THE EFFECTS OF SHILLING ON FINAL BID PRICES IN ONLINE AUCTIONS

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Last revised: April 4, 2004

ABSTRACT

An increasing number of reports of online auction fraud are of growing concern to auction operators and participants. In this research, we discuss *reserve price shilling*, where a bidder shills in order to avoid paying auction house fees, rather than to drive up the price of the final bid. We examine the effect that *premium bids*, since they are linked with reserve price shill bids, have upon the final selling price. We use 10,260 eBay auctions during April 2001, and identify 1,389 auctions involving 493 sellers and 1,314 involved in concurrent auctions that involving the exact same item. We find that premium bidding occurs 23% of the time, in 263 of the 1,389 auctions. Using a theoretical perspective involving *valuation* s*ignals*, we show that other bidders may view high bids as signals that an item is worth more. Thus, they may be willing to pay more for the item than items that do not receive premium bids. The implications are disturbing in that sellers may be more motivated to enter a shill bid in order to drive up the final price in an online auction. We also examine and report on alternative hypotheses involving winner's curse and the possibility of reserve price shill bids. Our results are developed in the context of a weighted least squares regression model that predicts an *item selling price*-to-*average selling price* ratio.

KEYWORDS: Auctions, econometric analysis, economics, e-markets, Internet auctions, Internet fraud, premium bidding, reserve price shilling, weighted least squares, winner's curse.

ACKNOWLEDGEMENTS

The authors thank the anonymous reviewers of an earlier paper in the *Proceedings of the 2003 International Conference on Electronic Commerce*, held in Pittsburgh, Pennsylvania in October 2003. We also thank Alok Gupta, Jungpil Hahn, Dongwon Lee and Terence Ow for discussions on theory and methodology in online auction and Internet-based selling research, where similar data collection methods are used.

INTRODUCTION

The rapid diffusion of Internet technologies has made a made a number of new and interesting business models possible. Among them, online auctions are perhaps the biggest technology-driven, high value-producing innovations. Online auctions are made possible by technologies that support transaction-making across different geographical locations and over time. The value that is being developed in the marketplace through such innovation is evident in the experience of San Francisco Bay Area-based eBay (www.ebay.com), a global leader in Internet-based auction services. eBay (2004) recently announced a remarkable 78% annual growth in revenues from US$1.21 billion in 2002 to US$2.17 billion in 2003 in spite of the overall slowdown in the Internet economy.

However, although Internet technologies have been the catalyst for these new business models, online auctions and other Internet-based business models also are attracting new types of fraud and opportunistic behavior. The ubiquitous nature of the Internet also increases the anonymity of both the buyer and the seller within a transaction. Due to the sheer volume of transactions, online auctions have been particularly prone to deceptive practices. The National Consumers' League (2002) reports that online auctions accounted for 90% of all reported Internet fraud, compared to any other online service, up from 70% in 2001. The total reported losses in 2002 were US$14.6 million, up from US$6.2 million in 2001 and US$3.4 million in 2000.

One of the hardest types of online auction fraud to detect is shilling. *Shilling* occurs when a seller bids on her own auction in an effort to increase the price other bidders need to pay to win the auction. Because it is inherently deceptive (in that the seller hides her identity and pretends to be a bidder in order to make money from real bidders), shilling is considered to be an instance of criminal fraud in the United States and elsewhere, with the most severe cases punishable by a jail term or heavy fines.

Shilling is typically defined in terms of *competitive shilling*, where the seller starts bidding so that the final bidder is forced to bid higher than would otherwise be necessary to win the auction item. Various researchers (e.g., Riley and Samuelson 1981; Wang, Hidvegi and Whinston 2001) have pointed out that, with competitive shilling, the final bidder is motivated to shave some surplus off the highest bidder by making that final bidder pay more. However, Kauffman and Wood (forthcoming) discuss other motivations for shilling and illustrate the prevalence of *reserve price shilling*, which is motivated by the avoidance of auction house fees. Online auction houses, like eBay, typically charge a fee that is determined by the amount a seller sets for the initial bid, while bidding is typically free. By setting a low starting bid, and then secretly bidding that amount up by pretending to be a bidder, sellers can save money when selling goods in online auctions. Furthermore, the chance of detection is low, since the names and faces of the actual bidders are hidden from the other bidders, unlike a typical traditional live auction where everyone can see who is bidding. Kauffman and Wood go on to describe how a *premium bid*, a bid which is higher than other bids for the same item in different auctions, is often a reserve price shill bid.

There has never been an empirical study to determine the effect of reserve price shill bids on final prices in an online auction. In this research, we ask the following questions:

- □ How may the final selling price in an online auction be affected by the existence of a shill bid?
- □ What theories can help to explain why a shill bid may or may not affect the final selling price of an item in an online auction?

- What are the implications of any effects that a shill bid has on the final selling price in an online auction?

In this research, we will test contradictory predictions based on *winner's curse theory* and *signaling theory*. Using a weighted least squares (**WLS**) estimation model, we discover that the existence of a premium bid in an online auction has a positive effect on the final selling price of the auction. If premium bids are reserve price shill bids, then this effect may increase the motivation for shilling activity among sellers.

