Rising or Dropping: the Consumer Review-oriented Pricing Paradox

Completed Research Paper

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Abstract

Product pricing strategy and online word-of-mouth both influence consumer purchase. There have been increasing interests and conflict results on how to optimize seller’s pricing strategy in dealing with the interaction between price, consumer review, and sales. We focus on the early stage of product sales and develop a two-stage economic model. We find that the product type, that is, whether the product is horizontally differentiated or vertically differentiated, as well as the discrepancy between the expected and actual product quality/features play important roles in pricing, which lead to two opposite optimal pricing strategies, i.e., to set a high vs. low price in the initial stage to attract favorable consumer reviews. We obtain data from an online market and our empirical findings confirm our theoretical projections. Our research contributes to the literature of optimal pricing strategy under the influence of social media. It may help direct companies’ practice in strategic pricing.

Keywords: Product pricing, vertical differentiation, horizontal differentiation, consumer review, two-period model, panel data
Introduction

Product pricing strategy has always been a major instrument for companies to influence consumers and promote sales. For example, discount stores provide discounts while luxury brands maintain a high price to attract their targeted customers. With the advance of e-business and Web 2.0, several new factors, such as online word-of-mouth, join in this seller-buyer game. Particularly, online consumer review begins to show a significant impact on consumer purchase (ComScore, 2007). Online consumer reviews are comments provided by users of e-commerce Websites, which usually put next to the commented products. Without direct interactions, potential buyers can get more information from previous buyers on the product (and shopping experience) to support their decisions. Online consumer review enforces consumers' collective power in reducing uncertainty on products, which is critical to online transactions that have large uncertainties and information asymmetries (Gavish and Tucci 2008; IC3 2010). Due to its dynamic nature and capability of including multiple interest groups' opinions, in some cases, consumer review can be more useful than expert review provided by sellers in influencing sales (Piller 1999; ComScore 2007).

While pricing and consumers review both affect consumer decision, their interaction is complicated and has attracted academic interests. On one hand, a lower price and a better consumer review cause more sales (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004). On the other, product price setting may affect the ratings of follow-up consumer reviews (Li and Hitt, 2010). Sellers need to strategically control the price dynamics for both favorable comments and an overall higher profit. Nevertheless, there have been conflicting arguments regarding to whether a product that attracts positive review should charge higher or lower price than a product with poor review (Ba and Pavlou 2002; Ba et al. 2008; Baylis and Perloff 2002; Li et al. 2009). In practice, it is observed that some sellers reduce, while others increase price after obtaining positive reviews. Little research, however, has been done to understand these conflict findings.

In this study, we focus on the early stage of product sales, when the market is not saturated and consumers are not very familiar with the product. Assuming that price is the only instrument a company can manipulate, we aim to answer two questions: 1) Should a seller set a higher/lower price at the initial stage of selling a product by considering its potential impact on consumer review? 2) How should the seller adjust its product price after positive/negative reviews are obtained?

We first build a theoretical model to examine the optimal pricing strategy at the early stage of product sales considering the impact of price on consumer review, which will affect later adaptors' purchase as well as the product’s future price. We categorize products to be either horizontally differentiated or vertically differentiated and find that a seller may choose opposite pricing strategy on these two types of products to generate favorable product review, depending on the quality/features of the product. We then collect empirical data from a real e-commerce Website to illustrate the interaction between price and consumer review. Our empirical results confirm the theoretical conjectures derived from our economic model. This study not only (partially) explains the conflicted phenomenon of initial stage pricing strategy, but also provides guidelines for companies to setup their optimal price when selling a new product.

Literature Review

The emergence of social media enables collective intelligence among online users (Surowiecki 2005), which affects individuals' purchasing decisions and influences organizations' strategies. Previous research has investigated whether an online retailer with good reputation charges a higher or lower price than other retailers. It is commonly believed that buyers are likely to pay price premiums to high-reputation sellers, thus the high-reputation sellers should charge relatively higher prices (Ba and Pavlou 2002; Li et al. 2009; Luo and Chung 2010; Zhang 2006; Zhou et al. 2009). However, some studies find the reverse phenomenon. For example, Ba et al. (2008) identify the “advertise price effect” which shows the “low recognition” sellers may decrease their goods prices when they increase their service levels. Baylis and Perloff (2002) show that “good” internet retailers of digital cameras and scanners charge relatively low prices and provide superior services, while “bad” internet retailers charge relatively high prices and provide poor services.
In addition to seller reputation, consumer opinion in many cases appears as review to products. Online consumer review can shed a light on product quality (Chevalier and Mayzlin 2006). Furthermore, Chen and Xie (2008) argue that consumer review provides product-matching information for consumers to find products matched with their usage conditions. In online transactions, such supplementary information helps consumers reduce uncertainty on products and facilitate sales. Several studies have examined how online consumer review influences product sales (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004; Ghose and Ipeirotis, 2010; Liu 2006; Zhu and Zhang 2010). They have found significant effect of review informativeness (volume and helpfulness value), credibility (reviewer identity), and wording style, in addition to review rating on product sales.

