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A Better Price or Better Reputation: Evidences and Implications to B2C ecommerce

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Abstract

Through their use of comparison shopping websites, online shoppers encounter tradeoffs between a product's various prices along with the reputations of the various online retailers. As a first step in understanding the impact of comparison shopping websites on consumer buying behavior, we performed a set of exploratory experiments that systematically discover how online shoppers make decisions when faced with different combinations of price and reputations in their comparison-shopping. We found online shoppers are generally seeking a balanced combination of price and reputation. If a balanced solution cannot be found, then they prefer merchants with better reputation but not the premium price. The strategic implications to B2C ecommerce are discussed.

Introduction

Pricing and reputation-building in online retailing are critical strategic concerns for the merchants involved. The popularity of comparison-shopping websites like shopping.com where shoppers can easily compare prices and merchant reputations on a single product highlights their fundamental role in any retailer's strategy.

For each queried product or service, a typical comparison-shopping website presents a dozen or so offerings by online merchants. The comparison information is usually presented in a tabular format (Figure 1). Each row provides information on one offer including the logo of the merchant, the price (including shipping and tax cost), and the reputation score of the merchant (usually an average of customer ratings).

	Seller Rating	Discounts	Condition	Price	BottomLinePrice™
dbuys.com • FREE SHIPPING • Add Merchant to Favorites	6076 Reviews	Free Shipping!	New	$675.00	Your Best Price No Tax Free Shipping $675.00
42nd St Photo .com Add Merchant to Favorites	1168 Reviews	Free Shipping! Promo	New	$679.99	No Tax Free Shipping $679.99
BUYDIG Add Merchant to Favorites	FEATURED 29345 Reviews	Free Shipping!	New	$699.00	No Tax Free Shipping $699.00
ABE'S OF MAINE Since 1979! Add Merchant to Favorites	FEATURED 9858 Reviews	Free Shipping!	New	$699.00	No Tax Free Shipping $699.00
ADORAMA THE PHOTOGRAPHY PEOPLE Add Merchant to Favorites	3202 Reviews	Free Shipping!	New	$699.00	No Tax Free Shipping $699.00
amazon.com Add Merchant to Favorites	See all-time ratings 409 Reviews	Free Shipping!	New	$699.00	No Tax Free Shipping $699.00
PC Connection EXPRESS Add Merchant to Favorites	FEATURED 7936 Reviews	Free Shipping!	New	$699.95	No Tax Free Shipping $699.95

Figure 1: a typical comparison-shopping task

When an online shopper makes a decision from such comparison list, his or her decision is largely based on the combined utility of price and merchant reputation score. A low price from a less reputable merchant can result in the same utility as that from a higher price with a more reputable merchant, according to normative economic theory.

Thus, an effective pricing strategy for an online retailer must consider how the price interacts with its reputation score. But exactly how do these two interact with each other and influence online shoppers in making purchase decisions in the comparison-shopping context when offerings from multiple competitors are involved? In this research, we conducted a preliminary exploration of this and explore the price-reputation dynamics in the online shopping decisions by consumers.

We first review existing literature on this topic, and then we discuss our experiments and data analysis. Finally we conclude our study with a discussion on future research.

Literature Review

Product price and merchant reputation are both indicators of quality. The former is mainly a signal of product quality [1-2] while the latter is a signal of merchant service quality[3]. Merchants base a product price on the costs incurred in getting the product and their profit goal. Both fluctuate between merchants. The difference in price between two merchants can also be a signal of the differences in merchant service quality. Generally speaking, higher price is a signal of better quality. Better merchant reputation is another signal of better service quality. Online merchants are responsible for the listed price while the reputation of online merchants is typically obtained from averaging the ratings given by previous customers. Thus better ratings usually signal better service quality [4].

In traditional shopping environment, there are few contexts in which a consumer can compare price and the merchant reputation for the same product from many merchants with little or zero cost and effort. However, in the online environment, especially in the comparison-shopping mediated environment, such information is produced without consumers incurring any cost.