THEORETICAL BACKGROUND

We next examine literature that provides the theoretical background for our understanding of how to model premium bidding and shilling as they relate to how final prices are established in online auctions. There are several conflicting opinions stand out based on works in the *reserve price shilling* literature, the *winner's curse* literature and the *signaling* literature for how a premium bid should affect the final price of an auction item.

Reserve Price Shilling and Premium Bidding

Shilling is the act of a seller or seller agent bidding on his own item in an effort to receive more for that item. Sinha and Greenleaf (2000) analyze optimal reserves and shilling related to bidder aggressiveness. They identify shilling as an issue because of the growing popularity of online auctions. Kauffman and Wood (2000) empirically demonstrate this by showing the characteristics of auctions that receive a premium bid. Wang, Hidvegi and Whinston (2001) modeled the basis for strong motivation for shilling to occur in electronic auctions on the Internet. They point out how traditional auction theory assumes a small number of identifiable bidders that bid in a single isolated auction that cannot be repeated, and that buyers and sellers possess perfect information to inform their transaction-making, and do not collude. In contrast, online auctions have many repeated auctions and many bidders. Also, identities of the bidders and sellers are masked behind a "handle," so often there is no way to discover the identity of the trading partner.

Kauffman and Wood (forthcoming) discuss premium bidding in detail. They define a *premium bid* as a bid in an auction that meets four criteria: (1) there must be two auctions selling the exact same item; (2) one auction, *Auction A* ends after the other auction, *Auction B*; (3) *Auction A* receives a bid from a bidder, when that bidder could have placed a lower bid on *Auction B* to become the winning bidder at that time; and finally, (4) the bidder who placed the high bid in *Auction A* did not bid on both auctions.

Although the requirements seem highly restrictive, the intuition behind this definition is clear. A bidder ought to be motivated to bid on the auction that ends first, since there is less time left in the auction and, thus, less of a chance that the bidder's bid will be beaten. Kauffman and Wood (forthcoming) discuss how such premium bids received in an auction are likely to be shill bids. Their logic involves an assessment of the consistency of a bidder's bidding behavior. Bidders who enter premium bids are: (1) more likely to buy items from fewer sellers; (2) more likely to drop out early from the auction; (3) more likely to bid in statistically higher increments compared to the previous bidder; and (4) less likely to win an auction.

Kauffman and Wood discuss how these four stylized facts are consistent with reserve price shilling, and not consistent with other possible explanations such as *seller preferences* (in that they are unlikely to win and drop out early) or *bounded rationality* (in that they concentrate on fewer sellers and bid in high increments as opposed to default increments). Furthermore, the authors also show that the likelihood of an auction receiving a premium bid can be detected prior to the beginning of an auction by making predictions that are consistent with reserve price shilling.

Kauffman and Wood develop a *reserve price shilling theory* that describes how auction sellers are motivated to shill in order to avoid auction house fees, since listing fees are often a function of starting bid price. This is different than the traditional view of *competitive shilling*, described by Riley and Samuelson (1981), where the seller is motivated to shill in order to capture more of the surplus from the buyer. In this case, the shill is unlikely to stay until the end of the auction.

Whereas Kauffman and Wood (forthcoming) use reserve price shilling theory to predict auctions that will receive a premium bid, in this research we examine what effect a premium bid has on the selling price (or final bid) for an auction item after the premium bid has been submitted.

The Winner's Curse Adjustment and Premium Bidding

Cox and Isaac (1984) describe the logic behind the winner's curse in auctions. Since bidders derive a common valuation of an item from a distribution of values, only the highest valuation will result in a bid that wins the auction. As a result, the highest valuation will typically be above the expected common value of most auction participants. Cox and Isaac explain how the winner's curse can be alleviated by bidding on an item based upon a bidder's valuation for that item *conditional upon winning that item*, rather than simply bidding the pure valuation. This exact adjustment can be derived using Nash equilibrium analysis and is called the *symmetric risk-neutral Nash equilibrium* (**SRNNE**) *adjustment*. Bajari and Hortacsu (2003) test for a winner's curse adjustment in rare coin auctions on eBay. Using a winner's curse test advocated by Milgrom and Weber (1982), the authors find that eBay participants <u>do</u> adjust somewhat for the winner's curse. Thus, based upon research done in traditional auctions, and the fact that Bajari and Hortascu found evidence of a winner's curse adjustment in an online auction setting, we also should see a decrease in the bid levels for items as a buyer's experience with online auctions increases.

Carrying this logic forward from Cox and Isaac into the present work, we expect that an exceptionally high bid for an item should make other bidders bid less. Why? Because an auction item that attracts aggressive bidders should increase the likelihood of observing a winner's curse, which, in turn, will increase the SRNNE adjustment that other bidders make when bidding on the item.

The "Signaling Effect" and Premium Bidding

Bapna (2003), Roth and Ockenfels (2002) and Varian (2000) investigate *bid sniping*, which occurs when a bidder waits until the final moments of the auction before bidding. Based on empirical data collected prior to 2000, Varian (2000) notes that 37% of bids occurred in the last minute, and 12% in the last 10 seconds of an auction, which shows that bid sniping behavior was already evident earlier in the evolution of the eBay auction. Roth and Ockenfels note that bids can be seen as *valuation signals* for an item. The longer the signal is delayed for an item, especially if the signal is avoided until the final bids, the lower the price will be. Bid sniping and letting chance determine the outcome is better for both players than bidding high early in the auction and then precipitating a bidding war because the signals suggest that an item is worth more than the current bid rate. Bapna (2003) suggests that there are a number of mechanism design options that permit auction intermediaries to refine the incentives with respect to last-minute bidding that enhance the benefits for the intermediary itself, as well as the participants of its market.

