Managing Information Diffusion in Name-Your-Own-Price Auctions

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Abstract

In Name-Your-Own-Price auctions (NYOP), prospective buyers bid against a secret reserve price set by the seller and only win the auction at the price of their bid if it is equal or higher than the seller's reserve price. Thus, bidders who want to win the auction without too much overbidding have a strong incentive to learn more about the seller's secret reserve price, possibly via their own network of friends, digital networks or online communities. Information-sharing and information diffusion in digital networks can change bidding behavior and thus have important implications for sellers in NYOP markets. We develop a Decision Support System that enables sellers to assess the impact of information diffusion and to analyze the profitability of different seller strategies. We build the system from the bottom up by developing and testing a model of agents' bidding behavior which constitutes the basis for analyzing the effects of different network structures and seller strategies on profit. Sellers can react to information diffusion by setting the secret reserve price optimally, taking into account this strategic element by the provision of a forum and by decreasing the quality of information through forum intervention. Our results show that information diffusion can either decrease or increase seller profit depending on the buyers' initial beliefs about the seller's costs. We also show that the structure of the underlying social network is an important driver for information diffusion and that data about social networks might hence be of value to decision makers.

Keywords: Information Diffusion, Social Networks, Name-Your-Own-Price, eBay Best Offer, Decision Support System

1. Introduction

Auctions are an efficient method of price discovery and allocation in market transactions [29]. The interactive nature and low transaction cost of online media have led to a growing number of interactive pricing mechanisms on the Internet [22][24], e.g., open bid ascending auctions (eBay), descending auctions (azubo.de), Name-Your-Own-Price auctions (Priceline) or dynamic second-price auctions (Google). An important design option for sellers in Internet auctions is the setting of a secret reserve price which a buyer's bid must meet for a successful purchase [3]. Sellers may set a secret reserve price to ensure that the product is not sold below a minimum acceptable price in the auction. Previous research found that the use of secret reserve prices can have a positive effect on seller revenues [2][40].

Secret reserve prices can be found in various Internet auction formats such as eBay open-bid auctions, eBay's Best Offer auctions, and a number of other variants of the Name-Your-Own-Price (NYOP) auction. Name-Your-Own-Price (NYOP) auctions, pioneered by Priceline.com in 1998, have developed several variants. While Priceline combines the auction aspect of NYOP with opaque selling, other applications at European low-cost airlines (e.g., Germanwings.com), and software sellers like Ashampoo.com, use the NYOP auction to sell products under their own brand name. All variants of NYOP share a common feature in that prospective buyers bid for a product which is on sale at an unrevealed (i.e., secret) reserve price set by the seller. A transaction is initiated at the price denoted by the buyer's bid only if this bid amount is at least equal to the seller's secret reserve price. eBay's Best Offer auction is also a variant of a NYOP auction: the seller can permit buyers to submit an offer which the seller can automatically accept if it is at least equal to a secret reserve price set by the seller (http://pages.ebay.com/help/sell/best-offer.html). Since its introduction, the Best Offer feature has gained a significant market share in the B2C-auction market, while research examining this feature is scarce. A compendious analysis of recent ongoing auctions on the US and German websites of eBay found that about 9% of auctions listed on eBay made use of the Best Offer feature.

NYOP auctions such as Priceline or eBay's Best Offer auction usually entail no price competition among buyers since a prospective buyer has solely to meet the secret reserve price set by the seller in order to win the auction. Prospective buyers learn about the seller's secret reserve price from the seller's response to their bids. This information can be very helpful to other prospective buyers in determining their bid values in unfinished auctions for the same product, as long as the seller keeps the secret reserve price constant. Thus bidders have a strong incentive to learn more about the secret reserve price in NYOP auctions in order to bid close to the secret reserve price and avoid the possibility of overbidding, or at least only overbidding marginally.

The Internet provides a digital platform for social networks to spread and gather information that bidders in NYOP auctions may share with other (prospective) bidders. In this paper, we define information diffusion as the spread of information regarding previous bid values and bid outcomes among prospective buyers via digital networks such as instant messaging and email or via online information platforms such as communities and forums [8],[23]. Thus, information diffusion reduces information asymmetry among prospective buyers. For example, several online communities share information on bids placed in the NYOP channel. BiddingForTravel.com lists bids on flights and hotel rooms offered by Priceline and Expedia whereas BetterBidding.com reports bids at Priceline and Hotwire.[1]

Prospective bidders can update their beliefs about the secret reserve price based on the information that they receive via information diffusion, which has an impact on their bidding behavior [23]. This in turn is very likely to have an impact on seller profit, which we define as the difference between revenues and the cost of obtaining the product (i.e., production costs or wholesale prices for a retailer). Information diffusion potentially diminishes seller profit if similar information leads to more homogenous beliefs about the secret reserve price, and thus more homogeneous bids yield a lower degree of price discrimination. It may, however, increase profits if information diffusion alters bidders' beliefs about the seller's secret reserve price in such a manner that they bid higher. Since the Internet promotes information sharing by facilitating person-to-person communication (e.g., via e-mail or instant messaging) as well as creating

[1] BiddingForTravel.com had about 64,200 registered users in March 2008 and BetterBidding.com about 71,000 registered users in February 2010. Since only reading the comments does not require registration, we can expect an ever higher number of passive users (i.e., reading but not providing information).

new social networks (e.g., communities), we expect that information diffusion will have considerable impact on seller profit by altering the bidding behavior of prospective buyers.

Previous research on NYOP auctions has not examined the impact of information diffusion via digital and social networks on seller profit. This is surprising given the reported evidence for the impact of information diffusion in social networks on bidding behavior in NYOP auctions [23]. However, the authors do not test the impact and profitability of seller strategies in reaction to such information diffusion in [23]. Further, the impact of information diffusion on welfare and profit of web-based business models has been discussed in literature (e.g., [1],[10]) but has not been yet quantified. Sellers need to understand the effects of this information diffusion on bidders' strategies and their profit in order to be able to enhance the application and design of markets in general (see [6]) and NYOP auctions in particular.

Hence, especially sellers in a B2C context who want to sell a large quantity of identical products to multiple consumers via a Name-Your-Own-Price auction need a decision support system (DSS) to be able to evaluate the impact on their profits of information diffusion via different network structures, as well as different strategies to react. We define seller strategies as measures the seller can take to react and counter the effect of information diffusion. To apply and test our DSS, we analyze three important strategy alternatives, which previous research on the design of NYOP auctions (level of secret reserve price) and information diffusion (availability and quality of information) have separately studied: First, sellers can react to information diffusion by adjusting the secret reserve price. This might be beneficial for the seller depending on the proportion of informed buyers [13]. Second, the seller can manipulate the availability of information or, third, influence the quality of this information.

The goal of this paper is therefore to develop a decision support system that can simulate and quantify the impact of information diffusion on seller profit and analyze the profitability of different seller strategies when reacting to information diffusion among buyers in secret reserve price auctions.

Our DSS builds on an agent-based simulation which rests on two fundamental inputs: a model of agent behavior and a social network which embeds the economic behavior in a social context (see Figure 1). After a survey of the relevant literature (Section 2), we outline our model of agent behavior based on previous research, which we extend to the impact of low quality (i.e., false) information (Section 3). We empirically test the validity of our analytical model's representation of actual behavior in a laboratory experiment with induced valuations (Section 4). We develop our DSS enabling sellers to test the impact on profit of different information structures, bidder characteristics and strategies in Section 5. We test our DSS by comparing the predicted bids to actual bids under the same market conditions as in the laboratory study. We illustrate then a typical setting and show how the different seller strategies impact profit. Finally, we test the robustness of our results by varying the underlying social network structure and the market parameters to evaluate the sensitivity of the DSS' underlying model. The final section concludes the paper with general implications for sellers in markets with information diffusion among buyers.

