Price Discrimination in E-Commerce? An Examination of Dynamic Pricing in Name-Your-Own-Price Markets

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This is a preprint of the Paper
Hinz, Oliver / Hann, Il-Horn / Spann, Martin (2011): "Price Discrimination in E-Commerce? An Examination of Dynamic Pricing in Name-Your-Own-Price Markets", *MIS Quarterly*, Vol. 35(1), forthcoming.

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Abstract

The enhanced abilities of online retailers to learn about their customers' shopping behavior have increased fears of dynamic pricing, a practice in which a seller sets prices based on the estimated buyer's willingness-to-pay. However, among online retailers, a deviation from a one-price-for-all policy is the exception. When price discrimination is observed, it is often in the context of customer outrage about unfair pricing.

One setting where pricing varies is the Name-Your-Own-Price (NYOP) mechanism. In contrast to a typical retail setting, in NYOP markets, it is the buyer who places an initial offer. This offer is accepted if it is above some threshold price set by the seller. If the initial offer is rejected, the buyer can update her offer in subsequent rounds. By design, the final purchase price is opaque to the public; the price paid depends on the individual buyer's willingness-to-pay and offer strategy. Further, most forms of NYOP employ a fixed threshold price policy.

In this paper we compare a fixed threshold price setting with an adaptive threshold price setting. A seller who considers an adaptive threshold price has to weigh potentially greater profits against customer objections about the perceived fairness of such a policy. We first derive the optimal strategy for the seller. We analyze the effectiveness of an adaptive threshold price vis-à-vis a fixed threshold price on seller profit and customer satisfaction. Further, we evaluate the moderating effect of revealing the threshold price policy (adaptive vs. fixed) to buyers. We test our model in a series of laboratory experiments and in a large field experiment at a prominent NYOP seller involving real purchases. Our results show that revealing the usage of an adaptive mechanism yields higher profits and more transactions than not revealing this information. In the field experiment we find that applying a revealed adaptive threshold price can increase profits by over 20% without lowering customer satisfaction.

Keywords: Name-Your-Own-Price, Bargaining Games, Dynamic Pricing, Electronic Commerce, Customer Satisfaction

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1. Introduction

Recent advances in information technology have given online retailers an unprecedented ability to track and analyze customer behavior, promising valuable information about customers' preferences and greater insight into their true willingness-to-pay. Theoretically, by using customer browsing behavior to learn about aggregate and individual preferences, online retailers can personalize pricing through devices such as coupons, promotional pricing, and customized banner ads or pop-up windows (see, for example, Shapiro and Varian 1998). This type of price discrimination – called first-degree price discrimination (Pigou 1920) – minimizes deadweight loss and allows the retailer to capture the entire consumer surplus.

In reality, such dynamic pricing has been slow to take hold in mainstream electronic commerce. Indeed, deviations from a "one price for all" policy in traditional online retailing seem to be the exception (see, for example, Bergen et al. 2005). One often-cited reason for abstaining from dynamic pricing policies relates to fears of consumer backlash and potential negative publicity. For example, in one highly publicized case, Amazon upset its customers with a price discrimination policy that used buyer profiles to charge different prices (Baker et al. 2001). Reportedly, when a buyer deleted the cookies on his computer that identified him as a regular Amazon customer, the price of a DVD offered to him for sale dropped from $26.24 to $22.74. The resulting customer outrage resulted in Amazon.com publicly apologizing and refunding all customers who had paid higher prices (Ramasastry 2005).

In some cases, however, it has been reported that companies successfully engage in obfuscated pricing strategies without making it obvious to consumers (Baye and Morgan 2002; Ellison and Ellison 2004). Several online retailers have been able to capture some price variation through the use of IT-enabled price discovery processes in which buyers and sellers engage (Kauffman and Wang 2001). Sellers can be expected to prefer mechanisms with restricted transparency (Bakos 1997; Soh, Markus and Goh 2006).

One such pricing mechanism is called Name-Your-Own-Price (NYOP). A retailer using NYOP determines the minimum price (also called threshold price) at which he is willing to sell a product. The seller then asks a buyer to place an offer, indicating her willingness-to-pay for the product. If the offer value is equal to or greater than the seller's threshold price, the transaction is completed at the buyer's offer price. If, on the other hand, the offer fails to meet or exceed the threshold price, the buyer can make a subsequent offer. The buyer's ability to improve (i.e., to raise) her offer 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 offers or could charge a small fee if a buyer wants to place an additional offer. Previous research shows that such design considerations can represent significant frictional costs that increase the cost of submitting an offer (Hann and Terwiesch 2003; Spann, Skiera and Schäfers 2004). Depending on the buyer's willingness-to-pay, the buyer's subjective estimate of the threshold price, and the frictional cost of submitting offers, different sales prices can be obtained for the same good, even when using a fixed threshold price. Note that in contrast to auctions, prospective NYOP buyers do not compete with each other (Spann and Tellis 2006). This allows NYOP mechanisms to sell the same product simultaneously to a large number of buyers.

For some concrete examples, consider first the case of Priceline.com. In 1998 Priceline introduced NYOP to airline ticket and hotel room sales. Priceline has since become a major online retailer for travel service. With revenues of $1,885 million and gross profits of $956 million in 2008, [1] Priceline's experience indicates both the acceptance and success of NYOP mechanisms. Accordingly, a number of companies now employ an NYOP mechanism, for example, Expedia.com, several low-cost airlines in Europe and software producers such as Ashampoo. In a similar fashion, auction site eBay recently introduced a design option called "Best Offer" (http://pages.ebay.com/bestoffer). This feature allows prospective buyers to submit a binding offer to a seller who can accept or reject the offer; a rejected offer can be subsequently improved upon by the prospective buyer.

Pricing theory suggests that by adjusting the threshold price to individual prospective buyers' willingness-to-pay, sellers can extract greater profit: Low threshold prices can realize sales to low valuation consumers that are otherwise lost, whereas high threshold prices can extract surplus from high valuation consumers that is otherwise forgone when compared to a non-discriminating fixed threshold price. In practice, to realize such a segmentation of prospective buyers, incoming offers must be evaluated based on the buyers' offer history (if available) by using an automated proxy system. This is certainly feasible given the state of computer and communications technology and as outlined by Grover and Ramanlal (1999), sellers undoubtedly will continue utilizing computer and communication technology in the battle for more consumer surplus. Especially new pricing strategies enabled by the Internet seem to be of managerial interest (Oh and Lucas 2006) since pricing mechanisms can be designed to increase profits at little cost (Bapna 2003; Bapna et al. 2003).

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[1] Financial Reports 2009, Priceline.com

However, an informal search reveals that none of the current NYOP sellers use an *adaptive* threshold price.

Our discussions with sellers that employ an NYOP pricing mechanism, such as Germanwings and Ashampoo, revealed that sellers are acutely aware of the potential increase in profits that would accompany an adaptive threshold price policy. However, when asked why an adaptive threshold price policy was not implemented, the sellers pointed to several reservations:

- An adaptive threshold price could alter offering behavior. Buyers may try to hide their true willingness-to-pay; specifically, they may try to convince the seller of a lower willingness-to-pay. Such behavior, called “bid (offer) shading” (Krishna 2002), may jeopardize the seller’s profits.
- By adapting the threshold price based on individual offering behavior, the perception of the pricing mechanism is likely to suffer. There appears to be some merit to this argument. In a survey conducted amongst 116 students, we found that over 60% believe that adaptive threshold prices in an NYOP setting, whereby a seller accepts or rejects offers based on previous offers, are unfair. The assessment of this mechanism is only slightly better than that associated with the practice of posting different prices to different customers for the same product – the very behavior that outraged Amazon’s customers.

Given these considerations, some industry discussants questioned whether the adoption of an adaptive threshold price is really worthwhile, or if they are better off not deviating from a fixed threshold price policy. Interestingly, one suggestion was to use an adaptive threshold price while withholding any information regarding threshold price policy, a practice that is not unlike the one that Amazon.com used.

The purpose of this paper is to assess the viability of dynamic pricing in the context of NYOP markets. Our interest goes beyond the mere comparison of profits as predicted by economic theory. Pricing mechanisms such as dynamic pricing may offer theoretical benefits, but they are worth little, if consumers do not accept them. Hence, we are interested in how pricing policies affect the perception of customers. We test the effect of dynamic pricing policies in laboratory settings as well as in practice. While the laboratory experiment allows us to closely translate the theoretical model, the field experiment provides us with external validity.

For the field experiment, we were able to convince Ashampoo, a software vendor, to execute a series of experiments that are equivalent to the laboratory experiments. Ashampoo is one of the leading Internet-based companies worldwide in the field of software development, sales and web portal sites, with more than 9 million registered customers and over 95 million program installations. Besides a conventional online store, the company operates an NYOP-website where prospective buyers are invited to make offers for Ashampoo products.

For the purpose of our research agenda, we first outline our research model and hypotheses. Next, we establish prescriptive guidelines for the optimal seller strategies under a fixed and under an adaptive threshold price. In a set of experiments, in the lab and in the field, we compare the effects of an adaptive threshold price policy to those of a fixed threshold price policy on profits while controlling for the customer's information about the threshold price policy. In addition, we measure the impact of the threshold price policy on customer satisfaction.

The remainder of our paper proceeds as follows: In the following section we survey the relevant literature on NYOP, dynamic pricing, and customer satisfaction. Section 3 introduces our research model. We outline the optimal seller strategy for fixed and adaptive threshold prices, i.e., seller's optimal offer acceptance/rejection decisions in Section 4. We finally examine the effect of price discrimination in two empirical studies, one in the laboratory and one in the field, in Section 5. The first study is conducted in the laboratory where full control over input parameters allows us to asses the customers' perceptions of different dynamic pricing mechanisms. The second study describes a field study with a prominent NYOP seller where we applied our model in the field involving real purchases. We conclude the paper with a discussion of the results and their managerial implications in Section 6.

2. Related Literature

Electronic commerce has been a prominent topic in IS research. Early work (Malone et al. 1987; Clemons et al. 1992) defined the discussion on the impact of information technology on the boundary of the firm. The focus of their research was the buyer-supplier relationship. Subsequently, researchers examined the usage of electronic markets in specific contexts such as the loan origination system and the aircraft parts industry (see, for example, Hess and Kemerer 1997; Choudhury et al. 1998). Around the same time, Bakos (1991; 1997) examined the role of electronic markets in a buyer-retailer setting. This also led to a number of empirical studies in the retail and the travel agent industry (see for example, Brynjolfsson and Smith 2000; Clemons et al. 2002; Gregg and Walczak 2008). The underlying motive was the premise that electronic markets lower search costs for buyers, which should lead to more price competition among retailers. More recent work focused on the ability of retailers to learn from their interaction with their buyers in electronic markets (see for example, Gupta et al. 2000; Oh and Lucas 2006). This paper falls in this category; our research provides prescriptive advice in a dynamic pricing setting of an NYOP market and uses an experimental setting to examine profit and consumer surplus implications as well as customer satisfaction.

