Dynamic Pricing in Name-Your-Own-Price Channels: Bidding Behavior, Seller Profit and Price Acceptance

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Introduction

Recent advances in the ability to track and analyze customer traces in electronic commerce have led to a lively debate about the promise of dynamic pricing. On the promise side, online retailers may use the customer's browsing behavior to learn about aggregate and individual preferences. This type of information would enable online retailers to personalize pricing with coupons and promotional pricing through customized banner ads or pop-up windows (Shapiro and Varian 1998). Ideally, a retailer would learn the preferences and price sensitivity of his/her customers over time and subsequently be able to price discriminate perfectly. This type of price discrimination – called first-degree price discrimination after Pigou (1920) – allows the retailer to capture the entire consumer surplus and minimizes deadweight loss.

Technology providers have realized that the analysis of click-stream data allows retailers to look over their customers' shoulders while they shop. Nearly all e-commerce engines and host providers offer services to segment their customers; these range from descriptive statistics and capturing statistics of marketing campaigns to click-by-click retracing of a customer's browsing path. Similarly, academics have made great strides in modeling online customer behavior (Montgomery et al. 2004, Johnson et al. 2004).

In reality, dynamic pricing has been slow to take hold in mainstream e-commerce. In fact, deviations from a 'one price' policy in traditional online retailing seem to be the exception. One often cited reason appears to be consumer backlash and potential negative publicity. In one highly publicized example, Amazon upset its customers with a price discrimination policy by using buyer profiles to charge different prices in September 2000 (Baker et al. 2001). One buyer reportedly deleted the cookies on his computer that identified him as a regular Amazon customer. He watched the price of a DVD offered to him for sale drop from $26.24 to $22.74. Amazon.com ultimately ended up publicly apologizing and refunding all customers who had paid higher prices (Ramasastry 2005).

On the other hand, vendors sell the same product at different prices on EBay without any fear of customer retribution. As Dickson and Kalapurakal (1994) and Cox (2001) argue, price discrimination is considered fair as long as all buyers have the possibility to achieve all price levels. Thus price discrimination can be achieved by exploiting different level of search costs (e.g., online booking), quantity discounts, haggling efforts (e.g., auctions) or time of transactions (last minute offers).

Name-Your-Own-Price (NYOP) lets both, buyer and seller, influence the price of a product. At the outset, a seller defines a secret threshold price indicating the minimum price he is willing to sell the product for. Subsequently, a buyer is asked to place a bid indicating his willingness to pay for the product

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offered. If the bid value is equal or above the seller's threshold price, the transaction is initiated for the price denoted by the buyer's bid. However, if the bid fails to surpass the threshold price, the buyer's ability to raise his offer and place additional bids depends on the design of the NYOP mechanism specified by the seller. For example, a seller could specify a minimum waiting time between two consecutive bids of the buyer or charge a small fee if a buyer wants to place additional bids. Note that, prospective buyers do not compete with each other but try to hit or surpass the threshold price avoiding too much overbidding and NYOP is therefore a mechanism that allows the simultaneous offer of the same product to an unlimited number of prospective buyers.

Priceline.com introduced NYOP in 1998 for selling airline tickets and hotel rooms and became a major online retailer for travel service. With revenues of $962 million and a gross profit of $267 million in 2005, Priceline indicates both the acceptance and the success of the NYOP mechanism. Additionally, several companies now employ the NYOP mechanism in different formats such as Expedia.com, Combined Systems Technology, Inc. on its procurement platform ITProcurement.com and several European low-cost airlines (e.g. Germanwings.com, LTU.com). Recently, EBay introduced a design option called "Best Offer" that allows prospective buyers to submit an offer to a seller that can accept or reject this offer (http://pages.ebay.com/bestoffer/).

As discussed by Hann and Terwiesch (2003) and Spann et al. (2004) NYOP enables sellers to let buyers reveal themselves based on their frictional cost and their willingness to pay. Terwiesch et al. (2005) show that different threshold prices could be beneficial for sellers in heterogeneous markets resulting in higher profits and a higher number of transactions. In order to realize such a segmentation, incoming bids must be evaluated; based on the bidding sequence, the seller or an automated proxy system must adjust the threshold price optimally.

