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December 1999

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Recommended Citation

Vakrat, Yaniv and Seidmann, Abraham, "Can Online Auctions Beat Online Catalogs?" (1999). *ICIS 1999 Proceedings*. 13.
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CAN ONLINE AUCTIONS BEAT ONLINE CATALOGS?

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Abstract

In this paper, we report the results of an extensive study comparing the price paid in 473 online auctions with the prevailing prices of identical goods sold through online catalogs. Our results reveal a striking phenomenon: auction winners enjoy an average discount of 25% relative to the catalog prices for identical items sold at the same site. The average discount grows to 39% if identical items are on sale only on other sites. We also find that this discount is a function of the monetary value of the items being auctioned and more expensive items are typically associated with lower discount rates. We use these results to characterize the major costs that are imposed on online auction participants and we analyze the impact of these costs on the resulting auction closing price. Our information economics model provides an explanation for the deep discounts observed in our research and provides some conceptual guidelines for online auction design.

1. INTRODUCTION

In the past three years, we have seen an explosive growth in the number of virtual markets and trades conducted over the Internet. Among the various trade mechanisms, online auctions appear to revolutionize the way many goods and services are traded. Auctions have been an established method of commerce for generations. Through the interaction of buyers and sellers via an auction mechanism a market is formed. The Internet provides an infrastructure for running auctions much cheaper, with many more market participants that are not bounded anymore by their physical location. This form of electronic commerce is rapidly growing and holds great promise (Howe 1997; Rabinovitch 1998; Turban 1997). According to recent market research reports, the revenues derived from online auctions were approximately \$9 billion in 1998, up 400% from 1997. This form of electronic commerce poses a fundamentally different mercantile process and has a significant impact on the Internet commerce arena as evident from the revenue growth and the huge number of entrants to this marketplace. "It is only a matter of time before every retailer has an online auction," says a Forrester research analyst (Hof 1999).

There are now several hundred web sites that offer online auctions. Two of the more famous business-to-consumer sites are OnSale and EggHead. OnSale, for instance, offers a wide range of goods such as computer hardware, consumer electronics, sports and fitness accessories, collectibles, airline tickets, hotel rooms, and vacation packages. Most of the goods are factory-direct, in which case OnSale functions solely as an auctioneer, while on other goods OnSale takes title and functions as a retailer. Some goods are new and some are refurbished. OnSale also operates an online catalog channel called "OnSale at Cost."

EggHead.com operates two concurrent distribution channels: one is an online catalog (egghead.com) and the other is one of the most successful online auction site on the web, SurplusAuction. Its online auction site has a wide range of computer product selection. In addition, Egghead takes title on all the goods it sells. It is directly responsible for the merchandise it offers.

The most commonly used auction mechanism on the Internet is the discriminating-price¹ multiple-unit auction. This auction format is essentially an extension² of the classical English auction (Milgrom 1989; Milgrom and Weber 1982; Vickrey 1961) mechanism with observable bids and multiple units of the same item. For example, in the “Yankee auction” model used by a number of sites, identical items are offered simultaneously for sale. The number of items is publicly known and it is set before the auction begins. When the auction closes, the highest bidders win the available inventory at their actual bid prices. For illustration, consider an example from an actual auction file that took place at OnSale on March 18, 1999. Table 1 lists the highest bidders in that auction. There are eight HP PC units for sale and shoppers who arrive at the auction site can only see the highest bids. When each shopper submits his first bid, its time-stamp is recorded. These are the date and time fields that are shown in Table 1.

Table 1. A Sample Auction File (OnSale, March 18, 1999)

Lot: 1639910				
Total number of units offered: 8				
Increment Size: \$10				
Description: Brand new PC, HP Pavilion 8390 w/ PII 450, 128 MB, 10.2GB, 2X DVD, 56K, Win 98				
Bidder	Date	Time	Bid	Qty
SJ of Sun City West, AZ, USA	3/18/99	4:44pm	\$781	2
DD of Federal Way, WA, USA	3/18/99	4:59pm	\$771	1
DL of Washington, DC, USA	3/18/99	4:05pm	\$761	1
JL of San Francisco, CA, USA	3/18/99	4:11pm	\$761	1
CR of Highlands Ranch, CO, USA	3/18/99	4:16pm	\$761	1
LL of Potomac, MD, USA	3/18/99	4:43pm	\$761	1
RS of Sartell, MN, USA	3/18/99	5:22pm	\$761	1

