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Negative price premium effect in online market—The impact of competition and buyer informativeness on the pricing strategies of sellers with different reputation levels

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ABSTRACT

Motivated by the contradictory findings in literature regarding whether high-reputation sellers enjoy a price premium over low-reputation sellers, this paper examines the pricing strategies of sellers with different reputation levels. We find that a negative price premium effect (i.e., a high-reputation seller charges a lower price than a low-reputation seller) exists due to: (1) the presence of both informed and uninformed buyers, which makes sellers follow mixed pricing strategies. It is then possible for a high-reputation seller setting a lower price than a low-reputation seller. Moreover, when the proportion of informed buyers exceeds a certain threshold, the expected price of a high-reputation seller is even lower than that of a low-reputation seller; (2) the competition among the sellers, which reduces the high-reputation sellers' prices but increases the low-reputation sellers' prices. Consequently, a high-reputation seller is more likely to charge a lower price than a low-reputation seller when the competition intensifies. Our empirical findings also support our theoretical results on the negative price premium effect.

1. Introduction

Online markets attract a lot of sellers due to the low entry and operational costs [38]. For example, in the “Electronics” category of BizRate.com, a famous price comparison shopping website, there are 3830 retailers, and more than 50 distinct retailers offering “Canon PowerShot SX210 IS 14.1 Megapixel Digital Camera — Black”.[3] However, it is not easy to inspect seller identity as well as product quality in online markets. The sellers are often hidden under the masks of meaningless electronic IDs [19]. At the same time, payment and delivery for the products are also separated [2]. These online market characteristics create chances for opportunistic behaviors, such as non-delivery, identity theft, and miscellaneous fraud [15,18]. In the year 2009 alone, the Internet Crime Complaint Center (IC3)[4] website received 336,655 complaint submissions, corresponding to a $559.7 million dollar loss [18].

Fortunately, current information technologies help reduce these risks and facilitate buyers to infer seller quality through various reputation mechanisms, such as buyer ratings and reviews, feedback systems, online discussion forums, etc. [3,22,35,39]. It is commonly believed that buyers are likely to pay price premiums to high-reputation sellers, so the high-reputation sellers should charge relatively high prices [3,22,25,38,39]. However, some studies find the reverse. For example, Ba et al. [4–6] identify the “adverse price effect,” which shows a seller may decrease her price when her recognition level increases. Baylis and Perloff [10] 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.

Motivated by these contradictory findings in literature, this study aims to understand the pricing strategies of sellers with different reputation levels, and examine whether, and under what conditions, does a “negative price premium effect” occur (i.e., a high-reputation seller charges a lower price than a low-reputation seller). Note that this is different from the “adverse price effect” studied in Ba et al. [4–6], which refers to the phenomenon that when the low-recognition seller's recognition increases, both the low- and high-recognition sellers cut their prices [6]. In this paper, we first build a theoretical model to study the effect of competition. We extend Varian's sales model [36] in two ways: to allow sellers to have different reputation levels (the benchmark model); and to allow more than one seller with the same reputation level (the competition model). We find that the negative price premium effect exists due to: (1) the co-existence of informed and uninformed buyers, which makes it impossible for sellers to set their prices following pure strategies.

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[3] The data were collected on 18 Jan 2011.
[4] IC3 (http://www.ic3.gov/default.aspx) is a partnership between the Federal Bureau of Investigation (FBI), the National White Collar Crime Center (NW3C), and the Bureau of Justice Assistance (BJA).

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When the proportion of informed buyers exceeds a certain threshold, a high-reputation seller even sets a lower price than a low-reputation seller on average; (2) the competition among the sellers, which makes a high-reputation seller reduce the prices while a low-reputation seller increase the prices. So the negative price premium effect is more likely to occur when the competition intensifies. We also collect field data from BizRate.com. Our empirical testing supports our theoretical findings on the negative price premium effect.

To the best of our knowledge, this is one of the first few papers which study the negative price premium effect. It theoretically explains the negative price premium effect from the perspective of buyer informativeness, which is an extremely important factor in the economics of information [21,27]. Specifically, we show that sellers may play mixed strategies, so there is no simple and fixed relationship between seller reputation and pricing. Our study offers an explanation to the contradictory findings in the literature.

The rest of this paper is organized as follows: we review relevant literature in Section 2, and present the main theoretical model in Section 3. To better understand the impact of competition, we present a benchmark model in Section 3.1 in which there is only one seller for each reputation level, and relax this assumption in Section 3.2. We present the empirical study in Section 4 and conclude in Section 5.

2. Literature review

2.1. Price dispersion in online market

The online market features fierce competitions due to the increased number of sellers [23], reduced search costs [7,33] and price transparency, and it is claimed to be a frictionless market [12]. According to the classical Bertrand model, buyers may purchase from the lowest priced seller in an ideal frictionless market [13], so all sellers should set the same price—the "law of one price" (LOP) [8,12]. However, contrary to the theoretical prediction, researchers find substantial price dispersion in online markets [8,12,29]. For example, Brynjolfsson et al. [12] find that the internet retailer prices differ by an average of 33% for books and 25% for CDs. Baye et al. [9] find persistent price dispersion for 36 homogeneous consumer electronic products. The prices do not converge even after an 18 month period. The causes for price dispersion of homogenous goods may be the differences among sellers [13,25,30,37], or the differences among buyers [1,31,36].

2.2. Seller reputation

When facing competition, sellers usually differentiate themselves from each other [14], and one most important differentiation is seller reputation [16,17,35]. The seller reputation in online markets is commonly calculated by buyer ratings and reviews (e.g., the seller reputation in BizRate and eBay). A high reputation may indicate a high level of seller trustworthiness [3,11], accurate product descriptions [26], and better services [26]. Therefore, buyers may intend to pay price premiums to high-reputation sellers for low risks and better services [3]. Some studies find that service quality has a positive effect on price levels [30,37], especially for high value products [25]. However, some other studies find the reverse [10,23]. For example, Liu et al. [23] find that high-reputation sellers charge relatively low prices in online retailing marketplace of homogeneous goods.

Moreover, even after controlling for seller differences, there are still a large percent of price dispersion unexplained [9,29]. For example, based on an empirical analysis of 6,739 price observations for 581 items in eight product categories, Pan et al. [29] find that online price dispersion is persistent after controlling for seller heterogeneity, thus they conclude that the price dispersion explained by seller differences is limited.

