# PREMIUM BIDDING IN ONLINE AUCTIONS
*An Examination of Opportunism and Seller Preference*

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## ABSTRACT

We investigate *premium bidding* in online auctions, where an item receives a higher bid than other identical items that currently are for sale and available for a lower bid. We report empirical results that find that premium bidding shares many characteristics with *shill bidding*, where a seller establishes a new identity to bid on his own product. The results lead us to believe that much of the premium bidding on eBay is, in actuality, shill bidding. Although the Internet is useful for transferring information between buyers and sellers, transactions in Internet auctions can have a greater *information asymmetry* than corresponding transactions in traditional environments. This is because current auction market mechanisms allow the seller to remain anonymous and to easily change identities. In fact, Internet auction environments make opportunistic behavior more attractive to sellers because the chances of detection and punishment are decreased. In this research, we show how fee structures in online auctions may motivate shilling behavior. We distinguish between two different types of shilling that exhibit different motivations and behaviors: *competitive shilling* can be used to make the bidders pay more for an item, and reserve price shilling can be used to avoid paying auction house fees. We then use data on 10,234 eBay auctions during April 2001, with 30,395 bids on 6,954 of these auctions from 2,015 distinct bidders and 1,373 distinct sellers, to analyze a probit model that allows us to test for evidence of reserve price shilling. Our results show that with reserve price shilling, bidders tend to exhibit repetitive bidding behavior patterns, and also book value and starting bids are indicative of reserve price shilling.

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**Keywords**: Economic analysis, electronic markets, empirical research, fraud detection, information asymmetry, Internet auctions, opportunism, premium bidding, shilling.

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**INTRODUCTION**

E-commerce has brought about new ways of conducting transactions with customers. Online

auctions have emerged as a result of the transformations brought about by Internet technology.

Firms such as eBay, Amazon, and Yahoo! host auctions that join millions of sellers to millions of

buyers. The transfer of information in online auction environments is worthy of study, especially

to examine how information flows in online auction transactions, and the effects that this flow of

information have on the actions of buyers and sellers. Many researchers have discussed how

electronic markets reduce price dispersion because pricing information is so readily available in

electronic markets (e.g., Bakos 1997; Malone et al. 1987). However, sellers in online auctions

are often anonymous and products they sell often cannot be examined before payment. This is

the case for online auctions, which involve less transfer of information about product features

and quality between the buyer and an anonymous seller.

Seller opportunism is facilitated by the limited information about the seller that is available to

the buyer. In online auctions, sellers can remain anonymous. Sellers can even establish multiple

anonymous buyer and seller identities, thus allowing them to take advantage of anonymity to act

opportunistically, adopting and abandoning seller identities as they wish. [1] According to the

National Consumers' League (2005 NCL, www.fraud.org), in the first half of 2005, 44% of all

Internet fraud was occurring in the context of online auctions, for an average loss to the

consumer of $999 ($765). The NCL's 2005 report continues: "In the fall of 2003, the online

auction giant eBay removed the link from its Web site to the National Consumers League's fraud

center. As a result, the number of auction complaints reported to NCL has dropped to one-sixth

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[1] A Harris Poll Report survey (www.harrispollonline.com) (National Consumers' League 2001) states that 41% of buyers in online auctions have had problems: 20% received items sometimes later than expected, 11% received items different than the seller promised, 10% received damaged items, and another 10% never received items.

of the previous level. NCL estimates that the fraud center would have received 13,062 (32,916) auction complaints in 2005, representing 82% [of likely complaints]."

Because price information for identical or similar products is available within the online auction environment, a high level of price sensitivity should exist in online auctions (e.g., Bakos 1997). Notwithstanding the availability of pricing information, however, there are often products that receive premium bids. A *premium bid* occurs when a bidder in an auction can make a lower bid on the exact same item in a different, concurrent auction. Though sellers are not easily identified in online auctions, and sellers may not have a wide range of products available concurrently, seller preference may still result in premium bids. In this context, we ask:

- ❏ What are the primary drivers of an auction receiving premium bids?
- ❏ Does seller opportunism empirically affect premium bidding? If so, how?
- ❏ What empirical evidence is there to show that auctions receive premium bids?

To answer these questions, we examine two sets of literature. First, IS research has explored how *good reputation* can lead to price premiums (e.g., Ba and Pavlou 2002). Economics research on reputation and price premiums agrees with this finding, but also discusses how the development of a good reputation is contingent upon the benefits of acting opportunistically less the costs of opportunistic actions if detected (e.g., Shapiro 1982). On the Internet, *information asymmetry* between the seller and the buyer is *often increased* with regard to seller information, meaning that only the seller has complete access to seller information. Information about the seller is only available to the buyer if the seller chooses to share it. Akerlof (1970), Shapiro (1982), and Klein and Leffner (1979) bring up that an increase in information asymmetry can result in opportunistic behavior because the chance of detection of opportunistic behavior is reduced, thus making it more profitable to act opportunistically.

Of particular interest is the possible observation of *shilling*, an opportunistic and often

fraudulent practice where sellers establish new identities to bid on their own products. MSNBC reported that "[s]hilling is a holdover from brick-and-mortar auctions, but it is far harder to detect on the Internet, where anonymity and easy-to-shed electronic identities make it easy for a seller to single-handedly orchestrate a shilling without tipping off a legitimate bidder" (Brunker 2000).

We collected bid, bidder, seller, auction, and item data records. The results of our analysis are consistent with the contention that sellers use shilling to avoid auction house fees. Further, these shill bids are the primary source of premium bids. We find that seller preference is not the primary driver of premium bids. We introduce the concept of *reserve price shilling*, which occurs when a seller shills to reduce listing fees (i.e., fees that the seller pays to list an auction, which increase with the auction's declared starting bid). We provide evidence that reserve price shilling is the primary driver of premium bidding. [2]

**THEORETICAL BACKGROUND**

Economists have offered useful perspectives regarding auctions, both online and traditional, including Vickery (1961), Milgrom (1989), and Riley and Samuelson (1981). In addition, other sources have given useful insights into how technologies have changed online auction dynamics so that they differ from traditional auctions. These include IS, finance and cognitive science.

**Economic Perspectives on Valuation**

Auction theory in economics stresses the importance of a bidder's value of an item. Some

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[2] *Reserve price shilling* contrasts with *competitive shilling,* where the seller bids on his own item to run up the final bid amount. When researchers and practitioners discuss shilling, they are typically discussing competitive shilling. With competitive shilling, the seller would sell the item for the bid price, but feels that the high bidder is "shading" her bid by not bidding her true valuation. Competitive shilling by the seller targets the *final bidder*, the person who makes the final bid to win the auction, by capturing more of the final bidder's surplus, whereas reserve price shilling targets the auction house. See Riley and Samuelson (1981) for an in-depth discussion of competitive shilling.

literature assumes *common values* (e.g., Athey and Levin 2001; Bulow et al. 1999), where all bidders share the same valuation of the auctioned item. Other literature assumes *independent private values* (e.g., Tschantz et al. 2000), where each bidder can have a unique valuation. In this research, we examine rare coins, but not coins that are extremely rare. In fact, two identical coins (defined in terms of the same year, denomination, condition, and identical mint marks) need to be selling at the same time from different sellers to be considered for this study. Hence, we assume common values, since there is a public market for the goods, and bidders can easily discover the price of nearly identical items. For the coin auctions, we use *book value* listings from *Coin World* (Gibbs 2000), the "industry bible," as a proxy for common value. [3] Most coin dealers agree that this book value listing represents how much a coin is worth to a collector, and thus is a good representation of a coin's common value.

**Perspectives on Premium Bidding**

We examine how different factors can lead to higher bids in an online auction. Ba and Pavlou (2002) argue that seller reputations lead to higher bids. Other research in traditional markets discusses how buyers are willing to pay a premium price for reputable behavior (e.g., Shapiro 1982, Klein and Leffler 1981). Research that examines premium bidding also needs to consider seller preference as a motivation for higher bids. Auction characteristics, such as weekend bidding and the existence of a picture, can also have an effect on premium bids. For instance, both Kauffman and Wood (2006) and Lucking-Reiley (1999) find factors such as pictures or auction timing can affect the price received in an online auction.

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[3] Price listings for rare coins, like those found in *Coin World*, have been available and used by coin resellers for decades. Rare coins on eBay sell for, on average, about 60% of their book value listed in *Coin World*.

**IT and the Facilitation of Shilling**

In addition to being caused by seller or auction preference, we contend that premium bidding may be the result of shilling, where the seller, masquerading as a bidder, bids a high amount in order to avoid fees or to coerce the final bidder to pay more. Traditional auction theory assumes that a small number of identifiable bidders bid in a single isolated auction that cannot be repeated and that buyers and sellers possess perfect information to inform their transaction-making (Hidvegi et al. 2005, Wang et al. 2004). These assumptions are not true in online auctions where the buyer cannot examine seller and product characteristics until after the transaction is complete. Wang et al. (2004) note how seller anonymity can lead to shilling behavior.

A number of analytical models have been proposed for how intermediary fees can be used to limit shilling online. Sinha and Greenleaf (2000) analyze optimal reserve prices and shilling related to bidder aggressiveness. Hidvegi et al. (2005) and Wang et al. (2004) have proposed the idea of a "shill-proof intermediation fee schedule" in the context of single-round, independent private value English auctions with continuous bidding.

