PRICES IN ONLINE AUCTIONS FOR OFF-LEASE COMPUTERS

Draft: Comments Welcome

May, 2003

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Abstract

One of the most vibrant Internet business models is the online auction. As activity in this market increases it provides a test-bed for analyzing auction theory as it relates to bidding behavior and realized prices. One key area of interest relates to auctioning multiple units of identical items. This research develops a model for sequential auctions and analyzes behavior using realized prices from auctions of off-lease computers. The model of sequential auctions incorporates the opportunity cost of participating in consecutive auctions, to explain price declines. The empirical results also provide support for the "price decline anomaly". In consecutive auctions realized prices tend to be lower for later, contradicting "the law of one price". The empirical analysis confirms other theoretical facets of market-clearing prices. Prices are increasing in the number of bidders, they exhibit serial correlation, and prices tend to be lower on weekends. A surprising finding is that prices for used computers do not exhibit a downward trend, as new computers do. Results from this research can provide guidance for computer resellers, buyers at online auctions and facilitators of the exchange.

Keywords: Online auctions, Secondary markets, Computer sales, Bidding

I would like to thank Chester Chambers, Marion Sobol and two anonymous referees and conference participants at AMCIS 2002 for their helpful comment on previous versions of this paper. I am indebted to Anthony Rugely for his research assistance.

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I. Introduction

One of the most successful online business models is the online auction. The Internet provides an excellent platform for bringing together sellers and buyers for items that do not otherwise have well known trading venues and stable market prices. For example, selling collectible items, such as coins or stamps, benefits from assembling buyers in one physical or virtual location and auctioning goods to the highest bidder. Among online auction sites eBay.com is the dominant venue, facilitating more than $5 billion of bilateral trade and claims to be the most popular online shopping site.[1]

The auction also enables secondary markets for used goods, which often suffer from problems of price discovery (Lucking-Reiley, 1999). An interesting secondary market that is developing through the popularity of online auctions is the market for used computers. The opportunity stems from heterogeneity in computer uses. Some users, including businesses users, purchase new machines with fast processors, large RAM, current operating systems, and other advances features. These machines quickly become obsolete as newer machines are introduced. Price sensitive users, on the other hand, derive little marginal benefit from advanced features and would compromise on features for a lower price. The opportunity to sell used computers has not materialized until recently. In contrast to used cars or houses, used computers do not have stable reference prices or a commonly known trading venue. The online auction is one venue that enables developing this market. This market is quite active with thousands of computers offered each day on eBay.com

Liquidity in an auction market for used computers offers an excellent natural experiment for empirically testing hypotheses of auctions theory. Rarely do physical auction markets offer such a breadth of activity to investigate market behavior both of the individual auction and the implications for dynamic prices.

[1] From http://pages.ebay.com/community/aboutebay/overview/index.html based on Media Metrix data of total user minutes.

II. The Price Decline Anomaly

Among the many questions that this market may address, the “price decline anomaly” is of particular interest. Ashenfelter (1989) coined this term when investigating auctions for cases of wine bottles. When identical cases were sold in the same auction early auctions generated higher revenue, with prices declining thereafter, violating the “law of one price”. The finding is perplexing because it violates rational expectations. If buyers at an auction expect lower prices in the future they would abstain from bidding until the latter auction arrived, keeping expected prices constant. Since then this topic is discussed often (see the review in Ginsburgh, 1998) both for replicating the finding and for providing theoretical justification for it. McAfee and Vincent (1991) suggest that risk-averse bidders drive up prices in initial auctions. A bidder in an initial auction faces the risk of not winning any items in subsequent auctions. This generates a risk premium to cover the risk of not winning anything. Alternately, Menezes (1993) suggests that bidders face a delay cost for each auction they participate in. This provides an incentive to bid aggressively in early auctions, raising prices.[2] Finally, behavioral research can explain the phenomenon. If bidders decide their willingness-to-pay for an item based on results of previous auctions, the closing price of one auction becomes a “fair” price for the next auction (Thaler, 1985). Bidders would not want to bid higher than the price they saw, thinking that would be unfair. This limits prices in future auctions, leading to a price decline.

However, Ginsburgh (1998) dismisses this anomaly by showing that the empirical evidence has been mixed to date and by examining the way auction houses in London conduct wine auctions. Auction houses often receive bids for cases of wine by outside buyers, who do not attend the physical auction. The submission of these outside bids by the auctioneer to the auction floor generates price declines. The contradicting literature on this topic suggests that this large dataset of online auctions may be useful in addressing this question.

