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Pricing Price Information in E-Commerce

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Abstract

Shopbots and Internet sites that help users locate the best price for a product are changing the way people shop by providing valuable information on goods and services. This paper presents a first attempt to measure the value of one piece of information: the price charged for goods and services. We first establish a theoretical limit to the value of price information for the first seller in a market that decides to sell price information to a shopbot and quantify the revenues that the seller can expect to receive. We then proceed to discuss whether and how much of this theoretical value can actually be realized in equilibrium settings.

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shopbots, e-commerce, price dispersion, information value

Comments

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Pricing Price Information in E-Commerce

[Extended Abstract] *

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ABSTRACT

Shopbots and Internet sites that help users locate the best price for a product are changing the way people shop by providing valuable information on goods and services. This paper presents a first attempt to measure the value of one piece of information: the price charged for goods and services. We first establish a theoretical limit to the value of price information for the first seller in a market that decides to sell price information to a shopbot and quantify the revenues that the seller can expect to receive. We then proceed to discuss whether and how much of this theoretical value can actually be realized in equilibrium settings.

Keywords

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1. INTRODUCTION

Shopbots and Internet sites that perform comparisons of prices and product characteristics change the way people shop for goods and services.

Even though the reduction of consumers' search costs has caused increased competition among sellers, when compared with conventional markets of bricks and mortar retailers, the new Internet economy is far from frictionless and considerable and persistent price dispersion exists [2]. This price dispersion is big enough to make price information valuable to consumers who are price sensitive and want to compare prices before buying a good or service.

Traditionally, price information has been provided for free to potential customers. Even in cases where price information was provided to customers through third parties, who could potentially benefit from it, there were no technological means available to the sellers to either charge these intermediaries for the price information or prevent them from obtaining it.

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We argue that price information has economic value and hence should be bought and sold. If shopbots that provide free services and profit only by selling advertisment space do not want to pass the cost of price information on to consumers, they will have to share their advertising revenues with demanding sellers. This will be an issue particularly in markets with high price dispersion and might lead to the collapse of the free shopbot model (or, more accurately, the constant cost model) for these markets.

Two recent papers [3] [1] have considered price information on the Internet as a valuable good that can be traded. Both consider the intermediary selling price information, allowing it to realize some of the added value its service generates to market participants. Both papers strengthen our belief that the idea of selling price information has become plausible with the advent of economically motivated software agents.

Our approach differs from previous work as we consider sellers selling price information directly to price sensitive buyers. This paper is the first, as far as we know, that connects product prices with the information value they generate to the seller of the products, and its central contribution is that it proves that the issue is important in e-commerce and might influence the structure of future internet markets.

We present our model in section 2 and derive the marginal value of the price information of a single seller that sells price information, given that other sellers provide their price information for free. In section 3 we consider multiple sellers selling price information and drop our model assumption in section 4 to discuss practical considerations. We conclude in section 5.

2. MAXIMUM VALUE OF PRICE INFORMATION

Far from following the Bertrand view of markets, where prices are driven down to marginal cost, products sold on the Internet demonstrate a significant and persistent price dispersion [5]. This paper assumes for simplicity that the price dispersion on the Internet exists due to the presence of multiple classes of consumers that value products in different ways and demonstrate distinct shopping behaviors. The sellers have optimized by selecting a price for their products that maximizes their revenues across all these classes of consumers. We further assume that one such distinct class is composed of shopbot users who buy products only based on price.

We consider a market with N sellers that sell many dif-

Retailers at a Shopbot		
Bookstore	**ISBN**	**Price**
AllDirect.com	0156001314	\$8.96
A1Books	0156001314	\$10.75
Kingbooks.com	0156001314	\$11.20
BN.com	0156001314	\$12.00
Amazon.com	0156001314	\$12.00
Powell's Books	0156001314	\$14.00
Fatbrain.com	0156001314	Price Info: 10cents

Table 1: A hypothetical example of a seller charging for price information through a shopbot

ferent undifferentiated goods like books, CDs, electronics, etc. We assume that product prices follow a random distribution $f(x)$ with a corresponding cumulative distribution denoted by $F(x)$, constant across time, that is exogenous to our model, and the same for all sellers.

Prospective buyers know the distribution of the prices in the market, but do not know which seller is the cheapest for the particular product they are interested in. They have no preferences for particular sellers and they are willing to buy from the one that offers the lowest price. For this reason they shop through a shopbot site that displays the prices of all sellers in the market for the product that the buyers specify.