Building on Roth and Ockenfels' *valuation signal theory*, we believe that if a signal is received to suggest that an item is worth more than the current bid rate, then this should act as a signal to other bidders that an item is valuable. This should tend to drive up the final bid that an item in an auction receives. Note that this is the <u>opposite</u> of the *winner's curse extension*, which states that a high bid will increase a bidder's winner's curse adjustment, and drive down the overall final bid of an item in an auction.

HYPOTHESES

The purpose of this research is to examine electronic auctions with premium bids to determine their effects on the final bid amount. We begin with an extension to the winner's curse theory. In this theory, Cox and Isaac (1984) discuss how a large number of bidders indicates a greater likelihood that a bidder will receive a winner's curse. To alleviate this problem, sophisticated bidders will reduce their maximum bid as more bidders enter the bidding process.

Taking this logic further, sophisticated bidders should also adjust to a greater extent if there is an exuberant bidder who enters a premium bid, the logic being that a bidder who is bidding high will increase the probability of a winner's curse, since any winner will have to beat the exuberant bidder. Once the other bidders detect a premium bid, winner's curse theory suggests that the SRNNE adjustment for other bidders will increase. This leads to our first hypothesis.

- **Hypothesis 1 (The Winner's Curse Hypothesis)**: The existence of a premium bid within an auction will decrease the amount of the final bid on an auction item.

Conversely, Roth and Ockenfels (2002) propose that bids act as signals to other bidders about the quality of the item, which also includes the quality of service and honesty of the seller who is describing the item. As such, a premium bid may inflate the final price of an item, as bidders take the high bid as a signal of higher quality from buyers that may possess more information about the seller, the product, etc. This leads to our second hypothesis:

- **Hypothesis 2 (The Valuation Signal Hypothesis)**: The existence of a premium bid within an auction will increase the amount of the final bid on an auction item.

Finally, it is possible that rational and sophisticated bidders either believe that they already know as much as any other bidder, or that they understand that reserve price shilling can occur. As such, bidders will ignore the presence of a premium bid, and the final bid for an item will end up being the same as it would have been without the premium bid. This leads to our third hypothesis.

- **Hypothesis 3 (The Rational Bidder Hypothesis):** Observed premium bidding activity in electronic auctions has no effect on the final bid amount.

Thus, we have three competing hypotheses, each based upon theory, that predict different outcomes for the effect of a premium bid on the final selling price in an auction. Note that Kauffman and Wood (2000) have shown that the premium bids hardly win (8% of the time) compared with non-premium bids (23% of the time). When other bidders detect the premium bid on an item, then, we question what will be the effect that this has on their final bid.

EMPIRICAL MODEL, DATA AND ESTIMATION ISSUES

We now turn to the development of an empirical model to investigate the effects of premium bids on the final selling price of items that are transacted in online auctions. We also discuss the data that we collected for this study, as well as a number of issues that deserve attention prior to our estimation of the data, to ensure that we are appropriately handling the information structure of the empirical setting that is being considered.

Basic Specification of the Empirical Model

The starting point for our discussion is the primary hypothesized relationship that we presented in the last section: we argued that selling price, specified as the variable *SellingPrice*, is a function of whether an auction for an item is observed to received premium bids, also specified as the variable *AuctionHasPremiumBid*. Table 1 presents definitions for these two variables, and some others that we will discuss in greater depth in the development of our estimation model.

Table 1. Definitions of the Variables in the Model

VARIABLE	DEFINITION
□ ***Dependent Variable***	
$ln(SellingPrice_{asc} / AverageSellingPrice_{c-a})$	The *LogSellingPriceRatio*, the final *SellingPrice* for the item in an *auction a* selling *coin c* by *seller s*, expressed as a natural log ratio to the *AverageSellingPrice* for auctions selling *coin c* (calculated by excluding the selling price from *auction a*)
□ ***Independent Variables***	
$AuctionHasPremiumBid_a$	Dummy variable indicating whether *auction a* receives a premium bid
$WeekendSale_a$	Dummy variable indicating whether *auction a* ends on a weekend
$NumberBidders_a$	The number of bidders who bid in *auction a*
$ln(StartingBid_a / AverageSellingPrice_{c-a})$	The level of starting bid in *auction a*, expressed as a ratio to the average selling price for auctions selling *coin c* (calculated by excluding the selling price from *auction a*)
$AuctionHasPicture_a$	Dummy variable indicating whether the item description for *auction a* contains a picture
$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$	Regression parameters for the independent variables
ε_{asc}	Randomly distributed regression estimation errors for the final *LogSellingPriceRatio*, with a mean of zero
γ	Model intercept

To get a clearer understanding of the role of premium bids, we must also control for other factors that are likely to have an impact on the final bid price for the auction. Kauffman and

Wood (forthcoming) model a number of other factors that have been shown to affect how much an individual is likely to pay for an item that is purchased in an online auction. By examining bidder behavior on *losing bids* in a within-bidder quasi-experiment, Kauffman and Wood show how various factors affect bid levels. They find the ending time of the auction (whether on a weekend or not), the number of bidders, the level of the starting bid, and the existence of a picture affect the final selling price of an item in an online auction. Note, however, that only losing bids were examined, so that a bidder's final valuation can be determined. In the present study, we are examining the final selling price of an item, which may lead to somewhat different results. However, we use the prior work to help guide selection of the control variables.