III. A Model of Sequential Auctions

Realized prices in sequential auctions on Ebay.com can be analyzing using a general model of dynamic auction prices. The model derives equilibrium prices in a series of sequential

[2] Note that this result rests on the assumption that bidders must attend the first auction to be allowed to participate in the second one. Otherwise, bidders would choose randomly among the auctions, eliminating the price decline phenomenon.

auctions with participation costs for bidding. Assume there are K identical computers auctioned in K sequential, sealed-bid, second-price auctions.[3] Let there be n risk-neutral bidders each desires at most one item ($K<n$).[4] Each bidder privately knows his value for the item (denoted by v), which is drawn IID from a continuous, non-negative, commonly known distribution[5], with c.d.f. of $F(v)$ with support $[0, \bar{v}]$. To participate in an auction each bidder faces a cost of c, reflecting the opportunity cost of time to wait for the end of the auction.

Buyers in this market bid on computers sequentially. If a buyer wins a computer he leaves and does not bid in following auctions. Furthermore, it is assumed that if the expected profit from winning an auction does not cover the (opportunity) cost in auction r (r=1..K) he leaves and does not bid in following auctions. The bid (price) by a buyer reflects his value for the computer (v), the (opportunity) cost of participating in the auction (c), the number of computers offered that day (K), the rank of this computer within the set offered that day (r), the distribution of values ($F(v)$), and the number of other buyers (n). We investigate the symmetric, pure-strategy increasing-price bidding strategies in sequential auctions with participation costs. Using subscripts to denote auctions, bidding strategies are denoted by $B_r(v,c,K,n)$. Holding c, K and n constant $B_r(v,c,K,n)= B_r(v)$.

Before deriving equilibrium bidding strategies 2 restrictions are introduced. Corollaries 1 & 2 show that these restrictions are reasonable, in the derived equilibrium, in:

A1. The auction is efficient. (I.e., the K computers are awarded to the K buyers who place the highest value on them.)

A2. The auction participation cost (c) is low enough to assure that a buyer, who participates in the last auction, participates in all previous auctions.

For a buyer of value v denote the order of the values of the n-1 other buyers according to $Y_1 > Y_2 > .. > Y_K$. Thus, Y_r denotes the r-highest order statistic of n-1 draws from distribution $F(v)$. Denote the c.d.f. of Y_r by $G_r(v)$ with p.d.f. of $g_r(v)$. Since this is a distribution of order statistics (Wolfstetter, 1999):

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3 From revenue equivalence this is also the equilibrium of an oral auction (Vickrey, 1961). Alternately, see Bajari and Hortaçsu (2002) for justification on why eBay.com auctions are second-price, sealed-bid auctions.

4 If there are more items than bidders equilibrium prices are all equal to zero and the seller could increase prices by offering fewer items. On eBay.com with many potential buyers following offerings on the site this assumption is reasonable.

5 This describes an Independent Private-Value auction.

$$G_r(v) = \sum_{j=n-r}^{n-1} \binom{n-1}{j} F(v)^j \, [1-F(v)]^{n-j-1}$$

$$= \frac{(n-1)!}{(n-r-1)!(r-1)!} \int_0^{F(v)} t^{n-r-1} (1-t)^{r-1} \, dt \quad (1)$$

$$\text{and } g_r(v) = \frac{(n-1)!}{(n-r-1)!(r-1)!} F(v)^{n-r-1} [1-F(v)]^{r-1} f(v) \quad (2)$$

If computers are allocated to buyers in descending order of their value (from Restiction A.1.) a buyer of value v wins auction r if: $Y_r < v < Y_{r-1}$. In a second-price sealed-bid auction the price he will pay at that auction is equal to the bid placed[6] by the buyer with value just below v, i.e., with value Y_r. This price is $B_r(Y_r)$.

III.A. Bidding Strategies

Bidding in the last auction

The final auction (K) in the sequence is a sealed-bid, second-price auction for a single computer. A weakly dominant strategy in this auction is bidding the reservation value (Vickrey, 1961). Assuming that the K-1 previous computers were sold to the buyers Y_1 .. Y_{K-1}, the computer is sold to the buyer with $Y_K < v < Y_{K-1}$. This buyer pays $B_K(Y_K)$.

