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23. Simulative and Game-Theoretical Approaches for Strategic Behavior in Name-Your-Own-Price Markets

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Abstract

Name-Your-Own-Price is a popular interactive pricing mechanism in Electronic Commerce that 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 her willingness-to-pay for the product 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. In this paper we show how buyer and seller strategically behave in such markets and derive from the results what product classes seem suitable for sale in a Name-Your-Own-Price-channel. To address this question, we apply two different approaches - an agent-based simulation and a game theoretical approach - and illustrate thereby the advantages and disadvantages of both methods.

Keywords: Name-Your-Own-Price, Agent-based Simulation, Game Theory

Introduction

Due to lower transaction and menu costs the Internet enabled a plethora of dynamic pricing mechanisms (Bakos 1997). In the context of this paper we define the class of interactive pricing mechanisms as a subset of dynamic pricing mechanism where both, buyer and seller, interactively influence the final price by exchanging bids or messages.

Interactive pricing mechanisms have numerous advantages; mainly these mechanisms allow the seller to price discriminate. Price discrimination can yield on average higher prices and thereby increase the seller's profit. Moreover, interactive pricing mechanisms tend to increase allocation efficiency of markets since low valuation buyers who are priced out in a fixed price scenario can be served by a lower individual price in markets applying an interactive price finding (Bakos 1997).

Market places like eBay.com or Amazon apply interactive pricing mechanisms. Yet, these market places primary differ in the design of the applied pricing mechanism. Market leader eBay uses besides traditional posted price ("Buy now"-feature) a variant of the second price auction. Nevertheless, eBay recently started an additional interactive pricing format which allows buyers to send a bid to a seller, which he can accept or reject. This feature is called "Best offer" (eBay 2006).

This mechanism is closely related to the mechanism which literature (e.g. Hann and Terwiesch 2003) calls Name-Your-Own-Price (NYOP) or Reverse Pricing. NYOP was introduced in 1998 by the US-based company Priceline.com that uses this pricing mechanism for the sales of airline tickets, hotel rooms and rental cars. With revenues of \$1,123 million and a gross profit of \$401 million in 2006, Priceline indicates both the acceptance and the success of the NYOP mechanism and became a strong player in the tourism and airline industry. 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 various European low-cost airlines (e.g. Germanwings.com, LTU.com).

NYOP allows both, buyer and seller, to influence the final price. The seller can set a secret threshold price indicating the minimum price he wants to achieve. By submitting bids the buyer indicates her willingness-to-pay. The bid is accepted if it hits or surpasses the secret threshold price. The buyer's bid then denotes the final price.

In contrast to other common auction mechanisms, the price discriminating feature of NYOP is not based on the competition between buyers (or sellers in the case of reverse auctions). To close a deal, the buyer has solely to overbid the secret threshold price, whereas bids from other buyers do not have any influence on the final price or success probability. In the case of limited product capacity and high demand, products would be sold to successful bidders on base of a first-come/first-serve principle.

One of the characteristic features of NYOP is, that after the bidding process, information about neither accepted nor rejected bids is published. This leads to a very intransparent market, which allows sellers to use a NYOP channel for sales with very low prices without the cannibalization of traditional posted price sales channels. NYOP allows thereby addressing a very price sensitive buyer segment.

Finally, NYOP is suited for the simultaneous sales of large number of identical products, since a single offer has to be created. Indeed different auction sites allow so called "power" or "dutch"-auction (e.g. eBay.de or BesteAuktion.de), though these auctions lead to a uniform price for n units of the same product. This is suboptimal in terms of price discrimination. In contrast to these uniform prices, NYOP allows to charge differentiated prices for every single buyer and therefore a better extraction of consumer surplus.

Research on NYOP focused primary on bidding behavior and optimal design of NYOP mechanisms. Most of these models assume behavior of one side as exogenously given. The aim of this paper is therefore, to relax this assumption and present a model that addresses buyer's and seller's behavior simultaneously and takes strategic interaction effects into account. Thereby, we will show that Name-Your-Own-Price is not a suitable mechanism for all product classes.

