Pricing Strategy in Online Retailing Marketplaces of Homogeneous Goods: Should High Reputation Seller Charge More?*

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Abstract. There are two conflicting streams of research findings on pricing strategy: one is high reputation sellers should charge price premium, while the other is high reputation sellers should charge relatively low price. Motivated by this confliction, this study examines pricing strategy in online retailing marketplace of homogeneous goods. We conduct an empirical study using data collected from a dominant online retailing marketplace in China. Our research results indicate that, in online retailing marketplace of homogeneous goods, high reputation sellers should charge relatively low price, because the consumers of high reputation sellers are more price sensitive than the consumers of low reputation sellers.

Keywords: Pricing strategy, price sensitivity, seller reputation, online retailing marketplace, homogeneous goods.

1 Introduction

Online retailing marketplace of homogeneous goods is a major proportion in electronic commerce. For example, according to a prediction by eMarketer (http://www.emarketer.com/, a market research and statistics company), the most frequently transacted goods types in American online marketplaces may be computer hardware and software, books, toys and electronic games in the year of 2010. In China, five most frequently transacted goods types on Taobao (http://www.taobao.com, a dominant online marketplace in China) are clothes, cell phones, commodities, PC and accessories, and laptop computers (iResearch 2008). Except clothes, these goods are all homogeneous goods with little quality and value variance.

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A key decision for sellers to make in online retailing marketplaces is to set the goods price (Oh and Lucas 2006). How should sellers price their goods to maximize their revenue? It is commonly suggested that high reputation sellers charge relatively high price, because consumers are likely to pay price premium to high reputation sellers for the benefits of low transaction risks (Ba and Pavlou 2002; Lucking-Reiley, Bryan, Prasad and Reeves 2007). Researchers have also illustrated that consumers are less price sensitive when they perceive their sellers as high reputation sellers (Ba, Stallaert and Zhang 2007; Kim and Xu 2007).

However, contrary to these common suggestions, Baylis and Perloff (2002) examined prices of a digital camera and a flatbed scanner from online retailers, and found that high reputation online retailers (the reputation is rated by Bizrate, Gomez and other shopping comparison websites) charge relatively low prices, and low reputation online retailers charge relatively high prices. Baylis and Perloff (2002) explained that there are both informed and uninformed consumers in online marketplaces. Online retailers of low reputation target only uninformed consumers, thus they charge relatively high price, while online retailers of high reputation target both uninformed and informed consumers, thus they charge relatively low price (Baylis and Perloff 2002). This price discrimination strategy can be explained by economics models, such as price dispersion model (Salop and Stiglitz 1977; Salop and Stiglitz 1982) and "tourists and the natives" model (Carlton and Perloff 2000).

Since these two streams of research findings contradict with each other, they may confuse both researchers and practitioners on the pricing strategy of homogeneous goods in online retailing marketplaces. Should high reputation sellers charge relatively high price or relatively low price? To answer this research question, we need to examine consumers' price sensitivity in online retailing marketplace of homogeneous goods. Based on the answer to this question, we may propose some suggestions on the pricing strategy when seller reputation is given.

We conduct an empirical study to analyze the pricing strategy in online retailing marketplaces of homogeneous goods. We analyze the characteristics of online retailing marketplace of homogeneous goods, and propose several hypotheses. Then we verify our hypotheses using data collected from Taobao. We examine the relationship between consumers' experience and their sensitivity to price, and also the relationships between consumers' experience and their sensitivity to seller reputation. We also examine whether the high reputation sellers' consumers are more price sensitive. Based on all these findings, we discuss seller's pricing strategy in online marketplace of homogeneous goods.

This paper is organized as follows: in the next section, we review related theories, and propose our research hypotheses. Following this theoretical section, we introduce our research methodology, including data collection and analysis method. Afterwards, we present our research results. Finally, we conclude this paper with a discussion section.

2 Theoretical Background

2.1 Online Retailing Marketplace

Online marketplace is an "independently owned, IT−enabled intermediary" which connect sellers and consumers (Bakos 1991; Soh, Markus and Goh 2006).