Web-based comparison shopping first emerged in 1995. The BargainFinder demonstration project developed by then Andersen Consulting was the first shopbot that received large public exposure [5]. This led to online shoppers gradually adopting comparison-shopping methods. Since comparison-shopping reduces the search cost to near zero for online shoppers [6], its impact on product price and pricing strategy became an immediate interest to researchers.

Some economists predict that consumers will simply choose to buy the lowest price found on comparison-shopping sites which will lead to the convergence to equilibrium price for participating online merchants because of competition. Eventually that would make the participation in comparison-shopping profitless for merchants [7]. This prediction was partially confirmed for some service sectors like term life insurance [8], of which, there was significant drop in premiums since the introduction of Web-based comparison-shopping. But for most of the commodity market there are no conclusive findings about drop in price [9].

To explain why there is no convergence to equilibrium price, some researchers attribute this to online merchants blocking the shopbots access to their sites. This way they cannot be compared only on price and therefore be forced into a price war. Though we do observe the blockage of shopbots by a few online merchants [10], many online merchants find the opportunity to be part of comparison-shopping to be another channel to access consumers [5]. So there are an increasing number of online merchants participating in comparison-shopping. Popular comparison-shopping service providers have begun to charge online merchants a participation fee for merely being listed on their comparison list.

A more applicable explanation comes from the impact of merchants brand names [11-13]. Through empirical comparison-shopping data analysis, Brynjolfsson and Smith [12] find that branded merchants and merchants a consumer visited previously hold significant price advantages in head-to-head price comparisons, which explains why there is no convergence. They also find that consumers use brand as a proxy for a merchant’s service quality. Smith [14] further argued that Cournot competition won’t happen because online merchant can use strategies like product differentiation, leverage brand name, and set strategic prices, etc. to compensate for the negative impact brought by comparison shopping. This explanation has been widely accepted.

Though the brand name explanation justifies the non-convergence to equilibrium price, it does not satisfactorily explain why small and unknown merchants are still participating comparison-shopping en masse. These small online merchants seem to have to depend on lower prices to win online shoppers from brand name merchants. Yet they do survive in comparison-shopping. Some even are so prosperous that they pay large participation fees to the comparison shopping sites. So we need to ascertain that, at least, some online shoppers choose to buy from reputable online merchants while some prefer to buy those offer lowest prices. But are these two types the only online shoppers using comparison-shopping services? Are there any other types of online shoppers? What is the aggregate shopping pattern of all participating online shoppers? Will the merchants who offer the lowest prices benefit more or those will those who have the best reputations from the comparison-shopping channel? In terms of pricing strategy, what is the best pricing strategy for small online merchants who lack a known reputation? What is the best pricing strategy for online reputable merchants? Probably most interesting – what is the best pricing strategy for those in the middle range, with moderate reputations, should they offer lowest price to attract online shoppers?

To answer the above questions, we use a series of 3 Web-based shopping experiments which are now described.

Research Model and Experiment Design

We use classic decision-making research model by assuming an individual's decision outcome is influenced by one's previous online shopping experience, risk aversion level, and variation in preference to decision task attributes (price, merchant reputation, and product condition in our study). So the control variables in our research model are subjects' previous online shopping experience, risk aversion level, and preference to attributes. The dependent variables are the decision outcome for each comparison-shopping task.

Online shopping experience is measured with three questionnaires, and each has a *1-9* Likert scale as those used in [15]. Risk aversion level is measured with three questionnaires and a *1-9* Likert scale as those used in [16]. Preference to price, store rating and product condition are each measured with a *1-5* Likert scale single inquiry.

We created three simplified comparison-shopping decision tasks. Each task consists of 2 to 5 offerings. Though in most comparison-shopping context the shopbots present shoppers with 10 to 40 choices, such reduction does not affect our research outcome because online shoppers filter out most choices by using ranking tools embedded in the comparison-shopping website. A typical shopper only pays attention to options in a reduced choice set that usually has less than 5. So our decision task can be considered a reduced choice sets.