This paper is close to the stream of literature that studies the impact of product review on the pricing strategy of sellers. Previous research has found that early consumer reviews tend to be more positive than later ones (Dellarocas et al. 2007; Li and Hitt 2008), which may be due to self-selection bias or influenced by product pricing strategy. Li and Hitt (2010) specifically investigate the impact of pricing on consumer review and find that unidimensional ratings can be substantially biased by price. From information matching perspective, Jiang and Chen (2007) study a seller’s pricing strategy when the product can either match or mismatch a consumer’s taste, and find that it is optimal to set a lower price initially to attract expert users. Li et al. (2011)(Li et al. 2011) consider the possibility of consumer repeat purchase and argue that consumer review intensify price competition, depending on the informativeness of reviews. Limited research, however, has been done to examine the interaction between consumer review and pricing strategy.

**Economic Modeling**

We consider the early stage of a product sale (In the late stage of a product’s sale, there may be a significant discount for clearance or price increase due to out-of-stock. Furthermore, consumers are more likely to know the product from various channels.) We build a two-period model to study the pricing strategy of sellers in which consumer review could serve as a way to reduce the uncertainty that consumer faces when making online purchase. In the first period, there are no consumer reviews. Consumers can only interpret the quality/features of the product from product description provided by the seller, which inherits a lot of uncertainty. Consumers make their purchase decision based on this uncertainty as well as the product price. After consumption of the product, the consumer realizes the true quality/features of the product and offers review. In the second stage, with the reviews containing product information (Chen and Xie 2008) accumulated and the initial reputation build up, product uncertainty reduces. In this period, sellers may further tweak their price for profit considering existing reviews. We assume consumers are risk averse towards the uncertainty about products during this process.

To examine the impact of consumer reviews on purchase decision, we consider two types of products, namely, horizontally differentiated products and vertically differentiated products. According to previous product differentiation literature (Shaked and Sutton 1987), horizontally differentiated products are different from each other according to features that cannot be ordered in an objective way. Vertically differentiated products can be ordered according to their objective quality from the highest to the lowest, and it is possible to say that one is “better” than another. Book and food are good examples of horizontally differentiated products, where the matching between consumer taste and product features is the major reason for sales. Car and electronics usually contain enough quality difference across product lines and behave more like vertically differentiated products, i.e., everyone likes high quality cars although not everyone can afford one.

In this section, we model the change of uncertainties for the two types of products and then derive their most profitable pricing strategy (in the early stage of product sales).
Horizontally Differentiated Products

Consider a product that belongs to the category of horizontally differentiated products. Consumer preference (denoted by $\theta$) is a random variable uniformly distributed in a circle with length of 1. The distance between the location of the product and a consumer’s preference represents the “mis-match” of the product, while a distance of zero means perfect matching.

By just reading the product description provided by the seller/producer, we assume that consumers still cannot obtain 100% accurate information about the location (feature) of the product. Without loss of generality, assume that the perceived location of the product considered $(x)$ is a random variable centered at location 0 following a normal distribution, $x \sim N(0, \sigma^2)$. Thus the distance between the product and consumer preference is $|\theta - x|$.

Let $\varphi$ represent the price of the product, a consumer’s utility can be represented as:

$$U(\theta) = -\exp\left(-1 - \varphi - |\theta - x|\right),$$

where we normalize the consumer utility of consuming a product in the ideal location as 1. Let $\varsigma$ represent consumer risk-aversion factor with respect to the uncertainty of the product location. The expected utility of a consumer at location $\theta$ can be then represented using the mean-variance representation, that is,

$$\mathbb{E}[U(\theta)] = 1 - \varphi - \theta^2 \varsigma^2.$$

As consumers only make purchase if they expect to receive a positive payoff from purchase, the demand of the product is determined by $1 - \varphi - \theta^2 \varsigma^2 \geq 0$, that is, $\theta \leq (1 - \varphi - \theta^2 \varsigma^2)/\varsigma$.