== Please insert Figure 1 about here ==

2. Related Literature

Information is a key determinant of consumer and firm behavior as well as market performance. Information diffusion can be accomplished via the price mechanism of markets [21], corporate communication (e.g., advertising) or interaction in social networks (e.g., word-of-mouth). Whereas the former have been well analyzed in economics and business research over the past decades, research on information diffusion via digital social networks is an emerging field in information systems, marketing and economics. In this paper, we define information diffusion as the spread of information among consumers via digital networks such as instant messaging and email or via online information platforms such as communities and forums [23]. Thus, information diffusion reduces information asymmetry among consumers.

Nevertheless, previous research on auctions with secret reserve prices is predominantly concerned with whether or not to use secret reserve prices (with respect to auction design) and with its effects on revenue [3][31][33]. As yet, the literature does not discuss the profit implications of information diffusion in such auctions. Based on newly available information on social networks amongst bidders, Hinz and Spann [23] examined the partial revelation of the secret reserve price in a NYOP auction owing to information diffusion through social networks. In their study, they focus on the influence of shared information on bidding behavior and show that bidding success is a function of the bidder's social position. The authors sold virtual products in a virtual world ("HabboHotel" where users can meet and interact via avatars in a virtual Hotel) using an NYOP auction and exploiting data about friendship relations in this virtual world as proxy for potential communication channels. Using this approach, they find that social position determines the quantity and the quality of information about the previous bidding behavior of other peers and thus has a significant influence on the bidding behavior. Their analytical model is based on the assumption that the information flowing through the social network is reliable and truthful, so there is no attempt to account for low-quality (i.e., false) information that might influence bidding behavior nor do they test the impact and profitability of seller strategies in reaction to such information diffusion.

Changing the auction's design parameters seems to be one promising strategy: Fay [13] studies the optimal design of a NYOP auction in an analytical model where a single buyer may use multiple identities and thus learn more about the secret reserve price. Fay's work deals with multiple identities but does not offer decision support for the sellers' problem of information diffusion in such auctions. The topic of information diffusion has also been neglected by other research in the area of NYOP ([19], [35] and [37]).

For their part, sellers may also pursue strategies that are disputable: One such strategy is the systematic manipulation of the quality of available information. Harmon [20] discovered that many book reviews on Amazon.com are written by the book authors themselves, the publishers, or by the book's competitors. The music industry has been shown to hire agents to post positive opinions of new albums [41], [28]. Although the comments in anonymous online forums may be biased, rational consumers still pay attention**,** even when it is possible for sellers to pose as consumers [28]. We will show later that the more uncertain they are about the quality (i.e., truth) of information, the more carefully bidders weigh new information but still take it into consideration. The manipulation of information does not necessarily have to be harmful for the buyers; e.g., Dellarocas [11] finds that manipulation of online ratings can increase the usefulness of reviews under certain conditions.

Depending on the effect of information diffusion on a seller's profit, the seller might want to accelerate or decelerate the process by controlling the availability of information. While it might be a strategic choice for the seller to switch to a different Internet-based selling mechanism revealing or concealing market information [15], we allow the seller to change the structure of the social network amongst its prospective buyers while still using the same auction design. A seller might encourage communication amongst prospective buyers, e.g., by providing a forum for discussion and thus might foster the information sharing regarding bidding behavior and bidding outcomes. A forum artificially creates a link between the participants and thus alters the structure of the social network. Putsis et al. [32] show that the structure of the network has an important influence on the spreading of word-of-mouth. This insight is also important for the optimal seeding strategy in viral marketing campaigns, which has been addressed by Bampo et al. [30] and Kiss and Bichler [25]. Since the influence of the underlying social network cannot be expressed in closed-formed solutions, these authors apply a simulation approach. We also use an agent-based simulation for our decision support system to be able to test complex social network structures and their variations. We develop our DSS from the bottom up, starting with agents' individual behavior (see [38]) which we then embed in social contexts (see [17]). To build the simulation upon a reliable model of agent behavior, we first develop a microeconomic model (see also [9]) which we then validate in a laboratory study with induced valuations (see [34]).

Since auction design is an important success factor for sellers in electronic markets, research in the domain of management science has proposed several support systems for decision makers: Van Heijst, Potharst and van Wezel [39] create a decision support system for predicting end prices on eBay. Similarly, Gregg and Walczak [18] present a multi-agent auction advisor to improve decision making by auction participants. Bapna, Jank and Shmueli [7], use functional data modeling to analyze the price formation process in online auctions. This approach might also be useful in the case of information diffusion in NYOP auctions since it could be used to visualize the convergence of end prices to the secret reserve price. Edelman and Ostrovsky [12] present evidence of strategic bidder behavior in sponsored search auctions and estimate that preventing such behavior would increase Overture's revenue. This line of research is connected to this paper. We, however, address a different problem in the area of Internet auctions.

3. Agent Model for Impact of Shared Information on Bidding Behavior

We build our decision support system upon an economic model of agent bidding behavior in NYOP auctions where agents can be influenced by exogenously-given information (e.g., word-of-mouth or messages circulating in Internet communities, also called "word-on-line" [16]). For this model, we draw on previous research [23], which we extend for the impact of uncertainty about truth of information. We test the validity of our model in Section 4.

3.1. Analytical Model for Bidding Behavior with Shared Information

Hinz and Spann [23] model the impact of shared information on bidding behavior in a NYOP auction. In this model, the seller sets a secret reserve price and offers similar products using multiple parallel NYOP auctions over a period of time (without changing the secret reserve price). Typically, a seller offers a number (>1) of flight tickets (e.g., Germanwings), software downloads (e.g., Ashampoo) or hotel rooms (e.g., Priceline) in a Name-Your-Own-Price market and the products are sold on a first-come-first-served policy. This mechanism is used for the sale of excess capacity, oddments or products with very low variable costs and has also gained a substantial share in eBay B2C-auctions (in March 2009, about 9% of auctions listed on eBay made use of the Best Offer feature). In each auction, only one buyer enters the market and the buyer can place only one bid. They assume that bidders correctly expect the seller to offer an exogenous and constant secret reserve price. Bidders are considered to be risk-neutral.

The decision rule in this model is that the j^{th} bidder submits a bid b_j for a product if the expected consumer surplus ECS_j of the bid (accounting for frictional costs c_j which are incurred by submission of the bid) is not negative. The bidder optimizes the expected consumer surplus ECS_j of the bid over the bid amount (see equation (1)). The j^{th} bidder assumes the value of the secret reserve price p_T to be uniformly distributed on the interval $[LB_j, UB_j]$. Results also hold for other common distributional assumptions since only the strength of the effect may vary.[2] Bidders have a reservation price r_j for the product sold by the

2 A solution assuming a normal distribution is available from the authors upon request. We also tested left-censored normal distributions as negative prices can be ruled out. Only the strength of the effect varied slightly.

seller. This reservation price is determined by the minimum of bidders' willingness-to-pay WTP_j and the upper bound UB_j of the probability distribution for the secret reserve price [23].

$$ECS_j = \int_{LB_j}^{b_j} (r_j - b_j) \cdot \frac{1}{UB_j - LB_j} dp_T - c_j \quad \text{with } r_j = \min\left\{WTP_j, UB_j\right\} \tag{1}$$

The impact of shared information obtained by bidders (i.e., information about accepted or rejected bids) can be modeled as updating their beliefs using Bayes' rule. Information about a rejected bid leads to a left-truncation of the distribution if the amount of the rejected bid is higher than the lower truncation point *LB* of the prior. By contrast, information about accepted bids leads to a right-truncation of the distribution if the amount of the accepted bid is lower than the (prior) upper truncation point *UB*. We assume unrestricted rational behavior and hence bidders that always act on the most valuable information.

