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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Lucking-Reiley acknowledges the National Science Foundation for support under grants SBR-9811273 and SES-0094800. We thank Alex Shcherbakov, Mike Urbancic, David Mack, and Steven Reeves for their research assistance. We wish to acknowledge the fact that we allowed this paper to languish for over five years before actually submitting it, so the delay in publication is entirely our own responsibility. We apologize for not reciprocally citing any of the many authors who have done fine research on this topic subsequent to our initial draft; we decided to publish a paper as close to the original draft as possible (although considerably shortened) for the historical record. This includes keeping the surname Lucking-Reiley, even though that author has subsequently changed his name to back to Reiley.

1 Introduction

Since the birth of Web-based auctions in 1995, auctions on the Internet have grown at a tremendous rate. One of the largest consumer-oriented auction site is eBay, where individual sellers register their items for sale, and individual consumers bid on the items. After just three years of business, eBay already conducted over one billion dollars in transactions in 1998,[2] and by 2004 this figure had climbed to $34.2 billion[3] A total of 56.1 million users either bid or listed an item on eBay during 2004,[4] and according to a July 2005 survey conducted for eBay by ACNielsen International Research, an estimated 724,000 Americans report eBay as a primary or secondary source of income.[5] Clearly, eBay is one of the largest Internet commerce venues, and one of the largest marketplaces in the world.

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.[6] However, the emergence of eBay and other online auctions now makes it possible to obtain data from a wide variety of auction markets. Using the data on U.S. Cent auctions held at eBay over a 30-day period during July and August of 1999 we present a regression analysis of factors which affect prices in these auctions. This

[2] See Lucking-Reiley (2000a) for more details on the transaction volume at eBay and 140 other online auction sites.
[3] eBay calls this number Gross Merchandise Volume; see http://investor.ebay.com/news/Q404/EBAY0119-777666.pdf.
[4] "Key Q4 Financial and Operating Metrics" from eBay inc. Press Release (fourth quarter and full year 2004 financial results), January 19, 2005.
[5] http://investor.ebay.com/ReleaseDetail.cfm?ReleaseID=170073
[6] See Hendricks and Paarsch (1995) for a survey of past empirical research on auctions.

paper represents an early contribution to the literature on the determinants of price in online auctions, even though it is being published relatively late.[7]

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.

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. A seller can choose 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). A secret "reserve price" can be assigned 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.

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 have 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.[8] In addition to the numeric ratings, users may view the entire list of feedback comments left by other users about any individual.

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[7] The first draft of our paper, written in December 1999, has been cited widely. An amusing example can be found in the book by Cohen (2002, p. 195).

Despite the fact that conventional wisdom says that feedback ratings are essential on eBay, one can find a number of theoretical arguments both supporting and undermining such claims. Hence, another important question of this paper is whether eBay's feedback ratings really do have a measurable economic impact.

3 Data

The data for this study were collected by a "spider" program directly from eBay website. We collected data on "U.S. Cent" category auctions held at eBay over a 30-day period during July and August of 1999. The choice of the category was dictated by a wide variety of well-categorized goods and a wide variety of prices. The dataset 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 also collected feedback information on sellers, based on their IDs. We collected 20,292 observations in total. 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 dataset. Using the year and grade, we then manually collected estimated value, or book value, for each coin in the small data set.[9]

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

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[8] 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.

Table 1. Description of variables.

Description	Variable
The year of the coin	-
The grade of the coin	-
The coin's estimated value (from year and grade)	BOOKVAL
The minimum bid in the auction	MINBID
The realized price in the auction (If no bids were made, then this is the same as the minimum bid.)	PRICE
The number of bids made	#BIDS
Dummy for the presence of a secret reserve price	RESERVE
The length of the auction in days (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 ("unique positives")	-
The number of members who gave the seller a negative rating ("unique negatives")	-
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	-
We used the above to code the additional dummy variables:	
Dummy for an auction closing on a Saturday or Sunday	WEEKEND
Dummy for a 5-day auction	DAYS5
Dummy for a 7-day auction	DAYS7
Dummy for a 10-day auction	DAYS10

Our small data set of 461 observations includes 134 unique sellers and 182 unique buyers. 127 of the auctions (28%) received no bids, while 49 auctions (11%) received bids but had reserve prices that were not met. Thus 285 of the auctions (62%) resulted in a transaction. 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. In particular, 48% of the auctions were 7 days in length, 28% of the auctions have length of 5 days, and only about 9% were the maximum length of 10 days, with the remaining 15% of auctions having the

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

minimum 3-day length. Later, we will describe evidence indicating that longer auctions may be advantageous to the seller.