However, there are two concerns regarding the use of such an adaptive threshold price:

- Despite the theoretical benefits for the seller and buyers, an adaptive threshold price could lead to altered bidding behavior. Buyers may try to hide their true willingness to pay and try to convince the seller of a lower willingness to pay. Such a behavior is called "bid shading" (Krishna 2002) and may jeopardize the seller's profit.
- In addition, different threshold prices that are known to customers may hurt the perceived fairness the channel. In a survey conducted amongst 115 students, we found that only 10.4% would judge the adaptive NYOP as fair (see Figure 1). This result is only slightly better than the Amazon case (titled 'Same Shop') with different posted prices in the same shop for the same product which outraged Amazon's customer base.

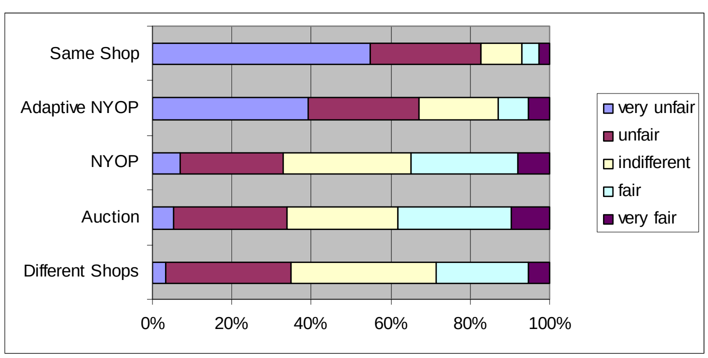

Figure 1. Perceived Fairness of Price Discrimination (n=115)

Research Objectives

In this research we are interested in analyzing the effect of a price discrimination strategy on consumer's bidding behavior:

- Does an anticipated adapted threshold alter bidding behavior? That is do consumers bid differently when they know that the threshold price is optimally adjusted compared to the case when it remains stable?
- Does an anticipated adaptive threshold price still allow for customer segmentation? What consequences does this have for profits?
- What is the impact of an adaptive threshold on acceptance and perceived price fairness of NYOP?

Research Design

To answer these research questions, we first develop normative models for both, NYOP with a fixed threshold price and NYOP with an adaptive threshold price, and analytically compare the outcomes with respect to buyers bidding behavior and seller profit. Second, we empirically test the predictions of our normative model in an experimental study with controlled valuations. Further, we assess consumers' perceived price acceptance of different designs of our dynamic pricing mechanism in our empirical study.

Normative Model

We assume that a buyer has a fixed willingness to pay (*WTP*) and a seller the valuation s for a product. The prospective buyer places a bid p, which the seller may accept or reject. If the bid is accepted, the product is exchanged for price p. Otherwise the buyer can place another bid at next stage of game. Buyers can submit an unlimited number of bids. We assume that the buyer and the seller face delay costs which are modeled in form of discount factors δ_b and δ_s with $0<\delta_s$, $\delta_b<1$. The payoffs for the accepted n^{th} bid p_n is thus his consumer surplus *C*S is $CS=(WTP-p_n)*\delta_b^{(n-1)}$ and the sellers profit is $\Pi=(p_n-s)*\delta_s^{(n-1)}$. The buyer is aware of his willingness to pay and expects the threshold price *TP* to follow the distribution function F(s) (*TP*~F(s)) with support [*LB*,*UB*]. The seller assess buyers' willingness to pay according to *WTP*~G(*WTP*) with support $[WTP_{\text{low}},WTP_{\text{high}}]$. The discount factors, distribution of traders' valuation, and the structure of game are common knowledge. Buyer and seller are risk-neutral and solely interested in maximizing their expected payoffs.

We derive the optimal dynamic path of buyers' bids and sellers' threshold prices from our normative model. Thereby, the seller yields a segmentation of buyers in terms of timing: high valuation buyers attempt to be successful with fewer bids than low valuation consumers due to their higher opportunity costs of delay (i.e. the discount of expected surplus related to a later acceptance). We show that bid shading is not a rational strategy for buyers since it is too costly for high valuation consumers to imitate the (longer) bid sequence of low valuation consumers.