For every remaining buyer after K-1 auctions the profit from continuing to the next auction is given by:

$$p_K(v) = v - \mathrm{E}[B_K(Y_K) \mid Y_K < v < Y_{K-1}] - c$$

$$= v - \mathrm{E}[Y_K \mid Y_K < v < Y_{K-1}] - c \quad (3)$$

The first term is the buyer's private value for the computer, the second reflects his expectation for the bid placed directly below his, and the third is the cost of participating in the next auction.

There are buyers who opt not to bid in this auction. For a buyer with sufficiently low value (v) the expected profit is negative. The fixed cost of participating does not cover the expected

6 Equivalently, in an English auction this is the highest bid placed by a buyer with value just below v, again $B_k(Y_k)$.

profit (value minus expected payment) from bidding. A Buyer participates in this auction only if $p_K(v) \geq 0$. From A2 any buyer who has positive expected profit in the last auction would not drop out earlier.

Bidding in auction *K*-1

A buyer in auction K-1 has the option of waiting and winning a computer in the subsequent auction. His willingness-to-pay in auction K-1, therefore, is reduced by the "option value" of waiting. The value of this option is the expected profit in the last auction: $p_K(v)$. This auction is, again, a second-price, sealed-bid auction. Now, each buyer has a weakly dominant strategy of bidding his willingness-to-pay (not his reservation value), which is given by:

$$B_{K-1}(v) = v - p_K(v)$$

$$= \mathrm{E}[Y_K \mid Y_K<v<Y_{K-1}] + c$$

The expected profit for a buyer entering this auction is:

$$p_{K-1}(v) = v - \mathrm{E}[B_{K-1}(Y_{K-1}) \mid Y_{K-1}<v<Y_{K-2}] - c$$

$$= v - \mathrm{E}[\mathrm{E}[Y_K \mid Y_K<Y_{K-1}] + c \mid Y_{K-1}<v<Y_{K-2}] - c$$

$$= v - \mathrm{E}[Y_K \mid Y_{K-1}<v<Y_{K-2}] - 2c$$

Bidding in auction *r*<*K*

A buyer of value v wins the computer in auction r=1..K if $Y_r < v < Y_{r-1}$. If $Y_{r-1} < v$ he would have won in a previous auction, because bids are symmetric and increasing in value. Similarly if $v < Y_r$ this buyer will be outbid in this auction. This buyer's willingness-to-pay in auction r is determined by his value and the option value of winning the item in the next auction, which is equal to $p_{r+1}(v)$. Placing a bid that equals his willingness-to-pay yields:

$$B_r(v) = v - p_{r+1}(v) \qquad (4)$$

The expected profit for a buyer entering this auction is:

$$p_r(v) = v - \mathrm{E}[B_r(Y_r) \mid Y_r<v<Y_{r-1}] - c \qquad (5)$$

Proposition 1: In the second-price, sealed-bid, sequential auction with unit demand and auction participation cost the symmetric, increasing equilibrium bids are given by:

$B_K(v) = v$

$\forall r < K$:

$$B_r(v) = \mathrm{E}[Y_K \mid Y_{r+1} < v < Y_r] + (K - r)c \tag{6}$$

With expected profit of:

$$p_r(v) = v - \mathrm{E}[Y_K \mid Y_r < v < Y_{r-1}] - (K - r + 1)c \tag{7}$$

where:

$\mathrm{E}[Y_K \mid Y_r < v < Y_{r-1}] =$

$$\int_0^v y \frac{(n-r-1)!}{(n-r-K-1)!(K-r-1)!} \frac{G(y)^{n-r-K-1}[G(v)-G(y)]^{K-r-1}}{G(v)^{n-r-1}} dy \tag{8}$$

Proof: See Appendix A

III.B. No Participation Costs

To understand this bidding function it is instructive to explore behavior without participation costs. If c=0, $B_r(v) = \mathrm{E}[Y_K \mid Y_{r+1} < v < Y_r]$ (Weber, 1983, Theorem 3; Krishna, 2002, Proposition 15.12). This expression indicates that a buyer with value v bids according to the expected price in the last auction, conditional on winning auction r. Note that in the last auction each buyer bids his true value for the computer. For a buyer with value v the expected price is the K^{th} highest order-statistic among the n-1 other bidders. Using backwards induction Krishna (2002) shows that expected prices do not change across auctions, and are equal to the expected value of the $(K+1)^{\text{st}}$ order-statistic, from the n auction participants.

