Empirical Investigation of Auctions for Off-Lease Computers

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Eli M. Snir
esnir@mail.cox.smu.edu
SMU, Cox School of Business, ITOM Department
374 Crow
Dallas, TX 75275-0333

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Abstract

Online auctions are enabling the secondary computer market. The immense popularity of eBay allows Dell Financial Services to auction $500,000 a month of off-lease computers. Auction participants enjoy a 25% discount when compared to retail prices of similar computers. The activity in this market also provides a test-bed for economic theories of auction participation. This research analyzes market-clearing prices for one configuration of used Dell computers in January-February 2002. The results from this research enlighten auction participants and researchers as to drivers of dynamic prices. Consistent with theory, the number of PCs offered for sale in an auction lowers seller's revenue. Even within a short period of time prices change. Impatient buyers participate actively in initial auctions letting patient buyers enjoy discounts of up to 10%. Impatient buyers also exert an externality on other auction participants. They raise prices both for items they win and for items they bid on and do not win. This leads to high serial correlation in final auction prices. The most surprising result from this research is that prices in the secondary market are increasing over time, as opposed to prices for new computers, which continuously decline. As the secondary market evolves and grows off-lease computers will become a viable alternative for price-sensitive consumers. In the future this secondary market will have a measurable impact on the sale of new computers. The online auction as an enabler of this market will be another example of the disruptive and far-reaching impact of electronic commerce.

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

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I. Introduction

Online auctions are one of the most innovative electronic commerce business models. Growing from the traditional classified ads they are becoming a dominant e-commerce force. The online auction is an effective sale tool for simultaneously reaching customers and determining prices for items without stable market prices. Using an online auction a seller can find the buyer who places the highest value on a collectible item, and consummate trade. In the online auction space eBay is the most successful site. eBay boasts that it facilitates over $5 billion in annual transactions and claims to be the most popular online shopping site[1].

The value of online auctions is not limited to the domain of collectibles. Most secondary markets suffer from problems of price discovery (Lucking-Reiley, 1999). Used cars and houses are two of the few examples where a viable secondary market exists and determining fair market price is relatively easy, based on published catalogs and previous transactions. Conversely, efficient secondary markets for computers are almost non-existent. While there may be opportunities for trade ineffective means of matching buyers and sellers and a lack of stable prices has inhibited the growth of this market. Opportunities for trade arise from heterogeneity in the use of the PC. Some computer users utilize advanced features and buy only the fastest computer with large RAM and all the latest gizmos. These “high performance” users are often businesses, which buy only the latest technology when procuring new computers. Other users derive little marginal value from advanced features. Thus, they are more price-sensitive and are willing to compromise on features for a lower price. With high levels of computer obsolescence quality-sensitive users could sell their old machines to price-sensitive users.

A key question in selling used computers is identifying their market value. While pricing new computers is fairly simple based on product characteristics and competitive pressure, pricing used computers is more difficult. Market clearing prices for used machines will ultimately be driven by supply and demand. Both of these, however, are difficult to evaluate for used PCs. Daily supply can vary greatly with large numbers of machines offered from different sources. Many offerings are off-lease computers from companies that use these PCs for a year or two and

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1 From http://pages.ebay.com/community/aboutebay/overview/index.html (visited March 1, 2002) based on Media Metrix data of total user minutes.

then resell them. A second source is individuals who want to sell their old PC and buy a new one. Together these factors make forecasting supply extremely difficult.

A second complication in pricing used computers is the ease of substitution between different machines (Bapna, Goes and Gupta, 2001). While a vendor knows precisely how many machines of a specific SKU he has to offer, it is unclear how customers view substitutes in this space. How do consumers trade-off product attributes, such as CPU speed and RAM? How important is brand recognition or a warranty? With a multitude of offerings in the market and limited market research into consumer preferences, substitution across products is unclear. A different tradeoff for the consumer is the purchase of a used PC against buying a new PC. With an active primary market for computers, the secondary market can exist only with lower prices. Research to quantify this price discount is still in its infancy.