Building on this prior work, our preliminary model for the present research is as follows:

$$ln(SellingPrice_{asc} / AverageSellingPrice_{c\text{-}a}) =$$

$$\gamma + \beta_1\ AuctionHasPremiumBid_a + \beta_2\ WeekendSale_a + \beta_3\ NumberBidders_a$$

$$+ \beta_4\ Log\ (StartingBid / AverageSellingPrice_{c\text{-}a}) \quad + \beta_5\ AuctionHasPicture_a + \varepsilon_{asc} \quad (1)$$

Thus, we incorporate variables that are shown to affect an individual's bidding price as control variables, so that we can better determine the effect of the $AuctionHasPremiumBid_a$ independent variable on the selling price (or final bid) in an online auction.

Data

Using a customized Internet agent, we collected data on rare coin auctions on eBay, including auction characteristics, item characteristics, and seller characteristics, among other information. The data collection agent employed an algorithm to identify coins that were sold in individual auctions. It returned the year of the coin (e.g., 1999), the coin denomination (e.g., nickel, quarter, etc.) and the coin type (e.g., New Orleans mint, double die, etc.). The grade of a coin grade is communicated using a language known to collectors that specifies a grade between

3 and 70. The resulting data include 10,260 rare coin auctions on eBay that occurred during April 2001. This data set, in turn, was filtered to only select auctions whose coins are concurrently sold within another auction. This resulted in 1,389 auctions from 493 distinct sellers and 1,314 distinct bidders. We refer to this overall procedure as *massive quasi-experimental data collection* (Kauffman and Wood, 2003). The general idea is that tools similar to the data collection software agent that we used permit "rifle shot" targeting of data items to be collected from much larger stores of data, such as are available on the Internet, to match the precise requirements for examining effects that are only likely to occur under a certain set of quasi-controlled conditions.

Estimation Issues for the Empirical Model

A number of estimation issues arise in our technical specification of an empirical model. In the paragraphs below, we discuss issues of correlation and multicollinearity, estimation efficiency and unobservable characteristics, and our approach to dealing with heteroskedastic residuals through the use of weighted least squares (**WLS**). We also discuss the statistical power that will characterize our tests of the hypotheses.

Efficiency, Unobservable Characteristics, Heteroskedasticity, and Weights. Kennedy (1998, p 15.) identifies *estimation efficiency* as a means of obtaining a *best linear unbiased estimator* in linear regression. An *efficient estimator* is "best" in the sense that it takes advantage of all of the relevant information that is associated with a given estimation problem. As a result, the model that is formulated will capture the relationship between a dependent variable and multiple dependent variables, resulting in the lowest possible error term or regression residual. An *unbiased estimator* is an estimator where the residuals are "constant:" they will be evenly distributed among all variables, without undue bias associated with any single independent variable. Typically, *ordinary least squares* (**OLS**) *regression* models assume that the residuals are distributed evenly relative to the independent variables with a mean of zero.

To maintain estimation efficiency, we analyzed this data set at the auction level. However, there are likely to be unobservable seller level characteristics, such as the propensity to shill, quality of presentation, feeling toward partners, and so on that cannot be directly observed. If these unobservable user characteristics are indeed evenly distributed among all users—a reasonable entry assumption in this research—then analysis at the user level ought to exhibit *homoskedasticity* of the residuals. As a result, the regression residuals will very likely capture these unobservable characteristics, and the error terms will still be evenly distributed.

However, if the analysis occurs at the user level, leading to homoskedastic residuals by individual, then by mathematical necessity, an analysis that is done to capture an individual's participation in several auctions will result in an information structure problem for estimation. We expect that the magnitude of the residuals of the highly active users will be smaller than those of the less active users. Moreover, the unobservable characteristics of highly active users are likely to be over-represented in the auction-level analysis, leading to biased estimators. This apparent heteroskedasticity will violate one of the basic assumptions necessary for OLS regression analysis.

Information structure problems with regression residuals can arise from both *known sources* and *unknown sources* of heteroskedasticity. We will argue in this study that the sub-sample size for each seller's bid-making participation in eBay auctions is a known source of heteroskedasticity. Following Duliba, Kauffman, and Lucas (2001), to test for *known-source heteroskedasticity*, we employ employ a test attributable to Goldfeld-Quandt (1965). This test is performed by splitting the dataset into two subsets and then comparing the error terms of each subset with an F-test. We split the data set into those sellers that have a low number of transactions and those sellers that have a high number of transactions within the dataset. As expected, we find that there is significant heteroskedasticity resulting from the number of transactions that each seller has in the study, as indicated by the Goldfeld-Quandt test (F-statistic = 1.56; $p < .001$).

To resolve the problem of known-source heteroskedasticity, Wooldridge (2003) suggests applying weights, which will cause some observations to be given more importance than others so as to create the basis for homoskedastic residuals through model estimation. To accomplish this, we weighted each observation in our data set by the inverse of the number of auctions in which that auction's item buyer participated. Thus, each observation of an active buyer is adjusted in weight so that every buyer contributes at the same level, restoring the homoskedasticity of the model, yet still every observation will add information to the regression analysis.