Denote by the random variable of price at auction r by P_r and the realization by p_r. Then (from (2) with n auction participants):

$\forall r=1..K \quad \mathrm{E}[P_r] = \mathrm{E}[Y_K] =$

$$\frac{n!}{(n-K)!(K-1)!} \int_0^{\bar{v}} [v \quad F(v)^{n-K} \quad [1-F(v)]^{K-1} \quad f(v)] \quad dv$$

When buyers do not face participation costs "the sequence of prices is a martingale; that is, on average, prices drift neither up nor down, over time" (Weber, 1983; pg. 173). The intuition behind constant expected prices is quite simple. Assume the opposite. Assume the expected price in a future auction is lower than the expected price in the current auction. Bidders would choose to participate in that future auction, instead of the current auction. This would continue until prices were equal in expectation. Similarly, if prices in future prices were expected to rise, bidders would bid more aggressively in earlier auctions. Thus, in equilibrium, expected prices do not change between auctions. Analogous to single-item auctions where the expected price is the second-highest valuation the expected price for all K auctions is equal to the $(K+1)^{st}$ highest value.

III.C. Positive Participation Costs

When buyers face positive participation costs their bids change. Specifically, a buyer's willingness-to-pay in auction r increases, because winning the item at a future auction is costly. Thus, in auction r equilibrium bids are raised by the expected cost that will be borne if the buyer bids in future auctions.

These equilibrium bids explain generate price declines. The cost of waiting reduces the option value of winning in future auctions increasing current bids and winning bids. Proposition 2 shows this formally.

Proposition 2: In the second-price, sealed-bid, sequential auction with unit demand and auction participation cost the symmetric, increasing equilibrium bids yield decreasing prices, i.e. $E[P_{r+1} \mid P_r = p_r] < p_r$

Proof: Assume buyer with value v wins auction r+1. This requires that $Y_{r+1}<v<Y_r$. The price paid is $p_{r+1} = B_{r+1}(Y_{r+1})$. In auction r, buyer Y_r wins the auction paying $p_r = B_r(v)$. Thus:

$$E[P_{r+1} \mid P_r = p_r] = E[B_{r+1}(Y_r) \mid Y_{r+1}<v<Y_r] =$$

$$E[E[Y_r \mid Y_{r+2}<Y_{r+1}] + (K - r - 1)c \mid Y_{r+1}<v<Y_r] =$$

$$E[Y_K \mid Y_{r+1}<v<Y_r] + (K - r - 1)c =$$

$$B_r(v) - c =$$

So: $E[P_{r+1} \mid P_r = p_r] = p_r - c < p_r$

QED

Prices in sequential auctions with costly participation are higher than those that would are attained when buyers do not face these costs. Costly participation causes buyers to raise their bids in early auctions, to avoid the costs of future participation. In the last auction the prices of both types of auction are equal, and they equal the $(K+1)^{st}$ highest order-statistic. Prices in earlier auctions increase with participation costs.

To complete the analysis of bidding strategies Restrictions A1 and A2 have to be validated. Corollary 1 shows that this equilibrium generates an efficient auction, while Corollary 2 places an upper-bound on participation costs for bidders not to drop out at an intermediate auction.

Corollary 1: The second-price, sealed-bid, sequential, auction with unit demand is efficient.

Proof: It is sufficient to show that bids are increasing in value (v), since this assures that auctions are awarded to buyers in decreasing value. But this is immediate from the equilibrium bids in Proposition 1. In the final auction each buyer bids his value (v), so bids are increasing in value. In earlier auctions (r) a buyer with value v bids according to his expectation of the K highest other buyer, conditional on valuing the computer more than the other remaining buyers. This conditional expectation is increasing in v.

QED

Corollary 2: If it profitable for a buyer to bid in the last auction and c is sufficiently small then it is profitable to bid in earlier auctions.

Proof: Given $p_K(v) > 0$; find an upper bound on c such that $p_r(v) > 0$ for $r < K$.

It is sufficient that for $r < K$:

$$p_r(v) > p_K(v) \qquad \Leftrightarrow$$

$$v - \mathrm{E}[Y_K \mid Y_r<v<Y_{r-1}] - (K - r + 1)c > v - \mathrm{E}\,[Y_K \mid Y_K<v<Y_{K-1}]$$

which places an upper-bound on c, requiring that:

$$\underset{r}{Min}\left\{\frac{E[Y_K \mid Y_K < v < Y_{K-1}] - E[Y_K \mid Y_r < v < Y_{r-1}]}{K - r + 1}\right\} \quad > \quad c$$

Note that the numerator is positive since $\mathrm{E}[Y_K \mid Y_r<v<Y_{r-1}]$ is increasing in r.

