

Bidding Behavior and Price Formation with competing Auctions: Evidence from eBay

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Abstract

Existing literatures consider on-line auctions as many independently running auctions and each bidder chooses only one auction. However, many substitutable goods are auctioned at the same time and bidders can bid several auctions at the same time. We examine a data set of eBay Pentium III 800 MHz CPU auctions to explore the bidding behavior and price formation for competing auctions. We also use a java program to simulate real time eBay auction of CPUs. The simulation shows the detailed process of bidding and bidders' behavior when there are competing auctions. We find that some bidders bid several items at the same time. The auction prices decrease when there are more ending auctions. The auction prices show significant dispersion. The auction price is highly correlated and the prices follow an AR(1) process with coefficient 0.22. However, bidders are not as responsive to the existence of competing auctions as predicted by the theory. One possible reason for this is that auctions end at different time. We also study the effect of behavior pattern on the price dispersion and the mean price.

1. Introduction

Recently we have seen a huge success of on-line auction market such as eBay. This success leads to many economic models and empirical tests for on-line auctions. Most of the papers consider the on-line auctions as many independently running auctions and bidders only bid on one auction. The papers focus on the study of the strategic behavior of market players (see Roth and Ockenfels (2000), Bajari and Hortacsu (2000)). On-line auctions are considered as a natural experiment for standard auction theory.

Roth and Ockenfels (2000) explains the late bidding in eBay by the existence of a fixed ending time of auctions. The reason is that very late bids have a positive probability of not being successfully submitted, and this opens a way for bidders to implicitly collude and avoid bidding war. Bajari and Hortacsu (2000) studies the costly entry for bidders and the choice of reserve price for sellers. Both models assume that bidders only match with one auction and do not participate several competing auctions at the same time.

On-line auction site, such as eBay, has evolved to act as clearinghouse for large number of homogeneous goods. These auctions are not running sequentially, i.e., one auction starts only after the previous one is finished. On-line auctions usually last for several days and there are many standing auctions each day. For example, currently every day there are around 100 Pentium III CPUs start to be listed on eBay. Many of them are almost the same in all characteristics. Different sellers run the auctions independently. At any time bidders can choose among many auctions.

The low bidding cost and the possibility to monitor several auctions at the same time for on line auctions permit bidders to bid several auctions at the same time. With several substitutable standing auctions, bidders bid on one auction and observe the standing bids of other auctions. When he is no longer the high bidder of one auction, he can choose to bid again on the same auction, or begin to bid another auction with lower standing bid.

Standard auction theory assumes that there is a single seller and several bidders. Seller acts as a monopoly and gets all information rent from bidders. From the mechanism design literature, when a seller wants to sell an item to several buyers, auction is the best way to do it. There are literatures in which sellers compete each other (McAfee (1993), Peters and Sergei (1997)). However, these papers assume that bidders can only choose one sellers. eBay auctions have the feature that the sellers are competing each other and the bidders can participate in several auctions at the same time, even though a bidder will trade with only one seller.

The paper of Peters and Sergei (2001) considers the competing auctions that are similar to those in eBay. Bidders do not stick to only one auction. All auctions are interdependent. When standing bid of one auction is low, bidders from other auctions switch to bid on this auction. With the possibility of cross bidding, bidders use strategies different from those for independent auctions. Bidding once and bidding the true

valuation is no longer a dominant strategy. If there is no bidding cost, bidders always bid auctions with minimum standing bid and bid with minimum increment. Intuitively, if bidders bid true valuation and bid only once, they may be trapped in very competitive auctions and do not have opportunity to switch to other less competitive auctions.

The consequence of the existence of competing auctions is that the final price of one auction is affected by the existence of other auctions. The prices tend to be uniform for competing auctions. In addition, the price is the same as the price under a double auction.

In this paper, we study the bidding behavior and the price formation with competing auctions. We use a data set of the auctions of Pentium III 800 MHz CPUs in eBay from June 5 to July 3, 2001. The most important feature of this data set is that it only includes the homogeneous goods. To include only the homogeneous goods and include all substitutes at any time, we choose all those CPUs without heat sink/fan.

WE use the real time simulation of eBay auctions. The information and events of the market are obtained from eBay real time data and are simulated intuitively with much smaller time interval. Most of the empirical analysis on auction use only the summary statistics and try to find the relations among these variables. The detail of the auction process and of bidding behavior is concealed. An important thing in studying the behavior pattern is to learn the process, not only the sample statistics. Some variables in this paper can only be obtained from our real time simulation (at least it is extremely difficult to get the data even it is possible to get them). In the simulation we can represent visually the competing environment.

We find that that there are bidders who bid on several ending auctions at the same time. However, most traders are not as responsive to the existence of competing auctions as the theory (without auction ending time) predicts. The proportion of bidders who bid on several (ending) auctions in a day is less than 10% of the total bidders. On average, only around 40% of the bids in the last day are submitted on the auctions with the lowest standing bid.

For auctions with the same seller and at almost the same ending time, there are significantly more bidders who cross bid and more bids are submitted on auctions with the lowest standing bid. This suggests one reason that bidders reluctant to cross bid and reluctant to bid on auctions with lowest standing bid is because that most of the auctions end at different time.

If auctions end at different time, at the time of submitting a bid bidders are expecting that to win another auction, they have to submit a bid at least with the same amount in order to win it. In the sample we find that on average 86% of the bids in a day is matched by bids in other auctions. Only 14% of the bids are not matched by bids in other auctions of the same day. Some of these bids are frenzy bids that are caused by the irrational response of outbid bidders.

The auction prices exhibit a high degree of dispersion. The time series of auction prices show a strong serial correlation, which could be described by an AR(1) process with coefficient 0.22. The prices in a day do not show a declining or increasing pattern, as seen in declining price anomaly in sequential auctions. When a rational bidder submits a bid on one auction with high standing bid, he is expecting that if he submits bids on another auction he must submit at least the same amount in order to win it. Therefore there should not be a declining or increasing pattern for auction prices in a day. This also leads to the serial correlation in prices: the price of an auction is high because bidders expect the price of future auctions could be high. A high price auction is more likely to be followed by another high price auction.

However, in case there are more responsive traders, the price tend to be less dispersed. Those auctions with bids submitted by cross bidders tend to have lower dispersion. If more bidders bid on auctions with the lowest standing bid, the price dispersion in a day decreases. Frenzy bids increase the price dispersion. For auctions with the same seller and almost the same ending time, the price dispersion is significantly smaller.

Auction prices decrease when there are more competing auctions and increase when there are more bidders in the last day, as expected by the competing auction theory.

We first briefly summarize a theory with competing auctions. In section 3 we describe our real time simulations. The results are collected in section 4. In section 5 we present some discussions.

2. Theory of competing auctions

There are literatures on auctions with many sellers and many bidders. When there are many competing auctioneers, if bidders cannot cross bid, independently run auctions lead to inefficient trade. When many bidders with independent valuation simultaneously choose among many sellers, the only equilibrium has the buyers randomizing over available sellers (McAfee (1993), Peters and Sergei (1997)). The profitable trade under double auction may end up impossible because of the random match. For homogenous goods and simultaneous auctions, the trading prices may end up being very different.

The assumption that bidders have to choose one and only one auction simultaneously is critical for the inefficiency. For on-line auctions, this assumption is no longer true. Peters and Sergei (2001) asks the question whether the independently organized auctions in a centralized exchange such as eBay can overcome the inefficiency of random match.