We also tested for heteroskedasticity using a less restrictive test advocated by Breusch and Pagan (1979) that can identify unknown-source heteroskedasticity both before and after weighting the observations. With five degrees of freedom, the test before weighting returns a significant value of $\chi^2 = 22.4$ ($p < .001$). After correcting for heteroskedasticity by weighting the observation, the test returns a value of $\chi^2 = 7.5$, which is not highly significant ($p > .05$). Thus, with our correction for a known source of heteroskedasticity, our subsequent Breusch-Pagan test shows no further significant problems with heteroskedasticity.

Collinearity and Multicollinearity. We first examined the pairwise correlations between independent variables. We note that the greatest correlation is 63%, between *ln(StartingBid / AverageSellingPrice)* and *NumberBidders*, as shown in Table 2. Pairwise correlations among all variables are below the criterion level of 90% suggested by Kennedy (1998), where problems may occur. We typically prefer to work with a more conservative cutoff of 70%, and the pairwise correlations in our data are all less than that. Thus, our regression estimates are unlikely to be corrupted due to collinearity between two estimators.

Table 2. Correlation Matrix in Equation 2 Analysis

VARIABLES	*AuctionHas PremiumBid*	*Weekend Sale*	*Number Bidders*	*ln (StartingBid / Average SellingPrice)*	*Auction Has Picture*
AuctionHasPremiumBid	1.00				
WeekendSale	-0.08	1.00			
NumberBidders	0.14	-0.02	1.00		
ln(StartingBid / AverageSellingPrice)	-0.06	0.02	-0.63	1.00	
AuctionHasPicture	0.10	-0.11	0.18	-0.10	1.00

Another issue is multicollinearity. Both a *condition index* test and a *variance inflation factor* (**VIF**) test typically are used to test for *multicollinearity* between one independent variable and a mathematical combination of other independent variables. Greene (2002) states that a condition index greater than 20 can be indicative of multicollinearity. Our condition index is 5.87. Hocking (1996) suggests that any VIF greater than 10 is indicative of multicollinearity. Each of our independent variables measures a VIF of less than 2. Thus, both the condition index test and the VIF test indicate that our coefficient estimates will not be unstable due to multicollinearity.

The Issue of Statistical Power

Earlier, we indicated that there are conflicting theoretical predictions about the effect of a premium bid on the final bid price in an auction. For example, our rational bidder hypothesis predicts that if bidders recognize that a premium bid is a reserve price shill bid, then the premium bid will have little or no effect on the final selling price, and the effect should be insignificant. However, regression tests are not sufficient to accept a null hypothesis (i.e., a null hypothesis indicates no significant difference from zero). Instead, one should only *accept* or *fail to accept* an alternative hypothesis to be true. When we fail to reject the null hypothesis, this does not mean that the null hypothesis is true and the alternative hypothesis is false. If our models indicate some lack of fit in estimation, then we need a way to determine if our models actually are powerful enough to be able to detect significance.

Andrews (1989) points out that a common problem in econometric analysis is how to interpret results when a test fails to reject a hypothesis, as we suspect may happen when forming the measures of risk. He recommends *power analysis* to enable the analyst to test a model for the likelihood of failing to reject a false null hypothesis. In other words, power tests enable an analyst to determine the likelihood of failing to find significance in a model when, in truth, there actually is a relationship.

Power analysis makes a distinction between different error types. Cohen (1988) argues that any statistical test has the possibility of a *Type II error*, where a rejected model or parameter is actually valid. He also argues that there is a chance of a *Type I error*, where the explanatory capability of a model or a single parameter are invalid, but they still end up being accepted due to statistical significance. Normal statistical inferences test for a Type I error. This may occur, for example, when a test is significant with a *p*-value of less than 5%. (This means that there is a 5% probability of a Type I error, and thus a 95% probability of no Type I error.) In this case, we also want to test for the probability of a Type II error. (That occurs when the estimated value of β is statistically the same as zero and the alternative hypothesis is true, but we do not find enough evidence to reject the null hypothesis).

Cohen describes how power analysis exploits the relationships among the four variables involved in statistical inference:

- N, the sample size is the number of observations.
- α, the significance criterion, often stated in terms of the p-value, is the probability that a Type I error will occur.
- $1 - \beta$, the statistical power, is the probability that a Type II error will not occur.
- the population effect size.

Note that the significance of β (based on its relationship to the p-value) is an indicator for whether a Type II error will occur. The population effect size is easily the most complicated of these measures. The effect size begins with estimation by the researcher as to the level of effect. The smaller the effect size, the more conservative the test.

By using a power test in conjunction with another statistical method, such as weighted least squares regression, we can more fully examine the probabilities of both Type I and Type II errors. Table 3 shows the power analysis for a model with five independent variables and a sample size of 1,389. The table also shows the power analysis for this study's sample size of 1,389 observations of final bids in eBay auction, with R^2 varying from 1% to 4%.