2.3. Buyer informativeness

Another cause of price dispersion is the differences in buyers' search costs. In online market, search cost still exists, even though greatly reduced [10,12]. Buyers may incur different search costs in online markets, due to their online shopping experiences, skills of using shop-bots and search engines [23,34], and wealth levels [1]. According to search costs, buyers can be classified as informed buyers (who can search and compare different products and purchase the one offering the highest utility) and uninformed buyers (who perform limited search and purchase as long as the product offers positive utility) [e.g., 10,32,36]. Sellers may play mixed pricing strategies to discriminate the informed and uninformed buyers [1,31].

We define buyer informativeness as the proportion of informed buyers. This proportion may be influenced by factors such as product value and the development of new technologies [3,28]. Online buyers are less likely to invest time and energy in searching for inexpensive products than for expensive ones [3,25]. Therefore, the proportion of informed buyers in a high-value product category should be higher than that in a low-value product category. Furthermore, the use of shop-bots may turn an uninformed buyer to an informed buyer. Tang et al. [34] find that a 1% increase in shopbot use is correlated with a \$0.41 decrease in price levels and a 1.1% decrease in price dispersion.

2.4. Pricing strategy

In literature, the effects of seller reputation and buyer informativeness are studied separately. The studies on seller reputation draw mixed findings about the effect of seller reputation on prices [3,10,23]. The studies on buyer informativeness usually ignore the seller differentiation and find symmetric pricing strategy for all the sellers [e.g., 36]. Little research combines both.

3. Model

3.1. Benchmark model: one low- and one high-reputation sellers

Consider two sellers (denoted by i, $i \in \{L,H\}$) selling one homogeneous product to m ($m \in N$) buyers in a market. The product costs c for the sellers, and offers utility u for the buyers [36]. Let r_i denote the reputation of seller$i$, where $0 \le r_L < r_H \le 1$, so that $1-r_L$ and $1-r_H$ represent the risk in transacting with the low- and high-reputation sellers, respectively [3,20]. Seller i charges a price p_i for the product, and will sell the product only when the profit is non-negative ($p_i - c \ge 0$). The buyers consist of a proportion of k ($0<k<1$) informed buyers and $1-k$ uninformed buyers [32,36]. Similar to Varian's sales model [36], a buyer's expected utility in a transaction with seller i can be specified as $r_i u - p_i$ and the buyer will purchase the product only when the expected utility is non-negative. Moreover, following Salop and Stiglitz [32] and Varian [36], we assume that an informed buyer will compare the products offered by each seller and purchase from the seller who offers the highest expected utility; while an uninformed buyer will randomly visit one seller and make the purchase if the expected utility is non-negative. By straightforward calculation, we can obtain that the low-reputation seller L's price domain is $p_L \in \left[c + \frac{1-k}{1+k}(r_L u - c), r_L u\right]$, and the high-reputation seller H's price domain is $p_H \in \left[c + \frac{1-k}{1+k}(r_L u - c) + (r_H - r_L)u, r_H u\right]$.[5] Define $p_H = c + \frac{1-k}{1+k}(r_L u - c) + (r_H - r_L)u$, $\overline{p_H} = r_H u$, $p_L = c + \frac{1-k}{1+k}(r_L u - c)$, and $\overline{p_L} = r_L u$.

[5] The proofs of the claims, propositions, and corollaries in this paper can be found in Appendix A.

In this model, the two sellers will equally share the $(1-k)m$ uninformed buyers, and compete for the km informed buyers. The seller i who offers the higher expected utility will win all the informed buyers with a profit of $(p_i-c)\left(km+\frac{(1-k)m}{2}\right)=\frac{(1+k)m}{2}(p_i-c)$, while the other seller $(-i)$ sells only to half of the uninformed buyers with a profit of $\frac{(1-k)m}{2}(p_{-i}-c)$. The two sellers equally share all the informed buyers if offering the same expected utility, and each obtains a profit of $\frac{m}{2}(p_i-c)$. Therefore, seller i's decision problem is to find an optimal price to maximize her expected profit, that is:

$$
\begin{aligned}
&Max_{p_i}\frac{(1+k)m}{2}(p_i-c)P(r_iu-p_i>r_{-i}u-p_{-i})\\
&+\frac{m}{2}(p_i-c)P(r_iu-p_i=r_{-i}u-p_{-i})\\
&+\frac{(1-k)m}{2}(p_i-c)P(r_iu-p_i<r_{-i}u-p_{-i}).
\end{aligned}
$$

Similar to Varian [36], this model does not have a pure strategy equilibrium. To understand, the presence of uninformed buyers gives incentive for sellers to charge relatively high prices, while the presence of informed buyers gives incentive for sellers to keep their price low. Consequently, the co-existence of informed and uninformed buyers makes it impossible for sellers to set a fixed price purely based on their reputation levels. Sellers end up randomizing their prices. Let $f_i^*(p_i^*)$ denote the probability density function (PDF), and $F_i^*(p_i^*)$ denote the cumulative distribution function (CDF) of seller i's equilibrium prices. The equilibrium price distribution functions can be calculated based on the following logic: for either of the two sellers, the profit of charging any price within the possible range is the same given the other seller's mixed pricing strategy. Proposition 1 summarizes the pricing strategies of the two sellers:

Proposition 1. *There exists no pure-strategy equilibrium in prices. Sellers' equilibrium prices* $\{p_L^*,p_H^*\}$ *follow a mixed strategy:* $p_L^*\in[\underline{p_L},\overline{p_L}]$, $f_L^*(p_L^*)=\frac{(1+k)(r_Hu-c)-2k(r_Lu-c)}{2k\left(p_L^*+(r_H-r_L)u-c\right)^2}$, *and* $P(p_L^*=\overline{p_L})=\frac{(r_H-r_L)u}{r_Hu-c}$; $p_H^*\in[\underline{p_H},\overline{p_H})$, *and* $f_H^*(p_H^*)=\frac{(1-k)(r_Lu-c)}{2k\left(p_H^*-(r_H-r_L)u-c\right)^2}$.

It is interesting to note that the low-reputation seller may charge the highest possible price $\overline{p_L}$ with a positive probability ($P(p_L^*=\overline{p_L})$.) This is because the low-reputation seller is at a disadvantage when competing for informed buyers with the high-reputation seller; therefore, the low-reputation seller may give up the informed buyers completely and sells only to the uninformed buyers at the highest possible price.

Fig. 1 illustrates two numerical examples.[6] As the price domain of the high-reputation seller overlaps with that of the low-reputation seller, it is possible for a low-reputation seller to charge either a higher or lower price than a high-reputation seller.