We address this problem with a game theoretical approach based on insights from the domain of bargaining games and additionally with the application of an agent-based simulation. The application of two different approaches allows us to demonstrate the strengths and weaknesses of both methods.

The remainder of this paper is organized as follows: Chapter 2 introduces Name-Your-Own-Price in detail, summarizes prior research in this area and places this work into perspective. Chapter 3 describes the general setup for the game which is then solved using insights from the domain of bargaining games in chapter 4. We then show how to approach the same question with an agent-based simulation before we finally compare and discuss the results in the concluding chapter.

Name-Your-Own-Price

Mechanism Description

As interactive pricing mechanism NYOP allows both, seller and buyer to have influence on the final price of a transaction. While the seller ascertains a minimum price for the transaction by setting the secret threshold price, the buyer determines the final price by her submitted bid. If her bid surpasses or hits the secret threshold price, it denotes the agreed price of the transaction.

A seller can moreover influence the process and thereby the outcome of the pricing by choosing an adequate design for his sale. Bernhardt (2004) terms these options that can be used to modify the pricing process “design variables”. For example, the number of bids is a very important design variable as shown by Spann, Schäfers and Skiera (2004). Also the price elicitation format and the minimum increment between bids are such design variables. A detailed classification can be found in Bernhardt (2004).

In contrast to traditional auction mechanisms Name-Your-Own-Price is not based on direct price competition between buyers. For a winning bid the buyer has solely to overbid the secret threshold price. Other bidders do not have any influence on the outcome of the pricing mechanism.

Figure 1 depicts the bargaining zone in case of a successful bid: The seller faces variable costs c for the product offered. He sets the threshold price TP normally to a price above or equal to his variable costs c . This ascertains in case of a successful bid a basic rent BR which is equal to $TP - c$. Additionally, the seller realizes some surplus due to the buyer’s overbidding. This surplus is called information rent IR . The buyer however has a certain willingness-to-pay WTP and tries to minimize the information rent IR by hitting exactly the threshold price. We term the difference between a successful bid b and the willingness-to-pay WTP the consumer surplus CS .

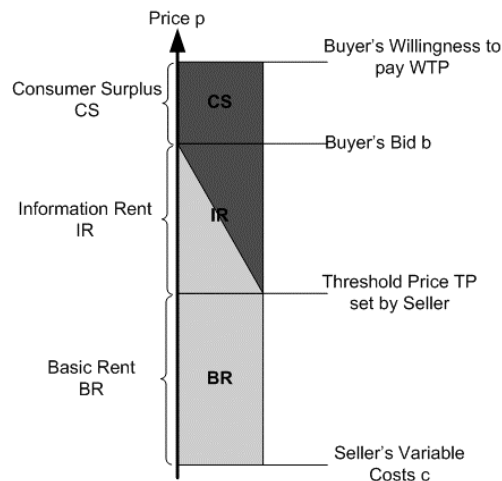


Figure 9: Zone of Bargaining in Name-Your-Own-Price

Figure 1 clarifies that buyer and seller haggle over the information rent IR . The buyer tries to minimize the overbidding while the seller wishes for significant overbidding on buyer’s side since this is the price discrimination feature of Name-Your-Own-Price.

Literature on Name-Your-Own-Price

The research on Name-Your-Own-Price has aimed at three different research goals: The first goal was to determine the optimal design for Name-Your-Own-Price, the second goal is to analyze bidding behavior in Name-Your-Own-Price markets and third, how to apply Name-Your-Own-Price optimally from an IS point of view. This paper thus combines the aim of the first two goals since we want to show how a seller should set the threshold price optimally and how buyers bid strategically.

Chernev (2003) focuses in his work on the single bid case and analyses the buyers' preferences in terms of price elicitation formats. Thereby, he examines in a laboratory experiment whether the buyers prefer to state their bid in a bidding box ("price generation") or whether they prefer to choose from a list of possible bid amounts ("price selection"). Chernev (2003) concludes that buyers prefer the price list but does not investigate further into bidding behavior.

