Online Auctions Efficiency: A Survey of eBay Auctions

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ABSTRACT

Online auctions have become a pervasive transaction mechanism for e-commerce. As the largest online marketplace in the world, eBay is an attractive case study that enables the study of online auctions utilizing data involving real people and transactions.

In this paper, we present a detailed investigation and analysis of multiple online auction properties including: consumer surplus, sniping, bidding strategy and their cross-relationships. Our goal is to evaluate the theoretical foundations of online auctions and discover patterns and behaviors hidden due to the lack of real and extensive transaction data. Among our findings, we uncover an important correlation among sniping and high surplus ratios, which implies the uncertainty of true value in a competitive environment. The key issue is the wrong assumption that bidders' valuations are independent from each other, which leads to inefficient auctions.

In order to address the inefficiencies of current online formats we introduce a declining price auction model customized for online transactions. Conceptually, this model ought to deal with the complexities of competition in an online environment while maximizing social welfare.

Categories and Subject Descriptors

H.4.m [**Information Systems**]: Miscellaneous

General Terms

Economics, Measurement, Performance, Thoery

Keywords

Auction Efficiency, Auction Theory, Online Auctions

1. INTRODUCTION

Online auctions have become increasingly popular over the last few years with a matching growth of research work in the subject. As the largest e-commerce web site in the world, eBay provides an extensive transaction platform for a wide range of items. This attracts millions of buyers and sellers daily with volumes in the order of US \$1800 per second. Such a platform has become an important transaction data source of great interest to researchers. In this paper, we explore this data further and identify interesting user behaviors and correlations.

We start this section by exploring some basic economic notions related to auction formats. We cover some of the related work and results in this area followed by a description of our data sources. We finish the section with the layout and structure of the rest of the paper.

1.1 Basic Concepts

An auction is defined as a selling mechanism where a plurality of goods or services are open to bids and then transferred to the winning bidder or bidders. Economic theory considers certain auction formats as efficient pricing mechanisms. When discussing efficiency in this paper, we specifically refer to *Economic Efficiency*, in particular, *Pareto Efficiency*. An allocation of goods is Pareto-Efficient if there is no movement to another allocation that would make one individual better without making any other individual worse off. We also use the terms *efficient* and *optimal* interchangeably.

Auctions may be characterized by common features in both the online and offline world. Some of these features are:

- Public vs. Private: In *public* auctions, the bidders' identities are open and anyone is welcome to attend the auction. *Private* auctions hide the bidders' identities and whoever wins the auction remains anonymous.
- Open vs. Sealed: In *open* auctions, all bid amounts are exposed to the world, while in *sealed* auctions, on the other hand, bid amounts are concealed, additionally, all bidders ignore the number of bids or bid amounts during the duration of the auction.
- First-price vs. Second-price: This feature refers to the price to be paid at the end of auction. In *first-price* auctions, the winner pays exactly the highest bid. In *second-price* auctions, the second highest bid is paid.
- English vs. Dutch: This feature defines the price direction during the auction's lifespan. An auction may start with a low price and increase as new bids arrive until the end of the auction: *English auction*; or, start with a high price, which drops in some fashion until it reaches someone's bid or the auction ends at a minimum price: *Dutch auction.*
- Fixed End-time vs. Auto-extend End-time: The end time of auction could be fixed or auto-extended depending of the activity at the end of the auction. For

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example, an auction is ended until N minutes have passed without new bids.

- Hidden Reserve Price: A *hidden reserve price* is the minimum amount that a seller is willing to receive for an item. This price remains hidden until the reserve is reached.

We define an *Auction Format* as a linear combination of the above features. When comparing auction formats, one of the most common questions is that whether two formats are *revenue equivalent* [1], meaning, the result in the same expected sale price. One of the most celebrated theorems in Auction Theory is the *Revenue Equivalence Theorem*. The theorem suggests that any two auction formats are revenue equivalent if:

- the bidder with the highest type/signal/value always wins,
- the bidder with the lowest possible type/value/signal expects zero surplus,
- where all bidders are risk neutral and
- drawn from a strictly increasing and atomless distribution.

The eBay marketplace offers multiple auction formats. The default format is an English Auction. Multiple item auctions, of the same item type, are referred as Dutch Auctions; however, this contradicts the textbook definition. In this paper, we only cover the former auction format as it is the most commonly used[2]. EBay's English auction format is a combination of second-price, public, either open or sealed[3], with an optional hidden reserve price and a fixed end-time.

1.2 Related Work

There is extensive research in the area of online auctions, specifically eBay auctions. Sniping and bidding strategies are one of the most sought after topics. Roth and Ockenfels[1] indicated in their paper that in view of the distinct rules for ending an auction, the proportion of sniping is substantially higher in eBay than in Amazon. Opposite to eBay, Amazon employs an auto-extend end-time format exclusively. Roth and Ockenfels[2], and Wang, et al.[3] have also addressed that sniping is an optimal strategy for incremental bidders. Barbaro and Bracht[4] have showed that sniping can effectively prevent being shilled, and it is a rational reaction to existing eBay rules that allows a bidder to retract and a seller to cancel a bid. Gray and Reiley[5] have found evidence of lower prices in the range of 2.54% of the final value for sniped auctions; however, the benefit is not statistically significant. Wilcox[6], Ockenfels and Roth[7] have investigated 535 electronic auctions spanning four categories on eBay and introduced the phenomenon that experts are more likely to bid late.