With these pricing difficulties an online auction is an efficient means for selling used PCs (McAfee and McMillan, 1987; Lucking-Reiley, 1999; Bapna, Goes and Gupta, 2000). The market facilitates the exchange between quality-sensitive users who want to sell their used machines with price-sensitive consumers who prefer old computers at a discount. These auctions are held for short periods of time (3 to 7 days) with large fluctuations in daily supply. Individual participation in the auction drives market-clearing prices. Understanding the drivers of clearing prices is important both for identifying costumer preferences and for suggesting improvements in auctioning used PCs.

This research investigates market-clearing prices in the dynamic-price secondary computer market (i.e., auctions for off-lease computers). One example of the opportunity of auctioning off-lease computers is the experience of Dell Financial Services[2] (DFS) on eBay. With nearly 3,000 auctions in January-February 2002 generating revenue of over $1 million, this market is quite active. The viability of this market enables empirical investigation into the drivers of clearing prices at auctions for off-lease, refurbished computers. Economic theory of auctions provides the basis for identifying factors that can impact prices in an online auction. This paper derives several hypotheses based on auction theory. These hypotheses are tested using data from DFS auctions on eBay.

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[2] Dell Financial Services LP is a joint venture between Dell Computer Corporation and the CIT group, formed in 1997. Since then it has financed over $8 billion of new Dell equipment (from http://www.dfsdirectsales.com/dfsdirect/about.asp, visited March 1, 2002).

Having a rich and broad dataset enables exploring areas that have not yet been studied in online auctions. Lessons from this research should enlighten both researchers and practitioners. For researchers this dataset provides a new opportunity to learn about bidding behavior in an electronic market. Auction participants also have an opportunity to learn from this research. The findings can help computer resellers identify revenue-enhancing opportunities. On the other hand, prospective buyers may discover how to find a bargain in an online auction. Finally, auction-hosting sites can measure the value of the exchange and price their services accordingly.

The important findings from this research provide partial support for theories of auction participation. There is substantial variance in market-clearing prices, justifying investigation into the specific attributes of each auction to understand the drivers of final prices. The analysis finds that, consistent with economic theory, offering more products depresses prices. A second important finding is that short-term prices are often driven by buyer impatience. Patient participants can realize price reductions as high as 10%. The most surprising result of this research is that prices are *increasing* over time. While new computers face high obsolescence, prices in this secondary market seem to behave differently.

The remainder of this paper is organized as follows: The next section develops the key hypotheses. This is followed by a description of the data and analysis in section 3. Discussion of the results from the findings is in section 4, followed by managerial implications in section 5. Section 6 concludes the paper.

II. Hypotheses

The online auction is viewed as an efficient means of allocating commodities to individuals (McAfee and McMillan, 1987; Milgrom, 1989). As a dynamic pricing model it leads to continuous price changes. Supply and demand vary constantly, based on the number of units offered, customer preferences and active participation in the auction. The auction allows the market to clear – matching temporal supply and demand. Understanding changes in auction prices requires evaluating the impact of both sides of the equation. As the supply of used machines increases we would expect prices to drop. Demand, however, is more complex, as it is driven by many factors. Buyers trade off product attributes and price among the different computers offered in an auction setting; new computers and operating systems are introduced reducing the attractiveness of used computers; buyers face an opportunity cost for their time, increasing participation on certain days or at specific times of the day. The interplay of these factors determines the market-clearing price at a specific auction.[3]

II.A. Supply

While some factors that impact prices are beyond the control of the seller, he[4] does have significant control over many auction parameters. The most important controllable factor is the number of units offered for sale (Pinker, Seidmann and Vakrat, 2000). Economic theory indicates that as the quantity supplied increases market prices decrease. This leads to our first hypothesis:

Hypothesis 1: Market-clearing prices decrease as the number of units offered increases.

In a dynamic environment such as an online auction supply has a complex relationship with dynamic prices. Supply should impact auction revenue both at an aggregate level and in a temporal respect. Over short periods of time (e.g., a single day or a few hours) items are sold, leading to a reduction in both quantity supplied and quantity demanded. The reduction in quantity supplied should lead to higher prices for the remaining items.