Fay (2004) develops an analytical model for seller profit in a NYOP market under varying restrictions for the possible number of bids consumers can submit. Thereby, he compares the single bid case with a case where experienced consumers can submit multiple bids at Priceline by applying various "tricks" such as the use of different "identities" via multiple credit cards. Hann and Terwiesch (2003) analyze empirically the bidding behavior in a market with repeated bidding. They first develop a microeconomic model with utility maximizing buyers to explain bidding behavior and apply this model then on data to measure frictional costs. Terwiesch, Savin and Hann (2005) extend this model and derive how to set the threshold price optimally. Our work is related to this paper. However, our paper applies a bargaining model and a simulative approach with reinforcement learning allowing both players, buyer and seller, to behave strategically. We finally show how our framework for the single bid case can be linked to the work of Terwiesch, Savin and Hann (2005).

Spann, Skiera and Schäfers (2004) also develop a normative model for the bidding behavior and estimate with its help the willingness-to-pay of participating bidders. Moreover, the authors derive optimal bidding behavior and can finally conclude that sellers should allow multiple bidding in Name-Your-Own-Price markets.

Hinz and Spann (2007) examine the influence of information diffusion amongst buyers in Name-Your-Own-Price markets. The authors find a significant influence of the social network amongst the buyers on the success of NYOP markets and derive managerial implications for NYOP markets with information diffusion.

Hann, Hinz and Spann (2006) find that it could be beneficial for a Name-Your-Own-Price seller to apply an adaptive threshold price. This could not only increase profit and welfare but also diminish buyers' frustration which is a counter-intuitive outcome of their work. They also consider the interesting case of infinite horizon where an unlimited number of bids are allowed.

The second research stream deals with bidding behavior only. The work by Ding et al. (2005) use the single bid case to show that buyers suffer from frustration in case of a rejected bid and excitement in case of a winning bid and show that these emotional aspects can have an influence on repeated purchase. Spann and Tellis (2006) utilize Name-Your-Own-Price to show that irrational behavior has not diminished since the raise of the Internet.

The third research stream examines Name-Your-Own-Price from an IT and IS perspective: Bernhardt (2004) classifies the possible design variables for the Name-Your-Own-Price design space. Amongst multiple bidding, he also categorizes the already mentioned price elicitation format, bidding costs and waiting time between consecutive bids. Hinz and Bernhardt (2005) analyze whether a seller should use an intermediary for the sales in Name-Your-Own-Price markets or develop a proprietary software solution with high total costs of ownerships. They conclude that a solution based on a service-oriented architecture might combine the advantages of both approaches without the specific disadvantages. This scalable solution is then described in Bernhardt and Hinz (2005) in detail.

Our framework incorporates both players simultaneously and shows thereby that the buyer's estimation about the seller's cost strongly influences her strategic behavior and is thus a crucial determinant for the seller's profit in NYOP markets.

General Setup

In NYOP markets buyer and seller bargain over the price of a product which is worth c to the seller and WTP to the buyer. The buyer submits bids b and the seller can only reject or accept these bids. If a bid is accepted the buyer's bid denotes the price of the transaction. However, if the bid fails to surpass the threshold price, the buyer's ability to raise her 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. In this paper, we will focus on the case where only one bid is allowed. This variant of NYOP is applied by Priceline.com and is therefore the most relevant variant.

The seller is aware of his valuation c but only assesses the buyer's valuation to be given by the distribution $F(WTP)$ with a positive density $f(WTP)$ on $[WTP_{low}, WTP_{high}]$. The buyer is aware of her WTP but can only assess the seller's valuation given by the distribution $G(c)$ with a positive density $g(c)$ on $[LB_C, UB_C]$ and additionally assess the threshold price to be given by the distribution $TP(c)$ with a positive density $tp(c)$ on $[LB_{TP}, UB_{TP}]$. Thereby, $LB_{TP} \geq LB_C$ and $UB_{TP} \geq UB_C$ must hold since the seller would not sell below his costs. Both players are solely interested in maximizing their payoff and are assumed to be risk-neutral. The distributions and the structure of the game are common knowledge.

As an example, assume a buyer with a willingness-to-pay of 110, who assesses the seller's costs with support of $[80, 135]$ and conjectures the threshold price to be distributed between $[80, 200]$. The seller's costs are $c=90$ and the seller assess the buyer's willingness-to-pay given by $f(WTP)$ on $[90, 150]$.