QED

This model of bidding in sequential auctions and the equilibrium bidding strategies describe realized prices we would expect on online auctions at eBay.com. The comparative statics of bidding strategies in (6) justify our hypotheses for the relationship between winning prices in auctions and explanatory variables including the number of computers offered that day (K), the rank of this computer within the set offered that day (r), the number of other buyers (n), and the (opportunity) cost of participating in the auction (c). These comparative statics are derived in Proposition 3.

Proposition 3: In the second-price, sealed-bid, sequential auction with unit demand and auction participation cost realized prices are:

i increasing in the number of bidders (n)

ii increasing in auction participation cost (c)

iii decreasing in sequential auctions (r)

Proof: The computer in auction r is awarded to the buyer with value $Y_r<v<Y_{r-1}$, since this auction mechanism is efficient (Corollary 1). To show the comparative statics of the winning bid it is sufficient to investigate the properties of $B_r(v) = E[Y_K \mid Y_{r+1}<v<Y_r] + (K - r)c$ from (6). The comparative statics of bids are immediate from equilibrium bids $B_r(v)$ and the properties of order-statistics. Proposition 2 proves part *iii*.

IV. Hypotheses and Data Analysis

The model of bidding in second-price, sealed-bid, sequential auction with unit demand and suggests that participation costs explain price declines in sequential auctions. However, empirical evidence has been mixed to date (see the review in Ginsburgh. 1998). Consistent with a model where bidders face a delay cost for purchasing in later auctions, it is hypothesized that the price decline anomaly prevails in auctions for used computers. Specifically, auctions held on the same day can be viewed as a single group of auctions.

<u>Hypothesis 1</u>*: Within each day, auction-closing prices decrease.*

Proposition 3 determines that realized prices are increasing in the number of bidders. The relationship between the number of computers auctioned in a day and realized prices is unclear.

<u>Hypothesis 2</u>: *Auction prices increase in the number of bidders.*

With new computer prices dropping more than 5% a month[7] we would expect substantial decreases in prices for used computers, as well. As new machines are offered on the market the value of used machines should decrease. First, the newer machines drive down prices for PCs that have been on the market for a while. Second, as CPU speed progresses new operating systems are introduced and new software for these PCs is often incompatible with older computers. Less software compatibility reduces the value of older computers. Together these lead to the following hypothesis on temporal prices of used computers at online auctions:

<u>Hypothesis 3</u>: *Prices for used computers decrease over time*

While over time we expect used computer prices to drop, this is not necessarily the case for consecutive auctions. Prices at consecutive auctions often reflect underlying factors that are not captured by observed variables. For example, the number of substitutes available to consumers, introduction of new technologies, or national sale campaigns of new computers.

<u>Hypothesis 4</u>: *Auction prices are serially correlated*

If the available measures of bidding activity are imperfect measures of the number of bidders (n), additional metrics of participation are useful. Previous research has shown that prices at online auctions may behave differently on different days of week or at different times in the day (Lucking-Reiley *et al.*, 2000). These controls are used as supplementary proxies for the number of bidders.

IV.A Data

To control for product attribute differences this analysis uses only the most common configuration offered by this reseller, between May and July 2002.[8] This configuration is a Latitude notebook, model CPXH 500GT, with an Intel-Pentium III 500 MHz processor, 128 MB RAM, a 12 GB hard-drive, and Windows 98 operating system. While all computers in this study have a similar configuration, they are not exactly identical. There are variations in minor

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7 For example, the lowest price available for a HP Vectra VL800 dropped from $1,700 in August 2001 to $1,100 in March 2002, reflecting a compounded reduction of 6% a month (from PriceSCAN.com visited 3/10/02 http://www.pricescan.com/graphs/graph128370.asp).

8 This is one of the few papers in the empirical online auction literature that controls directly for product attribute, instead of normalizing on some measure of retail price (e.g., Bajari an Hortacsu, 2002; Lucking-Reiley *et al*., 2000)

parameters, such as warranty duration or CD-ROM speed. 488 auctions of these computers are studied. Table 1 provides descriptive statistics for the data.

