reviews and explicitly model the rating generation process (e.g., assuming that all reviewers post their true valuation). Some of these studies assume that sellers cannot foresee how their pricing affects future online ratings (e.g., Zimmermann et al. 2018) whereas others establish that sellers exhibit forward-looking behavior by influencing future ratings with their price setting (e.g., Feng et al. 2019). While we build on various model components used in these prior studies, we also depart from them by letting online ratings be given exogenously. This is in line with Kwark et al. (2014, 2017) who employed this approach in their analyses of online reviews' impact on competition between manufacturers and retailers. In this way, we allow ratings to be influenced by manipulation (e.g., Dellarocas 2006; Mayzlin 2006) and biases (e.g., Hu et al. 2017). The key feature in our model is the incorporation of variety-seeking behavior as a driving factor of consumer behavior. Prior analytical work on online reviews has, to the best of our knowledge, hardly placed any emphasis on behavioral aspects, despite the multitude of research that documents how consumer behavior affects the generation of ratings (e.g., Muchnik et al. 2013) and their impact on decision making (e.g., Yin et al. 2016).

Furthermore, we consider research on variety-seeking behavior. There already are analytical models that study price-setting when consumers are variety-seeking (Seetharaman and Che 2009; Zeithammer and Thomadsen 2013). Zeithammer and Thomadsen (2013) for instance find that variety-seeking behavior softens price competition. Our study differs from previous work in this area since we explicitly consider the role of (biased) online ratings in such a market and thus introduce uncertainty to consumer decision making. From a behavioral perspective, especially marketing and consumer psychology have found many reasons for variety-seeking. As basic background for our study, we focus on the integrative review by Kahn (1995), who synthesizes three areas of motivating factors for variety-seeking. First, consumers have an *intrinsic desire* for variety. They might try out a new product for the sake of novelty (Berlyne 1970), curiosity (Raju 1980), or out of boredom (Faison 1977). Second, their variety-seeking behavior might be caused by *external factors*. For instance, consumers decide to add variety to their purchases by taking advantage of price promotions (Kahn and Louie 1990). Third, consumers exhibit variety-seeking tendencies because of *future preference uncertainty*. For example, to counteract a potential oversaturation with their preferred choice, they may switch to another product preventatively (Ratner et al. 1999). A central topic of this stream of literature is the distinction between true variety-seeking behavior and ‘derived varied behavior’ (e.g., van Trijp et al. 1996). The former corresponds to intrinsically motivated switching between products, whereas the latter corresponds to extrinsically motivated switching. Intuitively, one would expect positive online ratings to extrinsically encourage consumers to switch products. However, to the best of our knowledge, there is only one study that analyzes the relationship between variety-seeking tendencies and online ratings (Wang and Goh 2012). Their study, based on an empirical analysis, suggests that individual consumers seek out more variety if the ratings they previously gave were low. With our study, we contribute to the analysis of derived varied behavior by providing a novel perspective on online ratings as an external factor for variety-seeking and their interaction with true (i.e., intrinsically motivated) variety-seeking. The scenario we consider differs from the one studied by Wang and Goh (2012) in that we do not focus on the impact of previously given ratings on variety-seeking but rather on the impact that ratings by others have on variety-seeking and on economic outcomes.

3 Model

We consider a two-period model which is similar in its setup to the one proposed by Villas-Boas (2004). The sequence of events is presented in Figure 1.

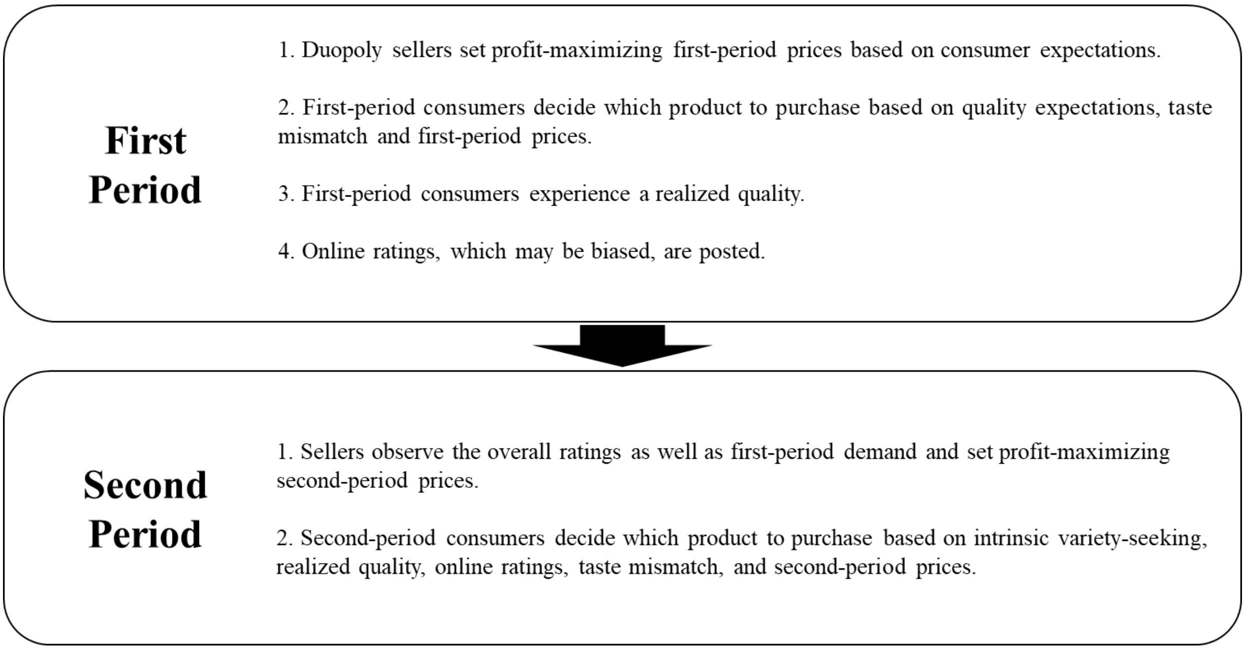

Figure 1 **Sequence of Events**

There are two sellers and a normalized market size of 1. We call the sellers A and B. The products/services (referred to in the model as products) offered by them are imperfect substitutes that both exhibit a base quality $Q \in \mathbb{R}^+$ (e.g., restaurants offering food that satisfies feelings of hunger). The products can differ in their marginal quality (e.g., cleanliness, quick service, range and mastery of cooking techniques), and different consumers can prefer one product over the other depending on their taste, so that our model considers both horizontal and vertical differentiation (e.g., Thai over Chinese food). Sellers have time-constant marginal production costs of c_A and c_B, respectively. We normalize the marginal costs of production so that $c_A = 0$. Moreover, c_B is normalized to represent the difference in the marginal production costs between the two sellers. The costs are unknown to consumers. In each period, the sellers set prices simultaneously and consumers choose either seller A or B. Similar to prior research (e.g., Zimmermann et al. 2018), the sellers in our models are myopic in the first period because they cannot anticipate the online ratings they receive after the first period due to the many external factors and market participants that may bias (e.g., Hu et al. 2017) or affect ratings (e.g., Luca and Zervas 2016). Table 1 summarizes the notation of our model.

Table 1: Model Notation

Variable	Meaning
$c_i \in \mathbb{R}^+$	Marginal cost of seller *i*
$\delta \in (0,1)$	Intrinsic variety-seeking behavior of consumers in the market
$Q \in \mathbb{R}^+$	Base quality for both products
$q_i \in \mathbb{R}^+$	Expected marginal quality of seller i's product
$q_i^r \sim U[q_i - \epsilon_i, q_i + \epsilon_i]$	Realized marginal quality of seller i's product
$\epsilon_i \in (0, q_i]$	Maximum deviation from expected marginal quality
$d \in \mathbb{R}^+$	Difference in q_i between the two sellers
$D_{i,j} \in [0,1]$	Demand for seller i's product in period *j*
$D_{i,2}^{stay} \in [0,1]$	Demand for seller i's product from their own consumer base in second period
$D_{i,2}^{inc} \in [0,1]$	Demand for seller i's product from their competitor's base in second period
$U_{i,j} \in \mathbb{R}^+$	Utility a consumer has for seller i's product in period *j*
$V_{i,j} \in \mathbb{R}^+$	Net utility a consumer has for seller i's product in period *j*
$\tau_i^r \in [0,1]$	Consumer's realized taste mismatch for seller i's product
$x \in [0, \min\{q_A - \epsilon_A, q_B - \epsilon_B\}]$	Unit mismatch costs
$p_{i,j} \in \mathbb{R}^+$	Price for seller i's product in period *j*
$q_i^e \in \mathbb{R}^+$	Consumers' quality expectations for seller i's product
$R_i \in \mathbb{R}^+$	(Aggregated) online rating for seller i's product
$r_1 \in (0,1)$	Consumers' reliance on own expectations instead of online ratings
$r_2 \in (0,1)$	Consumers' reliance on own experiences instead of online ratings

3.1 Product Properties and Consumer Behavior

Assumption 1 (Product Properties): A product is characterized by a fixed base quality and a realized marginal quality drawn from a fixed distribution.