Now consider the seller’s pricing strategy in two periods (denoted by the subscripts 1 and 2). Assume that consumers arrive in the two-periods independently. In the first period, consumers who obtain a payoff higher than a threshold value $\theta_{th}$ will supply a positive rating/review. That is, a positive review is provided when:

$$U(\theta) = -\exp\left(-1 - P_1 - t|\theta - x|\right) \geq -\exp(-\bar{u}),$$

i.e., $|\theta - x| \leq \frac{(1-P_1-\bar{u})}{t}$. Denote $p(G)$ as the probability of a positive review. Since $p(G)$ depends on the distance between the consumer and the actual location of the product, we have that:

$$p(G) = \min\left\{\frac{2(1 - P_1 - \bar{u})}{1 - P_1 - rt^2 \sigma_1^2}, 1\right\}.$$

A positive review helps expand the market size of the product in the second period to $\lambda_p$; while a negative review reduces the market size of the product in the second period to $\lambda_n$, where $\lambda_p > \lambda_n$. Assume that no matter whether a consumer in the first period supplies a good or bad review, it will help consumers in the second period to reduce the uncertainty about the product location. We thus have $\sigma_1 > \sigma_2$.

The seller’s expected profit in the two periods can be expressed as:

$$\pi = \pi_1 + \pi_2 = \frac{1-P_1-rt^2 \sigma_1^2}{t} P_1 + \left[\lambda_p p(G) + \lambda_n (1 - p(G))\right] \frac{1-P_2-rt^2 \sigma_2^2}{t} P_2.$$

The seller’s decision problem is to maximize its expected profit, that is,

$$\max_{P_1,P_2} \frac{1-P_1-rt^2 \sigma_1^2}{t} P_1 + \left[\lambda_p p(G) + \lambda_n (1 - p(G))\right] \frac{1-P_2-rt^2 \sigma_2^2}{t} P_2.$$

The optimal pricing strategy of the seller is obtained by working out the first-order condition and second-order condition:
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Proposition 1:

1) When \( t^2 \sigma^2 > \bar{u} \), i.e., there is a high uncertainty of product location or high sensitivity of consumer expectation, it is possible for a seller to set a higher price in the first period than in the second period, that is, \( P_1^* > P_2^* \). Moreover, the larger the \( t^2 \sigma^2 - \bar{u} \) or \( \lambda_p - \lambda_n \), the more likely that \( P_1^* > P_2^* \).

2) When \( t^2 \sigma^2 \leq \bar{u} \), \( P_1^* < P_2^* \). Moreover, the farther away the actual product from consumer's ideal location, the more likely for the seller to set \( P_1^* < P_2^* \).

The first clause of Proposition 1 gives conditions under which the seller would like to set a high price initially in order to generate a positive review. Even though it sounds counter intuitive, this strategy is not hard to understand considering the impact of a positive review on a horizontally differentiated product. For example, in the sales of books on Amazon, when consumer’s mis-fit disutility, or the location uncertainty of a book is large, it is hard to obtain a match between book and consumers. In order to gain a positive review, which has a large impact on the second-period demand, the seller can intentionally set a higher price, so that only those consumers who expect that the book is ideal enough will make purchase in the first period. These consumers are naturally more likely to give positive review. In the second stage, the seller can reduce price to attract more consumers to buy the book. With the reviews that reduce consumer’s uncertainty, the consumers in the second stage are more likely to find the fit of the book, which relax the dependency on price to select suitable consumers and will aid the future rating and sales.

According to the proposition, a larger impact of positive review on market size in the second period will give companies more incentives to carefully “choose” their customers by setting a higher price.

The second clause of proposition 1 specifies the case when consumers are less sensitive to the location of the product, i.e., they have a broad interest to the content of books, or the content of a book is with small positive review, which has a large impact on the second-period demand, the seller can intentionally set a

Vertically Differentiated Products

Products are generally inter-comparable according to their quality if they are vertically differentiated. Consumers always look for high quality products. However each consumer may weigh quality differently. We assume that consumer preference \( (\theta) \) towards the product quality are uniformly distributed between 0 and 1, that is, \( \theta \sim U[0,1] \). The seller offers a product at quality level \( q \), with a price \( P \). With the limited information provided in the product description listed on the web page, consumers expect that the actual quality of the product follows a normal distribution on the line, that is, \( q \sim N(\bar{q}, \sigma^2) \). This way, a consumer obtains a utility of \( U(\theta) = -\exp - (\theta q - P) \). Given \( r \) as consumer risk-aversion factor, the expected utility that a consumer obtains by choosing one product can be expressed as: \( E[U(\theta)] = \theta \bar{q} - \frac{r \theta^2 \sigma^2}{2} - P \).