Table 3. *Post Hoc* Power Analysis for a Five Predictor Model

VARIABLES FOR STATISTICAL INFERENCE	SMALL EFFECT SIZES (BASED ON R^2)			
R^2	.01	.02	.03	.04
α (p-value criterion required for significance)	.05	.05	.05	.05
N (sample size)	1,389	1,389	1,389	1,389
Statistical power (probability no Type II error)	0.838	0.993	0.999+	0.999+

Notes: Effect size is often specified in terms of R^2. Faul and Erdfelder (1992) provide a tool called GPOWER that performs the *post hoc* power test with multiple predictors used here. They recommend $R^2 = 4\%$ as the criterion for small effects evaluation.

Small effects are often difficult to detect because of sample size limitations. However, our data collection methodology allows for larger data sets through its use of a data collection software agent. This also permits our econometric analysis to obtain enough statistical power to determine if the hypothesized relationships exist among the study variables. Models built with sample sizes of 1,389 observations of the dependent variable are powerful relative to the five explanatory variables. This is true to such an extent that, with a restriction of $\alpha < .05$, there is less than a 0.01% probability of statistically rejecting any relationship with R^2 that is greater than 3%. This matches the requirements set out by Faul and Erdfelder (1992) of a small effect size. With the results in Table 3, we illustrate that our tests are powerful, and can statistically accept hypotheses involving a lack of relationship if they are shown to be insignificant by concluding that either: (1) there is no relationship between the dependent variable and the independent variable; or (2) the relationship is so small as to be practically and statistically insignificant and, thus, undetectable.

RESULTS

Table 4 shows our results from analysis of our empirical model shown in Equation 1, weighted by the seller's number of auctions within our dataset.

Table 4. Weighted Least Squares Regression Estimation Results

MODEL VARIABLES	ESTIMATED COEFFICIENT	STD. ERROR	t-STAT
γ (intercept)	-0.412	0.036	-11.498***
AuctionHasPremiumBid	0.241	0.031	7.896***
WeekendSale	0.053	0.033	1.615
NumberBidders	0.073	0.007	10.256***
ln(StartingBid / AverageSellingPrice)	0.159	0.016	9.982***
AuctionHasPicture	0.089	0.035	2.532**

Note: ** = $p < .05$; *** = $p < .001$; R^2=.224; number of auctions (observations) = 1,389; dependent variable is selling price [$ln(SellingPrice_{asc} / AverageSellingPrice_{c-a})$]

In Table 4, we can see that, after using weights to adjust for the idiosyncratic bidding behavior and the attraction of certain sellers, there is a positive effect on price (β_1 = 0.241; std. dev. = 7.896; p = .001) when an auction receives a premium bid, thus supporting our Valuation

Signal Hypothesis.[1] Thus, bidders are influenced to bid higher when they see an auction receiving a premium bid.

Kauffman and Wood (2004) point out that early reserve price shilling behavior has frequently occurred in online auctions, and this research identifies some of the motivation for such behavior. Reserve price shilling reduces the fees paid by the seller, and can have a positive effect on price. Thus, many sellers will be motivated to enter a reserve price shill bid after setting up an auction with a low starting bid. We next discuss how we interpret these results with the thought that premium bids may be indicative of reserve price shilling. We then describe possible alternative interpretations, and why we do not consider those to be as viable.

Interpretation

It is important to be able to recognize premium bids and why they may occur in large part as reserve price shill bids that are entered by the seller under a different identity, or by an agent of the seller. For further insight, Table 5 shows the results of three non-parametric t-tests that compare the bidding activity with auctions that contain a premium bid with those that do not. Consider the premium bidding comparative statistics in Table 5, using the variables described in Table 6.

[1] Note also that the *Weekend* bid is not significant, as was reported by Kauffman and Wood (forthcoming). The forthcoming study involves a multi-year within bidder study. The present study uses weighted least squares regression at the auction level. Nonetheless, the bid amount shows low significance (p-value = .106). Future research can be done to determine if the weekend effect weakens as the number of bidders on eBay increases, thus making for a more efficient market, with greater liquidity and depth.

Table 5. Premium Bidding Comparative Statistics

VARIABLE	AUCTIONS/BIDDERS WITH PREMIUM BIDS			AUCTIONS/BIDDERS WITHOUT PREMIUM BIDS			t-STAT
	Mean	*Std. Dev.*	*N*	*Mean*	*Std. Dev.*	*N*	
BidderAuctions/Seller	2.17	1.94	584	1.66	1.18	730	5.63***
AuctionDaysLeft	4.64	2.71	845	1.85	2.52	6222	28.22***
PercentWins	23.2%	0.42	845	29.8%	0.46	6222	-4.23***

Note: *** = $p < .001$. *The BidderAuctions/Seller* analysis is at the *bidder* level. *AuctionDaysLeft* and *PercentWins* analysis are at the *auction/bidder* level.

Table 6. Definitions of the Variables Used in the Non-Parametric t-Test

VARIABLE	DESCRIPTION
BidderAuctions/Seller	This describes the number of auctions per seller that a bidder bids upon. A high number indicates that the bidder goes to the same seller more often. For example, if a bidder bids on 10 auctions from 2 sellers, her *BidderAuctions/Seller* measurement would be equal to 10 / 2 = 5.
AuctionDaysLeft	This describes the number of days left in an auction when a bidder places her final bid.
PercentWins	This describes the percentage of items that are won by a bidder.