**Opportunism, Information Asymmetries and Reputation on the Internet**

Other authors have investigated how information asymmetries can lead to a mismatch in the promised quality of a product versus what is eventually received by the buyer. Akerlof (1970) discussed how markets with high information asymmetry diminish transactability because buyers believe that sellers will act opportunistically. Akerlof examines "lemons" in the used car market and notes that car buyers will assume the lowest quality and thus not pay additional amounts for a high quality car. The result is a market failure since sellers of high quality cars will be unable to transact at a price that reflects value. Klein and Leffler (1981) analyzed how opportunistic behavior will occur when the profit from misleading customers is greater than the profit from

lost sales due to reputation effects. Shapiro (1982) discussed how, when sellers control a market, product quality is reduced if products cannot be fully and accurately evaluated before the purchase. Central to these papers' models is the punishment given when a seller is caught misrepresenting product or identity. The Internet changes the way a seller's information flows from the seller to the buyer. Anonymous Internet transactions allow sellers to mask their identities, increasing information asymmetry and reducing chances of detection and punishment.

There are many papers (e.g., Bakos 1997) that discuss how information asymmetry is decreased in electronic markets with respect to prices since prices are more easily searchable and thus it is difficult for one online vendor to charge a price premium over another for an identical product. However, in areas of identity and product quality, other authors point out that there is an increase in information asymmetry with regard to seller and product information (e.g., Dellarocas 2003), and that this information is only available to the buyer if the information is accurately provided by the seller. This information asymmetry can result in seller opportunism. We examine a specific opportunistic behavior, shilling, and analyze how the design of an online auction's fee structure can motivate such opportunism among auction sellers.

**Detecting Deception**

DePaulo and Pfeifer (1986), and Johnson et al. (2001) discuss how deception detection has a low rate of feedback, meaning that occurrences of successful deception detection are so few that individuals do not get feedback to improve their mental models used for detection. They note that experienced auditors cannot outperform novices because auditors' judgments develop over a long period of time, and auditors are unsure what cues and rules lead to success at detection.

DePaulo et al. (1985) note that receivers tend to accept what is told to them, with little thought of deception, making deception detection more problematic. The Internet exacerbates

this problem as online sellers can assume many identities (e.g., Bunker 2001; Clemons et al. 2001), thus decreasing the rate of detection and motivating fraudulent behavior.

Johnson et al. (2001) describe how successful auditors appear to learn to identify occurrences of fraud in situations where it is or is not occurring. We use a similar method to see how an auction's outcome and bidding behavior will differ if that auction contains a shill bidder.

The finance literature also employs this technique to learn where market participants deliberately hide their fraudulent or opportunistic behavior. Christie and Shultz (1994a) note how NASDAQ dealers acted collusively in avoiding odd-eighth stock quotes, increasing spreads paid to the brokerage firm. By theorizing that the spread between the bidding and asking price should be higher in a collusive environment, and then theoretically justifying why collusion would be profitable, Christie and Shultz were able to detect collusive behavior. [4] Chen (2000) also found evidence this way for similar tacit collusion in the spreads for stock IPOs, where spreads clustered around 7% over a fourteen-year period, regardless of the size of the issue.

**WHY ARE SELLERS MOTIVATED TO ENTER PREMIUM BIDS?**

To predict the motivation for a seller's decision to shill, we must first understand two situations: auction houses charge fees that may impact a seller's behavior, and auction houses may have little incentive to strictly police shilling behavior. We next discuss how shilling can result from the environment and fee structure imposed by the online auction house.

**Do Online Fees Motivate Reserve Price Shilling?**

To place an item for sale on eBay, the seller first lists the item and gets charged a *listing fee*

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[4] Soon after the publication of Christie and Shultz (1994a), excessive even-eighth trading all but ceased (Christie and Shultz, 1994b). DeGraw (1999) reports that a related impact was a $1.03 billion settlement payment by market makers related to instances in which explicit collusion was shown to have occurred.

(or *insertion fee*). It is based upon the amount of the starting bid set by the seller. Higher starting bids require higher listing fees. During listing, the seller can select other options for a fee. Specifically, in the context of this research with data from 2001, the seller was able to declare a *secret reserve price* that the bidders must have exceeded if they were to win an item. Starting bid amounts and the existence of a secret reserve were known to bidders on an item screen that lists the auction information. If the seller opted for a secret reserve amount, then he was charged a *secret reserve fee*. If the item received at least one bid at or above the secret reserve amount, then eBay charged a *closing fee* (or *commission rate*, a decreasing percentage commission of the sale price), plus a *fixed fee*.

The fees that electronic auction houses on the Internet charge promote unexpected seller behavior. For example, consider eBay's schedule of fees during the time period of this study in April 2001, and compare it with the fee schedule of October 2005. (See Table 1.) When an item is successfully sold through an auction, eBay charges a commission. For auctions won at lower dollar amounts, the commission rate is a flat percentage fee. For auctions won at higher amounts, the fixed fee is added to the commission rate.

**Table 1. Sample Fee Schedules for Online Auctions at eBay (April 2001 and October 2005)**

| TRANSACTION AMOUNT | CLOSING VALUE FEE (FIXED FEE + COMMISSION RATE) | LISTING FEE ON STARTING VALUE | RESERVE FEE |
|---|---|---|---|
| *Fees as of April 2001* | | | |
| $0.01 - $9.99 | $0.00 + 5% of the winning bid | $0.30 | $0.50 |
| $10.00 - $24.99 | | $0.55 | |
| $25.00 - $49.99 | $0.625 + 2.5% of the winning bid | $1.10 | $1.00 |
| $50.00 - 199.99 | | $2.20 | |
| $200 - $1000 | | $3.30 | |
| > $1000 | $12.50 + 1.25% of the winning bid | | |
| *Fees as of October 2005* | | | |
| $0.01 - $0.99 | $0.00 + 5.25% of the winning bid | $0.25 | $1.00 |
| $1.00 - $9.99 | | $0.35 | |
| $10.00 - $24.99 | | $0.60 | |
| $25.00 - $49.99 | $0.6225 + 2.75% of the winning bid | $1.20 | $2.00 |
| $50.00 - 199.99 | | $2.40 | |
| $200 - $499.99 | | $3.60 | 1% of reserve price up to $100 |
| $500 - $1,000 | | $4.80 | |
| > $1,000.00 | $13.12 + 1.5% of the winning bid | | |

**Note:** A listing fee in eBay is called an *insertion fee* and the sale price for an auction item is called the *closing value* or *final value.* The *secret reserve price* of a sale item is the lowest price at which a seller is willing to sell, and is not disclosed to the bidders. For secret reserve prices, eBay charges *reserve fees* for the seller. During the time of this study, reserve fees were not refunded, but recently eBay has incorporated a policy of refunding reserve prices if an item is sold. Sellers could reduce their secret reserve price during an auction. No final value fees were paid if an item did not sell. These fees were expressed as a base fee plus a commission amount for the sale. For example, in 2005, eBay reported auctions whose final bids ranged from $25.01 to $1000.00, were charged a commission of "5.25% of the initial $25.00 ($1.31), plus 2.75% of the remaining closing value balance ($25.01 to $1,000.00)". This is equivalent to a $0.6225 fixed fee plus a 2.75% commission on the entire amount. According to Amazon.com's Web site (www.amazon.com/exec/obidos/tg/browse/-/1161240/ref=br_bx_c_2_1/ 103-5863818-5971819), Amazon also collects fees only when an auction item is sold, including the sales price and shipping costs from the buyer. Amazon deducts commission on the sales price, a per-transaction fee of $0.99, and a variable closing fee. The commission rates are: computers, 6%; cameras and photo, cell phones and service, and electronics, 8%; items in the Everything Else Store, 10%; musical instruments, 12%; and other products, 15%. This pricing scheme is largely intended for businesses that sell, though they also apply to consumers. As of June 6, 2005, Yahoo! Auctions removed all fees from its auction services. During 2001, Amazon and Yahoo did not have enough market share to generate sufficient data for our analysis. eBay, which controlled over 80% of the online auction market, is the only auction house whose data we were able to use.

Let's consider how fee structure at eBay may have motivated reserve price shilling in 2001. If the seller set the auction's starting bid at less than $10, the listing fee was $.30. If the seller set the auction's starting bid at greater than $200, the listing fee was $3.30. A seller who wanted to ensure that an item was sold for at least $200 could have set a starting bid of less than $10 and then entered a shill bid for $199.99. If another bidder bid more than $200, the seller would have

saved $3.00 in listing fees, but also risked inadvertently winning the auction, thus forgoing any sale and also forcing the seller to pay a commission.