In terms of consumer surplus, Bapna, Jank and Shmueli[8] have indicated that the median surplus level per eBay auctions is \$3.61 with at least 18.3% surplus ratio. Their work is based on a sample of 4514 eBay auctions. Brynjolfsson, Hu and Smith[9] analyzed the consumer surplus in the digital economy. Their results suggest that increased product variety made available through electronic markets have created significantly larger sources of consumer surplus gains. Ely and Hossain[10] compared sniping for DVDs on eBay to squatting in auctions and showed that sniping leads to a statistically significant increase in average surplus.

For all the related work reviewed, we have found that they only cover either a small group of goods or a limited set of item types. This has limited the scope of their analysis and results.

1.3 Data Source

The dataset analyzed comes from two sources: eBay Sojourner logs and eBay Data Warehouse. Sojourner is a live feed logging system which tracing the progress of each user session's page view activities. Given the amount of data, all analysis including this data source are limited to a 25% sampling rate. This feed is used to determine particulars about the user behaviour in the site, for instance, details about a user's search or bidding activity. eBay's Data Warehouse is an enormous database, which stores all information about items and users including cumulative metrics of long term user activity. Our analysis includes a 25% sampling rate of all auctions that ended from July 1st, 2007 to July 7th, 2007 in the US site[4] across all 34 top-level categories. This amounts to a total of 855420 auctions. For all statistical results reported we adopt medians instead of averages in order to prevent sparse outliers. The data we employ can be trusted authoritatively.

1.4 Structure

The rest of the paper is structured as follows. In the next four sections we dive into the topics of consumer surplus, sniping, other bidding features and bidding strategy. In Section 2, we depict the notion of consumer surplus in a second price auction, present a surplus ratio evaluation system, and investigate the determinants of surplus ratio by item category. In Section 3, we explore and discuss the phenomenon, cause, classification and strength of sniping thoroughly. In addition, we analyze the relation between surplus ratio and sniping. In Section 5, we render a detailed analysis of different bidding strategies and how they lead to distinct final values even in the presence of the same item. This result questions the ability of predicting a sale price for an auction and the validity of the revenue equivalence theorem. In the last section, we introduce a new auction format as a supplement to the existing formats.

2. CONSUMER SURPLUS

Consumer surplus is a traditional economic notion defined as the difference between the price a consumer is willing to pay for a good or service and the actual selling price. A positive consumer surplus represents an imbalance between supply and demand for any given market. In the case of auctions, a secondary cause of consumer surplus are inefficient formats.

[1] `http://en.wikipedia.org/wiki/Revenue_equivalence#Revenue_equivalence`

[2] Items sold by English Auction account for 92% among all the auction transactions.

[3] An auction will become private automatically when the price on an item reaches or exceeds a certain level. `http://pages.ebay.com/help/buy/bidding-ov.html#about`

[4] `http://www.ebay.com`

In contrast with a first-price auctions, in which the winner must pay his own highest bidding price, the winner of a second-price auction does not necessarily pay the amount of his or her maximum bid, therefore, creating a source of consumer surplus in auctions. Typically, consumer surplus in a second-price auction can be simply considered as the excess of the highest bid price over the final value.

eBay provides a proxy bid system, which turns the English format into a second-price auction format as well. In the proxy system, a bidder is supposed to place the highest amount that he or she is willing to pay, and the proxy bid system automatically raises the bid on the user's behalf, using only as much of the bid as is necessary to maintain the top position.

On eBay, the final value paid by the highest bidder is:

$$P = min\{V_s + I(V_s), V_f\}, \tag{1}$$

where P, V_f, V_s represent the final value, first and second highest bid amount respectively, and I is increment in conformity with the final price bracket[5]. $V_s + I > V_f$ if and only if $T_f < T_s$ and $V_f - V_s < I$, where T_x is the bidding time of bid x. A buyer may win an item for less than his or her maximum bid if $V_s + I < V_f$.

In order to protect the winning bidder, the actual value of V_f is kept confidential from other users including the seller. As a result, other researchers find challenging to calculate the accurate consumer surplus of eBay auctions. Bapna, Jank and Shmueli developed an automatic sniping agent for users to bid[8] so that they were able to know what the highest bidding price of the items won was. However, their data set is skewed toward more sophisticated users, most of which attempt to snipe deliberately. As it'll be shown in Section 3, items won via sniping have a median consumer surplus ratio twice as high as that of overall items. In addition, only 20.2% of the total auction items on eBay are won via late bidding.