The priority order file in online auction is more involved than the one used for the conventional English auction. The first priority is given for *price*. If multiple shoppers bid the same price, then a priority is given for the one who bids for a *higher quantity*. If the latter does not break the tie, priority is given for the earlier *time-stamp*. This may well be the case in our Table 1 example. There may be more bids of \$761 that we do not see on the screen since they have a later time-stamp³ and, therefore, will not be getting the PC. For example, a bidder for a single unit arriving for the first time at the auction site while Table 1 is on display must offer at least \$771 (= \$761 + an increment of \$10) in order to join the winners’ list. On the other hand, this newly arriving bidder may join the winners’ list at a unit price of \$761, if he bids for two units or more. When the auction ends, the top bidders at that moment are the auction winners. They get the goods for the price they bid. Typically, the auction closes at the posted closing time, or five minutes after the last bid is received, whichever is later.

The online auction business started as a mean for off-loading excess inventory or products that need liquidation in a time-efficient manner. However, most auctions now offer similar goods to the ones a consumer can easily find in online catalogs. We have observed that a growing number of retailers are selling identical goods (such as laptops, airline tickets, and consumer electronics) using both fixed price catalogs and online auctions. Typical examples include Egghead and the Sharper Image. Other sites—such as OnSale, uBid, travelBids, and 4Sale—auction standard items that are concurrently available for sale at a fixed price through third party web sites such as buy.com and travelocity.

¹Each bidder pays his actual bid. Hence, the price paid may differ across bidders when selling multiple items at the same auction.

²For a thorough explanation of the extension see Varian (1999) and Vakrat and Seidmann (1998).

³Suppose for example, that there are eight bidders who bid \$761 for one unit each. We see only five of them, since the rest submitted their first bid later than 3/18/99 5:22 p.m.

In an era of increasingly efficient markets, this phenomena raises some interesting research questions. There have been no systematic studies looking at the actual price differentials for identical items sold concurrently through auctions and fixed-price catalogs. Other unresolved issues include the impact of the unit price on the price differential between these two distribution channels, or the effect of the auction design parameters (i.e., number of units sold in a specific auction, auction length, or the bidding increment), on the relative desirability of purchasing an item using an auction versus a fixed price channel.

Recent studies have surveyed some of the early practices used in the marketplace (Beam and Segev 1998) analyzed the impact of the auction increment on the buyers and sellers surplus under various auction mechanisms (Bapna, Goes and Gupta 1999) and modeled the profit maximizing auction length for the seller (Vakrat and Seidmann 1998). There have been no research reports that look at the simultaneous sales of identical products using on-line auctions and fixed price catalogs.

In this paper we present our results of an extensive empirical study that looked at some of the issues discussed above. We introduce our empirical analysis and results in section 2, and we construct a theoretical model to explain our findings in section 3. Section 4 introduces the potential impact of emerging information technology (i.e., software agents) on that market. Section 5 summarizes our results.

2. EMPIRICAL EVIDENCE

In this section, we address the decisions made by consumers who can use both online catalogs and online auctions. We want to find how much consumers are willing to pay for products that are offered through online auctions and how this compares with the price they pay for the same good in an online catalog setting. To pursue this goal, we obtained real-world data from two different online auction businesses, SurplusAuction and OnSale. We chose these two sites for the following reasons:

1. *Popularity:* these two sites offer a significant volume of goods everyday, which also implies that they have significant web traffic. We needed a large site to provide a basis for randomized data collection with a significant sample size. OnSale and SurplusAuction are both leaders in the business-to-consumer market segment.
2. *Mechanism:* both sites use a multiple-unit English electronic auction (named Yankee Auction© by OnSale). This allows us to have a meaningful comparison across sites.
3. *Business-to-consumers:* many other auction sites such as Amazon and eBay provide a platform for a highly heterogeneous consumer-to-consumer sales. In that respect, they resemble more a garage sale than an orderly market, they have no corresponding catalog price, and were therefore excluded from our study. SurplusAuction and OnSale focus on the business-to-consumers market segment.

Table 2 presents several records from our research data set. It shows few *examples* of auction closing prices and the corresponding catalog prices. For each auction, we present the following information: A unique identifier for the auction (lot number and date conducted), a description of the item being sold, the quantity offered at the auction, and a list of winners; that is, the bidders who won the auction and the actual prices they paid. The last field presents the catalog price for those items at the time of the auction.

