Should Online Auctions Employ Dynamic Buyout Pricing Models?

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Abstract

Online auctions are inherently dynamic. Online auction designs that internalize temporal changes in the economic environment are generally expected to perform better than static designs. This is because providing opportunities for both buyers and sellers to inform each other about preference changes over time can increase market transparency and lead to more efficient markets. In this paper, we focus on a feature that is unique to online auctions, the buyout price. We introduce a dynamic buyout model and show analytically how the buyout price should change over time in order to maximize seller profit and buyer surplus. Based on our theoretical results, we suggest that online auction performance can be improved with the addition of more dynamic features. Finally, we describe an experimental design that can be used to estimate the benefits of a dynamic buyout option.

1. Introduction

As electronic markets are becoming the prevalent platforms for firms to manage operations and implement business strategies, IS researchers have been increasingly interested in the discovery of the optimal market mechanisms for various forms of electronic auctions. But most theoretical models to date are based on a limiting static view of the exchange process. Costs related to time are seldom considered because of their analytical complexity. In reality, of course, online auctions are truly dynamic in nature, and much more so even than traditional physical auctions. An online auction typically lasts longer than a conventional one, with the exception of some special formats. Another difference between online and traditional auctions is that buyers in online auctions arrive at different times during the auction. Therefore, we suggest that online auctions should be designed as dynamic processes in which market participants exchange information about the changing market conditions in real time.

Low search costs, large amounts of data, and the availability of efficient matching algorithms make information about cost and value of items more transparent to all participants in online auctions. Many research studies have concluded that the level of information transparency in markets has significant positive impact on market efficiency (e.g., [4, 25, 33]). In this paper, we show that increasing the level of information transparency by allowing buyers and sellers to communicate their time-related preferences can enhance market efficiency in auction settings as well. By market efficiency we mean, in this paper, that the market performs as best it can

We focus specifically on the buyout price as an instrument to convey useful information about preferences to market participants. In static buyout models, buyers can gain knowledge of a seller's expectation of the "fair" price through the buyout option. However, sellers do not get information about buyers' willingness to pay or their time preferences, because buyers typically wait until the end of an auction before they reveal that information. The optimal static buyout price is considerably harder to determine in the absence of this information. In addition, if sellers err when they set the buyout option price or if they learn about an external demand shift while the auction is in progress, they are stuck with their incorrect decision and cannot change it.

In this paper, we introduce a novel dynamic buyout model in which sellers can set a buyout price dynamically (or alternatively, buyers can submit sell-it-now bids, which the seller can accept and thus immediately end the auction). We show that auction efficiency improves when the buyout price changes through the course of the auction. Based on our theoretical results, we suggest that auction designs in industrial practice should offer buyers and sellers more flexibility with regard to the information they share with other market participants. Lastly, we also propose an experimental design that can be used to validate our theoretical findings and to estimate the benefits of a dynamic buy-out option.

2. Relevant literature

2.1. Online auctions

In the Information Systems (IS) literature, an electronic market is generally defined as "*an inter-organizational information system that allows the participating buyers and sellers to exchange information about prices and product offering*" [3]. Associated with electronic markets are usually e-commerce applications such as online auctions, electronic negotiations, electronic procurement, online retailing, and others. As a special case of an electronic market, an online auction may be viewed and analyzed as a game with incomplete information. Given the incomplete information environment, the bidder's strategy is based on some arbitrary function of the observed information. Bidders' decisions about entering and exiting auctions are likewise based on that. In general, the bidder is not only concerned with estimating the expected value of the traded product, but also with estimating how the competitors will bid [9]. Therefore, the amount and quality of information made available in an online auction has a significant impact on the auction outcome.

Theoretically, auctions are preferable over conventional market mechanisms for selling rare or unique items whose prices are hard to determine or whose valuations are largely a matter of personal taste. One of the fundamental differences between traditional and online auctions is that in the latter, bidders can arrive at any point after the start of the auction. Online auctions usually have a fixed, pre-defined duration that is rather long because sellers try to attract as many buyers as possible. The intuition is that a new buyer with a willingness to pay (WTP) higher than the current best may still appear as long as the auction continues [22].

Some previous research indeed supports this notion, citing evidence that longer auction lead to higher prices (e.g., [19]). However, other studies question the benefit of prolonging the duration of online auctions. While we may not be able to define the precise costs for waiting, time is a real concern for almost everyone in online auctions. According to Pinker et al [22] both sellers and buyers have substantial costs associated with time and delay of a sale. Sellers are primarily concerned with inventory costs and turnover while buyers have to trade off possible price savings for a postponement in receiving the product.

Delay and uncertainty about the auction outcome are two important transaction cost components that auction participants bear. Studies have found that because of higher transaction costs auction ending prices are 25%-39% lower than the posted prices of the same items sold online [20, 28]. And Ba et al [2] suggest that online buyers are really looking for balanced prices when they participate in auctions, taking cost-and-benefit factors related to time into consideration when making buying decisions.

2.2. Information transparency effects

The low search costs, the clearly described trading mechanism, and the abundance of transaction data available in electronic markets make information more transparent than in conventional settings [33]. Generally, search engines and various online information providers supply users with current, organized information free of charge. The abundance of information in electronic markets helps market participants learn more about sellers, customers, and competitors, and increases their general informedness about products available in the market [8].