Since consumers will only purchase the product when expecting positive utility, the demand of the product is determined by: \( E[U(\theta)] = \theta \bar{q} - \frac{r \theta^2 \sigma^2}{2} - P \geq 0 \). There are two roots for this function, \( \bar{\theta} = \left( \bar{q} + \sqrt{\bar{q}^2 - 2r \bar{q} \sigma^2 P} \right) / r \sigma^2 \), and \( \theta = \left( \bar{q} - \sqrt{\bar{q}^2 - 2r \bar{q} \sigma^2 P} \right) / r \sigma^2 \). Thus, the demand of the product can be expressed as: \( D = \bar{\theta} - \theta = 2 \sqrt{\bar{q}^2 - 2r \bar{q} \sigma^2 P} / r \sigma^2 \).

Similar as for horizontally different products, we consider a two-period framework for vertically differentiated ones. Again, assume that consumers in the first period will provide positive review only when they obtain a utility higher than a threshold value \( \bar{u} \). That is, when \( U(\theta) = -\exp - (\theta q - P_1) \geq \bar{u} \)
E-business

If a positive review is received, it helps expand the market size of the product in the second period to \( \lambda_p \); otherwise it reduces the market size of the product in the second period to \( \lambda_n \), where \( \lambda_p > \lambda_n \). Assume that no matter whether a consumer in the first period supplies a good or bad review, it will help consumers in the second period reduce the uncertainty about the product quality. We thus have \( \sigma_1 > \sigma_2 \).

Similar as horizontally differentiated products, the seller’s expected profit in the two periods can be expressed as:

\[
\pi = \pi_1 + \pi_2 = \frac{2q^2-2r\sigma_1^2P_1}{r\sigma_1^2}P_1 + \left[ \lambda_p p(G) + \lambda_n (1 - p(G)) \right] \frac{2q^2-2r\sigma_2^2P_1}{r\sigma_2^2}P_2.
\]

The seller’s decision problem is to maximize its expected profit, that is,

\[
\max_{P_1, P_2} \frac{2q^2-2r\sigma_1^2P_1}{r\sigma_1^2}P_1 + \left[ \lambda_p p(G) + \lambda_n (1 - p(G)) \right] \frac{2q^2-2r\sigma_2^2P_1}{r\sigma_2^2}P_2.
\]

The optimal pricing strategy of the seller is obtained by working out the first-order condition and second-order condition. After doing so, we get the following conditions for optimal pricing.

**Proposition 2:**

If \( q \leq \frac{1}{2} + \frac{\bar{u}}{2\bar{q}} \), it is optimal for the seller to offer a low price initially to attract positive review, that is, \( P_1^* < P_2^* \).

Proposition 2 gives conditions for the seller to set low price initially as a way of promotion, in order to generate positive review for the future consumers. If the actual product quality \( q \) is much lower than the expected product quality \( \bar{q} \), or when \( \bar{u} \) is large, the product can hardly meet consumer expectation and it is not easy to get a positive review. In this case, it is intuitive to offer a low price initially to provide higher utility to consumers, in order to generate positive reviews. On the other hand, if the product has a high quality, which is much better than consumer expectation, getting positive review will not be a concern at all in the first period. Then, sellers can just focus on the balance of profit and sales in pricing. In many case, that lead to a high initial price followed by gradual discounts.

**Empirical Study**

In our economic model, we derive different conditions for sellers to tweak their pricing strategy. For vertically differentiated products, sellers may increase or decrease price in the second period according to the quality of products. For horizontally differentiated products, that depends on the uncertainty of product location after consumers reviewing descriptions provided by e-commerce Websites. The higher uncertainty makes it more likely for price to decrease.

To verify the theoretical findings, we use book and electronics as examples of horizontally and vertically differentiated products and conduct an empirical study. We use consumer review rating to capture the match between products and consumer expectations and product perceived quality in the two scenarios.