As shown by Spann, Skiera and Schäfers (2004) risk-neutral buyers maximize their expected consumer surplus. In their work they also consider search costs sc which we set to 0 without the loss of generality.

$$ECS = \int_{LB_{TP}}^b (WTP - b) \cdot tp(c) dp_T - sc = (WTP - b) \cdot \frac{b - LB_{TP}}{UB_{TP} - LB_{TP}} - sc$$

With a higher bid b the buyer increases on the one hand the likelihood to surpass the threshold price but on the other hand he decreases the consumer surplus $(WTP-b)$.

To yield the optimal bid b^* we maximize ECS by differentiating with respect to p and set to 0:

$$\max ECS = \frac{dECS}{db} = \frac{1}{UB_{TP} - LB_{TP}} \cdot [(-1) \cdot (b) - LB_{TP} + (WTP - b) \cdot 1] \stackrel{!}{=} 0$$

Solving for b yields:

$$\Leftrightarrow b^* = \frac{WTP + LB_{TP}}{2}$$

The optimal bid is thus a function of the willingness-to-pay WTP and the buyer's beliefs about the lower bound of the threshold price distribution. If $UB_{TP} < WTP$ then the optimal bid is given by:

$$\Leftrightarrow b^* = \frac{UB_{TP} + LB_{TP}}{2}$$

However, we will show in this paper, that strategic behavior of seller and buyer reduces the problem to a guessing of the seller's costs.

In the following chapters, we therefore derive how a seller would infer optimal threshold prices in such a setting and how a buyer would react. From the results we can conclude that not all product classes are suitable for sales in a Reverse-Pricing-channel. We address this question with two different approaches. First, we solve the problem using insights from bargaining games and second, we run an agent-based simulation to evaluate the market outcome. Besides solving this relevant problem, we show that the outcomes are identical but that the application of both approaches can yield different insights.

Game-Theoretical Approach

The model by Spann, Skiera and Schäfers (2004) focuses on the bidding behavior of buyers in Name-Your-Own-Price and build upon the assumption of an exogenously given threshold price. In real markets however sellers would strategically take the buyers' behavior into account. The buyers in turn anticipate the seller's considerations. To model this kind of problem, game theory is a proper approach.

We model the seller's decision making in terms of setting the optimal threshold price as normal form game, i. e. both players, buyer and seller, set their strategy without knowledge of the strategy of their counterpart. Thereby, the game can be modeled as static bargaining game. As a game with two players $I = \{\text{buyer, seller}\}$, we face a limited set of possible strategies and thus the game can be depicted as a table. We assume that each player has a set of three possible strategies to outline the mechanism, before we then can extend the number of strategies arbitrarily.

In this three-strategy scenario, the seller can set the threshold price close to his variable costs, to a medium price or a high price. If the buyer hits or surpasses the threshold price, the transaction is initiated. The buyer realizes the consumer surplus as the difference between his willingness-to-pay and his bid. If the buyer's bid fails to surpass or hit the threshold price, the surplus for seller and buyer is 0.

The seller can choose one of the given three strategies: a low threshold price (L_S), a medium threshold price (M_S) and a high threshold price (H_S), whereas the buyer can bid low which would lead to high consumer surplus (H_B), bid medium (M_B) and bid high leading to a low consumer surplus (L_B). We consider only the case where the buyer's willingness-to-pay is higher than the seller's costs. Otherwise both counterparts would never reach an agreement. Overall, both players bargain over (WTP-c), thus (InformationRent+BasicRent+ConsumerSurplus) which is also called welfare. Each player's part of the welfare depends on the bargaining outcome. If the buyer bids very high, the seller realizes the larger part. If the buyer bids very low and the bid surpasses the threshold, she realizes a large part whereas the seller receives only a small part. However, if the bid is too low, both players receive a payoff of 0.

Let us assume the following numerical example: The seller's cost $c=50\$$ and the buyer's willingness-to-pay $WTP=110\$$. Thus both player haggle of $110\$-50\$=60\$$. Depending on the bargaining success these 60\$ are divided amongst buyer and seller. Table 1 shows the resulting payoff matrix in absolute values.