In the model, there are many sellers and many bidders. Each seller has a single good for sale. All goods for sale are identical. Each bidder only needs one good. Winning more than one auction gets no additional utility form the second auction. Auctions go roughly the same way as in eBay. The standing bid is the second highest bid and the highest bid is never revealed. However, bidders are not required to choose and stick to one auction. Under the assumption that bidding is costless and there is no fixed ending time for

auctions, the paper shows that competing auctions can overcome the inefficiency of random match. The paper gives a symmetric strategy for bidders and proves that this strategy is a perfect Bayesian equilibrium. In the equilibrium, all trades occur at the same price. The price is the same as that in a double auction.

The main result of Peters (2001) includes a lemma describing bidders' strategy and a theorem:

Lemma. The symmetric equilibrium σ^* is defined as:

- (a) if the buyer is the current high bidder at any auction, or if the buyer's valuation is less than or equal to the lowest standing bid, the buyer should pass;
- (b) otherwise, if there is a unique lowest standing bid, the buyer should submit a bid with the seller offering the lowest standing bid. The bid should be equal to the smallest valuation that exceeds this low standing bid;
- (c) otherwise, let L be the set of sellers who have the lowest standing bid. Let $L_1^+ \subset L$ be the subset of sellers in L whose current high bidder submit his bid while the standing bid was strictly below its current level; let L_1^- be the set of sellers in L who have not received a bid. If L_1^+ is not empty, the buyer should bid with equal probability with every sellers in L_1^+ . If L_1^+ is empty but L_1^- is non-empty the buyer should bid with equal probability with every seller in L_1^- . Otherwise if both subsets are empty, the buyer should bid with equal probability at every seller in L .

Suppose there are n sellers and m bidders. Let $v_{(m)}$ be the m -th lowest valuation of all $m+n$ traders. The theorem is:

Theorem: The outcome in which all buyers use the strategy σ^* is a (weak) perfect Bayesian equilibrium. Buyers trade if and only if their valuation is above $v_{(m)}$. Sellers whose reserve prices are lower than $v_{(m)}$ trade for sure. All trades occur at the price $v_{(m)}$.

The description of bidders' strategy seems lengthy. If a bidder is currently the high bidder of any auctions, he pauses until he is outbid. Otherwise, he always bids on the auction with lowest standing bid and bid with the minimum increment. The essential idea is that with cross bidding, bidders bid up price with each seller as slowly as possible. They try to pick up sellers where they can become high bidders by bidding the minimum increment. In this way, high valuation buyers are never trapped into high price by having another high valuation buyers accidentally bid against them. For example, if there are 3 competing auctions and 5 bidders, sellers' valuations are all 0 and bidders' valuations are 10, 10, 8, 7, and 6. If all bidders choose one auction and bid their true valuation, those two bidders with valuation 10 may end up bidding on the same auction; whoever wins the auction has to pay 10. If bidders use the strategy of cross bidding, these two high valuation bidders will end up to win two different auctions and pay much low price for sure. Cross bidding insures that any mismatch be fixed by always given bidders the opportunity to bid on other auctions with low standing bid. As a consequence, all trade

occurs at the same price. Most importantly, the achieved trading is the same as in a double auction.

Auctions in eBay have fixed ending time, as most other on line auctions do. There exists a cluster of bids in the ending period of auctions in eBay (Roth [2000]). Auctions are not perfectly competing each other when they end at different time. This makes eBay auctions similar to sequential auctions. In conventional sequential auctions, one auction starts only after the previous one finishes. This is not true in eBay. Auctions in eBay can overlap in time. Two 7-day auctions ending at the same day overlap all the time except for the first and last short period. Bidders can bid on them at the same time.

For sequential auctions in which no buyer is interested in more than one unit, under usual assumption, revenue equivalence holds (Weber [1993]). At any point of time of the game, players' strategies must be to yield them the same expected payoff as if all the remaining units were auctioned simultaneously in a simple ascending auction.

However, it is more common to observe a downward drift in auction prices (Ashenfelter [1989]). This has spawned a small literature attempting to explain the "declining price anomaly".

In this paper, we will see that the auction prices are not uniform, even for auctions ending at the same time and sold by the same seller. Auction prices are serial correlated and do not exhibit declining or increasing pattern.

III. The data and sample statistics

eBay provides a rich resource of data for the empirical study of auctions. We write a java program to download all the auctions for the category of 'Computer, Desktop Components, CPUs, Intel' from June 5 to July 3. The reason we choose Pentium III 800 CPUs is that there are many such CPUs on sale each day and the condition of all these CPUs are very similar. For non-homogeneous goods, regression on the auction price without book value often leads to spurious results. However, manual estimation of the book value is prone to bias and inaccuracy. For properly chosen homogeneous goods, we do not need to get book value of each good.

For each auction, there is a detailed CPU description provided by the seller. eBay provides complete information for ended auctions, such as the number of bids, the starting price, the last bid, whether the good is sold by buy it now method, all bids submitted and bid submission time with the identity of bidders¹. (The highest bid is not the actual bid since it is the second highest bid plus the minimum increment). eBay keeps the information of ended auctions public for one month.

All CPUs for auction are used CPU. We choose the Pentium III 800 MHz CPUs and choose the auctions with only one CPU. (There are some auctions with more than one CPU for sale). The size of this sample is 386.

In the sample around one third of the CPUs (size of 133) are tried to be sold with a predetermined fixed price using Buy It Now method of eBay. (47 such auctions turned out to end with bidding). The rest auctions are sold by auctions. Since the Buy It Now method and the standard auction are very different, we exclude all CPUs sold by Buy It Now from the sample. (We will study the buy it now feature in a separate paper).

The pure CPUs for 800 MHz are pretty homogeneous if they work properly. (We exclude the auctions if the CPUs are defect). They are pretty new even if they are used. However, some CPUs are sold with fan/fan. These include the CPU retail box and some CPUs with different kinds of fan/fan. These fans can be very different, the price ranging from several dollars to more than one hundred dollars. In order to get the homogeneous goods and get all available substitutes, we choose a small sample composed by only those Pentium III 800 MHz CPUs without fan. To insure that all CPUs are substitutable and have roughly the same book value, we also check all CPUs by hand in the sample and delete observations that are not working properly.

The small sample contains 103 observation ranged over 30 days. All these goods are almost identical from the description provided by the seller. (Several big sellers sell many identical CPUs. The CPUs sold by these big sellers have identical descriptions). In the sample, 10 auctions are with secret reserve price and the reserve prices are met for all of them. Therefore we do not consider the effect of secret reserve price².

The following variables used in the analysis are got directly from the eBay data:

- The last bid of the auction (lastbid)
- The seller of the auction and his feedback
- The starting bid of the auction (firstbid)
- The number of bids received (#bids)

¹Previously, eBay only provided the information of last bid of a bidder and the last bid submission time.

² The secret reserve price is more likely to appear in CPU auctions with fan. We find many such auctions have secret reserve price and many end up with reserve not met.

- The duration of the auction (duration)
- The starting time and ending time of the auction
- All bids of the auction, the bidders and the bid submission time

We produce a data set including daily data of all standing auctions of the day. The daily data can produce time series data for analysis.

We also derive other variables from the data and produce a data set of all bidders in the sample. The data set for bidders include the bidder, bidder's feedback, the auction he bids, each bid he submits, the bid submission time, and whether he is the high bidder.