Each choice offering is consists of a numerical merchant name, overall price, and merchant reputation. We do not include merchant name or logo to avoid subjects having previous shopping experience with such merchants that would affect the decision outcome. We also do not include the graphics and other background context, like banner ads, in the decision task. Though the decision outcome can be influenced by such factors, they are non-essential and can cancel out each other. For example, the advertisement by buy.com on the border of a comparison-shopping task screen may exert a subtle influence on the decision of some online shoppers. Some may feel that they need to select a merchant from the comparison list to purchase the item, especially if buy.com is one of them. However, other online shoppers may have a negative feeling about buy.com and avoid their offering because of the banner ad reminder. Thus, in our research model, we remove all context and potentially distracting information like store logo, product image, banner ads, etc. But our model retains the basic decision information that allows us to observe the subjects' decisions.

We also mask the brand name and product name in the design. Consumers often use brand name as a surrogate for service quality. We provide store reputation information, which is a more direct indication of service quality. We also mask the product name so there is no distraction when the online shopper engages in a final stage of comparison shopping, of which the focus is mainly on price and reputations. Product name can affect decision outcome but at this stage of our experiment, we temporarily isolate them out.

We present three decision tasks to each subject (see Figure 2). They contain 4, 2, and 5 choices respectively. To minimize the order effect, we fully randomize the order of these three decision tasks into six scenarios. Each subject is directed into one of the six scenarios. So the aggregate outcome cancels the order effect.

	Overall Price (incl. S&H)	Store Rating
Store 1:	$30	★☆☆☆☆ (1.0/5.0)
Store 2:	$40	★★☆☆☆ (2.0/5.0)
Store 3:	$60	★★★★☆ (4.0/5.0)
Store 4:	$70	★★★★★ (5.0/5.0)

	Overall Price (incl. S&H)	Store Rating
Store 1:	$40	★★☆☆☆ (2.0/5.0)
Store 2:	$60	★★★★☆ (4.0/5.0)

	Overall Price (incl. S&H)	Store Rating
Store 1:	$80	★☆☆☆☆ (1.0/5.0)
Store 2:	$90	★★☆☆☆ (2.0/5.0)
Store 3:	$100	★★★☆☆ (3.0/5.0)
Store 4:	$110	★★★★☆ (4.0/5.0)
Store 5:	$120	★★★★★ (5.0/5.0)

Figure 2: Decision Task 1, 2 and 3

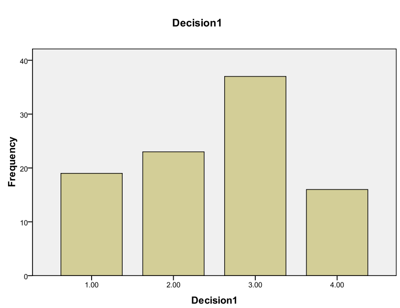
Data Analysis

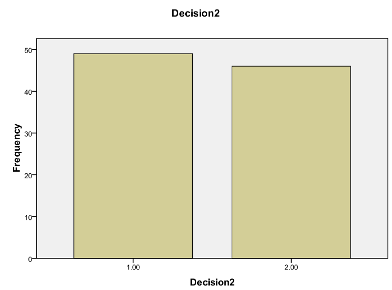
We recruited subjects from online forums and craigslist for this study. There are 95 valid responses with 61 males and 34 females. Of which, 83 subjects are between Age 20 to 49; 4 subjects are between Age 18 to 19; and 8 subjects older than age 50.

Each participant received $5 Amazon gift card as compensation for participation. Each subject rated their online shopping experience, and the importance of factors like price, store rating, and product condition on their decisions. They were also asked to rate their risk aversion level. The Cronbach's α for subjects' online shopping experience is 0.934.