Accordingly, online retailing marketplace is the online marketplace where goods are retailed rather than auctioned. In online retailing marketplaces, sellers publish goods offerings (including price and quality information) on the marketplace platform; consumers search, browse and compare goods offerings, and purchase goods from sellers. Examples of online retailing marketplace include Amazon.com and Taobao.com. Besides, eBay, the most prevalent online auction marketplace, has also cut its "Buy–It–Now" fees in the August of 2008 to encourage retailing in its marketplace.

2.2 Search Costs in Online Retailing Marketplace

It is commonly recognized that online marketplace sharply reduces consumers' search costs compared with conventional marketplace (Brynjolfsson and Smith 2000). In online marketplace, consumers only have to do a few clicks to search, browse and compare goods offerings from different sellers (Bakos 1997; Clemons, Hann and Hitt 2002; Zhang, Fang and Sheng 2006). However, online retailing marketplace also increases the difficulty for consumers to make purchase decisions. There are mainly two reasons: "overloaded" goods offerings and insufficient quality information.

On one hand, online retailing marketplaces usually have "overloaded" goods offerings for consumers to choose. Two characteristics of online marketplace make its goods offerings becoming "overloaded". First, online marketplace attracts plenty of sellers for its low set-up costs and operation costs. Sellers do not have to set up a "brick–and–mortar" storefront and hire clerks to conduct transactions (Zhang 2006). Therefore, it is easy for any participant to start a business in online retailing marketplaces. Second, inventory in online retailing marketplace is distributively held by all the sellers. This distributive nature of inventory allows online retailing marketplace to have a massive content storage and almost infinite number of listings (Zhang 2006). For example, there were more than 460 thousands online game card offerings, more than one million brand new cell phone offerings and even more than 18 million female clothes offerings on Taobao (the data were observed on 13-Feburary-2009). Even when consumers search for some specified goods, they can still find hundreds or even thousands of goods offerings. For example, if consumers search "Nokia N73" in "Cell Phone > Nokia > N73" category, they still can get more than 6,000 offerings. Obviously, the information in the thousands of goods offerings are beyond the information processing capability of online consumers. Without the help from some IT facilities, consumers may not be able to make optimum or even reasonable purchase decisions based on so abundant information.

On the other hand, the insufficient goods quality and seller trustworthiness information in online marketplace also increase the difficulty for consumers to make purchase decision (Andrews and Benzing 2007; Snijders and Zijdeman 2004). In online retailing marketplace, consumers can only examine goods quality via electronic quality cues (such as item descriptions, pictures, videos and other multi-media information posted by seller and other consumers) (Josang, Ismail and Boyd 2007; Kauffman and Wood 2006). They lose the opportunity of examining goods via traditional cues, such as observation, touch, taste and trial.

In online retailing marketplace, sellers and consumers are usually strangers before transactions (Resnick and Zeckhauser 2002). It is difficult for consumers to know whether sellers are trustable. Sellers can hide their behaviors under the mask of a meaningless electronic ID, and also can easily cheat and exit from the marketplace (Kalyanam and McIntyre 2001). Furthermore, the separation of payment and delivery also offers great chances for sellers' opportunistic behavior (Andrews and Benzing 2007). These uncertainties involve consumers into great risks of online transactions. Before making purchase decisions, consumers have to carefully evaluate and compare sellers' trustworthiness as well as transaction risks. Thus, even though alternative goods offerings are just a few clicks away, it still costs much for consumers to find a proper goods offering from an "endless" goods offering list.

2.3 IT Facilities in Online Retailing Marketplace

Because the goods offerings in online retailing marketplace are "overloaded" and quality information is insufficient, consumers may have to pay high search costs if they hope to browse and compare all the goods offerings. To maximum their utility, consumers should be able to (1) accurately verify seller trustworthiness and goods quality, and (2) efficiently narrow down the search range of goods offerings. Online retailing marketplace also offers IT facilities in these two perspectives.