2.1. Offering Behavior and Profits in Name-Your-Own-Price Markets

Previous research on NYOP mechanisms focuses on two research questions: First, the optimal design of NYOP mechanisms, and second, the offering behavior that arises in NYOP markets. We first discuss the literature on optimal design.

Using data obtained from an NYOP seller who uses a fixed threshold price, Hann and Terwiesch (2003) formulate a repeated offering model based on frictional costs and subsequently use the data to empirically measure the frictional costs. Chernev (2003) analyzes alternative designs for price elicitation in NYOP mechanisms by examining the case of a single offer and analyzing consumers' preferences for different design specifications in a paper-and-pencil experiment. These design options are restricted to elicitation formats and Chernev (2003) does not examine the influence of an adaptive threshold price on consumer behavior. Spann, Skiera and Schäfers (2004) develop a repeated offering model as well and estimate consumers' individual willingness-to-pay. Based on the assumption of a fixed threshold price, they derive a closed-form solution for the optimal offers in their estimation procedure and compare offering behavior and profit implications of the single offer model to the repeated offering model. Abbas and Hann (2010) extend the consumer model to incorporate risk averse customers. Fay (2004) develops an analytical model for seller profits in an NYOP market under varying restrictions with respect to the number of offers consumers can submit. For a fixed threshold price, Fay compares the single offer model with a model where experienced consumers can submit multiple offers on Priceline by applying various "tricks" such as establishing different "identities" via multiple credit cards. Hinz and Spann (2008) show that information diffusion through social networks can influence the bidding behavior in NYOP channels and communication amongst prospective buyers may influence the seller's profit. Wang, Gal-Or and Chatterjee (2009) explain why, in light of concerns among service providers of the adverse consequences of cannibalization of products sold in traditional posted-price channels, a service provider would seek to distribute its products through an NYOP retailer. For the case of myopic customers, Terwiesch et al. (2005) further investigate the impact of consumer haggling on an NYOP retailer's optimal pricing strategy, in terms of choosing an optimal threshold price that maximizes seller profit.

Turning now to studies that focus on consumer behavior under NYOP mechanisms, Ding et al. (2005) analyze the single offer case, whereby consumers acquire the product via "traditional" sales channels if their offer was not successful. They posit that offering behavior is a function of utility-maximization as well as one's emotions, i.e., "excitement" from a successful offer and "frustration" from a rejected offer. They show that these emotional drivers can have a significant influence on offering behavior for repeat purchases.

2.2. Dynamic Pricing Mechanisms and Customer Satisfaction

The possibility of changing prices dynamically has made satisfaction with the pricing mechanism itself a major issue in electronic commerce (Baker et al. 2001). Customer satisfaction has been studied in various industries and has been found to be a key factor to maintaining customer loyalty and long-term profitability (Campbell 1999; Lo, Lynch and Staelin 2006).

Dynamic pricing mechanisms that are based on negotiations or auctions in electronic commerce have largely avoided the customers' wrath that Amazon experienced in their dynamic pricing "experiment." As Dickson and Kalapurakal (1994) argue, price discrimination is typically considered fair as long as all buyers have the possibility to achieve all price levels. Thus, price discrimination can be achieved without fear of any customer retribution by exploiting different levels of search costs, quantity discounts, or time of transactions (Chandran and Morwitz 2005). This may not hold, however, when using an adaptive threshold price. While an adaptive threshold price will serve a higher percentage of consumers, dynamic pricing based on an individual's specific offer history may undermine the perceived fairness or satisfaction of participants in such markets.

The following section outlines our research model for the analysis of the impact of dynamic pricing on seller revenue and profit as well as customer satisfaction.

3. Research Model

Figure 1 depicts our research model for the impact of dynamic pricing on seller profit and customer satisfaction in the context of NYOP markets.

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In our research model, we analyze the impact of an adaptive threshold price vis-à-vis the impact of a static (fixed) threshold price on seller profit and customer satisfaction. Further, we analyze the effect of revealing the specific pricing policy to consumers on our variables of interest, i.e., profit and satisfaction.

We expect that the application of a dynamic pricing policy has a positive influence on seller profit, because a dynamic, adaptive threshold price enables the seller to better price discriminate between consumers with heterogeneous valuations. Hence, the seller is able to extract a higher surplus from high valuation consumers while still being able to serve some low valuation consumers, thus increasing overall market efficiency (Pigou 1920; Robinson 1933). More formally:

H1: The use of an adaptive threshold price has a positive effect on profit when compared to the use of a fixed threshold price.

The impact of dynamic pricing on customer satisfaction has several dimensions. First, dynamic pricing enables more consumers being served. This implies a positive effect of dynamic pricing on customer satisfaction. However, the actual consumer surplus realized in a successful transaction affects the positive influence on satisfaction (Gillespie, Brett and Weingart 2000; Devaraj, Fan and Kohli 2002). Dynamic pricing, while enabling more transactions, also captures more surplus from consumers, which leads to a reduction in the positive effect on customer satisfaction. Hence, dynamic pricing has two opposing effects on customer satisfaction. We hypothesize that the higher market efficiency of an adaptive threshold price should lead to more satisfied consumers:

H2: The use of an adaptive threshold price has a positive effect on customer satisfaction when compared to the use of a fixed threshold price.

Further, the disclosure of the dynamic pricing policy is also expected to moderate the impact of dynamic pricing on seller profit and customer satisfaction. A buyer, who is not aware of the seller's intent to learn from the buyer's offer history, will not consider the strategic aspect of an offer. Specifically, she will not use an offer to signal her willingness-to-pay. Instead, she will maximize the expected surplus; she needs to trade-off the advantages of a higher offer, which increases the odds of a successful offer in an early round against the potentially greater consumer surplus of a lower offer, which increases the odds of having to wait for another round. Unbeknownst to the buyer, she reveals signs of her willingness-to-pay to the seller in this process. The seller, in turn, can use an offer as information about the buyer's willingness-to-pay without having to consider the offer as a strategic signal from the buyer. Hence, we hypothesize:

H3: An adaptive threshold price will yield a higher profit when the threshold policy is not disclosed.

Moreover, the revelation of a dynamic pricing policy is expected to reduce customer satisfaction because of customers may not approve such a policy based on fairness considerations (Xia, Monroe and Cox 2004). Thus, we hypothesize the following moderating effects for the revelation of the dynamic pricing policy on customer satisfaction:

H4: Revealing a dynamic pricing policy decreases its positive effect on customer satisfaction.

We will test the impact of adaptive threshold vs. fixed threshold policy and full information vs. no information policy on these key outcome variables in two experimental studies using a 2x2 full factorial design. For this purpose, we first need to derive optimal seller behavior for both pricing strategies (fixed or adaptive threshold price), which we will do in the following section.

4. Optimal Seller Strategy for Fixed and Adaptive Threshold Price

An NYOP seller who uses a fixed threshold price will optimize differently than an NYOP seller who uses an adaptive threshold price. Under a fixed threshold price policy, the seller will set one optimal threshold price. The buyer learns the true threshold price during the offering process, but this information comes at the expense of cognitive costs or opportunity costs of time.

Under an adaptive threshold price, the seller can accept or reject an offer based on his current information set. This changes the behavior of both the buyer and the seller significantly from the fixed threshold price policy. Specifically, while the buyer is a price taker in the fixed threshold price scenario, she now acts strategically in the adaptive threshold price scenario. The buyer would like to learn the seller's valuation so that she can submit an optimal offer. But the buyer also realizes that the strategy that guides the seller is a response to her own strategy. That is, the seller acts strategically as well. He would like to learn the buyer's valuation, but is aware that his decision to accept or reject the offer will be seen as an optimal response to the buyer's offer.

4.1. Model Setup

In an NYOP setting a buyer and a seller bargain over the price of a product that is worth *s* to the seller and *WTP* to the buyer. The buyer submits an offer at price *p* and the seller can only reject or accept the offer. If an offer is accepted, the buyer's offer price is the price of the transaction. If the offer is rejected, the buyer can place another offer at the next stage of the game. The number of possible offers can be limited (e.g., Priceline.com, where only a single offer is allowed) or unlimited (e.g., Germanwings, where repeated offers are encouraged), with the latter describing an infinite-horizon game. Both the buyer and the seller face costs for delaying the purchase process. The payoff for subsequent offers is discounted by the factor δ_S for the seller and δ_B for the buyer with $0<\delta_S, \delta_B<1$. When the seller accepts the *j*-th offer *p*, the payoffs can then be calculated as $\delta_S^{(j-1)}(p-s)$ for the seller and $\delta_B^{(j-1)}(WTP-p)$ for the buyer. If the offer *p* is not accepted, the payoff for both players is zero.

The seller is aware of his valuation *s* but only assesses the buyer's valuation to be given by the distribution F(*WTP*) with positive density f(*WTP*) on [WTP_{low}, WTP_{high}]. The buyer is aware of her valuation *WTP* but can only assess the seller's valuation given by the distribution G(*s*) with positive density g(*s*) on [*LB*, *UB*]. Following previous literature (e.g., Hann and Terwiesch 2003; Stigler 1961), we assume that g(*s*) follows a uniform distribution. Both players are solely interested in maximizing their payoff and are assumed to be risk-neutral. The discount factors, the distributions, and the structure of the game are common knowledge.

4.2. Fixed Threshold Price Policy

Under a fixed threshold price, the buyer faces a tradeoff: If she submits a high offer, she increases the probability of obtaining the product early, but forgoes a potentially lower price. If she submits a low offer, she decreases the probability of leaving money on the table, but increases the probability of having to submit another offer and incurring the cost associated with an additional round. Maximization of the buyer's expected surplus function leads to their optimal offer strategy (see Appendix A.1). Knowing the optimal strategy of buyers, a seller can subsequently determine the optimal threshold price for a given distribution F(*WTP*).

A Numerical Example

This model can be used to calculate the optimal threshold price for the seller for a given distribution of willingness-to-pay. To illustrate this, we determine the optimal threshold price for two segments with WTP_1=90 and WTP_2=40 and seller's valuation of 20. Both buyer segments assess the seller's threshold price to be in the uniform distributed interval [0, 100] and seller and buyer face delay costs modeled by the discount factors $\delta_S=\delta_B=0.8$. Table 1 depicts the optimal offers by buyer 1 with WTP_1 and buyer 2 with WTP_2.

--- Please insert Table 1 about here ---

The seller determines the optimal offers from both buyer segments and sets the optimal threshold price to any value within the interval [$30.89, $33.69], which leads to an accepted offer for buyer 1 in the second round and an accepted offer for buyer 2 in the fifth round. To calculate the seller's expected profit, we assume that we have one buyer WTP_1 and one buyer WTP_2 in the market. The expected profit is then $27.23 (=$21.62 from buyer 1 + $5.61 from buyer 2) and the total expected welfare is $64.19 (=$27.23 seller profit + ($90-$47.03)*0.8 consumer surplus of buyer 1 + ($40-$33.70)*0.41 consumer surplus of buyer 2). For other values of WTP_1 and WTP_2, it may be optimal for the seller to price the low WTP-type buyers out of the market.