For example, eBay provides the transaction history of all their auctions. Using information made available on starting and ending prices of previous bids on specific items, users can more accurately estimate the price range or possible deal price of the later bids on them.

Moreover, the automated market mechanisms also make information more transparent as they process bids and execute trades according to clearly specified trading protocols [6, 18]. For example, buyers are eventually "forced" to reveal their private WTP information during the course of auctions in which they participate. Similarly, seller expectations are exposed in eBay by the Buy-It-Now (BIN) option.

Previous research studies have concluded that the transparency of information in markets enables them to develop better matching mechanisms, reduce transaction costs, and allocate resources more efficiently [33]. Transparent market information supports the use of dynamic pricing methods, especially for online businesses, because negotiation costs and waiting costs from both buyers and sellers can be reduced. Furthermore, sellers can more accurately identify their competitive position and respond more effectively to changes in the market.

A number of research studies have concluded that the level of information transparency has significant positive impact on market efficiency (e.g., [4, 24, 33]). It is commonly accepted that in an incomplete information environment (exhibiting some information asymmetry), the side with more information will benefit more from the market than the one with less information. Cason and Plott [7] and Srivastava et al [26] argue that information disclosures damage the disclosing party when transacting in a market. Vragov [30] demonstrates that, in open-bid online auction environments, bidders can use bids as signaling devices to cooperate against sellers.

Bakos [4] and Zhu [33] claim that high price transparency benefits buyers at the expense of sellers in a different way. High levels of seller information available in markets enable buyers to have multiple channels for acquiring an item they need. Consequently, it can lead to lower prices and possibly hurt sellers' profits [25]. Consequently, Oh and Lucas [20] suggest that online sellers change their prices frequently to make it more difficult for consumers to respond appropriately. On the other hand, sellers are also providing product and trust information, in addition to price information, and thus increasing information transparency, in order to better facilitate selling. Granados et al [13] examine how IT interacts with other forces to facilitate or inhibit a move to transparent electronic markets and they suggest that enhanced electronic representation of products, and competitive and institutional forces have played an important role in the process by which most sellers have come to favor transparent markets

3. Analysis of static buyout models

Some online auction service providers are trying to address the problem associated with long duration times with a one-time buyout option. eBay (USA), for example, uses a Buy-It-Now option to open a bidding war as soon as possible. This option allows a seller to set a fixed buyout price for her sales items, giving buyers the opportunity to purchase the item right away without having to run the auction to its scheduled end. Exercising the BIN option achieves time cost savings for both buyers and sellers. The Buy-it-Now option on eBay (eBay US) disappears when first bid comes in, so it usually does not shorten the duration of an auction once first bid comes in before anyone chooses the Buy-it-Now option. Other Internet auction houses, such as Yahoo and Ubid, use a bidding rule in which the buyout prices remain valid during the entire auction duration.

Dynamic buyout practices have been commonly adopted in financial markets in the upstairs block trading. The upstairs markets are an off-exchange market, where brokers contact potential counterparties and negotiate the transaction price and quantity for large institutional orders that would likely have a market impact if executed downstairs. The buyout price offered by a block trader enables him to trade-off execution speed and transaction price [24]. The seller benefits from the immediacy by limiting price discovery and quantity discovery in the markets. Since prices are likely to move adversely if the information about a large block offer /order is known, Grossman [14] concludes that potential block traders prefer to not fully quantify their trading interest.

While these experiences from financial markets can be applied to C2C online auctions for general merchandise, the two markets differ in some important aspects. Most auctions sell single items, which are often unique, there no large block trades, and many auctions sell items for use or consumption rather than investment.

The buyout option creates an environment with asymmetric information. Buyers see the buyout option and learn something about sellers' time preferences. Since buyers often wait until the end to submit a last-minute bid (snipe), sellers do not learn anything about buyers' current willingness to pay or the buyers' time preferences.

In auctions without buyout prices, the winner is the highest bidder by the end of the auction. In the auctions with buyout prices, the winner can be any bidder whose willingness to pay is higher than the buyout prices. The buyout option creates uncertainty in the auction outcome, affects buyers' bidding strategies, and results in different expected revenue functions.

For example, Figure 1 depicts an auction with three bidders who arrive with willingness to pay within [0, 1] over an interval of [0, T=1] (t1=0.21, t2=0.68, t3=0.91). The y-axis signifies the WTP of bidders, and the x-axis shows the time points when bidders arrive at the auction. In this case, the seller sets a permanent buyout price at 0.85 and schedules the auction to end at time T. If every bidder bids according to their WTP, then the second bidder will accept the buy price and pay 0.85 to end the auction earlier than scheduled. Bidder 3, who has the highest WTP, will not get the item due to his late arrival, after the auction is already over.