During 2001, eBay was charging a *secret reserve fee* of $.50 or $1.00, refunded if the item was sold at a higher price higher than the reserve price.  At the time, eBay discouraged secret reserve prices by disallowing them on the "Hot Items Auction List," containing auctions with over 30 bids.  Assuming no chance of detection and no ethical issues prevented such behavior, eBay sellers who were inclined to shill may have preferred shilling to setting a secret reserve price until the shill bid reached $10. Why? A seller could have won his own auctions, but still have owed less than the $.50 or $1 fee charged for setting a secret reserve price: [5]

*Break-Even Shill = Secret Reserve Fee / Commission Rate = $.50 / 5% = $10.*

During 2001, there was a chance on any bid over $10 that the seller could shill and not pay because a legitimate bidder could have outbid the shill seller.  Consider that eBay charged a 2.5% commission plus $0.625, and $1 for a secret reserve price at the time.  Given these parameters, if a seller had a 25% probability of winning an auction, then the seller would have saved money overall by shilling on any item up to $135.  This is because, with a 25% chance of winning, $1 is the expected value of the fee associated with a $135 shill bid:

*Expected $1 Reserve Fee  = ((ReserveFee/Probability of Winning)-Fixed Fee)/Commission Rate*
*= (($1 / 25%) - $0.625) / 2.5% = $135.*

So with eBay's fee structure for secret reserve fees and a 25% probability of winning, a

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[5] Today, eBay has a clearly stated policy on "Circumventing Fees."  "Users may not use systems or techniques to circumvent, or avoid, eBay fees. Sellers should review the 'Some Examples' section below to ensure they are not engaging in any practices that circumvent eBay fees.  Violations of this policy may result in a range of actions: listing cancellation; limits on account privileges; account suspension; forfeit of eBay fees on cancelled listings; loss of PowerSeller status. … Listings that circumvent (avoid) fees may provide a poor buying experience and always unlevel the playing field by putting sellers who pay all their eBay fees at a disadvantage. Further, these listings undermine the trust and legitimacy of eBay's marketplace."  See pages.ebay.com/help/policies/listing-circumventing.html.   In addition, eBay now stipulates that reserve fee avoidance, by canceling bids and ending a listing early because the seller's desired price has not been met, is not acceptable.

bidder may have been more inclined to shill than pay for a secret reserve price until the shill bid

for the auction exceeded $135.  This assumes that only the reserve fee was considered though.

Using eBay's fee schedule from April 2001, we can see how a seller's expected fees are based on

varying probabilities of winning.  (See Table 2.)

**Table 2.  Expected Fees on eBay from Shilling for a $1 Secret Reserve Price, April 2001**

| PROBABILITY OF WINNING A SHILL BID | BID AMOUNT FOR WHICH SHILLING COST > MINIMUM OF RESERVE FEE AND LISTING FEE |
|---|---|
| 10% | > $375 |
| 20% | > $175 |
| 25% | > $135 |
| 30% | > $108 |
| 40% | > $75 |
| 50% | > $55 |

The expected cost of shilling decreases when the probability of winning decreases.  So sellers

would have tried to reduce the chance of winning.  This shows how an auction house's fee

structure may have motivated shilling behavior.  For eBay in 2001, the secret reserve, insertion

and commission fees all motivated shilling behavior up to a fairly high-priced auction item.

In 2001, setting up a new identity with online auction houses like eBay was relatively simple,

quick, and had no real monetary cost.  It only required a credit card.  New users were allowed to

bid on any item, and were not excluded from online auctions until their reputation score reached

–3, or unless they were disciplined for violating eBay's online auction rules.  Time costs for

setting up a new identity did not deter users who wished to use multiple identities.

**How Do Auction Houses and the Internet Environment Motivate Competitive Shilling?**

To shill, a seller assumes a different identity to profit at the expense of the high bidder and

the auction house.  Shilling is considered to be criminal fraud in the United States, and is

punishable by both fines and/or jail terms.  Most auction houses suggest the possibility of severe

reactions if shilling occurs (Brunker, 2000), even if others perceive that the rules of market

microstructure they employ may actually create *mechanism-induced shilling* (Kuchinskas, 2005). [6,7] Since the perceptions of conflict of interest are strong, sellers must abide by rules that minimize shilling. Thus, the seller only will shill if the profit is greater than the cost to enter shill bids and the risk.

The possibility of detection of shilling is reduced online because Internet auction sellers and bidders can set up identity-masking "handles," hiding their identities. A seller can set up multiple identities or even "bidder rings" with Internet-active co-conspirators. Thus, widespread use of Internet technology can cause an increase in information asymmetry in online auctions compared to traditional auctions in that identifying information about product, seller, and other bidders cannot be examined before a decision to bid by each legitimate bidder. This increase in information asymmetry can motivate seller decisions toward opportunistic behavior.

The actions of the auction house, too, can lessen or compound the effects. Shilling results in higher bids, which leads to additional profit from commissions for the total sale price. Auction houses may be reluctant to make efforts to detect opportunistic sellers whose actions are profitable, even if they declare adherence to an anti-shilling code of ethics, and require

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[6] U.S. Code, Title 31, Money and Finance, Section 3729 states that on "false claims, there are many requirements that need to be met before some action can be classified and prosecuted as criminal fraud. These elements are: (a) the perpetrator "knowingly presents or causes to be presented . . . a false or fraudulent claim for payment or approval;" (b) the defendant knew the claim was false or fraudulent, (c) the party in the transaction suffered damages as a result of the false or fraudulent claim, and (d) the perpetrator profited from these damages. See www.smartwebmove.navsup.navy.mil/swm/documents/SWM22FalseSubmit3729.pdf. Shilling does not necessarily lead to damages. However, if it leads to the auction house receiving fewer fees or another bidder paying more because the seller presented himself falsely as a bidder, running up the bid, then the elements of fraud are often present and the perpetrator can be successfully prosecuted.

[7] In 2005, eBay was accused of shilling itself, according to an article in *InternetNews.com* (Kuchinskas, 2005). The article reports that when eBay bidders "reach their maximum bids, they get an automated e-mail confirmation that they're the highest bidder. But it includes the warning — Important: You are one bid away from being outbid. If another user places a bid, you will not win. To increase your chances of winning, enter your highest maximum bid. The bidder would assume that his bid would only be raised again if someone outbid him. However, in some cases, the system automatically increases the bidder's already high bid by enough to meet the minimum increment. … If a user accepts eBay's request to provide a higher maximum bid, eBay then acts as a shill bidder on behalf of the seller at the price level of the highest former competing bidder. As a result of eBay's hidden shill bid, eBay automatically

participants to do the same. Brunker (2001) noted how online consumers speculated that eBay ignores shilling because it involves some of their biggest clients, and they generate substantial income for eBay. Punishments meted out to transgressors in 2001 were light, involving first a warning and then a 30-day suspension from the site. eBay's 2003 announcement to no longer support a link to the National Consumer League's Web site, www.fraud.org, added friction to the reporting of auction fraud, and is indicative of how corporate concerns may cross with the concerns of consumers. Thus, the costs to the seller for detection of shilling are not very high.

If an online auction is unwilling to reduce the effects of the increase in information asymmetry brought about by anonymity intrinsic to the online environment, then the rate of detection is reduced further. This may motivate sellers to adopt shilling to achieve the goal of selling at the highest price in the market, while minimizing operational costs assessed by the auctioneer.

**DATA**

We used an Internet agent to gather eBay data, including auction, item, seller, bidder and bid characteristics. This agent examined archival data by category for each day of the previous month's data. The agent also drills online auctions for item and bid information.

**Context: Rare Coin Selling on eBay**

We focus on rare coins sold over eBay. A difficulty of our data collection is that we must distinguish between admissible and inadmissible data. To identify coins that are appropriate to include required us to develop an automated coin classification algorithm specifically for this purpose. The algorithm analyzes the text contained in the auction item name and a description of

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raises the hapless buyer's bid so as to out-bid eBay's shill.

each coin auction to classify the coin based upon the *coin year* (e.g., 1888, etc.), the *coin denomination* (e.g., penny, two-cent piece, etc.), the *coin type* (e.g., San Francisco mint, double die, etc.), and the condition, or *coin grade* (e.g., very good, poor, etc.). Coin grade is communicated using a language known to collectors. Collectors know the difference between *fine* and *very fine*, and that *fine+* and *fine/very fine* and *f15* are the same, for example. [8] We define two coins as "the same coin" when they share the same mint year, denomination, mint marks, and condition, as is the standard practice (e.g., *Coin World*, Gibbs 2001). To proxy for an item's common value, we use the listed *book value* for each auction item. Coin types and current book values for these coins were obtained from *Coin World*, whose book values represent market prices for collectors with a small store dealer margin.

We collected data on several different categories of rare coins whose mint dates spanned over a century, with denominations ranging from one-half to twenty cents, and book values from $1.30 to $5,750. [9] The data include 10,234 eBay auctions during April 2001, with 30,395 bids on 6,954 auctions from 5,290 distinct bidders and 1,373 distinct sellers.

**Classifying Premium Bids**

For a bid to be a *premium bid*, it must meet five criteria: (1) There are two auctions, *Auction*

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[8] A seller can use the notation *fine/very fine* to describe an overall condition of the coin of *f15* on both the obverse and reverse of the coin, which is better than *fine* but less than *very fine*. Occasionally, the notation *fine/very fine* is for a condition of *fine* for the obverse (heads) and *very fine* for the reverse (tails) of the coin. For professional coin raters, the end result is similar. They must give a single rating for a coin, and differing obverse and reverse conditions result in a rating that is the average of the two—giving an *f15* ranking for the above coin. It is difficult to grade coins with two extremely different grades for the obverse and the reverse (e.g., *good/extremely fine*). So we did not consider coins with multiple grades further apart than one classification grade.

