Pennies from eBay:
the Determinants of Price in Online Auctions

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Abstract

This paper presents an exploratory analysis of the determinants of prices in online auctions for collectible United States one-cent coins at the eBay Web site. Starting with an initial data set of 20,000 auctions, we perform regression analysis on a restricted sample of 461 coins for which we obtained estimates of book value. We have three major findings. First, a seller's feedback ratings, reported by other eBay users, have a measurable effect on her auction prices. Negative feedback ratings have a much greater effect than positive feedback ratings do. Second, minimum bids and reserve prices have positive effects on the final auction price. In particular, minimum bids appear only to have a significant effect when they are binding on a single bidder, as predicted by theory. Third, when a seller chooses to have her auction last for a longer period of days, this significantly increases the auction price on average.

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1. Introduction

Since the birth of Web-based auctions in 1995, auctions on the Internet have grown at a tremendous rate. By far the largest consumer-oriented auction site is eBay, which in 1998 had over one billion dollars in transactions. At a growth rate of more than 10% per month, eBay is likely to have over three billion dollars in transactions in 1999.[2] Individual sellers register their items for eBay's automated auctions, and individual consumers bid on the items. Its size places eBay among the largest Internet retailers in the world, possibly even the single largest one.[3] According to Nielsen Netratings, over seven million unique individuals visit the site each month, and consumers' average time spent browsing the site is considerably higher at eBay than at any other major Web site (twice as much as at Yahoo!, seven times as much as at Amazon).[4] Over three million individual auctions close at eBay every week, representing an unprecedented amount of economic auction activity.

Online auctions represent a rich environment for study. Despite much interest in auction theory over the past two decades, empirical studies of auctions have been limited by data availability. Most of the empirical literature on auctions looked exclusively at government auctions (oil drilling rights, logging rights, procurement auctions), and the data collection process has been a very labor-intensive one.[5] However, the emergence of eBay and other online auctions now makes it possible to obtain data from a wide variety of auction markets. In this paper, we demonstrate an automated method to quickly

[2] See Lucking-Reiley (2000a) for more details on the transaction volume at eBay and 140 other online auction sites.
[3] *Stores*, National Retail Federation, September 1999, http://www.stores.org/99top100int_1.html
[4] *Neilsen Netratings Reporter*, Nielsen Media Research and NetRatings, Inc., http://nielsen-netratings.com/, October 1999.

assemble a large set of auction data directly from eBay, and we conduct an exploratory study of the determinants of prices in eBay auctions.[6]

To collect our data, we created a “spider” – a piece of software designed to “crawl” over eBay’s Web pages and collect information on each auction. In a matter of hours, the spider collected comprehensive data on 20,000 auctions of U.S. collectible pennies auctioned during July and August, 1999.[7] We present descriptive statistics for these auctions, as well as a regression analysis of factors which affect prices in these auctions.

2. Institutional Details of eBay Auctions

A great deal of information on eBay auctions is publicly available. Anyone may view the listings of the items for sale, and in fact, all listings remain publicly available on eBay’s site for at least one month after they close. Figure 1 displays an example of a bidding page for an eBay auction; our spider collects its data by visiting pages just like this one and extracting the pertinent information from them.

An individual auction on eBay lasts between three and ten days. All eBay auctions use an ascending-bid (English) format, with the twist that there is a fixed end time and date set by the seller instead of a going-going-gone ending rule. This has caused many bidders to hold back their bids until the final seconds of the auction, so that they won’t reveal to others how high they are willing to bid. To counteract this tendency,

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[5] See Hendricks and Paarsch (1995) for a survey of past empirical research on auctions.

[6] Bajari and Hortacsu (2003) also perform an analysis of the determinants of price in eBay auctions, using a different data set of coin auctions (mint and proof sets, rather than individual cents). The focus of their paper is a structural model to distinguish between private-value and affiliated-value paradigms, but they also present some reduced-form regression results using a smaller set of variables than the one we use. For those variables which our studies have in common, the results appear to be broadly consistent between the two papers.

eBay installed a "proxy bidding" system that issues bids on the buyer's behalf. When bidding, buyers may specify the maximum bid they would submit for an item. The system keeps this amount private, bidding on the buyer's behalf at just one increment over the next highest bid, until it reaches the buyer's specified maximum bid. This provides the convenience of a Vickrey auction, where bidders do not need to engage in constant monitoring of the auction, and where the winner's price is determined by the second-highest bidder. Because the earlier bid wins in the case of a tie, this procedure restores some incentive for bidders to submit bids early. Many bidders make use of the proxy-bidding feature, though others persist in submitting bids at the very last minute.[8]

When a seller lists her goods or services for auction at eBay, she provides both a short title and a long description of the item. Bidders see the short titles when browsing lists of items up for auction, and the long description after they click on the short title of a particular item in order to view the bidding page for that auction. The seller may also choose to place digital photographs of the item online as part of the auction description. When a photograph is included, the auction's title is listed with an icon that indicates that a photo is available. For example, Figure 2 is the photograph included in the description of the auction listed in Figure 1.

The seller also chooses a number of parameters to specify how the auction will run. She may set the opening bid amount wherever she wishes. (The default is $0.01.)

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[7] It is a trivial matter to adapt the spider to collect data for other categories of auctions. In fact, during the course of a week, our spider collected data on approximately one million auctions in various other categories. For concreteness, we focus exclusively on the penny data in this paper.

[8] Two possible reasons for bidding at the last minute are: (1) bidders hope to get an item at a low price against an unsophisticated bidder who would be willing to bid high, but doesn't understand either proxy bidding or the ability to submit bids at the very last minute, or (2) bidders fear cheating by the eBay system, lying to the winner about the amount of the second-highest bid. The first reason seems much more common than the second, as no evidence has yet surfaced of eBay cheating in this manner. See Lucking-

She may also set a secret “reserve price,” such that if the highest bid remains below the reserve, the seller will not conduct the transaction with the high bidder. The seller may also choose the length of her auction: three, five, seven, or ten days. The auction starts as soon as the seller registers it at eBay, so the day and time when the auction starts and ends are controlled by the seller. One of the central questions of this paper is whether and how these parameters affect the auction price.

The seller pays two different types of fees to eBay. The first is a nonrefundable insertion fee, paid for the service of listing the item. The insertion fee ranges from $0.25 to $2.00, depending on the minimum bid and reserve price chosen. Then, after the auction concludes, the seller also pays a “final value fee” to eBay as a percentage of the selling price. This commission equals 5% of the first $25 of the selling price, plus 2.5% of the remaining value up to $1000, plus 1.25% of any amount over $1000. If the item does not receive any bids above the seller’s reserve price, then the item does not sell and no final value fee is assessed.[9]

eBay has a well-publicized reputation mechanism designed to make buyers and sellers feel comfortable conducting transactions with each other, exchanging cash and goods by mail with people they’ve never met. Under this system, buyers and sellers have the opportunity to rate each other as positive (+1), neutral (0), or negative (–1), and the cumulative total is displayed on the site as a Feedback Rating for that user.[10] Anytime a user is identified on the site (either as the seller or a bidder in an auction), his Feedback

Reiley (2000b) for more details about eBay proxy bidding, and its precursors in stamp auctions over the past century.

[9] Recently, eBay has developed separate fee structures for automobiles and real estate. The fee structures described here apply to all other items.

[10] At most one positive and one negative rating from each unique individual are counted in the total. Thus the most that an individual can affect another’s rating is ±1.

Rating number is displayed in parentheses. Users with ratings higher than 10 receive a "star," a graphic icon whose color changes to indicate larger and larger rating numbers.[11] Some sellers have accumulated Feedback Ratings in excess of 10,000. Anyone whose rating goes below –4 is prohibited from using the site any further.

In addition to the numeric ratings, users may view the entire list of feedback comments left by other users about any individual. Typical examples of positive comments are:

- *Quick turnaround. Item arrived in excellent condition.*
- *Smooth transaction...no problems here!! THANX!!"*

Negative comments can be even more informative:

- *Sent money out and after 2 months still have not received the items I purchased.*
- *Dishonest seller. Beware!! I had to file a fraud claim. It has been upheld.*
- *Prestige set did not come in box or with papers as advertised.*

Many observers have identified the feedback-rating system as the key to eBay's success. An example is the following excerpt from a *Business Week* article:

> *[eBay founder] Pierre M. Omidyar… hit on the idea of building a flea market in cyberspace – where people could buy and sell anything to anybody. There was one snag, though. How could he persuade complete strangers to trust one another enough to hand over merchandise or cash without ever having met? Omidyar's solution was to devise a system where buyers and sellers can rate their experiences with different traders… That provided the assurance people needed to feel comfortable trading with one another – and it helped Omidyar's eBay become the largest person-to-person auction site on the Web.*[12]

Not only do business observers repeatedly make such observations, but eBay itself also clearly considers its feedback ratings to be a key asset. When rival Amazon started its similar auction-listing service in spring 1999, it initially provided a method for users to import their existing feedback ratings from eBay. eBay protested vigorously,

[11] At this writing, the "star" categories in use represent ratings of 10–99; 100–499; 500–999; 1,000–9,999; and 10,000 or higher.

claiming that the feedback ratings were eBay property. In response, facing the possibility of a legal challenge, Amazon discontinued the rating-import service.