Demand reduction may have a more significant effect on market prices. Individual participants at the auction differ in their private value on the object (Maskin and Riley, 1985). Heterogeneity in value is caused by a number of factors. Different individuals have different tradeoffs between price and product attributes. Additionally, in the context of online auctions, they differ in their impatience for purchasing the item. Some participants value their time greatly, and are unwilling to wait for the conclusion of future auctions before purchasing. Others are risk averse and are worried about not finding an identical item. A participant's reservation price reflects a combination of her inherent value for the item (price/attribute tradeoff) and her impatience. When investigating behavior at auctions for commodities, such as used PCs, the latter effect has been shown to dominate (Ashenfelter, 1989). A sufficiently patient buyer, who

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3 For a description of the bidding process on eBay see Bajari and Hortacsu (2002) or Lucking-Reiley (1999).

4 Throughout the paper I use the convention of masculine for seller and feminine for buyer.

anticipates future buying opportunities, will wait for a future auction, even if she places great value on the item. If so, items sold at the beginning of the auction are sold to the most impatient buyers (Bapna, Goes and Gupta, 2001). As the auction progresses the most impatient buyers are “weeded out” of the market, leading to lower clearing prices (Pinker, Seidmann and Vakrat, 2000). This leads to the second hypothesis:

Hypothesis 2: Within a batch of auctions, prices decrease.

II.B. Temporal Effects

Temporal effects are known to be drivers of market prices for computers. Previous research also shows strong temporal effects in auctions (Ashenfelter, 1989; Tenorio, 1993). With new computer prices dropping more than 5% a month[5] 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:

Hypothesis 3: 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 phenomena and temporal adjustments (Hayek, 1945). When there are ample substitutes for a specific computer prices at all auctions will drop. Conversely, a sudden surge in demand may raise prices. For example, occasionally buyers arrive with an interest in purchasing multiple computers. Participants also adjust their notion of a “fair” price based on past prices, weighing recent auctions heavily (Thaler, 1985). Thus, prices have a tendency to have high serial correlation.

Hypothesis 4: Auction prices are serially correlated

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5 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).

II.C. Auction Participation

Finally, the extent of participation at an auction should determine clearing prices. As more people partake in an auction we would expect prices to rise (McAfee and McMillan, 1987). In traditional (physical) auctions it is well known that auctions held in bad weather or early in the day generate less participation and lower prices. For an online auction the day of the week or the hour in the day may impact auction-clearing price.[6] These factors are controls in this analysis.

III. Data and Analysis

Dell Financial Services LP, a joint venture between Dell and the CIT group, was formed in April 1997. Its primary business is leasing and financing Dell computers to corporations and large institutions. These leases typically range from one to two years. At the end of the lease the computers are returned to Dell Financial Services[7] (DFS) where they are refurbished to their initial specification and sold to the public. In the past, DFS resold these computers through their web site. In August 2001 DFS partnered with eBay to sell their used inventory through an eBay store called dell_financial_services. Partnering with the largest online auction house offers DFS an attractive outlet for their merchandise. Auctions on eBay are oral, increasing price (English) auctions. DFS chooses to hold all auctions for 3 days.

During the months of January and February 2002 DFS auctioned nearly 3,000 refurbished, off-lease, PCs on eBay, generating over $1 million in revenue. Each computer is offered in a separate auction. These computers include a wide variety of desktops and laptops ranging from laptop PCs with Intel-Pentium II processors of 266MHz through desktops with Intel-Pentium III processors of 933 MHz. In all there were more than 500 different configurations of computers, sold to over 2,000 different buyers. All computers in these auctions have warranties that vary with the original Dell warranty and the length of the lease. The data for this study is based on auction results as reported on the eBay web site.

6 The number of bidders in an auction is often used as a measure of participation. Participants bid in an auction only when their value is higher than the current price. Thus, it does not measure the level of interest in the auction.

7 For more on the resale of computer visit their site is at: http://www.dfsdirectsales.com/dfsdirect/ (visited March 10, 2002), where they have 2,000 computers for sale daily.

To control for product attribute differences this analysis uses only the most common configuration of DFS auctions.[8] The configuration used in this analysis is a Dell Optiplex model GX1/M with an Intel-Pentium III processor of 550MHz with 128MB RAM and a 6.4GB hard drive. While all computers in this study have a similar configuration, they are not exactly identical. There are variations in minor parameters, such as warranty duration or CD-ROM speed. There were 429 completed auctions of these computers in the two months studied.

