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# AN EXAMINATION OF AUCTION PRICE DETERMINANTS ON EBAY

**Wen Wan, Hock-Hai Teo**

*School of Computing, National University of Singapore,*
3 Science Drive 2 Department of Information Systems
wanwen@comp.nus.edu.sg

## ABSTRACT

*Online auction has become an intriguing new type of economic exchange mechanism. Given that Internet auctions differ from traditional physical auctions in terms of flexibility and synchronicity, there is much doubt as to whether existing theoretical and empirical literature on traditional physical auctions still holds. This paper seeks to unravel factors affecting Internet auction prices. Specifically, it draws on current Internet auction literature and features of eBay website to identify a set of five factors affecting online auction prices for two types of coins traded on eBay. The data consists of 1251 auction records, which were collected by a work group to insure data accuracy and completeness. Regression analyses on full samples and restricted small sample sets were performed. We have three major findings. First, the number of unique bidders and the minimum bid tended to have positive effect on the auction price. The effect of minimum bid was especially significant. Second, the duration of auction and the seller's feedback rating did not affect the auction price significantly. Third, whether the auction closed on weekend or not had little impact on the auction price. Implications for online sellers and auctioneers were drawn.*

## 1. INTRODUCTION.

There is much theoretical and empirical literature on auctions. However, much of this literature is focused on traditional physical auctions whereby the auctioneer and the participants convened at a specific place and a specific time to conduct their business. Since the launch of Web-based auctions in 1995, auctions on the Internet have grown at a tremendous rate. Promising increased convenience geographically and temporally, online auction is finding its way to millions of homes with the recent proliferation of auction sites on the Internet. By far the largest consumer-oriented auction site is eBay, which is also the world's largest personal online trading community. According to Nielsen//NetRatings, a leading Internet measurement service, eBay has 9,626,000 unique visitors by June 2000.[1] It registered highest in terms of pages viewed per person and time spent per person. eBay's net revenues increased from $49.5 million and $92.3 million in the three and six months ended June 30, 1999 to $97.4 million and $183.2 million in the comparable periods of 2000.[2]

Notwithstanding its growing importance, Internet auction is still not well understood. Indeed, our review shows that very few studies to date have attempted to identify factors critical to auction success on the Internet. Auction success on the Internet is determined by a wider set of parameters than in a traditional

1. See "http://www.auctionwatch.com/awdaily/"
2. See "http://biz.yahoo.com/e/000809/ebay.html"

physical auction setting, which is determined primarily based on the valuation of the item by the individual bidders and the chosen auction mechanism. In the Internet auction setting, the seller has a wide array of decisions to make pertaining to the starting minimum bid, the reserve price, the duration of the auction, the title and the description, the time when the auction should end, the category for the item to be listed under, besides the chosen auction mechanism. Under this complicated setting, sellers have little idea as to which of these factors play an important role in determining their revenue, and their relative importance.

Our paper seeks to fill this gap by conducting an exploratory analysis of factors affecting the final price in an online auction. Because there is much subjectivity in the descriptive data and that the reserve price is not easily obtained, we concentrated on five key factors: minimum bid, duration, the weekend effect, the reputation feedback, and the number of unique bidders. Sellers' reputation feedback was chosen because, being a surrogate measure of sellers' trustworthiness, it has been claimed by many as an important determinant of auction success. Number of unique bidders, cited by some researchers (e.g., Lucking-Reilly 2000, Vakrat & Seidmann 2000) as a key influence on the pricing of auction, was also included. Auction data of these factors from eBay were downloaded and analyzed. Findings from this study have strategic implications for both sellers and eBay. Understanding the role each of these factors plays will help the seller to not only successfully complete the transaction but also assure him of getting the best possible price for his/her item. Similarly, with this knowledge, eBay will be well positioned to provide useful advice to its clients and to improve the turnaround time for items listed so as to increase its revenue and its reputation as the premier auction site for C-to-C transactions.