4.3. *Adaptive Threshold Price Policy*

Under the adaptive threshold price policy both the seller and the buyer act strategically. Both parties have private information: The seller sets the threshold price, which is of great interest to the buyer; on the other hand, the seller is keenly interested in the buyer's willingness-to-pay. The buyer learns the seller's threshold price by offering sequentially, incurring a delay cost for each offer. However, by doing so, the buyer sends a signal about her willingness-to-pay to the seller. The buyer, being aware of this mechanism, therefore has incentives to conceal her true willingness-to-pay to maximize her consumer surplus. The seller is in a similar situation; he extracts information about the buyer's willingness-to-pay from every offer, but tries to set expectations on the minimum willingness-to-accept by rejecting insufficient offers. Similar to the buyer, the seller also incurs a delay cost for selling in later rounds. Gupta et al. (2000) show that offers are signals that can be used to extract private information.

We use a model for the optimal dynamic pricing strategy in an NYOP setting, where a buyer makes an offer that the seller accepts or rejects, based on the model of Cramton (1984). Our model allows us to determine the optimal adaptive threshold price policy of the seller.

The model setup is a bargaining model with infinite horizon under two-sided uncertainty. We describe the sequential equilibrium that characterizes the buyer and seller's optimal strategies given their beliefs such that starting from every information set the buyer or seller plays optimally from then on. The solution is a separating equilibrium that allows sellers to discern high value from low value buyers. A high WTP buyer is more impatient than a low WTP buyer and thus reveals her private information more quickly since her opportunity costs jeopardize her larger expected consumer surplus. However, a buyer with a low *WTP* signals with lower offers and longer offer sequences that she has a low *WTP*. The buyer certainly has incentives to hide her true *WTP* and signals that her *WTP* is so low that the seller is better off accepting low offers than making no successful sale. The seller, however, is aware of this incentive and only believes the buyer if the signals are backed up by actions. Therefore, the seller only believes that a buyer is a low WTP buyer if a high WTP buyer would never follow this strategy.

The buyer and the seller play a threshold strategy. For each stage *j*, the buyer submits an offer $p_j(WTP)$ that is strictly increasing in *WTP* if her *WTP* is higher than some cutoff valuation β_j; otherwise, she delays the negotiation by submitting offers that no seller is willing to accept. The seller accepts the offer if his valuation *s* is below some cutoff valuation $\sigma_j(p_j)$; otherwise, he rejects the offer (see Appendix A.2 for proof). A rejection of the offer indicates to the buyer that the seller has a valuation higher than σ_j. She then updates her belief that the seller's valuation is distributed on $[\sigma_j, UB]$. The seller's decision to accept an offer in stage *j* or to wait for a higher offer in a subsequent stage depends on his discount factor. His indifference equation is $p_j - \sigma_j = \delta_s(p_{j+1} - \sigma_j)$, which indicates that a seller with a valuation of minimum σ_j is indifferent between accepting p_j now and waiting for a higher offer in the next stage (p_{j+1}), when the profit will then be discounted by δ_s. This is quite intuitive since sellers with lower valuations are even more impatient and lose even more by delaying agreement. See Appendix A.3 and A.4 for buyers and sellers equilibrium strategies in case of one- and two-sided uncertainty.

In equilibrium, high valuation buyers reveal their private information by submitting an offer that is strictly increasing in *WTP*. The seller can then infer the buyer's *WTP* by inverting the offer schedule p(*WTP*) by calculating $WTP=p^{-1}(p)$ (see Appendix A.4). Then, the remainder of the game can be determined by the one-sided uncertainty case (see Appendix A.3). The offers of low valuation buyers, in contrast, remain too low and therefore unacceptable for the seller. The separating equilibrium also ensures that a buyer has no incentive to shade her offers and pretend to have a low valuation. In essence, the seller takes such a possibility into account and in comparison to the one-sided uncertainty case where the buyer's *WTP* is known, the buyer is required to submit higher offers.

Based on the equilibrium strategies it is possible to build a system that segments the market, which we do for our experimental studies. Such systems have been proposed by Jones, Easely and Koehler (2006) using a generalized combinatorial auction approach and Bapna et al. (2004) for a Yankee auction. However, especially combinatorial auctions present significant challenges in offer formulations (Adomavicius and Gupta 2005) and in all kind of auctions sellers have to wait for the closure of the auction at a predetermined time to choose the winning offers while NYOP allows the asynchronous determination of winning offers.

A Numerical Example

For given values of the discount factors δ_S and δ_B and the supports [LB, UB] and [WTP_{low}, WTP_{high}], we can calculate the offers and indifference values by an iterative procedure.

Let us assume a buyer with a willingness-to-pay of WTP=\$150 negotiates with an NYOP seller who has a valuation of s=\$100. It is common knowledge that the valuation of the seller is uniformly distributed between LB=\$60 and UB=\$160, and the seller is also aware of the buyer's exact willingness-to-pay (we start with the game when it has been already reduced to the game with one-sided uncertainty, this means that the buyer makes her first reasonable offer and reveals thereby her true willingness-to-pay). The discount factor for both parties is δ_S=δ_B=0.9.

Given her own willingness-to-pay of \$150, the buyer places an offer of \$127.16. This is a reasonable offer since the seller's valuation is somewhere between \$60 and \$160. The seller receives the offer and interprets the signal. He can predict the buyer's offers from there on and can anticipate that the profit with offer 3 will be \$29.35 after discounting. The seller rejects therefore the first offer and waits for better offers in the future (he expects that the third offer maximizes his profit). The buyer learns from the rejection that the seller's valuation must be more than \$80.90 since sellers with lower valuations would have accepted the first offer. She raises therefore her offer to \$132.30 which is again not accepted by the seller. The buyer can now infer that the seller's valuation must be greater than \$96.86 (see Table 2).

--- Please insert Table 2 about here ---

The bargaining in the example ends in the third round when the seller accepts the buyer's offer of \$136.24. Recall that the indifference valuation σ_j is the cutoff value at which the seller should accept the offer. Thus, while a seller with a valuation of \$95 would be more impatient and would have accepted the second offer of \$132.30, the seller with a valuation of \$100 can take advantage of his private information and realize a larger piece of the pie. Although both, the seller and the buyer, would be better off arranging a deal in the first round, the seller lacks the possibility to signal his valuation in this game and can only react by accepting or rejecting an offer.

5. Experimental Studies

In this section, we test our hypotheses based on the optimal seller strategies discussed in Section 4. First, we conduct a laboratory experiment where we have perfect control over the willingness-to-pay and control for entry. Different segments of potential buyers are induced through a resale value (see Smith 1976). By changing the resale value over subsequent periods, we can control for the cost of waiting which is an important driver in our models.

Our field experiment complements our laboratory studies; it provides us with perfect realism as the experiment was executed in the context of a software vendor Ashampoo. This also allows us to analyze the effect of dynamic pricing on the entry decision of customers, which is not possible in our laboratory experiment.

5.1. Laboratory Experiments

Study Design

We first tested our hypotheses in a series of computer-aided laboratory experiments. We applied a combined within-subject and between-subject design. Using an induced-values paradigm (Smith 1976), we controlled for subjects' product valuation by informing them about the resale value of the given product. Each product has a resale value that induces the subject's willingness-to-pay since the difference between the induced valuation and a successful offer represents the surplus for the subject, which is paid out in cash. On the individual level, the assigned willingness-to-pay was either high or low so that the market for the product consisted of a segment of high WTP buyers and a segment of low WTP buyers. Information about these two segments was given to the experiment's subjects. This simplified our model from a continuous distribution of valuations to a two-segment market.

We also controlled for the belief about the threshold price by providing information on the lower and upper bounds of the uniform distribution f~$[LB,UB]$. The seller's valuation s was drawn randomly from this distribution. We redrew the seller's costs when neither the high WTP nor the low WTP buyers would buy the product ($s>WTP_{high}$), since this case is degenerated.

Additionally, we varied the level of buyer's delay costs $\delta_B \in \{0.95;0.75\}$ on a within-subject basis for different hypothetical products. The delay costs δ_S for the seller were set equal to δ_B for a given product. Introducing these levels leads to a 2 (high and low WTP buyers) x 2 (high and low delay costs) factorial design for the within-subject treatment variation. We assigned three hypothetical products to each of these four within-subject treatments in different variations, thus creating twelve hypothetical products which were presented to subjects. The order of the 12 hypothetical products presented to subjects was kept constant across all subjects, but we systematically varied the treatment conditions assigned to products, which allowed us to control for order effects. Subjects were allowed to submit an unlimited number of offers for each of the twelve products.

We created four different between-subject treatments. Two markets applied a fixed threshold price whereas the remaining two applied an adaptive threshold price. We also varied the information provided to the subjects. In two markets the subjects were informed about the threshold rule (fixed or adaptive) whereas in the remaining two markets this information was omitted. This means that no information about the setting of the threshold price is given.

Table 3 summarizes the scenarios. A total of 92 graduate and undergraduate student participants from a Western European university were randomly assigned to the four different scenarios (Market 1: 22 participants, Market 2: 26 participants, Market 3: 21 participants, Market 4: 23 participants). See Appendix B for experimental instructions.

The between-subject design allows us to test for (i) the influence of an adaptive threshold vs. a fixed threshold on offering behavior and seller profit, and (ii) whether subjects' awareness about the specific threshold policy has an impact on their behavior.

--- Please insert Table 3 about here ---

In the markets with a fixed threshold price, offers are accepted when they hit or surpass the optimal threshold price, whereas in markets with an adaptive threshold price, an automated proxy system evaluates the offer sequence following our analytical 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). For both types of markets we determined the profit-maximizing threshold price according to the model of Section 4.

For the measurement of satisfaction, we follow the operationalization of satisfaction in negotiations suggested by Novemsky and Schweitzer (2004), applying a two-item construct and use the average as satisfaction score. Therefore we gather data on outcome satisfaction and process satisfaction after each (successful or unsuccessful) offering sequence for a product.

Results

Table 4 depicts the results of our laboratory experiments with respect to seller profit, consumer surplus, welfare, the acceptance rate of offers as well as customer satisfaction. To make outcomes comparable over products, we calculate the maximum welfare MW, which is the difference between *WTP* and seller's valuation *s* (*MW=WTP-s*). We standardize profit, consumer surplus and welfare by dividing by *MW*.

--- Please insert Table 4 about here ---

Further, we can calculate the percentage of subjects correctly classified by our automated proxy system in case of an adaptive threshold price. In case of potential buyers being informed about the adaptive threshold price policy employed (market 4), our automated proxy system correctly categorizes the buyers with an excellent hit rate of 90.22% even though we allowed all buyers to shade their true willingness-to-pay. The hit rate is significantly lower at 80.16% ($p<0.05$) if buyers are not informed about the adaptive threshold price policy (market 3).

Consistent to our model, buyers with a high willingness-to-pay tend to surpass their threshold price with early offers, whereas buyers with low willingness-to-pay use longer offer sequences to signal their low willingness-to-pay. Figure 2 illustrates that most offers by high WTP buyers are accepted within the first two (mean=2.33) offers, whereas the seller accepts low WTP buyers' offers significantly later (mean=4.39, $p<0.01$).