The entry for the catalog price field for SurplusAuction and OnSale were collected in two distinct ways. The SurplusAuction site auctions off items that are also being sold on its catalog-based site EggHead.com. Therefore, for each auctioned item on SurplusAuction we obtained the corresponding catalog price of an identical product from Egghead.com (having the same SKU). Interestingly, SurplusAuction has a hyperlink to the Egghead catalog for those consumers looking for a “prix-fixe” purchase option. Even with this hyperlink, one has to conduct a multistep search to retrieve the price of a given SKU trying to match between the online auction at SurplusAuction and the Egghead catalog.

Finding the corresponding catalog price for items auctioned by OnSale required a different research tactic. This site offers distinct merchandize on its two sales channels. Items that are auctioned off on its online auction channel (OnSale at auction) are not sold

Table 2. Data Description: Closing Prices for Several Auctions and Their Corresponding Catalog Price

Lot Number	Description	Qty avail	Bidder Name	Qty. Won	Auction Price paid	Weighted Auction Price	Catalog Price
SY151272 4/8/99	Gazelle PII 350MMX 64/8.0/40x/56K/W98	1					
			PF of MI	1	\$625	\$625	\$899
MM15930 4/9/99	Creative Modem Blaster K56 Flex/V90	2					
			DR of PA	1	\$49	\$49	\$70
			MP of MO	1	\$49		
SY151272 4/9/99	Gazelle PII 350MMX 64/8.0/40x/56K/W98	1					
			AS of FL	1	\$675	\$675	\$899
NB159918 4/15/99	CTX EzBook K6-266 32/4.0/20x/56K/12.1Tft	3					
			DR of OH	1	\$849	\$828	\$899
			JK of MT	2	\$817		

on its online catalog channel (OnSale at cost), and vice versa.⁴ Therefore, to obtain a catalog price, we conducted an extensive search on the web for each item. Due to the fast price erosion of technology goods, we conducted the catalog price search for each item on the same day it was auctioned. The search was performed using several shopping agents (e.g., Pricescan, PriceWatch, ExciteShopping powered by Jango, and others⁵). To account for special promotions, differences in service quality, brand recognition, and availability, we collected for each item up to five price quotes from different web merchants and then calculated an average catalog price. The catalog prices we obtained are for new products and we used data from auctions that offered new products as well.

The auction mechanism used by these two web sites typically results in multiple sales prices when more than a single item is being auctioned off. For instance, the fourth lot in Table 2 presents a three-unit auction where one unit is sold for \$849 and two units are sold for \$817 each. The weighted auction price is \$828 (i.e., $(1 * 849 + 2 * 817) / 3 = 828$).

Participating in an auction provides an entertaining consumption value for some consumers. Yet, buying in a virtual store (using an online catalog) is more convenient than participating in an auction. An online auction involves non-trivial investments in learning the auction mechanism (which can vary from site to site). Several other search and delay costs as discussed in section 3. Moreover, it is in general more difficult to return items for refund in online auctions as compared with items purchased in an online catalog. Therefore, one might expect that rational consumers would view the available catalog prices as an upper bound for the highest bid they would be willing to submit in an auction.

This analysis can be formally presented in the following hypothesis test,

Null Hypothesis H_0 : **There is no difference between the auction price and the catalog price,**

⁴OnSale also posts a field named "Max suggested bid" which is there for signaling to the bidders. Often times we find that one can find the item elsewhere for much less.

⁵Typical web sites: www.pricescan.com; www.pricewatch.com; jango.excite.com; www.bottomdollar.com.

Alternative Hypothesis H_1 : The auction price is lower than the catalog price.

We use the statistic $\hat{x} = \frac{p_a}{p_c}$ to measure the ratio between the weighted-average auction price defined above (p_a) and the corresponding catalog price for the same product (p_c). For each auction, we calculated \hat{x} , where $\hat{x} \in (0, \infty)$. The resulting hypothesis test is:

$$\begin{aligned}
 H_0: & \quad X = 1 \\
 H_1: & \quad X < 1.
 \end{aligned}$$

Our statistical analysis is based on the assumption that the sample data is normally distributed. We checked our statistic \hat{x} for normality and found a very good fit. Figure 1 plots a histogram of the final price ratio of 281 auctions collected from SurplusAuction. The continuous line represents a normal variate with a mean of 0.75 and a standard deviation of 0.15.