Despite the fact that conventional wisdom says that feedback ratings are essential on eBay, we are not aware of any empirical evidence which confirms this. And there are good economic reasons, often overlooked by the popular press, why these feedback ratings might not have much impact after all. First, any user can provide a rating point to any other user at any time; eBay does not require the user to have conducted a transaction with the person she is rating. The discussion board at the Auction Watch Web site often features complaints by individuals about others who abuse the feedback system at eBay in various ways. For example, a buyer might give negative feedback ratings to a seller merely because he doesn't like the merchandise she's advertising for sale. Or a seller might, in retaliation, negatively rate each buyer that negatively rates them. Further, a seller might convince dozens of friends to give him individual positive ratings, making her look like an experienced, reputable seller before she has ever participated in her first auction. In addition, there is a potential free-rider problem: when a buyer rates a seller, he gets very little personal benefit for doing so – the public-good benefit accrues to the people who will later be looking at the rating. Especially if a transaction goes well, there may be very little motivation for the parties to rate each other positively. If users are not motivated to take the time to provide feedback on every transaction, then the rating numbers might be meaningless, dominated by the manipulations of people trying to subvert the spirit of the system, and no one should pay attention to them. Clearly, there are some honest users who participate actively for the benefit of the community, but there are also some who abuse and manipulate the ratings. It is an empirical question whether

[12] Source: Green and Browder (1998).

the first group dominates the second. If ratings really have an important economic impact, then we should expect to see sellers with high positive feedback attracting more bidders and higher prices than sellers with lower feedback ratings, all else being equal. One of the questions of this paper is whether eBay's feedback ratings really do have a measurable economic impact.

3. Data Collection

The data for this study were collected by a "spider" written in the programming language *Perl*, running on a UNIX workstation.[13] We chose to focus on the eBay category "U.S. Cents," because this was a category with a wide variety of well-categorized goods and a wide variety of prices. Our spider proceeded as follows. It visited the eBay home page and extracted the link to the "Coins & Stamps" page. Then it visited the Coins & Stamps page and extracted the link to U.S. Cents. The U.S. Cents page is where the listing of current auctions begins. About 150 auctions are listed on this page. The page also contains links to about 100 other pages, each listing 50 current auctions of U.S. 1-cent coins. The U.S. Cents page also contains a link to "completed" auctions. Our spider followed this link to a listing of the U.S. Cent auctions that closed on the previous day. That page listed the first 50 such auctions, and included links to similar pages listing the remaining U.S. Cent auctions that closed on the previous day. By traversing these pages our spider collected the IDs of the auctions that closed on the previous day. Further, the "completed" page contained a link to auctions that closed two days earlier, and that page contained a link to auctions that closed three days earlier, and

[13] The *Perl* script can be found at <http://eller.arizona.edu/~reiley/papers/PenniesFromEBay.html>. Note that eBay considers the use of such spiders to be a violation of their user agreement. After our software made multiple requests per second to the eBay servers over a period of days (eBay at the time kept a

so on. By traversing this path our spider collected the IDs of all U.S. Cent auctions that closed in the previous month. Once we had the auction IDs, another spider used them to retrieve details about each auction.

Each auction ID was used to construct a Web URL. That is, IDs like 207495617 were added to Web addresses to form new addresses like,

<ttp://cgi3.eBay.com/aw-cgi/eBayISAPI.dll?ViewBids&item=207495617>.

In effect, the URL is a query to eBay's databases for information about auction number 207495617. The Web page created by eBay in response to the query contains details of the specific auction, including last bid (if any), opening and closing time and date, seller's ID and rating, minimum bid, number of bids, and a listing of bid history. The bid history contains information on each bidder, including buyer's ID and rating, as well as the price, time and date of bids. The spider that collected data on individual auctions collected buyer and seller IDs. Using these IDs a third spider could then collect more detailed information about participants.

The third spider collected feedback information on sellers, based on their IDs. Again a URL containing an ID was used. For example, the feedback information about seller "iras4" is generated using the following URL:

<ttp://cgi2.eBay.com/aw-cgi/eBayISAPI.dll?ViewFeedback&userid=iras4>.

Figure 3 displays an example feedback page for an eBay member. It includes the number of positive, neutral and negative ratings received. Additionally it contains this data for three recent time periods: the past 7 days, the past month and the past six months.

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month's worth of history on its site), eBay shut down access to their site from our IP addresses, and we promised not to spider them again.   See Cohen (2003, p. 191) for details.

The page also includes (but are not shown in Figure 3) comments made by other members.

We collected data on U.S. Cent auctions held at eBay over a 30-day period during July and August of 1999. Our spiders collected 20,292 observations. In this paper we refer to these as the large data set. A subset of these observations was used in the models presented later. For those models, we restricted our attention to auctions of U.S. Indian Head pennies minted between 1859 and 1909, where only one coin was being sold, and where the year and condition of the coin was clearly stated. All these coins were mint state (MS) with grades of between 60 and 66 on a 70-point scale. There were 461 such auctions and we refer to these as the small data set. Using the year and grade, we then manually collected estimated value, or book value, for each coin in the small data set.[14]

4. Data Descriptions

Our analysis began with the following data for each observation (variable names that are used in models presented later are given in all capital letters):

- The year of the coin
- The grade of the coin
- The coin's estimated value (BOOKVAL)
- The minimum bid of the auction (MINBID)
- The last bid of the auction (PRICE). If no bids were made then this is the same as the minimum bid.
- The number of bids made (#BIDS)
- Whether a reserve price was used (RESERVE); 1 if a reserve was used, else 0.
- The length of the auction in days, namely 3, 5, 7 or 10 (NUMDAYS).
- The date and time when the auction opened
- The ID of the seller
- The ID of the winning buyer (if any)
- The number of members who gave the seller a positive rating (a.k.a. unique positives)
- The number of members who gave the seller a negative rating (a.k.a. unique negatives)

[14] Book values where obtained from Collector's Universe (http://collectors.com/).

- The overall rating of the seller (i.e., unique positives minus unique negatives)
- The seller's total number of positive ratings received (POS)
- The seller's total number of negative ratings received (NEG)
- The number of neutral ratings received by the seller
- The number of ratings received by the seller that were changed to neutral because the reviewer is no longer a member of eBay's trading community.

Additionally the following variables were derived from the others:

- Whether the auction closed on a Saturday or Sunday (WEEKEND); 1 if so else 0.
- Whether NUMDAYS = 5 (DAYS5)
- Whether NUMDAYS = 7 (DAYS7)
- Whether NUMDAYS = 10 (DAYS10)

Our large data set contained nearly 7000 sellers and 3500 buyers. 92% of the sellers held just one auction during the month observed, while 45% of the buyers were highest bidder in just one auction. The following descriptions, as well as Figures 4 through 16, refer to the large data set.

Trading volume (that is, the number of auction closures) varied considerably over the data collection period, as seen in Figure 4. The dip at July 21st was caused by an eBay outage.[15] eBay's servers were down for more than an hour, causing them to postpone the closure of the auctions by one day, as per their policy. Thus, practically no auctions closed on the 21st. When viewed by day of the week (Figure 5), a clear pattern of heavy weekend volume emerges, as one might expect for a consumer-oriented site like eBay. Similarly, evening hours are the busiest time of the day on eBay, as illustrated in Figure 6. The highest volume is during the 6 P.M. hour.[16]

The mean prices of auctions also varied considerably over the observation dates, as seen in Figures 7 and 8. Both of these figures report the arithmetic mean of the price

[15] "eBay suffers outage despite assurances," Tim Clark, CNet News.com, July 22, 1999, http://news.cnet.com/news/0-1007-200-345242.html

[16] As eBay is based in California, the site records times in Pacific Time. Since our data were collected in July and August, all times mentioned are in Pacific Daylight Time.

(PRICE) of the auctions closing on each date. The spike on Figure 7 is due to five auctions with prices over $1000; Figure 8 displays the same data with these five outliers removed. Mean prices are shown for auctions that received at least one bid (the dashed line) and for auctions that transacted (the solid line). Figures 9 and 10 also report the mean prices but do so by day of the week and hour of the day respectively. Note that the five outliers absent in Figure 8 were included in these figures. Generally, auctions with bids have a higher price than auctions that transacted. This might be caused by the use of high reserve prices for expensive items, with fewer expensive items transacting.

Although overall, 60–70% of the 20,000 auctions transacted, throughout the observation period there were consistently substantial proportions of auctions that did not lead to transactions either because no bids were made or—to a lesser extent—because the auction's reserve was not met. Figure 11 charts these untransacted auctions by date, displaying both the percentage of auctions that received no bids and the percentage that had bids but failed to meet their reserve. Figures 12 and 13 show the same auction classes as Figure 11, but by day of the week and hour of the day respectively. Curiously, more than 50% of the auctions that closed between 2 A.M. and 4 A.M. received no bids. There are a number of possible explanations for this. One is that, due to eBay's fixed-length auctions, bidder activity is highest near the end of an auction, but there are few bidders available at 2 A.M. Another possible explanation is that sellers who are active at 2 A.M. tend to sell less desirable goods. We have not yet had an opportunity to investigate this issue.

As mentioned above, eBay auctions can be 3, 5, 7, or 10 days in length. However, the eBay sellers in our data set showed an unmistakable preference for 7-day auctions, as seen in Figure 14. Most auctions—over 60% of the total—were seven days in length, while only 12% were the maximum length of 10 days. As we will show later, there is evidence that sellers should select longer auction lengths.