In Fig. 1(a), the low-reputation seller's CDF line is totally above the high-reputation seller's CDF line, i.e., the high-reputation seller's price has the first-order stochastic dominance over the low-reputation seller's price ($F_H^*(p_H^*)\le F_L^*(p_L^*)$). In other words, the high-reputation seller enjoys a price premium over the low-reputation seller in terms of expected price. In Fig. 1(b), the increased proportion of informed buyers (from 30% to 70%) drives the sellers to compete more fiercely for the informed buyers. So both sellers lower their lower-bound of price domains ($\frac{d\,\underline{p_i}}{dk}<0$). They also charge relatively low prices at higher probabilities ($\frac{dF_i^*}{dk}>0$). As a result, both sellers' expected prices drop ($\frac{dE(p_i^*)}{dk}\le 0$). Moreover, the stochastic dominance of the high-reputation seller's price disappears, so the high-reputation seller may not enjoy a price premium in expected price. This is because both sellers reduce their prices when there are more informed buyers in the market; however, the low-reputation seller's expected price drops less rapidly than that of the high-reputation seller ($\frac{d(E(p_H^*)-E(p_L^*))}{dk}<0$),[7] as the low-reputation seller's profit relies less on the informed buyers.

3.2. Competition model: two low- and two high-reputation sellers

Now consider two high-reputation sellers (H1 and H2) with reputation r_H, and two low-reputation sellers (L1 and L2) with reputation r_L. Let p_{ij} denote the price charged by seller ij, where $i\in\{L,H\}$ and $j\in\{1,2\}$. In this model, each high-reputation seller has to compete not only with the low-reputation sellers, but also with the other high-reputation sellers. Similarly, each low-reputation seller also has to compete with all the other three sellers. We can infer that seller ij's price domain is $p_{ij}\in\left[c+\frac{1-k}{1+3k}(r_iu-c),r_iu\right]$. Define $\underline{p_{ij}}=c+\frac{1-k}{1+3k}(r_iu-c)$, and $\overline{p_{ij}}=r_iu$.

In the competition model, each seller has two options: (1) sells to all informed buyers and one quarter of uninformed buyers by occasionally charging the lowest price among the four sellers; and (2) gives up all informed buyers and sells only to one quarter of uninformed buyers by charging the highest possible price. In the benchmark model, the high-reputation seller and the low-reputation seller offer buyers the same expected utility at their lower-bound prices. In the competition model, as the high-reputation sellers lower their lower-bound price levels (compared in the benchmark model), the low-reputation sellers have no room to reduce their lower-bound price. Therefore, the low-reputation sellers settle for the uninformed buyers and set price at the highest possible level (which is the same as the upper-bound price in the benchmark model). Let $f_{ij}^*(p_{ij}^*)$ denote the PDF, and $F_{ij}^*(p_{ij}^*)$ denote the CDF of seller ij's equilibrium prices. Proposition 2 summarizes the pricing strategies of the two sellers:

Proposition 2. *There exists no pure-strategy equilibrium in prices. The high-reputation sellers' equilibrium price* p_{Hj}^* *follows a mixed strategy:* $p_{Hj}^*\in\left[\underline{p_{Hj}},\overline{p_{Hj}}\right]$ *and* $f_{Hj}^*\left(p_{Hj}^*\right)=\frac{(1-k)(r_Hu-c)}{4k\left(p_{Hj}^*-c\right)^2}$. *The low-reputation sellers' equilibrium price is:* $p_{Lj}^*=\overline{p_{Lj}}$, $j=1,2$.

Fig. 2 illustrates two numerical examples.[8] It shows that when the high-reputation sellers vary their prices, the prices of the low-reputation sellers remain unchanged. When the proportion of informed buyers increases from 30% in panel (a) to 70% in panel (b), the high-reputation sellers lower their prices to compete for the increased proportion of informed buyers; while the low-reputation sellers keep their prices the same since they only sell to the uninformed buyers. More specifically, the high-reputation sellers lower the lower-bound of their price domains ($\frac{d\,\underline{p_{Hj}}}{dk}<0$), charge relatively low prices at higher probabilities ($\frac{dF_{Hj}^*}{dk}>0$), and have lower expected prices ($\frac{dE\left(p_{Hj}^*\right)}{dk}\le 0$).

3.3. Price comparisons

In the benchmark model, Proposition 1 shows that it is possible for a low-reputation seller to charge a higher price than a high-reputation seller (see Fig. 1). This also applies to the competition model (see Fig. 2). Is the expected price of the high-reputation seller higher than that of the low-reputation seller? Are sellers setting lower prices when the competition among sellers intensifies?

[6] In the two numerical examples, $u=2$, $c=1$, $r_H=0.9$, and $r_L=0.8$. The proportion of informed buyers k equals to 0.3 in Fig. 1(a), and 0.7 in Fig. 1(b).

[7] Such comparative statics are straightforward, so we omit the proofs here.

[8] In the two numerical examples, $u=2$, $c=1$, $r_H=0.9$, and $r_L=0.8$. The proportion of informed buyers k equals to 0.3 in Fig. 2(a), and 0.7 in Fig. 2(b).

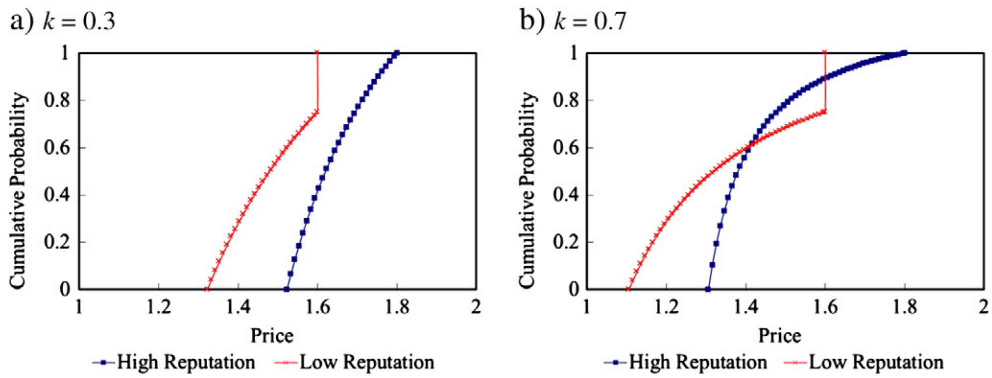

Fig. 1. Equilibrium CDF in the benchmark model.