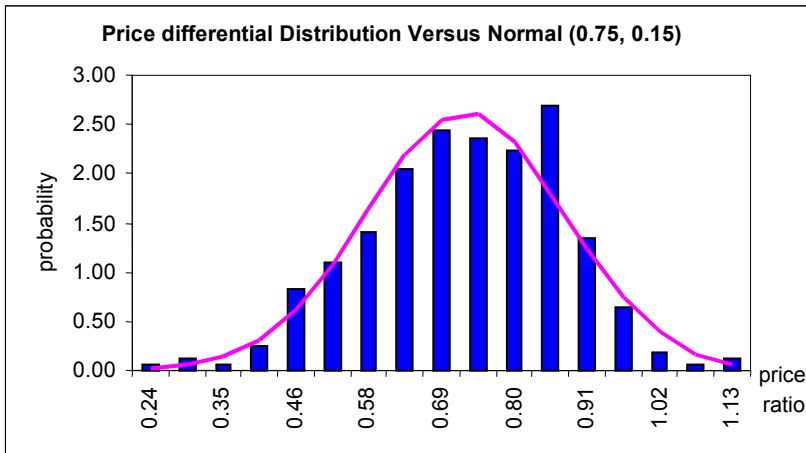


Figure 1. The Distribution of the Price

$$\text{Ration Statistic } \hat{x} = \frac{p_a}{p_c}.$$

It is interesting to see (in Figure 1) that there are few cases where probably uninformed shoppers bid for more than the catalog price (i.e., the resulting ratio is greater than 1). The figure shows that the majority of the bidders are well informed and have enjoyed a substantial discount over the catalog price. The histogram of the sample data distribution from OnSale is similar in structure.

We have used several goodness-of-fit tests to verify the normality assumption. The χ^2 statistic for the SurplusAuction price ratio turned out to be 17.02 with 26 degrees of freedom, which means that we can *not* reject the null hypothesis that the price ratio statistic is normally distributed with a 5% significance level. We also ran the Kolmogorov-Smirnov test and obtained a statistic of 0.048. This result also implied that we could *not* reject normality at the 5% significance level. The Anderson Darling

goodness-of-fit test resulted in a similar conclusion. Identical normality results were obtained for the price ratio data set from OnSale.

We ran two separate hypothesis tests on a sample of 281 auctions from SurplusAuction and 192 auctions from OnSale. The results are summarized in Table 3.

The hypothesis test presented in Table 3 shows that there is a statistically significant, and a practically significant, discount for auction prices relative to concurrent online catalog prices for identical items. Our data indicates an average discount of 25% and 39% at Surplus Auction and OnSale, respectively.

Another interesting research question is the impact of the unit price on the observed price ratio between the two channels. To further investigate that question we looked at the changes in the price ratio between desktops and notebooks. For instance, the average catalog price of desktops sold in our sample was \$836, while the average catalog price of notebooks was \$1,446. We wanted to test the impact of the expected catalog price on the magnitude of the price ratio. We collected data from 60 auctions selling desktop computers and a similar number for notebooks. The Anova results for difference in means between the average price ratio for desktop computers and notebooks are outlined in Table 4.

Table 3. Statistics for the Hypothesis Test

	Surplus Auction	OnSale AtAuction
Descriptive Statistics		
<i>Number of Auctions</i>	281	192
<i>Average Price ratio (\hat{x})</i>	75%	61%
<i>Sample Standard deviation</i>	0.15	0.14
<i>Number of participants</i>	5,174	3,025
<i>Number of Bids</i>	7,076	8,022
<i>Number of auction Winners</i>	1,372	857
Hypothesis Test Results		
<i>Standard Error</i>	0.009	0.016
<i>The standard normal z value</i>	-27	-24
<i>p-value</i>	0.000	0.000
<i>Confidence interval (95%)</i>	$\hat{x} \in [0.733, 0.768]$	$\hat{x} \in [0.578, 0.642]$

Table 4. ANOVA Test on the Difference of Means between the Price Ratio of Desktop Computers and the Price Ratio of Notebook Computers