Seller j decides to sell his price information and contracts the shopbot to deliver information for product availability, while withholding price information, which is available at an additional fee. The buyer can click on a button or a link and get j's price immediately by paying a price p. In Table 1 we show such a hypothetical agreement between a shopbot and $Fatbrain.com$.

There are three distinct entity classes in our market: the buyers, the sellers and the shopbots. Each class faces a different problem. We address each of these problems in turn.

2.1 The shopper's problem

The buyers have three choices: they either pay for the additional price, do not pay but simply accept the lowest price among the remaining $N-1$ sellers without bothering to learn j's price, or incur a fixed cost of inconvenience c, assumed to be the same for all buyers, to visit the seller website directly. Assuming that the buyers are rational, they will want to learn seller j's price if they expect that the cost reduction would be more than the cost of acquiring the price quote. Given that the minimum price for the good among the remaining $N-1$ sellers is q, the buyer knows that the expected decrease in the minimum price from another search is equal to:

$$g(q) = \int_0^q (q-x)f(x)dx \qquad (1)$$

She is willing to pay $j's$ price information price, p, to learn j's price if $p < g(q)$ and $p < c$. If $p > g(q)$ and $c > g(q)$ the buyer is better off by purchasing the item priced at q without requesting any additional information. Finally, if $c < g(q)$ and $c < p$, the buyer will visit j's website directly to learn j's price.

2.2 The seller's problem

Seller j's problem is how to price his price information to maximize revenue. Buyers have queried the shopbot site and found that the current lowest price for the product they require is q, where q follows some distribution[1] $f_1^{(N-1)}(x)$ that depends on $f(x)$ and the number of other sellers, $N-1$.

The seller can safely set the price of his price information to ϵ below $g(q)$, given by equation 1, knowing that rational buyers will always want to know his price. However, j cannot charge more than c, the inconvenience cost to the buyer of visiting j's website directly. So, the seller would set his price to be $p(q) = \min(g(q), c)$. The expected revenue per customer for seller j from selling price information as ϵ goes to zero is thus:

$$\Pi = \int_0^\infty f_1^{(N-1)}(q)p(q)dq \qquad (2)$$

It is interesting to estimate how much an online bookstore would be able to charge for its price information to shopbots or shopbot users. We use internet book price dispersion data, including all costs (shipping etc.), collected in [2] and assume that all books follow the same price distribution. That means that our results would be an underestimate in the cases of books that exhibit higher price dispersion than the average, and an overestimate for the books that have lower than average price dispersion. We have fitted the authors' de-meaned experimental data with the normal price distribution with mean zero and standard deviation two.

For the shopper session described in table 1, which is a representative case of price dispersion, described well by the normal distribution with standard deviation 2, the shopper has discovered a minimum price of \$8.96. The expected gain that a shopper would have from knowing one additional price is $p(\$8.96)$, close to 9.8 cents. The seller could charge just below 9.8 cents for this book's price, to make sure that rational shoppers would pay.

The average revenue per buyer, the seller would expect from selling price information in this market with seven sellers is, from equation 2, approximately 15.6 cents per shopper, assuming alternative search cost $c = 50$ cents[2] to learn a price. For 20 sellers the expected revenue per buyer drops to 4.3 cents.

If seller j prices his price information with the method suggested above, a rational buyer will always request seller j's price information. So, seller j makes the revenues described by equation 2 every time a consumer uses the shopbot. We use the term *"multiplicative effect"* to refer to the fact that a buyer requires multiple price quotes for a single purchase. Conversely, a seller would potentially be selling price information more often than products. For example in a market of seven bookstores, assuming each bookstore is equally likely to carry a cheapest book, each bookstore is expected to make 1/7 of total sales. If a seller is the only one that sells price information, pricing according to equation 1, rational buyers would always purchase this information. So for an average price information price of 15.6 cents, the bookstore's price information would on average generate $\$0.156 \times 7 = \$1.092$ per book that the bookstore sells.

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[1]This is simply the 1st order statistic, the distribution of the lowest value in $N-1$ draws from distribution f, $f_1^{(i)}(y) = i(1-F(y))^{i-1}f(y)$.

[2]Based on a back of the envelope calculation for what 2 minutes of time worth to the average shopper, given today's US salaries.

2.3 The shopbot's problem

The problem that the shopbots face is whether or not to accept an arrangement with a seller that wishes to sell price information. In our model, shopbots that compete for buyer traffic would be better off accepting the arrangement than providing data only from sellers that provide it for free. This is because a shopbot that would provide both free and for fee data would give buyers more options: a buyer visiting this shopbot would have all the information available at the shopbots that only provide the free price quotes plus an option to purchasing additional price quotes. The buyer is thus strictly better off visiting the shopbot with the extra option.