## 2. LITERATURE REVIEW AND HYPOTHESIS

Despite much interest in auction theory over the past two decades, empirical studies of auctions have been focusing on off-line auction. Theorists and empiricists mainly exploited themes on the optimal bidding strategies under four basic auction rules (English, Dutch, first-price sealed-bid, and second-price sealed-bid auctions) and two extreme auction environments (the independent private values model and the common value model) (Bierman and Fernandez, 1998). In particular, research on independent private values auction studied extensively the strategic revenue equivalence theorem and certain exogenous factors while research on common values auctions focused predominantly on explaining the winner's curse phenomenon (Kagel and Roth, 1986). In the traditional auction, the auction price is usually determined by the following variables: the employed auction rule, the bidder's valuation of the item, the auction environment (IPV3 or CV4), the number of bidders, the distribution of bidders' valuations, bidder's attitude toward risk, etc. For instance, in the IPV model, assuming that bidders are risk neutral, in the first-price sealed bid auction, the unique risk neutral Nash equilibrium (RNNE) bid function given the uniform distribution $[\underline{x}, \overline{x}]$ is

$$b(x) = x + \frac{(n-1)}{n}(x - \underline{x}),$$

where $x$ is bidder's valuation, $n$ is the number of bidders in the auction, while in a second-price sealed bid auction, the bid function is $b(x) = x$. Dutch auction is theoretically isomorphic to the first-price auction, and English is theoretically isomorphic to the second-price auction. With risk neutral bidders, the expected price under all four auctions is the same (Vickrey 1961, Meyerson 1981, Riley and Samuelson 1981).

However, as online auction provides different auction rules and environment, it is not clear as to whether theories and findings based on traditional physical auctions are still applicable. Online Internet auction

3 IPV: Independent Private Value. The IPV model corresponds to the case where each bidder knows his valuation of the item with certainty and bidders' valuations are drawn independently from each other. Although bidders do not know their rivals' valuation, they know the distribution from which they are drawn.

4 CV: Common Value. The CV model corresponds to the case where a bidder does not know his or any other rival's valuation of the item. All bidder receives is a noisy signals related to the value of the item. The noisy signals come from the same probability distribution which is known to each bidder.

differs from traditional physical auction in the following aspects. First, online bidders are provided with greater flexibility as they can stay at home or office and submit their bids anytime of the day for items they are interested in. Second, offline bidders' optimal bidding strategies are influenced mainly by their valuation of the item since they are required to congregate at the auction site at the scheduled time for the entire duration of the auction. In contrast, duration of online auction can be as long as ten days. Online bidders hence have more time to decide when and how much they will bid. Moreover, they may choose to submit their bids on weekend when they have more leisure time. They might examine if the minimum bid given by the seller is reasonable. Third, online buyers cannot inspect the goods being auctioned before bidding. Fraudulent behavior is possible because the buyers must trust the "unknown" sellers to actually send the goods after they have made the payment. In order to mitigate this problem, the Internet auctioneers incorporate the reputation mechanism into the auction institution design (Kollock, 1994). For example, eBay has a well-publicized feedback rating system to make it comfortable for sellers and buyers to conduct transactions. Under this system, anyone whose numeric rating goes below –4 is penalized in the form of debarment (de-registration from the site). Online bidders might consider the feedback rating of the seller when bidding. To summarize, the auction price in Internet auction may depend on many other factors besides the valuation of the item. Drawing on our understanding of eBay institutional design (see Lucking-Reiley 1999 for description), on Lucking-Reiley (2000) study of Indian-head pennies, and Vakrat and Seidmann's study on consumer goods auctioned in some business-to-consumer websites, we identified the following determinants which might play an influential role in auction success.

### 2.1. Duration

Duration is the period between the starting and the ending time of the auction. Usually the Internet auctioneers allow the seller to choose the duration in days. On eBay's web site the duration is normally 3, 5, 7 or 10 days. Intuitively, more potential bidders can see the auctioned item when the duration is longer, which in turn is likely to result in a higher final price. Lucking-Reiley (2000) found that longer durations of auction tend to fetch higher prices. Prices of 7-day and 10-day auctions are higher than those of 3-day and 5-day auctions. Vakrat & Seidmann (2000) shows that the duration is an important factor in determining an auction's profit. Hence, we hypothesize that:

$H_1$: Duration is positively related to auction price.