Analysis on decision outcomes

The basic distributions of decision task 1 to 3 are shown in Figure 3:





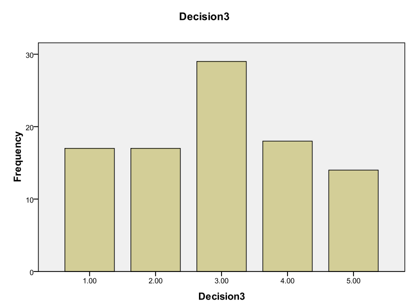


Figure 3: Decision Outcomes for Decision Task 1 to 3

We used regression analysis to analyze the relationship between decision outcome and the independent variables:

$$
\begin{aligned}
Decision = \beta_0 + \beta_1 Age + \beta_2 Price \\
+ \beta_3 StoreRating \\
+ \beta_4 ProdCondition + \beta_4 Risk \\
+ \beta_5 OnlineShopExp
\end{aligned}
$$

We found price and store ratings are consistently significant factors in predicting decision outcomes. Risk aversion is a significant factor for Decision Task 1 but not for the other two tasks. The standardized coefficients for each variable are summarized in Table 1 in parenthesis. They indicated subjects generally prefer lower price, higher store ratings as well as less risk (in Decision Task 1). In addition, store rating has higher impact on decision outcome than price.

Table 1: Summary of Regression Analysis for Decision Outcome

Regression Analysis	Significant Independent Variables
Decision Task 1	Price (-0.256)**, Store Ratings (0.435)**, Risk Aversion (0.210)*
Decision Task 2	Price (-0.316)**, Store Ratings (0.432)**
Decision Task 3	Price (-0.265)**, Store Ratings (0.401)**

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

We then conducted correlation analysis among the three decision outcomes. All decision outcomes are significantly correlated with each other especially between decision 1 and decision 3.

Table 2: Summary of Correlation Analysis for Decision Outcomes

	Decision1	Decision2	Decision 3
Decision1	1	.589**	.801**
Decision2	.589**	1	.561**
Decision3	.801**	.561**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Discussion

Subjects are highly consistent in their decision process

From results in table 1 and 2, we find that subjects are highly consistent in their decision process. Not only price and store ratings are significant factors throughout the three decision tasks, the decision outcomes are also significantly correlated. It is interesting to note risk aversion may play an important role in the decision outcome but it is only significant in the first task when subjects have four choices.

In correlation analysis, decision 1 and 3, which have four and five options respectively, show high correlations with each other than their correlations with decision 2, which has two options. This indicated that: 1. Subjects have consistent price and store rating trade-off strategies in their own decision especially when dealing with increasing number of choices; 2. some subjects use different decision strategies when making decision 2 compared with decision 1 and 3, which lead to comparatively lower correlations. This is understandable since when we need to make a decision with only two options, we are more likely to use compensatory strategies; however, when we make a decision with four or five options, we probably tend to use non-compensatory strategies [17].

Online shoppers do not mind a little exposure to risk if the price is better

We use decision task 1 to test the reaction of online shoppers on a typical shopping task with two better price and two better ratings options. It turns out 20% and 24.2% of respondents chose the better prices (option 1 and 2) while 39% and 16.8% of respondents chose better ratings (option 3 and 4). So there are more respondents who chose better store ratings over better prices (55.7% vs. 44.2%).

The regression results indicated that though both price and store rating are significant predictors of consumer decision, the coefficient beta for Store Rating (.435) is much higher than that for Price (-.256). This indicated store rating has more impact on decision outcome than price in task 1. In addition, Risk Averse is also a significant predictor of in this case though have less impact than price and store rating (coefficient beta is .210). It indicated that the more risk averse the consumer, the more likely they will choose better store ratings options

A most interesting finding in this study is that a significantly higher proportion of subjects chose option 3 as their preferred choice. Option 3 has a better store rating but has lower price compared with the other options in the same range. This indicates though online shoppers prefer better store rating to avoid risk, they select a lower price with a small risk exposure.