3. SELLER COMPETITION

In this section we present a model where all sellers charge money to reveal their price.

We consider a shopbot that displays price information of N different sellers that sell many different undifferentiated goods. Again, product prices follow a random distribution $f(p)$ with the equivalent cumulative distribution denoted by $F(p)$, constant across time, that is exogenous to our model. Shopbot users know the distribution of the prices in the market, but do not know which seller is the cheapest for the particular product they are interested. They have no preferences for particular sellers and they are willing to buy from the one that offers the lowest price.

3.1 The shopper's problem

In the extreme case where all sellers charge for price information, the prospective shopper cannot find any shopbot that provides price information for free. The optimal consumer behavior has been explored in the economic literature. For a review see [4]. The buyer would keep searching as long as the expected decrease in the minimum price for another search is less than what the buyer has to pay for it. If the buyer believes that all the product prices follow the same distribution, the search would start from the prices that are cheaper to acquire. We assume that if two price information prices are the same, the buyer chooses one at random. If the current minimum price is q, then the expected decrease in the minimum price from another search is a function of q and F, as described by equation 1, above.

The shopper would start by requesting price information on the products that is cheaper to acquire and stop when the lowest price p requested by a seller to reveal price information is greater than the expected marginal product price decrease: $p > g(q)$. The optimal sequential decision rule is for the shopper to continue searching if the lowest price observed up to that point is greater than R, where R is the solution to $g(R) = p$.

3.2 The seller's problem

The first problem a seller would face, in a market for price information, is knowing the product prices of competitors, which would not be available for free to shopbots or price-comparison web sites. Instead of incurring this cost, a seller might choose to buy only price information for some of the competitors products and make price information pricing decisions based on estimates of product price dispersion. Or, sellers may provide price information to a shopbot that would then sell it to potential buyers for a commission. That shopbot would function as a trusted seller proxy. It would have all available information to make optimal pricing decisions to maximize its own commission and seller revenue from selling product price information.

The model we presented in this paper is actually a somewhat simplified version of reality. In fact, selling product price information might actually make the seller worse off if the pricing is not done carefully: As we saw in section 3.1, it is not guaranteed that the buyer will actually discover the cheapest seller's price. Thus, the cheapest seller, who would have captured all shopbot users, had he provided price information for free, will now make only a fraction of sales and may end up lowering total revenue.

A solution to this problem would be for the cheapest seller to price price information cheaply enough so that a rational shopper would always request it, even though the second lowest price in the market has been discovered. If the cheapest seller knows that the second lowest price in the market is q_2, then by charging $\int_0^{q_2}(q_2 - x)f(x)dx - \epsilon$ for price information, he makes sure that the buyer will always eventually discover the lowest price. One Nash equilibrium of the one-shot game dictates that all other sellers follow by setting their price information price to the same value as the cheapest product seller.

In general the expected revenue per buyer, given that N sellers sell their price information is:

$$R_{buyer} = \int_0^{\infty} f_2^{(N)}(q)p(q)(\frac{1}{N} + \frac{1}{2}(1 - \frac{1}{N}))dq \qquad (3)$$

given that the cheapest product seller sets information rent according to the second cheapest product in the market ($\int_0^{q_2}(q_2 - x)f(x)dx - \epsilon$), and that other sellers pool by charging the same amount. $f_2^{(N)}$ is the second order statistic for N sellers[3]. That is because, for every second lowest product price q the average revenue per customer is $p(q)$, with probability $1/N$ (corresponding to the case where the seller is the cheapest product price seller and will definitely sell his price information) plus $p(q)$, with probability $\frac{1}{2}(1 - \frac{1}{N})$, which corresponds to the case where the seller is not the cheapest and only half the times his price information will be requested, before the actual cheapest seller is found.

The expected value that the price information of a product generates, before the product is sold, in a market of N sellers that sell their price information is:

$$R_{product} = N \cdot R_{buyer} \qquad (4)$$

We have plotted R_{buyer} and $R_{product}$ in Figure 1, assuming normal product price distribution, for different number of competitors and different price distribution standard deviations. A seller is always better off, though, by selling his price information than giving out price information for free. This suggests that in our model, no seller will want to reveal price information for free to a shopbot.

3.3 The shopbot's problem

It is clear from Figure 1 that the expected cost per customer served rises as price dispersion increases — sellers take advantage of the higher shopper uncertainty about prices. This means that the shopbot that covers a market with smaller price dispersion would have better chances in managing to absorb the customers costs in searching for the

[3]In other words, this is how the second lowest price in the market is distributed.