The effect of shared information is then straightforward: On the one hand bidders who overestimate the secret reserve price are corrected downwards and on the other hand bidders who underestimate the secret reserve price are corrected upwards. This can lead to higher or lower bid amounts depending on the prior relationship between bidders' willingness-to-pay and bidders' beliefs [23]. Using this base model, Hinz and Spann [23] showed that additional information and more dispersed information monotonically decrease the difference between bid amounts and the secret reserve price.

3.2. Extension for Uncertainty about Truth of Information

We now extend this model to the case where bidders receiving shared information face uncertainty about the truth of this information. Information about accepted or rejected bids posted in forums, or received from friends may be false due to error, neglect or malice. We assume that the probability for a piece of information being true is α. For simplicity and without loss of generality, we assume for each piece of information that α is independent of other pieces of information, because truth depends on the degree of potential error, neglect or malice of the individual provider of this information. If bidders receive multiple pieces of information, bidders augment their objective function (expected consumer surplus) for this information. In a case where multiple pieces of information about accepted (rejected) bids are present, and each piece of information has the probability α of being true, the possible states of nature for the example of three pieces of information about accepted bids are depicted in Figure 2. The bid amounts reported in this example about accepted bids $B_{A,i}$ are sorted in ascending order (e.g., $B_{A,1} < B_{A,2} < B_{A,3} < UB$.), i.e. the most valuable information is the first element in the set. For information about rejected bids, the information is sorted in descending order.

== Please insert Figure 2 about here ==

We also assume that the initial lower (upper) bound is lower (higher) than any message about rejected (accepted) bids ($\forall B_R \in \{B_R\} : B_R > LB$ and $\forall B_A \in \{B_A\} : B_A < UB$) or that messages below (above) the initial lower (upper) bound are discarded unprocessed.

In case $B_{A,1}$ is true, $B_{A,2}$ and $B_{A,3}$ have to be true as well given the nature and structure of this information (If $B_{A,1}$=15\$, i.e., information that a bid of 15\$ was accepted implies that the secret reserve price is ≤ 15\$; in this case, information of accepted bids higher than 15\$ have to be true as well). If all messages about accepted bids are false, which occurs with a likelihood of $(1-\alpha)^3$ in this example, then the original upper bound UB is used.

Following this rationale, we can formulate a general formula for the expected consumer surplus for bidder j who received the sorted set $\{B_{A,j,k}\}$ of messages regarding accepted bids and the sorted set $\{B_{R,j,k}\}$ of messages about rejected bids:

$$ECS_j = (r_j - b_j) \cdot \sum_{k=1}^{n} \alpha \cdot (1-\alpha)^{k-1} \cdot f(B_{A,j,k}) + (1-\alpha)^n \cdot f(UB_j) - c_j \tag{2}$$

$$\text{with } f(B_{A,j,k}) = \sum_{l=1}^{m} \alpha \cdot (1-\alpha)^{l-1} \cdot h(B_{A,j,k}, B_{R,j,l}, b_j) + (1-\alpha)^m \cdot h(B_{A,j,k}, LB_j, b_j) \tag{2a}$$

$$\text{with } h(B_{A,j,k}, B_{R,j,k}, b_j) = \begin{cases} 0 & \text{if } B_{A,j,k} \le B_{R,j,k} \\ \dfrac{b_j - B_{R,j,k}}{B_{A,j,k} - B_{R,j,k}} & \text{otherwise} \end{cases} \tag{2b}$$

$$\text{and } r_j = \sum_{k=1}^{n} \alpha \cdot (1-\alpha)^{k-1} \cdot B_{A,j,k} + (1-\alpha)^n \cdot WTP_j \tag{2c}$$

Note that the function $f(\bullet)$ accounts for the statements about the lower bound (2a). In this case, α=1 (all information is true) is a special case of equation (2) and leads to equation (1). Function $h(\bullet)$ yields 0 if there is contradicting information, e.g., "A bid of 100 has been accepted" and "A bid of 110 has been rejected" (2b). Information about accepted bids decreases the reservation price r_j (2c). If all messages about accepted bids are false, which happens with probability $(1-\alpha)^n$, then the initial willingness-to-pay WTP_j sets the reservation price.

We now develop a new hypothesis for the impact of uncertainty of the truth of information on bidding behavior. A piece of information is valuable if it reduces the uncertainty about the secret reserve price. First, information about a rejected (accepted) bid reduces the probability of the secret reserve price being at or below (above) the amount of the rejected (accepted) bid. The more restrictive the piece of information (information about a higher (lower) rejected (accepted) bid amount), the greater is this reduction in probability for the location of the secret reserve price. Second, the higher the probability that the information is true, the greater this reduction in probability for the secret reserve price location. With α=1 a new piece of information can make all previous information redundant (in cases where it is more restrictive), whereas a probability of $0<\alpha<1$ leaves some uncertainty about the truth of the new information and thus old information still is valuable. In case of α=0 new information is worthless. The higher the probability of information being true, the more valuable is this information for bidders, enabling them to bid closer to the secret reserve price. We can thus state:

H1: A higher probability α of true information decreases the difference between bid amounts and secret reserve price.

Since Hinz and Spann [23] assume that all pieces of information are always true and do neither model nor control for uncertainty about the truth of information, we test H1 and the validity of our model for agent behavior in the experimental study outlined below. This also enables us to make further use of data from this experimental study to test the accuracy of our DSS.

4. Laboratory Test of Impact of False Information on Bidding Behavior

We test the hypothesis H1 in a laboratory experiment with induced valuations [34], and we systematically manipulate the stimuli to gain maximum control. More specifically, we test the impact of the dispersion of information and uncertainty about the truth of information on bidding behavior. In so doing, we can also test for the potential interaction effect between the amount of information, dispersion of information and uncertainty about the truth of information.

4.1. Experimental Design and Setup

We conducted a computer-assisted laboratory experiment to test the hypothesis derived in Section 3 for the effect of uncertain exogenous (i.e. shared) information on individual bidding behavior. We experimentally manipulated information presented to subjects via a controlled web-based information board. This method has been used in the area of decision support systems to experimentally test propositions from analytical models with real human behavior (see e.g., [4]).

The subjects were systematically confronted with different stimuli which we derived from the following factorial design: (1) amount of information and (2) dispersion of information (high / low) and (3) probability of false information ($1\text{-}\alpha=20\%$ / $1\text{-}\alpha=50\%$). The number of available messages is displayed in Table 1 and consists of four treatment levels, with at least two pieces of information about accepted (rejected) bids in treatment 1 (2) in order to be able to create dispersion of information. "A bid of x EUR has been accepted" indicated an accepted bid, while "A bid of y EUR has been rejected" indicated that a bid of y did not meet the secret reserve price.

== Please insert Table 1 about here ==

We generated the dispersion in bid amounts as follows and illustrate the procedure using the case of three messages about rejected bids: For the high dispersion case, we drew three random numbers from the uniformly-distributed interval between the lower bound and the secret reserve price. For the case of low dispersion in contrast, we divided the interval between the lower bound and the secret reserve price into five intervals of equal size and then drew all three messages from the same sub-interval [23].

To examine the influence of false information, we varied the degree of false information by turning "accepted" into "rejected" and vice versa to a pre-determined proportion. One half of the subjects started with messages from a forum with 20% false information, the other started with 50% false information. After eight products (4 information treatment levels × 2 treatment levels for dispersion), the subjects were then confronted with the second forum. The proportion of false information was common knowledge and was also communicated above the active message board. All treatments were systematically varied and combined with the hypothetical products using induced valuations in random order to control for product and order effects. We had 16 different treatments (4 information treatment levels × 2 treatment levels for dispersion × 2 treatment levels for uncertainty) and subjects thus could bid for 16 generic products. Subjects were randomly assigned to treatments.