2.1 Surplus Ratio Evaluation Model

Given the wide range of item prices on eBay, using the absolute consumer surplus value is not enough to render an accurate picture of eBay's consumer surplus. We define the Consumer Surplus Ratio (CSR) as the ratio of the surplus amount over the final value. Giray, Hasker and Sickles introduced a Median based CSR in order to derive an estimate for the ratio's lower bound.[11]

$$\operatorname*{Median}_{\forall i}\left(\frac{V_{H_i} - V_{F_i}}{V_{H_i}}\right), \tag{2}$$

where V_{H_i}, V_{F_i} are the highest bid and the final value of any item i. In accordance with this rough CSR lower bound, an upper bound can be defined as:

$$\operatorname*{Median}_{\forall i}\left(\frac{V_{H_i} - V_{F_i}}{V_{F_i}}\right). \tag{3}$$

The problem with these two metrics is the existence of items may end at an extremely low price with only one bid throughout the whole auction duration, due to the lack of users' demand or excess supply at any given time. Based on the fact that the number of bids on an item is a powerful factor of confidence on the final value, we propose a refined criterion for CSR:

$$\operatorname*{Median}_{\forall i}\left(\frac{(V_{H_i} - V_{F_i}) \cdot (N_i + N_m)}{V_{F_i} \cdot N_i + V_{H_i} \cdot N_m}\right), \tag{4}$$

where N_i is the number of bids of item i and N_m is the median number of bids across all items in our dataset[6]. The refined equation takes number of bids into account and present a more reasonable evaluation of the consumer surplus ratio, we use this standard criterion to gage the surplus ratio in the following context.

Equation (2), (3) and (4) are called Surplus Ratio Evaluation Model.

2.2 Surplus Ratio Factors

Consider iPhones as an example. Fashionable and prevalent as they are, CSR is minuscule, 1.59%. This can be easily explained given that its market price is open and the supply is stable to most buyers in a short period of time. One is hardly willing to bid over the market price only to win that auction. The wiser approach is to bid slightly lower than the market price, and just transfer to another identical product if outbid. By contrast, Pre-1940 photographic image collectibles get over 50% median CPR. Our analysis suggests that the surplus ratio is generally impacted by the nature of the market and the ability to find a replacement. Rareness itself makes the valuation process difficult, therefore bidder valuation vary widely leading to high surplus ratios. In addition, attractiveness only corresponds with number of bids and bidders. Thus, it is not the popularity but the rarity that matters when determining the cause for surplus ratio.

We zoom out from items to categories, which, for the most part, represent a classification of homogeneous items. Our results in Figure 1 show that those categories with scarce identical replacement have a higher surplus ratio than those of commodity items.

Given that surplus ratio differs a lot even within one single top-level category, we select the category "Music", which has the largest variance, as an instance and take a deeper insight into its subcategories. Analogous to the previous result, Figure 2 suggests that the subcategory "Cassettes", which has the highest Median CSR also contains the most rare items. Since cassettes are no longer the popular container for music, we can scarcely find them in the marketplace; consequently, people's valuation have a higher variance.

3. SNIPING

3.1 Concept Definition

Sniping is defined as the process of watching a timed online auction, placing a winning bid at the last possible moment, usually seconds before the End of Auction (EoA), and giving the other bidders no time to react. In order to crystallize the ambiguity of the concept, we should indicate that, sniping is not only a late bid (within the last T seconds before the EoA), but a deliberate bid as well. Those who bid through the process of search sorted by time ending-soonest, and bid on an item during the last few seconds are not deemed as snipers. Neither are those incremental bidders who happen to bid during the last few seconds, because they are not deliberately. A late bid is not regarded

[5] http://pages.ebay.com/help/buy/bid-increments.html

[6] The median number of bids is 2 among all the items.