3.3.1. Low-reputation seller vs. high-reputation seller

Corollary 1. *In the benchmark model, there exist one threshold k_1^* such that when $k<k_1^*$, the expected price of the high-reputation seller is higher than that of the low-reputation seller; and when $k>k_1^*$, the expected price of the high-reputation seller is lower than that of the low-reputation seller.*

Corollary 2. *In the competition model, there exists one threshold k_2^* such that when $k<k_2^*$, the expected price of the high-reputation sellers is higher than that of the low-reputation sellers; and when $k>k_2^*$, the expected price of the high-reputation sellers is lower than that of the low-reputation sellers.*

Corollaries 1 and 2 both show that when the proportion of informed buyers is high enough, the expected price of a high-reputation seller may be even lower than that of a low-reputation seller—the negative price premium effect. Figs. 3 and 4 illustrate a numerical example of Corollaries 1 and 2, respectively.[9] The numerical examples also show that the negative price premium effect is more likely to occur in the competition model as $k_1^*>k_2^*$.[10] The next subsection will provide a more formal proof.

3.3.2. The effect of competition

It is easy to see that $F_H^*(p_H^*)\leq F_{Hj}^*(p_{Hj}^*)$, i.e., the high-reputation seller's price in the benchmark model has the first-order stochastic dominance over the high-reputation sellers' price in the competition model. In other words, the expected price of the high-reputation sellers in the competition model is lower than that in the benchmark model. For the low-reputation sellers, the price in the competition model is $r_L u$, which is the upper-bound of the low-reputation seller's price domain in the benchmark model. Given that competition reduces the high-reputation seller's price but weakly increases the low-reputation seller's price, it is easy to prove that $k_1^*>k_2^*$. Therefore, we have:

Corollary 3. *It is more likely for a high-reputation seller to charge a lower price than a low-reputation seller when competition intensifies.*

In summary, the negative price premium effect exists due to the coexistence of informed and uninformed buyers. Moreover, it is more likely to occur when competition intensifies. Interestingly, competition has opposite effects on the pricing strategies of sellers with different reputation levels: when there are more sellers in the online market, the high-reputation sellers reduce their prices to compete for the informed buyers with each other; the low-reputation sellers, however, increase their prices instead because they give up the competition for the informed buyers.

4. Empirical analysis

4.1. Data collection

Our data was collected from BizRate in December 2010. BizRate compares product offerings from multiple online retailers, and offers integrated consumer ratings of each online retailer. BizRate has also been studied in plenty of research [e.g., 5,25,29].

There are hundreds of product categories in BizRate, such as "Hard Drives" and "TV." Within each product category, there are multiple products. Each product is given a unique product ID. Each product may correspond to multiple product offerings since it can be sold by multiple sellers. A typical product offering in BizRate is illustrated in Fig. 5. It usually shows the product name, ID (visible in HTML code), price; the retailer's name, ID (visible in HTML code), rating; the shipping rate, and others. BizRate exhibits 20 product offerings on each webpage, and no more than 100 pages in each product category.

We developed an HTML parser to automatically collected data in six product categories following Ba et al. 2008 [5] (Hard Drives, GPS, Projector Accessories, TV, Software, and DVDs). Since BizRate no longer treats DVDs and Software as single categories, we picked two random categories of Software ("Office, Tax and Accounting Software", denoted by "Software1", and "Multimedia Software", denoted by "Software2"), and two random categories of DVDs ("Drama DVDs and Videos", denoted by "DVD1", and "Comedy DVDs and Videos", denoted by "DVD2").

We collected 15,771 product offerings of the eight product categories. Among these product offerings, 11,337 of them (5603 distinct products) have the "compare prices from other stores" link. We then "clicked into" each such link and collected all the comparative product offerings. This step assures that all the offerings of each product are included in our dataset. After this step, 72,891 product offerings were collected. We then "clicked into" each seller's rating page, and collected the ratings of each online retailer. In total, 706 sellers were collected.

The data is cleaned in the following steps:

(1) To make sure the offerings of each product are homogeneous, we removed all "used" and "refurbished" product offerings. (The number of product offerings removed is 850, or 1.2% of the total.)
(2) We removed the offerings related to Amazon marketplace

[9] In the numerical examples of Figs. 3 and 4, $u=2$, $c=1$, $r_H=0.9$, and $r_L=0.8$.

[10] More extensive numerical analysis can show that, k^* increases with c or r_H, and decreases with u or r_L. This is because under these conditions, the competition disadvantage of the low-reputation seller becomes greater. Consequently, the gap between the low- and high-reputation seller's average prices grows larger, thus the negative price premium effect is less likely to happen (i.e., k^* increases).

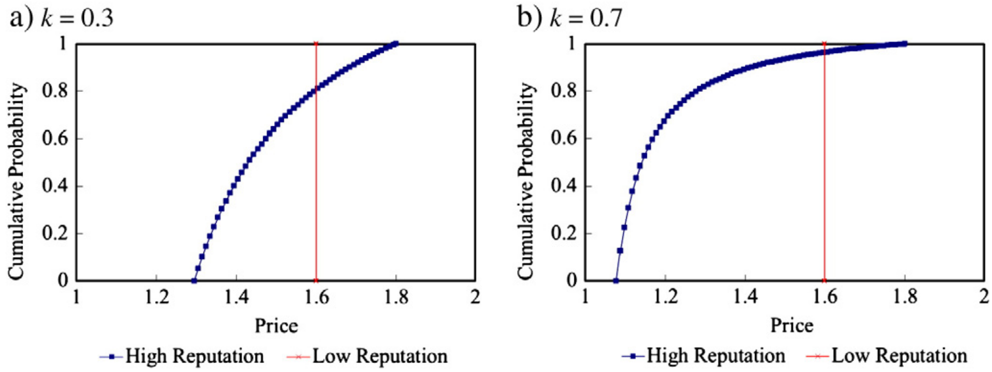

Fig. 2. Equilibrium CDF in the competition model.

and eBay. This is because both Amazon marketplace and eBay have a lot of sellers. However, BizRate only lists the lowest prices of each product in either Amazon Marketplace or eBay, without listing the rating of the seller who offers the lowest price. (5875, or 8.1%)

(3) We also eliminated some extreme prices as they may be listed there by error. For example, BizRate listed the price of DVD "The Boondock Saints II: All Saints Day DVD" offered by the seller "ITISDVD" as $2233.00. However, seller "ITISDVD" actually sells this DVD on its website for $6.99. To clean the data, we divided each offering price by the median price of its corresponding product, and dropped the offerings with the "price per median price" larger than 3. (205, or 0.3%)

(4) We omitted the product offerings with no price listed on BizRate. (135, or 0.2%)

Table 1 shows the summary statistics. Note that the average offering prices (see the AVG column) of the two DVD categories are much lower than that of the other categories. While the average prices in other categories vary from $200 to $900, the average prices in the two DVD categories are only around $20.

4.2. Negative price premium effect

In our brief data analysis, we hope to examine the pricing behaviors of sellers with different reputation levels. More specifically, we want to explore whether the negative price premium effect exists, i.e., whether the average prices of high-reputation sellers is higher than that of the low-reputation sellers.