Most of the eBay individual auctions observed had few if any bids. In fact, the proportion of auctions receiving a given number of bids decreases as the number of bids increases, as illustrated in Figure 15 (caution: note the nonlinear horizontal scale). As discussed earlier, more than 20% received no bids. Over 90% received less than 20 bids, but there was one auction that received more than 90 bids.

There was a wide range in seller experience in the data collected, as seen in Figure 16, which categorizes auctions by the eBay rating of the seller (again, note the nonlinear horizontal scale). The chart indicates that more than 20% of sellers have a rating between 100 and 200, while less than 10% have a rating between 200 and 300.

Our small data set of 461 observations includes 134 unique sellers and 181 unique buyers. 127 of the auctions (28%) received no bids. 49 auctions (11%) received bids but had reserve prices that were not met. Thus 285 of the auctions (62%) resulted in a transaction. Table 1 gives descriptive statistics for selected fields of the small data set. As in the large data set, sellers most often chose seven days for auction length: 221 (48%) of the auctions were seven days long. Ten days was the least often selected, with only 41 (9%) of the auctions running for 10 days.

Within the small data set, the majority of the auctions used minimum bids that less than half of the book value of the coin in question, as seen in Figure 17. This histogram indicates that many sellers seem to be using the default minimum bid ($0.01), while about 40% are setting a minimum bid within 40–80% of book value.

For the 285 auctions of the small data set that transacted, we observed a clustering of prices around 0.6 of book value (see Figure 18). In general, U.S. Indian Head pennies seem to be selling on eBay for about 60% of their book value.

5. The Empirical Determinants of eBay Auction Prices

Table 2 displays regression results on the determinants of prices in the eBay coin auctions in our sample. In each regression, the dependent variable is the natural logarithm of the final price obtained in each auction. Note that when an auction has a reserve price, this observed auction price might not actually result in a transaction, in those cases where the reserve price was not met. We include all observations, whether the reserve price was met or not, in order to get as much information as possible on the factors which influence the outcome of the auction price mechanism. Also, note that nearly 30% of the auctions had no bids at all. In such cases, we consider the price variable to be censored at the minimum bid level (i.e., the latent auction price could not be observed, because the minimum bid amount was set too high). We use a censored-normal maximum-likelihood estimation procedure, exactly like a standard Tobit regression except that the censoring point (the minimum bid level) is different across observations.

In the first column of Table 2, we present regression results for the full set of 20,292 auctions for pennies. In general, we do not know anything about the average market value for the coins in this data set, so the BOOKVAL variable is omitted from this regression. This regression gives results which look quite peculiar: in particular, the POS coefficient has a negative sign and the NEG coefficient has a positive sign, and both are statistically significant. This would indicate that a seller's cumulative positive feedback ratings tend to decrease the price she can earn in an auction, while negative feedback tends to increase the price. These turn out to be spurious results caused by omitted variable bias.[17] On average, sellers with higher feedback ratings appear to be auctioning more low-value pennies, and this causes the spurious negative correlation. To correct for this bias, we next focus on a smaller sample of coins: 461 uncirculated Indian cents for which we obtained book values from the Coin Universe Web site. These book values take into account the coin's date, its rated condition (MS-60 to MS-70), and its color (red, red/brown, brown), all of which have important effects on the appraised value of the coin.

One variable conspicuously absent from our regressions is the number of participating bidders. The number of bids clearly should affect the auction price, but we chose not to include it as a regressor in the above models because it is endogenously determined by the bidders' choices.[18]

The second, third, and fourth regressions present results for this sample of 461 uncirculated Indian cents, including the log of book value as an additional regressor. The log-book-value coefficient is 0.81, statistically significantly lower than 1, which indicates that the auction prices of higher-valued coins tend to be relatively lower fractions of book value. In the following subsections, we highlight our most important results.

5.1 Feedback

[17] Deltas (1999) also illustrates the estimation problems inherent in exploring the determinants of auction price without an appropriate measure of each auctioned item's average value to bidders.

[18] To see what factors cause more entry by bidders, we did estimate a few regression models with the number of bids as the dependent variable. The general results were similar to those of the price regressions, so we don't present them in detail here. The number of bids increases with book value (elasticity = 2), decreases with the minimum bid level (elasticity = –2.3), does not change significantly (perhaps increases slightly) with the presence of a reserve price, increases with the number of positive seller ratings, decreases with the number of negative seller ratings, and increases with the length of the auction.

In the regression models on the small sample, the coefficient estimates for the reputation variables (POS and NEG) do have the expected signs. This result is robust across all specifications we tried, including other functional forms not reported in the table.

In our initial modeling efforts, we did not separate positive from negative rating points, but instead used eBay's Feedback Rating score, namely the difference between the two numbers. eBay reports this value in parentheses every time it identifies a user. This variable had no statistically significant effects on price. We conclude that eBay users do not react significantly to eBay's Feedback Rating summary measure.

However, we find that eBay users do focus on sellers' negative rating points. Specifically, we find that a 1% increase in the seller's positive feedback ratings yields a 0.03% increase in the auction price on average. The effect of negative feedback ratings is much larger, and—as expected—in the opposite direction: a 1% increase causes a 0.11% decrease in auction price on average. The effect of negative feedback is statistically significant at the 5% level, while the effect of positive feedback is not. We also note that the disparity in the effects of positive and negative rating points is consistent with findings in risk management (Slovic, 1996) and marketing (Haskett, 1997).

5.2 Auction Length and End Dates

Our second finding, also robust across all model specifications we have tried, is that the length of the auction positively influences the auction price. Models 2 and 3 each use the number of days as a quantitative regressor, while Model 4 treats the number of days as a qualitative variable (3, 5, 7, or 10 days).

Longer auctions tend to fetch higher prices. The elasticity of auction price with respect to number of days is +0.06, and is statistically significant at the 5% level. 3-day auctions and 5-day auctions yield approximately the same prices on average. 7-day auction prices are approximately 24% higher and 10-day auctions are 42% higher, on average, with both effects statistically significantly different from zero.

We also investigated the effects of having the auction end on different days of the week; our preferred day-of-week specification (model 3) added a single WEEKEND dummy variable for auctions ending on Saturday or Sunday. The point estimate indicates that weekend auction revenues are 7% higher than weekday auction revenues on average, but this difference is not significantly different from zero at the 5% level.

5.3 Minimum Bids and Reserve Prices

Our third major result concerns minimum bids and reserve prices. In Models 2, 3, and 4, we find that the presence of a secret reserve price increases the auction price by about 15% on average, and the effect is statistically significant. We also find that as the minimum bid increases by 1%, the auction price increases by less than 0.01% on average, and the effect is not statistically significant. That is, minimum bids and reserve prices both tend to increase the auction price, but the effect of the minimum bid is relatively small.

We were initially puzzled to see that reserve prices affected price positively, because we thought the presence of a reserve price might deter bidder entry. The presence of an unknown reserve price (whose presence, though not the amount, can be seen by bidders) reduces the probability that the winning bid will actually result in a transaction. Thus, the presence of a reserve price may cause some bidders not to bother bidding in the first place, because it might not be worth the effort. However, our regression results in Models 2 through 4 indicate an increase, rather than a decrease, in auction price when a reserve price was in effect.

We realized that an important reason why the reserve price may increase the final auction price is that the reserve acts as if it were another competing bidder, at least until the reserve has been met. A concrete example may help to illustrate this idea. If a bidder submits a proxy bid of $100 when the highest bid by someone else is $50, his bid will be executed as $55 in the absence of a reserve price. In the presence of an $80 reserve price, however, that same $100 bid will be executed as $80 instead of $55. It is possible that this is the major source of the reserve-price effect found in our regression. Unfortunately, the available data from eBay make it very difficult to say anything about the seller's optimal reserve price level, because we observe only the presence of the reserve price—not its magnitude.

By contrast, we do observe the levels of the public minimum bids. And with minimum bids, auction theory has a clear prediction to make. In an English auction with privately known bidder values, the level of the minimum bid should increase prices only in those cases where it is binding on the winning bidder—that is, only in those cases where one person bids.

To examine how the effects of the reserve price and the minimum bid change when the number of bidders changes, we present Models 5 and 6 in Table 2. Model 5 restricts the Indian-cent sample to only those auctions with at least one bid, while Model 6 restricts the sample even further to those auctions with at least two bids. With at least one bid, the minimum-bid coefficient becomes four times as large as before, and also becomes statistically significant. Minimum bids can have no positive effect on price in auctions where there are no bids, so it makes sense that the average effect goes up when excluding such auctions. With at least two bids, the effect decreases in size again, and is no longer statistically significant, consistent with the zero effect predicted by theory. (Competition between at least two bidders causes the minimum bid to be non-binding, and its level irrelevant.)

As for the reserve price, its estimated coefficient is only half as large in the restricted samples as in the full sample. For the case of at least one bid received, the minimum-bid effect goes up, apparently taking away some of the effect previously attributed to the reserve price in the full sample. For the case of at least two bids received, the effect goes up again somewhat, but remains statistically insignificant.

Thus, the presence of a reserve price and the level of the minimum bid both have positive estimated effects on the final auction price, though not always statistically significantly. In confirmation of economic theory, the level of the minimum bid has a significant positive effect for auctions with only one bidder, but an insignificant effect when there are two or more bidders.