**Dataset**

For the empirical study, we collect two data sets from Amazon.com. The book dataset contains 5 categories of books (Contemporary Fictions, General Science, International Politics, Investing, and Pregnancy & Childbirth). In general, the book descriptions provided by Amazon are quite basic.
Consumers usually highly depend on reviews to get more understanding about book contents. We consider books as a good example of horizontally differentiated products with a high uncertainty. The electronics dataset contains 3 types of electronics (Hard Drives, Home Theater Systems, and Vehicle GPS). These products, especially products provided by the same vendor, usually have clear quality difference targeting at different levels of consumers. We consider electronics a good example of vertically differentiated products. We collect all products in the three electronics categories. For the five book categories, since there are a large number of books in each category and Amazon restricts the number of items one can retrieve from a search query (1200 products per query when we collected data), we enrich the collection by searching both most popular books and latest books in each category. (We believe these two queries supported by Amazon can provide the most relevant sample to the products we want, i.e., relatively new and with adequate consumer reviews, in this study). We collect price, seller, and review information for each item every three days from July 13 2010 to Nov 7 2010 for books and from Aug 12 2010 to Nov 7 2010 for electronics. In order to control market competition that may affect company’s pricing strategy, we also collect the same information from BN.com for books and Buy.com for electronics as indicators of major competitors.

Our research focuses on the interaction between consumer review and company’s (i.e., Amazon) pricing strategy. Thus, we only keep items which have Amazon price and at least one consumer review. Furthermore, our economic model focuses on the early stages of product sale, where the market is not yet saturated. To simplify our analysis, we keep products that are on the market for less than 1,000 days when we started data collection. (We identify this date using book release date. Some book may be on presales before the release date.) After systematic data cleaning, we get two unbalanced panel data. Table 1 shows summary of our data set. Overall, our dataset has 2,087 books and 289 electronics. They on average receive about 40~60 reviews. The average rating is around 4.

<table>
<thead>
<tr>
<th>Table 1. Data Descriptive Statistics</th>
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<tbody>
<tr>
<td>Book</td>
</tr>
<tr>
<td>Periods</td>
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<tr>
<td># Items</td>
</tr>
<tr>
<td>From-To</td>
</tr>
<tr>
<td># Items</td>
</tr>
<tr>
<td># Reviews per item</td>
</tr>
<tr>
<td>Rating</td>
</tr>
<tr>
<td>AZPriceRate</td>
</tr>
<tr>
<td># 3rd Party Sellers</td>
</tr>
<tr>
<td>% has Major Competitor</td>
</tr>
<tr>
<td>% has Sales Rank</td>
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</table>

* Numbers in parenthesis are standard deviation corresponding to the mean.

**Models & Results**

To capture Amazon’s pricing strategy along with the change of consumer review, we create a variable AZPriceRate as Amazon price divided by list price for representing discounts applied to each item. As shown in Table 1, in general, Amazon gives about 20~30 percent discount to its products (i.e., 1/AZPriceRate). We examine how AZPriceRate is depended on number of Amazon reviews ln(AZNreview). The number of consumer reviews naturally provides a timeline that aligns different products’ life cycle, where a larger number of reviews usually indicates a long history on market for a product. In our two-period economic model, we care about the effect of price on reviews in the first period and the effect of review on price in the second period. The differentiation of the two periods depends more on the number of reviews received rather than the clock time. Thus, we choose it as the independent variable to inspect the temporal dynamics of price under the impact of reviews.
According to the suggestion of our theoretical model, the trend of price change depends on the match between product and consumer expectations in term of quality/location. In this study, we take review rating as an indicator of perceived product quality level and location matching. For vertically differentiated products, a higher rating indicates a better quality. For horizontally differentiated products, a higher rating indicates a better match between the product and consumer taste. In addition to these factors embedded in our theoretical model, the discount given to a product may be due to features of the item, seasonal promotion, and competitions on the market. To address the endogeneity concern, we adopt a two-way fixed effect model to capture item endogenous features and seasonal effects. We account the competitions on the market using Amazon third party sellers (hasAZ3rdParty) and the listing on major competitors’ Websites (hasMajorCompetitor), and whether the product has an Amazon sales rank (hasAZSalesRank, i.e., whether the product is popular enough to appear in sales rank list). After controlling these issues, we expect the change of AZPriceRate is not a linear relationship with the development of number of review, and thus add quadratic variables into the model (model 1):

$$AZPriceRate_{lt} = \alpha + \beta_1\text{hasAZSalesRank}_{lt} + \beta_2\text{hasMajorCompetitor}_{lt} + \beta_3\text{hasAZ3rdParty}_{lt} + \beta_4\text{N3rdParty}_{lt} + \beta_5\ln(AZNreview)_{lt} + \beta_6\ln(AZNreview)^2_{lt} + \beta_7\text{AZrating}_{lt} + \mu_i + \tau_t + \epsilon_{lt}$$ (1)