Further, we controlled for bidders' product valuation using an induced-values paradigm [34] by informing them about the resale value of the given product. Each product had a resale value inducing the subject's willingness-to-pay (*WTP)*. The difference between the induced valuation and a successful bid thus represents surplus for subjects. The induced valuation for the different products ranged from 60 EUR to 755 EUR. The subjects were also informed about the lower and upper bound of the interval for the secret reserve price. The lower bounds were set between 33.3% and 88.2%, while the upper bounds were between 115.8% and 183.3% of the induced valuations for the product. In the information treatments, messages about rejected bid amounts were always higher than the initial lower bound *LB* and messages about accepted bid amounts were always lower than the initial upper bound *UB* according to our assumption $\forall B_R \in \{B_R\} : B_R > LB$ and $\forall B_A \in \{B_A\} : B_A < UB$. The bid amounts were drawn from a uniform distribution subject to the previously mentioned condition.

We controlled for order effects by systematic variation and counterbalancing of treatments in our within-subject design. The subjects' success was measured by the consumer surplus they generated and subjects were remunerated accordingly (experimental instructions are available from the authors). We paid subjects a 5 EUR-show up-fee and 0.0075 EUR for every unit of realized consumer surplus. All subjects were informed about this rule, only the multiplier being kept secret. Average remuneration per participant was 8.42 EUR (~13.30 USD).

We conducted the experiment in a lab equipped with PCs and separators between subjects to prevent visual and verbal communication. Participants were randomly assigned to different sessions of 15-20 subjects each. For each product, subjects were presented with different sets of messages about rejected and accepted bids according to the specific treatment and could submit a single bid for this generic product. For this reason, subjects could not learn from their own bids. All treatments were systematically varied and combined with the hypothetical products by means of induced valuations in random order to control for product and order effects. After the completion of bidding rounds, subjects had to answer an additional questionnaire where we elicited demographics and additional information.

4.2. Results

Sixty-three subjects participated in the laboratory experiment. The subjects were mainly MBA students (62 students, 1 non-student) and the majority was male (22 female, 41 male). Subjects placed a total number of 1,008 bids, 439 of them were rejected and 569 accepted.

We use the standardized absolute deviation $SAD_j = |b_j - p_T| / WTP_j$ between a bidder's bid b_j and the secret reserve price p_T to test our hypothesis H1 about the impact of uncertainty regarding the truth of information acquired. We analyze the impact of our experimental treatments on the SAD_j via a repeated-measures ANOVA (see Table 2). We find that the amount of information has no significant direct influence on SAD_j ($F_{3,59}$=.32, p>.8), and thus cannot confirm the results of previous studies. However, going from three (treatments T1 & T2 in Table 1) to five messages (treatments T3&T4 in Table 1) is only a moderate increase of the amount of information. Hinz and Spann [23] do find a significant impact when the amount of information is increased from zero to five messages.

We can however confirm that more dispersed information significantly decreases the standardized absolute deviation SAD_j between a bidder's bid and the secret reserve price ($F_{1,61}$=10.78, p<.01), which is consistent with previous literature [23]. Literature in information economics (e.g., [27]) revealed that a greater dispersion of information may make the searcher better off, and prolong optimal search, even if the searcher is risk-averse. Given a fixed mean, more variation regarding, e.g., wage offers, prices or bids may make the searcher want to search longer, expecting to receive an exceptionally valuable piece of information. The possibility of receiving some exceptionally worthless piece of information has less impact on the optimal search, since worthless pieces of information can be ignored. In our context, this means that information about the acceptance or rejection of bids is more valuable for the searcher if the dispersion in bid amounts is high. For a mathematical solution of this problem see McCall [27].

However, how false information may change these results is unclear and has not been studied before. We assumed in our model that subjects tend to mistrust information and only take information partly into account if the probability for false information is high. In our laboratory experiment we challenge this assumption but find that a higher probability of information being true significantly decreases the standardized absolute deviation SAD_j between a bidder's bid and the secret reserve price ($F_{1,61}$=9.47, p<.01). This is consistent with our hypothesis H1. Subjects behave rationally and use some kind of Bayesian updating to cope with the challenge of potentially false information. The higher the probability of false information, the more the information becomes worthless until shared information is totally ignored.

It is also interesting that the interaction effect between dispersion and the probability of true information is significant at the 10% level ($F_{1,61}$=3.27, p=.08), which is apparently driven by the low SAD_j of .0854 in the case of both high dispersion and a high probability of true information. This means that the two factors which make information valuable in this context, mutually reinforce one another.

== Please insert Table 2 about here ==

Further, comparing low and high dispersion treatments for a high and a low probability of true information separately, reveals the significant impact of dispersion in the case of a high probability of true information ($F_{1,61}$=14.42, p<.01) but no significant impact of dispersion in the case of a low probability ($F_{1,61}$=.64, p>.4). Additionally, we find a significant interaction effect between dispersion and the information treatment ($F_{3,59}$=4.59, p<.01), which is apparently driven by the strong impact of dispersion on information treatment T3 (with two messages about a rejected bid, three messages about accepted bids: high dispersion: SAD_j of .0829; low dispersion: SAD_j of .1410). There are no other significant interaction effects.

Hence, the results of the laboratory study support our hypothesis H1 and partly confirm findings from previous literature [23]. We can thus conclude that dispersion of information and the level of uncertainty both influence the impact of information diffusion on bidding behavior in secret reserve price auctions. Further, these results provide some evidence that our model sufficiently reflects actual bidding behavior in NYOP auctions with shared information. Additionally, the collected bids can be used to test our decision support system.

5. Development, Test and Application of Decision Support System

5.1. Development of the Decision Support System

In this section we describe the development of our decision support system. It allows a seller who conducts NYOP auctions in an environment with possible information diffusion among consumers to analyze the impact of different strategies he or she might want to pursue. In order to account for (variations of) complex underlying social network structures, the system is based on an agent-based simulation. As the base network for social interactions between bidders in NYOP auctions the seller can use artificially created or existing network data. For the evaluation of our system we use empirical social network data. The agents behave as outlined in section 3. We evaluated the analytical model of individual behavior in a laboratory experiment in section 4 and found support for the predicted behavior. We moreover make use of the collected bids from the laboratory experiment to test the accuracy of our decision support system below (see Section 5.2).

The system allows the analysis of the following seller strategies: First, it allows the calculation of the optimal secret reserve price for different market scenarios to be the sellers' response to information diffusion. Second, the seller can examine the impact on profit of the introduction of a forum as a potential strategy to alter the availability of information for bidders. Third, the systems allows analysis of the impact of influencing the quality of available information ("online forum intervention") on bidding behavior and seller profit.

Our experimentally tested model of individual bidding behavior (agent model), and data on the network structure of bidders provide a wealth of information which allows the setting up of a meaningful simulation study using our system in order to analyze these three strategies. This prototype decision support system allows marketers to test different strategies in different market scenarios. We developed the DSS in C# using the .net-framework. Figure 3 shows a screenshot of the system.

== Please insert Figure 3 about here ==

Based on the analytical model tested in Section 4, we developed software agents that behave according to our model from Section 3 but have heterogeneous individual willingness-to-pay and beliefs about the secret reserve price, and finally have different social ties. Each agent represents a bidder who intends to buy a certain product which is offered by a seller adhering to a single bid policy for each bidder. Each agent has an individual willingness-to-pay and individual beliefs about the secret reserve price. Further, agents have friends (i.e., contacts) who are also interested in buying the offered product.