Following previous studies (e.g., Kwark et al. 2014, 2017; Zimmermann et al. 2018), we characterize products by assigning them a quality attribute and a fit attribute. We let each consumer prefer high quality over low quality. The quality attribute describes the maximum value that a consumer can realize from the product's consumption. We denote a product's expected marginal quality as $q_i \in \mathbb{R}^+, i \in \{A, B\}$. Without loss of generality, we let seller B offer a higher marginal quality than seller A so that $q_B = q_A + d$ with $d > 0$. Furthermore, due to offering a higher quality, we let B have higher marginal production costs $c_B > 0$. After consuming the product, the consumer experiences a realized marginal quality $q_i^r \sim U[q_i - \epsilon_i, q_i + \epsilon_i]$ where $\epsilon_i > 0$ describes the maximum deviation from the expected marginal quality. This captures potential deviations in the quality that occur for each unit of a product.[3] For instance, a restaurant's quality might differ depending on which chef is working the current shift (e.g., Dai et al. 2018). To reduce formula complexity, we focus on those scenarios where sellers exhibit a similar level of deviations in the experiences they offer and thus let $\epsilon = \epsilon_A = \epsilon_B$. Additionally, we restrict our model to scenarios where both products provide a base quality Q which is large enough so that consumers will definitely buy one of the two products regardless of its price $p_{i,j}$ in period j (in line with Zeithammer and Thomadsen 2013). Thus, we look at scenarios where for instance visiting any of the two restaurants is worth it to satisfy one's hunger. We normalize the utility of not buying any product to zero and let each consumer have a sufficiently large budget enabling them to choose freely between the two products.

Assumption 2 (Consumer Heterogeneity): Consumers are heterogeneous in their taste.

A product might not optimally match a consumer's taste. In line with previous models of continuous horizontal differentiation (e.g., Zimmermann et al. 2018; Sajeesh and Raju 2010), we model the realized taste mismatch as the distance between the consumer's location and the product's location on a line from 0 to 1. Let the realized taste mismatch τ_i^r describe this relationship and measure the distance between consumer location and product location, with 0 indicating a perfect match. We further introduce unit mismatch costs $x \in [0, \min\{q_A - \epsilon_A, q_B - \epsilon_B\}]$. If a consumer's taste is not perfectly matched, they experience mismatch costs in form of their realized taste mismatch times the unit mismatch costs (i.e., $\tau_i^r x$). Similar to previous work (e.g., Kwark et al. 2014; 2017), we let $\tau_A^r \sim U[0,1]$

[3] Alternatively, this deviation from the expected marginal quality could also be interpreted as differences in the consumers' quality perceptions. In general, every consumption experience is unique so that multiple visits to the same seller result in different experiences.

and $\tau_B^r = 1 - \tau_A^r$. This reflects a situation where there are, for instance, consumers who favor one restaurant over the other ($\tau_A^r = 0$ or $\tau_A^r = 1$) but also those who like both to some extent ($\tau_A^r = 0.5$). The utility $U_{i,j}$ that a consumer derives from consumption in period j is given by the difference between product quality and mismatch costs. The net utility $V_{i,j}$ is the difference between utility and product price $p_{i,j}$. We conclude that for a consumer with taste τ_i^r, their net utility for product i is given by Equation 1:

$$V_{i,j} = Q + q_i^r - \tau_i^r x - p_{i,j} \tag{1}$$

In each period, consumers decide which product to consume based on the difference $V_{A,j} - V_{B,j}$. Note that because Q is sufficiently large and the two products are imperfect substitutes, all consumers buy exactly one product. Thus, if the difference in net utilities is positive, consumers buy product A. If it is negative, they buy product B. Generally, the products' expected marginal quality q_i and its maximum deviation ϵ are unknown to consumers whereas the base quality Q, the realized taste mismatch τ_i^r, and mismatch costs x are known prior to consumption.

3.2 First Period

In the first period, consumers have no information on the products' marginal quality distribution, but they can observe their realized taste mismatch[4]. For instance, consumers know that they prefer Thai food over Chinese food.

Assumption 3 (Consumer Expectations): Consumers share common quality expectations.

To assess the marginal quality, consumers need to rely on their own expectations. Similar to Li and Hitt (2010), we assume that all consumers share common expectations q_i^e regarding the marginal quality. Furthermore, to keep our results mathematically tractable, we let $q^e = q_A^e = q_B^e$. This means, for example, that consumers cannot tell the difference between the two restaurants' qualities just from observing them from the outside, which adds to the importance of additional information. Consequently, consumers consider the following expected difference in net utilities:

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[4] An unobservable taste mismatch could also be captured by ϵ. In such a case, q_i^r would capture all unobservable components whereas τ_i^r captures all observable ones.

$$E\big(V_{A,1} - V_{B,1}\big) = q^e - \tau_A^r x - p_{A,1} - \big(q^e - \tau_B^r x - p_{B,1}\big) \tag{2}$$

From the position of the indifferent consumer $\tilde{\tau}_A^r = \frac{(x - p_{A,1} + p_{B,1})}{2x}$, we derive the first period demand $D_{i,1}$ as follows:

$$D_{A,1} = \frac{\big(x - p_{A,1} + p_{B,1}\big)}{2x}, D_{B,1} = 1 - \frac{\big(x - p_{A,1} + p_{B,1}\big)}{2x} \tag{3}$$

3.3 Second Period

In the second period, consumers need to decide whether to consume the same product again or choose the other product (we say they 'seek variety' or are 'variety-seeking'). We call the set of consumers that have consumed product A (B) in the first period 'consumer base A (B)'. We refer to the product they have consumed as 'base product'. Because consumers of each base have consumed the respective product once, they know their last realized marginal quality from its consumption.

Assumption 4 (Intrinsic Variety-Seeking): All consumers experience a common decrease in utility from consuming the same product multiple times, i.e., they exhibit intrinsic variety-seeking behavior.

The consumers in the market are intrinsically motivated to seek variety. Thus, if they repeatedly consume the same product, they will experience a diminished utility. In line with Zeithammer and Thomadsen (2013), this variety-seeking behavior is modelled as diminished marginal quality. After consuming a product in the first period, another consumption instance of the same product will lead to a reduction of the experienced marginal quality by a factor of $\delta \in (0,1)$. Thus, without knowing q_i but q_i^r, the resulting expected net utility for consuming the same product i in the second period is given by Equation 2.

$$E\big[\, V_{i,2}\big] = Q + \delta q_i^r - \tau_i^r x - p_{i,2} \tag{4}$$

This diminishing marginal quality captures variety-seeking behavior that stems from boredom and the need for novelty (Berlyne 1970; Faison 1977). Eating at the same restaurant again will mean consumers experience a familiar environment which will not satisfy their desire for variety (but still satisfy their hunger due to a sufficient base quality). Following Zeithammer and Thomadsen (2013), this conceptualization is well-suited for restaurant markets and the leisure industry. This modeling choice is particularly interesting in our case, given that we consider online ratings as a form of quality information (see below). Thus, both of our key model components, namely intrinsic variety seeking and ratings, apply to the same product dimension (i.e., quality).

Assumption 5 (Online Ratings): In the second period, each product is associated with a (potentially biased) rating.

The main difference between our work and previous analytical models for markets with variety-seeking consumers is the introduction of uncertainty regarding product quality and online reviews which mitigate this uncertainty. Thus, after the first period, online ratings appear on a third-party platform, for instance, posted by some of the consumers of each base.

While consumers know the marginal quality they have experienced for one of the two products, they can now rely on online ratings to form quality expectations for the other. Let $R_i \in \mathbb{R}^+$ measure the aggregated quality assessments (i.e., online rating). Note that R_i is not necessarily equal to the true expected marginal quality as ratings can be biased and market participants can intentionally or unintentionally influence ratings. This choice of not explicitly modeling the generation process of online ratings is in line with prior literature (e.g., Kwark et al. 2014, 2017) and supported by the many empirical irregularities in consumer behavior, which affect ratings and make imposing a specific rating generation process difficult. For instance, not all consumers post an online review after consumption, which can substantially affect aggregated measures such as average ratings (Hu et al. 2017). Furthermore, several factors may contribute to consumers not revealing the quality they have experienced during consumption such as the time difference between consumption and review publication (Huang et al. 2016) or whether the seller is known to respond to negative reviews (Proserpio and Zervas 2017). Due to such biases in ratings and because consumers are bounded in their rationality, they cannot derive the true quality from observing the ratings (Jiang and Guo 2015). Empirical support for bounded rationality of consumers regarding ratings can be found in the literature (e.g., Hu et al. 2017). Consumers incorporate ratings into their quality expectations so that they expect the quality of product i to be $r_1 q_i^e + (1 - r_1) R_i$ where $r_1 \in [0,1]$ indicates the reliance on own expectations instead of online ratings (Bates and Granger 1969; Kwark et al. 2014, 2017). If r_1 is close to 0, the reliance is low and consumers rather rely on online ratings. To reduce formula complexity, we set $r_1 = 0$ so that every consumer fully relies on the quality information of the rating and ignores prior expectations. In a similar way, we introduce $r_2 \in [0,1]$ as the consumer's reliance on their own experiences instead of online ratings. Accordingly, the expected utility from consuming the same good again is $\delta(r_2 q_i^r + (1 - r_2)R_i)$. This captures the situation where consumers, knowing that marginal qualities differ with every visit, might incorporate online ratings of a product that they have already consumed. Generally, it seems unlikely that consumers were to conduct a search for product information concerning a product they have already consumed. Additionally, given that ratings can be biased while q_i^r is drawn from the actual underlying distribution, r_2 should be relatively high. Thus, we let $r_2 = 1$ to keep mathematical tractability. Finally, we can combine the features of online reviews with the notion of net utilities from Equation 4 to calculate the expected difference in net utilities for the second period.