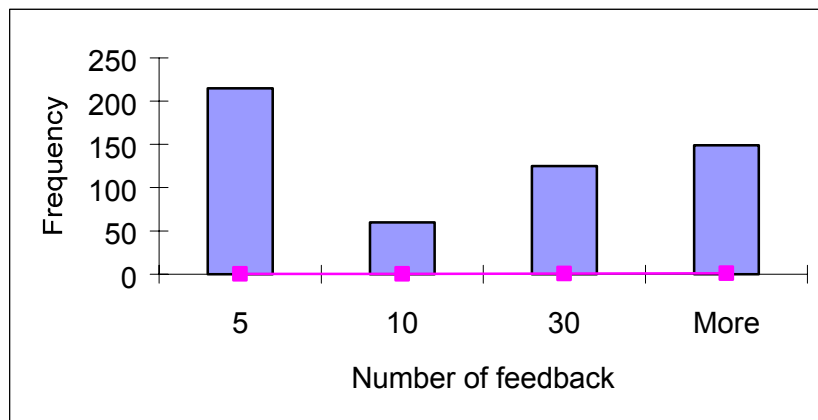
We report the summary statistics of the sample:

Table 1 Summary statistics (N=103)

Variable	Mean	Std	Min	Max
FIRSTBID	38.20	40.20	0.01	141.00
LASTBID	116.07	15.83	80.99	147.50
#BIDS	13.13	7.72	1.00	38.00
#BIDDERS	7.67	3.41	1.00	18.00

Bidders for CPUs are buying the CPU for their own use. Most of the buyers are pretty experienced buyers in eBay. Bidders, especially the novice, may not fully understand the mechanism in eBay auction. They might not use optimized strategies. We use the feedback as an indicator of traders' experience in eBay³. eBay also uses heavily the number of feedback in daily trade, for example, to use the Buy It Now feature, sellers must have a feedback greater than 10. Figure 1 is the distribution of bidders' feedback numbers. Most bidders have feedback greater than 5. We can be confident that the observed behavior is not very different from the optimal one for most individuals.

Figure 1 Histogram of bidders' feedback



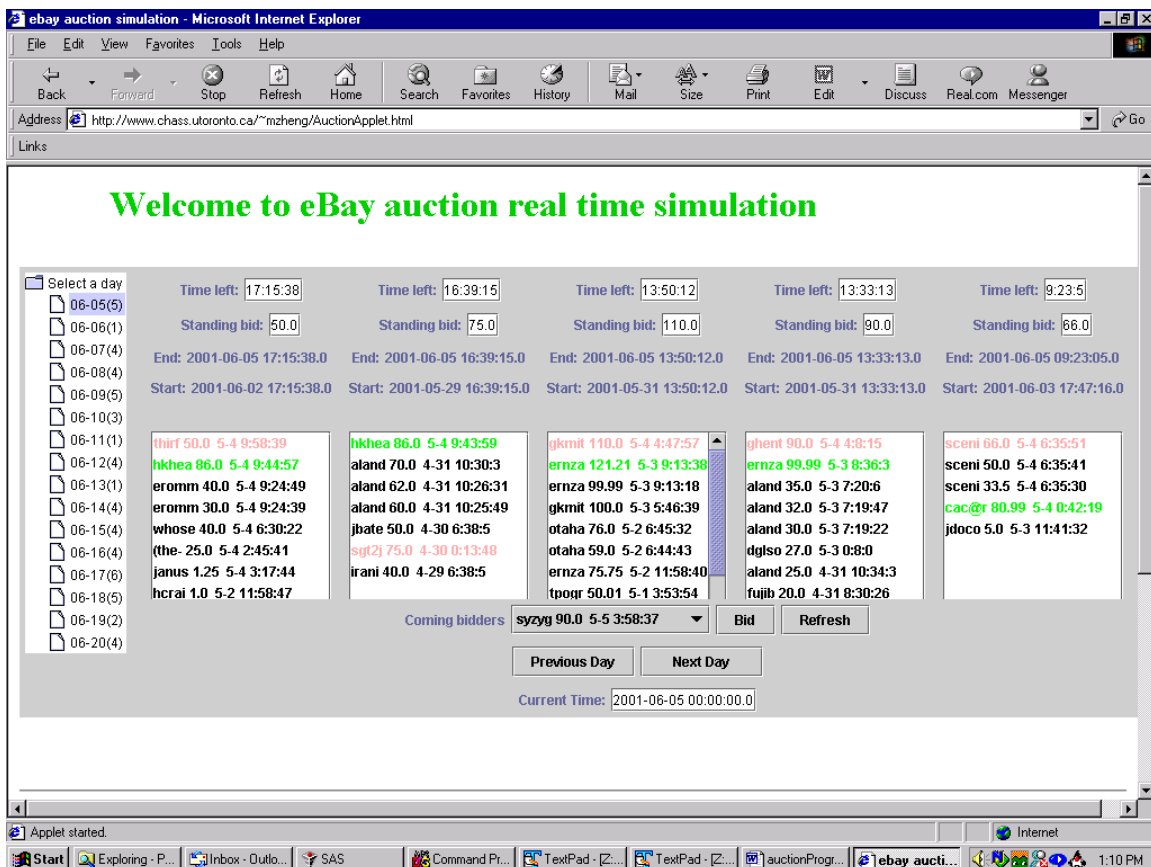
³ The feedback number in eBay is the sum of positive and negative feedbacks.

3. The real time simulations

The simulations repeat what happened in eBay Pentium III 800 MHZ CPU auctions during June 5 to July 3 2001. eBay is a list site and most auctions in eBay are second price auctions. We first downloaded all necessary data from eBay. These Pentium III 800 MHZ CPUs are all second handed (used or never used). They are pretty homogenous if working properly (we exclude the CPUs that are defected), except that the heat sink/fan can be very different in price. To include only the homogenous goods and include all substitutes at any time, we choose all those CPUs without heat sink/fan (see Zheng [2001] for more detailed description of the data). All these data are fed into a java program to exhibit the auctions process.

The program can run either as a standalone application or a java applet in a web browser at www.chass.utoronto.ca/~mzheng/AuctionApplet.html. (See a brief introduction of the design of the program in the appendix). Figure 2 is a screen shot of the applet.

Figure 2 Screen shot the applet for simulation



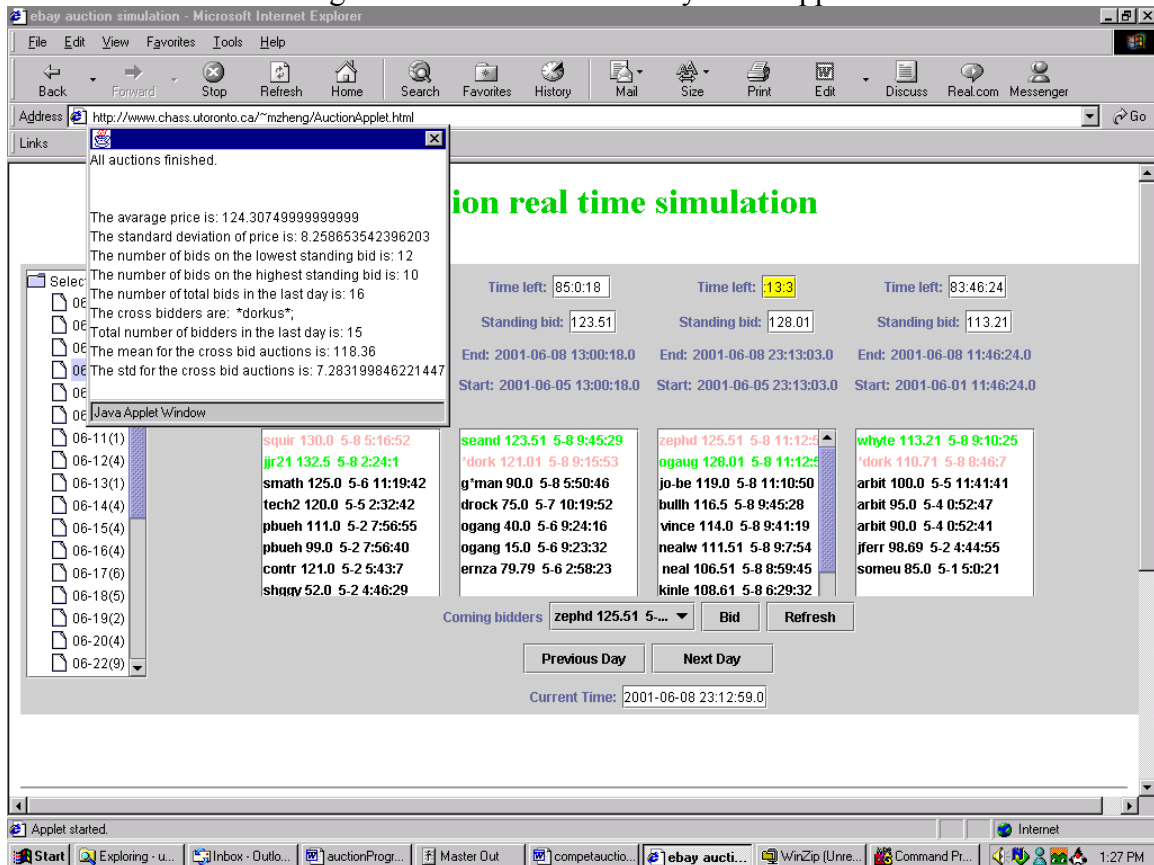
The program shows all data in each day and users can use the tree in the left panel to select a date. For each day, all information of the ending auctions (which are considered as competing auction of the day) is shown in the same screen side by side. At any time