A forced tradeoff between price and store ratings may lead to random choice

Decision task 2 is a simple tradeoff task between price and store ratings. Subjects are forced to make a choice between price or store ratings. Interestingly 51.6% of respondent chose better price whereas 48.4% chose better ratings. This is in contrast with decision task 1, in which 44% prefer better price. We found that while there were slightly more subjects preferring better price, there is no statistically significant difference between these two options.

Previous regression analysis indicated store rating has bigger impact than the price from the coefficients (|.428| >| -.316|). So the outcome of task 2 is not consistent with the results from regression analysis. Specifically, we find 12 subjects that chose better store rating in Task 1 then chose better price option in Task 2. In contrast, there are 5 subjects chose better price in Task 1 then chose better reputation in Task 2. This results in a net increase of 7 subjects choosing better price in Task 2. We didn't find significant difference for the profiles of these two groups from the overall sample we used. Thus, we may attribute such discrepancy to the use of different decision strategies by some subjects.

The most balanced option is more preferred

Decision task 3 is similar to decision task 1 except there is an additional balanced option with median price and median store ratings (*option 3*). The regression results on Task 3 showed that both price and store ratings are significant predictors of consumer decision. The coefficient beta for Store Rating (.401) is higher than that for Price (-.265). Slightly more respondents (35.8%) chose the first two options (better price) and 33.6% of them selected the last two options (better ratings). The largest percentage of people (30.6%) chose the median option 3, which has the median price and median store ratings among the five options.

This finding is very interesting because it indicates online shoppers' choice in a comparison list is highly context-dependent. Option 3 in decision task 1 and in decision task 3 is the most selected option in each of them. However, though option 3 in decision task 3 has lower store ratings than option 3 in decision task 1, about 1/3 subjects still chose it. Compared with other options, the distinctive feature of option 3 is its balanced combination of price and store ratings among the five options. So we suspect that this is the reason it is the most selected option.

Industry implications and limitations

These results have important implications for the pricing strategies of online merchants especially those with better ratings. For example, the conventional pricing strategy is that branded online merchants can charge premium prices because consumers are willing to pay that for better service. However, our results indicate that charging a lower price especially a midpoint price will capture more sales volume compared with charging higher prices. This may explain the strategy of Amazon.com, whose item price often appears in the middle range in comparison-shopping lists. In addition, for those online merchant with moderate ratings from online shoppers, charging the lowest price or a price in lower range to compete with other merchants might not be a good idea. Instead, they should charge a price comparable to their rating rank.

The implementation of these indicated strategies is delicate and depends on context configurations such as the number of merchants in the product list, the range of price and merchant ratings distributions, as well as the overall online marketing strategy of each merchant. But with the increasingly powerful monitoring tools provided by data feeding services, soon the deployment of a sophisticated pricing strategy will not be far-fetched.

This study is part of a larger collaborative research project. It is limited in its external validity. For example, different types of products can incur different levels of quality concerns for online shoppers thus leading to different selection patterns. Items in different price ranges may also lead to different selections in terms of price and merchant reputations. We are conducting a new series of experiments to explore these details in this direction.

Conclusion

Exploring the dynamic of consumer decision patterns between price and merchant reputations is important for making effective pricing and marketing strategies for online merchants in B2C ecommerce. Comparison shopping is a popular yet very competitive online channel for online merchants in reaching consumers. Existing research indicates offering lowest price or building brand names are two effective strategies for online merchants that compete in a comparison-shopping environment. However, both of them only explain part of the dynamics of online shopping. We demonstrate that the collective behavior of online shoppers in far more complex than previously understood. We find that there is an overall tendency for online shoppers to avoid picking extreme choices. That is, consumers shun selecting either the lowest price or the best reputation option (if it incurs the higher premium price). An effective pricing strategy should be adaptive to the specific product category and comparison-shopping environment. This finding has important implications to online merchants when they are developing and implementing their pricing and product listing strategies in the comparison-shopping environment and B2C ecommerce in general.

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