In the first step, we standardized the offering prices for each product, to make the offering prices between different products comparable. In the second step, we calculated the median of sellers' rating scores within each product category (see Appendix B). According to the median values, we classified the data (both sellers and their product offerings) in each product category into two sub-categories: low-reputation (the rating is less than the median value, denoted by "L"), and high-reputation (the rating is not less than the median value, denoted by "H").[11] We then calculated the average (AVG) of the standardized offering prices in each sub-category, as shown in the "AVG" column of Table 2. We also counted the number of offerings with standardized price above zero, below zero, and zero, respectively, and listed them in the "The number of offerings" columns in Table 2.

[11] We omitted the sellers who are "not yet rated" in BizRate. According to BizRate, "not yet rated" means that "BizRate is in the process of evaluating the store but has not yet collected enough customer reviews [20 surveys in the past 90 days] to issue a rating" (http://about.bizrate.com/ratings#4), thus may not be classified as a low or a high rating.

As shown in the "The number of offerings" columns in Table 2, in all categories, a high-reputation seller may charge a price higher or lower than the average price (i.e., zero, since the prices are standardized). So does a low-reputation seller. As a result, a high-reputation seller may charge either a higher or lower price than a lower-reputation seller. This is consistent with Propositions 1 and 2 that when multiple sellers with different reputation levels compete for the informed buyers in the online market, they employ mixed strategies.

We compare the average of standardized offering prices of the low- and the high-reputation sellers ($E(p_L^*) > E(p_H^*)$?) using t-test in each product category. The comparison results are listed in the "t-test" columns of Table 2.

We find that, the low-reputation sellers charge significantly higher prices than the high-reputation sellers on average in all categories except the DVD category. For example, in the Hard Drives category, the average standardized price of low-reputation sellers is 0.20, while that of high-reputation sellers is −0.31. This is consistent with our theoretical finding that the low-reputation sellers may charge higher prices than the high-reputation sellers on average, i.e., the negative price premium effect. When both the low- and high-reputation sellers compete for the informed buyers, the low-reputation sellers are more likely to give up the competition and charge high prices to the uninformed buyers. So the average price of the low-reputation sellers becomes higher than that of the high-reputation sellers.

The exceptions of the DVD categories are also intuitive. The DVD product categories have low value with average prices around 20 dollars. Buyers may not be willing to spend a lot of time and effort comparing offerings with such low values [3], thus are more likely to be uninformed buyers. In other words, the proportion of informed

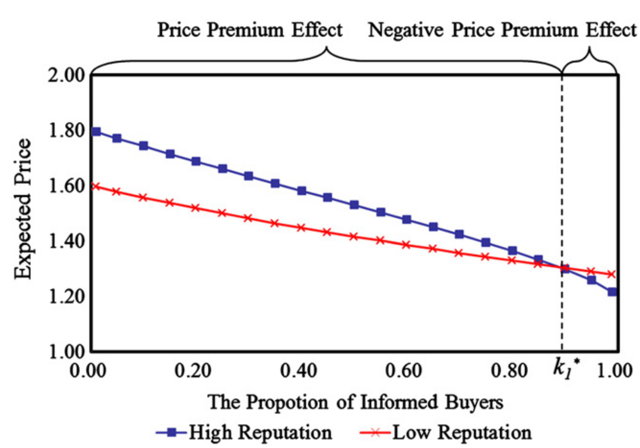

Fig. 3. Expected price in the benchmark model.

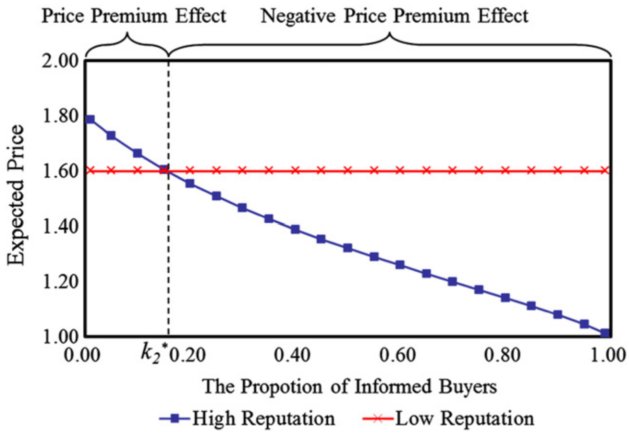

Fig. 4. Expected price in the competition model.

buyers for DVD category (k) is relatively low. From Corollaries 1 and 2, the high-reputation sellers are more likely to charge higher prices than the low-reputation sellers with a relatively low proportion of informed buyers. Therefore, it is reasonable that the high-reputation sellers enjoy a price premium in the DVD product categories.

4.3. Summary of empirical results

In summary, our data show that seller may play mixed strategies in their pricing, thus confirm Propositions 1 and 2. The high-reputation sellers selling high-value digital products are more likely to charge lower prices than the low-reputation sellers, which exhibits a negative price premium effect. This negative price premium effect reduces or even reverses when the proportion of informed buyers decreases (e.g., when products are of low value), so our finding in Corollaries 1 and 2 is supported.

5. Conclusions

In this paper, we study the pricing strategies of sellers with different reputation levels in online markets. We identify three factors, that is, seller reputation, competition, and buyer informativeness, which impact a seller's pricing strategy. We find that a negative price premium effect exists due to: (1) the co-existence of informed and uninformed buyers in the market, which makes sellers' prices follow mixed strategies, so that it is possible for a high-reputation seller to set lower prices than a low-reputation seller. Furthermore, when the proportion of informed buyers exceeds a threshold, a high-reputation seller may even set lower prices on average than a low-reputation seller. (2) The competition among sellers. Competition has different effects on sellers with different reputation levels. The competition makes the high-reputation sellers reduce their prices while the low-reputation sellers increase their prices. Therefore, the negative price premium effect is more likely to occur when the competition intensifies. Our empirical data also confirm our theoretical findings of the negative price premium effect.

This paper offers an explanation on the contradictory findings in literature [3,10,23,38] regarding whether and when a high-reputation seller enjoys a price premium. The existing explanations of such mixed findings include whether the reputation score is properly calculated (e.g., whether the reputation score is calculated by the number of positive ratings, or the difference between the number of positive ratings and negative ratings) [25], or whether a proper regression model is used (e.g., OLS or Tobit) [24]. Different from these findings, our results show that there is no simple and fixed relationship between seller reputation and pricing. Sellers may play mixed pricing strategies when informed buyers coexist with uninformed buyers, so a negative price premium effect may occur. This also indicates that, simply attributing price dispersion to seller differentiation may not be sufficient. This research also extends our understandings on the effect of competition. The common knowledge is that the competition reduces seller price. However, our model shows that, a low-reputation seller may give up the competition for informed customers and increase their prices when competition intensifies, a “counter-intuitive” phenomenon in online market.