6. Concluding Remarks

We present three primary findings on the determinants of eBay auction prices. First, seller reputation points on eBay have a measurable effect on auction prices, but not necessarily in the way that the eBay's summary Feedback Rating might suggest. Rather than positive and negative ratings having equal effects, we find that negative ratings matter considerably more than positive ones. Second, longer auctions on eBay tend to attract more bidders and earn higher prices. Third, reserve prices and minimum bids tend to have positive effects on the auction price, but the overall effect of these seller strategies is hard to determine, given that the use of these instruments sometimes causes the good not to sell at all. Minimum bids increase auction price when they are binding, but have no significant effect when there are two or more bidders. This is consistent with a standard model of bidding up to one's reservation value in an English auction.

We believe that eBay represents a rich source of data for studying empirical behavior in auctions, and that automated online collection will likely continue to produce large amounts of useful data.

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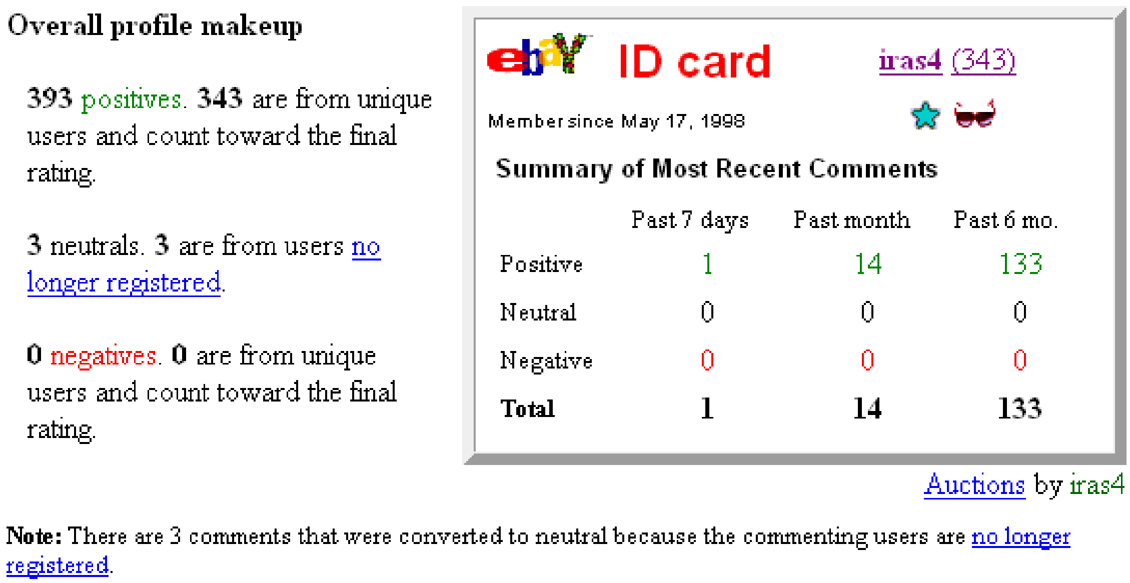
Figure 1. An example eBay auction Web page.

Figure 2. An example auction item photograph.

Figure 3. An example feedback page for an eBay seller.


Overall profile makeup

393 positives. 343 are from unique users and count toward the final rating.

3 neutrals. 3 are from users no longer registered.

0 negatives. 0 are from unique users and count toward the final rating.

ebay ID card iras4 (343)

Member since May 17, 1998

Summary of Most Recent Comments

	Past 7 days	Past month	Past 6 mo.
Positive	1	14	133
Neutral	0	0	0
Negative	0	0	0
Total	**1**	**14**	**133**

Auctions by iras4

Note: There are 3 comments that were converted to neutral because the commenting users are no longer registered.

Figure 4. Number of U.S. Cent auctions closing per date.

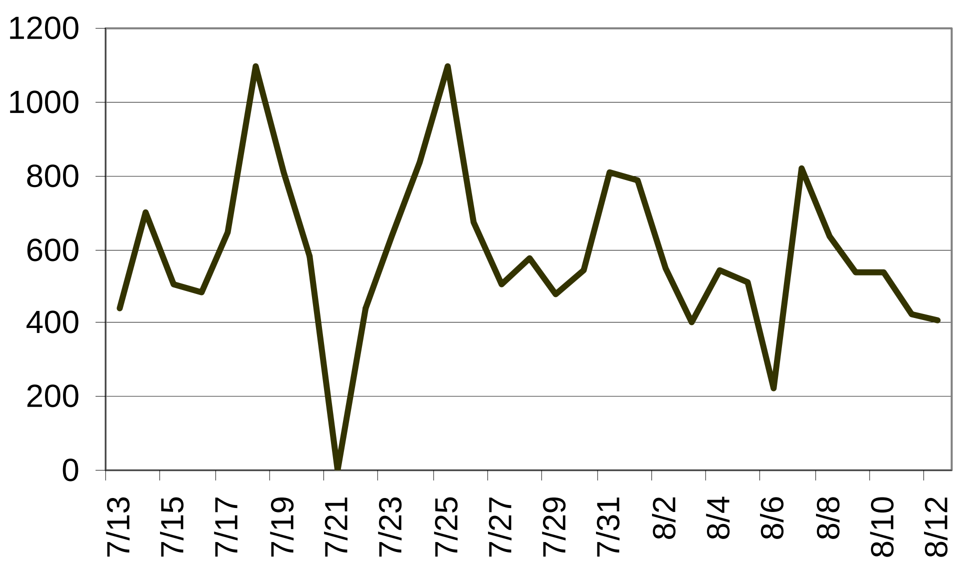


Figure 5. Trading volume (number of auctions) by day of the week.

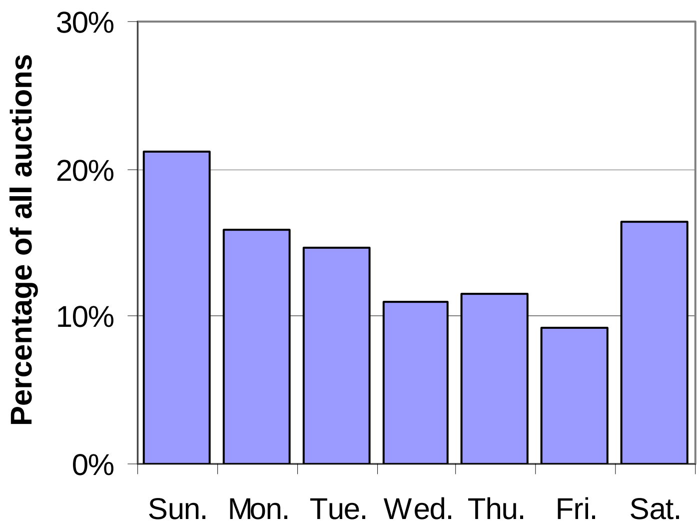


Figure 6. Trading volume (number of auctions) by hour of the day (see footnote 16).
(Each bar represents the number of auctions closing over the previous hour. For example, the bar for 17 represents the number of auctions from 4:01pm to 5:00pm, PDT.)

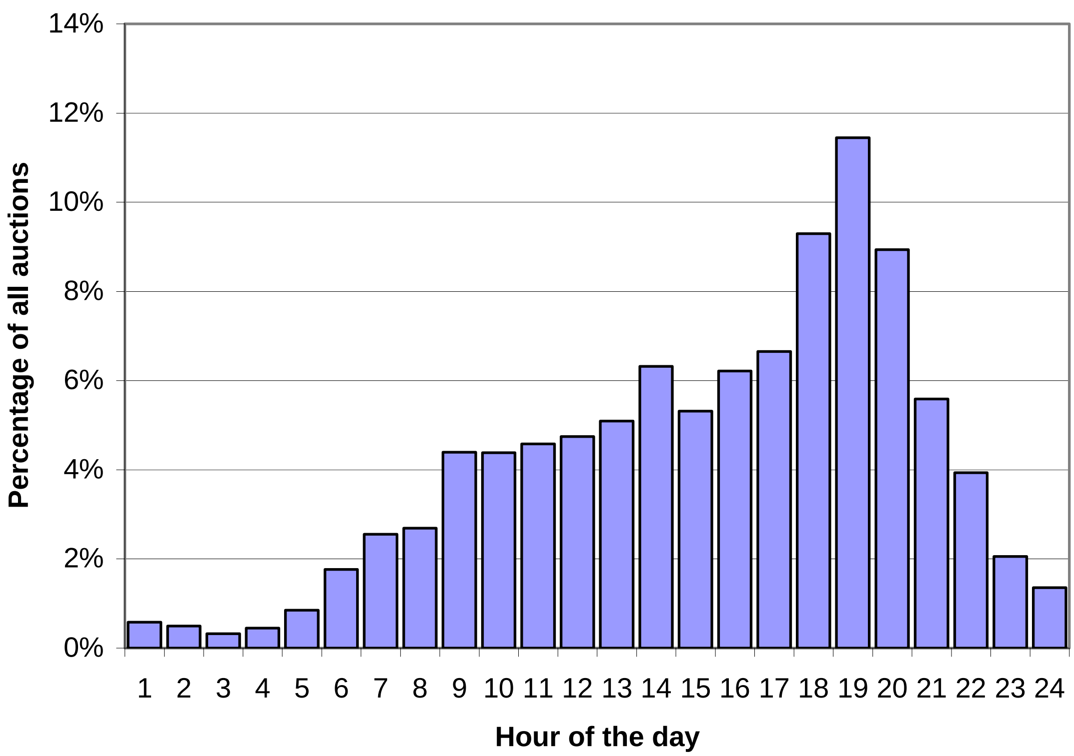


Figure 7. Mean prices per date.