While model 1 captures how AZPriceRate changes align with ln(AZNreview), it takes the effect of rating as a constant one. In model 2, we include the interaction between rating and number of Amazon reviews to study how products with different ratings have a different shape for this curve:

$$AZPriceRate_{lt} = \alpha + \beta_1\text{hasAZSalesRank}_{lt} + \beta_2\text{hasMajorCompetitor}_{lt} + \beta_3\text{hasAZ3rdParty}_{lt} + \beta_4\text{N3rdParty}_{lt} + \beta_5\ln(AZNreview)_{lt} + \beta_6\ln(AZNreview)^2_{lt} + \beta_7\text{AZrating}_{lt} + \mu_i + \tau_t + \epsilon_{lt}$$ (2)

Aligned with our theoretical propositions, we have the following hypotheses for the empirical study.

**Hypothesis 1:** In the early stage of book sales (horizontally differentiated products with big uncertainty), the price should show a decreasing trend with respect to the number of reviews received.

**Hypothesis 2:** In the early stage of electronics sales (vertically differentiated products), the price of electronics with a high rating (high quality) should show a decreasing trend with respect to the number of reviews received. The price of other electronics should show an increasing trend with respect to the number of reviews received.

Table 2 reports our regression model results on the two datasets. During the process, we conduct F-tests to test the poolibility of the model. The test shows that we should not use pooled PLS to estimate model parameter. We also compare fixed effect vs. random effect using the Hausman test under the null hypothesis that the individual effects are uncorrelated with the other regressors in the model (Hausman 1978). The test statistics is significant to reject null hypothesis, which means that a random effect model produces biased estimators and a fixed effect model is preferred. Thus, the fixed two-way model is suitable to analyze our data. We employ the PLM package in R to conduct the panel data analysis.

The regression results are shown in Table 2. First, we notice that hasAZSalesRank has a significant effect and cause about 1.5% discount on book price. In Amazon, only top (1 million) books have a sales rank, and hasAZSalesRank indicates the popularity of books. In general, a more popular book is cheaper than less popular ones, which shows sellers’ marketing strategy to enlarge customer base on well-accepted books. On the electronics dataset, we do not observe this effect. One possible reason is that electronics usually have a much smaller customer base and the sales rank usually change rapidly. Furthermore, if a book is also sold by major competitors at the same time (B&N in our case), Amazon would give about 0.7% more discount to the book. This is consistent with our intuition. For electronics, such effect is not significant. This is probably because that big electronics sellers often differentiate them from competitors by holding similar but non-identical models. For both book and electronics, we notice that (small) third party sellers (or resellers) have significant effect on pricing. For electronics, products having a third party seller will have about 3% more discount than those without third party sellers. For books, however, products having a third party seller will be about 2% more expensive. This difference may be due to the control of distribution channels in the two types of products. For electronics, small third party distributors compete with big distributors in selling new items. For books, small third party distributors are usually second-
hand sellers. The existence of second-hand books indicates that the product has reached a later stage in its life cycle, which is usually featured by fewer promotions. For both types of products, the more third party sellers, the lower the price. In general, 25 more third-party book sellers or 7 more third-party electronics sellers will cause 1% more discount in Amazon’s product price.

Table 2. Panel Data Analysis Results

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<th>Book-1</th>
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<th>Electronics-1</th>
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<td>Poolability Test</td>
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<td>Fixed vs. Random (Hausman)</td>
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*p<0.1; ** p<0.05; *** p<0.01