--- Please insert Figure 2 about here ---

Effects on Seller Profit. The application of an adaptive threshold price increases the rate of accepted offers by 19% (from 74.0% to 88.4%; $p<0.01$) and the seller's profit by approximately 14% (from 45.4% to 51.6%; $p<0.05$) if consumers are informed about the policy (market 2 and 4). Thus, our results are consistent with H1; the adaptive threshold price policy is more profitable than the fixed threshold price policy.

We also measure the influence of information on the threshold price policy provided. Therefore, we compare the results in market 3 to the results in market 4 (see again Table 4). The seller's profit decreases by 18% (from 51.6% to 42.3%; $p<0.01$) when not disclosing the usage of an adaptive threshold price policy, which is contrary to H3. Welfare ($p<0.01$) and acceptance rate ($p<0.01$) also decline significantly when buyers are not informed about the use of an adaptive threshold price. Ex ante, it may seem surprising that the seller is better off being honest to his buyers about the adaptive threshold price mechanism. However, it turns out that not informing the buyer about the adaptive threshold price cuts both ways. While buyers who do not have this information may reveal their willingness-to-pay without any strategic consideration, she may also not take the seller's rejection as a signal that the seller has a prior on the buyers' willingness-to-pay. Not knowing that sellers base the adaptive price threshold on the buyer's offering history, the buyer may continue to optimize her surplus based on a perceived fixed threshold rule. Hence, we reject H3 that an adaptive threshold price will yield a higher profit when the threshold policy is not disclosed. We find that it is necessary for NYOP sellers to inform buyers that the adaptive threshold policy is being employed. If this information is omitted, buyers do not use the offers as signals, which results in a significantly lower hit rate. In contrast, we do not observe any significant changes in profit, consumer surplus, welfare and accepted offers when comparing markets with fixed threshold prices (market 1 with market 2, Table 4). The uncertainty about the rules encourages testing and thus longer offer sequences, which lead to lower consumer surplus. Interestingly, under this condition the consumer suffers most from the uncertainty while profit does not change significantly.

In order to test the direct effects of the threshold price policy and the information policy as well as its interaction effect simultaneously, we conduct an ANOVA where we test these effects between groups. We find that both direct effects are insignificant when tested simultaneously in the ANOVA (threshold price policy: $F=.05$, $p>.8$; information policy: $F=1.73$, $p>.1$). However, the interaction effect is significant at the 10%-level ($F=3.72$, $p=.057$) and positive, i.e., the disclosure of an adaptive threshold price increases profit.

Our results suggest that sellers are better off revealing the rules of the game. A concealment of the pricing policy may beyond that jeopardize trust which then in turn can influence the tendency for repeated purchases negatively (Gefen, Karahanna and Straub 2003).

Effects on Customer Satisfaction. Because the revelation of adaptive threshold prices might change the perception of the pricing mechanism, and in turn lead to a change in consumer behavior, we also evaluate the perception of the pricing mechanism. We focus on satisfaction as the key measure. Based on our discussion in Section 3, we believe that the use of an adaptive threshold price might increase buyers' satisfaction.

We find that outcome satisfaction and process satisfaction were highly correlated (r=0.76) and separate analyses of outcome and process satisfaction produced similar patterns of results. This has also been reported by Novemsky and Schweitzer (2004), so we follow their approach and use an overall measure of satisfaction, namely, the average of outcome satisfaction and process satisfaction.

We compare the average results in terms of satisfaction with the dynamic markets to the average satisfaction with the fixed threshold price markets. All markets consist of an equal proportion of high and low WTP buyers. Interestingly, we find in our experiment that the aggregate consumer surplus is relatively constant. The aggregate consumer surplus for the fixed threshold price is 20.66% whereas the aggregate consumer surplus for the adaptive threshold price is 20.48%. We find a significant increase of satisfaction (from 3.50 in fixed threshold markets 1+2 to 3.69 in adaptive threshold markets 3+4) at the 10% level ($p<0.068$), which is consistent with H2. This result suggests that the higher rate of accepted offers with an adaptive threshold price policy is an important determinant of satisfaction in NYOP markets. Additionally, the variance in customer satisfaction decreases in case of an adaptive threshold price compared to a fixed threshold price ($p<.05$). However, controlling for consumer surplus as covariate, the impact of the threshold price policy turns insignificant ($p>.1$) as the impact of consumer surplus is significant ($p<.01$). The consumer surplus, however, is influenced by the threshold price policy and thus this result was expected.

Further, to test the direct effects of the threshold prices and the information policy as well as its interaction effect on satisfaction simultaneously, we conduct an ANOVA where we test these effects between groups. Again, we only find a 10%-level significant effect for the threshold price policy (an adaptive threshold price increases satisfaction compared to a fixed threshold price; F=3.452, p=.063), but no significant effect for the information policy (disclosure of the threshold price policy; F=.77, p>.3) as well as no significant interaction effect (F=.18, p>.8) on customer satisfaction. Further, all effects are insignificant if we add consumer surplus as (significant, p<.01) covariate. Thus, this result is inconsistent with H4, i.e., revealing a dynamic pricing policy *does not* decrease its positive effect on customer satisfaction. Please note that the results of the ANOVA/ANCOVA have to be interpreted with caution due to the ordinal nature of satisfaction which we use as dependent variable.

5.2. Field Experiment at Ashampoo

Study Design

Based on the positive evaluation of our model in the laboratory, we were able to attract an NYOP seller who was eager to test an adaptive threshold price for real purchases. From a scientific point of view such a field experiment provides external validity to our laboratory results. In addition, such a setting allows us to control for possible entry biases. In the laboratory we induced all subjects to participate in bidding. In the field experiment we may observe differences in consumers' entry decisions between treatments. The adaption to a real setting posed a few challenges: First, it required us to learn about the customer base. For example, we had to learn the distribution of valuations across customers. Similarly, we had to learn abut the customers' discounting behavior.

In order to estimate the a priori unknown market parameters we conducted a pre-study. For this purpose, our industry partner Ashampoo invited 40,000 randomly drawn customers via a newsletter to participate in an NYOP sale. The customers had the opportunity to make an offer for Ashampoo's best selling product; WinOptimizer 5. This program is designed to enable both novice and advanced users to cleanse and optimize their Windows system and adapt it to their own needs. The free-to-trial version is one of the most popular downloads at download.com with over 4 million downloads. We adapted a static threshold price and revealed the bidding policies. We stated that the secret threshold price lies between 4.99 EUR and 49.99 EUR (setting thereby the lower and the upper bound) and set the secret threshold price deliberately to the recommended retail price (49.99 EUR) to generate as many long offer sequences as possible. We allowed an infinite number of offers but introduced a one-minute waiting time between consecutive offers to increase the opportunity costs for waiting. Based on the offer sequences of a bidder we were able to estimate the discount factor and the willingness-to-pay using a modified approach of Hann and Terwiesch (2003) and Spann et al. (2004). We fit the predicted sequence of offers according to the optimal offering behavior (see Appendix A.1) to the observed offer sequence, thus imputing the bidders WTP and discount factor via least squares estimation. Applying a hierarchical clustering procedure, we identified two different segments of consumers, a high valuation segment and a low valuation segment.

We estimate a mean willingness-to-pay WTP_{high}=28.38 EUR for the high valuation segment and WTP_{low}=9.67 EUR for the low valuation segment. We also allowed for segment-specific discount factors. This is an extension compared to the homogenous discount factor for the buyers in our laboratory experiment but it can easily be used in our analytical model. Our estimation yielded $\delta_{B,high}$=0.69 and $\delta_{B,low}$=0.85 for the two segments. This means that high valuation bidders are also more impatient on a relative base and not only in absolute values. This finding is in line with previous literature in marketing (e.g., Tellis 1986). The discounting is quite substantial but has also been reported as hyperbolic discounting (see Frederick, Loewenstein and O'Donoghue

(2002) for a literature review on time discounting and time preferences). For example, Thaler (1981) showed that subjects can have an average (annual) discount rate of 345 percent over a nine-month horizon, 120 percent over a twelve-month-horizon and 19 percent over a ten-year horizon. In other words, shorter time horizons suggest higher discount rates. Given our wait time of 1 minute, our observed discount factors can be classified as one of the discounted utility anomalies which are well documented in literature. In contrast, we can expect the seller to have a rational discount factor. Based on input from Ashampoo, we set the seller's discount factor to δ_S=0.99.

For the imputed values we estimated the optimal threshold prices for the fixed threshold scenario and used an automated proxy system based on our analytical model for adapting the threshold price in the adaptive scenario. In the fixed scenario the profit maximizing secret threshold price was 10.99 EUR. For the adaptive scenario threshold prices varied between 9.51 EUR and 13.10 EUR. Based on market simulations we expect that the adaptive threshold price should increase sales by 30% and revenues by approx. 16%. These estimates were made without considering the effect of possible entry biases.

To have the highest degree of consistency with the laboratory experiment, we tested the four different market scenarios listed in Table 3 also in the field study.

For the field study, Ashampoo distributed a large part of their customer base (excluding the subjects who were part of the pre-study sample) randomly into four groups and sent out four variants of a newsletter leading to different landing pages. Furthermore, every landing page checked for the unique customer-id to assure that every selected customer could only place an offer in the assigned scenario.

Figure 3 shows the newsletter with the invitation to make offers (“Name Your Price!”) and one out of the four landing pages which allowed prospective buyers to place an offer. We allowed customers to make an infinite number of offers. We also allowed them to leave the website by clicking a button “Not interested anymore.” Clicking on that button as well as a successful offer led to a very brief survey where we measured the process and outcome satisfaction according to Novemsky and Schweitzer (2004). In contrast to the laboratory setting, we can not completely rule out that subjects left the website without completing the survey.

--- Please insert Figure 3 about here ---

Results

Overall, the newsletter was sent out to 619,760 registered users of Ashampoo’s software. The mails were distributed over the market scenarios evenly (market 1: 154,941; market 2: 154,938; market 3: 154,941; market 4: 154,940) and there were no significant differences in terms of measured mail openings (market 1: 33,636; market 2: 33,715; market 3: 33.443; market 4: 33,707).

We allowed offering for one month and then shut down the landing pages. We received a total of 2,400 offers from 1,479 unique bidders. The bulk of offers were submitted in the first two days of the campaign.

Overall, the campaign had a response rate of 0.074%, which is generally lower than the response rate of catalog retailers, but higher than the response rate for unsolicited mail. Our system accepted 459 offers which yielded an acceptance rate of 31%. In contrast to Priceline.com, our industry partner does not charge the credit card immediately and therefore allows customers to leave the transaction uncompleted. Based on our data, about 72.1% of the accepted offers were settled, which included the completion of our survey. The process satisfaction was on average 4.31 while the outcome satisfaction was on average 4.05 on a 7-point-likert scale which was appraised as a good result by the management. Both satisfaction measures were again highly correlated (r=0.79).