Table 17: Payoff matrix for the numerical example $c=50\$$ and $WTP=110\$$

| Buyer/Seller | H_S Threshold Price=100\$ | M_S Threshold Price=80\$ | L_S Threshold Price=60\$ |
|-----------------|--------------------------------|-------------------------------|-------------------------------|
| H_B Bid=60\$ | 0; 0 | 0; 0 | 50\$; 10\$ |
| M_B Bid=80\$ | 0; 0 | 30\$; 30\$ | 30\$; 30\$ |
| L_B Bid=100\$ | 10\$; 50\$ | 10\$; 50\$ | 10\$; 50\$ |

Table 2 depicts the payoff for a generalized case. W denotes the welfare ($WTP-c$) that is negotiated over, moreover $1 > A_H > A_M > A_L > 0$ and $W > 0$ must hold.

Table 18: General payoff matrix for three strategies

| Buyer/Seller | H_S High Threshold Price | M_S Medium Threshold Price | L_S Low Threshold Price |
|------------------|-------------------------------|---------------------------------|------------------------------|
| H_B Low Bid | 0; 0 | 0; 0 | $W^*(A_H; 1-A_H)$ |
| M_B Medium Bid | 0; 0 | $W^*(A_M; 1-A_M)$ | $W^*(A_M; 1-A_M)$ |
| L_B High Bid | $W^*(A_L; 1-A_L)$ | $W^*(A_L; 1-A_L)$ | $W^*(A_L; 1-A_L)$ |

We conduct now an iterative elimination of weak dominated strategies. In favour of comprehensibility we use typical values ($A_L=0.1$; $A_M=0.5$; $A_H=0.7$ und $W=1$) in Table 3.

Table 19: Initial payoff matrix of evaluated game

| Buyer/Seller | H_S High Threshold Price | M_S Medium Threshold Price | L_S Low Threshold Price |
|------------------|-------------------------------|---------------------------------|------------------------------|
| H_B Low Bid | 0; 0 | 0; 0 | 70%; 30% |
| M_B Medium Bid | 0; 0 | 50%; 50% | 50%; 50% |
| L_B High Bid | 10%; 90% | 10%; 90% | 10%; 90% |

Looking at the payoff matrix, we observe that the seller's strategy H_S is weakly dominated by M_S since he would prefer a payoff of 50% compared to 0 which is the outcome when the buyer picks strategy M_B . The outcome of the remaining strategies stays the same. A seller would therefore never play strategy H_S (high threshold price) since he has better strategies that result in favorable outcomes. We therefore eliminate this column and result in Table 4.

Table 20: Payoff matrix after elimination of strategy H_S

| Buyer/Seller | M_S Medium Threshold Price | L_S Low Threshold Price |
|------------------|---------------------------------|------------------------------|
| H_B Low Bid | 0; 0 | 70%; 30% |
| M_B Medium Bid | 50%; 50% | 50%; 50% |
| L_B High Bid | 10%; 90% | 10%; 90% |

An anticipating buyer would now consider strategy L_B (high bid) as unattractive, since strategy M_B strictly dominates strategy L_B (payoff 50% or 50% versus 10% or 10% when choosing strategy L_B). Therefore, we eliminate strategy L_B which yields Table 5.

Table 21: Payoff matrix after elimination of strategy L_B

| Buyer/Seller | M_S Medium Threshold Price | L_S High Threshold Price |
|------------------|---------------------------------|-------------------------------|
| H_B Low Bid | 0; 0 | 70%; 30% |
| M_B Medium Bid | 50%; 50% | 50%; 50% |

A seller could in turn now take the buyer's considerations into account and regards thus strategy L_S as weakly dominant strategy since the seller receives 30% if the buyer plays strategy H_B whereas there is no change (still 50%) if the buyer plays M_B .