The range of high bids is between $165 and $350. During this period an identical machine could be purchased directly from DFS for $340. eBay participants could opt to buy a PC at this price at the beginning of the auction (using the "Buy Now" service), instead of bidding in the auction. Figure 1 shows the wining bids in these auctions. A number of observations can be made from looking at winning bids. First, there is a lot of variation in clearing prices (see also Table 1). Second, the Reserve Price is binding for a few auctions at the beginning of the period.[9] The high bid in 14 auctions is lower than the (secret) reservation price and these auctions ended without a sale.[10] These 14 auctions are dropped from the analysis. DFS varied the reserve price a few times in January and by mid-January lowered it to $204. Reserve prices did not bind in future auctions. Finally, 52 computers were bought for $340 using eBay's "Buy Now" service. A participant who purchased the item at "full price" terminated the auction early, instead of waiting for the auction to run its course. These data points are removed from the analysis because they do not reflect bidding behavior in auctions.[11]

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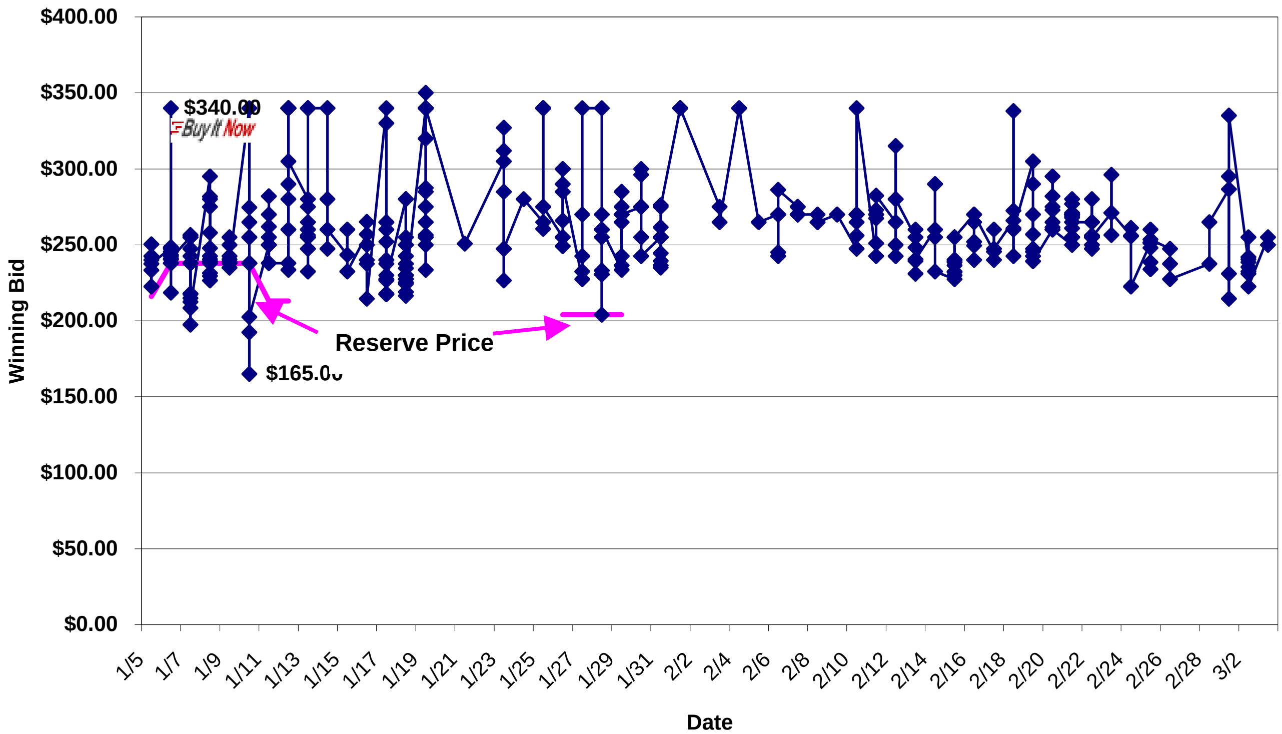
8 This is one of the few papers in the empirical online auction literature that controls directly for product attribute, instead of normalizing on some measure of retail price (Bajari an Hortacsu, 2002; Bapna, Goes and Gupta, 2001, 2000; Vakrat and Seidmann, 1999)

9 DFS uses hidden Reserve Prices throughout their eBay auctions. The auction rules stipulate that if the highest price in the auction is lower than the reserve price, the auction is not binding. Throughout the auction buyers know whether the reserve price has been met.