Summary stats for samples		Price ratio-Desktop computers	Price ratio-Notebook computers			
	Sample sizes	60	60			
	Sample means	0.710	0.873			
	Sample standard deviations	0.104	0.115			
	Sample variances	0.011	0.013			
	Weights for pooled variance	0.500	0.500			
One Way ANOVA table						
		Sum of Squares	d.f.	Mean Squares	F	p-value
	Between variation	0.802	1	0.802	66.778	0.0000
	Within variation	1.417	118	0.012		
	Total variation	2.219	119			
Simultaneous confidence intervals for the difference in means						
	Confidence level	95.0%				
	Difference	Mean difference	Lower	Upper	Significant	
	Mean Desktop - Mean Notebook	-0.163	-0.203	-0.124	Yes	

Table 4 shows that desktop computers have a mean discount of 29% over the catalog price, while notebooks have a mean discount of only 13%. The difference between the means (16%) is statistically significant at 1%. One possible explanation for this result is the different monetary values of the transactions. We hypothesize that the costs that are imposed on bidders in online auctions are (mostly) *independent* of the dollar value of the product. The *search and delay costs*⁶ and the *monitoring costs* are mainly a function of the auction length, but are not a function of the product's value. Consumers will participate in an auction as long as their savings (relative to a catalog purchase) exceed their *search and delay* and *monitoring costs*. Since these participation costs are not a function of the item's price, consumers will expect higher relative savings when purchasing less expensive items through auctions. Everything else being equal, consumers would be expected to end up with higher bids (relatively closer to the catalog prices, from below) for more expensive items. This result is clearly evident in Table 4.

3. ANALYZING ONLINE AUCTIONS

In this section, we construct a comparative model between online auctions and online catalogs. It captures the nature of the price formation in an online auction and help us better understand the empirical analysis described above.

The following simplifying assumptions are made:

- Assumption 1. A seller offers a product for sale both through its catalog and its online auction mechanism. For most of the product markets analyzed in section 2, the seller is a price-taker. Hence, the product catalog price is given and is denoted by p_c . It is a competitive price, which can not be controlled by the individual retailer.
- Assumption 2. The seller offers exactly *one unit* in the auction (for multiple-units analysis, see Venkat and Seidmann 1998).
- Assumption 3. There are n independent bidders and each one bids for exactly *one unit*.
- Assumption 4. Bidder i , $i = 1, \dots, n$, has a fixed reservation value, v_i , for the good. This reservation value is private and collusion among the bidders is not possible. Each bidder draws his reservation price (v_i) independently from the same distribution. These values are distributed uniformly on $[v, \bar{v}]$. Each bidder does not know the others' reservation values.

The consumer who participates in an online auction does not want to wait a long period for the good. He prefers a short auction to a long one. Consider a consumer who bids now for the good, then has to wait for a couple of days (typically these auctions last one to three days). At the end the consumer may not even win the auction at all. The cost has three components:

- *Monitoring costs*: A bidder who participates in such an auction has to learn its rules and regulations, sign up, and then monitor it continuously. During the course of the auction, he may have to increase his bid parameters. Automated tools such as BidWatch™ (provided as a free download at OnSale) can reduce the monitoring costs, but do not eliminate them entirely (see section 4 for a discussion on software agents).
- *Delay costs*: Not all items in the catalog are being auctioned off continuously. Consumers incur a consumption *delay* cost when they have to wait for the right auction to conclude. Some items may be auctioned only once a week at a particular site and the typical online auction may last anywhere from one hour to three days.
- *Search costs*: Consumers have to spend time looking for the site selling the particular items of interest. They are also uncertain about the closing price of the auction and whether they are going to win the auction below their reservation price. When the items are sold to others, they incur additional search costs as they look for alternative sources. At that time, the product may be sold out or backordered.

⁶A detailed discussion of these cost components can be found in section 3.

Let w denote the consumer's *disutility of delay* per time-unit (due to the *monitoring, delay and search costs*) and t denote the auction length. The consumer's total disutility is denoted by $w t$. Formally, we state the following assumptions:

- Assumption 5. Each bidder has a utility function $U_i = v_i - w t - p_a$, where p_a is the auction price paid by bidder i for his single unit.
- Assumption 6. Given his utility function, each bidder submits a bid $b_i(U)$, $i = 1, \dots, n$ to the auction mechanism to maximize his expected utility.
- Assumption 7. The catalog price, p_c , is public knowledge. That is, a consumer who arrives at the web site can check for the price of the good in online catalogs. The consumer is well aware of the price he would have to pay in a catalog before he bids at the auction for the same exact product.

In this setting, a consumer faces a decision whether to buy in an online catalog or to buy in an online auction. If he decides to buy in an auction, he faces all of the cost components we discussed above.