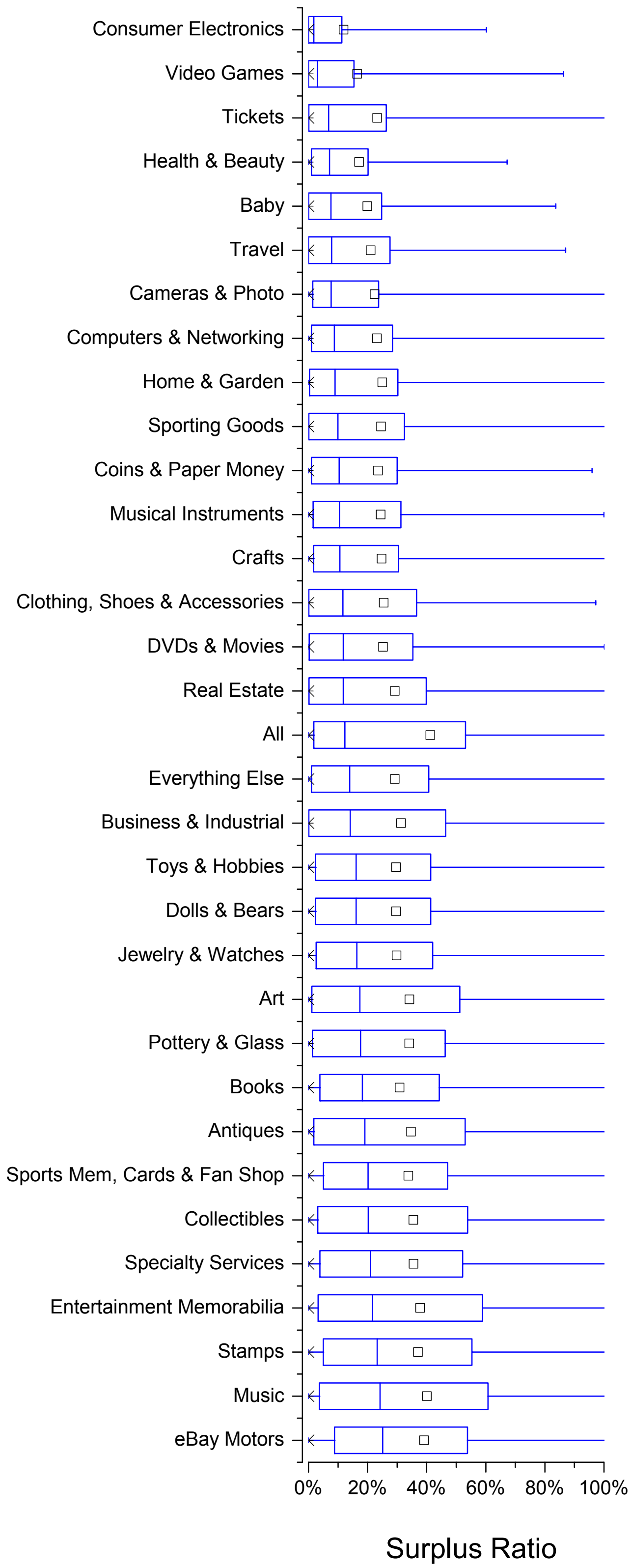

Figure 1: Box Plot for Meta-categories. The box represents values from 25^{th} percentile to 75^{th} percentile. The line and square in the box means median and average respectively.

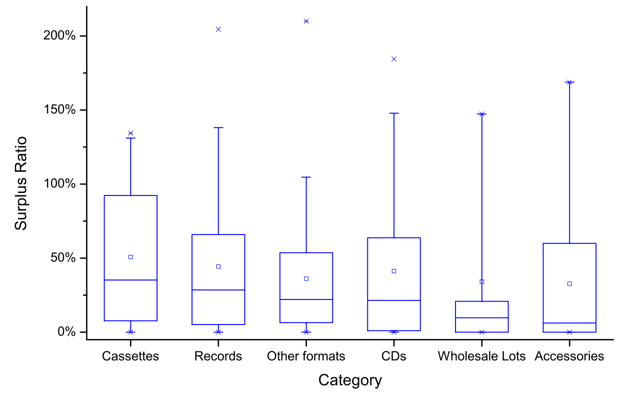

Figure 2: Box Plot for Category Music

as a sniping bid unless it is intentional and there is no previous bid from that bidder. In fact, snipers never expose themselves until the last fatal strike.

3.2 Screen Sniping and Automatic Sniping

We divide sniping into two parts by user behaviors, screen sniping and automatic sniping. Screen sniping, a.k.a. manual sniping, is the traditional way of sniping. Buyers are squatting in front of the screen, judging upon other competitors' behaviors, waiting until last seconds, clicking the mouse nervously so as to beat other potential buyers at the last moment. Exciting as it is, buyers are not always able to perform such strategy. It is impractical, for most snipers, to stay up till 3 a.m. only to wait for the last second, even in the case of a very attractive auction. As a result, the use of automatic sniping agents have prevailed. One may either use sniping software installed locally or allow a sniping service to snipe on the user's behalf. By means of automatic sniping, the potential buyer only needs to set up the estimated price several hours or days before the EoA, and automatic sniping tools will bid few seconds before the EoA. Snipping has important implications on user behavior up to the point of changing the explicit format of the snipped auction. A snipe bid can be deemed to be a sealed bid to a certain extent, as the bidding time and price remains concealed until the EoA. For situations where sealed bids (or snipe bids) coexist with open bids in the same auction, sniping has an advantage as open bidders found their valuation upon imperfect information.

3.3 Sniping Estimation Model

As our statistics show, automatic sniping, especially sniping services, are most likely to bid during the last 5 to 10 seconds before the EoA. The goal has two points:

- Avoid bid rejections due to network delays, and to allow for retries in the case of a network transmission error.
- Giving other potential bidders no time to react.

From our data set, we can precisely distinguish whether a snipe bid was placed via a sniping service by checking its IP address against our sniping services list. However, bid from sniping software is hard to distinguish. In order to estimate the total sniping percentage including both screen and automatic, we take a detailed analysis on the bid arrivals.

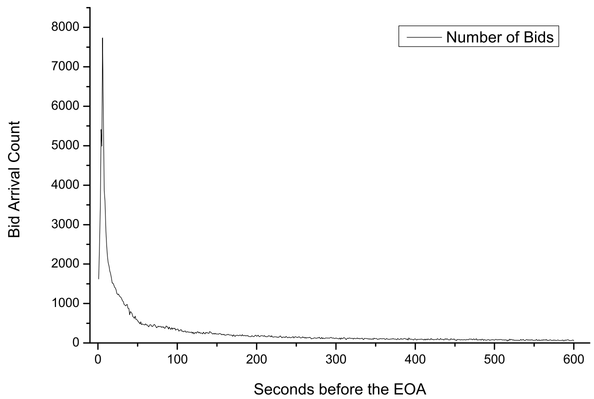

Figure 3: Bid Arrival Strength in the Last 10 Minutes. The peak occurs at exact 5 seconds before the EoA.