Table 22: Payoff matrix after elimination of strategy M_S

| Buyer/Seller | L_S Low Threshold Price |
|------------------|------------------------------|
| H_B Low Bid | 70%; 30% |
| M_B Medium Bid | 50%; 50% |

Finally, we obtain a weakly dominant strategy equilibrium in (H_B, L_S) by eliminating M_B since the buyer can realize 70% by playing H_B vs. 50% by playing M_B .

The number of strategies can be extended arbitrarily for both, buyer and seller (proof by induction); we will always observe equilibrium in the upper right corner of our payoff matrix. This means, that a seller will always set the costs very close to his variable costs. A strategic buyer would anticipate this and would therefore always place a bid which is based on the beliefs about the seller's costs. This means that $[LB_{TP}, UB_{TP}]$ can be reduced to $[LB_C, UB_C]$ for the single bid case. The optimal bid can then be determined by the maximization of the consumer surplus which was exposed in chapter 2.

For Name-Your-Own-Price with n possible bids and neglect of frictional costs we can derive an equilibrium where the buyer submits $(n-1)$ unacceptable offers, in order to submit a n -th bid as take-it-or-leave-it-offer (backward induction).

Simulative Approach

Although we already derived equilibrium behavior by applying a game theoretical approach, we will develop an agent-based simulation since this allows us for comparing these different methods illustratively.

Fudenberg and Levine (2006) state that it is crucial, to define the context precisely for a valid market simulation: One such example is the difference between an environment in which a fixed pair of agents plays each other in every period and environments with a large population

of roughly similar agents. In the simulation where the same two agents play each other every period, they may try to influence each other's future play with their current behavior, so that the natural benchmark solution concept is that of equilibrium in the repeated game. However, this kind of equilibrium is not applicable in most environments with a large population of agents. To clarify this, consider first games with anonymous random matching: In each period we match all players to play a one-shot simultaneous-move game and at the end of each round each player observes only the play in his own match. Thereby, the player's behavior today will influence the way his current opponent plays tomorrow, but if the population is sufficiently large then the player is unlikely to be matched with his current opponent or anyone who has met the current opponent for a long time. This implicates for learning theory that myopic play is approximately optimal if the population is finite but sufficiently large (Fudenberg and Levine 2006).

Let us assume m sellers (e.g. Priceline, Expedia and Germanwings or rather single decision makers in such companies who aim to sell flight tickets) that have heterogeneous variable costs c_m drawn from an interval $[LB_C, UB_C]$ which is common knowledge. Then we have n buyers who have heterogeneous valuation wtp_n for the airline tickets and try to maximize their utility by maximizing their expected consumer surplus.

The seller i picks a strategy $s_{i,t}$ from a fixed strategy set for the setting of the threshold price for the round t . At the beginning in $t=0$ he picks a strategy randomly. In subsequent rounds $t>0$ he picks myopically the strategy that generated the highest profit on average in the past with probability $(1-\alpha)$ and picks a strategy randomly with probability α . This trial-and-error-coefficient α prevents the agents to stuck to suboptimal strategies and makes them to try alternatives from time to time.

Each buyer j chooses a seller randomly. She then determines her strategy $b_{j,t}$ for round t . She also starts with picking a strategy from the strategy set randomly in $t=0$. Later on in $t>0$ she chooses the strategy that yielded the highest consumer surplus on average in the past with probability β or picks randomly a strategy with probability $(1-\beta)$. Based on the strategy she determines her optimal bid and submits it to the paired seller. The negotiation is assumed to be costly for buyer and seller so that a strategy that resulted in a failed negotiation is less likely to be chosen compared to a strategy that never was chosen.

If the bid is successful, the buyer realizes consumer surplus=(wtp -bid-negotiation costs) and the seller realizes profit=(bid-variable costs c -negotiation costs). Otherwise both face a loss in form of negotiation costs.

In the next round $t+1$, we reroll wtp_n for all buyers n and c_m for all sellers m since new products are up for sale. Due to the very simple reinforcement learning rule we expect, according to Fudenberg and Levine (2006), that the agents select profitable strategies more often over time. To speed up the process, we also apply evolutionary game theory where the buyer and seller with the highest fitness (=most successful in terms of consumer surplus and profit respectively) breed another agent whereas we eliminate the buyer and the seller with the lowest fitness.