10 Bajari and Hortacsu (2002) show that hidden reservation prices reduce seller profits.

11 Dropping these observations is important for understanding drivers of market-clearing prices in online auctions. Having a "Buy Now" option invariably increases seller revenue.

Figure 1 – Auction Closing Prices



III.A. Empirical Analysis

The resulting dataset consists of 354 observations for auctions initiated in January-February 2002. Table 1 displays variable descriptions and summary statistics. The average winning bid is $256.48, with a standard error of $21.48. This represents a 25% discount to the price of an identical machine bought directly from DFS. Nearly all auctions close in one of two time frames. More than 25% of the auctions end between noon and 3 PM. An additional 45% of the auctions end between 4 PM and 8 PM. These distinct time frames justify grouping auctions into 2 batches every day (before or after 4 PM). The mean number of computers auctioned in a batch is 6.4, with a range of 1 to 14 auctions. The Rank variable measures the auction's place within its batch. DFS auctions computers evenly over the days of the week, with a preference for auctions that end after 4 PM (all times PST).

Table 1 – Variables and Descriptive Statistics

Variable	Notation	Mean	Standard Error
Price	P	\$256.44	\$21.479
Supply (number auctioned in a batch+)	S	6.40	3.725
Rank in Group (Ordinal ranking within a batch+)	R	3.54	2.677
Days (from 1/1/2000)	D	759.57	17.427
Time Group (“1” if auction closed after 4 PM)	G	0.76	0.426
Sunday	W_1	0.14	0.346
Monday	W_2	0.13	0.334
Tuesday	W_3	0.12	0.320
Wednesday	W_4	0.13	0.340
Thursday	W_5	0.18	0.385
Friday	W_6	0.16	0.371
Saturday	*base*	0.14	0.349

There are 354 observations in the dataset

\+ A batch (or group) of auctions includes the auctions in a certain time group during a single day. The time groups are either before or after 4 PM (PST). The Rank in Group variable measures the place of a specific auction within the batch. For example, on January 30th 5 computer auctions closed after 4PM. Thus, the Supply variable equals 5 and the Time Group variable equals 1, for all items in this batch. Within this batch, the earliest item auctioned is assigned a Rank in Group value of 1, the second is assigned a value of 2, and so on.

Correlations in Table 2 provide indications for the drivers of variation in auction prices. Consistent with theory supply is an important driver of price. As the quantity supplied increases prices decrease. 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 batch) is decreasing during the investigated period, which may be the underlying cause for price increases. As is expected the rank of the auction within a batch behaves similarly to the total quantity supplied. Prices exhibit serial correlation indicating that market clearing prices move together.

Table 2 – Correlations

	Price	**Price$_{-1}$**	**Supply**	**Rank In Group**	**Days**	**Time Group**
Price	1.000	0.366***	-0.302***	-0.271***	0.198***	-0.196***
Price$_{-1}$ (lag)	0.366***	1.000	-0.246***	-0.230***	0.202***	-0.110**
Supply	-0.302***	-0.246***	1.000	0.576***	-0.315***	0.230***
Rank In Group	-0.271***	-0.230***	0.576***	1.000	-0.187***	0.163***
Days	0.198***	0.202***	-0.315***	-0.187***	1.000	0.041
Time Group	-0.196***	-0.110**	0.230**	0.163***	0.041	1.000

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

III.B. Hypothesis Testing

Testing the hypotheses developed in Section 2 requires a statistical model that relates the explanatory variables of Supply, Rank in Group, Time Trend and Time Group with the dependent variable – Auction Price, controlling for day of week effects. This model can be written as follows (see Table 1 for variable notation):

$$P_i = b_0 + b_1 S_i + b_2 R_i + b_3 G_i + b_4 D_i + b_5 \Sigma W_j + e_i \qquad (1)$$

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 phenomena that are not captured by other factors in the model. Column (c) shows the result for Model 3 that replicates this analysis without the Rank in Group variable. This is useful in assessing the importance of the number of units offered in a time group (Supply). Since Rank in Group is highly correlated with Supply, Model 3 evaluates the direct impact of auctioning more computers.