This research also offers practical implications. First, a high-reputation seller may seek a mixed strategy in pricing, such as offering discount from time to time, when the competition is fierce or when they serve many informed buyers. Second, our findings encourage sellers to adjust their pricing strategies across different product categories based on the product value, or, the proportion of informed buyers.

This research is not without limitations. First, it is difficult to empirically measure the buyer informativeness, i.e., the proportion of informed buyers. According to the findings in the literature [3,25], we assume that it is less likely for online buyers to invest in searching for low value products (such as DVDs). In other words, this study uses product category as a proxy of buyer informativeness. It would be helpful to develop a more formal approach. Second, our theoretical model only considers four players, i.e., two high-reputation sellers vs. two low-reputation sellers. A real online market is more complex. Furthermore, there may be other explanations on the negative price premium effect: the sellers may have different cost structures caused by economies of scale or advertising cost [6]; the low-reputation sellers may charge relatively high prices in order to signal their quality, etc. It will be interesting to study the impact of these factors and empirically test these effects.

Future study may focus on the following extensions: (1) collecting data in more product categories, or from multiple websites, to verify our theoretical findings; (2) developing a more formal empirical model to better understand seller pricing strategies; and (3) developing a theoretical model of a large number of sellers with their reputation randomly distributed, to simulate the online markets more accurately.

Acknowledgments

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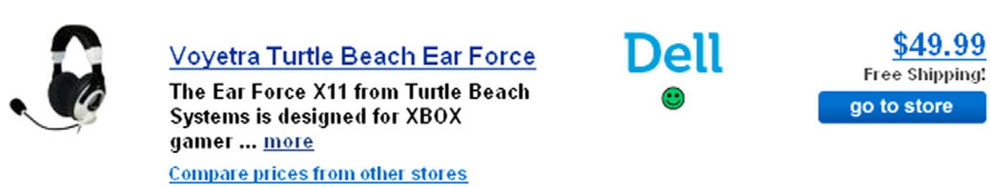

Fig. 5. An example of product offering in BizRate.

Table 1
Summary statistics.

Product category	Sample size			Offering price			
	Sellers	Products	Offerings	AVG	SD	MIN	MAX
GPS	334	346	8257	406.71	472.31	8.4	3999.99
Hard drives	202	957	12,625	211.29	321.39	4.95	5599.99
Projector accessories	136	1008	9738	357.23	475.87	12.99	14,143.95
TV	241	550	9232	983.98	941.28	49	14199
Software1	106	171	1619	437.18	1086.65	5.94	13,899.99
Software2	72	124	1765	603.35	607.98	11	5294.95
DVD1	64	1056	12,203	27.24	32.33	0.01	517.76
DVD2	67	963	10,085	17.8	17.61	0.01	235.69

Appendix A. Technical details

Proof of Proposition 1. We prove Proposition 1 in the following three steps:

(1) The domain of the low- and high-reputation seller's price:
First, seller i will not charge a price p_i lower than the cost c or higher than buyers' reservation price $r_i u$, thus

$$c \le p_i \le r_i u. \tag{A.1}$$

Second, when $c \le p_i \le r_i u$, the two sellers equally share the $(1-k)$ m uninformed buyers, and compete for the km informed buyers. If $r_i u - p_i > r_{-i} u - p_{-i}$, i.e., seller i offers buyers higher expected utility than seller $(-i)$, seller i wins all the informed buyers, and gains the profit $(p_i - c)\left(km + \frac{(1-k)m}{2}\right) = \frac{(1+k)m}{2}(p_i - c)$. If $r_i u - p_i < r_{-i} u - p_{-i}$, seller i loses all the informed buyers, and gains the profit $\frac{(1-k)m}{2}(p_i - c)$. If $r_i u - p_i = r_{-i} u - p_{-i}$, the two sellers equally share all the informed buyers, and seller i gains the profit $\frac{m}{2}(p_i - c)$.
Seller i can try to win the informed buyers by cutting the price p_i. However, if p_i is too low, the profit of winning all the informed buyers may be lower than the profit of giving up all the informed buyers and charging the reservation price $r_i u$ to half of the uninformed buyers. That is, p_i should satisfy $\frac{(1+k)m}{2}(p_i - c) \ge \frac{(1-k)m}{2}(r_i u - c)$, which is equivalent to

$$p_i \ge c + \frac{1-k}{1+k}(r_i u - c). \tag{A.2}$$

Combine the inequalities (A.1) and (A.2), we have

$$c + \frac{1-k}{1+k}(r_i u - c) \le p_i \le r_i u. \tag{A.3}$$

According to Eq. (A.3), the highest expected utility seller L can offer buyers is $r_L u - \left[c + \frac{1-k}{1+k}(r_L u - c)\right]$. To offer buyers the same expected utility, seller H only need to charge the price $c + \frac{1-k}{1+k}(r_L u - c) + (r_H - r_L)u$, which is higher than $c + \frac{1-k}{1+k}(r_H u - c)$. It is easy to prove that,

$$p_H \ge c + \frac{1-k}{1+k}(r_L u - c) + (r_H - r_L)u. \tag{A.4}$$

Combine the inequalities (A.3) and (A.4), it is proved that, the domain of the low-reputation seller L's price p_L is $p_L \in \left[c + \frac{1-k}{1+k}(r_L u - c), r_L u\right]$, and the domain of the high-reputation seller H's price p_H is $p_H \in \left[c + \frac{1-k}{1+k}(r_L u - c) + (r_H - r_L)u, r_H u\right]$.

Note that (a) the domain of p_L and the domain of p_H have the same length; (b) the lower-bound of seller L's profit is $\frac{1-k}{2} m(\overline{p_L} - c) = \frac{1-k}{2} m(r_L u - c)$, and the lower-bound of seller H's profit is $\lim_{\varepsilon \to 0} \frac{1+k}{2} m(\underline{p_H} - \varepsilon - c) = \frac{1-k}{2} m(r_H u - c) + km(r_H - r_L)u$..