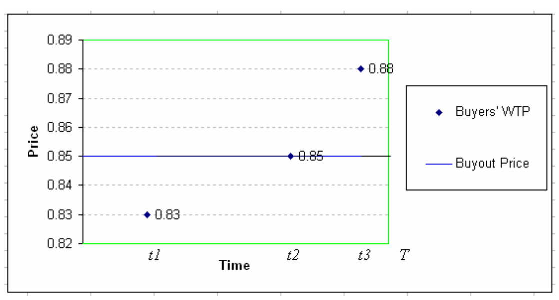

Figure 1. The basic static buyout model

In the static buyout model, if both the seller and buyers are risk-neutral and the buyout price is at least as high as the expected value of the maximum WTP among (n-1) buyers, the seller's expected profit is the same as in a traditional auction, and the auction is efficient. However, online auctions are dynamic in nature. Sellers incur costs that depend on time, or their utilities might be discounted because of time preferences. Buyers arrive at the auction at various times and also incur costs related to time or have time-discounted utility functions. Since the temporal property of a trade becomes increasingly important [15], we can assume that every seller has some cost of time *b*. Therefore, with the marginal cost of time, simply setting a buyout price at least as high as the expected value of the maximum WTP among (n-1) buyers will not guarantee efficiency.

To illustrate this point, Figure 2 shows how the incorporation of time-related costs can impact auction efficiency. If there is no time cost, a buyout price of 0.88 will result in an efficient outcome. But when time costs are included, the same buyout price of 0.88 will generate a lower profit (0.79) for the seller than, for example, a buyout price of 0.83, which will generate 0.81 revenue when marginal cost of time, b = 0.1[1], is included. The static buyout model with time costs is more efficient than standard auctions without.

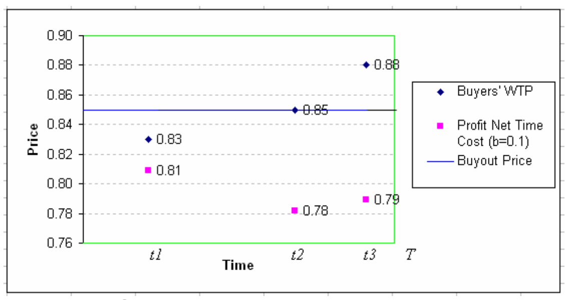

Figure 2. Static buyout model with time costs

However, a static buyout model of an online auction leaves important dynamic details out of the analysis. The prices in the above buyout models are pre-determined and kept unchanged. Clearly, the setting of an appropriate buyout price is crucial to the efficiency of the auctions. If the buyout price is too high, no bidder will accept. Both the seller and the bidders stay on until the end of the auction. The example shown in Figure 3 illustrates that this case. Here, the seller chooses a buyout price of 0.90. No bidder is able to accept the price, and the auction will end at the predetermined time T. The seller ends up selling the item at 0.88 to bidder 3 who had the highest WTP. If the buyout price, on the other hand, as the figure also indicates, had been lower so that either bidder 1 or bidder 3 could have accepted early on in the auction, then the seller could have been better off because of savings in time cost. For example, a buyout price of 0.88 would have generated the same direct profit as with the previous higher price, but the seller would have been able to collect earlier, in $t_3 < T$, and hence come out better off.

If, however, the chosen buyout price had been lower still, say 0.83, the seller would have sold to bidder 1 as well, but lost out 0.05 in possible direct profits. But since he would still achieve considerable time savings, $T - t_1$, he would again be better off as long as those time savings were valued higher than the forfeited direct profit.

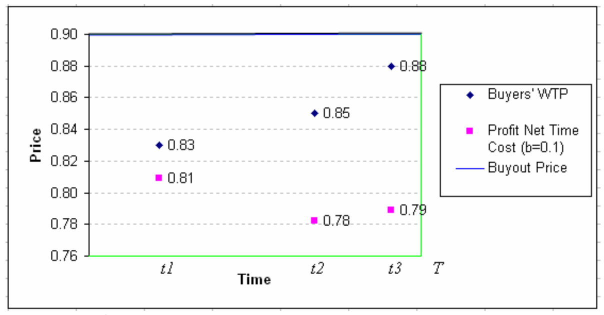

Figure 3. Buyout model with high buyout price

Because bidders' willingness to pay and their time of arrival are unknown to a seller, it is impossible for her to determine an ex-ante optimal buyout price. If there is an unanticipated sharp shift in demand or supply sometime during the auction and the seller is aware of the change, he is not allowed to change the buyout price in the static model. This will often lead to an inefficient auction. A continuous double auction can enable the seller to better solve the unanticipated shift during the auction. Sellers and bidders keep exchanging their bids and asks until transactions occur. The exchange process enables sellers and bidders to learn about others' private values. However, Gode and Sunder [11] suggest that double auctions are too complicated to generate a clear game-theoretic solution for them. Sellers and bidders have to experience the course of the double auction to bid competitively with better information. Double auction models are commonly practiced in the area of financial markets, where sellers and buyers join the auction in a specific period of time. The value and volume of traded products in financial markets justify the transaction costs of involving the double auctions. However, in the case of online auctions of commodity-like products, double auction models are not applicable due to the long predetermined auction duration (normally three to seven days), which will results in extremely high transaction costs. Therefore, a dynamic buyout model

[1] The profit net time cost equals WTP minus cost of time. For a buyout price of 0.88, the generated profit net time cost yields 0.79.

can be a solution that results in better economic outcomes and avoids the high transaction costs that occur in double auctions.