(current time), the following information of an auction is shown: time left, current standing bid, ending time, starting time, and the bidding history up to the moment. The bidding history includes the information of each bid it received: the bidder⁴, bid amount and the bid submission time. (In eBay the bid amount is not shown unless the auction is finished. However, the standing bid is shown at each moment). The highest bid is shown with purple color and the second highest bid, which is the standing bid, is shown with green color.

Each day starts with current time 00:00:00. When a user clicks on the ‘Bid’ button, the first bidder submits his bid. The auction on which the bid is submitted is shown with yellow-backgrounded ‘Time Left’. The ‘Current Time’ is set to the bid submission time of the bid. The standing bid is updated. The bid is added to the bidding history. The highest and the second highest bid of the auction are updated. The ‘Time Left’ is also updated for all auctions of the day.

The process continues until there is no more bid and all auctions are finished. When all auctions are finished, clicking on ‘Bid’ button pops up a window show the statistics of the day.

Figure 3 The statistics of a day in the applet



⁴ Bidder ID shown here is the first five characters shown in eBay.

These statistics includes:

- the mean and the standard deviation of the prices,
- the total number of bids and total number of bidders,
- the number of bids submitted to the auction with the lowest standing bid,
- the number of bids submitted to the auction with the highest standing bid,
- the identity of all bidders bidding on more than one auctions (cross bidders),
- the mean and standard deviation of auctions receiving cross bids.

At any time, users can click on the 'Refresh' button to go back to the state at the beginning of the day.

This simple program exhibits a clear and intuitive real time process of eBay auctions. All real time variables are shown (except the description of the item). All competing auctions are shown side by side to illustrate how bidders response to the existence of competing auctions. (The only inconvenience is that the program uses Swing of Java 2™ and users need to download a java add-in to view it properly in a browser. The add-in is approximately 5 MB in size. If such add-in does not exist in the browser, the download process will start automatically. All what a user needs to do is to confirm that he wants to download the add-in. The add-in is safe and will not pose any potential risk to computer system).

The simulation gives an intuitive sense how bidders bid in eBay. It also obtains the value of useful variables such as the number of bids submitted on auctions with the highest (lowest) standing bid, the bidders who cross bid and the identity of the auctions with cross bidders. Such variable cannot be obtained from simple statistical tool (at least extremely difficult to get even if it is possible to get them).

Most of the empirical analysis only gets the summary statistics and the relation about these variables. Auction process and the details of bidding behavior are concealed. An important thing in studying the behavior pattern is to learn the real time environment and behavior, not only the sample statistics. For example: How bidder response if he submits a bid and finds that he is not the high bidder? Are bids on last day are more likely submitted on auctions with low standing bid? What are the considerations when bidders cross bid?

With our GUI, all auctions repeat again in real time in a short period and under users' full control.

4. Results

In the period we studied, there is one day without any auction of Pentium III 800 MHZ (without fan), 4 days with only one such auction. Table 2 reports the basic data in each day. The data includes the mean and the standard deviation of the prices, the number of bids submitted on auctions with the lowest and the highest standing bid (#lowbid,

#highbid), the number of bids not matched by bids in other auctions of the same day, the number of all bids (total bid), the number of different bidders (total bidder), the number of bidders who submit bids on more than one auction (#cross bidder) and the mean and standard deviation of prices for auctions receiving cross bids (sub-mean, sub-std).

Table 2 Basic result from the simulation

Date	N	MEAN	STD	#LOW BID	#HIGH BID	TOTAL BID	#CROSS BIDDER	TOTAL BIDDER	SUB-MEAN	SUB-STD
6/5/01	5	113	24	4	16	30	0	13		
6/6/01	1	123	0	6	6	6	0	4		
6/7/01	4	125	13	5	4	11	0	9		
6/8/01	4	124	8	8	10	16	1	15	118	7
6/9/01	5	100	8	9	2	21	2	14	93	9
6/10/01	3	113	8	8	12	17	1	6	113	8
6/11/01	1	92	0	2	2	2	0	1		
6/12/01	4	131	10	8	8	17	1	15	128	7
6/13/01	1	134	0	6	6	6	0	3		
6/14/01	4	116	22	1	4	13	1	8	103	25
6/15/01	4	136	6	7	10	17	0	14		
6/16/01	4	124	11	8	5	16	0	8		
6/17/01	6	121	16	7	8	26	3	14	120	20
6/18/01	5	114	14	13	6	26	1	13	106	6
6/19/01	2	123	0	6	8	10	0	6		
6/20/01	4	119	10	2	2	5	0	3		
6/22/01	9	104	9	8	15	38	4	19	104	5
6/23/01	6	120	8	13	6	28	0	11		
6/24/01	5	108	12	5	11	22	0	17		
6/25/01	4	136	6	7	10	17	0	14		
6/26/01	6	110	19	15	10	34	5	17	99	8
6/27/01	3	126	2	10	8	11	0	6		
6/28/01	2	119	5	5	2	7	0	5		
6/29/01	3	112	20	3	3	12	0	5		
6/30/01	2	118	14	6	2	8	0	6		
7/1/01	3	108	4	8	4	11	0	7		
7/2/01	2	124	27	1	3	4	0	3		
7/3/01	1	143	0	11	11	11	0	6		

We report the results on two subsections. Section 4.1 reports the behavior pattern of bidders. Section 4.2 presents the result of auction prices and the effect of bidder behavior on auction prices.

4.1 Behavior pattern of bidders

4.1.1 Revise bid

For each auction we get all bidders and the number of bids that bidders submitted, together with the bid submission time. On average every bidder of an auction submits 2 bids on the auction. Bidders are not following the advice from eBay to submit the true valuation at the beginning and let the proxy to bid for them.

The proxy bid mechanism in eBay is believed to save bidders from revising their bid too often. eBay's help page about proxy bid explains the proxy bid as the following:

A proxy bid and a maximum bid are the same thing. To place a proxy bid, just enter the maximum amount you are willing to pay. eBay will then automatically bid up to your maximum amount for you.