Since we do not know each consumer's individual willingness-to-pay, we cannot estimate their consumer surplus and overall welfare. On the other hand, the field experiment allows us to analyze entry effects between treatments, the effects on satisfaction as well as calculate the profit in each treatment condition. Thus, we can answer the following questions: Are subjects still willing to enter the market when the seller applies an adaptive secret threshold price and honestly reveals his policy? Is dynamic pricing a viable strategy or would the seller face lower customer satisfaction?

The results of the field study are in general consistent with the laboratory experiment (see Table 5 and Figure 4). Market 4 (adaptive and honestly revealing) yields the highest profit, revenue and number of sales. Profit is 21.8%, sales are 28.6% higher and revenue is 25.4% higher compared to market 2 (fixed and honestly revealing). This is consistent with our hypothesis H1. Apparently, prospective buyers are more stimulated to enter the market when the rules of the game are explicitly explained. Comparing market 4 with market 3, the number of offers increases by about 19.9% while profit increases by 31.1%, sales increase by 6.8% and revenue by 16.5%. Thus, honestly revealing the rules of the game is important as this also leads to more entrants. The field experiment hence provides additional evidence contrary to hypothesis H3 and thus confirms the result of our laboratory study. Sellers can not benefit from not disclosing the applied threshold price policy and need to reveal that they employ an adaptive threshold price. The effect on profit is even amplified by the higher number of entrants if the policy is revealed.

We do observe small differences between the results of the laboratory and field experiment: Market 3 (adaptive threshold price and no information) is slightly more profitable than market 1 (fixed threshold price and no information) in the field experiment while we observed the opposite in the laboratory experiment. This result is sensitive to the cost assumption: Both markets would perform equally well if we assumed costs of 10.50 EUR.

--- Please insert Table 5 and Figure 4 about here ---

Regarding sales, revenues and profits the price discrimination is working as intended. Although prospective buyers may try to hide their true willingness-to-pay and shade their valuations, the time separating equilibrium helps the NYOP seller to identify different segments and to successfully price discriminate. We do not find any evidences that prospective buyers turn away from this mechanism but are actually attracted and enter the process. The perception might, however, change between the time the customer makes the first offer and when the sale is completed. We therefore measured the satisfaction when the transaction is completed. Table 6 shows a slightly higher process and outcome satisfaction for market 4, which is consistent with our laboratory experiment and hypothesis H2. Apparently, the price discrimination was well accepted and seems therefore to be a suitable strategy for this e-commerce retailer. The results in the field study are again contrary to hypothesis H4, thus confirming our conclusions from the laboratory study.

Our results show that price discrimination is feasible as long as all prospective buyers can access any price level. In our case all prospective buyers can negotiate a good price; it only depends on their willingness-to-wait for better prices. Since their willingness-to-wait is negatively correlated with their willingness-to-pay we can cater to high valuation buyers first. Subsequently, the lower offers of low valuation buyers are accepted. Note that our model certainly allows having more than two segments but in our case two segments were already effectual.

--- Please insert Table 6 about here ---

6. Discussion and Conclusions

The objective of this paper is to evaluate the potential of dynamic pricing in the context of NYOP channels. For this purpose, we start with a prescriptive analysis of the impact of fixed and adaptive threshold price policies on optimal seller behavior. We use these results to set up an experimental study wherein a software proxy acts as a profit-maximizing seller. The focus of our analysis goes beyond customers' offering behavior, customer welfare and seller profit, however, and includes an evaluation of the impact of dynamic pricing on customer satisfaction. Our results indicate that in the context of NYOP mechanisms, dynamic pricing is viable and preferable over a fixed threshold price. Not only does profit and welfare increase if sellers apply an adaptive threshold price, but customer satisfaction increases as well.

We further compare customer satisfaction in markets with dynamic pricing mechanisms against satisfaction in markets with fixed threshold prices in our laboratory experiments. We find that the application of a dynamic pricing mechanism that discriminates between individual consumers need not decrease, and indeed may even increase satisfaction compared to a fixed, i.e., non-discriminating, threshold price. This surprising result can be explained by the higher percentage of successful offers and a related increase in welfare in the case of an adaptive threshold price. Such a rule sets a lower threshold for low valuation consumers thus enabling a transaction that would not take place in the case of a fixed threshold, which is set equal for all buyers. In a field experiment, we find consistent results: Seller profit and sales are highest for the application of an adaptive threshold price policy which is revealed to consumers. Further, satisfaction was higher in this case than for a fixed threshold price.

From a research perspective, a primary contribution of this work is the comprehensive evaluation of an IT-enabled price discrimination strategy. Electronic markets, with their ability to track and evaluate every buyer-seller interaction, allow online retailers to deploy a much more fine-grained pricing strategy than traditional retailers. This offers researchers a venue to bring general principles of price discrimination into specific contexts. While researchers (Acquisti & Varian 2005) have recognized this potential, very few studies to date focus on providing online firms prescriptive guidance in relation to price discrimination and evaluating the overall effect on the buyer and seller. To our knowledge such an effort has also never been evaluated with respect to the impact of price discrimination strategies on customers. Our work is a first step in providing such a comprehensive analysis.

Our results have important implications for sellers applying dynamic pricing policies in NYOP markets: First, as expected, the application of an adaptive threshold price increases profits. Since offers can be interpreted as signals in a market with adaptive threshold prices, sellers can react accordingly, leading to faster agreements. This also leads to diminishing delay costs and hence an adaptive threshold price seems especially suitable in markets with high bargaining costs. Further, the results suggest it is imperative to announce the rules of the game as outcomes can change significantly when the buyer needs to learn the rules by playing the game.

Second, and perhaps more interestingly, dynamic pricing policies which allow customers to participate in the pricing process apparently do not have such negative effects on price perceptions as anecdotal evidence from the domain of posted prices suggests. Hence, the participative nature of dynamic pricing mechanisms mitigates the negative perceptions of price discrimination. User participation has been reported to have a significant positive impact on user satisfaction in other domains as well, see McKeen, Guimaraes and Wetherbe (1994) for a survey on user participation and user involvement. Further, the increased efficiency of adaptive thresholds increases the percentage of purchases and in turn increases consumer surplus and welfare, having a positive effect on satisfaction.

Third, sellers can apply the rules for setting optimal threshold prices derived in our paper for their pricing algorithms. One could think of an enhanced negotiation system for eBay's Best Offer. This feature could substantially increase sellers' profit, eventually consumer surplus and finally total welfare. The field experiment and its results demonstrate the potential of bargaining models that get implemented in software systems and thus the potential of IT enabled pricing systems.

Our study has a few limitations that provide avenues for future research: Specifically we cannot test for long-run effects within the scope of our study. Our result, that adaptive pricing increases consumer satisfaction, might be only a short-term effect and the increase in satisfaction could by a byproduct of the experimental setting combined with the lack of feedback to the consumers on the difference in outcomes across consumers. We do not believe so, since price discrimination in auction-like negotiations is typically accepted as fair since the allocation of rewards on the basis of individual contributions to an exchange relationship is perceived as fair (see e.g., Spiekermann 2006). However, it would be interesting to test for long-term effects in future work.

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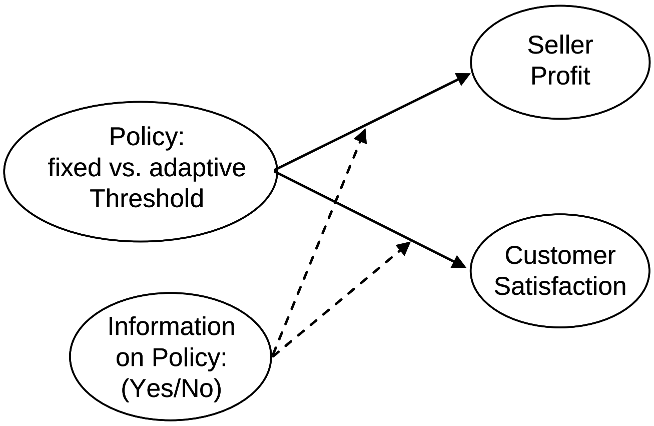