$$\begin{aligned} E(V_{A,2} - V_{B,2}) &= \left(\delta(r_2 q_A^r + (1 - r_2)R_A) - \tau_A^r x - p_{A,2}\right) - \left(rq^e + (1 - r_1)R_B - \tau_B^r x - p_{B,2}\right) \text{ (Base A)} \\ E\left(V_{B,2} - V_{A,2}\right) &= \left(\delta(r_2 q_B^r + (1 - r_2)R_B) - x\tau_B^r - p_{B,2}\right) - \left(rq^e + (1 - r_1)R_A - \tau_A^r x - p_{A,2}\right) \text{ (Base B)} \end{aligned} \tag{5}$$

Demand Functions

As q_i^r and τ_i^r are independent and uniformly distributed, each consumer base can be represented by a rectangle with height 2ϵ. Based on first-period demand, the width of the rectangle is $\frac{(x - p_{A,1} + p_{B,1})}{2x}$ for consumer base A and $1 - \frac{(x - p_{A,1} + p_{B,1})}{2x}$ for consumer base B. Figure 2 presents an illustration of the two consumer bases. Throughout this study, we consider, in line with prior work (Kwark et al. 2014; Villas-Boas 2004), a scenario in which consumers who have experienced low marginal quality (e.g., if $q_i^r - q_i = -\epsilon$) always seek variety even if they have realized a perfect taste match. Analogously, those who have experienced high marginal quality (e.g., $q_i^r - q_i = \epsilon$) always stay with their first-period choice even if they have a relatively low realized taste match. Formally, this is achieved by a sufficiently high ϵ. This modeling choice is reasonable in our setting given that consumers know their taste match in advance so that it should not be the driving force for their second-period decisions. Geometrically, this means that the separating lines in Figure 2 cannot cross the corners of the squares. Note that this is equivalent to introducing minimum and maximum thresholds for marginal quality that drive consumers away or bind them to the seller, respectively. Therefore, consumers do not need to know ϵ to make their second-period decisions. In a restaurant setting, these thresholds would mean that consumers expect certain levels of quality. If these are not met, they leave the seller. It also means that in case of a very high level of quality, they stick to a seller.

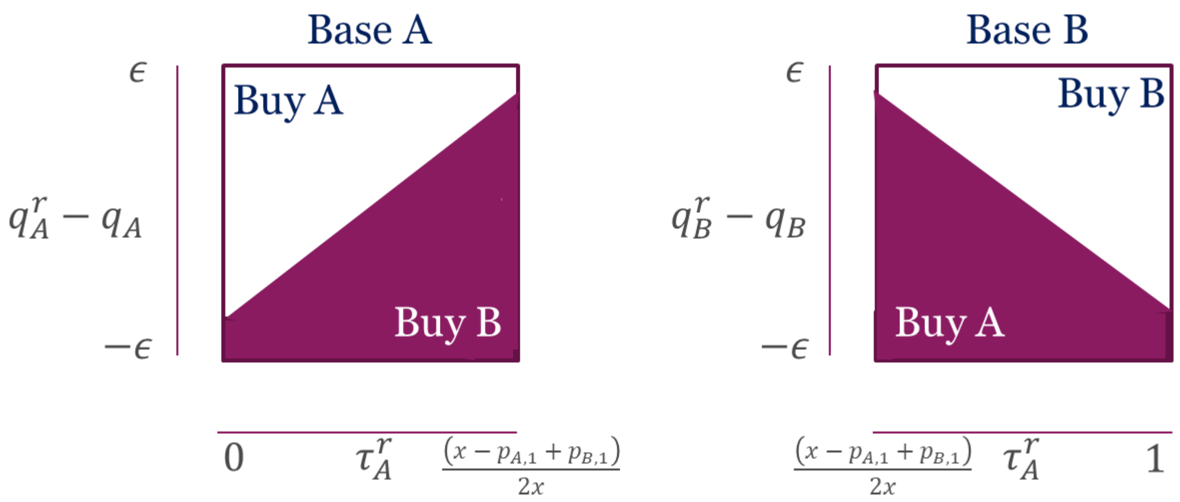

Figure 2 Consumer Bases in the Second Period

The taste axis in Figure 1 describes a taste match for a consumer's base product. The quality axis shows the deviation from the expected marginal quality that the consumer experienced in the first period. We first derive the demand for A resulting from its respective consumer base. We determine the experienced deviation from the expected marginal quality of the consumer who is indifferent between buying A and B from consumer base A with $\tilde{\epsilon} = \frac{R_B - \delta q_A + x(2\tau_A^r - 1) + p_{A,2} - p_{B,2}}{\delta}$. The number of consumers who stay with product A can then be derived as expressed in Equation 6.

$$D_{A,2}^{stay} = \int_0^{\frac{(x - p_{A,1} + p_{B,1})}{2x}} \int_{\frac{R_B - \delta q_A + x(2\tau_A^r - 1) + p_{A,2} - p_{B,2}}{\delta}}^{\epsilon} \frac{1}{2\epsilon}\, dt\, d\tau_A^r \tag{6}$$

Naturally, the demand for product A does not only come from its respective consumer base but also from all the consumers of base B who seek variety. The calculation of the variety-seeking consumers from base B is as follows.

$$D_{A,2}^{inc} = \int_{\frac{(x-p_{A,1}+p_{B,1})}{2x}}^{1} \int_{-\epsilon}^{\frac{R_A-\delta q_B+x(1-2\tau_A^r)+p_{B,2}-p_{A,2}}{\delta}} \frac{1}{2\epsilon} dt\, d\tau_A^r \tag{7}$$

By adding the demand from the respective consumer base (Equation 6) to the demand from the variety-seeking consumers of the opposite consumer base (Equation 7), we get the total second-period demand for seller A. The total second-period demand for seller B is derived in a similar way.

4 Model Analysis

To analyze the model, we first derive equilibrium conditions. Second, we focus on the producer side and scrutinize how intrinsic variety-seeking relates to the economic impact of online reviews. Third, we examine how the number of variety-seeking consumers is externally driven by online ratings. Finally, we consider consumer surplus and social welfare.

4.1 Equilibrium Conditions and Impact of Intrinsic Variety-Seeking

In each period, both sellers choose their prices simultaneously and must solve the following optimization problems.

$$\max_{p_{i,j}} \pi_i = (p_{i,j} - c_i) D_{i,j} \text{ with } p_{i,j} \geq c_i \text{ for } i \in \{A, B\} \text{ and } j \in \{1,2\} \tag{8}$$

Using first-order conditions, we can derive each seller's reaction function depending on the competitor's price and the resulting equilibrium prices.

Lemma 1: In the first period, there exists an equilibrium if $c_B \leq 3x$. Equilibrium prices, profits, and demands are as follows.

$$\begin{gathered} \textit{Prices: } p_{A,1} = \frac{3x+c_B}{3}, p_{B,1} = \frac{3x+2c_B}{3}, \textit{Profits: } \pi_{A,1} = \frac{(3x+c_B)^2}{18x}, \pi_{B,1} = \frac{(3x-c_B)^2}{18x} \\ \textit{Demands: } D_{A,1} = \frac{3x+c_B}{6x}, D_{B,1} = 1 - \frac{3x+c_B}{6x} = \frac{3x-c_B}{6x} \end{gathered} \tag{9}$$

PROOF: Please see the appendix for all proofs.

Note that the demand in equilibrium for both sellers is only greater than 0 if $c_B < 3x$. Therefore, we let the difference in the marginal production costs be sufficiently small so that this condition holds.[5]

We can now use the first-period equilibrium prices to calculate the second-period demand and determine the equilibrium in the second period.