Figure 3 illustrates the arrival strength in the last 10 minutes before the EoA on eBay U.S. site. The arrival strength is in the form of a slowly attenuated trend except the last minute, which confirms the strong relationship between sniping and bid arrival time. The rest of the curve follows a stable long tail that lasts until the the start of auction, which can be considered as infinite. The dramatic burst within last minute before the EoA shows the great enthusiasm from those snipers. If we define $B(t)$ as the bid arrival strength on time t,[7] then we have:

$$B(t) = B_s(t) + B_n(t)$$

where $B_s(t)$ is the sniping bid arrival strength and $B_n(t)$ is the non-sniping normal bid arrival strength. As the definition of sniping in Section 3.1, we also have:

$$B_s(t) \begin{cases} \geqslant 0 & (t \leqslant 60) \\ = 0 & (t > 60) \end{cases}$$

In order to estimate the proportion of B_s in B, we calculate B_n instead.

Most of the normal users look for their interests via "eBay search". Instead of sniping, those normal bidders make their bids the right time they find their interested items. Currently eBay provides different sort methods such as "ordered by time" and "ordered by price". Statistically the latter one should have a randomly uniform distribution on time. However, the former one is significant to bid time distribution. Our statistics show that 70% of the total search events are ordered by ending soonest, which is the default sort method among all kinds of sorts.[8] We know that when a search result page is presented, those items on the top of the page will attract more attention than those on the middle and bottom. So if we use ordered by ending soonest to make a search, the most attractive items are those to be end in a time interval from time 0 to t, which will cause a higher probability of items in that slot to be bid on. In addition, t is bigger when less items returned in search result page, and vice versa. Assume the Probability Density Function (PDF) of slot length is $l(t)$ $(t > 0)$, then the bidding influence intensity distribution of ending soonest search $f_e(t)$ is:

$$f_e(t) = \int_t^{\infty} l(t)dt \quad (t > 0) \tag{5}$$

Regarding that $l(t)$ is massive distributed, it can be considered as Gaussian Normal distribution: $N(\mu, \nu^2)$ $(t > 0)$, and if $\Phi_{\mu,\nu^2}(t)$ is the corresponding Cumulative Distribution Function (CDF) of $l(t)$. then we have:

$$f_e(t) = 1 - \Phi_{\mu,\nu^2}(t)$$

Assume ordered by ending soonest search has an influence I_e among all the searching methods, then $I_e \cdot f_e(t)$ is the bidding influence function on different time t. Also, if I_p is the influence intensity, $f_p(t)$ is the bidding influence intensity distribution of ordered by price search. Then $I_p \cdot f_p(t)$ represents the bidding influence function of ordered by price search. Since $f_p(t)$ is independent of time, f_p can be regarded as uniformly distributed. Given that 93% of the search operations are via ending soonest and price lowest, total non-sniping bidding influence I_n equals to $I_e + I_p$ approximately.

Besides, once a normal bidder is informed that he or she has been outbid, the bidder will then consider of whether to rebid for that item based on his or her estimation, and iteratively. If the influence ratio on time t is $\sigma(t)$, then we have:

$$I_n(t - \Delta t) = \sigma(t)I_n(t) \tag{6}$$

From Equation (5) we know that $\sigma(t) > 1$.

Considering of Figure 3, if there is no deliberate sniping, the bid arrival strength curve ought to be smoothed throughout the whole auction duration. Therefore, we can consider $I_n(t)$ to be continuous and differentiable. Solve Equation (6), we have:

$$I_n(t) = e^{t - \int \sigma(t)dt} \tag{7}$$

Assuming that $I_n(t) = I_e(t) + I_p(t)$, then we have:

$$\sigma(t) = 1 + \frac{I_e}{I_n}\Phi(t)l(t) \tag{8}$$

Considering that $I_n \propto B_n$, and $\sigma(t) > 1$, then we know that B_n applies to negative exponential like distribution.

Figure 4 shows the curve fitting for B_n. Then we can give a prediction of the continuous and differential curve in last minute, B_{np}, and figure out the percentage that sniping contributes to the whole bids:

$$P_s = \frac{\int_0^{t_s} (B(t) - B_{np}(t))dt}{\int_0^{t_s} B(t)dt}$$

t_s is the defined sniping boundary time 60 seconds. Finally we obtain that 61.4% of the events in last minute tend sniping, including both manual and automatic.

[7]Time here is reverse to the normal, it is the exact relative time before the EoA.

[8]Since March 2008, Best Match becomes the default sort in search.