Figure 1. Research Model

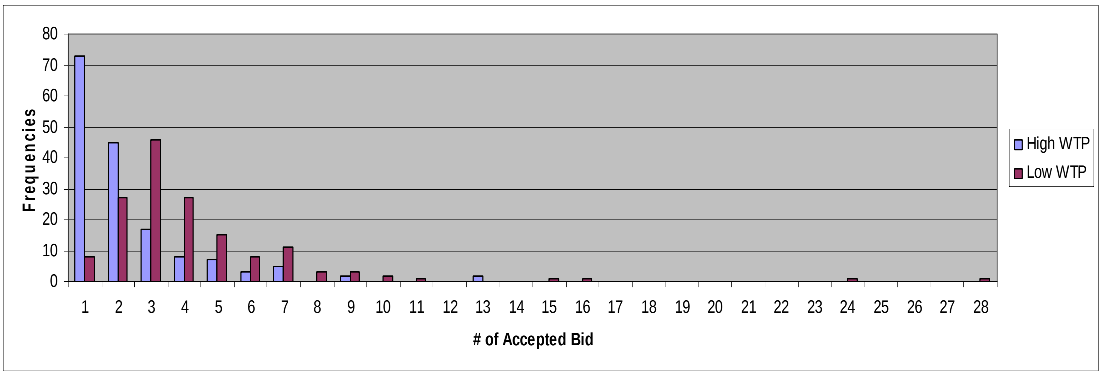

Figure 2. Separation of Segments by Number of Offers

Figure 3. Mailing and Website for NYOP sales

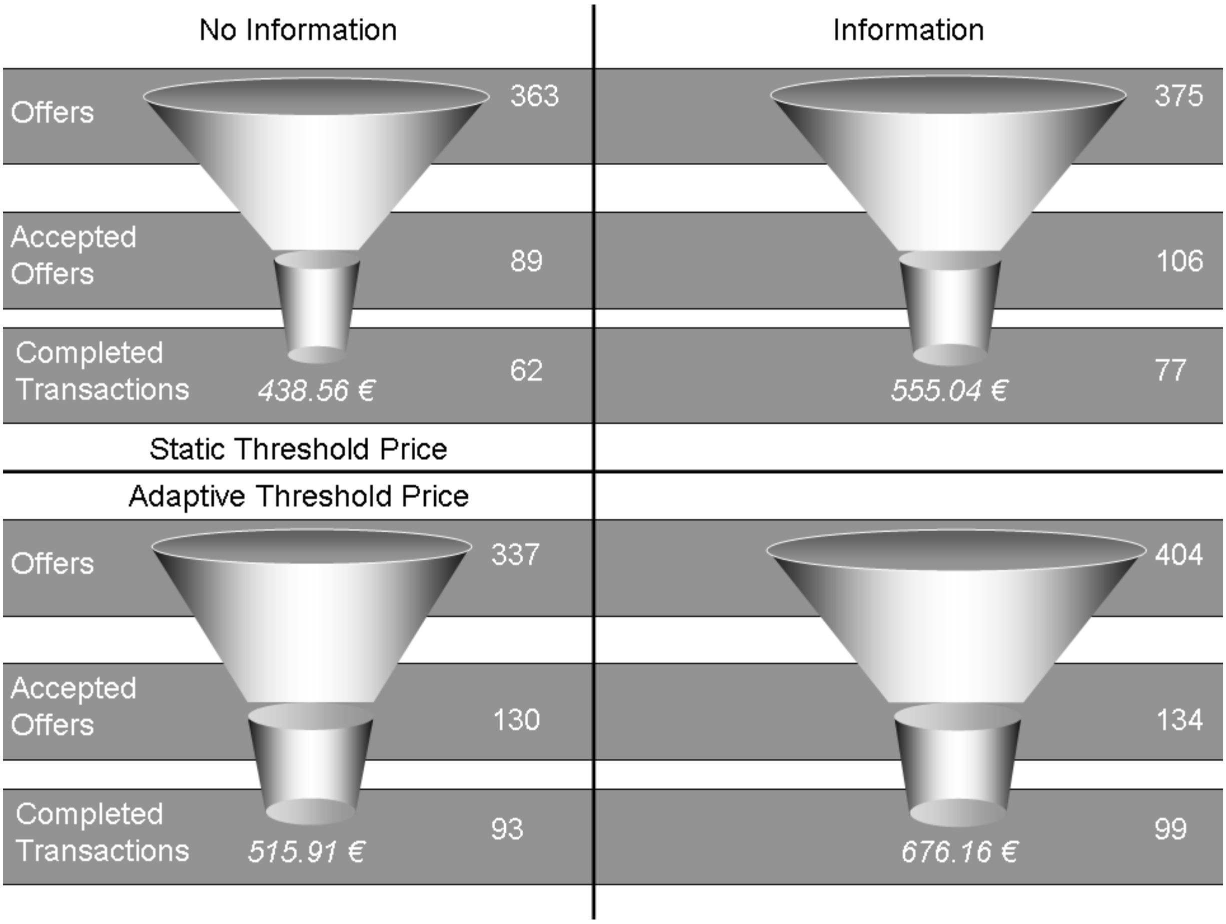

Figure 4. Conversion Funnel starting with Submitted Offers and ending with Profit

Offer No.	*1*	*2*	*3*	*4*	*5*
Discount δ_S	1	0.8	0.64	0.51	0.41
Profit Seg1 in $	0	**21.62**			
Profit Seg2 in $	0	0	0	0	**5.61**
Offers* by WTP_1 in $	27.81	**47.03**	(60.31)	(69.48)	(75.82)
Offers* by WTP_2 in $	12.81	20.90	26.80	30.88	**33.70**

Table 1. Numerical Example: Optimal Offers in an NYOP Market with Fixed Threshold Price

Round j	*1*	*2*	*3*	*4*	*5*	*6*
Offer p in $	127.16	132.30	136.24*	139.26	141.58	143.37
Indifference Valuation σ_j in $	80.90	96.86	109.04	118.36	125.49	130.96
Trade (0/1)	0	0	1			
Discount $\delta_S^{(j-1)}=\delta_B^{(j-1)}$	1	0.9	0.81	0.73	0.66	0.59
Consumer Surplus in $	22.84	15.93	11.15	7.83	5.53	3.92
Profit in $	27.16	29.06	29.35*	28.61	27.28	25.06

Table 2. Numerical Example: Offering Behavior in the Game with One-sided Uncertainty

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

Table 3. Experimental Setup

Threshold Price	*Info*	*Measured Std. Profit*	*Measured Std. CS*	*Measured Std. Welfare*	*Accepted Offers*	*Satis-faction*
1 Fixed	No Info	47.18 %	18.32 %	65.50 %	78.79 %	3.43
2 Fixed	Info	45.41 %	20.66 %	66.07 %	74.04 %	3.56
3 Adaptive	No Info	42.26 %	20.93 %	63.19 %	82.14 %	3.66
4 Adaptive	Info	51.60 %	20.48 %	72.08 %	88.41 %	3.71
F-Test (p-value)		4.77 (0.00)	1.31 (0.27)	2.82 (0.04)	6.87 (0.00)	1.43 (.23)

Table 4. Results of Laboratory Experiment

Threshold Price	*Info*	*Revenue in EUR*	*Of-fers*	*Sales*	*Sales (compared to market 2)*	*Profit in EUR (assuming costs=8 EUR)*	*Profit (compared to market 2)*
1 Fixed	No Info	934.56	363	62	-19.48 %	438.56	-20.99 %
2 Fixed	Info	1171.04	375	77	±0 %	555.04	±0 %
3 Adaptive	No Info	1259.91	337	93	+20.78 %	515.91	-7.05 %
4 Adaptive	Info	1468.16	404	99	+28.57 %	676.16	21.82 %

Table 5. Results of Field Experiment

	Threshold Price	*Info*	*Mean Process Satisfaction (Std.Dev.)*	*Mean Outcome Satisfaction (Std.Dev.)*	*Number of Observa-tions*
1	Fixed	No Info	4.29 (2.25)	4.07 (2.26)	123
2	Fixed	Info	4.30 (2.14)	4.02 (2.18)	162
3	Adaptive	No Info	4.32 (1.99)	4.01 (1.96)	155
4	Adaptive	Info	4.37 (1.99)	4.11 (2.12)	166

Table 6. Measured Satisfaction in Field Experiment

Appendix A.1: Optimal Offers for 2-offer-case for Market with fixed Threshold Price

A buyer who can make a maximum of two offers maximizes the expected consumer surplus:

$$\max_{p_0, p_1} ECS_0 = \frac{1}{UB - LB}\left[(WTP - p_0)\cdot\left(p_0 - LB\right) + \delta_B{}^1 (WTP - p_1)\cdot\left(p_1 - p_0\right)\right]. \qquad \textbf{(A1)}$$

The (unrestricted) optimization of equation (A1) for the two-offer model results in the following equations for the optimal first and second offers:

$$\frac{d\,ECS_0}{d\,p_0} = WTP - 2p_0 + LB - \delta_B{}^1 (WTP - p_1) \overset{!}{=} 0 \Rightarrow 2p_0 = WTP + LB - \delta_B{}^1 (WTP - p_1)$$

$$\frac{dECS_0}{d\,p_1} = \delta_B{}^1 (WTP - 2p_1 + p_0) \overset{!}{=} 0 \Rightarrow p_1 = \frac{WTP + p_0}{2}$$

Mutual insertion yields for the optimal first and second offer:

$$p_0 = \frac{WTP\left(1 - \frac{1}{2}\delta_B\right) + LB}{\left(2 - \frac{1}{2}\delta_B\right)}, \quad p_1 = \frac{WTP\left(3 - \delta_B\right) + LB}{\left(4 - \delta_B\right)}$$

The model can be generalized to the n-offer case where the offers p_0 to p_n are given by the following equations:

$$p_0 = \frac{LB + WTP - \delta_B\left(WTP - p_1\right)}{2}$$

$$p_j = \frac{1}{2}p_{j-1} + \frac{1}{2}\delta_B p_{j+1} + \frac{WTP\cdot(1-\delta_B)}{2} \qquad \text{for } 0<j<n$$

$$p_n = \frac{p_{n-1} + WTP}{2}.$$

It can also be shown that the model converges since p_0 monotonically decreases and p_n monotonically increases with increasing n and p_0 and p_n are bounded.

Appendix A.2: Seller's Decision in Terms of Offer Acceptance

We want to show that any seller with valuation lower than *s* strictly prefers to accept the offer p_j now instead of waiting for better offers in the future if a seller with valuation s is willing to accept the offer.

Define *V(s)* to be the equilibrium payoff at time *j+1* of a seller with valuation s and let *Q(s)* be the discounted probability of a trade for the seller *s*. Suppose a seller with valuation *s* chooses to accept a offer p_j, then $p_j - s \geq \delta_S V(s)$ must hold.

Now consider a seller with a valuation $s' < s$. We want to show that a seller with valuation *s'* is also better off to accept the offer p_j now and thus $p_j - s' \geq \delta_S V(s')$. The seller with valuation *s* imitates *s'* only if the expected payoff is at least as high as the payoff he expects when he is following his own equilibrium behavior. Thus:

$$V(s) \geq V(s') - Q(s') \cdot (s - s')$$

and since $Q(s') \leq 1$

$$\begin{aligned}
&V(s) \geq V(s') - Q(s') \cdot (s - s') \geq V(s') - s + s' \\
&\Leftrightarrow p_j - s \geq \delta_S (V(s') - s + s') \\
&p_j \geq \delta_S V(s') + s(1 - \delta_S) + \delta_S s'
\end{aligned}$$

since $s' \leq s(1-\delta_S) + \delta_S s'$

$$p_j \geq \delta_S V(s') + s'$$

$$p_j - s' \geq \delta_S V(s') \qquad \text{q.e.d.}$$

Intuitively, it is clear that a seller with valuation *s'* (remember $s' < s$) loses more money due to the discount factor than a seller with valuation *s* and thus the seller with valuation *s'* will always accept an offer if a seller with valuation *s* is willing to accept the offer.

Appendix A.3: Behavior in Markets with n and infinite Offers and one-sided Uncertainty

The equilibrium is described as a collection of functions $\left\{p_j(\cdot),\beta_j(\cdot),\sigma_j(\cdot),\mu_j(\cdot)\right\}_{j=0}^{\infty}$,

where $\mu_j(\cdot)$ is a probability distribution representing the seller's conjectures about the buyer's valuation for the events when the buyer's offer is not in the range of the equilibrium offer schedule p_j.[2] The solution strategy for this bargaining model is to reduce the two-sided uncertainty problem (seller's valuation, buyer's *WTP*) to a case with one-sided uncertainty where the buyer's *WTP* is known. Subsequently, the two-sided uncertainty case is solved.

For the one-sided case the seller knows the buyer's valuation *WTP*, but the buyer only knows that the seller's valuation is uniformly distributed on [*LB*, *UB*].[3] The buyer chooses an offer that maximizes the present value of current and future surplus, given her knowledge of the seller's valuation and subject to the constraint that the seller will accept the offer only if his valuation is sufficiently low so that the seller is better off accepting now than waiting for higher offers in the future. An offer that is rejected provides learning; σ_{j-1} is then used as a new lower bound of the distribution assumption applying Bayes' rule. With *i* periods remaining in the *n*-stage bargaining game, define *j* to be *n+1-i*, so the buyers chooses to maximize her expected gain u(WTP,σ_{j-1}) given the seller's valuation is uniformly distributed on [σ_{j-1}, *UB*]:

$$u_j(WTP,\sigma_{j-1}) = \max_p \frac{1}{UB-b_{j-1}}\left[(WTP-p)\cdot(\sigma_j-\sigma_{j-1})+\delta_B(UB-\sigma_j)u_{j+1}(WTP,\sigma_j)\right]$$

such that

$$p_j-\sigma_j=\delta_s(p_{j+1}-\sigma_j),$$

[2] A player could leave the equilibrium path with updating of beliefs not being possible. Cramton (1984) shows how such conjectures should be constructed to support a very similar equilibrium.

[3] We can safely assume that $WTP\geq LB$, since any buyer with $LB>WTP$ would not enter negotiations.

where σ_j is the indifference valuation in j.