Lemma 2: In the second period, there exists an equilibrium if $c_B \leq 3x$. Equilibrium prices and profits are as follows.

a) Prices:

$$
\begin{aligned}
p_{A,2} &= \frac{-3x(\delta q_B - \delta q_A - 6\delta\varepsilon - 2c_B + R_B - R_A) + c_B(\delta q_B + \delta q_A - R_B - R_A)}{18x} \\
p_{B,2} &= \frac{3x(\delta q_B - \delta q_A + 6\delta\varepsilon + 4c_B + R_B - R_A) - c_B(\delta q_B - \delta q_A + R_B + R_A)}{18x}
\end{aligned} \tag{10}
$$

b) Profits:

$$
\begin{aligned}
\pi_{A,2} &= \frac{(3\delta q_B x - 3\delta q_A x - 18\delta\varepsilon x - 6c_B x + 3R_B x - 3R_A x - c_B\delta q_B - c_B\delta q_A + R_B c_B + R_A c_B)^2}{648\delta\varepsilon x^2} \\
\pi_{B,2} &= \frac{(3\delta q_B x - 3\delta q_A x + 18\delta\varepsilon x - 6c_B x + 3R_B x - 3R_A x - c_B\delta q_B - c_B\delta q_A + R_B c_B + R_A c_B)^2}{648\delta\varepsilon x^2}
\end{aligned} \tag{11}
$$

In this equilibrium[6], both sellers base their price setting on online ratings. Reacting optimally to the competitor's behavior in this case means that they expect their competitor to also set their prices based on online ratings. If a seller considers ratings in their pricing and anticipates their competitor to do the same, we refer to this as *rating-based pricing policy*. Even though empirical research suggests that sellers do indeed change their prices in response to changes in their online rating (e.g., Feng et al. 2019; Li and Hitt 2010), this may not necessarily hold for all sellers. It has been shown that firms may exhibit bounded rationality in their price setting (e.g., Che et al. 2007) or refrain from adjusting prices due to menu costs (Hobijn et al. 2006). Therefore, in the following model analysis, we also study market situations in which sellers' competitive pricing is not based on the observed online ratings but on initial consumer expectations. Not only this, but they also anticipate that their competitor's reaction is to also

---

[5] As most of our results are built on outcomes in the second period, setting a fixed positive value for $D_{B,1}$ would yield similar results without restricting the cost structure. This also extends to letting a rating system exist in the first period by substituting expectations with first-period ratings.

[6] Note that as ϵ, c_B, q_A, and q_B are unknown to consumers, they cannot derive the expected marginal quality by observing the equilibrium prices and the online ratings.

consider consumer expectations instead of ratings. Thus, we say that the seller adopts an *expectation-based pricing policy*. Note that one can get the second-period price for seller i who adopts an expectation-based policy by substituting R_A and R_B with q^e for $p_{i,2}$, which is captured by the following lemma.

Lemma 3: In the second period, if both sellers adopt an expectation-based pricing policy, there exists an equilibrium if $c_B \leq 3x$. Equilibrium prices $p_{i,2}^o$ are as follows.

$$p_{A,2}^o = -\frac{3x(\delta q_B - \delta q_A - 6\delta\varepsilon - 2c_B) + c_B(2q^e - \delta q_B - \delta q_A)}{18x},\ p_{B,2}^o = \frac{3x(\delta q_B - \delta q_A + 6\delta\varepsilon + 4c_B) + c_B(2q^e - \delta q_B - \delta q_A)}{18x} \quad (12)$$

Equilibrium profits follow from inserting $p_{A,2}^o$ and $p_{B,2}^o$ into the profit function. Unless stated otherwise, the following results pertain to the case where both sellers act rationally and adopt a rating-based pricing policy.

4.2 Economic Value of Online Ratings under Intrinsic Variety-Seeking

In this section, we analyze the impact of online ratings on second-period prices and profits as well as how valuable increases in one's online rating are for a low-quality seller compared to a high-quality seller.

Lemma 4: Second-period prices, demand and profits are strictly increasing in their respective seller's rating and decreasing in their competitor's rating.

Lemma 4 confirms the positive influence of online ratings on prices and profits as postulated by previous theoretical and empirical work (e.g., Chevalier and Mayzlin 2006; Li and Hitt 2010). We will use this lemma to further explain the intuition behind our propositions, where necessary.

Proposition 1: Let $\epsilon > \frac{-3dx + 2c_B q_A + c_B d}{6c_B}$. For equilibrium conditions, a marginal increase in seller A's online rating is more profitable for seller A than a marginal increase in seller B's rating for seller B if and only if $\delta < \frac{3x(2c_B - R_B + R_A) + c_B(-R_B - R_A)}{3dx - 2c_B q_A + 6c_B\varepsilon - c_B d}$.

Proposition 1 shows for a sufficiently strong intrinsic variety-seeking behavior (i.e., sufficiently small δ), that the low-quality seller has a stronger incentive to strive for an improvement of their rating than the high-quality seller. This also partially supports empirical findings which demonstrate that low-quality sellers in the restaurant market are more likely to manipulate online reviews than high-quality sellers (Luca and Zervas 2016). The intuition behind this proposition is as follows. If intrinsic variety-seeking is strong, ratings become increasingly important. While the high-quality seller still benefits from customers who stay with their product choice, more customers of the low-quality seller switch to the competitor. Therefore, the low-quality seller needs to convince the high-quality seller's customers to also switch products which can be achieved by an increase in ratings. Note that this only holds if the maximum deviation from the marginal qualities of the sellers (ϵ) is sufficiently large. The underlying intuition behind this restriction for ϵ is as follows. If ϵ is small, there are fewer customers who experienced a rather low quality after consuming the product of seller B. Therefore, fewer customers switch to seller A after an increase in their rating, which would make an increase in ratings more profitable for seller B despite strong variety-seeking tendencies. Altogether, Proposition 1 shows that the economic value of an improved reputation depends on consumers' intrinsic variety-seeking behavior and is heterogenous across different qualities.

4.3 Rating-based Pricing versus Expectation-based Pricing

In the following, we study the impact of sellers neglecting online ratings in their pricing strategy. Proposition 2 captures the role of intrinsic variety-seeking behavior in this setting.

Proposition 2: Let seller A (B) adopt an expectation-based pricing policy, whereas seller B (A) adopts a rating-based pricing policy. Then, seller A (B) suffers a loss in profit compared to the profit from adopting a rating-based pricing policy. This loss increases with stronger intrinsic variety-seeking (i.e., the loss decreases with δ).

Proposition 2 reveals that pricing competitively based on ratings is particularly important for markets where consumers exhibit strong intrinsic variety-seeking behavior. Intuitively, if intrinsic variety-seeking is strong, more consumers are convinced to switch to the competitor's product which can be exploited by pricing based on the quality signal they rely on (i.e., ratings). Furthermore, consumers have a higher willingness to pay for the competitor's product. Thus, adjusting the price according to one's own and one's competitor's online rating becomes even more profitable. Figure 3 illustrates prices and profits for the setting of Proposition 2.

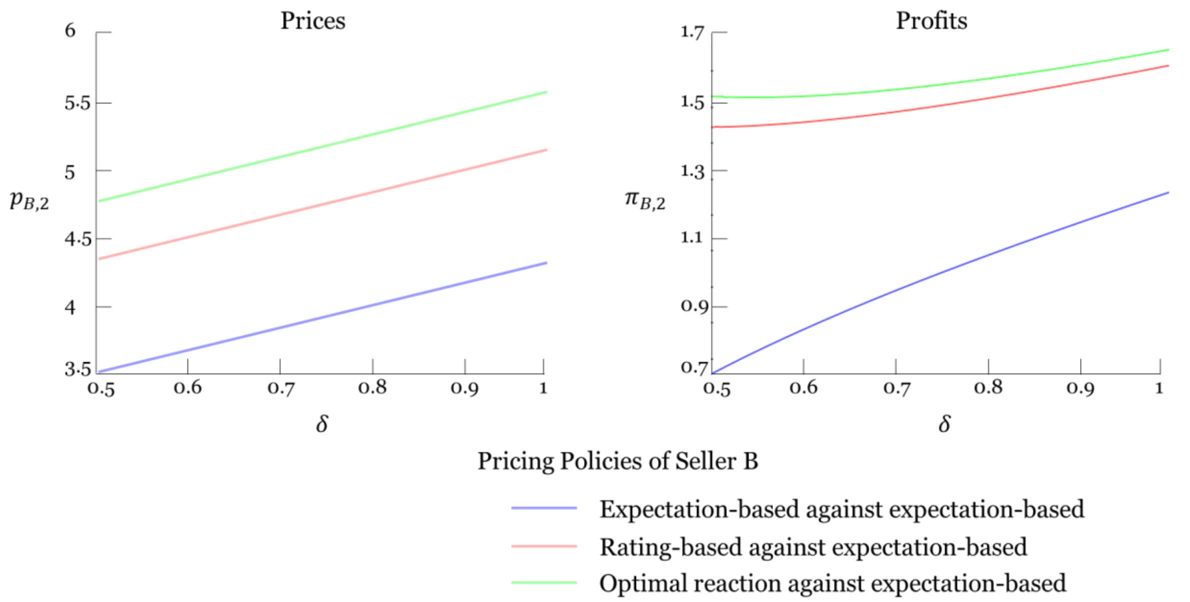

Figure 3 Illustration of the Relationship between Different Pricing Strategies and Intrinsic Variety-Seeking for Seller B. Note: Seller A always adopts expectation-based pricing, here, and thus sets their price as given in Lemma 3. Seller B's price differs as indicated in the legend of the figure.

$$(\boldsymbol{q_A = 3, q_B = 5, q^e = 4, x = 2, R_A = 3, R_B = 7, c_B = 3, \epsilon = 2})$$

Additionally, the figure shows a setting where seller B anticipates seller A's price-setting based on expectations and chooses an optimal reaction accordingly. In these settings, the price asked by seller A, who employs an expectation-based pricing strategy is too high. Thus, if seller B anticipates this pricing policy, they can demand higher prices and benefit from an increased profit. One can see that stronger intrinsic variety-seeking behavior increases potential gains for seller B.