Within the 461-observation dataset, the majority of the auctions used minimum bids that less than half of the book value of the coin in question. About 45% of sellers are setting a minimum bid at 40% or higher of book value. For the subset of 285 auctions resulting in a transaction, we observed a clustering of prices around 0.6 of book value. That is, the U.S. Indian Head pennies we observed often sold on eBay for about 60% of their book value.

The table below present summary statistics for the 461-observation dataset.[10]

Table 2 Summary statistics for the small data set used in estimation

Variable	Mean	S.D.	Min	Max
BOOKVALUE	277.77	541.68	21	5200
MINBID	134.80	362.80	0.01	3500
PRICE[11]	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
POS	383.74	351.63	0	1992
NEG	1.90	2.94	0	19
DAYS3	0.15	0.36	0	1
DAYS5	0.28	0.45	0	1
DAYS7	0.48	0.50	0	1
DAYS10	0.09	0.29	0	1

4 The Empirical Determinants of eBay Auction Prices

The table 3 below displays regression results on the determinants of prices in the eBay coin auctions in our sample.

[10] Description of the large dataset can be found in a working paper version of this article.
[11] Statistics presented for this variable include both censored and uncensored observations, with price for censored observations equal to the minimum bid assigned by the seller

Table 3 The determinants of price in eBay coin auctions

	Full sample, 461 obs.			
Model Number	**1**	**2**	**3**	**4**
ln(BOOKVALUE)	0.8144	0.8129	0.8136	0.7705
	(0.0251)	*(0.0251)*	*(0.0249)*	*(0.0276)*
ln(MINBID)	0.0065	0.0083	0.0084	0.1722
	(0.0127)	*(0.0127)*	*(0.0127)*	*(0.0419)*
RESERVE	0.1542	0.1601	0.1521	0.1242
	(0.0622)	*(0.0624)*	*(0.0619)*	*(0.0612)*
ln(POS+1)	0.0384	0.0378	0.0444	0.0459
	(0.0271)	*(0.0271)*	*(0.0272)*	*(0.0266)*
ln(NEG+1)	-0.1104	-0.1054	-0.1122	-0.0699
	(0.0461)	*(0.0462)*	*(0.0460)*	*(0.0457)*
NUMDAYS	0.0614	0.0610	—	—
	(0.0133)	*(0.0133)*		
WEEKEND	—	0.0652	—	—
		(0.0561)		
MT1BID*ln(MINBID)	—	—	—	-0.1463
				(0.0433)
MT1BID	—	—	—	0.9164
				(0.1838)
DAYS5	—		-0.0148	-0.0019
			(0.0768)	*(0.0753)*
DAYS7	—		0.2188	0.1508
			(0.0724)	*(0.0717)*
DAYS10	—		0.3544	0.2833
			(0.1019)	*(0.0999)*
constant	-0.4050	-0.4188	-0.1941	-0.8460
	(0.1756)	*(0.1788)*	*(0.1694)*	*(0.2023)*
R^2	0.4908	0.4920	0.4950	0.5306

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.

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.[12] We attempt to include as many variables as we can measure that are relevant to the bidders' participation and bid choices. Thus, for example, suppose that longer auctions result in higher auction prices because they attract more bidders. Even though we exclude the number of bidders from our regression, we will correctly draw the correct inference about the effects of longer auctions on auction price.

Some caveats about omitted variables may be in order. While we have attempted to control for all variables relevant to bidders, there are some important exceptions. For one, we do not quantify the attractiveness of the auction listing; some sellers may have more skill at Web design, photography, and verbal descriptions of coins than do others, but we did not feel competent to assess the quality of these listings. For another we do not verify the condition of each coin; we instead take at face value the seller's claim about whether a coin is grade MS-62 versus MS-63. Either of these omitted variables could bias our results if they happen to be correlated with our variables of interest. For example, if auctioneers with more experience (and hence more positive feedback ratings) tend to write better auction listings, then by

[12] 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

omitting a quality assessment of the auction description we might be overestimating the impact of positive feedback ratings.