### 2.2. Weekend

Online auction enthusiasts suggest that sellers should end their auction on the weekend, reason being that it might attract more bidders since people have more leisure time to participate the auction on weekend and a great of late bidding has been observed in auction on Internet. Bajari and Hortacsu (2000) claimed that bidding activity was concentrated at the very end of the auction. More than 50% of final bids are submitted after 90% of the auction time has passed and the median winning bid arrives after 98.3% of duration has elapsed. However, Lucking-Reiley (2000) pointed out that the effect of weekend on auction price is not statistically significant at the 5% level. In light of the reasoning that auctions ending during the weekend might attract a larger pool of bidders, we hypothesize that:

$H_2$: Auction price should be higher for auctions ending on weekend than on weekdays.

### 2.3. Feedback Rating:

Seller's reputation is an important concern of the bidder, especially in the Internet auction where the two sides of transaction do not meet each other in face. Reputation feedback serves as a surrogate measure for the sellers' trustworthiness. eBay designed a well-known feedback rating system under which buyers and sellers have the opportunity to rate each other as positive (+1), neutral (0) and negative (-1). The cumulative total of ratings is displayed beside the ID of every participant. Buyers can use these ratings as reference of sellers' reputation. Lucking-Reiley (2000) found that a seller's total feedback ratings do not have a statistically significant effect on his auction price.

*$H_3$:* Feedback rating of the seller is positively related to auction price.

### 2.4. Minimum Bid:

Minimum bid is the opening bid amount the seller set (The default is $0.01). Bajari and Hortacsu (2000) claimed that the minimum bid is the most important determinant of entry into the auction. A high minimum bid reduces the potential bidder's incentive to spend time and effort to enter the auction. Hence, sellers should set a low minimum bid and a secret reserve price. Lucking-Reiley (2000) concluded that the level of minimum bid had a significant positive effect on auction price when there was only one bidder, but an insignificant effect for auctions with two or more bidders.

*$H_4$:* Minimum bid is negatively related to auction price.

### 2.5. Number of Unique Bidders:

An almost universal-agreed principle in economics is that increase in demand should raise prices. In independent private value auctions, auction prices tend to increase with the number of bidders because increased bidders stimulate greater competition which should in turn result in higher prices (Harris and Raviv, 1981, Kagel 1995). On the other hand, in common value auctions where there is a high possibility of the winners' curse, increased number of bidders may actually stifle pricing because bidders would be particularly conscious of the competition they are facing and would be extra cautious not to become the "cursed" winner (Hansen and Lott, 1991; Kagel and Levin, 1986). Our study focused on categories of auctions that are similar to the independent private values auction model. Hence, we hypothesize:

*$H_5$:* Number of unique bidders is positively related to the auction price.

Overall, the linear model for this study is as follows:

$$\mathbf{TPa}=\beta_0+\beta_1\mathbf{Duration}+\beta_2\mathbf{Weekend}+\beta_3\mathbf{Feedback}$$
$$+\beta_4\,\mathbf{Minibid}+\beta_5\,\mathbf{UB}\,+\boldsymbol{\varepsilon}$$

- **TPa** is the adjusted total price (**TPa =** the final price + the fee of shipping & handling **-** book value**.** Book value is the coin's estimated value in market).
- **Duration** is in days, namely 3, 5, 7 or 10 (**Duration**=the ending date – the starting date).
- **Weekend** is a dummy variable, which is 1 if the auction closed on a Saturday or Sunday, else 0.
- **Feedback** is the seller's overall feedback rating (i.e. unique positives minus unique negatives).
- UB **is the number of unique bidders.**
- **Minibid** is the minimum bid of the auction.

In this model, we use the adjusted total price as the dependent variable instead of the final price in Lucking-Reiley (2000). The **TPa** measures the auction price by subtracting the book value from the sum of final price and shipping and handling fees which are paid by the bidders. This approach controls for the effect of book value on the auction price of the item, thus allowing the other factors on auction price to be properly assessed.