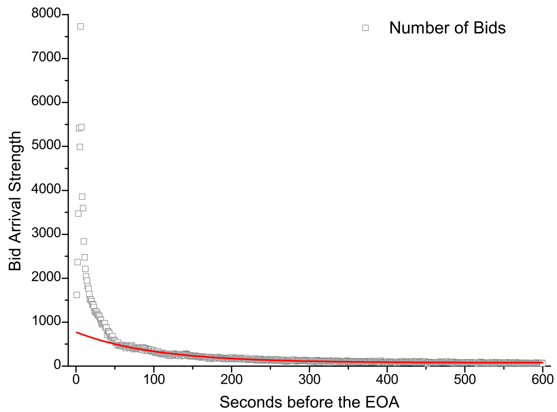

Figure 4: Bid Arrival Strength in Last 10 Minutes before the EoA.

3.4 Winning Rate

Late bidding, a.k.a. last minute bidding, has a higher winning rate than early bidding, because the sniper yields other competitors less time to respond. The winning rate of the whole bids is 21.79%, namely five bids lead to one winning bid approximately. As a contrast, late bidding winning rate is 51.71%. Screen sniping's winning rate is 66.73%, which is slightly higher than sniping services' 57.87%. The reason is that sniping services' actual bidding time is more likely to be several hours or days before the EoA, which is earlier than screen sniping. Generally, winning rate increases while the bidding time approaches the EoA.

3.5 Experts and Amateurs

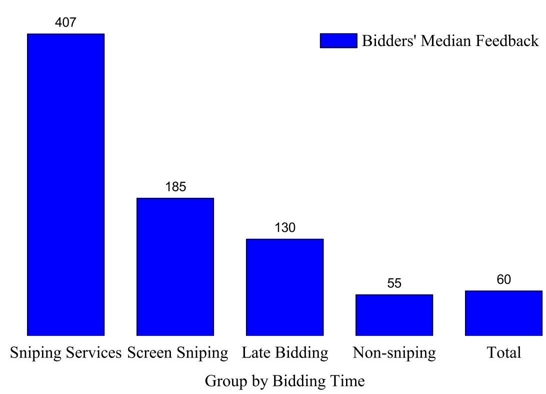

Figure 5: Bidders' median feedback grouped by bidding time.

We have also accomplished a detailed statistics on the snipers, and find that there's obvious distinct on bidders' feedback between sniping and non-sniping. Although it has been indicated by other researchers[6], we present this analysis quantitatively. Figure 3.5 has illustrated that the median feedback of all buyers at bidding time is 60, that of late bidding is 131, and that of sniping services bidders is 407. If we regard buyers with higher feedback as experts and lower feedback as amateurs, Figure 3.5 suggests that experts are more likely to snipe, especially to employ sniping service.

3.6 Surplus Ratio

When considering the surplus ratio in terms of sniping, we find that about 81.5% of the entire items have consumer surplus, but 88.8% of the late bidding items have consumer surplus. Among the whole items, the median surplus ratio is 14.91%, in which sniping contributes enormously. However the two sniping modes are extremely distinct. The median surplus ratio of screen sniping 18.36%, slightly higher than that of overall bids, but the surplus ratio of sniping services is 35.10%.

For each meta-category, we calculate its late bidding rate and sniping services bidding rate among the total bids, and we illustrate the results in Table 1.

Table 1: Late Bidding Rate (LBR) and Sniping Services Bidding Rate (SSBR) per Meta-category

Meta-category	LBR	SSBR
eBay Motors	79.60%	21.72%
Stamps	11.59%	1.64%
Antiques	10.90%	1.33%
Art	10.70%	1.32%
Business & Industrial	10.65%	1.69%
Entertainment Memorabilia	10.29%	1.07%
Computers & Networking	10.05%	0.94%
Collectibles	9.99%	1.13%
Cameras & Photo	9.46%	0.78%
Coins & Paper Money	9.20%	0.64%
Sports Mem, Cards & Fan Shop	9.05%	0.83%
Music	8.97%	1.04%
Dolls & Bears	8.83%	0.51%
Consumer Electronics	8.70%	0.44%
Pottery & Glass	8.66%	0.88%
Toys & Hobbies	8.58%	0.41%
Jewelry & Watches	8.48%	0.76%
All	8.40%	0.67%
Musical Instruments	8.27%	0.55%
Books	8.16%	0.91%
Video Games	7.62%	0.36%
Cell Phones & PDAs	7.58%	0.18%
Tickets	7.54%	0.21%
Home & Garden	7.50%	0.48%
Clothing, Shoes & Accessories	7.40%	0.49%
Crafts	7.20%	0.40%
Sporting Goods	6.97%	0.40%
Everything Else	6.64%	0.28%
Travel	6.47%	0.68%
DVDs & Movies	6.26%	0.35%
Health & Beauty	6.01%	0.26%
Baby	6.01%	0.81%
Real Estate	5.10%	0.21%
Gift Certificates	4.66%	0.28%

However, stable and accurate as sniping services are, they mostly charge for additional sniping fees. So besides the following reasons, buyers adopt sniping services only if they are extremely anxious to win that item. The fact is that once one misses the item, it is really hard to find a repetition, which reflects the rarity of that type of items. In addition, we find that the order of Table 1 is exactly analogous with that of Figure 1, therefore we consider that it is the rarity that leads to high surplus ratio, and rarity causes high sniping services rate, which accelerates surplus ratio as well.