The results of all 3 models show strong support for Hypothesis 1. Supply is an important driver of market-clearing prices. Model 3 captures the direct effect of increases in supply, with a strong negative correlation. 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 Group measures quantity offered. In batches with more items this variable realizes higher scores. 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 item, lowering prices.

Table 3 – Statistical Analysis

Dependent Variable – Price
(Standard Errors in parentheses)

Variable	**Model 1** (a)	**Model 2** (b)	**Model 3** (c)
Intercept	145.84*** (51.748)	145.95** (62.325)	142.08** (62.95)
Price$_{-1}$ (lag)		0.19*** (0.053)	0.20*** (0.053)
Supply	-0.72* (0.408)	-0.66 (0.456)	-1.14*** (0.406)
Rank in Group	-1.15** (0.490)	-1.19** (0.533)	
Days	0.17** (0.067)	0.17** (0.081)	0.17** (0.082)
Time Group	-7.03** (2.626)	-7.26*** (2.579)	-7.45*** (2.591)
Sunday	-5.29 (4.224)	-5.86 (4.790)	-5.47 (4.829)
Monday	-7.09* (4.188)	-6.87 (4.853)	-6.37 (4.893)
Tuesday	-4.80 (4.237)	-5.71 (4.935)	-5.24 (4.977)
Wednesday	-3.69 (4.090)	-4.10 (4.779)	-4.04 (4.825)
Thursday	-3.69 (4.090)	-2.06 (4.711)	-1.91 (4.753)
Friday	-9.34** (4.020)	-9.24*** (4.607)	-8.98* (4.648)
R^2	0.154	0.186***	0.174***
F-stat	6.25***		
Durbin Watson stat		2.063	2.068
F-stat testing day of week controls	1.22	0.96	0.87

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

The Rank in Group variable offers insight into how changes in supply affect prices. Consistent with Hypothesis 2, successive auctions generate less revenue for the seller. This effect is negative and significant in both Models 1 and 2. As noted earlier buyers differ in their impatience for purchasing a used computer. Impatient buyers drive up prices in early auctions within a group. Later auctions find patient buyers who pay less when they purchase a computer. Some buyers, who are patient enough, opt not to buy within that batch and wait for a better opportunity (lower price) to buy an identical machine.

The most surprising result from this analysis is that Hypothesis 3 is *not* supported in this data. Prices are *increasing* over time! This result is dominant over different model specifications using different controls. 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 and increasing.

Serial price correlation is an important determinant in online auctions for identical machines, supporting Hypothesis 4. Serial correlation captures two phenomena. First, there are temporal effects that cannot be measured with this dataset. 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. A second explanation for serial correlation is that participants base their notion of "fair" prices on prices at recent auctions for identical computers (Thaler, 1985). If reservation value is derived from both buyer-specific value and a measure of fairness, serial correlation should be high.

Exogenous drivers of participation are used as control variables in this study. The statistical results indicate that time of day is a significant driver of clearing prices. Auctions that close later in the day (after 4 PM) realize lower prices than those that close during working hours. This may indicate that auction participation is more active during work hours, or that during working hours participants may behave differently. A few buyers at auctions may purchase these computers for resale[12]. More likely, bidders who bid during work hours may be less price-sensitive either because they are buying these computers for business use or they may have less time to follow the auction, and place higher bids. When looking at day-of-week effects, prices on Saturday appear to be highest. The only day that has significantly lower prices, however, is Friday. Prices on Friday are $9 less than on Saturday.

IV. Discussion

The dynamic-price secondary computer market is quite active. Dell Financial Services (DFS) is able to sell over $500,000 of used PCs a month, with an average price of $350. These computers are off-lease machines that have been used for a year or two and then refurbished to their original specifications. While not being state-of-the art machines the breadth of activity in the market proves that they have significant value. Partnering with eBay – the largest online auction site in the world – enables DFS to offer their used computers to the general public, realizing significant revenue. Buyers of used computers are often individuals who purchase these computers for personal use. They prefer buying an older, name brand PC, at lower cost to a new machine at more than twice the price.