Experimental Test

To test the results of our normative analysis we conduct a series of computer-aided laboratory experiments. We apply a combined within-subject- and between-subject-design. Using an induced-values paradigm (Smith 1976, Smith 1982), we control for subjects' product valuation by informing them about the resale value of the given product. Each product has a resale value which induces the subject's willingness to pay. The difference between the induced valuation and a successful bid thus represents the surplus for the subject and was paid out in cash. On the individual level, we systematically vary the willingness to pay $(WTP/LB)\epsilon\{\sim2.15;\sim2.7\}$ resulting in a high-WTP buyer and a low-WTP buyer. We also control for the belief about the threshold price by providing the information on the lower and upper bound of the uniform distribution *TP*~[*LB*,*UB*]. Moreover, we varied the delay costs $\delta_b\epsilon\{0.95;0.75\}$ for buyers within-subject. Overall, twelve hypothetical products were presented to subjects, who were allowed to submit an unlimited number of bids for each product.

We created four different between-subject treatments: Two markets applied a static threshold price whereas the remaining two applied an adaptive threshold price. We also varied the information we gave to the subjects. In two markets the subjects were informed about the threshold-rule (static or adaptive) whereas in the remaining two markets this information was omitted. Table 1 summarizes the scenarios.

This between-subject design allows us to control for (i) the influence of an adaptive threshold vs. a static threshold on bidding behavior and seller profit and (ii) the subjects' awareness about the specific threshold policy has an impact on their behavior.

	Static Threshold	*Adaptive Threshold*
No Info	Market 1	Market 3
Info	Market 2	Market 4

Table 1. Experimental setup

In the markets with a static threshold price, bids are accepted when they hit or surpass the threshold price whereas in markets with adaptive threshold price an automated proxy system evaluates the bid sequence following our normative model and applies an optimal threshold price for a high-WTP or a low-WTP buyer based on its current estimate of consumer type (i.e. low-WTP or high-WTP).

We further gathered data on the acceptance and perceived fairness of the specific mechanism in a post-purchase survey.

Current Research Status, Preliminary Results and Timeline

116 students at a large Western-European university participated in the first series of laboratory experiments. Table 2 shows that markets applying an adaptive threshold price have higher rates of accepted bids ($p<.01$). The adaptive threshold price also allows the retailer to capture a significantly higher ($p<.01$) proportion of consumer surplus (i.e. realized consumer surplus is lower) which leads to additional profits. Comparing market 3 and market 4 reveals that we can not observe a significant change in bidding behavior when the subjects were informed about the adaptive threshold price ($p>.5$). This finding encourages our conclusion that even an anticipated adaptive threshold price allows for customer segmentation when the market is adequately designed.

	Accepted Bids	*Realized Consumer Surplus*	*Price Acceptance*	*Satisfaction*
Market 1 (static, no Info)	84.47%	11.28%	3.36	3.01
Market 2 (static, Info)	85.98%	11.15%	3.45	2.83
Market 3 (adaptive, no Info)	90.48%	8.44%	3.37	3.19
Market 4 (adaptive, Info)	90.09%	8.60%	3.61	3.23

Table 2. Results of different markets in terms of accepted bids, realized consumer surplus, price acceptance, and satisfaction

Perhaps even more surprising that people accepted the realized price (1=very unfair…5=very fair) and were even significantly more satisfied (1=very unsatisfied…5=very satisfied) after doing purchases in a market with an adaptive threshold price ($p<.05$). This is contrary to the results of the survey presented at the beginning of this proposal. Although the adaptive threshold price skims the consumer surplus and increases vice versa the producer surplus, prices were still considered as fair since we did not find a significant difference among the static and adaptive design ($p>.5$). Overall, subjects were more satisfied with the results of the auction. We believe that the higher rate of accepted bids is the main driver for this increase satisfaction. Subjects seem to be more eager to close a deal successfully than to realize on average higher consumer surpluses. This irrational behavior might hence be a source for additional profit and welfare for NYOP-sellers without having negative effects on price acceptance, which could be achieved by the application of an adaptive threshold price in NYOP-markets.

On account of the positive preliminary results of these experiments, we are planning to conduct a second series of laboratory experiments in October to validate our findings and conclusions. We expect to finish this round of data collection by the end of October. Data analysis will be conducted in November and results from this round of data collection will also be ready for discussion at WISE.

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