Table 2 presents results for four different regression models on the sample of 461 uncirculated Indian cents. The log-book-value coefficient is 0.8, statistically significantly less than 1, which indicates that the auction prices of higher-valued coins tend to be less than book value.[13] In the following subsections, we highlight our most important results.

4.1 Feedback

In the regression models, 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. Formal LR test of the equality of coefficients on

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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.

[13] In our experience, auction transaction prices for collectibles are usually much lower than published "book values." Perhaps this is because "book values" come from surveys of dealers' list prices, which may or may not reflect actual transaction prices.

the positive and negative feedback results in χ^2-statistic of 5.61, which implies that the null hypothesis can be rejected at significance level of 0.018.[14]

The different magnitudes of effect of the positive versus negative feedback is quite interesting. Perhaps buyers' prior is that "people are basically good," as eBay asserts at the top of its Community Values.[15] Thus, a positive feedback rating would do little to update buyers' prior beliefs about a previously unknown seller, while a negative feedback rating would be much more informative. 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).

4.2 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 1 and 2 each use the number of days as a quantitative regressor, while Model 3 treats the number of days as a qualitative variable (3, 5, 7, or 10 days).

Longer auctions tend to fetch higher prices. Three-day auctions and five-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. An LR test for joint significance of the 5-, 7-, and 10-day dummy coefficients yields a χ^2-statistic of 21.34, thus rejecting the null hypothesis at any reasonable significance level. Auction length, then has a surprisingly large effect on the auction price, with 7-day and 10-day auctions providing significantly higher auction prices than 3-day and 5-day auctions. Perhaps longer auctions yield higher prices because they allow

[14] The test was performed for model 3.
[15] See, for example, <http://pages.ebay.com/help/community/values.html>.

for more accumulation of potential bidders. The disadvantage of longer auctions is one of higher transaction costs for buyers and sellers, who would need to monitor their auction for a longer period of time before realizing an outcome. It seems reasonable that in our data, the effect of gaining more potential bidders would outweigh the possible transaction-cost effect discouraging bidders from participating in longer auctions. However, we note that this effect might well be declining over time, as the number of eBay bidders per day has increased dramatically since 1999. At some point, the markets may become thick enough that 3-day auctions will achieve prices as high as 10-day auctions, and the extra days will become superfluous.

We also investigated the effects of having the auction end on different days of the week; our preferred day-of-week specification (model 2) 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. A positive coefficient on WEEKEND seems intuitively appealing because consumers are more likely on weekends to have time to pay close attention to closing auctions. The results on auction length indicated to us that weekends might be important, since auctions realize higher prices when they run for at least a week. On the other hand, if this were true one might expect sellers to increase the supply of weekend-closing auctions to the point where prices were approximately equal across days of the week. So it makes sense to us that the effect should be relatively small and statistically insignificant.

4.3 Minimum Bids and Reserve Prices

Our third major result concerns minimum bids and reserve prices. In Models 1, 2, and 3 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 1 through 3 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 minimum bid change with the number of bidders, we present Model 4. In particular, using standard auction theory we would expect the minimum bid to have no effect on price when more than one bidder chooses to submit a bid in the auction, because in this case the minimum bid is not binding. (Alternatively, we can imagine a world in which, for example, the minimum bid serves as a reference point that affects the levels of bidders' bids, even in cases where the minimum is not binding. This is what makes the empirical test interesting.) Model 4 therefore introduces two additional regressors: (1) MORETHN1 – a dummy variable equal to 1 when the auction has more than one bidder, and (2) MORETHN1*ln(MINBID) – an interaction term between the new dummy variable and the log of minimum bid. The coefficient on MT1BID is +0.91, indicating the unsurprising result auctions with at least two bidders yield higher prices than auctions with fewer bidders. The interesting coefficients to compare are those on MINBID and MT1BID*ln(MINBID), which are +0.17 and -0.15, respectively. Because these two coefficients sum to approximately zero (an LR test of this null hypothesis yields $\chi^2 = 3.45$, p=0.063), we conclude that the minimum-bid level is irrelevant when there are more than two bidders. That is, ln(MINBID) has a statistically significant, positive effect when the number of bidders is less than two, and an approximately zero effect when the nuber of bidders is two or more, just as predicted by the standard theory.[16]

5 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.

[16] Note that the point estimate of +0.17-0.15=+0.02 is positive, and would be significant at the 10% level. This hints that perhaps there is a small anchoring effect of reserve prices on bids, which would be interesting to explore in future research.

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