4.4 Online Ratings as an External Factor for Variety-Seeking Behavior

In the previous section, we focused on the relationship between *intrinsic* variety-seeking behavior and the economic impact of online ratings. As pointed out in the literature (Kahn 1995), there are also *external factors* for variety-seeking behavior. In our model and in empirical research (Wang and Goh 2012), online ratings are considered to be one such external factor. In other words, a higher online rating for a seller can increase the number of consumers that switch from the competitor's consumer base in the second period. However, there is a second effect resulting from higher online ratings; an increase in online ratings also increases the willingness to pay of consumers (also shown empirically by Wu and Gaytán 2013) coming from the seller's competitor. Due to this twofold nature of online ratings, sellers in our model have two options when their online ratings increase. First, they can increase prices to benefit from an increased willingness to pay. Second, they can keep prices low to benefit from an increased demand. In the following, we analyze whether the first option outweighs the second one, or vice versa.

Proposition 3: For equilibrium conditions, a marginal increase in a seller's rating is always associated with an increase in incoming variety-seeking consumers from their competitor and an increase in outgoing variety-seeking consumers leaving the seller.

Combining the findings of Lemma 4 with those of Proposition 3, we can determine the seller's reaction to an increase in their rating. Even though sellers respond to this by increasing their prices (Lemma 4), this increase still generates an increased demand from the competitor's customers and a decrease in demand from the seller's own consumer base (Proposition 3).

4.5 Impact of Online Ratings on Consumer Surplus

To study the impact of ratings on expected consumer surplus in the light of variety-seeking behavior, we first determine the expected consumer surplus of a single consumer as presented in Equation 13.

$$Q + \delta q_i - \tau_i^r x - p_{i,2} \text{ (Stayed with seller } i\text{)} , \ Q + q_i - \tau_i^r x - p_{i,2} \text{ (Came to seller } i\text{)} \quad (13)$$

Then, aggregating these over all consumers of the four different types (i.e., stayed/came to seller A/B, respectively) yields the following:

$$
\begin{aligned}
CS_{A,2}^{stay} &= \int_{0}^{\frac{(x-p_{A,1}+p_{B,1})}{2x}} \int_{\frac{R_B-\delta q_A+x(2\tau_A^r-1)+p_{A,2}-p_{B,2}}{\delta}}^{\epsilon} \left(Q+\delta q_i-\tau_i^r x-p_{i,2}\right) dt\, d\tau_A^r \\
CS_{A,2}^{inc} &= \int_{\frac{(x-p_{i,1}+p_{j,1})}{2x}}^{1} \int_{-\epsilon}^{\frac{R_A-\delta q_B+x(1-2\tau_A^r)+p_{B,2}-p_{A,2}}{\delta}} \left(Q+q_A-\tau_A^r x-p_{A,2}\right) dt\, d\tau_A^r \\
CS_{B,2}^{inc} &= \int_{0}^{\frac{(x-p_{A,1}+p_{B,1})}{2x}} \int_{-\epsilon}^{\frac{R_B-\delta q_A+x(2\tau_A^r-1)+p_{A,2}-p_{B,2}}{\delta}} \left(Q+q_B-(1-\tau_A^r)x-p_{B,2}\right) dt\, d\tau_A^r \\
CS_{B,2}^{stay} &= \int_{\frac{(x-p_{A,1}+p_{B,1})}{2x}}^{1} \int_{\frac{R_A-\delta q_B+x(1-2\tau_A^r)+p_{B,2}-p_{A,2}}{\delta}}^{\epsilon} \left(Q+\delta q_B-(1-\tau_A^r)x-p_{B,2}\right) dt\, d\tau_A^r
\end{aligned}
\tag{14}
$$

The sum of $CS_{A,2}^{stay}$, $CS_{A,2}^{inc}$, $CS_{B,2}^{stay}$, $CS_{B,2}^{inc}$ represents the expected aggregate consumer surplus, which enables us to analyze the impact of biased ratings, i.e., ratings that deviate from the expected marginal quality q_i.

Proposition 4a: For equilibrium conditions, a marginal increase in seller A's rating R_A is associated with an increase in expected consumer surplus if and only if $\delta < \delta_1^{Prop4} := -\frac{27x^2+(-54q_A-18d+15c_B-12R_B+12R_A)x-12c_Bq_A-6c_Bd+(-4R_B-4R_A)c_B}{(54q_A+24d)x+20c_Bq_A+10c_Bd}$

Proposition 4b: Let $c_B < \frac{27}{10}x$. For equilibrium conditions, a marginal increase in seller B's rating R_B is associated with an increase in expected consumer surplus if and only if

$\delta < \delta_2^{Prop4} := -\frac{27x^2+(-54q_A-36d-15c_B+12R_B-12R_A)x+12c_Bq_A+6c_Bd+(4R_B+4R_A)c_B}{(54q_A+30d)x-20c_Bq_A-10c_Bd}$.

Proposition 4a and 4b[7] inform us that, regardless of the actual expected marginal quality, an increase in a seller's rating results in an increase in expected consumer surplus if intrinsic variety-seeking is sufficiently strong. Specifically, this means that even if their rating is upward biased, i.e., $R_i > q_i$, a further increase in the seller's rating still results in an increased consumer surplus. Corollaries 1a and 1b capture the relationship between consumer surplus maximizing ratings and intrinsic variety-seeking.

Corollary 1a: Seller A's consumer surplus maximizing rating is positively biased (i.e., greater than q_A) if and only if $\delta < -\frac{27x^2+(-42q_A-18d+15c_B-12R_B)x-16c_Bq_A-6c_Bd-4R_Bc_B}{(54q_A+24d)x+20c_Bq_A+10c_Bd}$.

Corollary 1b: Let $c_B < \frac{27}{10}x$. Seller B's consumer surplus maximizing rating is positively biased (i.e., greater than q_B) if and only if $\delta < -\frac{27x^2+(-42q_A-24d-15c_B-12R_A)x+16c_Bq_A+10c_Bd+4R_Ac_B}{(54q_A+30d)x-20c_Bq_A-10c_Bd}$.

At first glance, it may seem surprising that an inaccurate rating would be beneficial for consumer surplus. There are three effects captured by the results of Lemma 4 and Proposition 3 that govern the impact of an increase in seller i's rating on consumer surplus.

Incoming Customers: First, an increase in one's rating lures in more customers who have had a relatively bad experience with the competitor. Not knowing that the average experience is better than what they have experienced, they seek variety. Given that the seller benefitting from the improved rating also increases their price whereas their competitor reduces theirs (Lemma 4), this behavior can reduce consumer surplus. More formally, customers of competitor *j* consider their own realized marginal quality q_j^r in their decision-making, not knowing q_j. Thus, any increase in ratings drives more consumers with relatively low q_j^r to seek variety with seller i (see Proposition 3). We term this the *Experience Effect* because it is driven by consumers making their decisions based on their realized marginal quality. For these consumers, if $\delta q_j - \tau_j^r x - p_{j,2} < q_i - \tau_i^r x - p_{i,2}$ expected consumer surplus increases. Because $p_{i,2}$ increases and $p_{j,2}$ decreases (Lemma 4), this equation might not be

[7] Note that for $c_B > 27/30\ x$ the sign of the second inequality in Proposition 4 is flipped, i.e., $\delta > \delta_2^{Prop4}$. In this case, the marginal costs of seller B are so high that increases in their rating under strong intrinsic variety-seeking behavior hurts consumer surplus. That is because their consumer base is relatively small (i.e., <20%) and, to cover the costs, an increase in ratings is used to demand a high price from the relatively high number of incoming variety-seeking consumers.

fulfilled. However, if δ is sufficiently strong the impact of this effect on consumer surplus could still be positive. Note that, if consumers would fully rely on ratings to evaluate the product they already know (i.e., $r_2 = 0$), or if they would learn the expected marginal quality after consumption, ratings being equal to the expected marginal quality would maximize consumer surplus.

Outgoing Customers: Second, the price changes of both sellers (Lemma 4) have an additional effect. The price increase and the competitor's price decrease cause more consumers to switch to the competitor. Consequently, the increase in seller i's rating lets consumers leave i for j (see Proposition 3). We term this second shift in consumer bases the *Rating-based Pricing Effect*, because it is driven by sellers adjusting their prices to a change in ratings. For these consumers, similarly to above, if $\delta q_i - \tau_i^r x - p_{i,2} < q_j - \tau_j^r x - p_{j,2}$, then expected consumer surplus increases. The price changes postulated by Lemma 4 contribute to the fulfillment of this inequality. Further, note that, again, the left-hand side of the inequality is decreasing in δ, implying that strong intrinsic variety-seeking behavior leads to more variety-seeking consumers that contribute to an increase in consumer surplus.

Staying Customers: Finally, while the first two effects consider consumers who switch between the sellers, there is also another effect on those who stay with a seller. Due to the increase in a seller's price, all the consumers who are staying obtain a lower consumer surplus. On the contrary, due to the decrease by the competitor, all consumers staying with the competitor enjoy a higher consumer surplus. We term this the *Loyalty Effect*. Taking all three effects into consideration, there is a point where the gain in consumer surplus driven by seller j's price decrease (*Rating-based Pricing Effect+Loyalty Effect*) is equal to the loss in consumer surplus caused by seller i's price increase (*Experience Effect+Loyalty Effect*). Any further increase in i's rating would yield a decrease in consumer surplus. At this point, the rating maximizes consumer surplus.