The surprising activity of this secondary online auction warrants investigation into the drivers of market-clearing prices. This research uses the economic theory of auctions to identify important factors and verify their impact in the setting of online auctions for used Dell computers hosted by eBay. The empirical data available enable studying auction prices. To control for product attribute concerns the data used in this study is a sub-sample of the entire dataset. This sub-sample includes only one PC configuration: a Dell Optiplex model GX1/M with an Intel-Pentium III processor of 550MHz with 128MB RAM and a 6.4GB hard drive. While the basic configuration is similar, these computers do differ in minor parameters such as speed of DC-ROM or warranty length. The dataset for this study includes 354 PC auctions held in January-February 2002. The average winning bid in these auctions is $256.44, giving auction buyers a 25% discount from the price published by DFS.

[12] It is unlikely that many resellers are active in this market because there are over 300 different buyers (identified as eBay users) of these computers in this dataset, with 80% of the buyers buying only one machine.

The results of this research provide partial support for economic theories of auctions. Overall, the results show that bidding behavior is an important determinant of auction prices. Market-clearing prices involve more than the intersection between the long-term supply and demand curves. The coefficient of variation of 8.3% shows that individual auction prices differ from market equilibrium prices. Factors that determine the closing price for an auction include short-term supply and demand; the location of an item within a batch of auctions; time of day; and day of week. Finally auctions exhibit serial correlation. Similar to the behavior of financial markets serial correlation of prices is high. In the commodity auction, however, this is not driven by “news”. In an auction setting heterogeneity in value and impatience is inherent to the buyers. Buyer attributes replace “news” as the source for temporal shifts. Instead of news arriving and changing the objective value of a security, changes in the group of auction participants (in terms of their impatience) drive prices in online commodity auctions.

The most surprising result of this study is the long-term change in price. While new computer prices are declining over time, there appears to be a positive time trend for price of off-lease computers, even when controlling for product attributes, supply and other factors that impact market-clearing prices in the short-term.

This analysis 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 increased over time. It is easy to explain price discounts over time for used computers, which experience high obsolescence, but explaining premiums at auctions is not well understood. 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 like Dell Financial Services (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?

V. Managerial Implications

Understanding the drivers of auction prices should enlighten all auction participants. A vendor, such as DFS can use this research to identify ways to increase their revenue from online auctions. Buyers, on the other hand, can identify opportunities for finding bargains at auction sites. Auction hosting sites, such as eBay, can realize the value they offer both sides of the exchange and price their service accordingly.

Sellers at auctions want to know the relationship between offering more units for sale and market-clearing prices. The findings from this research corroborate the law of supply and demand. Short-term increases in PCs offered for sale lead to lower prices (Hayek, 1945). For example, when DFS auctions 3 computers or less in a batch the average price is $262.80. On occasions that they offer more than 10 computers the average price declines by 7% to $245.01. This does not immediately lead to a recommendation to use smaller batches. Analyzing the optimal auction size depends also on inventory holding costs (Pinker, Seidmann and Vakrat, 2000). This does, however, provide one side of the equation in terms of the impact on price from increasing supply.

Buyers at auctions want to know if they should bid on items that come up early in the auction, or will they find better prices later in the auction. The results of this research indicate that patience is rewarded. Impatient buyers and risk-averse participants bid extensively for items that come up early in the auction, driving their price up. Successive auctions are left to patient bidders who find bargains. For the computers in this dataset the reward can be more than a 10% discount for bidding on the tenth or higher item in a batch of auctions, instead of the first item.

Of interest to an auction site like eBay is the difference in price over different times of the day. The data shows that prices are higher during working hours (before 4 PM), indicating higher participation or less price-sensitivity at these times. Since most participants are not resellers eBay should realize that it has many customers that participate in auctions while at work. This may be driven by better Internet access at work or by people bidding on online auctions in their spare time. In either case better understanding of customer behavior is useful in tailoring marketing campaigns.

VI. Conclusion

The popularity of online auctions enables the formation of a secondary market for off-lease computers. Dell Financial Systems is a leader in this innovative online market, with more than $500,000 a month in revenue. 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. 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 more units in a short time frame lowers expected revenue. Buyers at auctions can find bargains if they are patient. Computers sold in later auctions within the same group enjoy a discount of up to 10%.

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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