IT facilities for verifying seller trustworthiness and goods quality include reputation system, peers' forum, third party certification and escrow services. Reputation system is the most frequently adopted IT facility in online marketplace in signaling seller trustworthiness (Josang, Ismail and Boyd 2007). The reputation system calculates a reputation score for each seller based on consumers' ratings on the seller's performance, and then new consumers can identify trustworthy sellers through comparing sellers' reputation scores. They also can further verify sellers' trustworthiness and goods quality by the detailed information obtained from peers' reviews (from reputation system or peers' forum). Besides, consumers also can use third party services, such as third party quality certification (Dewally and Ederington 2006) and escrow service (Antony, Lin and Xu 2006; Hu, Lin, Whinston and Zhang 2004), to verify and guarantee sellers' trustworthiness and goods quality.

Online retailing marketplace also adopted several IT facilities in helping consumers to narrow down the search range of goods offerings. These IT facilities include basic search engines, advanced search engines, goods categories, search results sorting mechanisms, and goods comparison mechanisms. Generally, consumers can search their desired goods offerings by keywords via basic search engines. They also can search goods with specified characteristics using advanced search engines, and filter the search results using goods categories. Furthermore, consumers also can sort the search results of goods offerings according to price or seller reputation (or other criterion), and then selectively view the goods offerings of low prices or the goods offerings from high reputation sellers. They also can compare the goods offerings of interests via goods comparison mechanisms.

Obviously, it requires knowledge and skills for consumers to use these IT facilities. Consumers' abilities and experiences of using these IT facilities will influence their search costs and perceived difficulties in making purchase decisions, and then influence their browse and purchase behavior.

2.4 Experienced and Inexperienced Consumers

Traditional price dispersion studies modeled consumers as informed and uninformed consumers (Salop 1977; Salop and Stiglitz 1977; Varian 1980). Informed consumers are efficient searchers and have low search costs. They know the whole distribution of prices and the lowest available price, so that they can directly purchase the goods of lowest price without searching any of the stores (Varian 1980). Uninformed consumers are inefficient searchers and have high search costs (Salop 1977). They randomly visit stores, and then purchase from a store with goods price lower than their reservation price (Salop 1977). Similarly, in online retailing marketplace, we also can classify consumers as experienced and inexperienced consumers, according to their abilities and experiences of using IT facilities. We use the terms of "experienced" and "inexperienced" rather than "informed" and "uninformed", because there are no definitely informed or uninformed consumers in real online marketplace.

Generally, consumers who have conducted more transactions in the online retailing marketplace are more likely to be experienced consumers, while new registers in the online marketplace are usually inexperienced consumers. On Taobao, more than 40 percent of online consumers in each year are new registers.

Compared with inexperienced consumers, experienced consumers are more familiar with the transaction platform and IT facilities in online retailing marketplaces. They are more likely to use accurate keywords, adopt advanced search engines, filter the search results via goods categories and sort the goods offerings according to goods price or seller reputation. Therefore, experienced online consumers are more likely to know the range of goods prices and seller reputations, and also the lowest goods price and the highest seller reputation. Contrarily, inexperienced consumers are less likely to possess the skills. If inexperienced consumers do not possess these skills, it is nearly impossible for them to know the range of goods prices and seller reputations when they face thousands of goods offerings. They may randomly browse the goods offerings in their search results, and choose one to purchase when the goods price is less than their reservation price. Moreover, because inexperienced consumers are less likely to know the distribution of seller reputation (they may be even unfamiliar with the reputation system), they are also less likely to be sensitive to seller reputation too.

In summary, experienced consumers are more likely to have the ability to choose goods of low prices and from high reputation sellers, while inexperienced consumers are less likely to have the abilities. Therefore, we hypothesize:

Hypothesis 1: In online retailing marketplace of homogeneous goods, experienced consumers (vs. inexperienced consumers) are more likely to browse and purchase low price goods.

Hypothesis 2: In online retailing marketplace of homogeneous goods, experienced consumers (vs. inexperienced consumers) are more likely to browse and purchase goods from high reputation seller.