## 3. RESEARCH METHOD

A work group was formed to collect the "Lincoln Cent" and "Buffalo Nickel" datasets from eBay. "Coins" were chosen because these categories have rich transactions and a wide variety of goods and prices. Besides, there are accurate estimates of book values for coins, making auction prices on eBay amenable to comparison. The book values of coins were obtained from "Collectors' Universe" (www.collectors.com), the world's leading provider of grading and authentication services.

The dataset consists of 1230 observations of the two categories that met certain criteria. Auctions with a reserve price were included only when the reserve price was met. Auctions were considered only if they attracted at least one bidder. "Dutch Auctions", in which buyers bid for multiple quantities of a single item, and "Private Auctions", in which the identities and feedback numbers of individual bidders were secret, were excluded. Transactions were also excluded if book values for the item being auctioned were not available. Auctions in which the item was sold in package were excluded also. Besides, to insure data accuracy, transactions were only included if the seller described the coin's year and grading clearly. A good example is:

*"This is a Beautiful 1938-D Buffalo Nickel Graded MS65 By PCGS. Coin has Wonderful Surfaces along with a Strong Strike. Insured Postage set at 2.00."*

The following excerpt is an example of vague description of coin's condition. Transactions with statement like this were excluded.

*"Nice circulated coin that I would love to call VF but am not convinced it quite makes the grade. Anyway, a scan is provided for you to decide. The horn is a little more defined in person than on the scan."*

The grading scale used in "Lincoln Cent" and "Buffalo Nickel" could be found at the website of "Collectors Universe", from which the book value for the coins of this study are obtained. To increase the study's validity, those transactions in which the seller's description of the item did not match the grading standard were also excluded.

We searched the "Buffalo Nickel"(or "Lincoln Cent", "Lincoln Cent MS" in other two cases) under the category of "Coins" on eBay's Web site and collected the auction records that met the criteria. 556 transaction records of "1909-1964 Regular Strikes" completed between August 14th and September 4th, 2000, and 295 transaction records of "1909-1964 Regular Strikes, Uncirculated, MS60-MS68" completed between September 21st and October 21st, 2000 were downloaded for the Lincoln cent dataset. 379 transaction records of "1913-1938 Regular Strikes" completed between August 14th and September 4th, 2000, were downloaded for the Buffalo nickel dataset.

The book value for each coin in the dataset was found from "Collectors Universe" according to the year, grade and color (in Lincoln cent) indicated in seller's description of the coin. For each completed transaction, the following data (variable names that are used in models are given in all capital letters) were recorded:

- The year of the coin
- The grade of the coin
- The color of the coin (i.e. Red, Brown or Red/Brown in Lincoln Cent)
- The coin's book value
- The minimum bid of the auction (**Minibid)**
- The final price of the auction
- The number of bids made
- The number of unique bidders (**UB**)
- The seller's overall feedback rating (**Feedback**)
- The fee for shipping & handling (if reported by the seller)
- The length of the auction in days (**Duration**)
- Whether the auction closed on a Saturday or Sunday (**Weekend**); 1 if so else 0.

Additionally the following variables were derived from the others:

- Total Price (i.e., the final price plus the fee of shipping & handling)
- Adjusted Total Price (i.e., total price minus book value)(**TPa**)

## 4. DATA ANALYSIS AND RESULT

Regression analyses were performed on the three full datasets. All tests were conducted at 5% significance level. ***Table 1*** shows that the Adjusted R Square in the three datasets are all small.

Dependent variable: TPa

| | **Full Set of "Lincoln Cent"** | | **Full Set of "Buffalo Nickel"** | | **Full Set of "Lincoln Cent MS"** | |
|---|---|---|---|---|---|---|
| **Model** | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. |
| | .015 | *.018** | -.008 | .751 | .281 | *.000*** |

***Table 1**: Regression result for the three full samples*

$R_a^2$ *represents the adjusted R-Square*

* *Significant at 0.05 level*

** *Significant at 0.01 level*

We reasoned that this was because of the great variation of TPa in the full datasets. In the "Lincoln Cent", the TPa ranges from -1525.01 to 553; In the "Lincoln Cent MS", the TPa ranges from -4025.01 to 1478; In the "Buffalo Nickel", the TPa ranges from -512 to 22.85. The coins are still quite different in values although the TPa is an adjusted price. Coins with lower book value had a small TPa (absolute value) while coins with higher book value had large TPa (absolute value). Book value is still a very important factor in explaining the variation of TPa. The variation of TPa in "Buffalo Nickel" was the smallest, so the R-Square of the sample is bigger than those in the other two samples.