[9] We included rare coins minted predominantly in the 1800s: all half-cents minted between 1793 and 1857, all two-cent pieces minted between 1864 and 1873, all silver and copper/nickel three-cent pieces issued between 1851 and 1889, all Indian Head (small cent) pennies from 1859 to 1909, and all Draped Bust large cents minted between 1796 and 1807. We included all Classic Head large cents struck between 1808 and 1814, all Coronet large cents from 1816 to 1836, all Braided Hair Coronet large cents from 1837 to 1857, all Flying Eagle small cent pennies minted between 1856 and 1858, and all twenty-cent pieces from 1875 to 1878. We did not include auctions with multiple items (e.g., "a roll of Indian Head pennies," or "a 1857 Flying Eagle with an 1857 Braided Hair large cent"). We did not include a non-coin items (e.g., "gray sheet" coin prices, cleaning kits, etc.), or those without a year or grade.

*A* and *Auction B*, selling identical items. (2) A bid is submitted in *Auction A*. (3) The bidder could have placed a lower bid in *Auction B*. (4) *Auction B* ends before *Auction A*. (5) And the bidder did not bid in both auctions.

Table 3 illustrates an instance of what we define as premium bidding, based on data we collected. The bid entered by *PremiumBidder* meets the criteria for a premium bid: (1) *Auctions A* and *B* sell the same item, a 1802 Draped Bust large cent in almost good (AG-3) condition. (2) A bidder, *PremiumBidder*, bid $13.00 in *Auction A*. (3) *PremiumBidder* could have made a lower bid in *Auction B* where the same coin was $9.01. (4) *Auction B* ends on 4/20, before *Auction A* on 4/21. And (5) *PremiumBidder* did not bid in both auctions.

**Table 3. Premium Bidding: 1802 Draped Bust Large Cent, Almost Good (AG-3) Condition**

| BIDDER | BID DATE | BID AMOUNT | BIDDER | BID DATE | BID AMOUNT |
|---|---|---|---|---|---|
| • Auction A with 4/21 Ending Date | | | • Auction B with 4/20 Ending Date | | |
| *PremiumBidder* | 4/15 | $13.00 | *Bidder2B* | 4/14 | $9.01 |
| *Bidder1A* | 4/14 | $9.99 | *Bidder2A* | 4/13 | $8.95 |

To analyze premium bidding, we must examine concurrent auctions since premium bidding can only be detected when a bidder bids on one auction when the same item is for sale in a different concurrent auction. In the 10,234 coin auctions that we examined for this study, 1,313 had the same coin (i.e., same mint year, coin denomination, coin type, coin grade) being sold that was also sold in another auction concurrently, and thus these are the only records that we can use for our analysis. The resulting data set contains 1,313 auctions with 5,031 bids from 2,015 distinct bidders and 480 sellers.

**Characteristics of Premium Bids**

There are several reasons why seller preference may be problematic in online auctions. In our data on every rare coin auction in certain categories during April 2001, there is one seller for every four buyers. For sellers to be as successful as they are, buyers have to be attracted to a

large number of sellers. Further, sellers do not sell an entire inventory, as in traditional markets, but usually one product at a time. However, we point out that certain characteristics, such as the seller reputation score that is provided by eBay, may have an impact on the final bid amount.

Following fraud detection advice from DePaulo and Pfeifer (1986), and Johnson et al. (2001), we first examine our data with an attempt to discern the effects of reserve price shilling if it were prevalent in online auctions. We examine characteristics that should exist for bidding data with reserve price shilling. (1) Shills concentrate on a specific seller, and will tend to concentrate on fewer sellers than other bidders. (2) Reserve price shills will tend to more often bid early and then drop out (to set an early reserve price), while competitive shills will tend to bid later to run up the final bid. (3) Shills will bid in larger increments to run up the bid or to set a higher reserve price that is many bid-increments away from the current bid. (4) Shills generally will not try to win. They would rather have a legitimate winner, and will not bid if they perceive bidding to be tapering off, or the bid level has passed their reserve price.

We next describe characteristics for comparing auctions with premium bids with those that do not at the bid and bidder analysis levels. Non-parametric t-test results compare the difference between auctions with and without premium bids. (See Table 4.)

**Table 4. Descriptive Statistics for the Premium Bidding Data Set**

| VARIABLES | AUCTIONS WITH PREMIUM BIDS | | | AUCTIONS WITHOUT PREMIUM BIDS | | | t-STAT |
|---|---|---|---|---|---|---|---|
| | Mean | Variance | N | Mean | Variance | N | |
| *Seller Concentration* | 1.22 | 0.26 | 490 | 1.08 | 0.15 | 1,525 | 5.27*** |
| *Days Left in Auction* | 4.76 | 7.39 | 705 | 1.94 | 6.52 | 4,326 | 25.75*** |
| *Bid Increment* | 258% | 52.3 | 694 | 135% | 4.59 | 2,982 | 4.28*** |
| *Amount of Wins* | 21% | 0.16 | 705 | 27% | 0.20 | 4,326 | -3.75*** |
| **Note:** The analysis of *Auctions per Seller* is at the *bidder* level, with bidders who have entered *any* premium bid compared against those that have not. Analysis of *Days Left in Auction*, *Bid Increment* and *Amount of Wins* is at the *bid / auction* level, where only the final bid was considered for bidders that entered any premium bid in the auction. We analyzed *Bid Increment* with 71 outliers removed (out of 5031 records) to give a more accurate picture. Our analysis with outliers had inflated means and variance, but was otherwise similar overall in terms of the results. Parameter significance: *** = $p < .01$. | | | | | | | |

We see different measures of how auctions with and without premium bids compare. *Seller Concentration* determines whether those who have ever entered premium bids typically bid on fewer sellers, as shills probably do. *Seller Concentration* is the number of auctions that a bidder has bid upon divided by the number of sellers on whose auctions a bidder bids. A higher *Seller Concentration* indicates that a bidder concentrates on fewer sellers; a lower *Seller Concentration* means a bidder uses more sellers. *Seller Concentration* has a lower bound of 1 (1 auction per 1 seller), but with so many sellers, *Seller Concentration* will be close to one. We show that those bidders who have entered premium bids tend to concentrate on fewer sellers. This is not surprising: both seller preferences and reserve price shilling both predict that bidders who make premium bids are more likely to concentrate on fewer sellers.

*Days Left in Auction* compares the number of days left in auctions when a premium bid is detected with the number of days left in auctions when a non-premium bid is detected. The descriptive statistics indicate that premium bidders tend to drop out early, which is consistent with reserve price shilling. *Bid Increment* compares the average percentage increase over the displayed previous bid. The actual dollar amount viewed is what we measure. Premium bids appear to have a larger percentage included in the bid increment (154%) when compared with other bids (75%). [10] These numbers may seem high, but low bids are often entered early in the auction. *Amount of Wins* shows how likely a bid is to succeed. Premium bids are less likely to win (23% of the time) than other bids (30% of the time). We expected premium bids to win more often. These are evidence that premium bidding may be reserve price shilling. The characteristics of auctions that receive premium bids match what is consistent with reserve price

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[10] For *Bid Increment*, bids were only considered that were higher than the initial bid. Initial bids were ignored. This gave more consistent, lower variance results. Including first bids gave similar results, but with higher variance. So excluding first bids was more conservative and accurate. Also, including actual bids of competing bidders, rather

shilling.  We next hypothesize and test what we would expect if reserve price shilling were the primary driver of premium bids.

**RESEARCH HYPOTHESES**

We have argued that premium bids can be received because of seller and auction characteristics, and shilling.  Our results support the contention that reserve price shilling, rather than seller preference, primarily drives premium bids. [11]  Sellers who perform above average in setting up an auction or who have good characteristics, such as a good reputation, should consistently attract premium bids. Conversely, auction sellers who decide to shill accept risks and ignore the social mores against this behavior. These assumptions are in line with research on reputable selling done by Shapiro (1982) and Klein and Leffner (1979). Thus, if a seller shills in previous auctions, he has justified the practice of shilling to himself in terms of risk and ethics. [12] These contentions indicate that both shilling and seller/auction preference require that sellers who receive premium bids do so consistently:

❑ **REPEATED PREMIUM BIDS HYPOTHESIS (H1).** *Sellers that have received a premium bid in other auctions are more likely to receive a premium bid in the observed auction.*

However, there is less agreement between seller preference theories and shilling theories for other predictions, especially in the area of reputation and starting bids. Theories of seller preference would indicate that sellers with high reputation would receive a price premium for

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than the bid to beat that is displayed on eBay, reduced both numbers by a large amount, but yielded similar results.

[11] These results are consistent with data gathered by the authors from auctions during 1999 and 2000.