Note that one can show thresholds similar to δ_1^{Prop4} and δ_2^{Prop4} for social welfare. Figure 4 illustrates Propositions 4a and 4b as well as Corollaries 1a and 1b and the impact of ratings on social welfare. One can see that the area of positively biased ratings being beneficial for consumer surplus increases with stronger intrinsic variety-seeking.

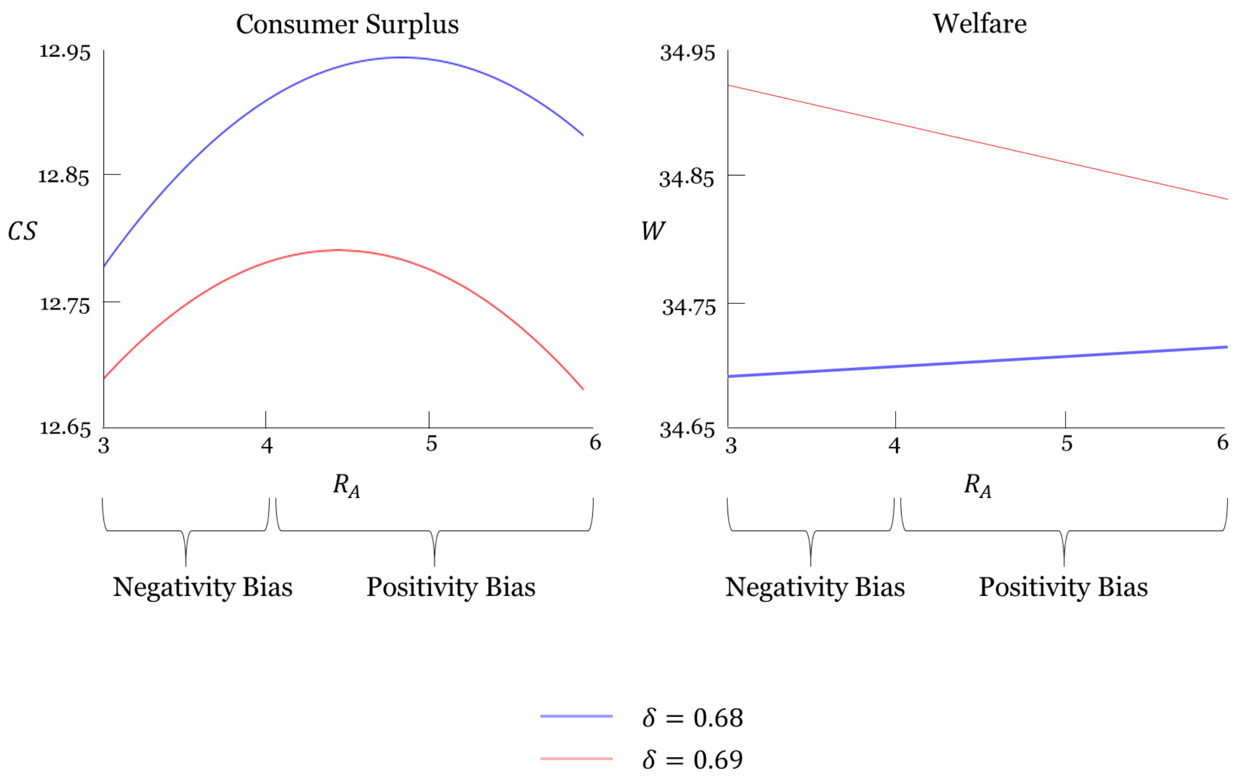

Figure 4 Welfare and Consumer Surplus in Relation to Seller A's Rating.
Note: ($\boldsymbol{Q = 2, q_A = 4, q_B = 7, x = 3, R_B = 6, c_B = 2, \epsilon = 4, q^e = 4}$)

As another illustrative example for the potentially positive impact of biased ratings on consumer surplus, consider the following setting in a restaurant market. Suppose that in the first period, there is a unit-sized mass of consumers which consists of locals. Additionally, there are some consumers who are travelers. While travelers influence online ratings, they leave the market after the first period. Empirical research suggests that travelers coming from a less popular city exhibit a positive popularity bias in their online ratings as opposed to locals (Kokkodis and Lappas 2020). In our model, this means that the distribution of q_i^r experienced by travelers is shifted in an upward direction relative to the distribution of q_i^r experienced by locals (i.e., there are two independent distributions). Consequently, ratings after the first period are likely to be biased upwards with regards to the expected marginal quality experienced by the population of locals. Because intrinsic variety-seeking is relatively strong in such a market, this upward bias documented by the literature could indeed be beneficial for overall consumer surplus according to our results.

Our analysis, overall, suggests that biases in online ratings have a heterogenous impact on consumer surplus and social welfare that strongly depends on the variety-seeking nature of the consumers.

5 Model Extension: Consumers' Reliance on Own Expectations

In the second period of our model, we let consumers fully rely on ratings instead of their own expectations when they form their quality expectations regarding the competitor's product. With the presence of fake reviews (e.g., Luca and Zervas 2016) and associated media coverage (Ovide 2020), consumers might lose trust in reviews and increasingly incorporate their own expectations into their purchase decisions. In this extension, we account for this relationship by letting $r_1 > 0$ to investigate its impact on our findings related to profit and consumer surplus. Note that one can obtain the profit maximizing second-period prices for $r_1 > 0$ from substituting R_i with $r_1 q^e + (1 - r_1)R_i$ in the prices presented in Lemma 2.

Proposition 5: Let $r_1 > 0$ *and* $\epsilon > \frac{-3dx+2c_B q_A + c_B d}{6c_B}$*. For equilibrium conditions, a marginal increase in seller A's online rating is more profitable for seller A than a marginal increase in seller B's rating for seller B if and only if*

$$\delta \coloneqq \delta^{Prop5} < \frac{((3R_B-3R_A)r_1+6c_B-3R_B+3R_A)x+((R_B+R_A)c_B-2c_B q^e)r_1+(-R_B-R_A)c_B}{(3q_B-3q_A)x-c_B q_B-c_B q_A+6c_B\varepsilon}.$$

Proposition 5 represents a generalization of Proposition 1 and allows us to analyze how consumer expectations influence the impact of ratings under variety-seeking behavior, which is captured by the following corollary.

Corollary 2: The threshold δ^{Prop5} *is decreasing in consumer expectations* q^e*.*

Based on Corollary 2, we can conclude that high consumer expectations contribute to the profitability of higher ratings for the high-quality seller. If consumers hold higher expectations for both sellers, they are driven to seek variety regardless of ratings. Therefore, higher ratings become less profitable, especially for the low-quality seller who otherwise would have to rely on the intrinsic variety-seeking tendencies of consumers. Naturally, this effect of consumer expectations grows stronger with consumers' reliance on these expectations.

Proposition 6a: Let $r_1 > 0$*. For equilibrium conditions, a marginal increase in seller A's rating* R_A *is associated with an increase in expected consumer surplus if and only if* $\delta < \delta_1^{Prop6} :=$

$$-\frac{27x^2+((12R_B-12R_A)r_1-54q_A-18d+15c_B-12R_B+12R_A)x+((4R_B+4R_A)c_B-8c_Bq^e)r_1-12c_Bq_A-6c_Bd+(-4R_B-4R_A)c_B}{(54q_A+24d)x+20c_Bq_A+10c_Bd}$$

Proposition 6b: Let $c_B < \frac{27}{10}x$ *and* $r_1 > 0$*. For equilibrium conditions, a marginal increase in seller B's rating* R_B *is associated with an increase in expected consumer surplus if and only if* $\delta < \delta_2^{Prop6} :=$

$$-\frac{27x^2+\left((12R_A-12R_B)r_1-54q_A-36d-15c_B+12R_B-12R_A\right)x+(8c_Bq^e+(-4R_B-4R_A)c_B)r_1+12c_Bq_A+6c_Bd+(4R_B+4R_A)c_B}{(54q_A+30d)x-20c_Bq_A-10c_Bd}$$

Proposition 6a and 6b show that our results pertaining to consumer surplus also hold if consumers do not fully rely on ratings to form their expectations regarding the competitor's product. Whether consumers' reliance on their own expectations instead of on ratings increases or decreases consumer surplus maximizing ratings depends on the other model factors such as quality expectations, marginal qualities, and ratings.

6 Conclusion

Online reviews help potential consumers with finding products and services that are of high quality and match their taste (e.g., Hong and Pavlou 2014). This support in decision-making is particularly important in markets where consumers exhibit variety-seeking behavior, which means that consumers have an intrinsic desire to seek variety in their choice of goods just to avoid consuming the same good multiple times (e.g., Kahn 1995). Since variety-seeking consumers regularly need to decide between staying with a product or service and switching to another one, the online ratings attached to each review are essential for decision-making when consumers compare these two options. Despite the importance of online reviews and ratings in the process of variety-seeking, no study has yet carried out an investigation into their role across markets with differing levels of variety-seeking consumers. To address this gap, we propose an analytical model, comprising two periods. In the first period, consumers decide between two sellers based on their expectations. In the second period, they have experienced one of the two products and receive information on the other product's quality from an online rating. Then, consumers must decide whether to switch to a new product or experience a diminished utility from consuming the same product.