We have already shown that a premium bidder enters a bid amount larger than the typical bidder. Now we examine other statistics with reserve price shilling in mind. Primarily, we expect a reserve price shill to enter a premium bid. Why? Because a bidder who shills on the reserve price (1) does not care about other auctions, but rather only on inflating his own auction's price and (2) the reserve price shill will bid in higher increments in an effort to inflate the minimum selling price of an item, and not the minimum price that the item is likely to sell for.

We expect a reserve price shill to concentrate on fewer sellers. If a seller is likely to shill, then that seller will establish a bidder identity that is used to bid on items from that seller's identities, which would increase the number of auctions per seller where the bidder engages. In Table 5, we show that bidders enter premium bids bid upon 2.17 different auctions per seller in this dataset, whereas those bidders who were not detected entering premium bids only bid upon 1.39 auctions per seller, a significantly lower number.

We also expect a reserve price shill to drop out of bidding early compared with other bidders. In Table 5, we show that reserve price shills drop out, on the average, 4.64 days before the auction ends. Other bidders drop out, on average, 1.85 days before the auction ends. Thus, we see a bidder who enters a premium bid, yet does not want to bid higher.

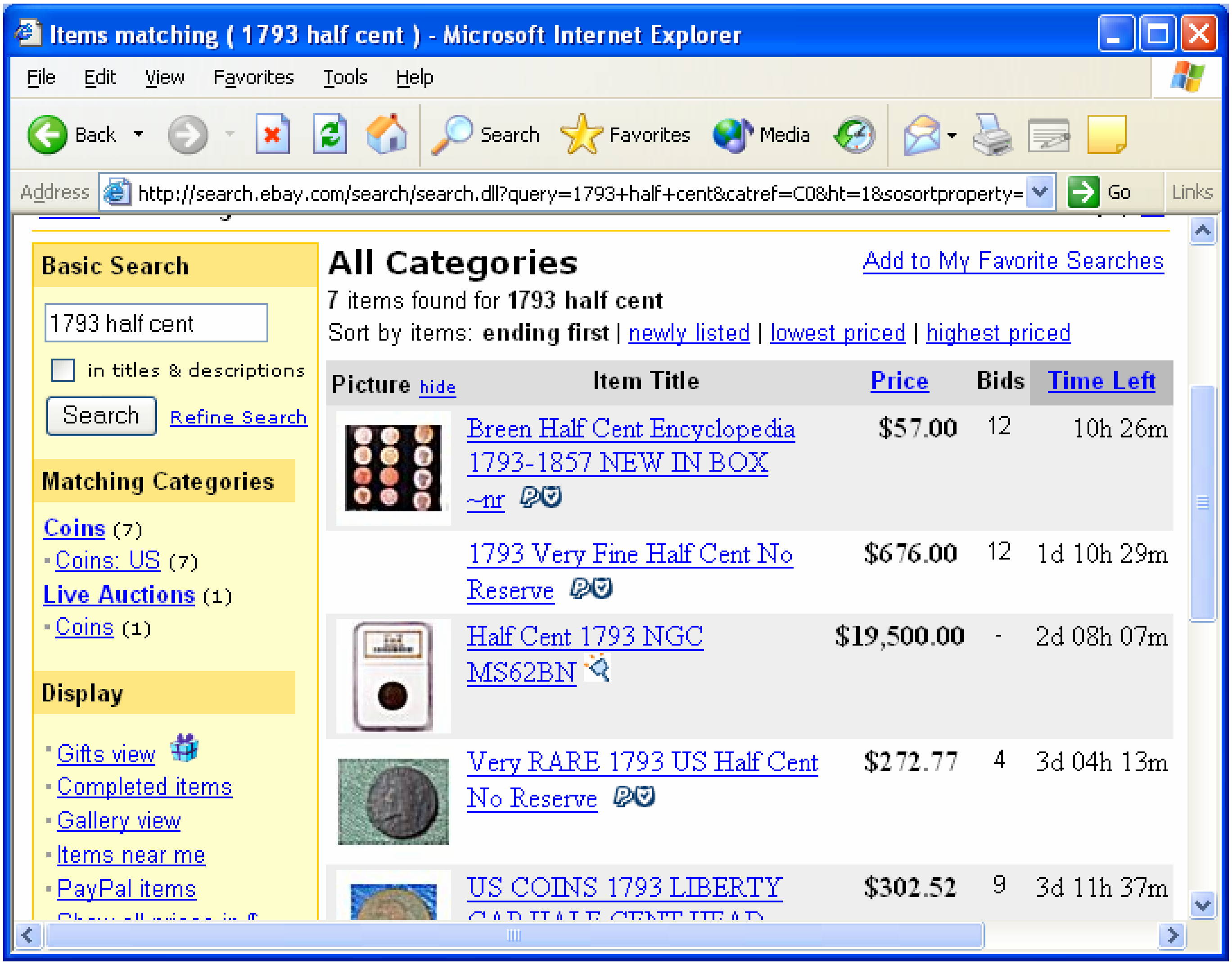
Finally, we show that when there is a premium bidder who enters a high bid, that premium bidder is less likely to win the auction. For a reserve price shill, we interpret this to mean that the seller will enter a high bid early in the auction, but, of course, the seller will not want to win the auction but rather will want to bid high enough to reduce the risk of a low selling price, but low enough so that other bidders are attracted to the auction.

Alternative Explanations

We now examine two alternative explanations for premium bidding besides reserve price shilling: bounded rationality and seller preference.