[12] A possibility that we only briefly consider in this research is that premium bids may be entered by bidders who are *boundedly rational* or *irrational* and, thus, cognitively unable to completely search for similar auction items before bidding on a specific item in a specific auction.  We allow that it is possible that some bidders have made mistakes and bid for the incorrect item or the incorrect amount.  However, we doubt that bounded rationality is the *primary driver* of premium bids since eBay has easily-mastered search and sort capabilities. There is no reason why bidders who have mastered the bidding process would ignore salient search information that is easily available.  However, if

their actions (Ba and Pavlou 2002). Thus, if premium bids are due primarily to seller preference, we should see a positive relationship between seller reputation score, provided by eBay, and premium bids. However, if shilling were the primary driver of premium bids, opportunism theory would predict the opposite. Shapiro (1982) and Klein and Leffner (1979) describe how experienced or highly reputable sellers can be punished for opportunistic behavior more severely, through loss of reputation, than those with little experience in the auction channel, who have little reputation to lose. Thus, if premium bids are due primarily to shilling, we propose that experienced sellers and sellers with stronger reputations are motivated against deciding to shill. Detection could result in a greater loss, leading to a predicted negative relationship between seller experience and premium bids.

- ❑ **THE INEXPERIENCED SHILL HYPOTHESIS (H2).** *Sellers with high reputation scores will be <u>less</u> likely to receive a premium bid.*

Seller preferences do not predict premium bids to be associated with low starting bids. A low starting bid would receive low bids at first as an auction's final price approaches the current price in other concurrent auctions for the same item. Thus, low starting bids should result in a lower probability of premium bids, since a lower starting bid, all else being equal, would result in bidders entering lower bids, and thus a positive correlation should exist between starting bids and premium bids. Conversely, if premium bidding is driven primarily by reserve price shilling, then sellers can save money by setting a relatively low starting bid for an auction and then, after bidders start bidding, sellers can shill to a higher level to ensure that they do not receive a final bid below their own valuation. Thus, we hypothesize that there will be a negative relationship between the level of starting bid and the existence of premium bids in an online auction.

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premium bidding is primarily driven by boundedly rational behavior, then all relationships predicted by auction preference, seller preference, or opportunism (i.e., shilling) will be insignificant.

❑ **THE LOW STARTING BID HYPOTHESIS (H3).** *A low starting bid is associated with future premium bids.*

**A Conceptual Model for Premium Bidding Driven by Reserve Price Shilling**

We next present a conceptual model for premium bidding. We contrast the predicted effects of premium bidding for reserve price shilling and seller preference to illustrate the differing predictions. (See Figure 1.)

**Figure 1. Predicted Primary Drivers for Premium Bidding**
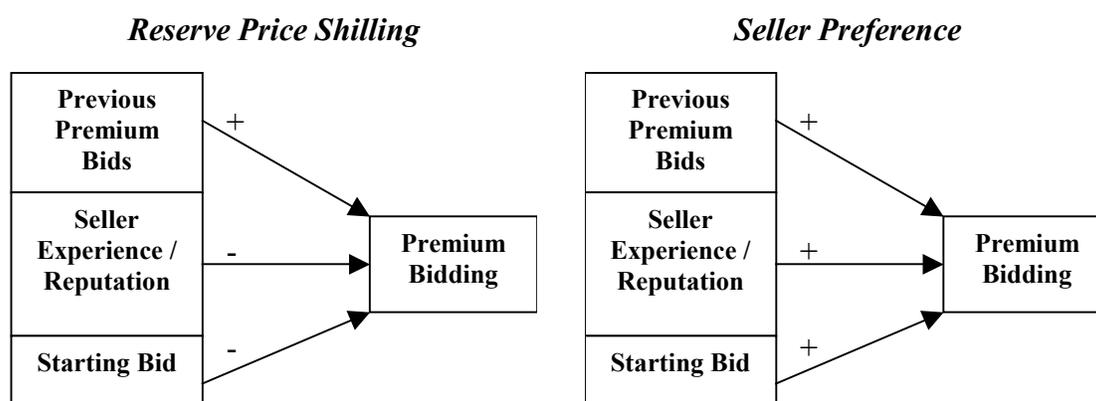


Overall, our theory asserts that in environments where there is incomplete information transferred about the seller or the product, seller opportunism in transaction-making should increase. In Internet-based auctions, the amount of information transferred between the seller and the buyer is especially incomplete (e.g., Resnick and Zeckhauser 2002, Dellarocas 2003).

**MODELING ISSUES AND EMPIRICAL MODEL**

We now specify a model and analyze the data to gain insights on premium bidding.

**A Conceptual Model to Predict Premium Bidding in Auctions**

The hypotheses that we discussed give rise to our specification of a general model, which also includes appropriate control variables: [13]

*Premium Bidding = f (SellerPBPropensity, SellerExperience, StartingBid, BookValue, TimeLength, OtherAuctionBidAmount, Picture, Weekend)*

Hausman and McFadden (1984) recommend probit models for testing binary dependent variables because of the few assumptions required of probit and the reliability of the coefficient estimates. We will build a model to predict whether an auction's bidders submit a premium bid using only item, seller, and auction characteristics, and not any bidder characteristics. Our goal is to show that we are able to predict the auctions that will receive these premium bids and which bidders enter a premium bid. To accomplish this, we will use a probit formulation for our empirical model (Mittal and Kamakura 2001, Kennedy 2003). [14]

Variables in our general empirical model were selected so that this information was available before the bidding actually begins on the item. Hence, endogeneity is not a concern since all independent variables are determined before the bidding begins, and any premium bids will be submitted after the seller defines the variables in the auction. We can show that a large amount of premium bidding is not due to personal characteristics, such as an individual's inexperience or seller preference: it can be predicted without personal data. Second, since premium bidding

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[13] We considered controlling for the existence of a secret reserve price, which is a price stated above the public reserve price, or starting bid, where the seller is not obligated to deliver the item unless bidding surpasses a secret amount known only to the seller. However, in auctions where a premium bid might be detected, no seller opted to pay the additional amount required for a secret reserve price. We attribute this not only to the possibility of reserve price shilling to avoid paying a secret reserve price, but also to the limitations of auctions containing secret reserve prices that eBay enforced during the time of this study, such as a refusal to list your auction in the "Hot Auctions" section of the eBay Web site if your auction is bid upon by many bidders.

[14] With a binary dependent variable—a bidder enters a premium bid or a normal bid—a linear model is inappropriate. Estimates of the dependent variable may fall outside the appropriate range, a *logical misspecification* (Greene, 2002; Kennedy, 2003). The normalized probability of a bidder entering a premium bid must be between 0 and 1. Least squares regression can lead to an estimated dependent variable exceeding 0 and 1. Probit models

appears to be statistically similar to reserve price shilling, there are characteristics that can make

shilling more attractive to the seller.

**Binary Choice.**

**The Probit Model**

Our empirical model to detect premium bidding behavior is a probit, specified as:

$$Prob[y_{PB}=1] = f(\alpha, SellerPBPropensity, SellerExperience, StartingBid, BookValue,$$
$$TimeLength, OtherAuctionBidAmount)$$

The definitions of the variables are shown below. (See Table 5.)   If it is true that a large

portion of premium bidding results from reserve price shilling, then we should be able to use

variables in the table to predict auctions that are bid upon by premium bidders.

**Table 5.  Variables Used in the Probit Model**

| VARIABLE | DEFINITION AND COMMENTS |
|---|---|
| *Prob[ y_{PB}=1]* | Auction-level dependent binary variable; *y*=1 if auction receives premium bid, *y*=0 if not. |
| *α* | Intercept. |
| *SellerPB Propensity* | Ratio of number of auctions with premium bids compared to the total number of auctions held, not including current auction.  Measures seller propensity for attracting (or, if shilling, participating in) premium bidding. If premium bidding is a bidder characteristic due to lack of experience, and thus not evidence of shilling, this variable should not be significant. If a seller often bids on his or her own auctions, then this variable should be positive and significant. |
| *SellerExperience* | Experience level of the seller in terms of eBay's reputation score. |
| *StartingBidBook ValueRatio* | *StartingBid* in the auction, as a measure of the stated reserve price, as a ratio to *BookValue*.  If there is a high *StartingBid* relative to *BookValue*, then a seller has no need to shill.  When a seller enters a high *StartingBid*, it may show a high valuation of an auction item. |
| *BookValue* | *BookValue* of a coin.  Because the risk of financial loss increases with the book value of the coin, we expect larger book values to exhibit higher occurrences of shilling. |
| *TimeLength* | Length of time that an auction, as a measure of propensity of drawing a premium bid.  eBay allows auctions in one, three, five, seven, and ten-day increments. |
| *OtherAuction BidAmount* | Lowest amount to be bid for an identical item in different auction when current auction starts. |
| *Picture* | Dummy variable indicating if a picture exists for an auction. |
| *Weekend* | Dummy variable indicating if the auction ends on a Saturday or Sunday. |
| **Note:** The number of negative comments is significantly positively correlated with the number of positive comments and with the reputation score.  This is understandable: the reputation score is a proxy for experience. Experienced sellers have a higher probability of both positive and negative comments. | |

resolve this by forcing the estimated value of the dependent value to be in the interval [0, 1].

**Specification Issues.**  The ratios in our model give rise to specification issues.  One is with the ratio between *StartingBid* and *BookValue*, in which large ratios are disproportionately larger than small ratios. If *StartingBid* is \$20 and *BookValue* is \$100, then *StartingBidBookValueRatio* is 0.2 (\$20/\$100).  If the values are reversed, the ratio is 5.0 (\$100/\$20).  When *BookValue* exceeds *StartingBid*, the ratio is limited to values between 0 and 1.  When *StartingBid* exceeds *BookValue*, the ratio is greater than 1 with no upper limit.  Thus, a specification problem exists: large ratios are disproportionately larger than small ratios.