Hence, in order to control for the effect of book value in the model, it is necessary to categorize the full datasets according to the book values of the coins. The data of "Lincoln Cent" were separated into eight sets (See ***Table 2.1***). The data of "Buffalo Nickel" were separated into five sets (See ***Table 2.2***). The data of "Lincoln Cent MS" were separated into four sets (See ***Table 2.3***). After grouping, the book values of items are similar to a certain degree.5

| | Book Value Range (Unit: US$) | Number of Data |
|---|---|---|
| **Lset1** | 1.43 ~ 5.20 | 66 |
| **Lset2** | 6.50 ~ 11.00 | 76 |
| **Lset3** | 13.00 ~ 18.00 | 69 |
| **Lset4** | 20.00 ~ 30.00 | 72 |
| **Lset5** | 31.00 ~ 41.00 | 55 |
| **Lset6** | 43.00 ~ 53.00 | 86 |
| **Lset7** | 55.00 ~ 100.00 | 89 |
| **Lset8** | 108.00 ~196.00 | 43 |

***Table 2.1:** Small sets of "Lincoln Cent"*

5 The total number of data in the separated sets is smaller than the full data set because the TPa of those coins with high book values varies greatly. They can not be included in a small data set.

| | Book Value Range (Unit: US$) | Number of Data |
|---|---|---|
| **Bset1** | 0.52 ~ 5.20 | 51 |
| **Bset2** | 5.85 ~ 11.00 | 48 |
| **Bset3** | 23.00 ~ 33.00 | 44 |
| **Bset4** | 44.00 ~ 54.00 | 49 |
| **Bset5** | 63.00 ~ 95.00 | 44 |

***Table 2.2:*** *Small sets of "Buffalo Nickel"*

| | Book Value Range (Unit: US$) | Number of Data |
|---|---|---|
| **LMSset1** | 2.60 ~ 7.80 | 50 |
| **LMSset2** | 20.00 ~ 40.00 | 48 |
| **LMSset3** | 41.00 ~ 61.00 | 46 |
| **LMSset4** | 63.00 ~ 92.00 | 42 |

***Table 2.3:*** *Small sets of "Lincoln Cent MS"*

Regressions analyses were again performed on the small sets separately. ***Tables 3***, ***4*** and ***5*** show the regression results.

Dependent variable: TPa

| | **Lset 1** | | **Lset 2** | | **Lset 3** | | **Lset 4** | |
|---|---|---|---|---|---|---|---|---|
| **Model** | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. |
| | .935 | *.000*** | .637 | *.000*** | .780 | *.000*** | .784 | *.000*** |
| | CE | Sig. | CE | Sig. | CE | Sig. | CE | Sig. |
| **Constant** | - | *.032** | - | *.000*** | - | *.000*** | - | *.000*** |
| **Duration** | -.038 | .273 | .147 | *.045** | .137 | .051 | -.028 | .623 |
| **Weekend** | .018 | .616 | -.023 | .758 | -.112 | .085 | .023 | .680 |
| **Feedback** | -.024 | .468 | -.040 | .573 | .113 | .094 | .008 | .887 |
| **Minibid** | .962 | *.000*** | .846 | *.000*** | .942 | *.000*** | 1.013 | *.000*** |
| **UB** | .221 | *.000*** | .467 | *.000*** | .528 | *.000*** | .373 | *.000*** |