(http://pages.ebay.com/help/basics/e_item1.html)

Roth and Ockenfels (2000) explains the bid revising at eBay by their need to snipe (bid at the last minute and try to be the last one to bid). However, the data indicates that all bidders, whether they want to bid at the last moment or not, are revising their bids.

Bid revising is a natural consequence of the existence of competing auctions. If there is no bidding cost, bidders should bid with minimum increment. Intuitively, if bidders bid true valuation and bid only once, they may be trapped in very competitive auctions and do not have opportunity to switch to other less competitive auctions. Even if with bidding cost, bidders still revise their bids very often if the cost is not too high compared to the risk of bidding high. (They do not always bid the minimum increment, which is too costly).

4.1.2 Late bidding

The data in the sample shows that bidders tend to bid in the late period of the auction. We have information about all the bids and the time the bids are submitted. Figure 4 and figure 5 show the bid submission time.

Bids are clustered at the ending period. Almost all auctions received their last bid in the last several hours. In addition, 30 auctions (28% of the samples) receive their last bid within the last 60 seconds.

In Roth and Ockenfels (2000) the reason for delaying bids is that eBay auction has a fixed ending time. If the bids are submitted at the last minute, there is some probability that bids may not be submitted successfully. This can explain the very last minute bidding, but cannot explain the late bidding. (Roth and Ockenfels (2000) also finds that

even in auctions like Amazon auctions that have no fixed ending time, there are significant late biddings). Simply bidding late does not have effect that bids might not be submitted successfully.

The existence of competing auction can provide an explanation for late bidding. With the existence of competing auctions, bidders cross bid to avoid being trapped in one auction if another high valuation bidder happens to bid against them. If there is no bidding cost, bidders should bid the minimum increment each time and bid again and again. With bidding cost, it is too costly to bid very often. Bidders can bid with a significant jump and bid less frequently. However, this increases the risk of being trapped in a very competitive auction. Another alternative for bidders is to bid only at the late period, and bid with small increment. In this way, they do not need to bid too frequently, at the same time they can effectively cross bid and avoid being trapped in very competitive auctions.

Figure 3 Histogram of Bids Submission Time

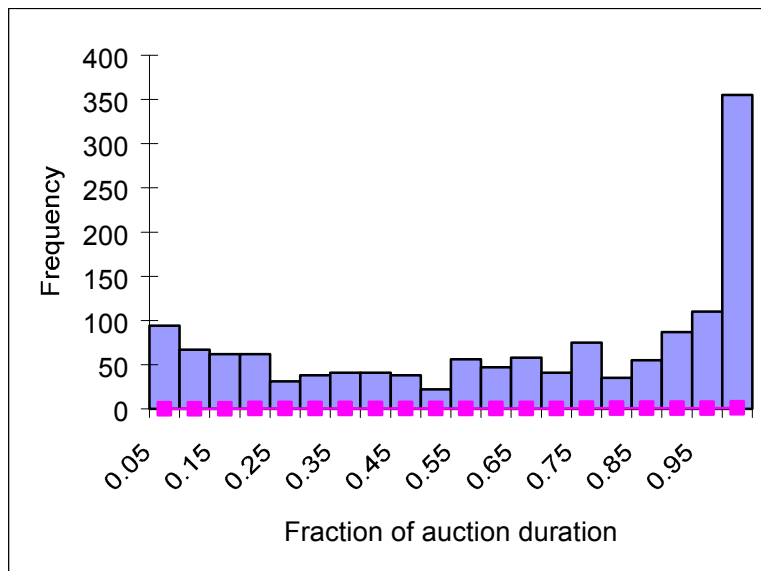
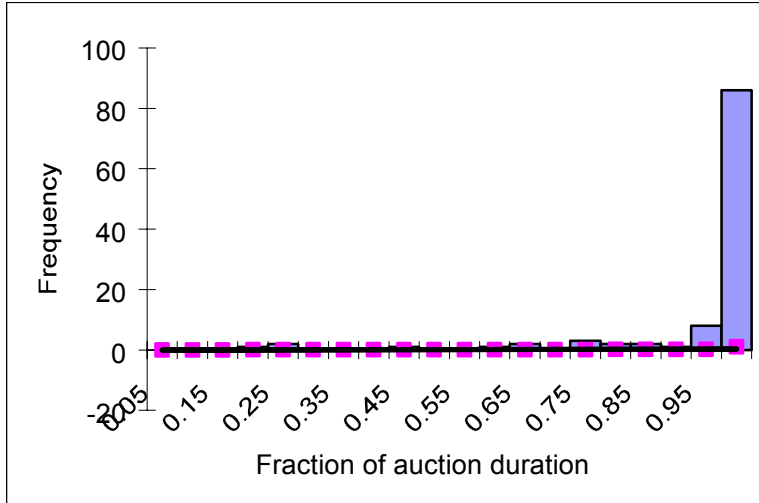


Figure 4 Histogram of time of last bis of auctions



4.1.3 Cross bidding and bidding on low standing price auction

Since we are interested in the environment with competing auctions, we focus on the days with at least 2 ending auctions. Table 3 reports the basic statistics in these 24 days. On average there are 4 competing auctions each day. There are 10 bidders submitting 17 bids on these auctions.

Table 3 Statistics of the variables

<i>Variable</i>	<i>N</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Minimum</i>	<i>Maximum</i>
N	24	4.125	1.6235361	2	9
MEAN	24	118.3464583	9.1851994	99.7	135.63
STD	24	11.4604167	6.8776611	0	26.52
#LOW BID	24	6.9583333	3.5567348	1	15
#HIGH BID	24	7.0416667	4.1228859	2	16
TOTALBID	24	17.375	9.121463	4	38
#CROSSBIDDER	24	0.7916667	1.3824731	0	5
TOTAL BIDDER	24	10.3333333	4.8424452	3	19
SUB-MEAN	9	109.0933333	11.2565314	92.51	127.5
SUB-STD	9	10.66	6.732234	5.34	24.75

In eBay there are bidders bid on more than one ending auctions in the same day. However, the proportion of such bidders is small. Most of the bidders do not cross bid among auctions. On average there are only 0.8 bidders, around 8% of all bidders, submitting bids on more than one auction. It seems that once a bidder chooses an auction, he becomes loyal to the auction and neglects the existence of other competing auctions. This is still true when there are other auctions with similar ending time and much lower standing bids. If some bidders take such opportunity, it will be very likely they can win those auctions with lower price.

Example 1 For auction in June 23, there are 6 ending auctions. Three auctions (say, auction one, auvtion2, auction3) are listed by seller finalcallauc ending at almost the exactly the same time: 12:26:35, 12:26:35 and 12:26:36. In the previous day (June 22), a bidder (rein) submit a bid on each of the three auctions, with 112.5 on auction one, 126.5 on auction two and 127.5 on auction three. (These bids are jump bids). On the final day, bidder stop2 bids against rein for auction one, bidder dchow bids against rein for auction two, and bidder I_kai bids against rein for auction 3. The final price is 112.5, 128.5 and 127.5. Bidder rein wins auction one and auction three. Bidder dchow wins auction two.

We wonder why most bidders are not responsive to the existence of competing auctions. In the sample, there are 6 days in which there are ending auctions listed by the same seller with almost the same time (June 9, June 12, June 17, June 22, June23 and June26). These include 17 auctions of 7 different sellers (Table 4). We find that there are significantly more bidders submitting bids on more than one such auction. For all these auctions there are at least one bidder submitting bids on more than one of these auctions. (There are only 9 days in the sample that have bidders submitting bids on more than one ending auction). For al bidders bidding auctions in this small sample, 11 of the overall 37 bidders cross bid. Among all 68 bids submitted in the last day, 44 (65%) are submitted on the auctions with the lowest standing bid. This proportion is only around 41% for the whole sample.