This situation is readily resolved using a natural logarithm transformation involving *ln(StartingBid BookValueRatio)*.  When *StartingBid* is \$20 and *BookValue* is \$100, $ln(.2) = -1.6$ and, when *StartingBid* is \$100 and *BookValue* is \$20, $ln(5) = 1.6$.  Logarithms adjust ratios so that when the denominator is smaller than the numerator the log-transformed value is of the same magnitude as when the denominator is larger than the numerator, differing only in sign.  We also transform *ln(SellerPBPropensity)* and *ln(OtherAuctionBidAmount / BookValue)* in this way.  Also, high *SellerExperience* scores are less distinguishable to the buyer than low *SellerExperience* scores.  A logged variable adjusts for the non-linearity: *ln(SellerExperience)*.

**Collinearity, Multicollinearity and Interactions.**  We examined the correlation matrix from each model and found that the highest pairwise correlation was 16%.  A pairwise correlation test only tests linear relationships between two variables, and not relationships between an independent variable and a linear combination of two or more other independent variables (Kennedy 2003).  So we also employed a *condition number test* (Belsley, Kuh and Welsch, 1980; Greene, 2002).  This yielded a condition number of 14.3, below the level of 20 suggested by Greene (2002), indicating multicollinearity is not a problem.  We confirmed this with a multiplicative terms method suggested by Neter et al. (1996), but found no problems.

**Final Estimation Model.**  The final estimation model with log-transformed terms is:

$$Prob[y_{PB}=1] = \alpha + \beta_1 \ln(SellerPBPropensity) + \beta_2 \ln(SellerExperience)$$
$$+ \beta_3 \ln(StartingBidBookValueRatio) + \beta_4 BookValue + \beta_5 TimeLength$$
$$+ \beta_6 \ln(CurrentOtherAmount / BookValue) + \beta_7 Weekend + \beta_8 Picture + \varepsilon$$

We expect a positive relationship for *ln(SellerPBPropensity)* (i.e., $\beta_1$ positive and

significant), a negative one for *ln(SellerExperience)*, and a positive one for *BookValue.*


## MODELING RESULTS

Our results show that premium bidding may be reserve price shilling.  We are able to predict

instances of auctions for which there are premium bids, and when premium bids will be made.

### Estimation Results

We used Stata 9.0 to estimate the probit model.  (See Table 6.)

**Table 6.  Probit Model Estimation Results for Premium Bidding**

| VARIABLE | HYPO-THESIS | COEF-FICIENT | STD ERROR | MARGINAL EFFECTS | t-STAT |
|---|---|---|---|---|---|
| $\alpha$ (Intercept) | None | 0.662 | 0.330 | -- | 2.006** |
| *ln(SellerPBPropensity)* | H1 | 0.633 | 0.068 | 0.121 | 9.325*** |
| *ln(SellerExperience)* | H2 | -0.261 | 0.038 | -0.050 | -6.809*** |
| *ln(StartingBidBookValueRatio)* | H3 | -0.061 | 0.029 | -0.012 | -2.079** |
| *BookValue* | Control | -6.012 | 2.242 | -1.151 | -2.681*** |
| *Time Length* | Control | 0.001 | 0.001 | 0.000 | 1.291* |
| *Reserve* | Control | 0.054 | 0.195 | 0.011 | 0.276** |
| *ln(CurrentOtherAmount / BookValue)* | Control | -0.572 | 0.054 | -0.109 | -10.546*** |
| *Picture* | Control | 0.246 | 0.124 | 0.043 | 1.982** |
| *Weekend* | Control | -0.402 | 0.111 | -0.069 | -3.616*** |

**Note**: Model—probit. Analysis at auction level for 1,313 rare coin auctions with 5,031 bids from 2,015 distinct bidders and 480 distinct sellers.  Significance: *** $p < 1\%$, ** $p < 5\%$.

Recall that we used a binary coding for a premium bid.  A positive coefficient indicates that

an increase in the variable is associated with more premium bidding.  A negative coefficient

indicates that an increase in a variable reduces the occurrence of premium bidding.

A seller's propensity to host other auctions that attract premium bids can be used to predict

attraction of premium bids in this auction. Thus, the evidence supports the *Repeated Premium*

*Bids Hypothesis* (H1). This is in line with either the contention that premium bids are primarily the result of seller preference, or that premium bids are mostly a result of reserve price shilling, since both theories would indicate that the same sellers are likely to receive premium bids.

The results from the second and third hypotheses suggest premium bids result from reserve price shilling and are not driven by seller preference. We have a significant negative coefficient on the parameter for the *Inexperienced Shill Hypothesis* (H2), indicating that more experienced sellers receive fewer premium bids. We predicted this surprising result. Many premium bids are, in fact, reserve price shilling, and so experienced sellers will not want to tarnish their reputation by being caught acting opportunistically.

We also show that the higher the starting bid to the published book value, the less likely that premium bidding occurs, thus supporting our *Low Starting Bid Hypothesis* (H3). One would think that a low starting bid would allow for fewer premium bids since low starting bids allow more bids at lower levels. But this was not the case, which is consistent with our *Low Starting Bid Hypothesis* (H3) and with reserve price shilling, where bidders begin with a low price to avoid startup fees and then shill at a higher price—to avoid fees.

The hypotheses are seller-level or based on auction characteristics set by the seller. None are based upon bidder characteristics. We find evidence that premium bidding is a seller characteristic not brought on by seller preference or bounded rationality. Our results are consistent with the contention that reserve price shilling is the primary driver of premium bidding.

**Marginal Effects.** Liao (1994) and Greene (1996) describe how the magnitudes of coefficients in a probit model can be misleading. The dependent variable is a probability. Unlike linear models, a change in a coefficient of an independent variable should not be used to predict

the dependent variable. Greene (1996) develops a *marginal effects measure* for probit

coefficients. The independent variable must be scaled using a variable, *z*, derived from the *Z*

distribution, on which the probit model is based. The effect of a change in

*ln(SellerPBPropensity)* on premium bid likelihood, when all other independent variables are held

constant, can be calculated over the continuous variable *z*:

$$\text{Effect on } E \; [Prob[y_{PB}=1]_1| \; ln(SellerPBPropensity_1)] =$$
$$E \; [Prob[y_{PB}=1]_1| \; z * ln(SellerPBPropensity_1) = 1]$$
$$- E[Prob[y_{PB}=1]_1 \,|\, z * ln(SellerPBPropensity_1) = 0]$$

Marginal effects loosely mimic the role of coefficients in linear regression. Probit

independent variables do not have a linear effect. Marginal effects are used to estimate the

impact for one unit of change in an independent variable when all other independent variables

are held fixed at their mean values.

**Model Fit and Prediction Capabilities.** There is no universally accepted *goodness of fit*

*measure* for probit models (Kennedy 2003). Veall and Zimmermann (1996) argue for a *pseudo-*

*$R^2$ test* of Zavoina and McKelvey (1975), which helps to avoid overstating model fit. This test

yielded a pseudo-$R^2$ = 36%, a reasonable predictive capability. Another statistic is the model $\chi^2$

which shows a good fit ($\chi^2$ = 565; $p < 0.001$). Table 7 shows a concordance analysis of actual

and predicted values of auctions that contain or do not contain a premium bid. (See Table 7.)

**Table 7. Frequencies of Actual and Predicted Outcomes for the Premium Bidding Model**

| ACTUAL OUTCOMES | PREDICTED OUTCOMES | | |
|---|---|---|---|
| | Auction Predicted to Have No Premium Bids | Auction Predicted to Have Premium Bids | Total |
| Auction Has No Premium Bids | 848 | 96 | 944 |
| Auction Has Premium Bids | 176 | 193 | 369 |
| *Total* | 1,024 | 289 | 1,313 |

Using only data available at the beginning of the auction, including the setup of the auction

and previous behavior of the seller outside of this auction, our model correctly predicts if an

auction will receive a premium bid 79% (i.e., $(848 + 193) / 1,313 = 79\%$) of the time.  McIntosh and Dorfman (1992) point out that only using the percentage correctly predicted can lead to erroneous conclusions regarding the validity of an empirical model.  They advocate using the sum of the percentages of correct predictions in each category and comparing the result to 100%. Using their criteria, we correctly predict auctions that receive no premium bids 90% of the time (i.e., $848 / 944 = 90\%$), and we correctly predict auctions that receive premium bids 52% of the time (i.e., $193 / 369 = 52\%$).  The sum of the percentage correct predictions of auctions not containing a premium bid (90%) plus the sum of the percentage correct predictions of auctions that do contain a premium bid (52%) is 142% (> 100%), and indicates a strong fit.  Our results are consistent with reserve price shilling.  Shills may try to hide their behavior. Yet by using reserve price shilling to explain premium bids, we predict premium bids over half of the time.

**IMPLICATIONS AND DISCUSSION**

Our model successfully predicts auctions that receive premium bids primarily driven by reserve-price shilling.  We do not contend that there is no seller preference in online auctions. Instead, we believe that the many buyers and sellers, coupled with the limited inventory from individual sellers, make it hard to maintain seller preference.  Buyers are forced to use general guidelines to determine if a seller is satisfactory.  We divided our 1,313 auctions into groups based on reputation score, with each group containing roughly the same number of auctions (from 117 to 125 auctions in each group). We then charted the average percentage of premium bids for each category. See Figure 2.