Based on these relationships, agents can ask their linked friends – if applicable – about the amount and outcome of bids placed on the product offered before placing their own bid. The probability for a willingness to share information about previous bidding behavior can also be varied in the system. Information obtained this way is also incorporated into the calculation of the individual optimal bid by updating the beliefs about the secret reserve price. Note that neighbors only report their own bidding experience, which may, however, be in turn influenced by information obtained from their neighbors. The information received is processed using our analytical model. In this way, this process yields the information diffusion over the social network. Agents' information gathering and processing activity can be described by the pseudo code in Figure 4.

== Please insert Figure 4 about here ==

After agents have placed a bid, they stay in the market and their experience is still available to their neighbors. Obviously, agents with many social ties or agents bidding late will potentially receive more information compared to agents with few neighbors or agents bidding early. To determine the sequence of agents placing a bid we choose a random order, where the subsequent bidder is randomly determined from the set of remaining agents who have not yet placed a bid. The following results are also robust if we posit that buyers with higher willingness-to-pay have higher search costs and opportunity costs for time [36], thus bidding first.

Starting from the input network structure, we systematically vary the communication network to assess the impact of communication through a forum on the NYOP auction business model. To test the impact of a forum provided by the seller and different network structures on the success of NYOP auctions, we vary the underlying social network structure systematically by changing the proportion of bidders who use the forum. Bidders that are linked to a forum are granted access to all other bidders participating in this forum. By doing so, we model the assumption that every bidder who has placed a bid posts a message on a shared asynchronous message board.

Further, we assume a monopolistic seller and that each agent is an instance of the modeled behavior from section 3 but possesses an individual willingness-to-pay and personal initial beliefs about the secret reserve price. Willingness-to-pay and beliefs are drawn from normal distributions which are open for specification by the user through a user interface. Moreover, the user can specify diffusion parameters and ranges for market parameters that he or she considers plausible. The user can use social network data (saved in matrix form, e.g., from Pajek) as input, which can either be artificially created or can be collected from field sources. Additionally the user has to specify the number of replications. All results are stored in a database and serve as input for further analyses by a statistic module. After the analyses, the results are available through the user interface. Figure 5 depicts the resulting architecture.

== Please insert Figure 5 about here ==

5.2. Test of Decision Support System using Real World Data

We first start with an accuracy test and check whether the developed system can provide accurate predictions of real subjects' bidding behavior. We therefore calibrate the software agents with the induced valuations and the information treatments that we used in the laboratory experiment and compare the software agents' bids with the actual bids of the human participants in the lab experiment. Note that the information does not flow through a social network at this point of the systems' evaluation but is exogenously given as in the laboratory experiment.

Moreover, we compare the subject's actual bids with bids predicted by our system when we apply a counterfactual design: We check what happens if the software agents use the exogenously given information correctly, if they disregard this information and if agents neglect the possibility of false information.

We find that if we correctly parameterize the agents, i.e., they use external information equivalent to that given in the laboratory study, the predicted bids match almost perfectly those of the subjects in the laboratory. We observe an explained variance (R^2) of 98.6% and a mean absolute percentage error (MAPE) between predicted and actual bids of 9.42%. If the agents disregard the exogenously given information about other bids, we observe a MAPE of 9.66% between the predicted and the actual bids while R^2 is still 98.6%. If the agents take the given information into account but assume that the pieces of information are perfectly true, while actually 50% in half of the cases and 80% in the other half of the cases, is actually false (cf. lab experiment), we see that our predicted bids substantially deviate (MAPE = 19.72%) from the observed bids in the laboratory study.

5.3. Analyzing Seller Strategies using the DSS

The previous test where we compare predicted bids to actual bids shows that our system yields accurate estimates for the bidding behavior in NYOP markets. Thus, we are confident that our DSS is applicable and appropriate for use in further analyses. The test in the previous section incorporated valuations, beliefs regarding the secret reserve price and information about other agents' bids. This information was, however, exogenously given and did not diffuse through a social network. Our system allows endogenizing information diffusion by using data on social network structure. To illustrate the benefits of our DSS, we analyze different market settings and present the implications for the seller.

We use social network data from the empirical field study in [23] to create the initial social network. The empirical social network data is based on friendship relationships amongst bidders in a NYOP auction (200 bidders with a total of 364 ties), which is visualized in Figure 6, part A (on the left hand side). The social network was created based on observed friendship relationships. This data can nowadays be obtained quite easily, e.g., it can be extracted from the ICQ or Skype contact list or the friend's list in Facebook or mySpace. The average degree is quite low with 1.82, but the maximum degree of 90 reflects that there are some very prominent agents in such community networks which are quite influential while there is a high number of agents with no connections (in our case 45 agents are not connected to any other agents). The clustering coefficient is 16.6% and thus the network is not very dense.

== Please insert Figure 6 about here ==

We analyze seller strategies for three different scenarios: First, we simulate a market where bidders initially underestimate costs and thus implicitly the secret reserve price, e.g., due to a shift in factor prices such as energy. Following our model this should lead to lower bids and could also lead to a higher number of rejected bids. The agents optimize their expected consumer surplus and since their expectation about the lower truncation point is biased in this scenario, we expect bids that are rather low and in some cases too low to exceed the secret reserve price which has to be met for a successful bid. In the second scenario, bidders have more or less correct (i.e., adequate) beliefs about the seller's costs and secret reserve price, respectively. Third, we calibrate the simulation so that bidders overestimate seller's costs. Table 3 summarizes the settings for the respective simulation runs. Negative random numbers were prohibited by censoring the normal distribution. We run 50 replications to avoid outliers and in each replication 200 agents (equivalent to the empirical social network data) place bids at a NYOP auction seller.

== Please insert Table 3 about here ==

Setting the Secret Reserve Price optimally

In this section, we determine the optimal secret reserve price depending on the communication structure among the buyers. To start with, we assume all information to be true and set $\alpha=1$. Further, we assume there is no communication through forums and keep the social network constant to compute the optimal level of the secret reserve price in such a person-to-person communication network for the three different scenarios of bidders' initial beliefs. The optimal secret reserve price in the case of *no communication* is 100 EUR since we assume variable costs of 100 EUR.

Table 4 lists the total profit in the three scenarios. Intuitively, the seller profit is substantially higher when buyers overestimate the reserve price. Interestingly, if sellers do not account for information diffusion they lose money in all three scenarios (compare column 2 and column 3). In all scenarios with information diffusion the bids converge to the secret reserve price until it is fully revealed under some circumstances. The seller loses surplus that is normally realized due to overbidding. Obviously, it is thus crucial for the seller to take into account the information diffusion by increasing the secret reserve price in all market scenarios. By raising the secret reserve price by 1% the seller can not only dampen the negative effect of information diffusion on profits but can even increase profits between 1% and 67% depending on the market scenario. The seller can increase profits in all scenarios due to information diffusion (compare column 2 and 4) if the seller accounts for this effect by adjusting the secret reserve price. Our simulation can be used by decision makers to calculate the optimal level of the secret reserve price as a function of the market scenario and information diffusion.

== Please insert Table 4 about here ==

Modification of Network Structure by the Provision of a Forum

The strength of the effect of information diffusion on seller profit increases when bidders are better connected than in a pure person-to-person network. This can be the case when bidders are organized via a forum and the effect can increase or decrease seller profit depending on bidders' initial beliefs.