Given that most of the time buyers render the estimated value to sniping services several hours or days before the EoA, when they know nothing about the price trend of that item, nevertheless, it deserves to pay the estimated value plus sniping fees for that item to the sniper. Consider that high surplus ratio may not reflect the real value of those rare items because of sniping, especially sniping service, as a result, we come up with a new heuristic auction model in order to prevent the aberrant high surplus ratio.

4. OTHER FEATURES OF BIDDING

In order to present a detailed analysis on auction theory, we depict some other interesting features that we have discovered.

4.1 Trace of Bid Source

Buyers make bids via various processes. Some buyers like to do a keyword search, looking for an interesting item among the results, reviewing the bid history and seller's feedback, making a bid at last. Some buyers like to use yahoo or google search at first, comparing items in different sites and bid on eBay at last. Others would like to save the item in the bookmark of browser or "my eBay", and bid them several minutes before the EOA. In order to find the percentage of the bid sources, we trace each bid in Sojourner and group them by bidding time. We can find from Figure 6 that about 50% of bids are via "eBay search", however when the time approaches the EOA, less bidders use "eBay search". Instead, bids from bookmark and sniping services increasing intensely in the last minute.

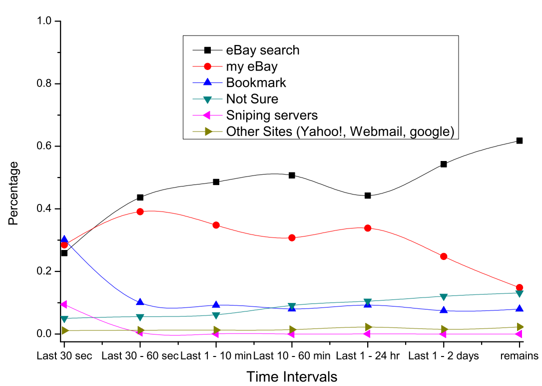

Figure 6: Percentage of different bid sources.

4.2 Shipping Fee

In order to find out the shipping fee influence on final value and buyers' total payment, we select all the "8GB Apple iPhone" items sold on eBay U.S. site since June 29 to August 31.

Figure 7 shows that when shipping fee is about $5.00, final value is at the lowest, and total payment gradually increases according to the rising of shipping fee. Free shipping items seem to be more attractive event though the total payments are much higher.

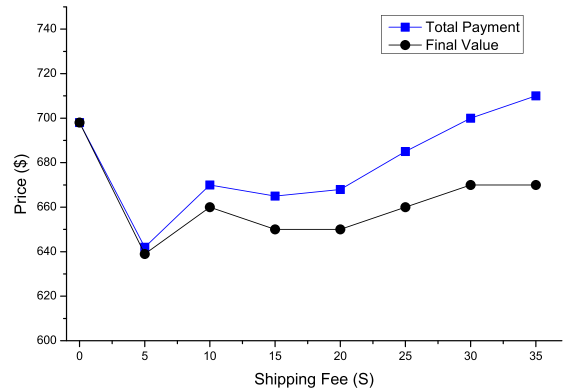

Figure 7: Final value and total payment on shipping fee. (Total Payment = Final Value + Shipping Fee)

4.3 Seller's Feedback Score

Seller's feedback score is another important factor that influences buyer's judgement. The fact that buyers trust power sellers[9] more than normal sellers can be recognized from Figure 8, which shows that final value increases with the growing of seller's feedback score.

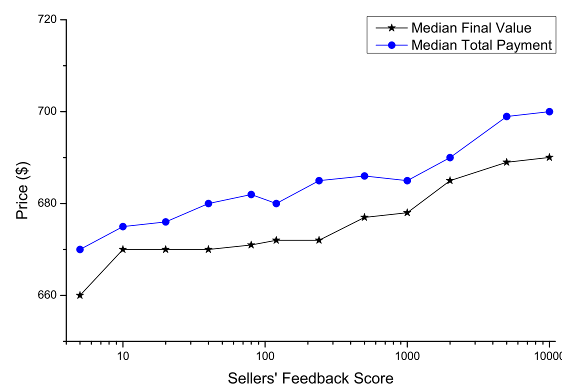

Figure 8: Prices of sellers' feedback score.

5. BIDDING STRATEGY

From Section 3.5, we have illustrated the distinct bidding behaviors among various bidders. Generally, more experienced bidders are more likely to place their bids during the last minute than less experienced bidders. In a second-price online auction, for the sake of simplicity, we divide bidders into three types according to their distinct bidding strategies: naïve, frank and sophisticated. Naive bidders do incremental bidding, considering the game as a traditional live

[9] http://pages.ebay.com/help/sell/sell-powersellers.html

Table 2: Matrix of Winner. (H in column is willing to pay higher than L in the row. N, F and S means Naïve, Frank and Sophisticated bidder.)

H \ L	L_N	L_F	L_S
H_N	H_N	H_N	L_S
H_F	H_F	H_F	H_F
H_S	H_S	H_S	H_S

auction. They monitor the auction and manually bid just one increment over current price. Frank bidders obey eBay's guidelines, entering the maximum price they are willing to pay and leaving everything to the proxy bidding mechanism. Sophisticated bidders only snipe.