Table 4 Auctions with almost the same ending time

seller	Lastbid	end time	start time	Std	#LOWBI DD	#HIGH BID	TOTA LBIDS	CROS SBID	#bid der
reisdond	107.5	6/9/01 19:33	6/4/01 19:33	1.760696	3	4	7	0	5
reisdond	105.01	6/9/01 19:31	6/4/01 19:31						
its4sale	99.01	6/9/01 17:38	6/6/01 17:38	9.199459	7	7	14	2	9
its4sale	86	6/9/01 17:38	6/6/01 17:38						
chesterkingpin	132.5	6/12/01 16:40	6/5/01 16:40	7.071068	5	2	7	1	5
chesterkingpin	122.5	6/12/01 16:37	6/5/01 16:37						
shane-jake	107.5	6/17/01 17:09	6/12/01 17:09	3.535534	5	4	9	2	5
shane-jake	102.5	6/17/01 17:08	6/12/01 17:08						
cw12	107.5	6/22/01 20:22	6/19/01 20:22	3.944933	5	3	8	3	4
cw12	100	6/22/01 20:20	6/19/01 20:20						
cw12	99	6/22/01 20:19	6/19/01 20:19						

cw12	100	6/22/01 20:18	6/19/01 20:18						
finalcalla uction	127.5	6/23/01 12:26	6/20/01 12:26	8.962886	1	1	2	0	1
finalcalla uction	128.5	6/23/01 12:26	6/20/01 12:26						
finalcalla uction	112.5	6/23/01 12:26	6/20/01 12:26						
pcs-101	96	6/26/01 18:03	6/21/01 18:03	2.828427	18	3	21	3	8
pcs-101	92	6/26/01 18:02	6/21/01 18:02						

(Mean of the price: \$107.3835 Mean of the standard deviations: \$5.3290)

This suggest that bidders are reluctant to bid on more than one auction and to bid on the auction with the lowest standing bid can be caused by the different ending time of the auctions. Cross bidding can let bidders win auctions with the lowest price by always bidding in the auction with the lowest standing bid. However, when the ending times are different, a low standing bid for a later ending auction does not necessarily signify that it will still have a low standing bid when at the ending moment. Especially there is possibility of the new entrant at the last moment, and there are cluster of bids at the late moment.

For these auctions, the prices are still not uniform. However, the prices becomes much more homogenous for auctions with almost the same ending time, with the average standard deviation of \$5.3290. The prices on average are less than those of the auctions in the whole sample.

If there is no ending time, the theory predicts that in the Bayesian Nash equilibrium, bidders will bid on auction with the lowest standing bid. Our real time simulation shows that only 40% of the bids are submitted on auction with the lowest standing bid.

When auctions end at different ending time, it is natural that bidders will not always submit bid on the auction with the lowest standing bid. An auction ending in one minute may have a high standing bid, but there are not many rooms for the standing bid to increase. An auction ending in one hour may have a much lower standing bid. However, there are many rooms for the standing bid to increase, especially as the bids are clustered in the ending period.

When a rational bidder submits a bid on one auction with high standing bid, ex ante, he expects that if he bids on another auction, he must submit at least the same amount to win that auction. Ex post in the sample, for all bids submitted on any auctions, 86% of the bids are matched by at least one bid in another auctions of the same day. Only 14% of the bids are not matched by bids in other auctions. These bids do not necessarily be irrational. Bidders may just be unlucky that all bidders in other auctions are with low valuation. Some of these bids could be irrational frenzy bids. Bidders who are outbid by

others become frenzy about being outbid and submit irrational high bid, ending with regrettable high price for winner.

In the data, on average there are 7 out of the total 17 bids submitted on the auction with the lowest standing bid. There are also around 7 bids submitted on the auction with the highest standing bid. (According to the rule, when there is only one auction left, bidders are bidding on both the auction with the lowest and highest standing bid).

On average, each auction receives 4 bids in the last day. Even though the number of bids submitted on auctions with the lowest standing bid and the highest standing bid are roughly the same on average, in some days most of the bids are submitted on auction with the lowest standing bid, while in some other days most of the bids are submitted on auctions with the highest standing bid. If most of the bids are submitted on auctions with the lowest standing bids, it indicates that on average bidders are more cautious.

On the contrary when most of the bids are submitted on the auctions with highest standing bid, bidders are more likely to bid emotionally and there is fierce price war. Bidders bid on the auctions with highest standing bid even though other auctions have much lower standing bids.

In the sample, for 10 days there are more bids submitted on auctions with the low standing bid than on auctions with the highest standing bids. For 11 days there are more bids submitted on auctions with the lowest standing bid than on auctions with the highest standing bid. For three days there are equal number of bids submitted on the auctions with the highest and the lowest standing bid.

We also noticed that many bidders do not bid the minimum increment in the last day.

4.2 Market price

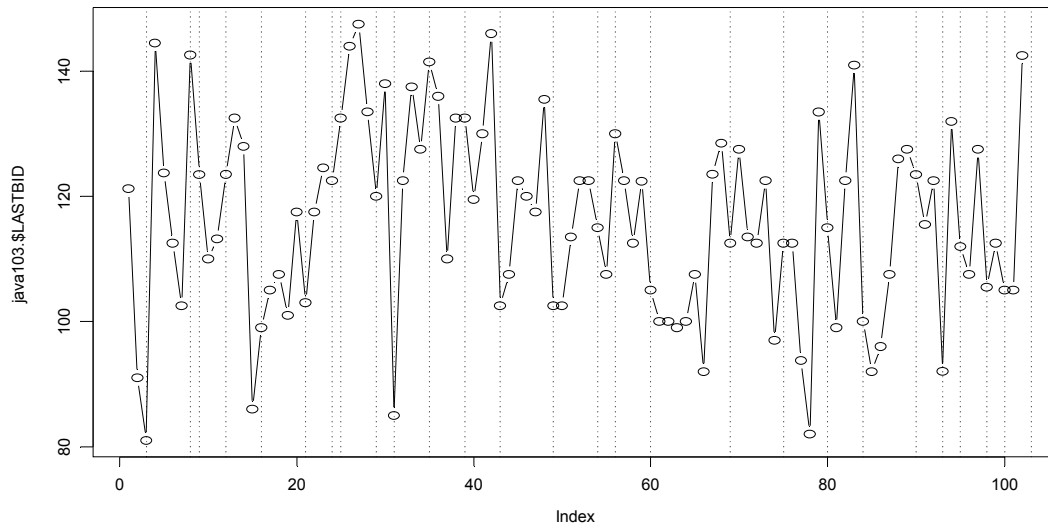
The theory of competing auctions with no fixed ending time predicts that the prices should be uniform. In our data, we find that auction prices in a day show significant dispersion. On average, for all days with competing auctions, the mean of the price is \$118, and the standard deviation is \$11.5. The standard deviation of the prices in a day is about 10% of the mean of the prices.

4.2.1 Prices follow a AR(1) process

We construct time series consists of all auction prices of the sample, ordered by the ending time. Figure 6 is the time series plot of the auction prices. The time series plot shows clearly the price dispersion. To explore possible daily price pattern, we use the vertical line to separate auctions in different days. It seems that there is no pattern of declining or increasing prices.

The process of auction price is stationary. The time series of auction prices show significant serial correlation. The auction prices follow an AR(1) process, with coefficient 0.217. The coefficient is significant at 95% level (with t value 2.22), see figure 7 and Table 5.