The range of winning bids in the dataset is \$511 to \$750, with a mean price of \$560. On average eBay.com buyers received a 17% discount when compared to the price of an identical machine purchased directly from the manufacturer (\$680). The number of bids in the auction is a proxy, albeit imperfect, for the number of bidders that "attend" the online auction. An auction receives 8.3 bids, on average. The measure for the number of units offered (*K*) is the number of computers auctioned in a day, with an average of 11 and a range of 1 to 22 auctions. The Rank in Day variable measures the auction's place within the day (*r*). Computers were auctioned evenly over the days of the week, with slightly more auctions closing at the end of the week (Friday through Sunday).

Table 1 – Variables and Descriptive Statistics

Variable	Notation	Mean	Standard Error
Price	P	\$560.66	\$35.442
Number of Bids	n	8.30	5.002
Supply (number auctioned in a day)	K	10.99	5.105
Rank in Day (Ordinal ranking within a day)	r	6.00	4.270
Days (from 1/1/2002)	D	148.76	21.930
Sunday	W_1	0.15	0.353
Monday	W_2	0.11	0.319
Tuesday	W_3	0.14	0.351
Wednesday	W_4	0.13	0.338
Thursday	W_5	0.14	0.347
Friday	W_6	0.17	0.374
Saturday	*base*	0.16	0.365

There are 488 observations in the dataset

Correlations in Table 2 provide indications for the drivers of variation in auction prices. The number of units auctioned (Supply) is negatively correlated with price. As the quantity supplied (*K*) increases prices decrease. As expected the Rank of the auction within a day behaves similarly to the total quantity supplied. Bidding activity also has the expected sign with the number of bids (a proxy for the number of bidders *n*) positively correlated with price. The temporal trend, however, is not consistent with accepted notions of computer prices. Prices appear to be *increasing* over time. This correlation may be spurious, because it does not control for changes in supply. Supply (the number of auctions in a day) is decreasing during the investigated period, which may be the underlying cause for price increases. Prices exhibit serial correlation indicating that market clearing prices move together.

Table 2 – Correlations

	Price	**Price$_{-1}$**	**# of Bids**	**Supply**	**Rank In Day**	**Days**
Price	1.000	0.491***	0.264***	-0.290***	-0.334***	0.109**
Price$_{-1}$ (lag)	0.491***	1.000	0.155***	-0.273***	-0.285***	0.109**
# of Bids	0.264***	0.155***	1.000	-0.074	-0.121***	-0.085*
Supply	-0.290***	-0.273***	-0.074	1.000	0.598***	-0.394***
Rank In Day	-0.334***	-0.285***	-0.121***	0.598***	1.000	-0.236***
Days	0.109**	0.109**	-0.085*	-0.394***	-0.236***	1.000

488 Observations * $p< 0.1$; **$p<0.05$; ***$p<0.01$

IV.B. Hypothesis Testing

A direct test of the price decline anomaly (Hypothesis 1) is possible by comparing changes in prices of consecutive auctions in each day. If prices follow a martingale then these changes should even out. If, however, the price decline anomaly is prevalent in auctions for off-lease computers price reductions appear more often than increases. To identify behavior of price changes, consecutive changes within a day are coded as either an “Increase” “Unchanged” or a “Decrease”, with the first auction of the day coded as “Unchanged”. Of the 488 auctions there are more Decreases than Increases with 190 and 160 respectively. There are 138 Unchanged prices in consecutive auctions. The c^2 test for the trinomial distribution (d.f.=2) tests whether consecutive prices are unchanged. The statistic for this data is 8.377 (*p-value* 0.015), indicating that prices do not follow a martingale.[9] The price decline anomaly is evident in auctions for used computers.

Testing the other hypotheses requires a statistical model that relates the explanatory variables of Number of Bids (a proxy for n), Supply (K), Rank in day (r), Time Trend (D) with the

[9] Alternately, the first auction in each day can be removed from this analysis. This reduces the number of “Unchanged” to 78, yielding a test statistic of 47.125 (*p-value* < 0.001).

dependent variable – Auction Price, controlling for day-of-week effects (W_l). This regression model is:

$$P_i = b_0 + b_1 n_i + b_2 K_i + b_3 r_i + b_4 D_i + \Sigma b_l W_{li} + e_i \quad (9)$$

Results for this model (Model 1) are in column (a) of Table 3. Column (b) adds the autoregression component of P_{i-1} as an explanatory variable. The AR technique developed by Box and Jenkins (1970) is used in parameter estimation of Model 2. This incorporates the importance of underlying short-term phenomena that are not captured by other factors in the model. Column (c) shows the result for Model 3 that replicates Model 2 without the Rank in Day variable. This is useful in assessing the importance of the number of units offered (Supply). Since Rank in Day is highly correlated with Supply, Model 3 evaluates the direct impact of auctioning more computers (increasing K).