Table 7 lists the available strategy sets for both types of agents.

Table 23: Strategy set for bargaining parties

| Strategy | Description |
|-------------------|--|
| Seller Strategy 1 | Seller sets threshold price to his costs c |
| Seller Strategy 2 | Seller sets threshold price to $(LB_{TP}+UB_{TP})/2$ |
| Seller Strategy 3 | Seller sets threshold price to UB_{TP} |
| Seller Strategy 4 | Seller sets threshold price to $(LB_C+UB_C)/2$ |
| Seller Strategy 5 | Seller sets threshold price to UB_C |
| Seller Strategy 6 | Seller sets threshold price to $LB_C=LB_{TP}$ |
| Seller Strategy 7 | Seller sets threshold price to $c+Random(0, UB_C)$ |
| Buyer Strategy 1 | Buyer bids $LB_{TP} \rightarrow$ best response to Seller Strategy 6 |
| Buyer Strategy 2 | Buyer bids $(LB_{TP}+UB_{TP})/2 \rightarrow$ best response to Seller Strategy 2 |
| Buyer Strategy 3 | Buyer bids $UB_{TP} \rightarrow$ best response to Seller Strategy 3 |
| Buyer Strategy 4 | Buyer bids $(LB_{TP}+Min(wtp, UB_{TP}))/2 \rightarrow$ best bidding strategy according to Spann, Skiera and Schäfers (2004) |
| Buyer Strategy 5 | Buyer bids $(LB_C+Min(wtp, UB_C))/2 \rightarrow$ hypothesized to be the best strategy according to game theoretical model in chapter 4 |

We developed an agent-based simulation (see Tesfatsion 2002 for an introduction) under .NET in C# from the scratch. The agents' strategy choice was stored in a database for every t and we visualize the strategy choice probability over time with Excel. We set $m=50$, $n=1000$, $\alpha=0.05$, $\beta=0.10$ and terminate the simulation in $t=1000$.

Figure 2 depicts a lot of fluctuations at the beginning when the agents start to learn their best strategies. The seller's best strategy choice becomes evident quite early: The seller should set the threshold price to his costs (Seller Strategy 1, blue line) which was also the recommendation by Terwiesch, Savin and Hann (2005). This is also quite intuitive, since every bid over the seller's variable costs c generates surplus for the seller. A threshold price above the costs would cause bids to be rejected that would have been beneficial and would thus mean a loss in profit. Further, a threshold price below the costs could cause accepted bids that would force the seller to sell his products below his costs. This is usually not a profit-maximizing strategy.