**Figure 2. Percentage Premium Bids as a Function of Scaled Reputation Scores**
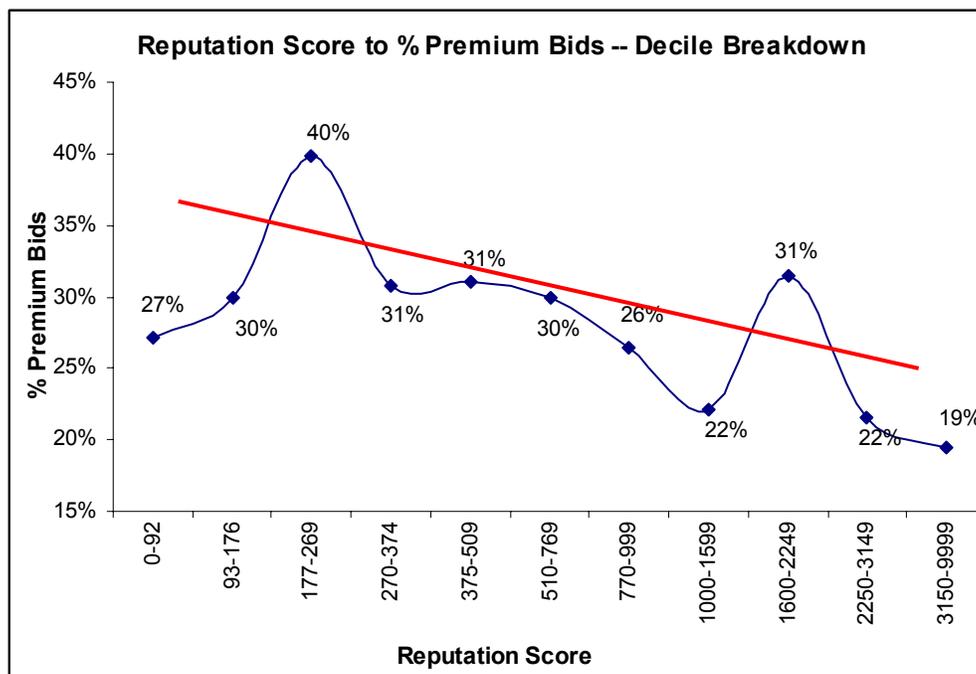


Overall, Figure 2 shows the trend that premium bids decrease as reputation scores increase, in line with the opportunism theory we discussed and our empirical analysis. Seller preference theory predicts that, as a seller increases her reputation score, the buyer should be more willing to by from that seller. Thus, premium bids should increase in seller reputation. This appears to be true at lower ends of reputation. Conversely, opportunism theory also predicts that sellers will act opportunistically if there is only a low chance of detection and punishment, but that as a seller develops a reputation, punishment of opportunistic behavior results in greater losses of established reputation. Thus, premium bids should decrease with seller score. For our data, this appears to be true after a reputation score of 177 to 269 has been established. Similarly, a low starting bid would result in fewer premium bids: low starting bids allow bidders to bid lower amounts than those items with higher starting bids. We find that listing prices are at or below $9.99 in 709 of 1,313 auctions, the lowest price point for starting bids. See Table 8.

**Table 8.  Data Broken Down by Starting Bid**

| STARTING BID RANGE | AUCTIONS | % PREMIUM BIDS | AVERAGE SELLING PRICE |
|---|---|---|---|
| $0.01 - $9.99 | 736 | 30.2% | $33.26 |
| $10.00 - $24.99 | 309 | 22.7% | $25.03 |
| $25.00 - $49.99 | 150 | 25.3% | $44.82 |
| $50.00 - $199.99 | 98 | 33.7% | $111.01 |
| $200.00 - $1,000 | 20 | 30.0% | $342.55 |

If the seller intends to enter a reserve price shill to avoid paying fees, that seller will list the item with the lowest possible fee and then use another identity to bid the item up to the reserve price.  The data support the premise that there is a high level of reserve price shilling occurring in online auctions. 56% of all auctions in our study (736/1,313) have a starting bid of $0.00 to $9.99.  This, in and of itself, is not enough evidence to support the occurrence of reserve price shilling, as the low starting fees can be predictive of the low starting bid range.   However, the auctions with this low starting bid level have premium bids 30.2% of the time.  This is higher than the next level, 22.7%.  A low starting bid level should allow for a lower level of premium bidding, since the average selling price at the lowest starting bid level is higher than the next level.  In every other fee breakpoint (with starting bids at $10.00-$24.99 to $199.99 and $200.00-$1,000), premium bids occur with a lower percentage at lower starting bid levels.  An elevated level of premium bids at lower fee levels cannot be explained by seller preference, but can be explained if sellers are using reserve price shilling to avoid paying auction fees.

**Implications for Electronic Auction Design**

There are some noteworthy implications for auction design that arise from this research.  Competitive shilling benefits the seller and the auction house, since it increases the price paid by the bidder (Brunker, 2000).  However, the shilling that we detected can have a negative effect on eBay, because the seller uses shilling to avoid paying auction fees.  Any type of shilling can be

detrimental in the long run, as bidders price downward to avoid opportunism.  With opportunistic sellers, honest sellers will not be able to sell products for their proper market value (Akerlof 1970).  Consumers will factor opportunism into the prices they are willing to pay. A side effect is that fewer commission-based fees will accrue for the online auction because products are being sold at a reduced value.  Thus, auction houses need to motivate reputable behavior by their participants and pursue those who decide to profit at the expense of the best interests of the market.

Online auctions can impose a fee structure to reduce the motivation for shilling.  Online auction services vendors can develop capabilities to catch shilling sellers.  Increasing detection risk will boost the willingness-to-pay on the part of potential buyers of auctioned items, so they mimic their common values in a fair market setting.

**Applicability to Internet-Based Selling**

Although we studied online auctions, our results generalize to other e-commerce settings. Since the mid-to-late 1990s, we have seen sellers of traditional retail products (e.g., books, music CDs, software, computers, etc.) also sell over the Web.  Low costs of entry permit new sellers to participate, and they can effectively mask their identities.  Our research shows that many sellers are likely to use the increased information asymmetry brought about by anonymity intrinsic to the Internet environment to take advantage of consumers.

**CONCLUSION**

In this research, we examine *premium bidding*, where a seller bids on an item in an auction when he could have bid less for the same item in a different auction. We also develop the concept of *reserve price shilling*, where sellers shill to avoid paying auction house fees.  This differs from the traditional *competitive shilling*, where the seller drives up the final bid. Our

results are consistent with the contention that reserve price shilling is the primary driver of premium bidding, more so than seller preference. We show that a primary victim of shilling is the auction house, whose fee structures may have the unintended consequence of motivating shill bidding.

We support our hypotheses by estimating a probit model that describes how premium bidding may be driven by reserve price shilling. Our model can be used to predict when a seller will receive a premium bid based upon previous seller behavior and auction characteristics chosen by the seller before the auction begins. We find that prior receipt of premium bids increases the likelihood of receiving a premium bid. Further, a low starting bid can indicate a higher probability of an auction receiving a premium bid. Sellers specify low starting bids to avoid auction fees and then enter higher bids in the auction to avoid selling an item below their own valuation. Finally, we find that as experience increases, sellers are less likely to receive a premium bid. If reserve price shilling primarily drives premium bids—as we surmise—then it makes sense that experienced sellers would not endanger their reputation by engaging in opportunistic behavior. This suggests that the operators of online auctions need to try to detect shilling and design fee structures that minimize its likelihood, while maximizing profit from appropriate insertion and reserve fees.

**Limitations**

This study has three limitations. First, we only considered coin auctions. But we believe that these results probably can be generalized to other auctions and to e-commerce and Internet-based selling in general, to reveal the extent of opportunistic behavior. Tests on other auctions are required before such statements can be asserted as being globally true. Second, we do not claim that reputable sellers cannot receive premiums for their reputable behavior. Nor do we claim that

bidders cannot mistakenly enter a bid higher than is warranted had they examined all available information. The results of this research should be interpreted to be that a primary driver of premium bids in this environment at this time appears to be reserve price shilling. Reserve price shilling is not the only driver of premium bids, but rather one that really seems to matter.

Finally, our method of detecting a premium bid deserves comment. It involves the idea that another auction with the same item for sale occurs concurrent with the auction in question, and that this other auction ends first. This ensures that we are comparing the auction in question to an auction that is closer to finishing, and not an auction that has just started. We think it is reasonable to assume that auctions will be bid up close to their conclusion. So it is erroneous to compare bid levels in one advanced auction against others that have just started. Defining the process this way makes it difficult to detect premium bids during the final hours and minutes of an auction, at the time when competitive shilling is most likely to occur. Thus, a different research design may be appropriate to examine competitive shilling that occurs in the final minutes of an online auction. Future research can examine this aspect in greater detail.