The results of all 3 models show strong support for Hypothesis 2. The number of bids in an auction, a proxy for the number of bidders (n), is positively correlated with auction price.

Supply has a negative effect on market-clearing prices. Model 3 captures the direct effect of increases in supply, with a significant negative coefficient of –1.34. In Models 1 and 2 the effect of increasing supply is captured in two ways. First, the Supply variable is negatively correlated with auction price (although insignificant in Model 2). Second, Rank in Day also measures quantity offered, and has a negative coefficient. On days where more items are sold this variable realizes higher values. Both of these factors indicate that offering more products depresses prices. Selling more units, when demand is unchanged, spreads buyers thinly across products. Increased substitutability reduces participation and demand for an individual computer, lowering prices.

The negative coefficient on Rank in Day provides additional support for the price decline anomaly. There is a decline of approximately \$2 in consecutive auctions, controlling for other effects. This shows that on a day with 11 identical auctions the difference in winning bid between the first and last auction is \$22, on average.

The most surprising result from this analysis is that Hypothesis 3 is *not* supported in this data. Prices are *not decreasing* over time! The time effect is positive, but insignificant, in all three models. While prices for new computers are declining over time, used computers appear to behave differently. Prices in the market for a specific, off-lease, PC configuration, appear to be stable. This has implications for spreading auctions over time. With increased daily supply depressing prices, but no measurable obsolescence effect auctions should be spread over longer time periods.

Table 3 – Statistical Analysis

Dependent Variable – Price
(Standard Errors in parentheses)

Variable	Model 1 (a)	Model 2 (b)	Model 3 (c)
Intercept	546.57*** (13.887)	543.04*** (20.217)	540.54*** (20.658)
Price$_{-1}$ (lag)		0.40*** (0.042)	0.40*** (0.042)
Number of Bids	1.55*** (0.293)	1.25*** (0.284)	1.35*** (0.289)
Supply	-0.67* (0.382)	-0.34 (0.520)	-1.34*** (0.472)
Rank in Day	-1.86*** (0.419)	-2.02*** (0.477)	
Days	0.07 (0.072)	0.09 (0.108)	0.09 (0.111)
Sunday	-4.22 (5.254)	-4.90 (6.880)	-5.23 (7.022)
Monday	10.19* 5.670)	12.24 (7.656)	11.87 (7.817)
Tuesday	17.44*** (5.246)	18.48** (7.186)	18.15** (7.339)
Wednesday	15.84*** (5.484)	18.90** (7.479)	18.32** (7.632)
Thursday	17.37*** (5.411)	18.62** (7.406)	18.35** (7.562)
Friday	10.54** (5.086)	9.87 (6.699)	9.39 (6.837)
R^2	0.226	0.145***	0.112***
F-stat	13.91***		
Durbin Watson stat		1.92***	1.905***
F-stat testing day-of-week controls	5.18***	3.22***	3.03***

488 Observations * p< 0.1; ** p<0.05; *** p<0.01

Serial price correlation is an important determinant in online auctions for identical machines, supporting Hypothesis 4. Serial correlation captures unmeasured temporal effects. In an ideal world the researcher would know each buyer's reservation value. Drivers of changes in clearing prices could then be analyzed while controlling for buyer heterogeneity. Controlling for serial correlation replaces some of this missing information. Different buyers participate in different auctions, driving prices up or down. Buyers with high reservation values or high opportunity costs exert an externality on other auction participants. They raise prices not only at the auctions they win, but also for other auctions where they participate and do not tender the highest bid. This suggests that price increases occur in consecutive auctions. When the only participants are those with low reservation values, prices decrease.

Exogenous drivers of participation are used as control variables in this study. The statistical results indicate that there are day-of-week effects. Midweek prices on Tuesday through Thursday are about $15 higher than on Saturday. One explanation for this finding, consistent with our model of bidding, is that during the week participation costs are higher. If people at work determine prices, their impatience is greater on workdays. This finding has economic significance since it suggests how to auction items over the week.