(2) The model has no pure-strategy Nash equilibrium:
First, we prove that the two sellers H and L equally share all the buyers, i.e. any $\{p_L^*, p_H^*\}$ satisfies $r_L u - p_L^* = r_H u - p_H^*$, is not a pure-strategy Nash equilibrium. Assume it is a pure-strategy Nash equilibrium. If $p_L^* > \underline{p_L}$, seller L has the incentive to charge slightly less, say $p_L^* - \varepsilon$, to win the other $\frac{km}{2}$ informed buyers. If $p_L^* = \underline{p_L}$, the low-reputation seller L's profit is $\frac{m}{2}\left[\frac{1-k}{1+k}(r_L u - c)\right]$, which is less than the lower-bound profit $\frac{1-k}{2} m(r_L u - c)$. Therefore, the two sellers equally sharing all the buyers is not a pure-strategy Nash equilibrium.
Second, we prove that one seller wins all the informed buyers, i.e. any $\{p_L^*, p_H^*\}$ satisfies $r_L u - p_L^* \ne r_H u - p_H^*$, is also not a pure-strategy Nash equilibrium. Assume it is a pure-strategy Nash equilibrium. Suppose seller i offers buyers a higher expected utility $(r_i u - p_i^* > r_{-i} u - p_{-i}^*)$ and wins all the informed buyers. Since $r_{-i} u - p_{-i}^* \ge 0$, we have $p_i^* < r_i u$, i.e., seller i's equilibrium price p_i^* is not her upper-bound price. In this case, seller i has the incentive to slightly increase the price (without losing the informed buyers) to increase her profit. Therefore, one seller wins all the informed buyers is also not a pure-strategy Nash equilibrium.
In summary, there is no pure-strategy Nash equilibrium.

(3) *Sellers' equilibrium prices* $\{p_L^*, p_H^*\}$
For the high-reputation seller H, the expected profit at each p_H is

$$\frac{(1+k)m}{2}(p_H - c)P(p_L > p_H - (r_H - r_L)u) + \frac{m}{2}(p_H - c)P(p_L = p_H - (r_H - r_L)u) + \frac{(1-k)m}{2}(p_H - c)P(p_L < p_H - (r_H - r_L)u).$$

Omit the point probability, we get[12]:

$$\frac{m}{2}(p_H - c)[1 + k - 2kP(p_L \le p_H - (r_H - r_L)u)].$$

Given seller L's mixed strategy, seller H should be indifferent between all her pure strategies. Therefore, seller H's expected profit should be equal to the profit when she charges the lower-bound price $\underline{p_H}$, i.e.,

$$\frac{m}{2}(p_H^* - c)\left[1 + k - 2kF_L^*(p_H^* - (r_H - r_L)u)\right] = \frac{(1-k)m}{2}(r_H u - c) + km(r_H - r_L)u$$

$$\Rightarrow F_L^*(p_L^*) = \frac{kp_L^* + p_L^* - r_L u + kr_L u - 2kc}{2k(p_L^* + (r_H - r_L)u - c)} \tag{A.5}$$

$$\Rightarrow f_L^*(p) = \frac{(1+k)(r_H u - c) - 2k(r_L u - c)}{2k(p_L^* + (r_H - r_L)u - c)^2}. \tag{A.6}$$

Note that $F_L^*(\underline{p_L}) = 0$ and $F_L^*(\overline{p_L}) = \frac{r_L u - c}{r_H u - c}$, which means the probability that seller L charges the upper-bound price is $1 - F_L^*(\overline{p_L}) = \frac{(r_H - r_L)u}{r_H u - c}$. It is also worthwhile to note that seller H

[12] For the moment, we directly omit the point probability. The proof will show that the only point mass is at $\overline{p_L} = r_L u$, and the calculations are still holding given this point mass.

Table 2
Average prices.

Category		Sample size			Standardized price		The number of offerings			t-Test	
Product	Rating	Seller	Product	Offerings	AVG	SD	Positive	Negative	Zero	$E(p^*_L) > E(p^*_H)$?	Sig.
GPS	H	49	332	1653	−0.28	0.87	589 (35.6%)	1064 (64.4%)	0 (0.0%)	Yes	***
	L	48	308	2181	−0.05	1.06	868 (39.8%)	1313 (60.2%)	0 (0.0%)		
Hard drives	H	38	836	3682	−0.31	0.84	1101 (29.9%)	2581 (70.1%)	0 (0.0%)	Yes	***
	L	36	750	3503	0.20	0.98	1777 (50.7%)	1725 (49.2%)	1 (0.0%)		
Projector accessories	H	33	451	2250	−0.02	0.63	984 (43.7%)	1266 (56.3%)	0 (0.0%)	Yes	***
	L	25	552	1924	0.10	0.78	1072 (55.7%)	852 (44.3%)	0 (0.0%)		
TV	H	39	525	3419	−0.28	0.84	986 (28.8%)	2433 (71.2%)	0 (0.0%)	Yes	***
	L	32	476	1907	−0.05	0.99	751 (39.4%)	1156 (60.6%)	0 (0.0%)		
Software1	H	27	160	855	−0.14	0.91	355 (41.5%)	500 (58.5%)	0 (0.0%)	Yes	***
	L	18	70	190	0.43	0.98	127 (66.8%)	63 (33.2%)	0 (0.0%)		
Software2	H	23	120	615	−0.04	0.84	315 (51.2%)	300 (48.8%)	0 (0.0%)	Yes	***
	L	17	117	519	0.19	1.21	235 (45.3%)	281 (54.1%)	3 (0.6%)		
DVD1	H	13	1043	4637	−0.12	0.86	2026 (43.7%)	2611 (56.3%)	0 (0.0%)	No	***
	L	8	974	1725	−0.31	0.95	565 (32.8%)	1160 (67.2%)	0 (0.0%)		
DVD2	H	10	961	4035	−0.11	0.89	1859 (46.1%)	2176 (53.9%)	0 (0.0%)	No	***
	L	9	795	1369	−0.36	0.95	423 (30.9%)	946 (69.1%)	0 (0.0%)		

*** Means significant at 0.01 level (two-tailed).

will not charge the upper-bound price $\overline{p_H}$, because seller H's expected profit at $\overline{p_H}$ is $\frac{r_Hu-r_Lu}{r_Hu-c}\frac{m}{2}(r_Hu-c)+\frac{r_Lu-c}{r_Hu-c}\frac{(1-k)m}{2}(r_Hu-c)$, which is less than her lower-bound profit.
The proof of seller H's equilibrium price follows exactly the same way as the proof of seller L's equilibrium price, thus is omitted.
Done.

Proof of Proposition 2. Similar to the proof of Eq. (A.3), it is easy to prove that the domain of seller ij's price p_{ij} is$p_{ij}\in\left[c+\frac{1-k}{1+3k}(r_iu-c), r_iu\right]$.
Now we prove Proposition 2 in the following two steps:

First, suppose the low-reputation sellers' optimal strategy is sticking to their upper-bound price, they will never win the competition. Similar to the proof of Eq. (A.6), it is easy to prove that the high-reputation sellers' equilibrium price follows a PDF of $f^*_{Hj}\left(p^*_{Hj}\right)=\frac{(1-k)(r_Hu-c)}{4k\left(p^*_{Hj}-c\right)^2}$. High-reputation sellers' any deviation from this mixed strategy will cause a loss of profit.