Our results provide valuable insights for practitioners. First, we find that a low-quality seller has a higher incentive to improve their online rating compared to a high-quality seller in markets where intrinsic variety-seeking behavior is sufficiently strong. Thus, we reveal a heterogeneous economic value of online ratings depending on the variety-seeking nature of the market. If consumers exhibit a strong intrinsic need for variety, low-quality sellers should not rely too much on attracting customers merely due to the variety-seeking nature of the market but, instead, should actively aim to improve their online ratings and invest in online reputation management. For instance, they could reply to negative reviews to improve future ratings (Proserpio and Zervas 2017). Platforms like Yelp and TripAdvisor can support this endeavor by, for example, changing the aggregation window for average ratings (Aperjis and Johari 2010). If platforms calculate average ratings based on the last few months, (low-quality) sellers who take measures to improve their reputation benefit from the design change. High-quality sellers benefit less from an increase in ratings and should therefore place a relatively higher emphasis on measures aimed at customer retention. Notably, we show that the seemingly intuitive result regarding low-quality sellers benefitting more from an increase in ratings does not always hold. If intrinsic variety-seeking is weak, a marginal increase in ratings is indeed more beneficial to the high-quality seller, which suggests that, in such a case, high-quality sellers should not rely solely on their established consumer base.

Second, our results suggest that the gain that sellers can realize from a strategic approach to pricing based on online ratings, instead of consumer expectations, is seen to increase in markets where consumers exhibit greater intrinsic variety-seeking. In markets where consumers exhibit these strong variety-seeking tendencies, sellers might complacently neglect their pricing, since consumers come and go to fulfill their need for variety. In contrast, our results emphasize that sellers in such markets substantially benefit from adjusting their prices based on their online rating. Additionally, these markets, for instance restaurant markets, often face high menu costs (Hobijn et al. 2006) that keep sellers from adjusting their prices to changes in their rating. This finding suggests that sellers in such markets should implement measures aimed at reducing menu costs (e.g., displaying prices in a digital format) so that they can benefit from these additional gains.

Third, we show that an increase in online ratings yields an increase in consumer surplus if intrinsic variety-seeking is sufficiently strong. In particular, we identify conditions where positively biased ratings are more beneficial to consumer surplus than accurate ratings. In contrast, negatively biased ratings reduce consumer surplus in these conditions. This heterogeneous impact of biased ratings on consumer surplus informs review system designers that de-biasing ratings is not always in the interest of their system's users. For instance, Kokkodis and Lappas (2020) identify a popularity-difference bias in restaurant ratings and suggest de-biasing these ratings to get a more accurate ranking of restaurants in a city. Based on our results, positively biased ratings could be beneficial for consumer surplus in such a case, which suggests a more careful examination of de-biasing strategies both from research and practice.

Our results contribute to the growing stream of literature that suggests that prices should be set dynamically based on online reviews and ratings (Feng et al. 2019; Li and Hitt 2010) and extends previous findings on pricing strategies in markets with variety-seeking consumers (Zeithammer and Thomadsen 2013). With this study, we advance analytical work on online reviews by emphasizing behavioral aspects in consumer decision making modeling. Even though there are many behavioral studies on online reviews (e.g., Ho et al. 2017; Muchnik et al. 2013; Yin et al. 2016), only few incorporate these behavioral aspects into their analytical work. In this way, we answer the recent call to include such aspects into theory on online reputation (Chen et al. 2020). Uncovering positive outcomes of biased ratings, we also add more depth to the scholarly discussion on biases in online ratings (e.g., Hu et al. 2017; Huang et al. 2016; Kokkodis and Lappas 2020) and show that biased ratings are not always detrimental for consumers. Finally, we also add to the analysis of external factors driving consumers to seek variety (e.g., Kahn 1995) by analyzing how changes in ratings affect the observable number of variety-seeking consumers (1) directly, through communicating a sufficiently high product quality, and (2) indirectly, through rating-based pricing.

Naturally, there are limitations to this study that open up avenues for future research. We do not consider a more complex multi-period model as in Li et al. (2011) for instance. Such a model could consider an increasingly diminishing utility for consumers who stay with a product over multiple periods, menu costs, and sellers taking turns in updating their prices. One could also consider variety-seeking due to uncertainty of future tastes as this is the only cause for variety-seeking that we do not consider in our study. In such a model, consumer taste might change with a certain probability. Online reviews also provide information on the unobservable taste-related aspects of a product or service (Hong and Pavlou 2014), e.g., in form of review texts. Future work could extend our model to account for such signals from online review texts (e.g., as in Kwark et al. 2014). Incorporating other behavioral aspects such as expectation disconfirmation (e.g., Ho et al. 2017) into sellers' pricing strategies is also an interesting avenue that future research could pursue.

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Appendix

Proof of Lemma 1

Both sellers maximize their own profit function based on the price setting behavior of the competitor. The first-order conditions for maximum profit in the first period are:

$$\pi'_{A,1}(p_{A,1}, p_{B,1}) = \frac{\partial \pi_{A,1}}{\partial p_{A,1}} = \frac{x + p_{B,1} - p_{A,1}}{2x} - \frac{p_{A,1}}{2x} = 0$$

(14)

$$\pi'_{B}(p_{A,1}, p_{B,1}) = \frac{\partial \pi_{B,1}}{\partial p_{B}} = -\frac{x + p_{B,1} - p_{A,1}}{2x} - \frac{p_{B,1} - c_B}{2x} + 1 = 0$$

The resulting reaction functions for the prices are given by:

$$p_{\mathrm{A},1}(p_{B,1}) = \frac{x + p_{B,1}}{2}$$

(15)

$$p_{\mathrm{B},1}(p_{A,1}) = \frac{x + p_{A,1} + c_B}{2}$$

The solutions to Equation 14 are the optimal prices given in Equation 9. Optimal profits and demand follow from inserting the prices into the profit and demand functions.

QED.

Proof of Lemma 2

We can now use the optimal prices of the first period to calculate the optimal prices for the second period. The first-order conditions for maximum profit in the second period are:

$$\pi'_{A,2}(p_{A,2}, p_{B,2}) = \frac{\partial \pi_{A,2}}{\partial p_{A,2}}$$
$$= p_{A,2}\left(-\frac{3x + c_B}{12\delta\varepsilon x} - \frac{3x - c_B}{12\delta\varepsilon x}\right)$$
$$- \frac{(3x - c_B)(3x + 6\delta q_B - 6p_{B,2} + 6p_{A,2} - 6\delta\varepsilon + c_B - 6R_A)}{72\delta\varepsilon x}$$
$$+ \frac{(3x + c_B)(3x + 6\delta q_A + 6p_{B,2} - 6p_{A,2} + 6\delta\varepsilon - c_B - 6R_B)}{72\delta\varepsilon x} = 0$$

(16)

$$\pi'_{B,2}(p_{A,2}, p_{B,2}) = \frac{\partial \pi_{B,2}}{\partial p_{B,2}}$$
$$= (p_{B,2} - c_B)(-\frac{3x + c_B}{12\delta\varepsilon x} - \frac{3x - c_B}{12\delta\varepsilon x})$$
$$+ \frac{(3x - c_B)(3x + 6\delta q_B - 6p_{B,2} + 6p_{A,2} + 6\delta\varepsilon + c_B - 6R_A)}{72\delta\varepsilon x}$$
$$- \frac{(3x + c_B)(3x + 6\delta q_A + 6p_{B,2} - 6p_{A,2} - 6\delta\varepsilon - c_B - 6R_B)}{72\delta\varepsilon x} = 0$$

The resulting best response functions for the prices are given by:

$$p_{\mathrm{A},2}(p_{B,2})$$
$$= -\frac{(3\delta q_B - 3\delta q_A - 6p_{B,2} - 6\delta\varepsilon + 3R_B - 3R_A)x - c_B\delta q_B - c_B\delta q_A + (R_B + R_A)c_B}{12x}$$

(17)

$$p_{\mathrm{B},2}(p_{A,2})$$
$$= \frac{(3\delta q_B - 3\delta q_A + 6p_{A,2} + 6\delta\varepsilon + 6c_B + 3R_B - 3R_A)x - c_B\delta q_B - c_B\delta q_A + (R_B + R_A)c_B}{12x}$$

The solutions to Equation 16 are the optimal prices given in Equation 10. Optimal profits in Equation 11 follow from inserting Equation 10 into the profit functions.

QED.

Proof of Lemma 3

Note that the equilibrium prices for the expectation-based pricing policy are based on the assumption that both sellers expect consumer expectations in the second period to be equal to q^e. Therefore, substituting R_A and R_B with q^e in Equation 10 yields equilibrium prices for this policy.

QED.