V. Discussion

The dynamic-price secondary computer market is quite active. One large reseller is able to sell nearly $700,000 of used PCs a month on eBay.com. These computers are off-lease machines that have been used for a year or two and then refurbished to their original specifications. This secondary market flourishes because of heterogeneity in computer uses. Quality sensitive users can sell their obsolete machines to price sensitive buyers, at a price that covers the transaction costs of exchange in an online market.

This research is an important first step in understanding the viability of a dynamic secondary market for computers. It confirms the importance of understanding auction participation as determinants of market-clearing pricing. These results also raise questions for future research. The first issue that needs to be addressed is why prices in this study remain unchanged over 3 months. This result should be verified in future empirical studies and deserves theoretical discussion in the context of auction participation. Second, a more detailed theory of participation in these auctions is warranted. How do buyers choose in which auction to participate, given the large number of similar PCs (Bapna, Goes and Gupta, 2000)? Modeling the buyers' decision process will enable more precise predictions of market-clearing prices. Deciding how to auction excess computer inventory is critical for leasing companies (Bapna, Goes and Gupta, 2000; Pinker, Seidmann and Vakrat, 2000). Finally, an active secondary market has implications for the primary computer market. Do opportunities to buy reasonable used computers reduce demand for new machines?

VI. Conclusion

The popularity of online auctions enables the formation of a secondary market for off-lease computers. As the secondary market grows in popularity more consumers will find it a convenient and cost-effective means of purchasing computers. Eventually, the secondary PC market will stabilize and posted-price markets will match excess inventory with price-sensitive consumers. Until consumer preferences are well understood an auction is an efficient mechanism for matching buyers and sellers.

Active participation in the dynamic-price secondary computer market offers a test-bed for economic theories of auctions. This market provides strong evidence of the price decline anomaly in sequential auctions. While economic theory suggests stable prices in these auctions, this research provides additional empirical support for the phenomenon. The analysis of multiple auctions of a single PC configuration shows that market-clearing prices are driven by temporal factors of supply and demand that differ from long-term equilibrium prices. A vendor selling used PCs at an auction should realize that offering items for sale sequentially, when buyers face participation costs, raises expected revenue. Buyers at auctions can find bargains if they are patient.

Ongoing research in the secondary PC market facilitates a better understanding of consumers' tradeoffs between price and product attributes. In the not so distant future purchasing a used computer may be a viable alternative for price-sensitive consumers. When we reach that day this secondary market will have a measurable effect on the sale of new computers. Following that evolution will provide another example of the disruptive and far-reaching impact of electronic commerce.

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Appendix A: Proof of Proposition 1

By backwards induction. Assume (6) and (7) holds for some auction r+1 ($r \leq K$-1). We will show that (6) and (7) hold for auction r.

From (4) $B_r(v) = v - p_{r+1}(v) = v - \{v - \mathrm{E}[Y_K \mid Y_{r+1}<v<Y_r] + (K-r)c\} =$

So: $B_r(v) = \mathrm{E}[Y_K \mid Y_{r+1}<v<Y_r] + (K-r)c$

proving (6)

From (5) $p_r(v) = v - \mathrm{E}[B_r(Y_r) \mid Y_r<v<Y_{r-1}] - c$

Inserting (6): $p_r(v) = v - \mathrm{E}[\{\mathrm{E}[Y_K \mid Y_{r+1}< Y_r] + (K-r)c\} \mid Y_r<v<Y_{r-1}] - c$

$= v - \mathrm{E}[Y_K \mid Y_r<v<Y_{r-1}] - (K-r+1)c$

proving (7)

The p.d.f. of the conditional probability of Y_K conditional on $Y_r < v$ can be derived analogous to (2). This is the p.d.f. of Y_K in the smaller sample of $n - r$, with $K - r$ draws. Based on the derivation of (2) $g_{K|r}(y)$ is (xx complete the proof with Davis, 1970):

$$g_{K|r}(y) = \frac{(n-r-1)!}{(n-r-K-1)!(K-r-1)!} \frac{F(y)^{n-r-K-1}[F(v)-F(y)]^{K-r-1}}{F(v)^{n-r-1}} \qquad \text{(A.1.)}$$

Note that in this case the probability of a draw falling between y and v is $F(v) - F(y)$.

Taking the expectation of this p.d.f. yields (8).

QED