Figure 2. Consumers' Valuations

Figure 2 illustrates the consumer's values. As we described above, initially customers value the good between v and \bar{v} . Then each potential buyer with a prior of v_i conducts his own research and obtains the competitive catalog price denoted by p_c .

Proposition 1: The feasible range for the auction price is: $0 \leq p_a \leq p_c - w t$. That is, the auction price is less than the catalog price by at least the consumers' disutility of delay.

Proof:

We can split the consumers into two disjoint sets.

Type I: Consumers whose value $v < p_c$. These consumers *can not* buy the good via the catalog (since they end up with negative utility) and, therefore, can only bid for the good in the auction. A consumer of type I will bid in the auction *if and only if* he has a positive utility, i.e.

$$\text{or} \quad \begin{aligned} v - w t - p_a &> 0 \\ v &> p_a + w t \end{aligned}$$

recall that by assumption $v < p_c$,

$$\text{therefore,} \quad \begin{aligned} p_c &> v > p_a + w t, \\ \text{i.e.,} \quad p_a &< p_c - w t. \end{aligned}$$

Type II: Consumers whose value $v > p_c$. These consumers can buy *both* via the catalog and via the auction. They would buy at the auction only if their utility from the auction is higher than the one from the catalog, i.e.

$$\text{or} \quad \begin{aligned} v - w t - p_a &> v - p_c \\ p_a &< p_c - w t. \end{aligned}$$

Q.E.D

Let us next derive the expected auction price p_a . Recall first, from the description of online auctions in the introduction that the bidder observes the auction price continuously.⁷ Hence, this is essentially an English auction as defined in auction theory literature (Vickrey 1961). The English auction procedure is iterative. The bidders electronically submit bids and the price ascends until there is only one bidder left.

When the price ascend halts, it means that the second-highest bidder has just quit the competition. It happens exactly when he reaches his own (the second highest) reservation price.⁸ Therefore, the price that the winner of the auction pays equal theoretically to the second-highest reservation price.

Let r_i be the reservation price of bidder i . From the discussion above and assumption 5

$$r_i = v_i - w t.$$

Let $r_{(1)}, r_{(2)}, \dots$ be sorted actual reservation prices where $r_{(1)}$ is the highest bid, $r_{(2)}$ is the next highest, etc. From the analysis above the winner of the auction pays a price equal in expected value to

$$E[p_a] = E[r_{(2)}]. \quad (1)$$

Before the bidders find out the catalog price, their private values are distributed uniformly on $[\underline{v}, \bar{v}]$. Assumption 7, which states that bidders are informed of the corresponding catalog price, induces the result of proposition 1 as well as a posterior distribution of consumers' values. The probability distribution function of consumers' value conditioned on the catalog price is,

$$p(v|p_c) = \begin{cases} \frac{1}{\bar{v} - \underline{v}} & v < p_c - wt \\ \frac{\bar{v} - p_c + wt}{\bar{v} - \underline{v}} & v = p_c - wt \end{cases} \quad (2)$$

The second highest order statistic when sampling from the distribution in (2), which also equals the expected auction price according to (1), is

$$E[p_a] = \begin{cases} p_c - wt & \text{if } \frac{p_c - wt - \underline{v}}{\bar{v} - \underline{v}} \leq \frac{n-1}{n+1} \\ \frac{\bar{v} - p_c + wt}{\bar{v} - \underline{v}} \underline{v} + \frac{n-1}{n+1} (\bar{v} - \underline{v}) & \text{else} \end{cases} \quad (3)$$

First notice that $n - 1/n + 1$ is an increasing function of n . Therefore, as more consumers participate in the auction (i.e., n gets larger), the expected auction price increases. In fact, this computes a known fact that a competitive pressure (in the form of more bidders) increases the auction price. Furthermore, when the number of auction participants n is relatively high, the auction price is more likely to be asymptotically approaching $p_c - w t$.

These results explain the significant price discount in auctions relative to fixed-price catalogs as depicted in Table 3. Bidders are well informed about the catalog prices and only 2% of the auctions ended up with a price ratio greater than one. Given the catalog

⁷For all auction sites we know, the highest bid is posted on the web site throughout the auction.