This yields the following function for the buyer's optimal offering behavior and the seller's cutoff valuations:

$$p_j(WTP, \sigma_{j-1}) = \frac{(1-\delta_S + \delta_S c_{j+1})^2}{2\cdot(1-\delta_S + \delta_S c_{j+1} - \frac{1}{2}\delta_B c_{j+1})} \cdot (\sigma_{j-1} - WTP) + WTP$$

$$\sigma_j = \frac{(1-\delta_S + \delta_S c_{j+1})}{2\cdot(1-\delta_S + \delta_S c_{j+1} - \frac{1}{2}\delta_B c_{j+1})} \cdot (\sigma_{j-1} - WTP) + WTP$$

with $c_n = \frac{1}{2};\ for\ i > 1: c_j = \frac{(1-\delta_S + \delta_S c_{j+1})^2}{2(1-\delta_S + \delta_S c_{j+1}) - \delta_B c_{j+1}}$.

The proof is by induction on n. With one period remaining, the buyer wishes to choose p according to the following program:

$$u_n(WTP, \sigma_{n-1}) = \max_p \frac{1}{UB - \sigma_{n-1}}\left[(WTP - p)\cdot(p - \sigma_{n-1})\right] = \max_p \frac{pWTP - p^2 - \sigma_{n-1}WTP + p\sigma_{n-1}}{UB - \sigma_{n-1}}$$

$$\frac{du_n(WTP, \sigma_{n-1})}{dp}$$

$$0 \overset{!}{=} WTP - 2p + \sigma_{n-1}$$

$$p = \frac{WTP + \sigma_{n-1}}{2}$$

so

$$u_n(WTP, \sigma_{n-1}) = \frac{1}{UB - \sigma_{n-1}}\left[(WTP - \frac{WTP + \sigma_{n-1}}{2})\cdot(\frac{WTP + \sigma_{n-1}}{2} - \sigma_{n-1})\right]$$

$$= \frac{(WTP - \sigma_{n-1})^2}{4(UB - \sigma_{n-1})}$$

With i periods remaining, the buyer's expected consumer surplus is given by

$$u_j(WTP, \sigma_{j-1}) = \max_p \frac{1}{UB - \sigma_{j-1}}\left[(WTP - p)\cdot(\sigma_j - \sigma_{j-1}) + \delta_B(UB - \sigma_j)u_{j+1}(WTP, \sigma_j)\right]$$

Assume by the induction hypothesis that

$$u_{j+1}(WTP,\sigma_j)=\frac{1}{2}c_{j+1}\frac{(WTP-\sigma_j)^2}{UB-\sigma_j}$$
$$p_{j+1}(WTP,\sigma_j)=c_{j+1}(\sigma_j-WTP)+WTP$$

with $c_n=\frac{1}{2};\ for\ i>1: c_j=\frac{(1-\delta_S+\delta_S c_{j+1})^2}{2(1-\delta_S+\delta_S c_{j+1})-\delta_B c_{j+1}}$

then

$$\begin{aligned}&p=\sigma_j(1-\delta_S)+\delta_S(c_{j+1}(\sigma_j-WTP)+WTP)\\&\Leftrightarrow p=(1-\delta_S+\delta_S c_{j+1})(\sigma_j-WTP)+WTP\end{aligned} \qquad \textbf{(A2)}$$

Substituting yields **(A3)**

$$\begin{aligned}&u_j(WTP,\sigma_{j-1})=\\&\max_{\sigma_j}\frac{1}{UB-\sigma_{j-1}}\left[(WTP-(1-\delta_S)\sigma_j-\delta_S\left[c_{j+1}(\sigma_j-WTP)+WTP\right])\cdot(\sigma_j-\sigma_{j-1})+\delta_B\frac{1}{2}c_{j+1}(WTP-\sigma_j)^2\right]\\&=\max_{\sigma_j}\frac{1}{UB-\sigma_{j-1}}\left[(WTP(1+\delta_S c_{j+1}-\delta_S)-(1-\delta_S+\delta_S c_{j+1})\sigma_j)\cdot(\sigma_j-\sigma_{j-1})+\delta_B\frac{1}{2}c_{j+1}(WTP-\sigma_j)^2\right]\\&\frac{du_j(WTP,\sigma_{j-1})}{d\sigma_j}=WTP(1+\delta_S c_{j+1}-\delta_S)-2\sigma_j(1-\delta_S+\delta_S c_{j+1})+(1-\delta_S+\delta_S c_{j+1})\sigma_{j-1}-2\delta_B\frac{1}{2}c_{j+1}(WTP-\sigma_j)\overset{!}{=}0\end{aligned}$$

which has an unique maximum when

$$2\sigma_j(1-\delta_S+\delta_S c_{j+1}-\delta_B\frac{1}{2}c_{j+1})=WTP(1+\delta_S c_{j+1}-\delta_S-2\delta_B\frac{1}{2}c_{j+1})+(1-\delta_S+\delta_S c_{j+1})\sigma_{j-1}$$

and for strict concavity of u when $c_{j+1}(\delta_B-\delta_S)+\delta_S\le 1$

which is clearly satisfied since $0<c_{j+1},\delta_B,\delta_S<1$

$$\begin{aligned}&\sigma_j=\frac{WTP(1+\delta_S c_{j+1}-\delta_S-\delta_B c_{j+1})+\sigma_{j-1}(1-\delta_S+\delta_S c_{j+1})}{2\cdot(1-\delta_S+\delta_S c_{j+1}-\frac{1}{2}\delta_B c_{j+1})}\\&\sigma_j=\frac{(1-\delta_S+\delta_S c_{j+1})}{2\cdot(1-\delta_S+\delta_S c_{j+1}-\frac{1}{2}\delta_B c_{j+1})}\cdot(\sigma_{j-1}-WTP)+WTP\end{aligned} \qquad \textbf{(A4)}$$

Then by substituting (A4) into (A2) and (A3) we get

$$p_j(WTP,\sigma_{j-1}) = \frac{(1-\delta_S+\delta_S c_{j+1})^2}{2\cdot(1-\delta_S+\delta_S c_{j+1}-\frac{1}{2}\delta_B c_{j+1})}\cdot(\sigma_{j-1}-WTP)+WTP \qquad \text{q.e.d.}$$

and

$$u_j(WTP,\sigma_{j-1}) = \frac{1}{2}\frac{(1-\delta_S+\delta_S c_{j+1})^2}{2\cdot(1-\delta_S+\delta_S c_{j+1}-\frac{1}{2}\delta_B c_{j+1})}\frac{(WTP-\sigma_j)^2}{UB-\sigma_j} = \frac{1}{2}c_j\frac{(WTP-\sigma_j)^2}{UB-\sigma_j} \qquad \text{q.e.d.}$$

as required by the induction hypothesis.

Fudenberg, Levine and Tirole (1985) show that the latter-described equilibrium is a unique equilibrium in the infinite-horizon game. The buyer's equilibrium offer p_j, the seller's indifference valuation σ_j and the expected consumer surplus u_j for period j in the infinite horizon game is given by:

$$p_j = c\cdot(LB-WTP)\cdot d^{j-1}+WTP$$
$$\sigma_j = (LB-WTP)\cdot d^{j-1}+WTP$$
$$u = \frac{1}{2}c\cdot\frac{(LB-WTP)^2}{UB-LB}$$

where

$$c = \frac{(1-\delta_S+\delta_S c)^2}{2(1-\delta_S+\delta_S c)-\delta_B c}$$
$$d = \frac{1}{\delta_B}(1-\sqrt{1-\delta_B}) = \frac{c}{1-\delta_S+\delta_S c}$$

Appendix A.4: Behavior in Markets with infinite Offers and two-sided Uncertainty

In the case of two-sided uncertainty the assumption of a known buyer's valuation *WTP* is relaxed. The seller only assesses the buyer's valuation to be given by the distribution F(*WTP*) with a positive density f(*WTP*) on [WTP_{low}, WTP_{high}]. In this case, the buyer must be concerned about the information that her offer reveals to the seller, and the seller must interpret this offer as an indication of the buyer's true willingness-to-pay carefully.

The separating equilibrium that distinguishes high valuation buyers from low valuation buyers is achieved through discounting over time. The class of high valuation buyers is described by a valuation that is higher than a certain cutoff value β_j in j: $WTP>\beta_j$. To determine the equilibrium we must follow an iterative procedure: First, compute the offer sequence and indifference values that result after the buyer's willingness-to-pay has been revealed according to the case with one-sided uncertainty. Determine the offer sequence for the buyer with the highest willingness-to-pay $\text{WTP}=\text{WTP}_{high}$ and her optimal number of offers.

Second, stepwise decrease WTP from WTP_{high} by some small amount $\Delta\text{WTP}>0$ so that the buyer WTP is indifferent between offering p(WTP) and p(WTP-ΔWTP). With decreasing WTP there will come a point β_1 at which no seller will accept the offer $p(\beta_1)$. All buyers with $\text{WTP}<\beta_1$ will thereby offer too low and in this way signal their low willingness-to-pay. For a buyer with willingness-to-pay $\text{WTP}>\beta_1$ the value of the subsequent offers can easily be calculated since she already revealed her private information. All buyers with $\text{WTP}<\beta_1$ will wait for subsequent rounds to reveal their true willingness-to-pay. For these buyers we go back to the first step and determine the offer sequence and the optimal number of offers for a buyer with willingness-to-pay $\text{WTP}=\beta_1$. This process is repeated until the offers of all buyers $\text{WTP}\in[\text{WTP}_{low}, \text{WTP}_{high}]$ are determined. By this procedure the NYOP seller has disjunctive classes of buyers that reveal their true willingness-to-pay in the first round, e.g. buyers with $\text{WTP}\in(\beta_1, \text{WTP}_{high}]$, in the second round, e.g. buyers with $\text{WTP}\in(\beta_2, \beta_1]$, and so on and so forth.