Proof of Lemma 4

We show that the partial derivatives with respect to the sellers rating are positive.

$$\frac{\partial p_{A,2}}{\partial R_A} = \frac{3x - c_B}{18x} > 0$$

$$\frac{\partial p_{B,2}}{\partial R_B} = \frac{3x + c_B}{18x} > 0$$

$$\frac{\partial \pi_{A,2}}{\partial R_A} = \frac{(3x - c_B)(-3\delta q_B x + 3\delta q_A x + 18\delta\varepsilon x + 6c_B x - 3R_B x + 3R_A x + c_B\delta q_B + c_B\delta q_A - R_B c_B - R_A c_B)}{324\delta\varepsilon x^2} > 0 \tag{18}$$

$$\frac{\partial \pi_{B,2}}{\partial R_B} = \frac{(3x + c_B)(3\delta q_B x - 3\delta q_A x + 18\delta\varepsilon x - 6c_B x + 3R_B x - 3R_A x - c_B\delta q_B - c_B\delta q_A + R_B c_B + R_A c_B)}{324\delta\varepsilon x^2} > 0$$

These equations hold since $c_B < 3x$ and the second term in the nominator of the last two equations is positive if and only if second-period prices are positive.

QED.

Proof of Proposition 1

Let $\epsilon > \frac{-3dx+2c_B q_A + c_B d}{6c_B}$. Seller A benefits more from an increase in their rating if the increase in profits is larger for seller A than for seller B. Therefore, we investigate conditions in which the difference in partial derivatives of the profit functions is positive.

$$\frac{\partial \pi_{A,2}}{\partial R_A} - \frac{\partial \pi_{B,2}}{\partial R_B}$$

$$= -\frac{3d\delta x - 6c_B x + 3R_B x - 3R_A x - 2c_B \delta q_A + 6c_B \delta \varepsilon - c_B d\delta + R_B c_B + R_A c_B}{54\delta\varepsilon x} > 0 \qquad (19)$$

$$\Leftrightarrow \delta < \frac{(6c_B - 3R_B + 3R_A)x + (-R_B - R_A)c_B}{3dx - 2c_B q_A + 6c_B \varepsilon - c_B d}$$

QED.

Proof of Proposition 2

We examine the differences between the profits of the two equilibria.

$$\pi_{A,2}(p_{A,2}^o, p_{B,2}) - \pi_{A,2}(p_{A,2}, p_{B,2}) = -\frac{(3R_B x - 3R_A x - 2c_B q_e + R_B c_B + R_A c_B)^2}{648\delta\varepsilon x^2} < 0$$

$$\pi_{B,2}(p_{A,2}, p_{B,2}^o) - \pi_{B,2}(p_{A,2}, p_{B,2}) = -\frac{(3R_B x - 3R_A x - 2c_B q_e + R_B c_B + R_A c_B)^2}{648\delta\varepsilon x^2} < 0 \qquad (20)$$

Note that the loss increases if the denominator decreases, which occurs with stronger intrinsic variety-seeking (i.e., a smaller δ).

QED.

Proof of Proposition 3

We need to show that $D_{A,2}^{stay}$ is decreasing in R_A and $D_{A,2}^{inc}$ is increasing in R_A.

$$\frac{\partial D_{A,2}^{stay}}{\partial R_A} = \frac{(2c_B - 6x)(3x + c_B)}{216\delta\varepsilon x^2} < 0$$
$$\frac{\partial D_{A,2}^{inc}}{\partial R_A} = \frac{(12x + 2c_B)(3x - c_B)}{216\delta\varepsilon x^2} > 0 \tag{21}$$

Note that these conditions hold because $c_B < 3x$. The proof is analogous for seller B.

QED.

Proof of Propositions 4a and 4b

We analyze the partial derivatives of the expected consumer surplus with respect to R_A and R_B. Let $c_B < \frac{27}{10}x$.

$$\frac{\partial\left(CS_{A,2}^{stay} + CS_{A,2}^{inc} + CS_{B,2}^{stay} + CS_{B,2}^{inc}\right)}{\partial R_A}$$

$$= \frac{-81x^3 - 72\delta(q_A + d)x^2 + 54(q_A + d)x^2 - 90\delta q_A x^2 + 108q_A x^2 - 18c_B x^2 + 36R_B x^2 - 36R_A x^2 - 6c_B\delta(q_A + d)x}{324\delta x^2}$$

$$+ \frac{-18c_B q_A x + 15{c_B}^2 x + 24R_A c_B x + 10{c_B}^2\delta(q_A + d) - 6{c_B}^2(q_A + d) + 10{c_B}^2\delta q_A - 6{c_B}^2 q_A - 4R_B{c_B}^2 - 4R_A{c_B}^2}{324\delta x^1} > 0$$

$$\Leftrightarrow \delta < -\frac{27x^2 + (-54q_A - 18d + 15c_B - 12R_B + 12R_A)x - 12c_B q_A - 6c_B d + (-4R_B - 4R_A)c_B}{(54q_A + 24d)x + 20c_B q_A + 10c_B d} \tag{22}$$

$$\frac{\partial\left(CS_{A,2}^{stay} + CS_{A,2}^{inc} + CS_{B,2}^{stay} + CS_{B,2}^{inc}\right)}{\partial R_B}$$

$$= \frac{-81x^3 - 90\delta(q_A + d)x^2 + 108(q_A + d)x^2 - 72\delta q_A x^2 + 54q_A x^2 + 18c_B x^2 - 36R_B x^2 + 36R_A x^2 + 18c_B(q_A + d)x + 6c_B\delta q_A x}{324\delta x^2}$$

$$+ \frac{15{c_B}^2 x - 24R_B c_B x + 10{c_B}^2\delta(q_A + d) - 6{c_B}^2(q_A + d) + 10{c_B}^2\delta q_A - 6{c_B}^2 q_A - 4R_B{c_B}^2 - 4R_A{c_B}^2}{324\delta x^2} > 0$$

$$\Leftrightarrow \delta < -\frac{27x^2 + (-54q_A - 36d - 15c_B + 12R_B - 12R_A)x + 12c_B q_A + 6c_B d + (4R_B + 4R_A)c_B}{(54q_A + 30d)x - 20c_B q_A - 10c_B d}$$

Note that the last equivalence holds because $c_B < \frac{27}{10}x$.

QED.

Proof of Corollary 1a and 1b

We analyze the partial derivatives of the expected consumer surplus with respect to R_A and R_B. Let $c_B < \frac{27}{10}x$.

$$\frac{\partial\left(CS_{A,2}^{stay} + CS_{A,2}^{inc} + CS_{B,2}^{stay} + CS_{B,2}^{inc}\right)}{\partial R_A}$$

$$= \frac{-81x^3 - 72\delta(q_A + d)x^2 + 54(q_A + d)x^2 - 90\delta q_A x^2 + 108 q_A x^2 - 18c_B x^2 + 36R_B x^2 - 36R_A x^2 - 6c_B\delta(q_A + d)x}{324\delta x^2}$$

$$+ \frac{-18c_B q_A x + 15{c_B}^2 x + 24R_A c_B x + 10{c_B}^2\delta(q_A + d) - 6{c_B}^2(q_A + d) + 10{c_B}^2\delta q_A - 6{c_B}^2 q_A - 4R_B{c_B}^2 - 4R_A{c_B}^2}{324\delta x^1} > q_A$$

$$\Leftrightarrow \delta < -\frac{27x^2 + (-42q_A - 18d + 15c_B - 12R_B)x - 16c_B q_A - 6c_B d - 4R_B c_B}{(54q_A + 24d)x + 20c_B q_A + 10c_B d}$$

(23)

$$\frac{\partial\left(CS_{A,2}^{stay} + CS_{A,2}^{inc} + CS_{B,2}^{stay} + CS_{B,2}^{inc}\right)}{\partial R_B}$$

$$= \frac{-81x^3 - 90\delta(q_A + d)x^2 + 108(q_A + d)x^2 - 72\delta q_A x^2 + 54q_A x^2 + 18c_B x^2 - 36R_B x^2 + 36R_A x^2 + 18c_B(q_A + d)x + 6c_B\delta q_A x}{324\delta x^2}$$

$$+ \frac{15{c_B}^2 x - 24R_B c_B x + 10{c_B}^2\delta(q_A + d) - 6{c_B}^2(q_A + d) + 10{c_B}^2\delta q_A - 6{c_B}^2 q_A - 4R_B{c_B}^2 - 4R_A{c_B}^2}{324\delta x^2} > q_A + d$$

$$\Leftrightarrow \delta < -\frac{27x^2 + (-42q_A - 24d - 15c_B - 12R_A)x + 16c_B q_A + 10c_B d + 4R_A c_B}{(54q_A + 30d)x - 20c_B q_A - 10c_B d}$$

Note that the last equivalence holds because $c_B < \frac{27}{10}x$.

QED.

Proof of Proposition 5

Substitute R_i with $(1 - r_1)R_i + r_1 q_e$ in the second-period equilibrium prices. Then, the proof is analogous to the proof of Proposition 1.

QED.

Proof of Corollary 2

Let $\epsilon > \frac{-3dx+2c_Bq_A+c_Bd}{6c_B}$.

$$\frac{\partial\delta^{Prop5}}{\partial q_e} = -\frac{2c_Br_1}{(3q_B - 3q_A)x - c_Bq_B - c_Bq_A + 6c_B\varepsilon} < 0 \tag{24}$$

QED.

Proof of Propositions 6a and 6b

Substitute R_i with $(1 - r_1)R_i + r_1q_e$ in the second-period equilibrium prices. Then, the proof is analogous to the proof of Propositions 4a and 4b.

QED.