The provision of a forum can be beneficial for the seller when the bidders systematically underestimate the costs of the product and thus the secret reserve price. The additional communication through a forum can help to correct this incorrect belief and thus increase bid values and the number of accepted bids. Hence, seller profit can increase and a higher number of accepted bids increases welfare. This scenario is depicted in scenario 1 in Figure 7. In this scenario seller profit is highest when all bidders participate in a forum. In such markets the seller should encourage (prospective) bidders to communicate by the provision of a forum. The seller, however, has to account for the impact of this stimulated information diffusion and has to raise the secret reserve price to 110 EUR (=110% of variable costs). The steep increase in profit which results from small increases in the secret reserve price near 100% also illustrates that adjusting the secret reserve price is a substantial control lever for the seller. A secret reserve price below 100% of the variable costs is never recommendable since a sale at a price below the variable costs yields a negative contribution.

== Please insert Figure 7 about here ==

When bidders overestimate the costs and the secret reserve price, a seller is better off when the communication is as limited as possible and should hence not provide a forum. Scenario 3 depicted in Figure 7 illustrates this case.

In the case of adequate beliefs, the optimal proportion of forum users lies between these two extremes: As shown in Figure 7 the seller is best off when there is moderate information diffusion. If the magnitude of information diffusion, however, gets too intense (e.g., >40% of the bidders participate in a forum), the seller should provide a forum, encourage its usage (to yield 100% forum participation) and raise the secret reserve price.

These scenarios show that the active management of the social network among prospective buyers is also a key instrument for profit management. Our DSS can be used to calculate the optimal proportion of forum users and the appropriate secret reserve price. If the proportion of forum users cannot be actively managed, the seller can, however, set the secret reserve price according to the recommendation of our DSS.

Online Forum Intervention

Prior research has documented several cases where online forum intervention took place, for example in the case of book or music reviews (see our discussion of previous literature in section 2). The finding of Mayzlin [28] that sellers' postings in a forum, disguised as information from consumers, influence consumers is consistent with our results: Rational bidders weigh new information with greater uncertainty more carefully, but still take it into consideration. Dellarocas [11] finds that manipulation of online ratings can increase the usefulness of reviews under certain conditions. In this section we therefore evaluate the strategy of manipulating the proportion of false information.

In the case of underestimation of the secret reserve price (scenario 1), the seller is intuitively best off with a high degree of true information. In the case of adequate estimation (scenario 2) and overestimation (scenario 3) the seller might want to intervene in forums and spread false information. This would lead to a higher degree of false information and thus would lower the value of available information.

Spreading false information is especially beneficial for the seller if a high proportion of prospective buyers participate in such a forum. The seller, however, then has the opportunity to alter the buyers' beliefs and indirectly influence bidding behavior. Figure 8 shows that the seller can exploit information diffusion by spreading false information which will lead to substantially increased profits. This figure also illustrates the interaction effect of false information and the proportion of forum users and thus the degree of information diffusion.

If the degree of false information reaches some critical level (in scenario 2: α<10%), the value of information converges to zero and thus the influence of information diffusion is negligible. The profit of markets with 100% false information (α=0%) is equal to the profit without information diffusion.

The profit effects shown in Figure 8 for scenario 2 can also be found in the other scenarios. The active spreading of false information can increase profits by +24.95% in scenario 1 (optimal α^*=30%) and +32.18% in scenario 2 (optimal α^*=10%) compared to the same situation without the provision of false information. Note that we use a simplistic rule for the creation of false information in our simulation by changing the outcome information (from accepted to rejected or vice versa). A seller could pursue strategies that make use of behavioral aspects like price anchoring and thereby may increase profits even more substantially. The result of our simulation is hence a lower bound for the effect of forum intervention on profits.

== Please insert Figure 8 about here ==

Online forum intervention is therefore another promising strategy for sellers to manage information diffusion in secret reserve price auctions. This strategy may be unethical but business practice has shown that it happens nonetheless. Although the findings by Dellarocas [11] indicate a need for suitable policies, we are not experts regarding the legal situation in different countries. Since strategic manipulation is hard to track, legislative and executive authorities may find it difficult to develop and implement adequate laws. Friedman and Resnick [14] discuss a number of possible solutions from an economics point of view for this problem. For the time being, our tool can be used to determine the impact of parameters like proportion of false information, proportion of forum users and different secret reserve prices.

The system also allows the calculation of the loss in profits for given parameters. For example, the system can be used to quantify the influence of increasing or decreasing the proportion of forum participants on profits while holding all other variables constant. By doing this, a seller could calculate the (negative) profit effects that would result from not adjusting the secret reserve price to information diffusion.

Thus, this system enables better seller decisions and can directly influence the business success of a NYOP seller.

5.4. Robustness Tests

To test the robustness of our findings we systematically vary the parameter assumptions and test different settings. We especially check for the impact of the social network structure on our results and use a second set of data on social networks that we collected for this purpose. We surveyed 121 randomly picked graduate and undergraduate students at a large European University who agreed to participate in a questionnaire. We thus implicitly applied an event-based approach as boundary specification strategy ([26]) and focused on the subjects participating in this questionnaire, where they reveal their data on a leading social networking site which is very similar to Facebook. Based on the friendships recorded at this social networking site we constructed the social network which is visualized in Figure 6, part B (on the right hand side). This figure illustrates the connections and potential communication channels amongst the students and may be a proxy for potential information diffusion amongst prospective buyers in a NYOP channel. It also illustrates the differences to the network we used in the previous section. The maximum degree, i.e., the number of friendships in this case, is 17 while very few nodes are not connected to the network and thus have a degree of 0. On average an agent in this network has about 4.4 friends. The average clustering coefficient is about 34.8%, meaning that with a probability of about 35% one's friends are also friends. Compared to the network from the field study in a virtual world, the network is denser and more evenly distributed. There are no nodes that are extraordinarily well-connected while there are also very few agents that are not connected at all. Thus the comparison of these two different social networks based on real data seems promising for a robustness test.

We further vary the variable costs for the product (0 ≤ costs ≤ WTP), the mean of willingness-to-pay WTP, lower bound LB, and upper bound UB.[3] We normalize all values and vary WTP between 0 and

[3] We keep the variance of these variables constant (variance is 0.05 for all market parameters). We further assume that the probability of sharing information is 1 which can be easily set by the user (different value or range of values). We run only 1 replication since computation time would exceed feasible values.

1. We then measure the influence of these factors and potential interaction effects on seller profit. We used the following variations for the robustness test listed in Table 5.

== Please insert Table 5 about here ==

To test the effect of the different parameter variations and different network structures on seller profit, we analyze the results from the robustness simulation via an ANCOVA with network structure as quasi-experimental factor and mean willingness-to-pay, the degree of forumization and the probability of the truth of information as covariates. Further, we introduce an additional covariate for prospective buyers' overestimation of the secret reserve price and therefore implicitly the costs. In case of overestimation, information diffusion is not beneficial for the seller, because the seller benefits from a low degree of information diffusion and a low quality of information (low α). Vice versa the seller benefits from high quality information which diffuses sufficiently if prospective buyers underestimate the costs. To operationalize *Overestimation,* we subtract costs from the mean beliefs about the secret reserve price ([upper bound+lowerBound]/2-costs). We further test the interaction effects of *Overestimation* and the quality of information (α), and *Overestimation* and the degree of forum participation.

Table 6 displays the results of the ANCOVA. The results show that seller profit is significantly influenced by the network structure. The second network is denser than the network from the virtual community and the impact of information diffusion is thus higher in the second network. Further, buyers' willingness-to-pay positively influences seller profit, which is a straightforward conclusion from the analytical model. As expected, we also see a significantly positive impact of overestimation on seller profit. The quality of information and the degree of forum participation both have a significant positive impact on profit. Further, the interaction effect of overestimation with forum participation is significant and negative but the interaction of overestimation and quality of information is insignificant. Thus, if bidders overestimate the seller's costs, a high degree of information diffusion through a forum decreases the seller's profit. The interaction between overestimation and forum participation overcompensates the benefits from the parameter *Forumization*. If bidders underestimate seller's costs though, high information diffusion is desirable from a seller's perspective. Our robustness tests thus indicate the stability of our previous findings and support the generalizability of our findings.