***Table 3.1:*** *Regression result for "Lincoln Cent"-small sets*

Dependent variable: TPa

| | Lset 5 | | Lset 6 | | Lset 7 | | Lset 8 | |
|---|---|---|---|---|---|---|---|---|
| **Model** | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. |
| | .899 | *.000*** | .592 | *.000*** | .469 | *.000*** | .806 | *.000*** |
| | CE | Sig. | CE | Sig. | CE | Sig. | CE | Sig. |
| **Constant** | - | *.000*** | - | *.000*** | - | *.000*** | - | *.000*** |
| **Duration** | .057 | .270 | -.038 | .603 | .070 | .375 | .043 | .615 |
| **Weekend** | .005 | .910 | .067 | .368 | .043 | .597 | -.035 | .671 |
| **Feedback** | -.118 | *.016** | .094 | .191 | .103 | .200 | .015 | .855 |
| **Minibid** | 1.032 | *.000*** | .899 | *.000*** | .852 | *.000*** | .985 | *.000*** |
| **UB** | .238 | *.000*** | .642 | *.000*** | .500 | *.000*** | .451 | *.000*** |

***Table 3.2:*** *Regression result for "Lincoln Cent"-small sets*

Dependent variable: TPa

| | Bset 1 | | Bset 2 | | Bset 3 | | Bset 4 | | Bset 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Model** | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. |
| | .135 | *.040** | .448 | *.000*** | .623 | *.000*** | .311 | *.001*** | .410 | *.000*** |
| | CE | Sig. | CE | Sig. | CE | Sig. | CE | Sig. | CE | Sig. |
| **Constant** | - | *.050** | - | *.000*** | - | *.000*** | - | *.000*** | - | *.000*** |
| **Duration** | .174 | .260 | -.026 | .828 | .187 | *.070* | -.138 | .292 | -.154 | .226 |
| **Weekend** | .051 | .743 | .060 | .601 | .118 | .228 | -.043 | .740 | .033 | .78 |
| **Feedback** | -.124 | .416 | -.209 | .084 | -.231 | *.021** | .009 | .944 | .066 | .586 |
| **Minibid** | .372 | *.015** | .594 | *.000*** | 1.022 | *.000*** | .760 | *.000*** | .962 | *.000*** |
| **UB** | .344 | *.025** | .677 | *.000*** | .786 | *.000*** | .871 | *.000*** | .743 | *.000*** |

***Table 4****: Regression result for "Buffalo Nickel"-small sets*

Dependent variable: TPa

| | **LMSset 1** | | **LMSset 2** | | **LMSset 3** | | **LMSset 4** | |
|---|---|---|---|---|---|---|---|---|
| **Model** | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. | $R_a^2$ | Sig. |
| | .403 | *.000*** | .995 | *.000*** | .605 | *.000*** | .819 | *.000*** |
| | CE | Sig. | CE | Sig. | CE | Sig. | CE | Sig. |
| **Constant** | - | *.000*** | - | *.000*** | - | *.003*** | - | *.000*** |
| **Duration** | .360 | *.006*** | .028 | *.015** | -.192 | *.103* | -.024 | .774 |
| **Weekend** | -.019 | .875 | -.004 | .707 | .123 | .239 | .077 | .358 |
| **Feedback** | .272 | .063 | -.014 | .212 | -.203 | *.049** | .056 | .476 |
| **Minibid** | .284 | *.057* | 1.001 | *.000*** | .748 | *.000*** | .938 | *.000*** |
| **UB** | .420 | *.001*** | .056 | *.000*** | .312 | *.000*** | .550 | *.000*** |

***Table** 5: Regression result for "Lincoln Cent MS"-small sets*

$R_a^2$ *represents the adjusted R-Square*

** Significant at 0.05 level*

*** Significant at 0.01 level*

**Result 1.** The longer duration does not necessarily yield higher auction revenue. The effect is not always significant. Only in three out of the seventeen datasets, the duration has statistically significant positive effect on the price.

**Result 2.** Whether the auction ended on weekend does not contribute much to the auction price. Weekend revenue is not always higher than weekday revenue, and the difference is not significantly different from zero.

**Result 3.** The feedback-rating system has long been considered as a key asset of eBay. But the result of this study shows that its effect is not always significant. In some cases, the increase of overall feedback rating tends to decrease the revenue.

**Result 4.** Contrary to Bajari and Hortacsu (2000), results indicate that minimum bid has a significant positive effect on auction price. On average 1% increase in minimum bid leads to 0.83% increase in the adjusted total price, regardless of the number of unique bidder. The effect is statistically significant at 1% significance level in most cases.