⁸Plus possibly ϵ , i.e., a tiny increment to go above the second highest reservation price. "Reservation" price of bidder i is the highest price that he is willing to bid for, keeping his overall utility positive.

price, bidders update their private reservation price and hence bid lower. The result presented in Equation (3) quantifies the closing auction price and consequently the expected discount that bidders realize. The result implies that two factors determine the discount: the bidders' cost of participation (i.e., *search and delay* and *monitoring costs*) and the number of bidders who participate in the auction. The model also predicts that the discount will diminish as more bidders log on to the auction web site.

In the next section, we explore how software agents technology may potentially impact the market of online auctions and in particular the impact on the economic model presented in the paper.

4. SOFTWARE AGENTS AND AUCTIONS

Recently, software agents have been applied to electronic commerce (e-commerce), revolutionizing the way business transactions are taking place.⁹ Software agents can be used to automate several of the most time-consuming stages of the buying process. The major difference between so-called traditional software and software agents is that the latter are personalized, running continuously and are semiautonomous (i.e., are able to make decisions by themselves in certain situations). For example, ideally, buying agents will automatically collect information on vendors and products that may fit your needs, evaluate the different offerings, negotiate the terms, and finally even submit a bid and make the payment as an automatic balance transfer.

The adoption of this technology may affect Internet auctions. Monitoring the auction site is already delegated to software agents. For example, BidWatch by OnSale (also BidClick on Amazon) automatically resubmits bids whenever needed. This reduces the parameter w (the disutility of delay). Also, the cost due to the deferred consumption may be reduced considerably. In a future scenario, the auction takes place without human intervention, hence the interaction with the auction server would be a lot faster. Therefore, we conjecture that full deployment of software agents will reduce the price gap between catalogs and online auctions.

A subset of software agents is called "mobile agents." Mobile agents are different in that they are not bound to the computer system on which they begin execution. In fact, they are free to travel among hosts in the network. The agent transports its state¹⁰ and code with it to another execution environment in the network, where it resumes execution.

Figure 2 illustrates the mobility property of a mobile software agent. As we see in the figure the client initiates and sends a mobile software agent, which transports itself to the server platform where the auction is running.¹¹

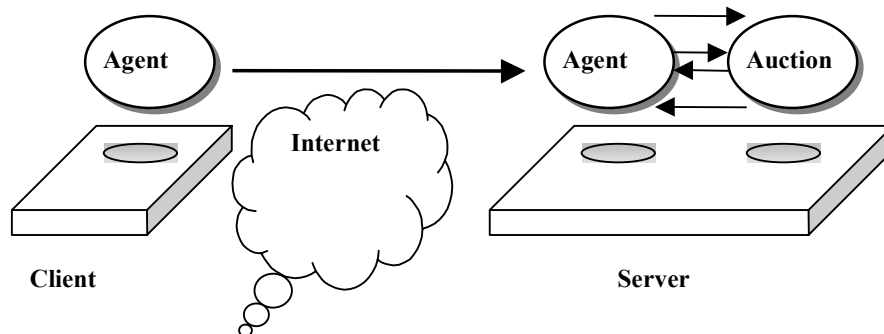


Figure 2. Mobile Agents Framework

⁹For a survey of the various existing agents, see Pattie, Guttman and Moukas (1999).

¹⁰In object oriented terminology, "state" means the agent's attributes or properties. By code, we mean the methods that accompany the agent class.

¹¹In the figure, we see only one such agent but in reality there will be many agents from various sources, all gathering on the auction server and each communicating *locally* with the auction mechanism.

The auction mechanism that by far dominates the online auctions market is a version of a multi-unit English auction. Hence, the bidding process is iterative and typically each consumer resubmits multiple bids. Thus, the framework of *mobile* software agents is attractive in this auction setting since it saves on communication bandwidth. The current technology model is to repeatedly access the auction server, whereas a mobile software agent ideally can be transported only once to the auction server and negotiate the transaction remotely. Let us emphasize that mobility of software agents is not critical to performing the monitoring task, it is merely advantageous.

Standards have traditionally been the bottleneck of distributed systems deployment. If indeed software agents can reduce the price gap between auctions and catalogs, it will provide an incentive to sellers (online auction merchants) to adhere to standard interfaces, which are critical to implementation of such distributed systems (such as Jave-concordia [Koblick 1999] or the Java-lets Tai and Kosaka 1999] project).

Another interesting emerging technology that is likely to impact online auctions is XML. The eXtensible Markup Language carries a promise to standardize the interface for business data communication and in particular online auctions. XML facilitates the interaction among software agents (see Glushko, Tenenbaum and Meltzer 1999) as well, since it standardizes the protocols they use.