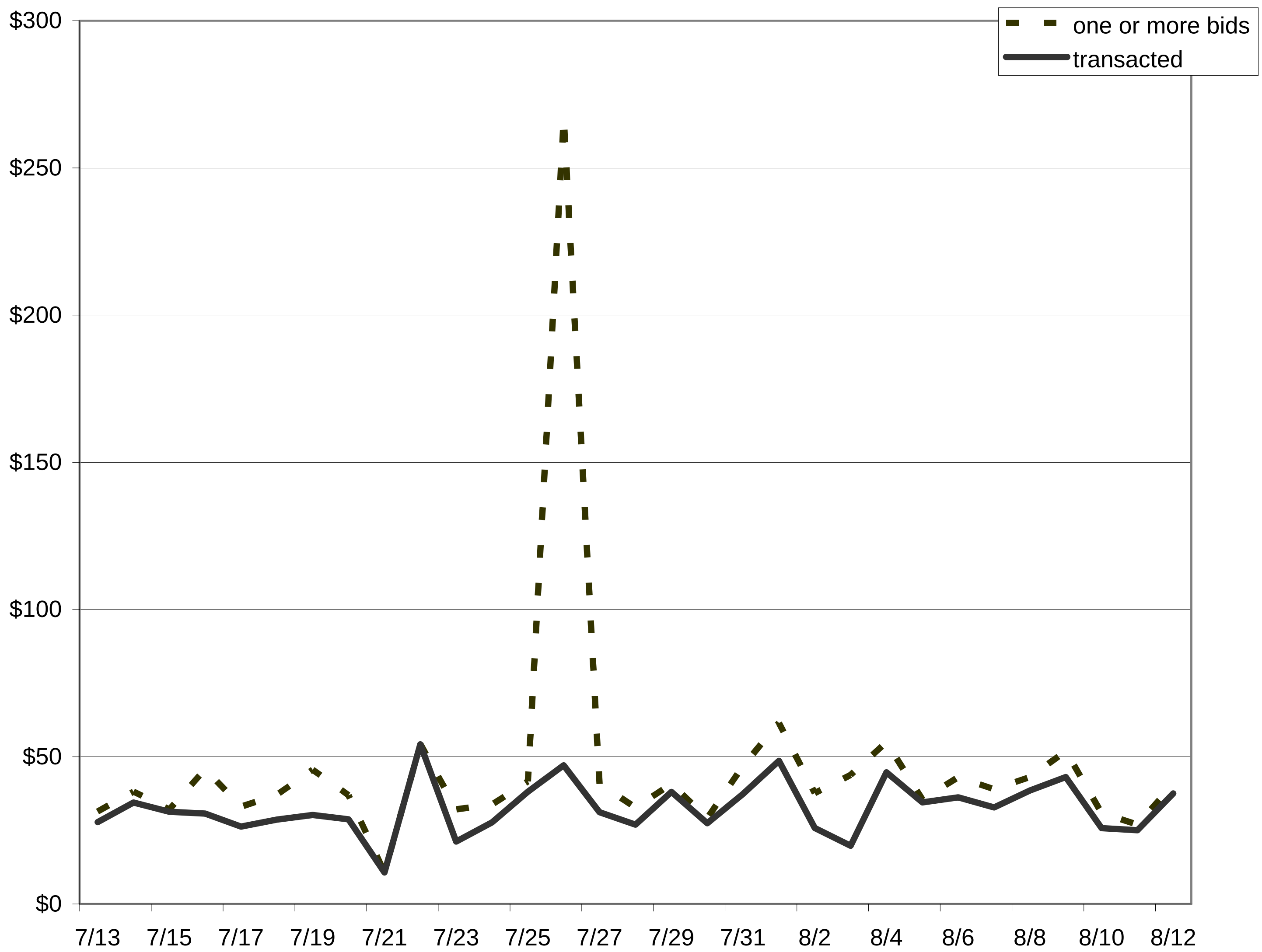


Figure 8. Mean prices per date (outliers removed).

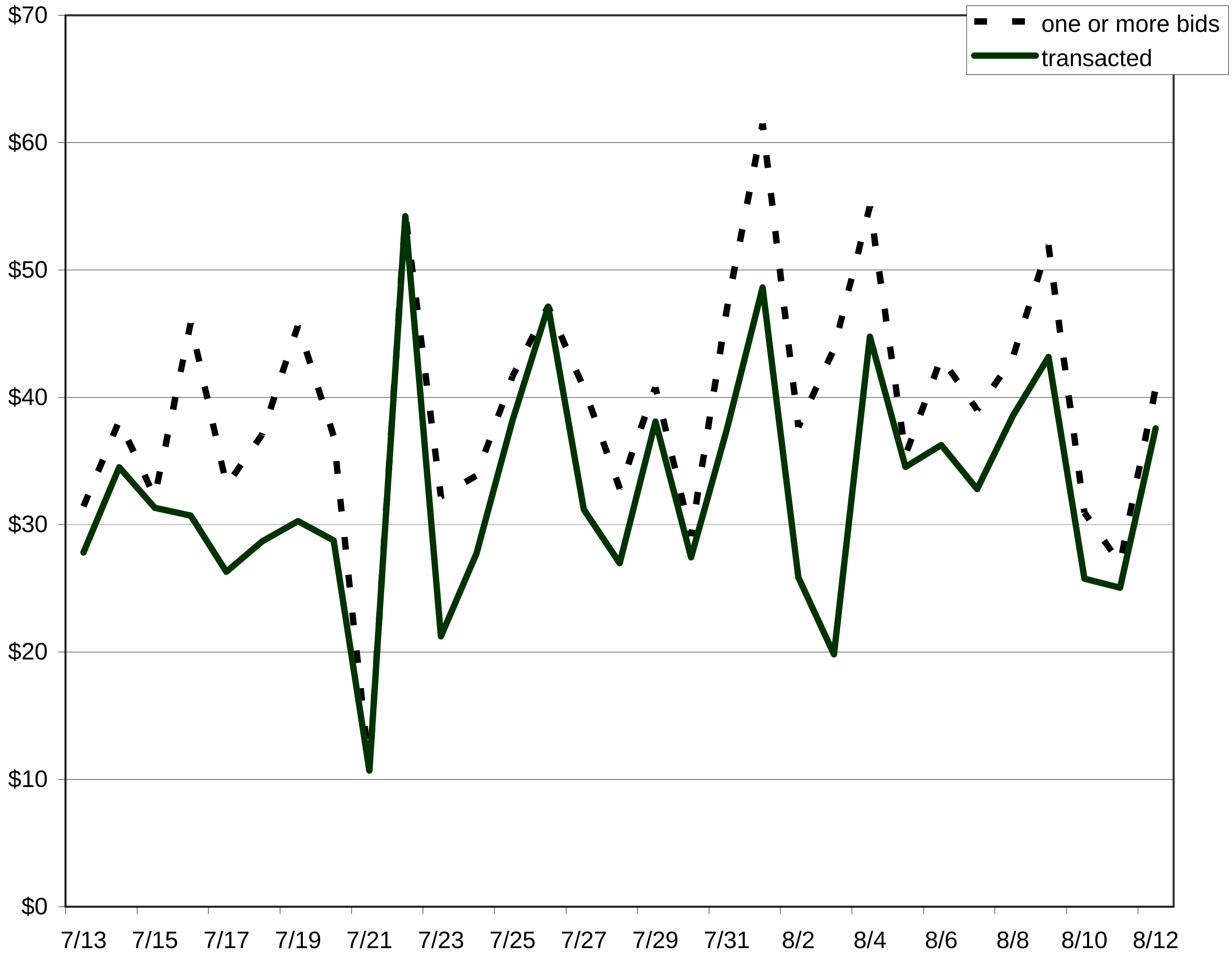


Figure 9. Mean prices by day of the week.

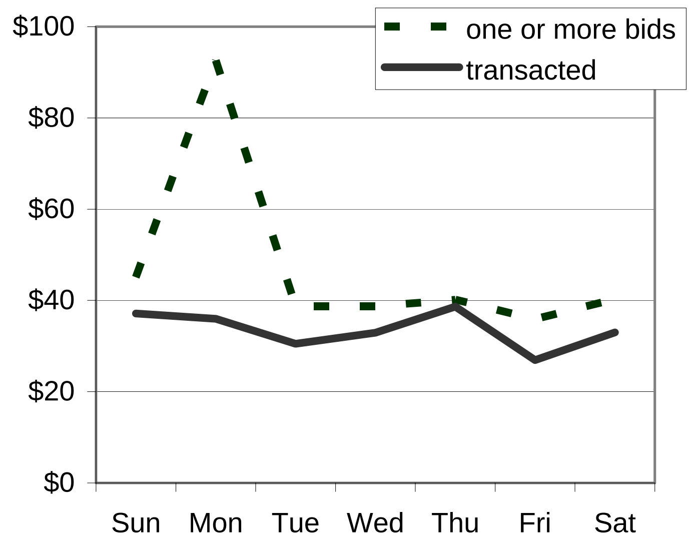


Figure 10. Mean prices by hour of the day (see footnote 16).