We next demonstrate a less apparent result in the following section where we use a dynamic auction model to show that even when the only reason for a slight shift in demand or supply are the sellers' marginal cost of time and buyers' impatience, efficiency requires that the seller is indeed able to change the buyout price throughout the auction.

4. A Dynamic buyout model

Let's consider a simplified auction model for the sake of our argument. Without loss of generality, let us suppose that an auction consists of $T=3$ periods. The third period is the last period, in which no new bidder arrives. We assume that the seller is risk neutral and has a cost of time c_t in period t. For model simplicity we normalize seller's fixed costs that are not related to time to 0. There are two buyers in the auction that are risk neutral and impatient. We assume that the first buyer arrives in period 1, the second buyer arrives in period 2, and no new buyers arrive in period 3. When a buyer arrives in period t, her WTP, v_t is distributed uniformly in the interval [0, 1].

All this information is public except c_t, which is not known to the buyers. The seller sets an initial buy price, p_1, in period 1. If the first buyer accepts the buy price, the auction ends. If the first buyer does not accept, the auction continues but the buyer's WTP is discounted by a factor $a < 1$. So if a buyer's WTP is k upon arrival, then her valuation decreases to ak in the following period, t and all the way till the end. In the second period both buyers can consider the second buyout price p_2. If either of the buyers accepts that price, the auction ends in period 2. Otherwise, the auction ends in period 3 as a second-price sealed bid auction.

Using the same example that we discussed in section 3, we can see that, in a static buyout model, setting a buyout price too high will result in no bidder accepting it. A dynamic buyout model that lets the seller change the buyout price during the course of the auction can result in increased efficiency. As shown in Figure 4, if the seller set an initial high buyout price of 0.90 for period 1, bidder 1 will not be able to take it. But if the seller is later able to lower the buyout price, he may be able to find a buyer before T. While a new buyout price of 0.89 for period 2 to would not be enough to satisfy either bidder 1 or bidder 2, a further decrease to 0.88 for period 3 will let bidder 2 accept and end the auction earlier than predetermined time.

Although 0.88 is not the optimal buyout price in this case (a buyout price at 0.83 can generate a higher profit of 0.81), enabling the seller to change the buyout price over time still gives the seller the opportunity to sell and turn over items faster and compensate possible revenue losses with savings in time-related costs.

Obviously, the precise amount of the dynamic price changes determine how fast an item can be sold and how much revenue is traded in for time-savings. Ad-hoc price changes, as applied in the above example, are likely to result in suboptimal outcomes, even if they achieve some improvement over static buyout pricing. In next section, we derive the optimal buyout pricing strategy.

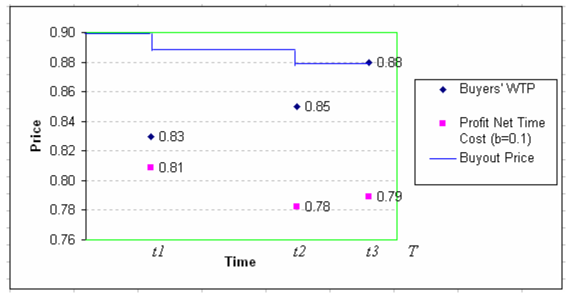

Figure 4. Buyout model with dynamic buyout prices

4.1. Optimal pricing strategy

In order to find the seller's optimal pricing strategy we use the method of dynamic programming for discrete time stochastic systems. We want to show that there is a reasonable set of parameters for which there exists a unique policy $\{p_1, p_2\}$ that maximizes the seller's expected pay-off. This is accomplished in Proposition 1. Here we start our analysis from period 3 and work backwards.

4.1.1. Buyer behavior and seller's expected profit in period 3. During the last period, the buyers' weakly dominant strategy is to set their bids equal to their WTPs for the product because they are participating in a standard second-price sealed-bid auction (see [29]). Because of value discounting, the WTP of each buyer in the last period is distributed uniformly in the interval [0, a]. In the last period, the pdf of the lower of the two WTPs designated by x can be written as $h(x)=\frac{2}{a}\left(1-\frac{x}{a}\right)$ because of the properties of order statistics. This means that the seller's expected revenue in the third period is $\int_0^a xh(x)dx=\int_0^a \frac{2x(a-x)}{a^2}dx=\frac{a}{3}$ and also that his expected profit is

$$\pi_3 = \frac{a}{3} - c_1 - c_2 - c_3 .$$

4.1.2. Buyer behavior and seller's expected profit in period 2. Next we analyze the seller's decision problem in period 2. Remember that dynamic programming assumes that the analysis is used to create a plan ahead of the actual auction. That's why time costs should be considered in every period, which means that the time cost for period 1 is not a sunk cost when decisions in period 2 are considered. If the seller's buy-out price in the second period is accepted, the seller will receive $p_2 - c_1 - c_2$ and if the seller's offer is not accepted then the seller has to wait for the last period, in which he will receive π_3. The expected profit at this point can be written as

$$\pi_2 = F_2(p_2)(p_2 - c_1 - c_2) + [1 - F_2(p_2)]\pi_3 \quad \textbf{(1)}$$

where $F_2(p_2)$ is the probability that the buyout price p_2 is accepted in period *2*. To find the form of $F_2(p_2)$ we need to analyze the behavior of the buyers and the intentions of the seller in period 2. There are three separate cases to consider.