Figure 5 Time series plot of auction prices



(The vertical lines separate the auctions in different days)

Figure 6 ACF plot of time series of auction price

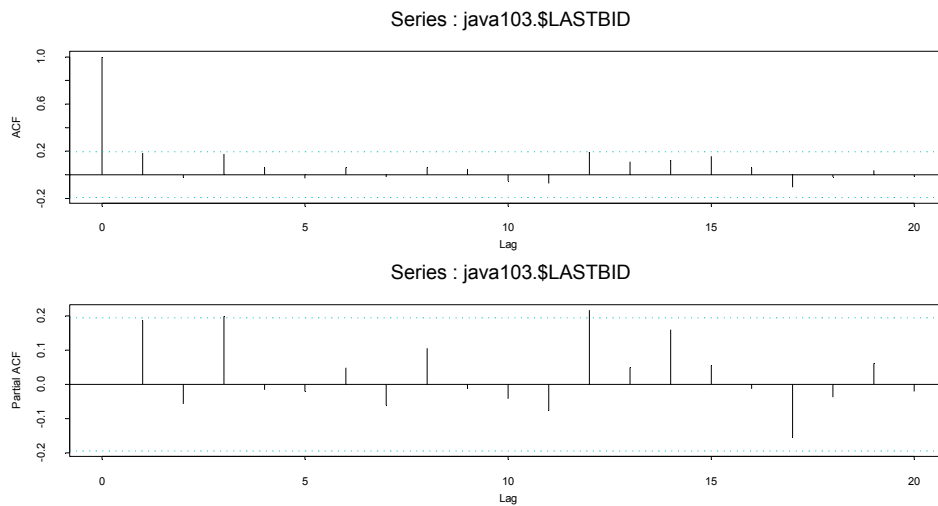


Table 5 Arima result (Conditional Least Squares Estimation)

Parameter	Estimate	Approx. Std Error	T Ratio	Lag
MU	116.37168	1.9077	61	0
AR1,1	0.21687	0.09759	2.22	1

The serial correlation on auction prices suggests that auction prices are not independent. Intuitively, if all auctions are independent, the deviation from the mean of the price should be pure white noise. Autocorrelation should be zero for all orders. The serial correlation suggests that it is no longer true to consider auctions in eBay as independent auctions.

To develop a sense of economic significance of the autocorrelations, observe that the R^2 value of a regression of price on a constant and its first lag is the square of the slope coefficient, which is simply the first order correlation. Therefore, an autocorrelation of 22% implies that about 5% of the variation in the price is predictable using the previous auction price.

Bidders in eBay have the choice to bid on more than one auctions. One auction ends up with high price because those bidders are anticipating that the future auctions would also end up with high price. This can cause the auction price to be serially correlated; a high price of one auction is usually followed by a high price in the next auction.

4.2.2 Prices do not have a decline pattern

eBay auctions bear some similarity to sequential auctions. In conventional sequential auctions, one auction starts only after the previous auction is ended. In eBay most of the auctions end at different time. However, the auctions are overlapped in time. As also noticed, many bids are clustered at the ending period.

Empirical research has documented that prices of similar or identical objects tend to decline over the course of a sequential auction. These include studies of wine auctions [Ashenfelter (1992)], condominiums [Ashenfelter and Genesove (1992)], painting, cable franchises, commercial real estate, Picasso prints, and others. However, there are also some studies that find the prices are increasing rather than decreasing. This includes Deltas and Kosmopoulou (1998).

Auction prices within a day in eBay do not show declining or increasing pattern. Since auctions in a day may be concentrated on afternoon or night, we do not use the absolute time in a day to describe the time sequence. Instead, for each auction, we associate with it a variable location, defined by:

location = order of the day/number of auctions ending in the day

This variable takes value from 0 to 1, with the last ending auction takes the value 1. The following relation does not provide any explanation of the auction price:

$$\ln(\text{price}) = \alpha + \beta \cdot \text{location} + e,$$

where e is the residue. In the regression, the adjusted R^2 is negative and the t-value is close to 0.

We group the auctions according to their locations, as defined above. First, in table 6, auctions are grouped as early or later (if location > 0.6, the auction is a later auction, otherwise it is an early auction). Then in table 7 we divided the auctions by early, first middle, second middle and late (if location is less than 0.4, the auction is an early auction. If the location is equal to 1, the auction is a later auction. The auction with location between 0.4 to 0.6, and 0.6 to 1 are first and second middle auctions.) The tables show the statistics of the auction prices for the grouping.

Table 6 Price for daily early and late auctions

	N Obs	Mean	Std Dev	Minimum	Maximum
early	51	116.9266667	16.3246687	80.99	147.5
later	51	115.4866667	14.6583726	85	144.01

Table 7 Price for daily early and late auctions

	N Obs	Mean	Std Dev	Minimum	Maximum
early	25	116.9724	17.7302908	80.99	146
middle	26	116.8826923	15.205158	97	147.5
middle	25	114.7204	14.9094429	85	141.5
late	26	116.2234615	14.6691581	91	144.01

In the first grouping, there are equal number of auctions in two groups. The average prices of the early auctions and later auctions are almost the same, with the late auctions a little bit less. In the second grouping, there are also roughly the same number of auctions in 4 groups. The average prices of early, first middle, second middle and late auction are again almost the same. Only the prices in the second middle group are a little bit lower.

On average auction prices do not show any declining or increasing pattern. However, looking only at the average price may lose some information. To have a clearer pattern of the prices movement in a day, we show the price movement in some special days.

In figure 8 we plot the sequences of auction prices in 2 days that have 6 ending auctions per day: June 23 and June 26. In figure 9 we plot the sequences of auction prices in 4

days that have 5 ending auctions per day. It is clear that there is no pattern of declining or increasing prices.

Figure 7 Price sequence in a day

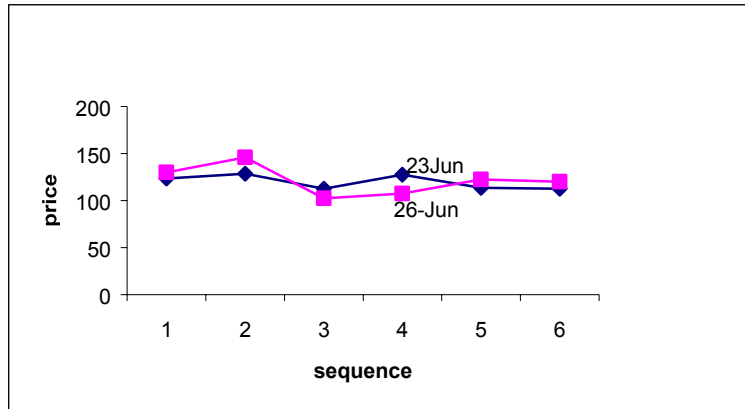
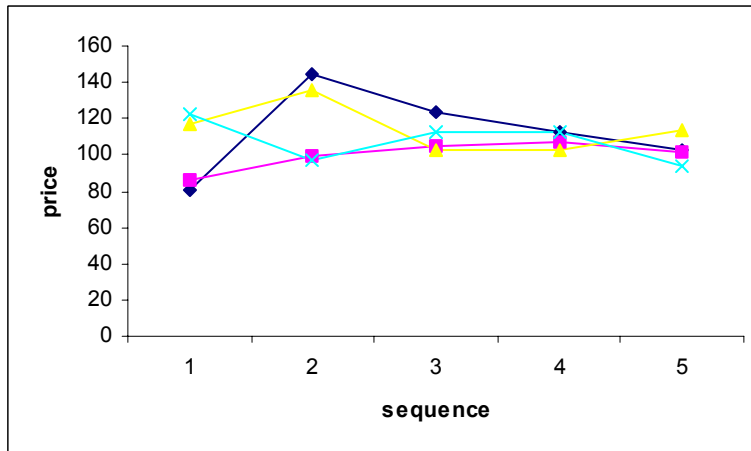


Figure 8 Price sequence in a day



In case of similar object and independent valuation, researchers try to explain the declining price in sequential auction by factors such as bidder risk aversion, decreasing of willingness to pay, etc. In eBay auctions, bidders can choose to bid several competing auctions at the same time. Even in case there are not active cross bidders, when a rational bidder submits a bid on one auction, ex ante, he expects that if he submits bids on another auction, he must submit at least the same amount in order to win it. The auction prices in day should not exhibit increasing or declining patterns.