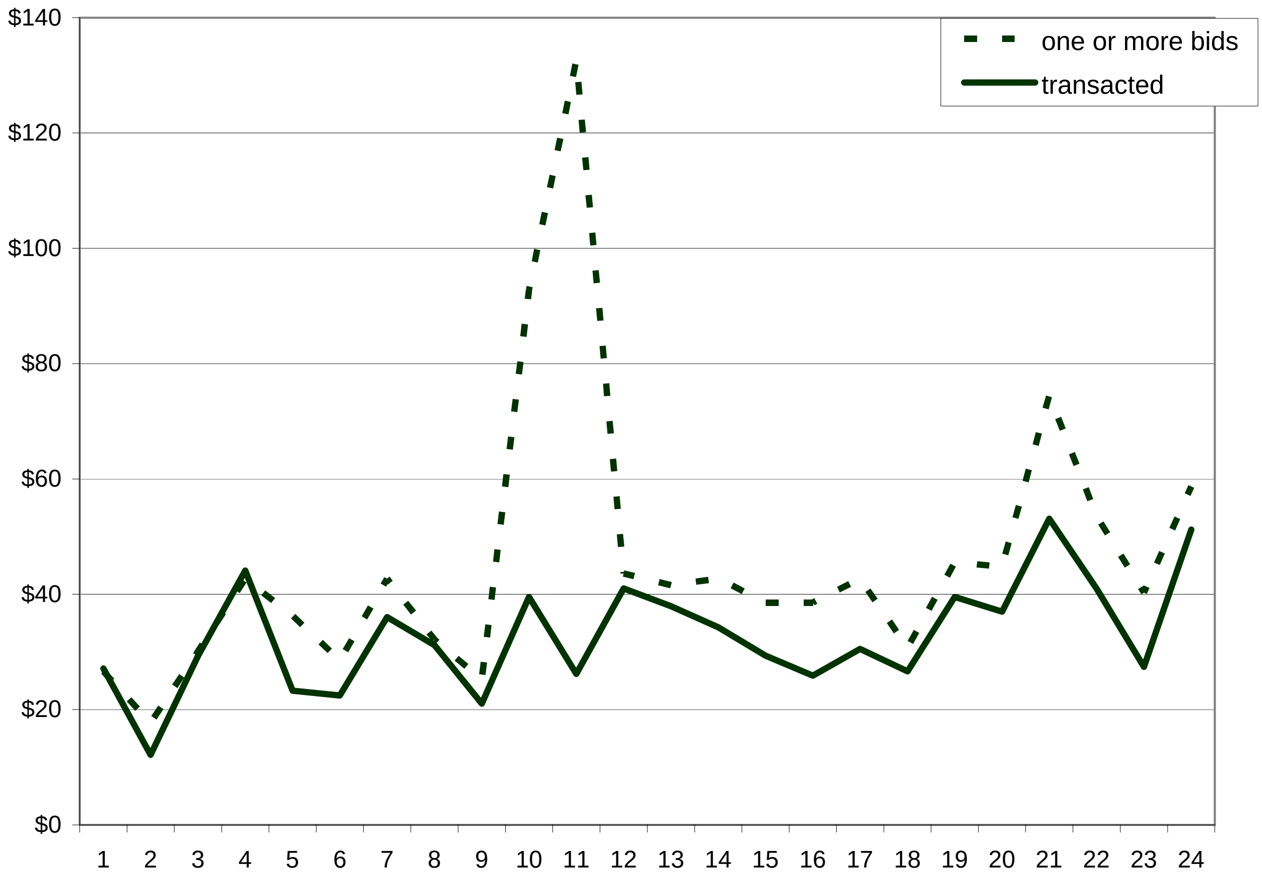


Figure 11. Stacked percentages of auctions that received no bids and that did not meet a reserve price.

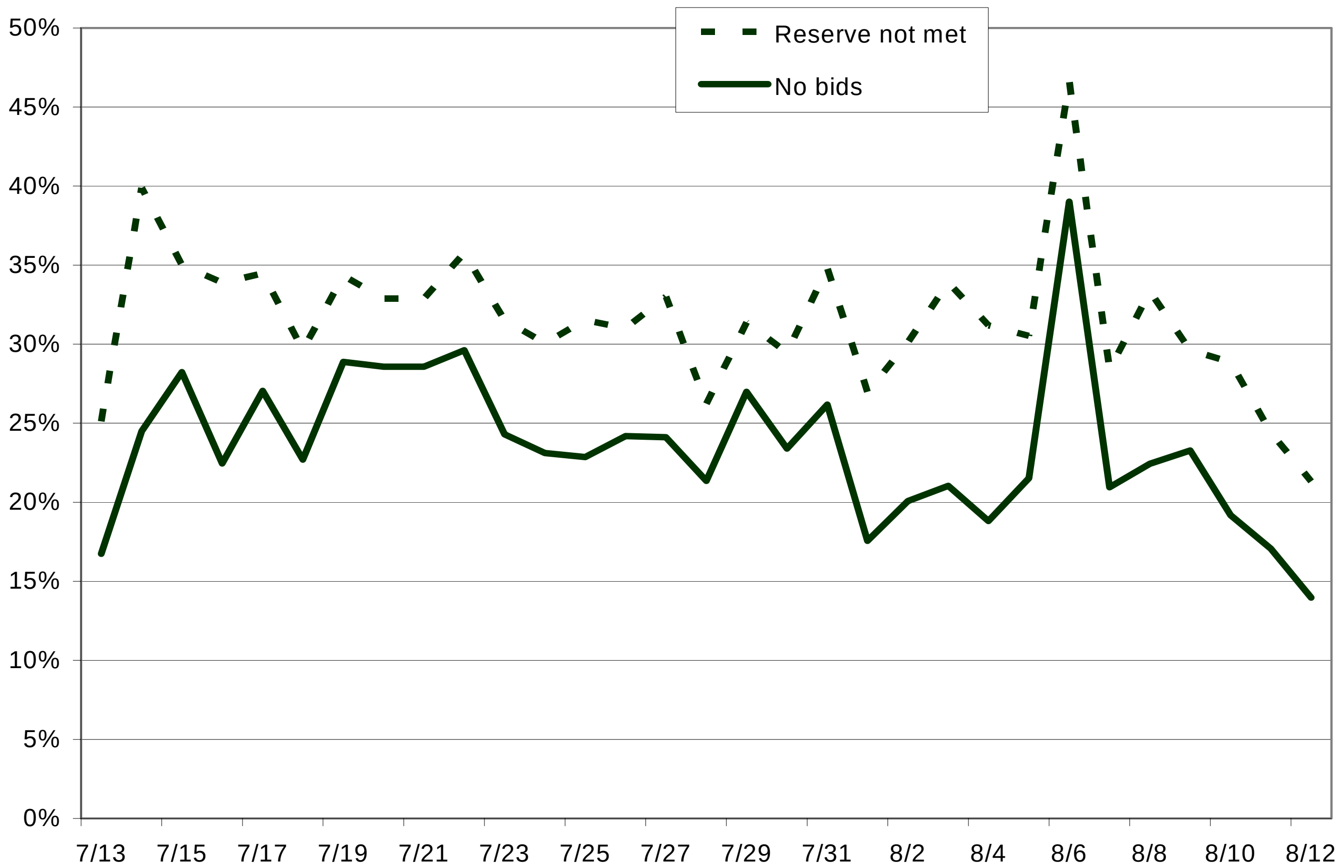


Figure 12. Stacked percentages of auctions that received no bids and that did not meet a reserve, by day of the week.

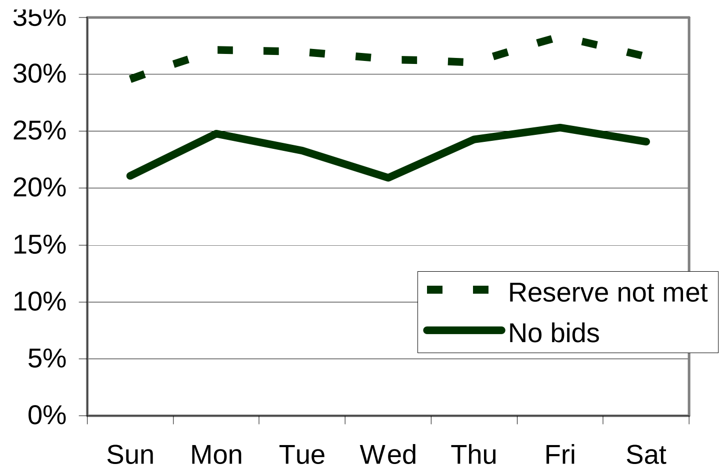


Figure 13. Stacked percentage of auctions that received no bids and did not meet a reserve, by hour of the day.