Case 1: $p_2 > a$

If the seller considers setting a price $p_2 > a$ then he is considering attracting the second buyer to accept this buyout price and end the auction. This is because the WTP of the first buyer is already weakly lower than *a*. The second buyer's expected pay-off if he waits until period 3 is equal to the probability that he has the highest WTP multiplied by his expected gain, conditional on her having the highest WTP. The probability that her WTP is the highest is equal to v_2 because of the properties of order statistics. Her expected gain, conditional on her having the highest WTP, is equal to his WTP in the third period minus the conditional expectation of his payment (or the conditional expectation of the other buyer's bid). The complete expression for the second buyer's expected pay-off is therefore $v_2\left(av_2 - \frac{av_2}{2}\right) = \frac{av_2^2}{2}$. This means that buyer 2 will accept p_2 if her profit in period 2 is at least as high as her expected profit in period 3 or

$$v_2 - p_2 \geq \frac{av_2^2}{2} \quad \textbf{(2)}$$

Since we know the pdf of v_2 , we can use (2) to find the pdf of the buyout price through transformation of random variables. We can then find the probability that the buyout price in the second period is accepted in the following way:

$$F_2(p_2) = \Pr[p_2 < v_2 - \frac{av_2^2}{2}] =$$
$$= 1 - \frac{1 - \sqrt{1 - 2ap_2}}{a} \quad \textbf{(3)}$$

We can now find the optimal p_2 by substituting (3) into (1), and by setting the derivative of (1) with respect to p_2 to 0. We can then substitute the optimal price for period 2 in (1) and get the optimal expected profit in the second period.

Case 2: $p_2 \leq a$

If the seller considers setting a price $p_2 \leq a$, then he is considering attracting either buyer 1 or buyer 2. Buyer 2 will accept if $v_2 - p_2 \geq \frac{av_2^2}{2}$ as discussed above. Buyer 1's expected pay-off if she waits until period 3 can be calculated in exactly the same manner as that of buyer 2, however keep in mind that buyer 1's WTP is already discounted by *a* in the second period. Buyer 1 will accept the buyout price in period 2 if $av_1 - p_2 \geq \frac{av_1^2}{2}$. If the auction is to end in the second period either $p_2 \leq v_2 - \frac{av_2^2}{2}$ or $p_2 \leq av_1 - \frac{av_1^2}{2}$ or both. The buyout price in this period will not be accepted if $p_2 > v_2 - \frac{av_2^2}{2}$ and $p_2 > av_1 - \frac{av_1^2}{2}$. It will be easier to proceed mathematically if we first calculate the probability of failure in this period as a function of p_2. To do that we need to define a random variable $z = \max\left\{av_1 - \frac{av_1^2}{2}, v_2 - \frac{av_2^2}{2}\right\}$ and calculate its cdf $G(z)$. The probability that the buyout price in the second period will not be accepted is $Pr[z<p_2]=G(p_2)$ and

$$F_2(p_2) = 1 - \Pr[z < p_2] = 1 - G(p_2) \quad \textbf{(4)}$$

Using transformation of variables once again we find that:

$$G(z)=\begin{cases}1-\dfrac{1-\sqrt{1-2az}}{a} & \dfrac{a}{2}\leq z\leq 1-\dfrac{a}{2}\\ 1-\dfrac{1-\sqrt{1-2az}}{a}\left(1-\sqrt{1-\dfrac{2z}{a}}\right) & 0\leq z<\dfrac{a}{2}\end{cases} \quad \textbf{(5)}$$

This means that we have to consider two sub cases:

Case 2.1: $\frac{a}{2} \leq p_2 \leq a$

The solutions discussed in Case 1 coincide with the solutions here. This is because the formula for $F_2(p_2)$ happens to be the same as in Case 1.

Case 2.2: $0 < p_2 \leq \frac{a}{2}$

For the remaining lower p_2's, we have to use the second expression in the right side of (5) and we will get a different formula and different solutions after substituting in (1).

4.1.3 Buyers' and seller's decision in period 1. Next we analyze the seller's decision in the first period. The expected profit in period 1 can be written as:

$$\pi_1 = F_1(p_1)(p_1 - c_1) + [1 - F_1(p_1)]\pi_2 \quad \textbf{(6)}$$

where $F_1(p_1)$ is the probability that the buyout price in period 1 will be accepted. Buyer 1 will choose to end the auction in the first period if $p_1 \leq v_1 - av_1 + p_2$ and $p_1 \leq v_1 - \frac{av_1^2}{2}$. Notice that $v_1 - av_1 + p_2 < v_1 - \frac{av_1^2}{2}$ for every possible p_2. The probability of rejection in the first period is then equivalent to (3) except that p_2 has to be substituted by p_1. We can now also find the optimal buyout price for the first period by setting up the first order conditions for a maximum. We now have enough background information to state our result.

Proposition 1: Under some specific constraints about the model's parameters, the dynamic programming problem discussed above has as a solution a unique dynamic optimal policy $\{p_1, p_2\}$ that maximizes the seller's pay-off.[2]

This is sufficient to show that according to our dynamic model the optimal policy for the seller is to change the buy price at least once during the auction. Using the results from the proposition and reasoning by induction, it is also possible to show that optimality can in fact be achieved only if the price changes in every period. If the buy price does not change then the optimum will not be achieved and the total expected profit from the auction will be reduced. Hence, in order to maximize expected efficiency, online auction designs should allow sellers to change their buyout prices. This makes sense also because the fact that a buyer did not accept the dynamic bin price in the first period brings additional information about buyer's preferences to the seller. In the second period the seller should be able to use this additional information to update the dynamic buyout price.