**Result 5**. Generally, increased number of unique bidders tends to fetch higher prices. The effects of number of unique bidders are almost all significant at 1% significance level in all small sets of the three categories (except in Bset1, it is significant at 95% confidence level). On average, 1% increase in number of unique bidder yields 0.48% increase in the price. This result is consistent with previous empirical independent private values auction literature.

The number of unique bidders instead of number of bidding was chosen as an independent variable in the model because it is the former factor that reflects the true demand for the item in auction. The number of bidding includes the multiple bids by the same bidder. "Cheap talks" (Farrell and Rabin, 1996) abound in the early period of auction. A bidder tends to be opportunistic and bid at a very low price in the beginning and bid seriously when competition increases. Number of bidding is hence not reliable in explaining the auction price.

One result worth noting is that coefficient of UB increases as the average book value increases. The influence of number of unique bidders on the price seems to be greater for coins with higher values.

## 5. DISCUSSION AND CONCLUSIONS

This paper seeks to unravel the determinants of auction price on the Internet. In this study, we used the adjusted total price as the dependent variable to measure the success of an Internet auction. There are three major findings:

1. The number of unique bidders and the minimum bid tend to have positive effect on the auction price. Some eBay observers have once suggested that the seller should set a low minimum bid so that more bidders can be attracted to bid on his item. But the regression result indicated a contrary influence. We reasoned that since all auctions in our data were successfully completed, in which the bidders were willing to pay for the coin in auction, regardless of the level of the minimum bid. Bidders deterred by the setting of minimum bid were not discussed in our study. Thus a high minimum bid could fetch a high auction price. The results suggest that setting a low minimum bid may not be as useful as setting one that is tied to the book value of the coin. Setting a reasonable minimum bid insures the seller against unproductive "cheap talks", which may be extremely useful when the duration of the auction is short. Results also pointed out that sellers should do whatever they can to engender a large pool of bidders. This result is consistent with Vakara & Seidmann's study of Internet auction. Further research should be done to identify key determinants of unique number of bidders.
2. The duration and the weekend effects on auction price were not significant. Usually, people who are interested in bidding online can access Internet easily. One advantage of auction online is that people can submit bids anytime anywhere. This suggests that it may not be that important whether the duration is three days or ten days, or whether the auction is closed on weekend. Results indicate that Internet auctioneers could take measures to urge the sellers to shorten their auction duration. In Lucking-Reiley's paper, he pointed out that longer duration fetched higher price. This could be attributed to the fact that he did not control for the influence of book value on the final price, contrary to our study. Vakrat & Seidmann concluded that profit was a unimodal function of an auction's length and the number of units. The different results could be because of the different natures of the data. They mainly studied the multi-unit auctions of consumer electronics, desktop computers, notebooks and monitors from business-to-business web sites, while we studied the single-unit coins from the consumer-to-consumer website – eBay.
3. Despite the assertion that feedback-rating system is the key to eBay's success, we found that the sellers' feedback rating did not have much impact on the auction price. After thinking about eBay's reputation mechanism, it is not hard to see that this kind of rating is not very reliable. First, feedback shilling is very common on eBay (Schwartz and Dobrzynski, 2001). It is relatively easy for users to get positive points from friends, which makes him look like an experienced and reputable seller. We have observed that feedback ratings for most sellers are positive. When people are aware of the drawback of this system, they might ignore the feedback rating when bidding. An alternative explanation may be that price is inherently determined largely by the perceived value of the item in question. Credibility of the feedback rating system also ought to be enhanced.

Since the three samples in this study are all coins, and two months of transaction histories were recorded, the results might be related with atypical behavioral patterns evolving in the specific market during the specific period. Besides, all data included in our study were single-unit auction records. Thus, the empirical results of our study apply for the consumer-to-consumer single-unit Internet auction of collectibles. For future research, we could analyze a larger sample of items of a different nature, so that the generalizability of the study can be improved. It is also interesting to explore the multi-unit auction in the online setting. Since the exact reserve price in eBay auction is not available, we intend to study the effect of reserve price in a laboratory experiment.

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