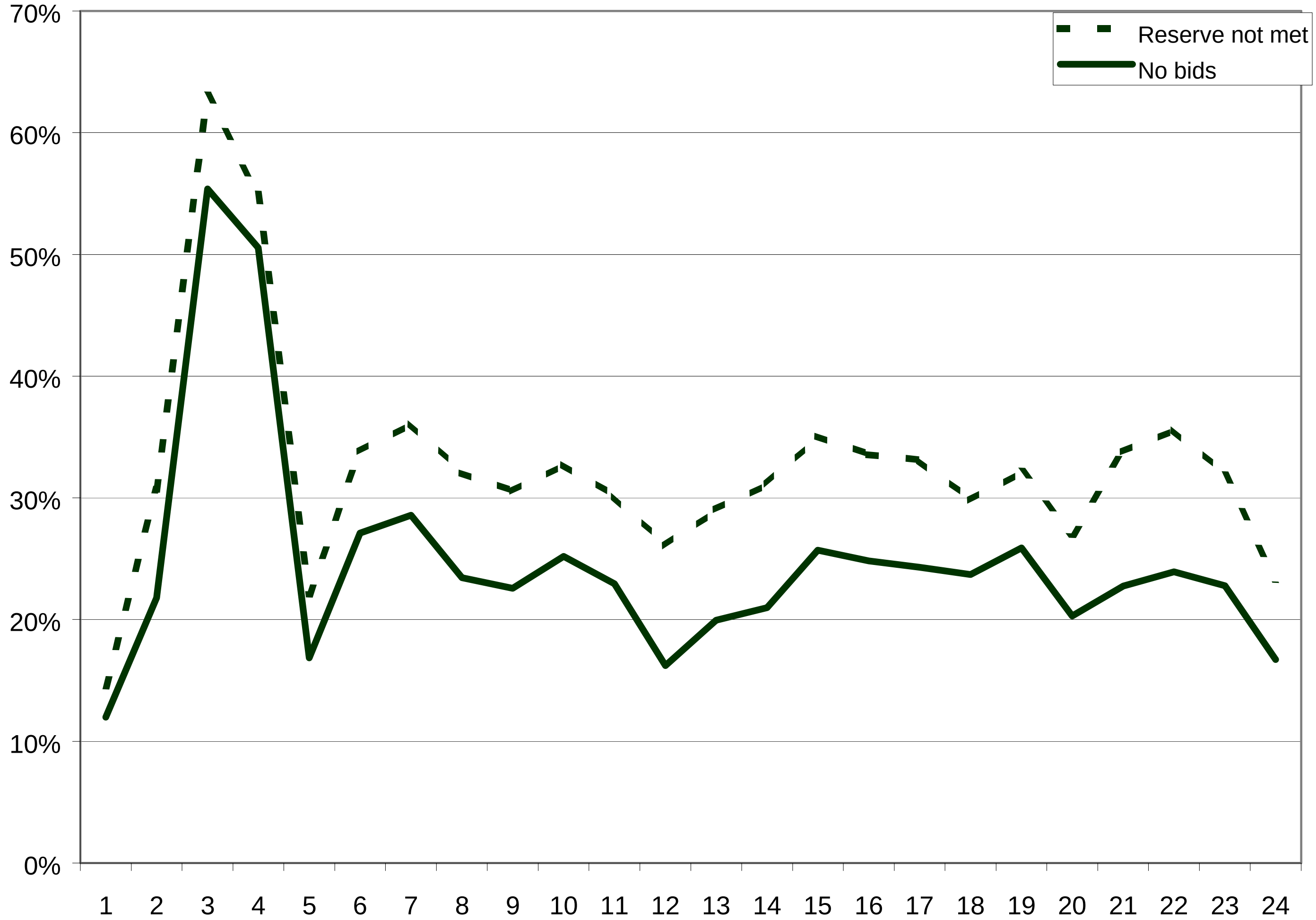


Figure 14. Histogram of auction length, for 20,000 U.S. Cent auctions.

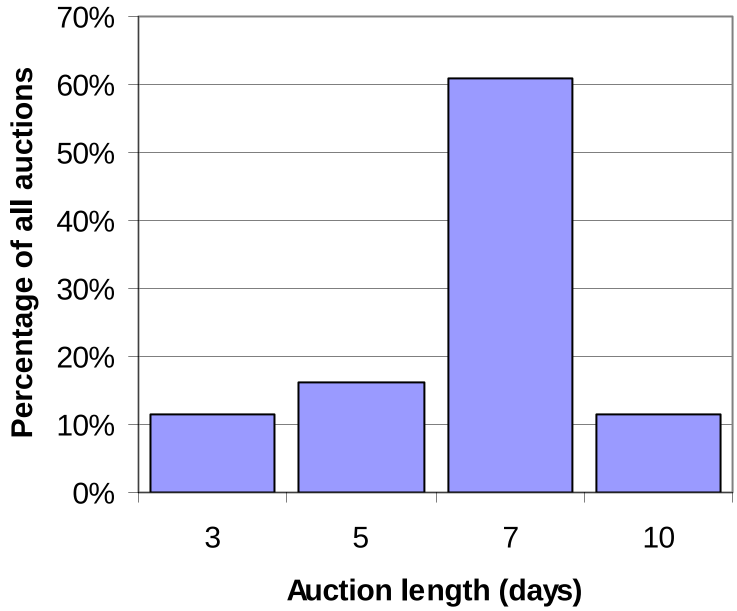


Figure 15. Histogram of number of bids received, for 20,000 U.S. Cent auctions.
(Note the nonlinear horizontal scale. The bar labeled "10" denotes auctions with 6-10 bids, the bar labeled "20" denotes auctions with 11–20 bids, etc.)

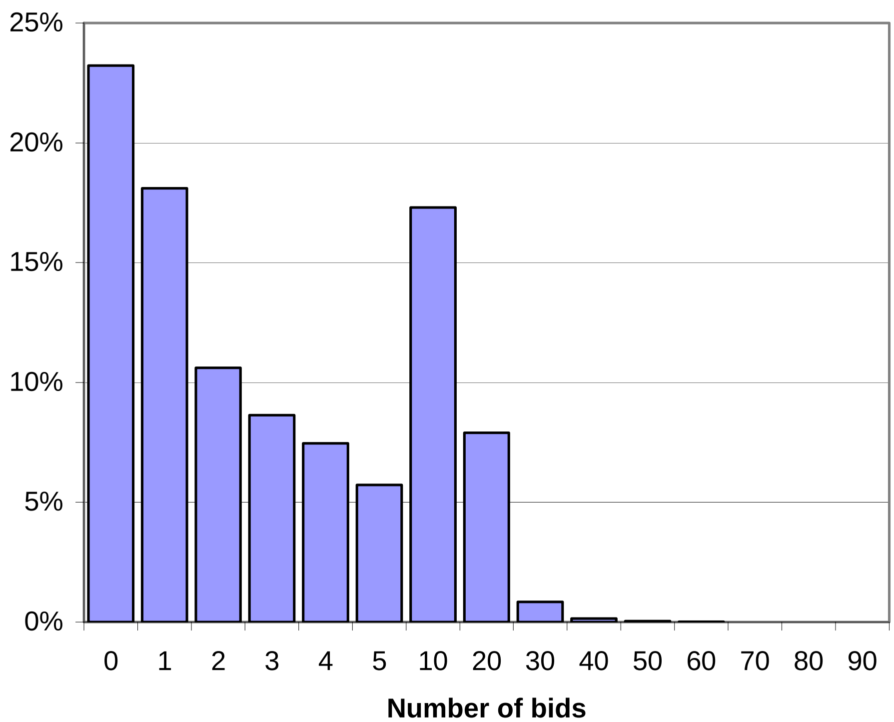


Figure 16. Histogram of auctions by seller's reputation, for 20,000 U.S. Cent auctions. (Note the nonlinear horizontal scale. The bar labeled "200" denotes sellers with a rating of 101–200.)