4.2 A numerical example

Here we will derive the optimal policy for one set of parameters in order to illustrate the model. Let a = 0.8, c_1 = 0.05, c_2 = 0.03, and c_3 = 0.04. Seller's expected profit in period 3 will be 0.147 (numbers are rounded to the third decimal place). The profit maximizing price in period 2 is 0.448, and the maximum expected profit in period 2 is 0.239. The profit maximizing price in period 1 is 0.472, and the maximum expected profit in period 1 and for the entire policy is 0.306.

4.3 Implementation of the dynamic buyout model

From a technical point of view, enabling online auction systems to support dynamic buyout prices is not problematic. However, since the calculations involved in finding the optimal policy are quite complex, it might be hard for human participants to use and understand the feature. Granados et al [12] suggest that dynamic and transparency is positively related, and better economic outcomes can be achieved from costless communication/coordination between buyers and sellers [1].

One way to implement dynamic buyout pricing is to allow sellers to set an initial buyout price and a constant marginal cost of time *b*. The system can then calculate the optimal policy and change the buyout price every time a new buyer arrives. This method is similar to Sandholm and Gilpin's [23] take-it-or-leave-it auction model, in which a seller announces the order in which the buyers receive offers and the amount of each offer. During a fixed time after receiving an offer, the buyer has to accept the offer, or reject the offer. They conclude that the mechanism generates close-to-optimal expected utility for the seller, and that each buyer's dominant strategy is to act truthfully. However, in that study, the cost of time is not included, and one assumption is that the seller can decide the order in which buyer receive her offers.

[2] The proof is available at http://cisnet.baruch.cuny.edu/vragov/Hicss08proof.pdf

An alternative way to achieve better results than with a constant buyout price is to allow sellers to submit an initial buyout price and buyers to submit temporary Sell-it-Now (SIN) bids when they arrive at the auction. The SIN bids work like an online oral auction. If the seller is satisfied with the price, she can accept the price to end the auction early. Just as buy prices enable buyers to balance their predicted ending price and waiting costs, the SIN prices enable sellers to balance potential later bids and waiting costs. These bids will be allowed to expire when the next period starts. If the buyer arriving in period i has a WTP higher than p_i than the buyer should submit a SIN bid of p_i and the seller could then end the auction by accepting that bid. Buyers should have all necessary information to discover the seller's optimal policy. The initial buy price can serve as a signal to buyers for the seller's marginal cost related to time, which is the only private information that the seller has in our model. One similar practice of this method is the name-your-own-price retailing method in which rather than posting a price the seller waits for potential buyers to submit offers for a given product and then chooses to either accept or reject them. Terwiesch et al [27] suggest that the NYOP model enables a multi-item wholesaler to practice discriminatory pricing and thereby increase profit compared to traditional posted-price retailing.

5. Experimental design

How a dynamic buyout price is implemented is an important question to online auction designers. For example, there are certain behavioral factors that are not considered in the model presented above. We could provide more practical guidelines on implementation issues if we conduct laboratory experiments with human subjects based on our model. Anandalingam et al [1] suggest that to incorporate behavioral aspects in the design of auctions in order to better explain the differences between empirical data and theoretical predictions.

Under naturally occurring circumstances actual WTPs and costs are hard to observe, so that efficiency is hard to determine. To the best of our knowledge there are currently no Internet auction web sites that actually offer dynamic prices. Next, we suggest a specific experimental design that can be implemented in order to study the performance of our theoretical dynamic buyout model in a laboratory setting.

We propose an experimental environment of 5 online auction bidders and a seller of a certain item. Each buyer has a unique independent willingness to pay within [0, 1] for the item. The 5 bidders arrive randomly in five periods within a round of length of 240 seconds (4 minutes). The bidders' WTP will be scrambled so that every buyer has the chance to be the highest WTP holder in a given round. The seller incurs a constant marginal cost of time b and knows the buyers' WTP distribution.

We suggest to run four treatments in our experiments: a baseline treatment, a static BIN price treatment, a dynamic BIN price treatment, and a SIN price treatment. The general rule for all treatments lets buyers submit bids, limited to their WTP, which they are not allowed to decrease. Bidding histories will be made available to all bidders. The baseline treatment is an auction without buyout price and acts as a benchmark for the other treatments. In the static BIN treatment, the seller needs to pre-determine a static buyout price based on estimated buyers' WTP and his time cost. The buyout price will stay the same during the entire auction. In the dynamic BIN price treatment, the seller needs to set an initial buyout price that is offered for the first period. Then the buyout price will change over the following periods according to the pre-calculated optimal policy. The bidders will know the initial buyout price and the rate b.