In equilibrium, high valuation buyers reveal their private information by submitting an offer that is strictly increasing in *WTP*. The seller can then infer the buyer's *WTP* by inverting the offer schedule p(*WTP*) by calculating $WTP=p^{-1}(p)$. Proof: Suppose buyer *WTP* chooses pretending to be buyer WTP_{shade} by offering the offer p. This means she is trying to imitate the behavior of a low valuation buyer although she is having actually a higher valuation of *WTP* for the product offered. Then her expected consumer surplus is determined by the first offer utilizing *LB* as starting point plus all other discounted surpluses that make use of the belief being updated by a rejection in the preceding offering round:

$$u_B(WTP_{shade}, p) = \frac{1}{UB-LB} \cdot \left[(\sigma - LB)(WTP - p) + \sum_{j=1}^{\infty} \delta_B^n (\sigma_j - \sigma_{j-1})(WTP - p_j) \right] \quad \textbf{(A5)}$$

where the future offers and indifference valuations are given by

$$p_j = c \cdot (\sigma - WTP_{shade}) \cdot d^{j-1} + WTP_{shade}$$
$$\sigma_j = (\sigma - WTP_{shade}) \cdot d^j + WTP_{shade}$$

with

$$\sigma = \frac{(p - WTP_{shade})}{1 - \delta_S + \delta_S c} + WTP_{shade}$$

Thus,

$$\sigma_j - \sigma_{j-1} = (\sigma - WTP_{shade}) \cdot d^j + WTP_{shade} - \left[(\sigma - WTP_{shade}) \cdot d^{j-1} + WTP_{shade} \right]$$
$$= (\sigma - WTP_{shade}) \cdot d^{j-1} \cdot (d-1)$$

$$WTP - p_j = WTP - (c \cdot (\sigma - WTP_{shade}) \cdot d^{j-1} + WTP_{shade})$$
$$= WTP - WTP_{shade} - c \cdot (\sigma - WTP_{shade}) \cdot d^{j-1}$$

so that

$$(\sigma_j - \sigma_{j-1})(WTP - p_j)$$
$$= (\sigma - WTP_{shade}) \cdot d^{j-1} \cdot (d-1)(WTP - WTP_{shade} - c \cdot (\sigma - WTP_{shade}) \cdot d^{j-1}) \quad \textbf{(A6)}$$
$$= (\sigma - WTP_{shade}) \cdot (d-1) \cdot \left[(WTP - WTP_{shade}) \cdot d^{j-1} - c \cdot (\sigma - WTP_{shade}) \cdot (d^2)^{j-1} \right]$$

Substituting into (A5) yields

$$u_B(WTP_{shade}, p) = \frac{1}{UB-LB} \cdot \left[(\sigma - LB)(WTP - p) + \sum_{j=1}^{\infty} \delta_B^j (\sigma_j - \sigma_{j-1})(WTP - p_j) \right]$$
$$= \frac{1}{UB-LB} \cdot \left[(\sigma - LB)(WTP - p) + \sum_{j=1}^{\infty} \delta_B^j \cdot (\sigma - WTP_{shade}) \cdot (d-1) \cdot \left[(WTP - WTP_{shade}) \cdot d^{j-1} - c \cdot (\sigma - WTP_{shade}) \cdot (d^2)^{j-1} \right] \right]$$
$$= \frac{1}{UB-LB} \cdot \left[(\sigma - LB)(WTP - p) + (\sigma - WTP_{shade}) \cdot (d-1) \cdot \sum_{j=1}^{\infty} \delta_B^j \left[(WTP - WTP_{shade}) \cdot d^{j-1} - c \cdot (\sigma - WTP_{shade}) \cdot (d^2)^{j-1} \right] \right]$$

Performing the summation for the geometric progression yields

(Remember: $\sum_{j=0}^{\infty} q^j = \frac{1}{1-q}$ for q<1)

$$\sum_{j=1}^{\infty} \delta_B^j \left[(WTP - WTP_{shade}) \cdot d^{j-1} - c \cdot (\sigma - WTP_{shade}) \cdot (d^2)^{j-1} \right]$$
$$= \delta_B \cdot \sum_{j=1}^{\infty} \left[(WTP - WTP_{shade}) \cdot (\delta_B d)^{j-1} - c \cdot (\sigma - WTP_{shade}) \cdot (d^2 \delta_B)^{j-1} \right]$$
$$= \delta_B \cdot \sum_{j=0}^{\infty} \left[(WTP - WTP_{shade}) \cdot (\delta_B d)^{j} - c \cdot (\sigma - WTP_{shade}) \cdot (d^2 \delta_B)^{j} \right]$$
$$= \delta_B \cdot \left[(WTP - WTP_{shade}) \cdot \frac{1}{1-\delta_B d} - c \cdot (\sigma - WTP_{shade}) \cdot \frac{1}{1-d^2 \delta_B} \right]$$

and thus

$$u_B(WTP_{shade}, p)$$
$$= \frac{1}{UB-LB} \cdot \left[(\sigma - LB)(WTP - p) + (\sigma - WTP_{shade}) \cdot (d-1) \cdot \delta_B \cdot \left[(WTP - WTP_{shade}) \cdot \frac{1}{1-\delta_B d} - c \cdot (\sigma - WTP_{shade}) \cdot \frac{1}{1-d^2 \delta_B} \right] \right]$$

It can be shown that $(d-1)/(1-\delta_B d^2)=-0.5$ and $(d-1)/(1-\delta_B d)=-d$, so that we can simplify to

$$u_B(WTP_{shade}, p)$$
$$= \frac{1}{UB-LB} \cdot \left[(\sigma - LB)(WTP - p) + \delta_B \cdot \left[\frac{1}{2} c \cdot (\sigma - WTP_{shade})^2 - d \cdot (WTP - WTP_{shade}) \cdot (\sigma - WTP_{shade}) \right] \right]$$

Differentiating the consumer surplus u_B with respect to p yields the first order condition

$$0 \overset{!}{=} LB - \sigma + \frac{d\sigma}{dp} \cdot (WTP - p) +$$
$$\delta_B \cdot \left[c \cdot (\sigma - WTP_{shade})(\frac{d\sigma}{dp} - \frac{dWTP_{shade}}{dp}) - d \cdot \left[(WTP - WTP_{shade})(\frac{d\sigma}{dp} - \frac{dWTP_{shade}}{dp}) - \frac{dWTP_{shade}}{dp} \cdot (\sigma - WTP_{shade}) \right] \right]$$

At this point, the buyer can calculate her optimal offer p^* by substituting WTP_{shade}=WTP. This means the buyer has the same incentives to offer p^* as to shade her offers. This also implies

$$\frac{dWTP_{shade}}{dp}=\frac{dWTP}{dp},\ \frac{d\sigma}{dp}=\frac{1-\frac{dWTP}{dp}}{w}+\frac{dWTP}{dp} \text{ and } \sigma=\frac{p-WTP}{1-\delta_S+\delta_S c}+WTP=\frac{p-WTP}{w}+WTP$$

and results in the first order differential equation

$$0\overset{!}{=}LB-\sigma+\frac{d\sigma}{dp}\cdot(WTP-p)+\delta_B\cdot\left[c\cdot(\sigma-WTP)(\frac{d\sigma}{dp}-\frac{dWTP}{dp})+d\cdot\left(\frac{dWTP}{dp}\right)\cdot(\sigma-WTP)\right]$$

$$=LB-\frac{p-WTP}{w}-WTP+\left(\frac{1-\frac{dWTP}{dp}}{w}+\frac{dWTP}{dp}\right)\cdot(WTP-p)+\delta_B\cdot\left[c\cdot(\frac{p-WTP}{w})(\frac{1-\frac{dWTP}{dp}}{w})+d\cdot\left(\frac{dWTP}{dp}\right)\cdot(\frac{p-WTP}{w})\right]$$

$$=w^2(LB-WTP)-w(p-WTP)+\left[w\left(1-\frac{dWTP}{dp}\right)+w^2\left(\frac{dWTP}{dp}\right)\right]\cdot(WTP-p)+\delta_B\cdot\left[c\cdot(p-WTP)(1-\frac{dWTP}{dp})+d\cdot w\left(\frac{dWTP}{dp}\right)\cdot(p-WTP)\right]$$

$$=w^2(LB-WTP)+\left[2w+w^2\left(\frac{dWTP}{dp}\right)-w\left(\frac{dWTP}{dp}\right)\right]\cdot(WTP-p)+\delta_B\cdot\left[c\cdot(p-WTP)(1-\frac{dWTP}{dp})+d\cdot w\left(\frac{dWTP}{dp}\right)\cdot(p-WTP)\right]\cdot\frac{dp}{dWTP}$$

$$=w^2(LB-WTP)\cdot\frac{dp}{dWTP}+\left(2w\cdot\frac{dp}{dWTP}+w^2-w\right)\cdot(WTP-p)+\delta_B\cdot\left[c\cdot(p-WTP)(\frac{dp}{dWTP}-1)+d\cdot w\cdot(p-WTP)\right]$$

$$=w^2(LB-WTP)\cdot\frac{dp}{dWTP}+(p-WTP)\left[w-w^2-2w\cdot\frac{dp}{dWTP}+\delta_B\cdot c\cdot(\frac{dp}{dWTP}-1)+\delta_B\cdot d\cdot w\right]$$

which can be solved to yield p(WTP) which is typically lower than her optimal offer in the case where her valuation is known.

Appendix B: Experimental Instructions

Information given to participants

Surf to the following URL: … Please do not use the Back-Button on the navigation bar. It is not allowed to open any other program or window during the experimental session.

Once the website is loaded, you can log into the market platform using username and password from the dispensed cards. You are a prospective buyer who is offering for 12 hypothetical products. For these products you obtain information about the interval of the seller's costs given by a lower and an upper bound. Moreover, you suffer from bargaining costs in form of a percentage discount of your payoff. The seller faces opportunity costs as well and is therefore interested in a fast agreement. However, the seller will not sell below his costs and thus the information on the distribution of the seller's cost is important.

Furthermore, you see the number of offers you already submitted on the product and the amount of your last offer. For all products you have a resale value. Other buyers can have different resale values for the same product. Hereby, other buyers can value the same product higher or lower than you do. Overall, there are two different resale values for every product and you are randomly assigned to one of these. You also obtain information on the second resale value of the given product. However, the seller is aware of these two segments by thorough marketing research and tries to maximize his profit. The sequence of products you are trying to buy is different for all buyers.

Explaining the mechanism

The seller applies a mechanism called NYOP. This means that you as buyer make an offer indicating your willingness-to-pay. If you offer surpasses a secret threshold price set by the seller, you buy the product for the price denoted by your offer. If you offer is below the threshold price, it will be rejected. You can place another offer after a rejection. You can repeat the offering until you are successful or you are not interested anymore. Note that you do not compete with other buyers; you solely have to surpass the secret threshold price with your offer.

How to earn money

Your payoff in the game is the difference between your resale value and a successful offer. If you stop offering for a product, your payoff for this product is zero. If you offer more than your resale value, you realize negative profit. The payoff depends additionally on the number of offers you placed to get the product. Depending on the level of a discount factor, your payoff is discounted for every offer. There are two different discount factors: Either your payoff is diminished by 5% per offer or by 25% per offer. If you surpass the threshold price with your first offer, your payoff is always 100%. The seller suffers from bargaining costs as well. The discount factor is the same for both, seller and buyer for a given product. The closer you offer to the threshold price, the higher your profit. The less offers you need, the higher your profit.

Market 1 and Market 3 do not obtain any further information here.

Market 2: For every product the threshold price is static and already set and thus does not change. Remember that the seller does not sell below his costs.

Market 4: The secret threshold price is not static but changes due to your offering behavior. You actually haggle with the seller. It is therefore possible that an offer that was rejected in early offer rounds gets accepted later because the seller realized that you really have a low willingness-to-pay. The seller does not learn anything across products. The game starts anew with a new product. Do not forget that the seller does not sell below his costs.

Try to maximize your profit!

We will draw lots for winners (1/3) from the participants who we will remunerate with their virtual profit multiplied with some factor. The remuneration will take place in approx. two weeks. We will inform the winners about time and location of the remuneration. Subsequent to the offering process you will have to answer a questionnaire. Please answer in all conscience.