2.5 Price Sensitivity and Seller Reputation

As we discussed in the previous subsection, experienced consumers selectively browse and purchase goods offerings from high reputation sellers, while inexperienced consumers randomly browse among all of the goods offerings (Salop 1977; Varian 1980). Therefore, high reputation sellers can attract both experienced and inexperienced consumers, while low reputation sellers can only attract inexperienced consumers. Combining this consideration with hypothesis 1 (i.e. experienced consumers are more price sensitive than inexperienced consumers), we can infer that, on average, the consumers of high reputation sellers are more price sensitive than the consumers of low reputation sellers. There are several empirical evidences which can support this inference. For example, Baylis and Perloff (2002) observed the prices of digital cameras and flatbed scanners from online retailers, and found that low reputation online retailers charge relatively high prices, while high reputation online retailers charge relatively low prices. In a field experiment, Jin and Kato (2006) found that low reputation sellers target less experienced consumers and claim high quality to seize more revenues.

Notice that there are also some studies about online auction marketplace indicated that consumers are likely to pay price premium to high reputation sellers for the benefits of low transaction risks (Ba and Pavlou 2002; Lucking-Reiley, Bryan, Prasad and Reeves 2007). However, these conclusions were generated based on empirical data from online auction marketplace, and these conclusions may not match in our research context, i.e. online retailing marketplace of homogeneous goods. There are several reasons. First, the goods in online auction marketplace, such as arts (Highfall and O'Brien 2007), collections (Jin and Kato 2006; Kauffman and Wood 2006; Resnick, Zeckhauser, Swanson and Lockwood 2006) and second hand goods (Wolf and Muhanna 2005), are usually of large quality variance. Comparatively, the quality variance of homogeneous goods in online retailing marketplace is quite low. In the case of low goods quality variance, reputation has relatively weak or even no effects on final price (Lee, Im and Lee 2006; Ruiz 2004; Wan and Teo 2001). Second, studies in online auction marketplace overlooked the competition between sellers (Ba and Pavlou 2002; Kim and Xu 2007; Lucking-Reiley, Bryan, Prasad and Reeves 2007). Compared with online auction marketplace, online retailing marketplace of homogeneous goods is a high competitive marketplace. As we observed in Taobao, there are usually hundreds or even thousands of sellers who are retailing the same goods. In such a situation, a slight increase in price may drive away lots of consumers, especially experienced consumers.

Conclusively, in online retailing marketplace of homogeneous goods, we predict that the consumers of high reputation sellers are more price sensitive than the consumers of low reputation sellers on average:

Hypothesis 3: In online retailing marketplace of homogeneous goods, the consumers of high reputation sellers are more price sensitive than the consumers of low reputation sellers on average.

Based on hypothesis 3, we may suggest that high reputation sellers should charge relatively low price (because their consumers are more experienced and price sensitive on average), and low reputation sellers should charge relatively high price (because their consumers are inexperienced and less price sensitive). We will verify our hypotheses using field data collected from Taobao, and then we will discuss sellers' pricing strategy based on the empirical findings.

3 Data

3.1 Data Collection and Variables

We use field data collected from Taobao to verify our hypotheses. Taobao is the largest online retailing marketplace and the second largest marketplace in China. It has more than 80 million registered users. Its annual revenue (RMB43.3 billion) in 2007 overran the revenue summation of local Carrefour and Walmart. Moreover, the online marketplace platform of Taobao is similar to other prevalent online marketplaces, such as eBay and Yahoo! Kimo. These representative characteristics of Taobao may enhance the generalizability of our study.

We use World of Warcraft (WOW) game 600 points card as the representative of homogeneous goods. World of Warcraft is a popular online game developed by Brizzard. Its game card in online marketplace is actually a game fee recharging service. There are several advantages in using this type of goods. First, the game card is virtual goods and almost completely homogeneous. There is no quality variance among individual cards. The only difference between cards from different sellers is the seller characteristics (location, services, and reputation). Second, because game card is virtual goods, no shipment fee will be charged. Therefore, sellers' geographical distribution will not influence consumers' purchase decision. Third, the services related to game cards are also quite simple. There are usually two types of services related to game cards retailing. The first one is a type of guarantee service from Taobao. The content of the guarantee service is that Taobao will return payment to consumer with priority when there is a dispute in a transaction. The second service is thunder delivery, which requires sellers to deliver the goods within specified time duration (for example, 2 hours). We can easily observe and control these services in our study. After controlling these factors, the only differences between goods offerings are goods price and seller reputation.