After controlling the product endogenous variables and seasonal effects (by the fixed two-way model itself), we notice that Amazon has quite a different pricing strategy on book and electronics according to the number of reviews $\ln(\text{AZNreview})$ received. In model Book-1, $\text{AZPriceRate}$ has an overall negative coefficient on $\ln(\text{AZNreview})$ and a positive coefficient on the quadratic variable. Thus, in the early stage of book sales, $\text{AZPriceRate}$ shows a decreasing trend with the number of reviews. It shows that a book seller would like to give a relative higher price at the very beginning to target audiences with a better fit (hoping to get higher rating from them). Later they will reduce their book prices to cover a larger range of consumers. This is consistent with our theoretical projects on horizontally differentiated products. In model Electronics-1, $\text{AZPriceRate}$ has an overall positive coefficient on $\ln(\text{AZNreview})$ and a negative coefficient on the quadratic variables. Thus, in the early stage of electronics sales, $\text{AZPriceRate}$ shows an increasing trend with the number of reviews. It shows that a seller of electronics (vertically differentiated products) would like to give a relative lower price at the very beginning to induce higher ratings from buyers. Later they will increase price to gain more profit. (Note that our analysis focuses on the early stage of sales. When the product is on market for enough time, companies will further change their pricing strategy. A rough analysis based on our data set shows that the change point happens when about 4.7 reviews are generated or about 370 days on the market for books, or when 7.6 reviews are generated or about 418 days on market for electronics.)

In the model Book-2 and Electronics-2, we further inspect how relationships between $\text{AZPriceRate}$ and number of reviews $\ln(\text{AZNreview})$ are different across different rating. To ease our discussion, we visualize the two models’ effects on rating and $\ln(\text{AZNreview})$ in Figure 2. The curves indicate pricing trend for products with a certain rating (from 1 to 5). Clearly, on the book dataset, after controlling all other factors, a higher book rating increases a company’s incentives to reduce price after getting more consumer reviews (in other words, better book ratings usually happen on books with a relative higher
initial price). After receiving (on average) about 3 reviews, book price may decrease for about 2%. That is consistent with our economic model’s prediction when product uncertainty is high. Hypothesis 1 cannot be rejected at the 95% confidence interval. For the electronics dataset, the trend changes according to the level of rating, which again follows our economic model’s prediction. When the product’s rating is generally not excellent (either OK or bad), the seller should first lower its price and try to boost its rating at the early stage of sales. Thus AZPriceRate shows an increasing trend. After receiving (on average) about 3 reviews, the price of those products can increase from 2%–15%. However, if the product can easily get a top rating, there is no need to play this trick. Sellers can set a relative higher price at the beginning for more profits and gradually reduce price. After receiving (on average) three reviews, such products’ price can reduce 3%. Hypothesis 2 cannot be rejected at the 95% level, either.

To further illustrate our empirical findings, we visualize the average AZPriceRate for items with more than one review in our dataset in Figure 3. Even under the influence of many different factors, we can still observe an overall decreasing trend for books (except for rating 2–3) and an increasing trend for electronics (except for rating 5) on sale price at the early stage of product sales. This confirms that whether to raise or drop price at the early stage of product sales depends on whether the product is horizontally differentiated or vertically differentiated, together with the rating received.

**Conclusions**

In this paper we categorize products to two types (horizontally differentiated or vertically differentiated) and build an economic model to inspect the optimal pricing strategy in the early stage of product sales.
considering the impact of online consumer review. Our model offers two opposite optimal strategies, setting a higher price vs. a lower price initially to attract favorable review and then adjust price to respond to review ratings received. We find that the discrepancy between the expected and actual product quality/location play an important role in guiding seller’s pricing behavior to promote these two types of products. Our research provides the following suggestions for sellers.

1) For horizontally differentiated products, if the uncertainty on product features is high, a seller should set a higher price initially.

2) For vertically differentiated products, if the product quality is not high enough, a seller should set a low initial price in the very begging of product sales.

These two strategies may lead to more positive reviews than negative reviews, which may attract future consumers. Sellers can further increase or reduce price after receiving reviews for a higher profit margin or larger sales. We conduct an empirical study on a panel data collected from Amazon to test our theoretical conjectures. The empirical analysis confirms the existence of the two pricing strategies corresponding to these two types of products in practice. In our empirical analysis, price change that can be explained by consumer reviews may vary from about -3% to 15% across the two stages, which shows the critical role of considering consumer reviews in the theoretical pricing model.

This study not only (partially) explains the observation of conflict initial stage pricing strategies, but also provides guidelines for companies to setup their optimal price. In the future, we will further extend the research in the following directions: 1) For a longer time span, what is the optimal strategy to deal with the price-review interactions? 2) How to gauge the different impact of expert review and consumer review and utilize them in product pricing? 3) How to combine the effects of product review and seller reputation into one pricing model?