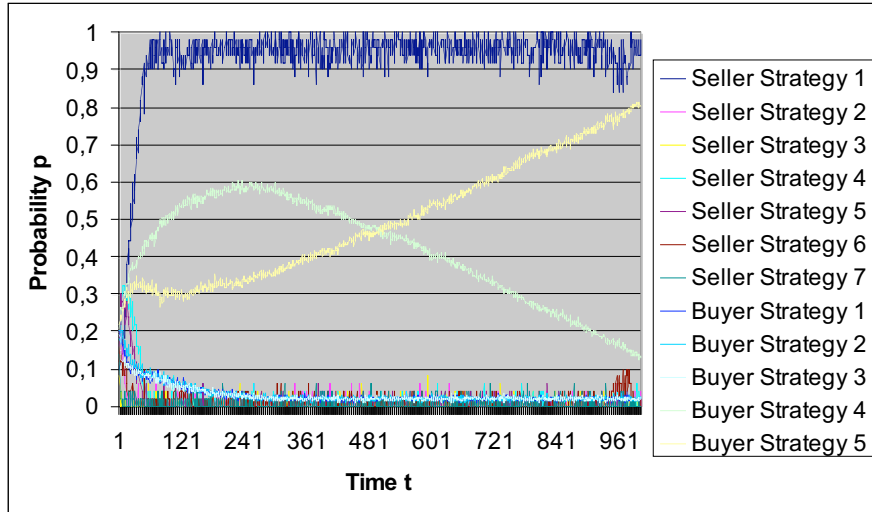


Figure 10: Probability of Strategy Picking over Time

In contrast, the buyer's optimal strategy is different for a market in equilibrium and a market that is still developing: When the market still consists of sellers that apply suboptimal strategies it is better for the buyer to follow a risk-averse strategy and bid higher which is implied by Buyer Strategy 4 (green line). Thereby, the buyer increases her probability to surpass a suboptimal threshold price but she is only able to realize a relative low consumer surplus. Not until there are enough sellers in the market that play the optimal strategy 1, this is the preferred strategy and it takes some time for the buyers to learn that Buyer Strategy 5 (yellow line) outperforms Buyer Strategy 4 slightly when enough player follow the optimal strategy. Nevertheless, the market converges to the predicted equilibrium.

It becomes also evident when we use different interval settings for $[LB_{TP}, UB_{TP}]$ and $[LB_C, UB_C]$ that sellers benefit from high uncertainty. The extreme example of $LB_C = UB_C$ leads to a take-it-or-leave-it-offer by the seller which is equivalent to the case where he sells his goods for a fixed price amounting to his costs. In this case Name-Your-Own-Price with a single-bid policy is not a suitable sales channel for the seller.

Discussion

We have shown with two different rigorous approaches how to solve a relevant problem: We have demonstrated by using two different methods how we can consider strategic buyer and seller behavior in a single framework. We conclude that our model is an improvement in understanding bidding behavior in Name-Your-Own-Price and finally it can be used to give advices for the seller how to set the threshold price optimally.

Moreover, our model shows that the assessment of the seller's costs is crucial for the success of Name-Your-Own-Price. When buyers can assess the seller's costs accurately and without a high grade of uncertainty, bids are primarily influenced by the assessment of the seller's costs. This leads to suboptimal price discrimination which can then in turn lead to lower profits.

We therefore recommend applying Name-Your-Own-Price in markets with high uncertainty about the seller's costs. In real markets we observe that Name-Your-Own-Price is mainly applied where the buyer can not infer the seller's costs, e.g. for flights, hotel rooms, rental car and vacation packages. It is very difficult for prospective buyers to estimate the opportunity costs for these perishable goods since they can still be sold with a positive unknown

likelihood in a traditional sales channel. Additional evidence for our hypothesis is the recent application of NYOP for the sales of software and the sales of virtual items in online games. Companies in the field of software development like Ashampoo (Ashampoo 2007) apply such a mechanism in an additional sales channel. Similarly, HabboHotel.com sells virtual items with NYOP that can be used to personalize in-game chat rooms. In both cases the marginal costs for an additional unit is approximately 0 since the products can easily be replicated. Buyers easily overestimate the marginal costs in such cases and NYOP seems then to be a profitable alternative to posted prices.

In markets with a low grade of uncertainty in terms of seller's cost, it might be beneficial to allow multiple bidding. For optimal threshold prices in such a setting we refer to Terwiesch, Savin and Hann (2005).

From a methodical point of view our work points out two different results: Firstly, simulation and game theory yield the same outcome. This is not very surprising but secondly it illustrates the advantages and disadvantages of both methods: Game theory is advantageous to determine the equilibrium since we can use paper and pencil and we do not have to put much effort into the development of software. Nevertheless, game theory can not make any normative statement in terms of dynamics. Based on the insights from game theory we are not able to determine how and how long the market fluctuates till it reaches its equilibrium.

Vice versa, simulation can be used to visualize this process and its timeline but normally we have to put more effort into the development of such a simulation system although simulation frameworks nowadays help to speed up the development. Depending on the intention, scientists should choose the adequate method. In our eyes, both methods are valid approaches for solving problems in the domain of Information Systems.

Future research could test our findings in laboratory experiments with induced valuation (see Smith 1976 and Smith 1982). Especially when buyers do not behave rationally and follow very risk averse strategies (see e.g. Tversky and Kahneman 1991), it might create untapped potential for sellers. Further research could also examine how buyers and sellers behave in Name-Your-Own-Price markets with multiple bid policy. From a methodical point of view it is very interesting how economics and computer science recently converge in the domain of game theory and multi-agent systems and we expect a further convergence in near future.

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