We used a spider program to collect data from Taobao on 11-November-2008. We have collected 2502 goods offerings of "WOW Game Card 600 Points". At the first step, we collected information of all the goods listings. From the listings, we collected goods id, goods name, goods price (*PRICE*) and goods services (dummy variables, *GGUARANT* and *GTHUNDER*). After the first step, our spider program "clicked into" each goods description page. From each item description page, we collected the number of hours since the item was posted (*CURRTERM*), the number of visitors (*NVISIT*) and the number of sales (*NSALE*) in the current sale term and the seller's reputation score (*RP_TOTAL*). As suggested in several empirical studies (Livingston 2005; Melnik and Alm 2005), reputation has a decreasing marginal effect on transaction outcomes, thus we used the natural logarithm of seller's reputation score plus 1 ($LN\_RP=\log(RP\_TOTAL+1)$) to measure sellers' reputation. Before conducting any analysis, we removed 10 extremely abnormal data points (for example, there was one consumer who has purchased thousands of cards at the highest price from a new seller). Finally, we have 2492 data points in total.

We also collected data on consumer experience. In the end of each goods description page, Taobao lists the purchase records in the latest one month. The purchase records include consumer name, range of consumer "reputation score", quantity of purchased goods, price and whether the transaction is successful. Consumers' "reputation score" is similar to sellers' reputation score, which is rated by sellers after each transaction. It commonly equals to the number of transactions the consumer has made in the marketplace. We collected the latest 50 purchase records for each goods offering (for the goods offerings which have less than 50 purchase recodes, we collected all the purchase records), and calculated the average range of consumers' reputation score for each goods offering. Totally we collected 1,459 pieces of consumers' "reputation score" data (the other 1,033 goods offerings have never been transacted in the latest one month before 11-November-2008). We use the average low bound of consumers' reputation score (*AVELOWRP*) as a proxy variable of consumer experience.

The variables we collected are described in Table 1, and a simple descriptive analysis of our data is illustrated in Table 2.

Table 1. Descriptions of Variables

Variables	Descriptions
NVISIT	The number of visitors who have browse the goods description page in the sale term
NSALE	The number of goods pieces which have been sold in the sale term
PRICE	Price of the goods
RP_TOTAL	Total reputation score (equals to number of positive ratings minus number of negative ratings) of the seller
LN_RP	Natural logarithm of *RP_TOTAL* plus 1
CURRTERM	The number of days since the listing of the goods offering was posted
GGUARANT	Whether the seller has join the consumer protection program; 1 means yes.
GTHUNDER	Whether the goods will be automatically delivered immediately; only for virtual goods; 1 means yes.
AVELOWRP	Average low bound of consumers′ experience score.

Table 2. Descriptive Statistics

	N	Minimum	Maximum	Sum	Mean	S.D.
NSALE	2492	0	244	8626	3.46	13.21
NVISIT	2492	0	320	12059	4.84	18.48
PRICE	2492	26.5	30	67364.50	27.03	0.60
RP_TOTAL	2492	0	137989	8869054	3559.01	9751.58
LN_RP	2492	0	11.83	14198.46	5.70	2.59
CURRTERM	2492	0	14	12348	4.96	3.41
GGUARANT	2492	0	1	615	0.25	0.43
GTHUNDER	2492	0	1	201	0.08	0.27
AVELOWRP	1459	0	501	50475	34.60	33.72

3.2 Analysis Method

To verify hypothesis 1 and hypothesis 2, we conducted a regression on consumer's experience (*LN_EXP,* equals to natural logarithm of *AVELOWRP* plus 1). The independent variables include seller reputation (*LN_RP*) and goods price (*PRICE*). To verify hypothesis 3, we conducted regressions on the number of visits (*NVISIT*) and the number of sales (*NSALE*) separately. We examined the regression coefficient of the interaction term between goods price and seller reputation on these two dependent variables. We controlled the length of sales term (*CURRTERM*) and seller services (*GGUARANT* and *GTHUNDER*) in these two regression models. Furthermore, we also controlled the number of visits (*NVISIT*) in the second regression model. To avoid the scale of variables influence the regression coefficients of the interaction term, we standardized all the variables in the regression models (Aiken and West 1991).