In the two BIN treatments, a bidder can either submit a bid or accept the buyout price if her WTP is higher than the buyout price. Once a buyer accepts the buyout price, the auction ends. Otherwise, the auction will finish at a predetermined end time. In the SIN treatment, the seller needs to set an initial buyout price valid in period one. The buyers can submit bids and temporary Sell-it-Now prices when they arrive at the auction. A SIN price will expire when the next bidder arrives and a new period begins. The seller can end the auction by accepting a SIN offer from a bidder.

In all treatments, the surplus calculation for the sellers is straightforward. The sellers' surplus is the transaction price (i.e., buyout price or winning bid) minus the time cost. This can help us evaluate how dynamic buyout models perform (in a lab setting), and which format is easier for buyers and sellers to grasp and use.

6. Discussion and conclusion

Internet has enlarged the product space for which auctions are appropriate to include general merchandise. The commonly prescribed long auction times are unnecessary, especially for commodity-like items. Under the realistic assumption that both sellers and buyers have costs associated with time and delay, shortening the auction duration benefits all participants if the optimal surplus is not harmed. This study contributes a dynamic buyout model, which takes advantage of the increased information transparency in online auctions to shorten auction duration by efficiently trading off price and time. The study provides some new insights on the effects of information transparency on auction efficiency.

In previous work, Vragov [30] has concluded that due to the relatively low level of information transparency present in auctions formats currently available on the internet, a few more participants, more experience, and more time are required to achieve efficiency levels that are comparable to those of centralized markets like the continuous double auction used on most commodity and stock exchanges around the world.

Given that information is intrinsically more transparent in electronic markets than in physical markets, online sellers can get better information regarding the market price range of an item. So it is easier for a seller to set her expectation price for an item. However, the distribution of buyers' WTP is hard to obtain, which creates markets with incomplete information and information asymmetries.

One problem with the static buyout model is that to set an optimal BIN price, sellers need to know the number of bidders, their willingness to pay, and the time they arrive. If a Buy-it-Now price is set too high, no bidder will be willing to exercise the option to end the auction. On the other hand, if a BIN price is set too low, items will sell too fast and damage seller surplus. The dynamic buyout model provides sellers the flexibility to adjust their expected prices over time, which increases auction efficiency. Because both seller and buyer disclose more information in the dynamic buyout model, information in this setting is more transparent than that in the static buyout models. Gallien and Gupta [10] suggest that while dynamic buyout prices may bring potential revenue, they question that the revenue increase will be significant given the implementation complexity and possible negative reactions from bidders. We expect that experimental results will give some additional insights in the tradeoff between possible revenue gains and implementation cost.

Sellers in markets are giving consumers additional market information in order to facilitate faster selling and turnover. The purpose of disclosure and increasing information transparency is to reduce uncertainty in markets. We observe large amounts of product, price, and trust information provided by sellers in markets. However, the commonly accepted notion that information disclosure always damages the disclosing side constrains the buyer participation. In contrast, our findings indicate that employing dynamic buyout models disclosing additional information to market participant increase the level of information transparency and thereby can enhance the market efficiency in online auctions.

The reduction of search costs in electronic markets generally results in allocational efficiency from better-informed buyers [3, 17]. If both search cost and time cost are zero, buyers will look at all products offered in the market until they find the one that best matches their needs. However, everybody has a cost associated with time, and buyout models for auctions are helping with buyers' desire to shorten the buying time. In previous research, the costs associated with the duration time of an auction have been largely ignored. It has been suggested that good mechanism designs that stimulate truth-telling would help prevent predatory and collusive behavior [5]. While there is some work studying buyout models, none of them have compared the effect of different levels of information transparency. In the present paper, we contribute a first dynamic buyout model and compare it with previous static buyout models, and conclude that the information transparency has a positive impact on online auction efficiency.

We will run lab experiments according to the design proposed in section 5 and expect to have empirical results ready for presentation to complement our theoretical analysis before year's end.

5. References

[1] Anandalingam, G., Day, R.W. and Raghavan, S. The Landscape of Electronic Market Design. Management Science. Vol. 51, No. 3, March 2005, pp. 316-327.

[2] Ba, S and Pavlou, P. A. Evidence of The Effect of Trust Building Technology in electronic Markets: Price Premiums and Buyer Behavior. MIS quarterly Vol. 26 No. 3, pp. 243-268 September 2002.

[3] Bakos, J. Y. A Strategic Analysis of Electronic Marketplaces. MIS Quarterly, Vol. 15, No. 3, Special Issue: Strategic Use of Information Systems. (Sep., 1991), pp. 295-310.

[4] Bakos J. Y, Reducing buyer search costs: implications for electronic marketplaces, Management Science, v.43 n.12, p.1676-1692, Dec. 1997

[5] Bapna, R. When Snipers Become Predators: Can Mechanism Design Save Online Auctions? Communications of The ACM. December 2003. Vol. 46, No. 12, pp. 152-158.

[6] Campbell C.M. and Levin D. When and Why not to Auction. Economic Theory. Vol 27, 583-596 (2006).

[7] Cason, T. N. & Plott, C. R.. Forced Information Disclosure and the Fallacy of Transparency in Markets, Economic Inquiry, Oxford University Press, vol. 43(4), pages 699-714, October 2005

[8] Clemons, E. K., Gao, G. G. and Hitt, L. , Consumer Information and Diverse Consumer Purchasing Behavior: Traditional Mass-market, Trading Down, and Trading Out into the Long Tail, Proceeding of 9th International Conference on eCommerce, Monnisota, May 2007

[9] Engelbrecht-Wiggins, R. Auctions and bidding models: a survey. Management Science, Vol.26, No.2 (Feb., 1980), pp. 119-142.