== Please insert Table 6 about here ==

6. Discussion

We developed a DSS for the analysis of the impact of information diffusion on seller profit in NYOP auctions. The DSS allows the assessment of different strategies that the seller might pursue to react to information diffusion among buyers. Our DSS rests on an extension of an economic model for the effect of shared information on bidding behavior when there is uncertainty about the truth of information. We empirically test the validity of our agent model in laboratory experiments with induced valuations. We find that the value of information is influenced not only by its quantity and dispersion, but also by the uncertainty about the truth of the information. We test our DSS using the data from the laboratory experiments and find a high degree of accuracy when predicted bids are used to explain actual bids.

We illustrate the benefits of our DSS by analyzing the impact of different strategies for a NYOP auction seller for reasonable market parameters and social networks from empirical studies. First, we find that the higher the degree of information diffusion, the higher the secret reserve price has to be set. Second, we find that information diffusion does not necessarily reduce seller profit. This question was also raised by practitioners applying NYOP auctions. It thus might be beneficial for the seller to provide a forum for bidders to foster communication when bidders underestimate the costs of the products sold. Third, uncertainty about the truth of information hampers the revelation of the secret reserve price. Thus an additional strategy for the seller is to intervene in forums and provide false information to dampen the effect of information diffusion. This strategy, however, is ethically disputable and it is questionable whether a practitioner would pursue this strategy. We test the robustness of our results by varying the underlying social network structure as well as the parameter assumptions of our model and find consistent results.

Our study has several limiting assumptions which can be used as avenues for future research. Although we tested our results for two different real network structures and various parameter assumptions, we assume homogenous behavior of agents. An extension of our simulation study could examine heterogeneity in agents' behavior and include different segments of bidders. It would also be interesting to test different degrees of false information so that information provided by friends has a higher probability of being true compared to information from forums, incomplete information or information that is too late. Further, for the purpose of our analyses we assume that all members of the network share their information, but we have already implemented the varying probabilities of sharing in our DSS. Further, future research could test additional seller strategies such as dynamically adapting their secret reserve prices to observed bidding behavior as well as extending the DSS to other types of secret reserve price auctions and competitive market structures. Additionally, sellers may provide suggestion tools for bidders with regard to acceptable bids. However, suggestion tools would entail additional bidder uncertainty about their truth, similar to the provision of false information.

In summary, our DSS can be used as a cost-effective and risk-free decision support tool for NYOP auction sellers in real markets, following the line of argumentation of Bapna, Goes and Gupta [5]. The DSS allows the testing of different social network structures among prospective bidders and of the changes to these structures that a seller might deliberately encourage or that might take place naturally over time.

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Tables and Figures

Treatment Levels	Information provided to subjects
T1	One message about a rejected bid, two messages about accepted bids
T2	One message about an accepted bid, two messages about rejected bids
T3	Two messages about a rejected bid, three messages about accepted bids
T4	Three messages about a rejected bid, two messages about accepted bids

Table 1 – Amount of Information Treatments in Laboratory Study

Dispersion	Proportion of true information (α)	Mean of SAD_j	N	SD
Low	80%	.1198	252	.1023
Low	50%	.1296	252	.1216
High	80%	.0854	252	.0921
High	50%	.1213	252	.1081
	Overall	.1140	1,008	.1077

Table 2 – Influence of Dispersion and Truth of Information on Bidding Behavior

Market scenario	WTP	LB	UB
Underestimation	~N(100, 25)	~N(50, 25)	~N(100, 25)
Adequate	~N(100, 25)	~N(75, 25)	~N(125, 25)
Overestimation	~N(100, 25)	~N(100, 25)	~N(150, 25)

Table 3 – Parameterization for Market Simulation

Market Scenario	Profit without Information Diffusion (SRP=100 EUR)	Profit with Information Diffusion (SRP=100 EUR)	Profit with Information Diffusion (Optimal SRP)	Optimal Secret Reserve Price
Underestimation	36.96 EUR	35.91 EUR (-2.92 %)	61.88 EUR (+67.42 %)	101.00 EUR
Adequate	219.30 EUR	208.09 EUR (-5.39%)	248.09 EUR (+13.13 %)	101.00 EUR
Overestimation	447.86 EUR	436.79 EUR (-2.53 %)	452.24 EUR (+0.98 %)	100.50 EUR

Table 4 – Optimal Reserve Price (Note: SRP=Secret reserve price)

Varied Design Option	Range
Network Structure	0: Virtual Community from [23], 1: Student Community
Willingness-to-pay (WTP)	0 ≤ WTP ≤ 1
Variable costs (c)	0 ≤ c ≤ WTP
Lower Bound (LB)	0 ≤ LB ≤ WTP
Upper Bound (UB)	WTP ≤ UB ≤ WTP+0.1

Table 5 – Parameter Variations for Robustness Tests

Independent Variables	*Seller Profit*
Intercept	-.035***
Net (0=Habbo, 1=Students)	.008***
Mean WTP	.105***
Overestimation	.549***
Forumization	.002***
Quality of Information	.012***
Forumization * Overestimation	-.004**
Quality of Information * Overestimation	.020
n	11,176
F	8,566.95
R^2	.843
p-value	.00

*** p<.01, ** p<.05, * p<.1

Table 6 – Results of Robustness Tests (ANCOVA)

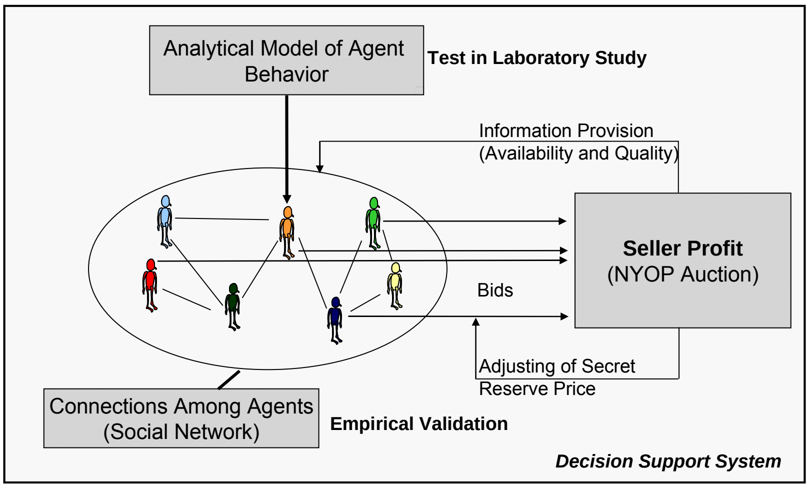


Figure 1 – Overview of Methodological Approach

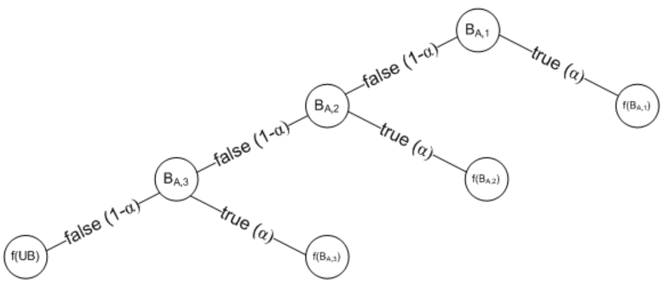


Figure 2 – Uncertainty of Truth of Shared Information – Possible Outcomes (Example for Three Pieces of Information about Accepted Bids)