Bounded Rationality. It is possible that bidders are confused about the myriad of auctions available on eBay and, thus, may mistakenly bid on products where the ending bid is later and that are selling for more. We find this explanation to be somewhat unlikely for two reasons. *First*, Kagel and Richard (2001) show us that inexperienced bidders are more likely to continue with a high bidding and win the auction. Thus, inexperienced bidders, who are most likely to be exhibit the effects of the bounds of their lack of experiential knowledge, are not as likely drop out early, as shown by the test results in Table 5. *Second*, eBay places search results in *ending date order* by default. Figure 1 shows the search results for the "1793 United States half cent." The bidder's search display lists auctions for this collectible coin at the top of the list that end first, based on "Time Left" in the right-hand column; auctions for the same item that end later are displayed further down in the list.

Figure 1. Search Results for the "1793 United States Half Cent" on eBay



Similarly, if a user simply goes to a category without searching, items are displayed in reverse date order based "Time Left." Thus, it is difficult to imagine that even an inexperienced user would often find a later ending auction before an earlier ending auction. A premium bid may be made by a bidder when another auction that ends earlier is overlooked or ignored by the bidder in favor of an auction selling the same item for a higher price. Given the Web design of eBay that we observe, we believe that premium bidding behavior is difficult to attribute to bounded rationality.

Seller Preference. Another possibility is that a bidder will enter a high bid because that bidder prefers to transact with one seller over another. However, while this undoubtedly contributes at some level to premium bidding, we contend that seller preference is not the primary driver of premium bidding. With 493 successful sellers and 1,314 bidders, each seller had bids, on average, from 2.7 bidders. Thus, there is a wide dispersion between bidders and sellers in online auctions, too much to indicate that there is one seller who is clearly preferred over another by a majority of bidders at the auction level. In addition, although seller preference can explain how premium bidders may be observed to aggregate around a single seller, seller preference cannot explain why these premium bidders do not end up winning items at the same level. Nor does it explain why these premium bidders tend to drop out earlier. As such, we conclude that reserve price shilling as a motivation for premium bidding is more consistent with the statistical analysis shown in Table 5 than seller preference as motivation for premium bidding.

LIMITATIONS AND EXTENSIONS

This study has a number of limitations. *First*, we only investigated coin auctions in this research, so our results should not be generalized to other areas without care and consideration of the underlying context that is present. We believe this to be true for several main reasons:

- Unlike most auctions, the strong language and standardized references to "coin condition" and "coin type" in coin collecting facilitates the examination and assessment of rare coins by bidders in online auctions.

- Trade studies have shown that coin collectors tend to be somewhat older and somewhat more affluent than many other online auction enthusiasts.
- Rare coins, for the most part, sell for under $100. Thus, our results may not be applicable to more expensive products sold in online auctions, such as automobiles (Lee, 1999).

Nonetheless, we assert that this research yields insights that are relevant for understanding other analogous auction formats, and call for future research into premium bidding within other auction formats.

Second, we have shown now an operationalization for premium bidding to proxy for reserve price shilling can be effective. However, such an operationalization is predisposed to include more cases where the shill bids in extremely high dollar amounts (as a ratio of the common value). It does not favor the fewer cases where the shill bids in small dollar amounts, below the current dollar bid level of identical items sold in other auctions. However, for our results, this limitation results in a more conservative estimate of shilling behavior. So we believe that the results would actually be stronger than indicated by the present study if we had definitive data indicating whether each seller actually was a shill bidder. Furthermore, this limitation makes it difficult to use this methodology to catch *competitive shilling* (as opposed to reserve price shilling) that occurs in the final minutes of an auction. Thus, we also call for a different empirical methodology to be developed that can be used to test for the presence of competitive shilling as auctions come to a close.

Third, we only examined bidding and seller behavior on eBay, and not other auctions. However, many competing auctions, such as Amazon and Yahoo!, have mimicked eBay's fee structure and auction design. So though we only studied eBay, our results should carry through to many other auctions that look to eBay for guidance on online auction system design.

CONCLUSION

This paper is the first to examine the effect that a premium bid, usually entered in the middle of an auction and usually not the winning bid, has upon the final selling price in online auctions. We develop a weighted least squares regression empirical model to examine the contrary predictions made by extensions to existing auction theory in an attempt to explain why premium bids can affect the final selling price. We find that a premium bid acts as a signal to other bidders that a higher bid is appropriate.

As with Kauffman and Wood's (forthcoming) research, we find that premium bidding is best motivated and explained by reserve price shilling, where a bidder enters a low starting bid and then bids on his own item to avoid paying auction house fees that are tied to starting bid level. We also examine two other likely explanations for premium bidding (e.g., bounded rationality and seller preference), and find that reserve price shilling is more consistent with the statistical results than the other two explanations.

Our findings suggest that not only are sellers motivated by eBay's fee structure to enter a reserve price shill bid, but doing so may make their auction more attractive to other bidders who look at premium bids as a signal of an item's worth within an auction. As such, reserve price shilling may have a more detrimental effect than only avoiding auction house fees.

Reputation and controls on opportunistic behavior are important to maintaining viable market transactions. As such, this research can be viewed as a call to auction houses on the Internet to place more controls on user identification and user activities to avoid the practice of shilling.

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