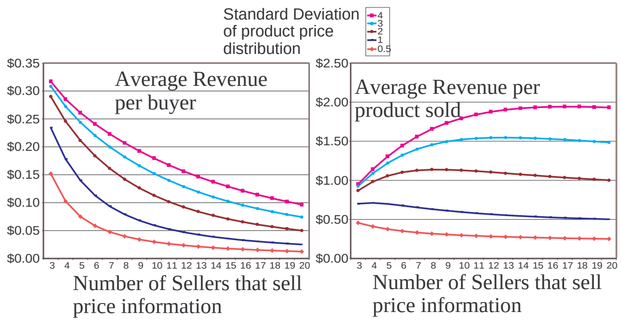

Figure 1: The series represent different standard deviations of the assumed normal product price distribution, in dollars. A reservation price of 50 cents per price quote is assumed for all buyers. The series that have standard deviation 2.0 correspond to real internet book price dispersion data.

best price. Shopbots in markets with higher price dispersion might find it difficult to cover for the shopper's costs by allocating part of the fixed revenue they make by advertising.

4. PRICE INFORMATION VALUE IN THE REAL WORLD

In the previous section we have calculated the maximum theoretical value of price information in an electronic market. The question that arises is how much of this theoretical value can actually be realized. We relax our model assumption to address a few important issues.

4.1 Power structure - Sellers, Buyers and Intermediaries

In section 2.3 we saw that rational price sensitive buyers will abandon a shopbot that refuses to sell price information on behalf of a buyer. But real buyers may still prefer to use the shopbot with the smaller market coverage. This could be because they only know or trust that particular shopbot or because they value other services that the shopbot offers to them, like better interface or customization. In this case the seller would lose sales because his product is not covered by the shopbot the buyers prefer.

In the case of a "popular" shopbot the intermediary clearly enjoys market power that allows it to dictate the rules. In other markets the power group might be the buyers and they would simply punish any effort by a seller or shopbot to charge for price information.

4.2 Practical and legal considerations

Sellers can theoretically use the information a shopbot provides to learn about their competitors prices and try to undercut them, instead of selling their price information. However this practice may ignite costly price wars and make sellers worst off. Selling price information appears to be a reasonable alternative.

Furthermore, it is not clear at this point whether an open web site has the right to block search engines and shopbots from accessing it. However, it seems that at least technologically, the seller will be able to effectively forbid shopbots from accessing its site, by employing mechanisms that stop non-human visitors. For example, randomly changing the user interface from session to session would foil any attempts from shopbots to access web site information. To our knowledge, none of these practices has been tested in a legal dispute yet.

5. CONCLUSIONS

Price information is valuable to shoppers who search for the best deal on the Internet, because considerable price dispersion exists. Sellers that do not face powerful intermediaries would want to sell their price information, earning substantial additional revenue. Today's dominant model of shopbot services, where the shopper has free access to the information might run into difficulties, in markets with high price dispersion, once multiple sellers demand a payment for their price information.

The first seller to charge for price information can set the price information price so that all rational shoppers would be willing to pay for it. However, when more than one seller sells price information, it could be the case that a shopper would stop short of requesting a particular seller's price information. Pricing price information so that it would be cheap enough for the buyer to always want it (even if the second lowest price is known) is a solution that guarantees that the cheapest product seller will not jeopardize the product sale, while earning extra revenue from his information.

The value of price information in e-commerce has been largely neglected by researchers. This value, as was shown in this paper, cannot be overlooked and could potentially influence the form of future internet markets. We have proposed a simple model which gives a first estimate of the value of price information. In future research we intend to explore the economic and game theoretic issues that arise in this new world of pricing price information.

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7. REFERENCES

[1] M. R. Baye and J. Morgan. Information gatekeepers on the internet and the competitiveness of homogeneous product markets. *American Economic Review*, 2001. Forthcoming.

[2] E. Brynjolfsson and M. D. Smith. Frictionless commerce? a comparison of internet and conventional retailers. *Management Science*, 46(4), 2000.

[3] J. O. Kephart and A. R. Greenwald. *Shopbot Economics*, chapter forthcoming. Kluwer Academic Publishers, 2000.

[4] M. Rothschild. Models of market organization with imperfect information: A survey. *The Journal of Political Economy*, 81(6):1283–1308, 1973.

[5] M. D. Smith, J. Bailey, and E. Brynjolfsson. *Understanding Digital Markets: Review and Assessment*, chapter forthcoming. MIT Press, 2001.