Imaging an auction with only two participants. We present a matrix to show the results on different situations. From Table 5 we can figure out that when a naïve bidder who has a higher willing-to-pay price competes with a sophisticated bidder, the winner is the sophisticated one, because the sophisticated one uses sniping and that naïve bidder will have no time to make an incremental rebid even if his or her willing-to-pay price is much higher, and the final value could be significantly lower. But if that sophisticated bidder follows eBay's guideline, behaving as a frank bidder, he or she will lose at all, because the naïve bidder has enough time to outbid him or her. The problem becomes much more complicated when multiple bidders are involved.

We can draw the conclusion for various bidding strategies among naïve, frank and sophisticated bidders. Frank bidders are more politic than naïve bidders because[10]:

- Frank bidder saves time on bidding activities.
- Frank bidder will win definitely if his or her bid is the highest.
- Frank bidder is a good strategy in response to those smug lowball bidders.

And sophisticated bidders are more sagacious than frank bidders since:

- sniping can avoid an emotional bidding war which drives up the final value irrationally.
- sniping can avoid showing up the estimation earlier.
- sniping can avoid the max amount being probed.
- sniping is a good strategy in response to incremental bidding.

Then one may consider that sniping is the best bidding strategy for buyers to minimize the cost. But if all bidders were snipers, then the auction format would transform into a sealed bid auction[11], which runs against the original design of eBay's auction format.

[10] http://www.moyen.org/snipe/

[11] http://www.reviews.com/hottopic/hottopic_essay_05.cfm

6. DECLINING PRICE AUCTION MODEL

Previously we discussed how the main goal of auctions is to determine the real value of a commodity via incremental bids. Traditionally, as a pricing mechanism, live auctions are largely employed for antiques, paintings, collectibles etc., which are comparatively hard for sellers to determine a fixed price. The fundamental result in traditional auction is Revenue Equivalence Theorem, addressed by Vickrey[12], which states that under certain conditions, various auction formats yield the same expected revenue to the seller. The Internet facilitates the transactions between sellers and buyers, which leads to online auctions for various types of goods. Using a field experiment technique, Lucking-Reiley compared revenue outcomes between first-price sealed-bid and Dutch auctions, and between second-price sealed-bid and English auctions[13]. His results indicate that Dutch auctions provide a higher rate of revenue compared to first-price auctions, which are conflicting results with that from laboratory experiments and the theory. His explanation is that a Dutch auction format generates more participation than the first-price auction format in a real market, as well as bidders' psychological effect from a real Dutch clock. We have shown that due to the effect of fixed end time and diverse bidding behaviors, revenue of online auctions differ from time to time. A noticeable deviation from real market value can be found in sniping and scarce items. If somehow the true value cannot be reflected via an auction format, we have to alternate among various formats. The results so far suggest that different auction format are more efficient depending on the type of item being sold.

In Section 2, we have introduced Surplus Ratio to measure how much higher the highest bidder is willing to pay over the final value. Rareness lead to high surplus ratio due to the uncertainty on its real price. In order to determine the price more precisely, we propose a declining price auction model for those popular but rare items. Usually, all the participants should be on-site when a Dutch Auction begins. We modify the traditional Dutch Auction format so is suitable for online activity.

- If a seller selects to list an item with declining price auction, he or she should set a starting price, a reserved price, starting time and auction duration. The starting should be the seller's expected highest price a potential buyer will be willing to pay. It may be equal or higher than the BIN (Buy It Now) price of similar items. [12]
- Once the auction begins, the current price decreases from the seller's starting price to the reserved price within throughout the auction duration by means of an optimal curve.
- When a buyer finds this item, he or she is able to bid the current price -from the buyers perspective this is a BIN operation-, or bid an amount lower than current price.
- All the bidding information is public to everyone, and the current highest bid price is equal to the second highest amount plus an increment.
- Once the current price drop to an amount equal or lower than the current highest bid, that bidder wins the item, at this point the auction ends.

[12] http://pages.ebay.com/help/buy/how-buy-bin.html

This new auction model is a combination of Dutch, public, second-price format. The distinctions between Declining Price Auction format and existing formats are:

- Declining Price Auction format employs a descending price while the existing format adopts ascending price.
- BIN price of Declining Price Auction format is dropping as the auction happens while that of the existing format is fixed.

Within this auction model, buyers have no incentive to snipe. Each bidder who is interested in that auction should offer the maximum amount that he or she is will to pay for that item. In order to raise the final value, we can adopt decreasing curve function in the format

$$y = A - B{\cdot}e^{Cx},$$

which has a low price drop rate beginning of the auction compared to a high price drop rate when time approaches the EoA.

Declining Price Auction also has a benefit on speeding up the auction duration. When the price reaches someone's valuation, the auction ends immediately, while in the existing English auction the highest bidder has to wait until the predefined fixed end time.

7. CONCLUSION

We have studied consumer surplus, sniping and other bidding features, and we have illustrated the relationships among sniping rate, consumer surplus ratio and rareness of items. We have demonstrated that distinct bidding behaviors lead to completely different final values. As a result, we propose a declining price auction format which aims to drive the auction final price to a more efficient allocation.

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