5. CONCLUSIONS

Internet auctions are a rapidly emerging trading scheme in the e-commerce arena. A growing number of items are offered through online auctions. This is due to new technologies that enabled a dramatic decline in the cost of running an auction. Using real-world data on closed deals from a couple of auction sites, we identified a remarkable phenomenon: the auction price is lower than the catalog price for the same product by an average of 25% when both are sold by the same retailer. A more dramatic price differential (39%) was found when we compared the auction price from a different online auctioneer versus an average catalog price from various online retailers. These results are shown to be statistically significant with an extremely small probability of an error.

We develop a theoretical model that verifies our finding. This model provides an economic explanation for the empirical phenomenon observed. Consumers who face the decision whether to bid in an online auction or to directly buy from an online store (i.e., fixed-price catalog) take into account the costs that they incur when deciding to participate in an online auction. First, the consumer has to learn the auction rules (which may vary from site to site), then she has to search for the item of interest. When she eventually finds the desired auction, she has to wait until the auction concludes and, therefore, incurs a delay in consumption. Throughout the auction, a bidder does not know the other bidders' reservation prices. Hence, the bidder is uncertain whether she will win the auction or not. In case she does not win the auction, she incurs additional search costs. Moreover, the consumer has to monitor the auction to be able to resubmit bids when needed. Depending on the auction length, this can be costly. Our model quantifies the impact of these participating costs on the auction closing price and consequently on the discount over the catalog price.

Furthermore, we show that the average discount varies depending on the unit price, such that more expensive items reveal lower percentage savings. Our theoretical model clearly explains this phenomenon. The discount required by consumers is a direct result of the costs they incur. In addition, these costs are independent of the monetary value of the good. Therefore, percentage-wise, consumers expect lower percentage savings on the more expensive items.

Based on our theoretical analysis, we explore the potential impact of mobile software agents on the future of Internet auctions. We explain why they may reduce the price-gap between the traditional posted-price selling method and the auction closing prices. We also show how software agents can provide an incentive to sellers to comply with market standards for software agents interaction. Provided that we indeed realize such a setting in the near future, we approach an ideal frictionless market.

6. REFERENCES

- Bapna, R.; Goes, P.; and Gupta, A. "A Theoretical and Empirical Investigation of Multi-item On-Line Auctions," Working Paper Department of Information Management, School of Business, University of Connecticut, 1999.
- Beam, C., and Segev, A. "Auctions on the Internet: A Field Study," Working Paper WP-1032, Fisher Center for Management and Information Technology, University of California, Berkeley, November 1998.
- Glushko, R. J.; Tenenbaum, J. M.; and Meltzer, B. "An XML Framework for Agent-based E-commerce," *Communications of the ACM* (42:3), March 1999.
- Hof, R. D.; Green, H.; and Judge, P. "Online Auctions: Going, Going, Gone," *Businessweek*, April 12, 1999.
- Howe, J. R. "Going, Going, Gone," *Computerworld*, November 1997.
- Koblick, R. "Concordia," *Communications of the ACM* (42:3) March 1999.
- Milgrom, P. R. "Auctions and Bidding: A Primer," *Journal of Economic Perspectives* (3), Summer 1989, pp. 3-22.
- Milgrom, P., and Weber, R. J. "A Theory of Auctions and Competitive Bidding," *Econometrica* (50:5), September 1982.
- Pattie, M.; Guttman, R.; and Moukas, A. "Agents that Buy and Sell," *Communications of the ACM* (42:3) March 1999.
- Rabinovitch, E. "Auction Sites" (Part of "Buy it on the Web" by David Lidsky), *PC Magazine*, November 17, 1998.
- Tai, H., and Kosaka, K. "The Aglets Project," *Communications of the ACM* (42:3), March 1999.
- Turban, E. "Auctions and Bidding on the Internet: An Assessment," *Electronic Markets* (7:4), 1997.
- Vakrat, Y., and Seidmann, A. "Analysis of Internet Auction," Working Paper, William E. Simon School of Business Administration, University of Rochester, October 15, 1998.
- Varian, H. "Economic Mechanism Design for Computerized Agents," 1999 (<http://www.sims.berkeley.edu/~hal/people/hal/papers.html>).
- Vickrey, W. "Counterspeculation, Auctions and Competitive Sealed Tenders," *Journal of Finance* (16), March 1961, pp. 8-37.