We used linear regression method in our study for the convenience of examining and interpreting interactions between variables (Aiken and West 1991). Furthermore, because the dependent variables (*NVISIT* and *NSALE*) in our study are count variables, we also used Poisson Regression method to test the robustness of our regression results (Greene 2008). Poisson regression method is used in the situation when dependent variable is a discrete variable, which in most cases will equals zero, and in other cases will takes a positive value (Greene 2008).

4 Results

We illustrate our regression results in Table 3. The regression results in the second column show the relationship between goods price, seller reputation, and consumers' experience. We find that the regression coefficient of goods price (*ZPRICE*) is significantly negative (-0.206, $p<0.01$). This means that the consumers of low price goods are on average more experienced than the consumers of high price goods. Thus, hypothesis 1 is supported. We also find that the regression coefficient of seller reputation (logarithm transformed, *ZLN_RP*) is significantly positive (0.327, $p<0.01$). This indicates that the consumers of high reputation sellers are on average more experienced than the consumers of low reputation sellers; in other words, experienced consumers are more likely to purchase from high reputation sellers. Therefore, hypothesis 2 is also supported.

Column 3 (linear regression) and column 4 (Poisson count regression) show the results of regression on the number of visits, and column 5 (linear regression) and column 6 (Poisson count regression) show the results of regression on the number of sales. Because the regression results of these four models are quite similar, we discuss them together. First, we find that the regression coefficients of goods price (*ZPRICE*) on both the number of visits and the number of sales are significantly negative, and the regression coefficients of seller reputation (logarithm transformed, *ZLN_RP*) on both of the two dependent variables are significantly positive. These results indicate that consumers are more likely to browse and purchase goods of low price and from high reputation sellers. Second, more importantly, the regression coefficients of the interaction term (*ZLN_RP**ZPRICE*) in all the four models are significantly negative. This indicates that price has stronger negative effects on the number of visits and the

Table 3. Regression Results

DV	*ZLN_EXP*	*ZNVISIT*	*NVISIT*	*ZNSALE*	*NSALE*
Model	LS	LS	Poisson Count	LS	Poisson Count
C	0.000	−0.072***	0.738***	−0.049**	0.495***
ZCURRTERM		0.060***	0.278***	0.079***	0.421***
GGUARANT		0.162***	0.509***	0.036	0.407***
GTHUNDER		0.181**	0.540***	0.322***	0.698***
ZNVISIT				0.489***	0.183***
ZLN_RP	0.327***	0.063**	0.149***	0.059***	0.251***
ZPRICE	-0.206***	−0.159***	−1.625***	−0.085***	−0.943***
*ZLN_RP*ZPRICE*		−0.085***	−0.570***	−0.070***	−0.447***
N	1459	2492	2492	2492	2492
R2	0.164	0.037	0.104	0.291	0.115
Adjusted R2	0.163	0.034	0.102	0.289	0.112
F−Statistic	142.178***	15.696***		145.767***	
LR−Statistic			8981.798***		11781.020***

Notes: * means significant at 0.1 level, ** means significant at 0.05 level, and *** means significant at 0.01 level (double-tailed).
"Z" before each variable name means the variable in the regression is standardized.

number of sales for high reputation sellers than for low reputation sellers. In other words, consumers who browse or purchase goods from high reputation sellers are more price sensitive than consumers who browse or purchase goods from low reputation sellers.

In the left part of Figure 1, we plot the regression lines of the linear regression model on the number of visits (column 3) at low and high levels of seller reputation (i.e., at the mean plus and minus one standard deviation). The figure illustrates that price has negative effect on the number of visits both in the cases of low seller reputation (the slope is −0.073, p<0.01) and high seller reputation (the slope is −0.244, p<0.01). However, the impact of goods price on the number of visits when seller has high reputation is stronger than when seller has low reputation. We also plot the regression lines of linear regression on the number of sales (column 5) at low and high levels of seller reputation in the right part of Figure 1. The figure shows that, when sellers have low reputation, consumers are insensitive to goods price (the slope is −0.015, *n.s.*); when sellers have high reputation, the number of sales is negatively influenced by goods price (the slope is −0.156, p<0.01). Therefore, consumers who purchase from high reputation sellers are more price sensitive than consumers who purchase from low reputation sellers. In summary, the regression results indicate that the consumers of high reputation sellers are more price sensitive than the consumers of low reputation sellers when they browse or purchase goods. Hypothesis 3 is supported.