4.2.3 Effect of behavior pattern on auction prices

In a big market such as eBay, the price effect of strategic behavior of single individuals is limited. However, behavior pattern of all players can have a significant effect on prices. We analyze how the price dispersion and the mean price in a day are affected by the behavior pattern of bidders.

Table 8 reports the regression of the standard deviation of the prices in a day with the following variables: the number of competing auctions, the ratio of bids submitted on auctions with lowest/highest standing bid to the total bids in the day (LBIDRAT/HBIDRAT), the number of bids submitted on the auctions of lowest/highest standing bid (#LOWBID/#HIGHBID), the number of cross bidders, the number of total bidders, and the ratio of bids that are not matched by bids in any auctions of the day (IRARATIO). This ratio can be a proxy for the frenzy bid. This regression fits the data quite well, with $R^2=0.7739$ and adjusted $R^2 = 0.6534$.

Table 8 Regression on the daily standard deviation (R-square =0.7739 Adj R-sq= 0.6534)

Variable	DF	Parameter	Standard	T for H0:	
		Estimate	Error	Parameter=0	Prob > T
INTERCEP	1	28.708328	7.91228286	3.628	0.0025
N	1	-2.248382	1.21616977	-1.849	0.0843
LBIDRATI	1	-34.097835	7.66936017	-4.446	0.0005
HBIDRATI	1	-8.300202	8.20296026	-1.012	0.3277
NLOWBIDD	1	0.895401	0.48765037	1.836	0.0862
NHIGHBID	1	0.34423	0.4545063	0.757	0.4606
TOTALBI1	1	-0.353986	0.3389105	-1.044	0.3128
CROSSBID	1	1.558801	0.8873281	1.757	0.0994
IRARATIO	1	22.200357	8.04699907	2.759	0.0146

We find that a high ratio of bids submitted on the auctions with lowest standing bid to the total bids in the last day greatly reduce the price dispersion in a day (p value =0.001). The ratio of those irrational bids in a day greatly increases the price volatility (with p value = 0.01). We do not find that the ratio and the number of bids submitted on auctions with the highest standing bid could increase the price dispersion. The number of competing auctions in a day tends to decrease the price dispersion (the effect is not significant). Also the number of total bidders does not have significant effect (the signs tend to be negative). The number of cross bidders does not have significant effect (and the sign tends to be positive; for days when there are crossing bidders, the standard deviation of the prices tend to be larger⁵!).

⁵ There are not many bidders who cross bid. Cross bidding makes the price uniform only if most bidders submit bids on auction with the lowest standing bid and bid with minimum increment. If this condition is not satisfied, the existence of cross bidding only indicates the existence of high price volatility.

When more bids are submitted on auctions with lowest standing bid, bidders are bidding more cautiously. Auction prices tend to increase simultaneously. There is not fierce pricing war in any auction. Bidders do not push the price too high in the auction with high standing bid. Consequently all auctions tend to end with similar price. The standard deviation of the prices in a day decreases. On the other hand, a high proportion of bids not matched by bids in other auctions of the same day indicate the existence of frenzy bids and the existence of price war in some auctions. Some auction prices are pushed high comparing to other auctions. The standard deviation of the auction prices in the day increases. It seems that the number of unmatched bids is a better way to describe the irrational bids than the number of bids submitted on the auctions with the highest standing bid.

Table 9 reports the regression of the mean price in a day with respect to following variables: the number of competing auctions, the ratio of bids submitted on auction with highest standing bid, the total number of bidders and the number of cross bidders. None of these variables has significant effect on the mean price.

Table 9 Regression on daily mean of price (R-sq 0.3371=Adj R-sq = 0.1976)

<i>Variable</i>	<i>DF</i>	<i>Estimate</i>	<i>Error</i>	<i>Parameter=0</i>	<i>Prob > T </i>
INTERCEP	1	113.08919	7.81067178	14.479	0.0001
N	1	-1.444659	1.98543208	-0.728	0.4757
HBIDRAT	1	15.512728	9.66569032	1.605	0.125
#TOTALBIDDER	1	0.608556	0.58317716	1.044	0.3098
#CROSSBIDDER	1	-2.232409	1.73347973	-1.288	0.2133

The regression shows that the when there are more competing auctions, the mean price tends to decrease. When there are more bidders in the last day, mean price tends to increase. This is the competition effect. When there is more supply, auction prices decreases. When there are more bidders, the mean price increases. This is the supply side effect. When there are more demands, the competition among bidders is intense and the mean auction price increases.

When there are more bids submitted on auctions with the highest standing bid, mean price in a day increases. The existence of cross bidding reduces the mean price. Bidders who cross bid will not participate in frenzy price war. When there are more bidders who cross bid, the mean price in a day tends to decrease.

5. Discussion

Since there exists significant price dispersion for auctions of similar CPU, we may wonder why there are not arbitrageurs in the market, ready to buy the CPU once the price is very low. The existence of such arbitrageurs can significantly reduce the price

dispersion. The reason that we do not observe such arbitrageurs can be that the benefit of doing so is not big enough. Such arbitrageur has to win the auctions easily and sell the items with a higher price easily. However, there is a listing cost in eBay. The cost of monitoring the process of all auctions can be large. If a CPU is not sold quickly, its value will devalue quickly.

In the paper, we do not consider whether such a market is efficient. The volume of the market and the successful transaction of most of the auctions suggest that the market is efficient, even though we do not have a criterion for it. However, we have shown that the market mechanism of eBay does not generate a uniform competitive price for similar or identical items. This is mainly caused by the following factors: auctions have fixed ending time and thus bids are clustered at the ending period. The price dispersion can be also a factor that an auction market can attract many traders: the uncertainty of the prices can make the trading more exiting.

We do not consider the transaction cost in the paper. This can include the bidding cost in eBay, the waiting cost associated with the immediacy requirement. The transaction cost may provide some explanation of the bidding behavior and price dynamics in eBay, which is beyond the scope of this paper.

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Appendix

Design of The Auction Applet

The applet is located www.chass.utoronto.ca/~mzheng/AuctionApplet.html

Function Buttons:

Bid: submit the next bid to an auction, updating all information in the user interface (current time, time left, standing bid and bidders list box)

Refresh: go back to the state of the beginning of the day

Previous Day: navigate to the previous day

Next Day: navigate to the next day

Selection tree:

Situated in the left panel

Showing the date and the number of ending auctions.

Click on a node will show the information of that day in the right panel.

Background Data Structure:

Class Bidder: describing a bidder:

Bidder ID

Bid amount

Bid submission time.

Class Auction: describing an auction:

Starting time

Ending time

Time left

Standing bid at the current time

All bids up to the current time

Class dayAuctions: initialize the data of all auctions and all bidders.

Other classes for processing the data and showing the data in the applet.

TreeSet of all bidders of the last day

TreeSet of bidders of an auction.

Comparators for the ordering in the TreeSet

ListCellRender for displaying the bidders of an auction and showing high, second high bidder.