Second, given the high-reputation sellers' optimal mixed strategy, it is not difficult to prove that it is also optimal for the low-reputation sellers to charge the upper-bound price $\overline{p_{Lj}}$, that is,

$$\frac{(1-k)m}{4}(r_Lu-c)>\frac{(1-k)m}{4}\left(p_{Lj}-c\right)+km\left(p_{Lj}-c\right)\left[1-F\left(p_{Lj}+(r_H-r_L)u\right)\right]^2$$

$$\Leftrightarrow 4k\left(p_{Lj}+(r_H-r_L)u-c\right)^2+(1-k)\left(p_{Lj}-c\right)\left(p_{Lj}-r_Lu\right)>0. \quad (A.7)$$

It is easy to show that the left hand side (LHS) of Eq. (A.7) is positive at the lower-bound of p_{Lj}, and is increasing in the whole domain of p_{Lj}. Therefore, the low-reputation sellers' optimal strategy is charging their upper-bound price $\overline{p_{Lj}}$.
Done.

Proof of Corollary 1. In the benchmark model, the expected price of the low-reputation seller is

$$E(p_L)=\int_{\underline{p_L}}^{\overline{p_L}} p_Lf_L(p_L)\,dp_L+r_Lu\frac{r_Hu-r_Lu}{r_Hu-c}$$
$$=\frac{(1+k)(r_Hu-c)-2k(r_Lu-c)}{2k}\ln\left(\frac{(1+k)(r_Hu-c)}{(1+k)(r_Hu-c)-2k(r_Lu-c)}\right)+c.$$

The high-reputation seller's expected price is

$$E(p_H)=\int_{\underline{p_H}}^{\overline{p_H}} p_Hf_H(p_H)dp_H=\ln\left(\frac{1+k}{1-k}\right)\frac{(1-k)(r_Lu-c)}{2k}+(r_H-r_L)u+c.$$

Consider $E(p_H)-E(p_L)$, we have $\frac{d(E(p_H)-E(p_L))}{dk}<0$, $\lim_{k\to0}\left(E(p^*_H)-E(p^*_L)\right)=(r_H-r_L)u>0$, and $\lim_{k\to1}\left(E(p^*_H)-E(p^*_L)\right)=\left(1-\ln\left(\frac{r_Hu-c}{r_Hu-r_Lu}\right)\right)\times(r_H-r_L)u$. When $\ln\left(\frac{r_Hu-c}{r_Hu-r_Lu}\right)\geq1$, $\lim_{k\to1}\left(E(p^*_H)-E(p^*_L)\right)\leq0$, there is one threshold k which satisfies $E(p_H)=E(p_L)$. In this case, we define $k_1{}^*$ as the threshold k. When $\ln\left(\frac{r_Hu-c}{r_Hu-r_Lu}\right)<1$, $\lim_{k\to1}\left(E(p^*_H)-\right.$

$E(p_L^*)) > 0$, there is no k which satisfies $E(p_H) = E(p_L)$. In this case, we define $k_1^* = 1$. Therefore, when $k < k_1^*$, the expected price of the high-reputation seller is higher than that of the low-reputation seller; and when $k > k_1^*$, the expected price of the high-reputation seller is lower than that of the low-reputation seller.

Done.

Proof of Corollary 2. In the competition model, the expected price of the low-reputation sellers is $E(p_{Lj}) = r_L u$. The expected price of the high-reputation sellers is

$$E\left(p_{Hj}\right) = \int p_{Hj} f_H\left(p_{Hj}\right) dp_{Hj} = c + \frac{(1-k)(r_H u - c)}{4k} \ln\left(\frac{1+3k}{1-k}\right).$$

It is easy to calculate that $\lim_{k\to 0}\left(E\left(p_{Hj}^*\right) - E\left(p_{Lj}^*\right)\right) > 0$, $\lim_{k\to 1}\left(E\left(p_{Hj}^*\right) - E\left(p_{Lj}^*\right)\right) < 0$, and $\frac{d\left(E\left(p_{Hj}\right) - E\left(p_{Lj}\right)\right)}{dk} < 0$. Therefore, there exist one threshold k, makes $E(p_{Hj}) = E(p_{Lj})$. Let k_2^* denote the threshold k. When $k < k_2^*$, the expected price of the high-reputation seller is higher than that of the low-reputation seller; and when $k > k_2^*$, the expected price of the high-reputation seller is lower than that of the low-reputation seller.

Done.

Proof of Corollary 3. To prove Corollary 3, we should prove $k_1^* > k_2^*$.

Since the competition introduced by more sellers has opposite effects on sellers with different reputation levels (it reduces the high-reputation seller's price, but increases the low-reputation seller's price), we have

$$E\left(p_{Hj}\right)\left(k_1^*\right) - E\left(p_{Lj}\right)\left(k_1^*\right) < E(p_H)\left(k_1^*\right) - E(p_L)\left(k_1^*\right).$$

Suppose $k_1^* \le k_2^*$. Since $\frac{d\left(E\left(p_{Hj}\right) - E\left(p_{Lj}\right)\right)}{dk} < 0$, we also have

$$E(p_H)\left(k_2^*\right) - E(p_L)\left(k_2^*\right) \le E\left(p_{Hj}\right)\left(k_1^*\right) - E\left(p_{Lj}\right)\left(k_1^*\right).$$

Combine these two inequalities, we have $E(p_H)(k_2^*) - E(p_L)(k_2^*)$-$E(p_H)(k_1^*) - E(p_L)(k_1^*) = 0$, which is contrast with $E(p_H)(k_2^*) - E(p_L)(k_2^*) = 0$. Therefore, it is impossible that $k_1^* \le k_2^*$.

Done.

Appendix B. Statistics on seller ratings

Product category	Sample size		Seller rating			
	N	N (with rating)	MIN	Median	Top 5%	MAX
GPS	334	97	6.9	8.95	9.4	9.6
Hard drives	202	74	5.7	8.9	9.3	9.4
Projector accessories	136	58	7.3	8.8	9.4	9.8
TV	241	71	7.9	8.8	9.3	9.8
Software1	106	45	7.2	8.8	9.4	9.5
Software2	72	40	7.8	8.9	9.4	9.5
DVD1	64	21	7.2	8.8	9.1	9.1
DVD2	67	19	7.2	8.8	9.1	9.1

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