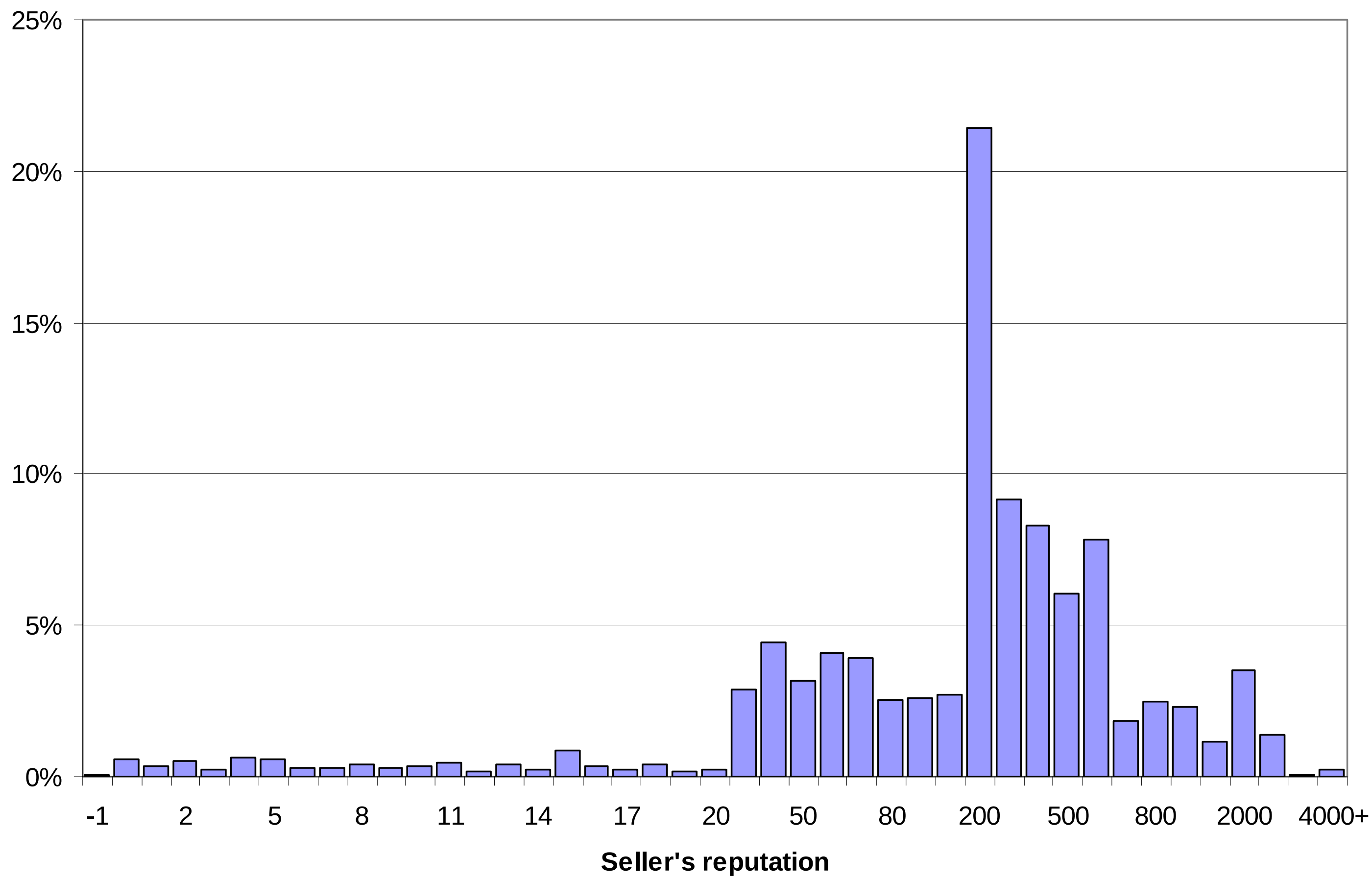


Figure 17. Histogram of the ratio of minimum bid to book value, for 461 Indian Head auctions. (Note: the horizontal scale is nonlinear.)

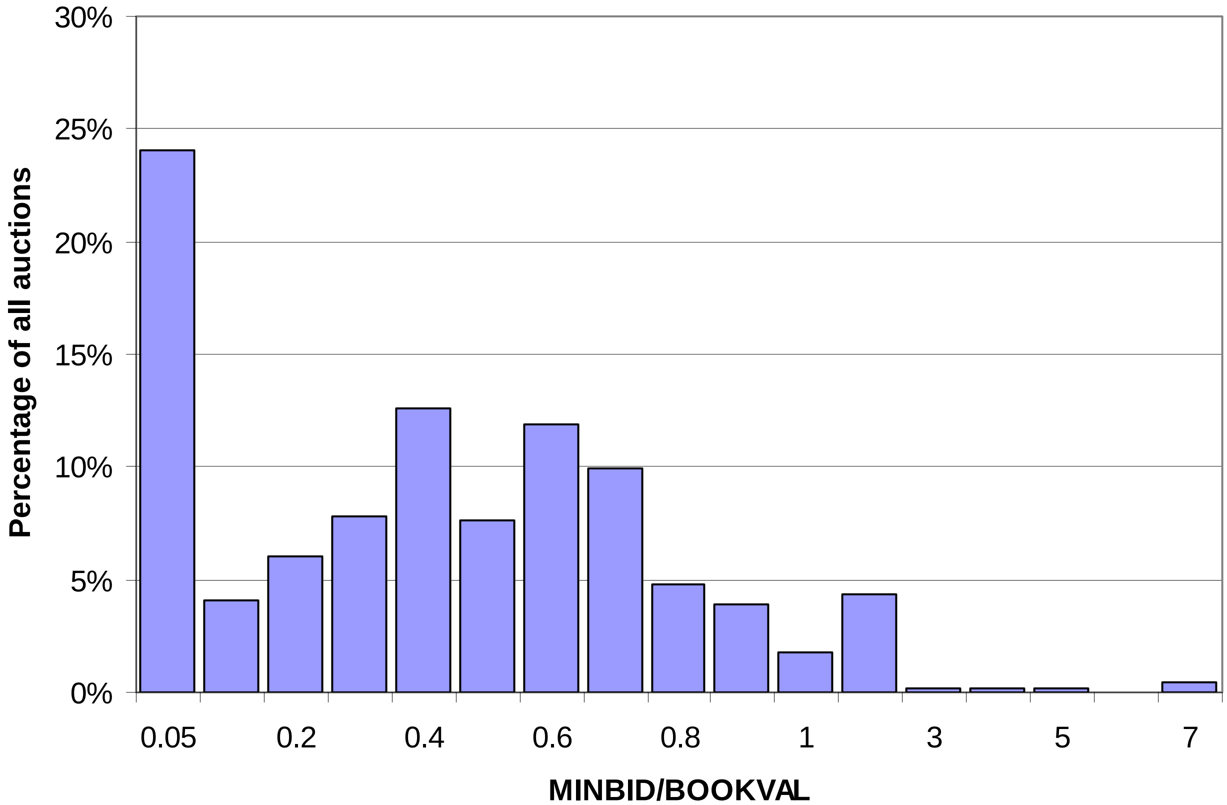


Figure 18. Histogram of the ratio of price to book value, for the 285 Indian Head auctions that transacted.
(Note: the horizontal scale is nonlinear.)

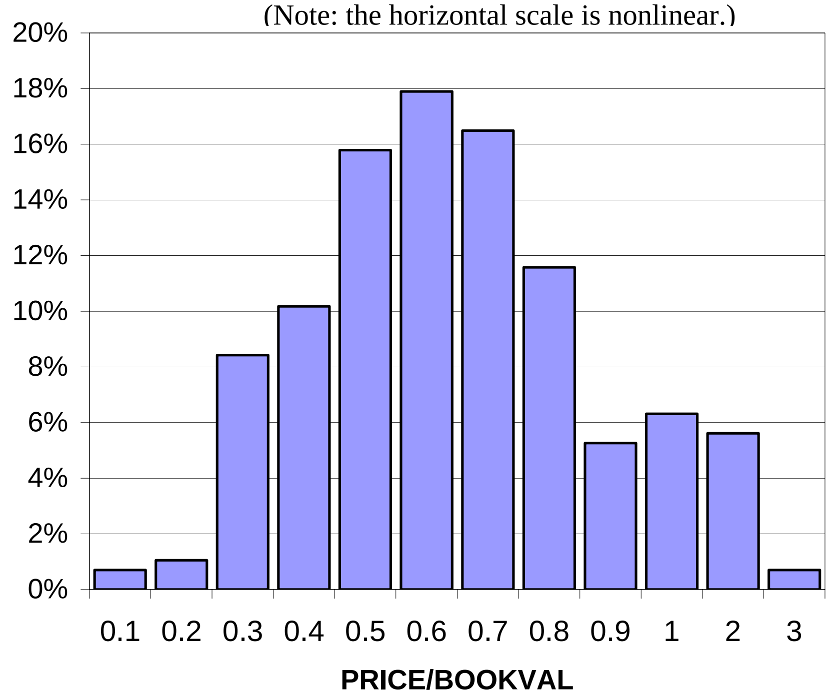


Table 1. Summary Statistics

	mean	std. dev.	min	max
BOOKVAL	277.77	541.68	21	5200
POS	383.74	351.63	0	1992
NEG	1.90	2.94	0	19
MINBID	134.80	362.80	0.01	3500
PRICE	173.20	362.96	4.99	3500
#BIDS	5.15	6.26	0	39
RESERVE	0.25	0.43	0	1
NUMDAYS	6.11	1.89	3	10

Table 2. The determinants of price in eBay coin auctions.

Dependent variable: ln(PRICE)

	All cents (no book values)	Uncirculated Indian cents, with book values			Restricted sample: #Bids>0	Restricted sample: #Bids>1
Model Number	1	2	3	4	5	6
ln(BOOKVAL)	—	.8144* (.0251)	.8129* (.0251)	.8136* (.0249)	.8393* (.0255)	.8422* (.0295)
ln(MINBID)	.4076* (.0054)	.0065 (.0127)	.0083 (.0127)	.0084 (.0127)	.0330* (.0125)	.0195 (.0139)
RESERVE	1.247* (.0245)	.1542* (.0622)	.1601* (.0624)	.1521* (.0619)	.0684 (.0615)	.0775 (.0670)
ln(POS+1)	–.0195* (.0079)	.0384 (.0271)	.0378 (.0271)	.0444 (.0272)	.0446 (.0273)	.0216 (.0291)
ln(NEG+1)	.0085* (.0148)	–.1104* (.0461)	–.1054* (.0462)	–.1122* (.0460)	–.1166* (.0471)	–.0676 (.0551)
NUMDAYS	.0610* (.0053)	.0614* (.0133)	.0610* (.0133)	—	.0417* (.0133)	.0309* (.0156)
WEEKEND	—	—	.0652 (.0561)	—	—	—
DAYS5	—	—	—	–.0148 (.0768)	—	—
DAYS7	—	—	—	.2188* (.0724)	—	—
DAYS10	—	—	—	.3544* (.1019)	—	—
constant	1.041* (.0528)	–.4050* (.1756)	–.4188* (.1788)	–.1941 (.1694)	–.3721* (.1772)	–.1915 (.1971)
N	20,292	461	461	461	334	262
R^2	.0979	.4908	.4920	.4950	.8068	.7892

In the first four models, the dependent variable [ln(PRICE)] is left-censored for those observations where the number of bids equals zero. In these cases, all we know is that the "latent" auction price is lower than the minimum bid amount. Therefore, these regressions are maximum-likelihood censored-normal regressions, where the censoring point for each observation is the minimum bid for that auction.

The last two models are limited to observations where bids were received, and thus we use ordinary least squares to estimate these models.

We add 1 to the POS and NEG variables before taking logarithms in order to avoid taking the logarithm of zero for some observations.

An asterisk (*) indicates an estimate which is statistically significantly different from zero at the 5% level.