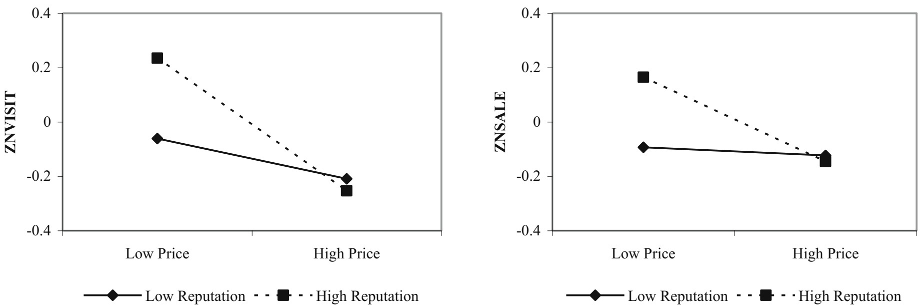

Fig. 1. Interaction effects between goods price and seller reputation on number of visit and number of sales

5 Discussions

In this paper, we verified consumers' price sensitivity in online marketplace of homogeneous goods, using sales data of WOW game cards collected from Taobao. We found that (1) low price goods offerings attract experienced consumers; (2) high reputation sellers attract experienced consumers, and (3) the consumers of high reputation sellers are more price sensitive than the consumers of low reputation sellers. Based on our findings, we may suggest that high reputation sellers should charge relatively low price to attract experienced consumers, while low reputation sellers should charge relatively high price because their consumers are inexperienced and less price sensitive.

Our study deepens the understandings on the effects of seller reputation in online marketplace. It is commonly recognized that the consumers of high reputation sellers are less price sensitive, so that they are likely to pay price premium to high reputation sellers (Ba and Pavlou 2002; Lucking-Reiley, Bryan, Prasad and Reeves 2007). Contrarily, our study reveals that, in online retailing marketplace of homogeneous goods, the consumers of high reputation sellers are more price sensitive than the consumers of low reputation sellers. The contradiction is possibly because of the differences between online auction marketplace and online retailing marketplace. Previous findings were usually derived from online auction marketplace. Goods in online auction marketplace are usually heterogeneous, and goods prices are unknown before auction is finished. These characteristics increase the difficulty for consumers to compare goods offerings in online auction marketplace. Differently, online retailing marketplace of homogeneous goods is a high competitive marketplace. If a high reputation seller try to increase the goods price to seize price premium, experienced consumers can easily switch to other high reputation sellers who offer the same goods with lower price. Therefore, sellers in online retailing marketplace of homogeneous goods should be cautioned if they hope to increase goods price to seize price premium.

Although existing studies usually stressed the reduced search cost and transparent marketplace characteristics of online marketplace (Bakos 1997; Brynjolfsson and Smith 2000), our study illustrates that there are still search costs in online retailing marketplace of homogeneous goods. The search costs are caused by “overloaded” goods offerings, insufficient quality information, and consumers’ knowledge and skills in using IT facilities in online marketplace. Consumers thus can be discriminated by their search costs. Experienced consumers (with low search costs) are more sensitive to both seller reputation and goods price than inexperienced consumers (with high search costs). When existing studies of online marketplace treated the marketplace as a whole (Bakos 1991; Soh, Markus and Goh 2006), our findings suggest that researchers in future may dive into the inside of online marketplace (e.g., by considering the different consumer segments in online marketplace). It will be more insightful to study the online marketplace from a deeper perspective.

Our study is quite preliminary in examining pricing strategy in the online retailing marketplace. There are some other factors which may influence consumers’ price sensitivity as well as sellers’ pricing strategy, such as the homogeneity of goods, goods value, the proportion of experienced consumers, the convenience of IT facilities, the level of market transparency and the competition in the marketplace. Future research should also examine the effects of these factors on consumers’ price sensitivity, and discuss pricing strategy in different settings.

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