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References


Appendix

Proof of Proposition 1

First we examine the first order conditions for the profit function.

\[\text{FOC}_{p_1} : \frac{1-2p_1-rt^2\sigma_1^2}{t} + \left(\lambda_p - \lambda_n\right)p'(G) \frac{1-p_2-rt^2\sigma_2^2}{t} P_2 = 0;\]

\[\text{FOC}_{p_2} : \frac{1-2p_2-rt^2\sigma_2^2}{t} = 0.\]

From FOC$_{p_2}$ it is easy to get that \(P_2 = \frac{1-rt^2\sigma_2^2}{2}\).

Note that if \(p'(G) = 0\) or if \(\lambda_p = \lambda_n\), since \(\sigma_1 > \sigma_2\), it is obvious that \(P_1^* < P_2^*\). That is, if positive review of the previous consumers has no impact on the second-period consumer’s purchase, sellers should set a lower price in the first period due to the larger uncertainty faced by consumers.

When \(p'(G) \neq 0\), consider the case when \(p(G) = \frac{(1-P_1-U)}{1-P_1-rt^2\sigma_1^2}\), then

\[\text{FOC}_{p_1} : \frac{1-2p_1-rt^2\sigma_1^2}{t} + \left(\lambda_p - \lambda_n\right)\frac{t^2\sigma_1^2(1-U)}{(1-P_1-rt^2\sigma_1^2)^2} \frac{1-p_2-rt^2\sigma_2^2}{t} P_2 = 0.\]

So, when \(t^2\sigma_1^2 \leq \bar{u}\), since \(\frac{1-2p_1-rt^2\sigma_1^2}{t}\) has to be positive to satisfy the FOC condition, \(P_1 < \frac{1-rt^2\sigma_1^2}{2}\). This is to say that \(P_1^* < P_2^*\).

It can also be seen that when \(t^2\sigma_1^2 > \bar{u}\), since \(\frac{1-2p_1-rt^2\sigma_1^2}{t}\) has to be negative to satisfy the FOC condition, \(P_1 > \frac{1-rt^2\sigma_1^2}{2}\). Moreover, the larger the \(t^2\sigma_1^2 - \bar{u}\) or \(\lambda_1 - \lambda_2\), the larger the \(P_1^*\). In this case it is possible for \(P_1^* \geq P_2^*\).

Proof of Proposition 2

First we examine the first order conditions:

\[\text{FOC}_{p_1} : \frac{-4r\sigma_1^2 P_1}{r\sigma_1^2 \sqrt{q^2-2r\sigma_1^2} P_1} + \frac{2\sqrt{q^2-2r\sigma_1^2} P_1}{r\sigma_1^2} + \left(\lambda_p - \lambda_n\right)p'(G) \frac{2\sqrt{q^2-2r\sigma_2^2} P_1}{r\sigma_2^2} P_2 = 0;\]

that is,

\[\frac{-4P_1}{\sqrt{q^2-2r\sigma_1^2} P_1} + \frac{2\sqrt{q^2-2r\sigma_1^2} P_1}{r\sigma_1^2} \left[2\bar{q} - \frac{\bar{q}+\bar{u}}{q}\right] \left(\lambda_p - \lambda_n\right) \frac{2\sqrt{q^2-2r\sigma_2^2} P_1}{r\sigma_2^2} P_2 = 0.\]

\[\text{FOC}_{p_2} : \frac{-4P_2}{\sqrt{q^2-2r\sigma_2^2} P_2} + \frac{2\sqrt{q^2-2r\sigma_2^2} P_2}{r\sigma_2^2} = 0.\]

Note that if \(p(G)' = 0\) or if \(\lambda_1 = \lambda_2\), we have \(P_1^* < P_2^*\), because \(\sigma_1 > \sigma_2\). That is, if positive review of the previous consumers has no impact on the second-period consumer’s purchase, sellers should set a lower price in the first period due to the larger uncertainty faced by consumers.

Otherwise, consider that the sign of \(p(G)’\) is determined by \(2\bar{q} - \frac{\bar{q}+\bar{u}}{q}\). If \(2\bar{q} \leq \frac{\bar{q}+\bar{u}}{q}\), that is, if \(q \leq \frac{1}{2} + \frac{u}{2q} \) we have \(P_1^* < P_2^*\). If \(2\bar{q} > \frac{\bar{q}+\bar{u}}{q}\), then it is possible for \(P_1^* \geq P_2^*\).