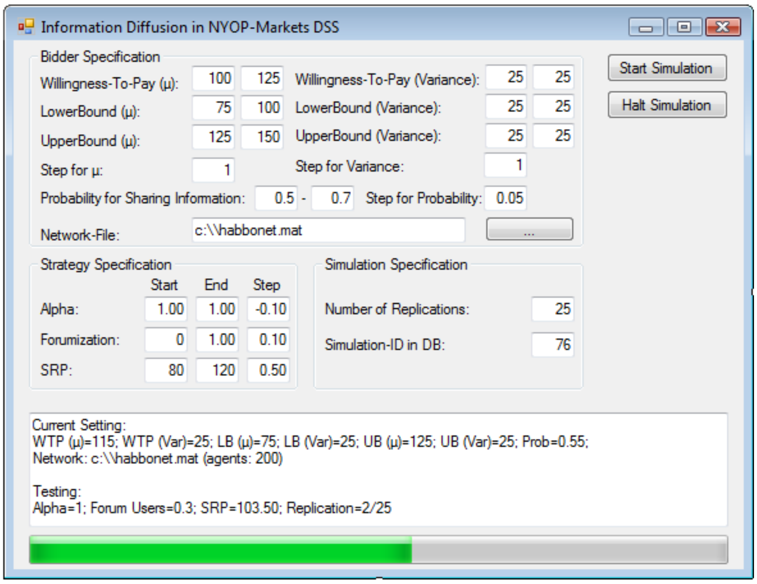


Figure 3 – Screenshot of the Frontend

```
while (biddersAreLeft)
{
  nextBidder=determineNextBidder(B, RULE);

  for (each neighbor of nextBidder)
  {
    if (neighbor.hasPlacedBid()==true)
    {
      bid=neighbor.getBid();

      if (bid.wasAccepted())
        if (bid.Amount<nextBidder.reservationPrice) reservationPrice=bid.Amount;
      if (bid.wasRejected())
        if (bid.Amount>nextBidder.lowerBound) lowerBound=bid.Amount;
    }
  }
  nextBidder.placeBid(calculateOptimalBid(reservationPrice, lowerBound));
}
```

Figure 4 – Agents' Information Gathering and Processing Activity

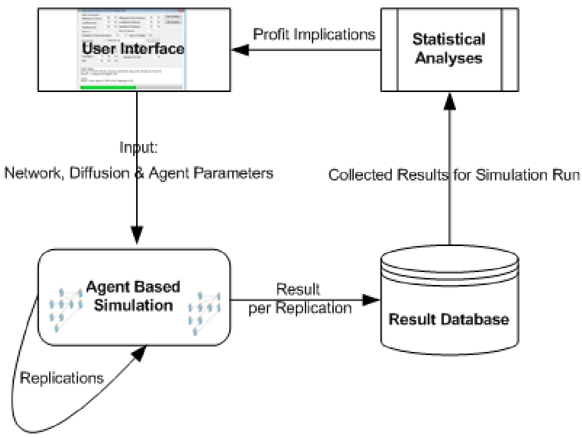
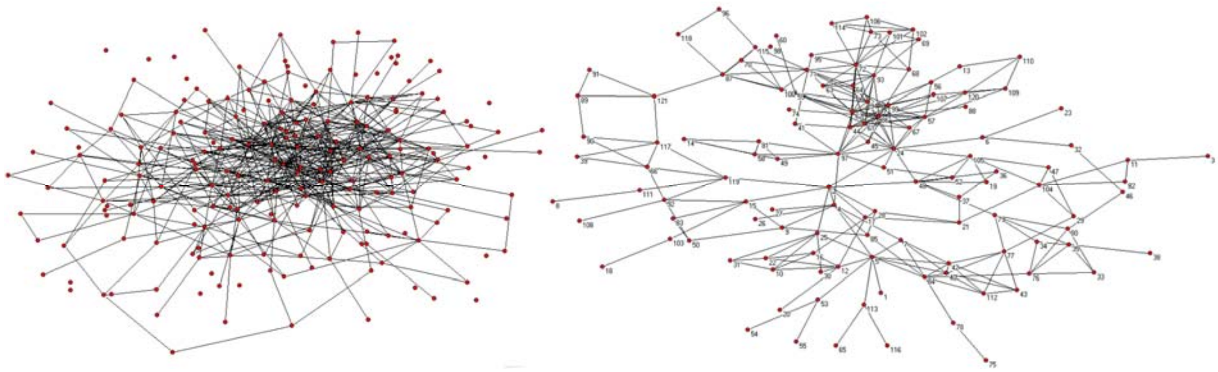


Figure 5 – DSS Architecture



A. 200 NYOP bidders connected in Virtual World **B.** 121 randomly picked MBA Students

Figure 6 – Social Network Structures Used for Tests of DSS

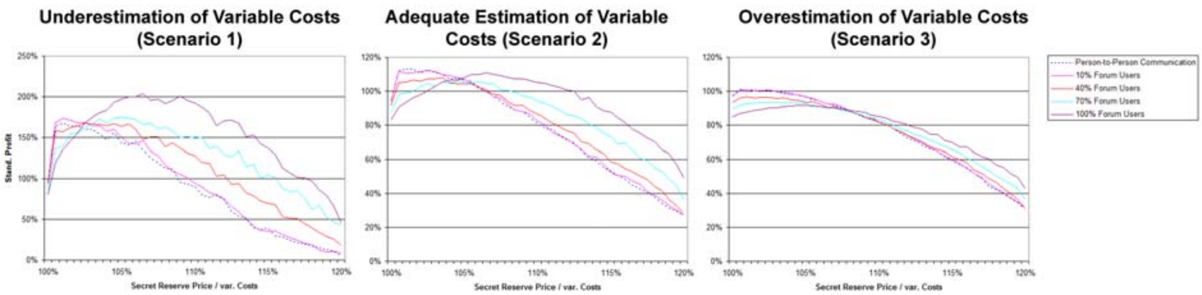


Figure 7 – Optimal Secret Reserve Price dependent on Degree of Forum Participation and Buyers' Estimation of Variable Costs

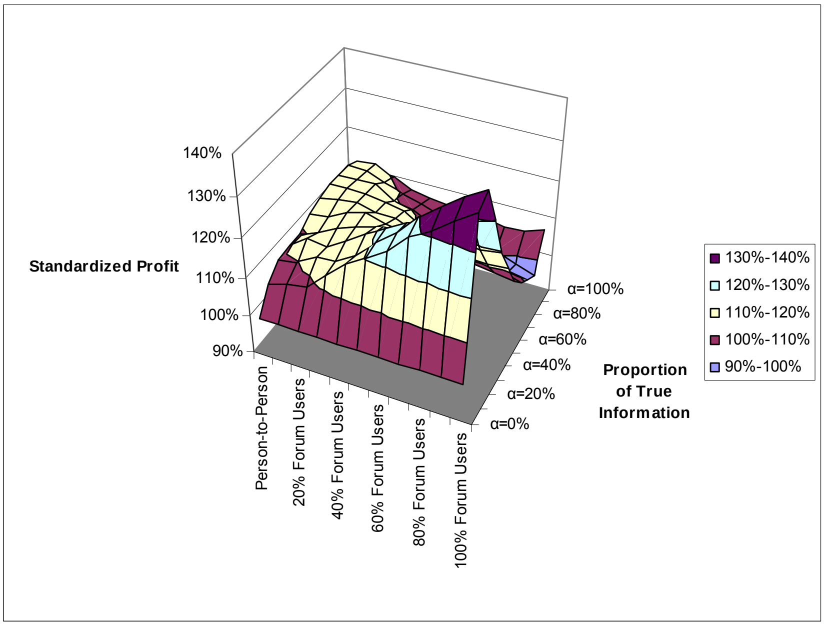


Figure 8 – Raising Profits by spreading False Information (Scenario 2)