[10] Gallien, J. and Gupta S. Temporary and Permanebt Buyout Prices in Online Auctions. Management Science. Vol. 53, May 2007, pp. 814-833.

[11] Gode, D. K. and S. Sunder, S. Lower Bounds for Efficiency of Surplus Extraction in Double auctions. In D. AFriedman and J. Rust, editors, *The Double Auction Market: Institutions, Theories and Evidence*, Santa Fe Institute Studies in the Sciences of Complexity, chapter 7, pages 199{219. Perseus Publishing, Cambridge, MA, 1993.

[12] Granados, N. F., Gupta, A. and Kauffman, R.J. Transparency Strategy in Internet-Based Selling. In K. Tomak (ed.), Advances in the Economics of IS, Harrisburg, PA: Idea Group Publishing, pp. 80-112 (2005).

[13] Granados, N. F., Gupta, A. and Kauffman, R.J. The Impact of IT on Market Information and Transparency: A Unified Theoretical Framework. Journal of the Association for Information Systems. Vol. 7 No. 3, pp. 148-178/ March 2006.

[14] Grossman, S. The Information Role of Upstairs and Downstairs Markets. Journal of Business, 65 (1992), 509-529.

[15] Hidvégia, Z., Wang, W. and Whinston, A. B., Buy-price English auction. Journal of economic theory. November 2004. pp 1-26.

[16] Klemperer, P. What Really Matters in Auction Design. Journal of Economic Perspectives Vol. 16, no. 1, Winter 2002, pp. 169-189

[17] Kumar, N. and Lang, K.R. Do Search Terms Matter for Online Consumers? Decision Support Systems, in press, 2007.

[18] Mathews, T. The Impact of Discounting on an Auction with a Buyout Option: a Theoretical Analysis Motivated by eBay's Buy-It-Now Feature. Journal of Economics. Vol. 81 (2004), No. 1, pp. 25-52.

[19] Ockenfels, A., Reiley, D. H. and Sadrieh, A., "Online Auctions." Forthcoming, Handbook of Information Systems and Economics, Terrence Hendershott, ed., Elsevier Science.

[20] Oh, W. and Lucas, H. "Information Technology and Pricing Decisions: Price Adjustments in Online Computer Markets," MIS Quarterly 30 (3), September 2006, pp.755-775

[21] Onur, I.; and Tomak, K. Buy-It-Now or snipe on eBay? In Proceedings of the Twenty-Fourth International Conference on Information Systems (ICIS-03). Seattle, WA: IEEE Computer Society Press, December 2003, pp. 841-845.

[22] Pinker E.J., Seidmann A. and Vakrat, Y. Managing Online Auctions: Current Business and Research Issues. Management Science Vol. 49, No. 11, pp. 1457-1484 November 2003

[23] Sandholm T. and Gilpin A. Sequences of Take-ti-or-Leave-it Offers: Near-Optimal Auctions Without Full Valuation Revelation. AAMAS'06 May 8-12 2006, Hakodate, Hokkaido, Japan.

[24] Schwartz, R.A. and Francioni, R. Equity Markets in Actions. The Fundamentals of Liquidity, Market Structure and Trading. John Wiley & Sons Inc., Hoboken, NJ.

[25] Soh, C., Markus, M. L. and Goh, K. H., Electronic Marketplace and Price Transparency: Strategy, Information Technology and Success, MIS Quarterly, vol. 30, no. 3, 705-723, 2006.

[26] Srivastava, R. K., Fahey, L. and Christensen, H. K., The resource-based view and marketing: The role of market-based assets in gaining competitive advantage. Journal of Management, Vol.27, No. 6. pp. 777-802 (2001)

[27] Terwiesch C., Savin, S. and Hann, I. Online Haggling at a Name-Your-Own-Price Retailer: Theory and Application. Management Science. Vol. 51, No. 3, March 2005, pp. 339-351.

[28] Vakrat, Y. and Seidmann A., Can online auctions beat online catalogs?, Proceeding of the 20th international conference on Information Systems, p.132-143, December 12-15, 1999, Charlotte, North Carolina, United States

[29] Vickrey, W. "Counterspeculation, Auctions, and Competitive Sealed Tenders" Journal of Finance, 1961, Vol. 16 Issue 1, p8-37.

[30] Vragov, R. Why is eBay the King of Internet Auctions?: An Institutional Analysis Perspective. e-Service Journal, Summer 2005, Vol. 3 Issue 3, p5-28.

[31] Vragov, R. C2C Internet Auctions and Neoclassical Economics: Preliminary Experimental Findings. Baruch College, CUNY. Working paper. 2005.

[32] Vulkan, N. The Economics of E-Commerce: A Strategic Guide to Understanding and Designing the Online Marketplace. Princeton: Princeton University Press, 2003.

[33] Zhu, K. Information Transparency of Business-to-Business Electronic Markets: A Game-Theoretic Analysis. Management Science, May 2004, Vol. 50 Issue 5, p670-685.