We empirically examined seller opportunism in an e-market. We showed reasons and evidence for why reserve price shilling may be present. We also showed that such behavior can be predicted based on seller actions. The intended victim of shilling is not just the bidder, but also could be the auctioneer, because the seller can avoid fees that the auction house has set. For these reasons, this paper is relevant for several audiences. Online auctions can learn to set fee structures that do not motivate such behavior. Sophisticated bidders and fraud detection services providers can use our techniques to examine an online auction for possible reserve price shilling. And, researchers can use our techniques to identify opportunistic behavior in other settings.

**REFERENCES**

Akerlof, G. A. "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism," *Quarterly Journal of Economics 84*(3), 1970, 488-500.

Athey, S., and Levin, J. "Information and Competition in U.S. Forest Service Timber Auctions." *Journal of Political Economy 109*(2), 2001, 375-417.

Ba, S., and Pavlou, P. A., "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior," *MIS Quarterly 26*(3), 2002, 243-268.

Bakos, J.Y. "Reducing Buyer Search Costs: Implications for Electronic Marketplaces," *Management Science 43*(12), 1997, 1676-1692.

Bapna, R., Goes, P., and Gupta, A. "Online Auctions: Insights and Analysis," *Communications of the ACM 44*(11), 2001, 42-50.

Belsley D. A., Kuh, E., and Welsch, R. E. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*, New York, NY: John Wiley and Sons.

Brunker, M. "eBay Reins in Anti-Shilling 'Posse'," *MSNBC*, October 26, 2000, available at www.msnbc.com/news/481550.asp?cp1=1, last accessed November 13, 2005.

Bulow, J., Huang, M., and Klemperer, P., "Toeholds and Takeovers," *Journal of Political Economy 107*(3), 1999, 427-454.

Chen, H. and Ritter, J. R., "The Seven Percent Solution," *J. Finance 55*(3), 2000, 1105-1131.

Christie, W. G., and Schultz, P., "Why Do NASDAQ Market Makers Avoid Odd-Eighth Quotes?" *Journal of Finance 49*(5), 1994a, 1813-1840.

Christie, W. G., and Schultz, P., "Why Did NASDAQ Market Makers Stop Avoiding Odd-Eighth Quotes?" *Journal of Finance 49*(5), 1994b, 1841-1860.

Clemons, E. K., Hann, I., and Hitt., L. M., "Price Dispersion and Differentiation in Online Travel: An Empirical Investigation," *Management Science 48*(4), 2002, 534-549.

DeGraw, I. "The Seven Percent Solution," *Wall Street Journal*, October 1, 1999, 1.

Dellarocas, C. "The Digitization of Word-of-Mouth: Promise and Challenges of Online Feedback Mechanisms, *Management Science* 49(10), 2003, 1407-1424.

DePaulo, B., and Pfeifer, R. "On-the-Job Experience and Skill at Detecting Deception," *Journal of Applied Social Psychology 16*(3), 1986, 249-267.

DePaulo, B.M., Stone, J. I., and Lassiter, G.D. "Deceiving and Detecting Deceit," in B. R. Schlenker (Ed.), *The Self and Social Life,* New York, NY: McGraw-Hill, 1985.

Easley, R. F., and Tenorio, R. "Jump Bidding Strategies in Internet Auctions," *Management Science*, *50*(10), 2004, 1407-1419.

Feldman, R. A., and Mehra, R. "Auctions: Theory and Applications," International Monetary Fund Staff Papers, International Monetary Fund, Washington, DC, September 1993.

Fudenberg, D. and Tirole, J. *Game Theory*, Cambridge, MA: MIT Press, 1991.

Geweke, J., Keane, M., and Runkle, D., "Alternative Computational Approaches to Inference in the Multinomial Probit Model," *Review of Economics and Statistics 76*(4), 1994, 609-632.

Gibbs, W. *Coin World 2001 Guide to United States Coins*, New York, NY: Signet, 2001.

Greene, W. H. "Marginal Effects in the Bivariate Probit Model," Working paper, Stern School of Business, New York University, New York, NY, 1996.

Greene, W. H. *Econometric Analysis, 5ᵗʰ Edition*, Englewood Cliffs, NJ: Prentice Hall, 2002.

Hausman, J., and McFadden, D., "Specification Tests for the Multinomial Logit Model," *Econometrica 52*(5), 1984, 1219-1240.

Hidvegi, Z., Wang, W., and Whinston, A. B. "Sequential English Auctions with Shill Bidding." Working paper, U. Texas, Austin, TX, 2005.

Johnson, P. E., Grazioli, S., Jamal, K., and Berryman, R. G., "Detecting Deception: Adversarial Problem Solving in a Low Base Rate World*," Cognitive Sci. 25* (3), 2001, 355-392.

Kauffman, R.J., and Wood, C.A. "On Reserve Price Shilling in Online Auctions," Presented at the Workshop on IS and Economics (WISE 2001), New Orleans, LA, December 2001.

Kauffman, R. J., and Wood, C. A. The Effects of Shilling on Final Bid Prices in Online Auctions," *Electronic Commerce Research and Applications 4*(1), 2005, 21-34.

Kauffman, R.J., and Wood, C.A. "Doing Their Bidding: An Empirical Examination of Factors that Affect a Buyer's Utility in Internet Auctions," *IT and Management*, *7*(2), 2006, forthcoming.

Kennedy, P. *A Guide to Econometrics, Fifth Edition*, Cambridge, MA: MIT Press, 2003.

Klein, B., and Leffler, K. B. "The Role of Market Forces in Assuring Contractual Performance," *Journal of Political Economy 89*(4), 1981, 615-641.

Kuchinskas, S. "eBay Charged with Shilling," *InternetNews.com*, February 23, 2005. www. internetnews.com/ec-news/article.php/3485301, accessed November 13, 2005.

Lee, H. G. "Do Electronic Marketplaces Lower the Price of Goods?" *CACM 41*(1), 1998, 73-80.

Liao, T. F. "Interpreting Probability Models: Logit, Probit and Other Generalized Linear Models," *Sage University Series on Quantitative Applications in the Social Sciences*, Series No. 07-101, Thousand Oaks, CA: Sage Publishers, 1994.

Malone, T.W., Yates, J., and Benjamin, R. I. "Electronic Markets and Electronic Hierarchies." *Communications of the ACM 30*(6), 1987, 484-497.

McIntosh, C.S., and Dorfman, J. H. "Qualitative Forecast Evaluation: A Test for Information Value," *American Journal of Agricultural Economics 74*(1), 1992, 209-214.

Milgrom, P. "Auctions and Bidding: A Primer," *J. Economic Perspectives 3*(3), 1989, 3-22.

Mittal, V. and Kamakura, W. A., "Satisfaction, Repurchase Intent, and Repurchase Behavior: Investigating Moderating Effect of Customer Characteristics," *J. Mktg Res. 38*(1), 2001, 131-143.

National Consumers League. "Online Auctions, 2001 Survey: Summary of Findings," Washington, DC, 2001, www.nclnet.org/shoppingonline/auctionsurvey.htm, accessed Nov. 13, 2005.

National Consumers League. 2004 Internet Fraud Statistics, Washington, DC, 2004. www.fraud.org/2004-internet%20scams.pdf, accessed November 13, 2005.

National Consumers League. Internet Scams: Fraud Trends, January – June 2005, Washington,

DC, 2005.  www.fraud.org/internet/internet_scams_halfyear_2005. pdf, accessed Nov. 13, 2005.

Neter, J. Kutner, M. H., Nachtsheim, C. J., and Wasserman, W.  *Applied Linear Statistical Models, Fourth Edition*, Irwin Press, Chicago, IL, 1996.

Rankin, K. "Scams Thwart Growth of E-Commerce," *Discount Store News 38*(9), May 3, 1999, 14.

Resnick, P., and Zeckhauser, R. "Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System," in M. R. Baye (Ed.), *Economics of the Internet and E-Commerce*, Volume 11 of  *Advances in Applied Microeconomics,* Amsterdam: Elsevier, 2002.

Riley, J. G., and Samuelson, W. F., "Optimal Auctions," *Amer. Econ. Rev. 71*(3), 1981, 381-392.

Selgin, G. A. and White, L. H.  "How Would the Invisible Hand Handle Money?" *Journal of Economic Literature* 32(4), 1994, 1718-1749.

Shapiro, C.  "Consumer Information, Product Quality, and Seller Reputation," *Bell Journal of Economics 13*(1), 1982, 20-35.

Sinha, A. R., and Greenleaf, E. A., "The Impact of Discrete Bidding and Bidder Aggressiveness on Sellers' Strategies in Open English Auctions: Reserves and Covert Shilling," *Marketing Science 19*(3), 2000, 244-265.

Tschantz, S., Crooke, P., and Froeb, L. "Mergers in Sealed Versus Oral Auctions," *International Journal of the Economics of Business 7*(2), 2000, 201-212.

Veall, M. R, and Zimmermann, K. F. "Pseudo-$R^2$ Measures for Some Common Limited Dependent Variable Models," *Journal of Economic Surveys 10*(3), 1996, 241-259.

Vickery W. "Counter-Speculation Auctions and Competitive Sealed Tenders." *Journal of Finance 41*(1), 1961, 8-37.

Wang, W., Hidvegi, Z., and Whinston, A. B. "Shill-Proof Fee Schedule: The Sunscreen against Seller Self-Collusion in Online English Auctions."  Working paper, U. Texas, Austin, TX, 2004.

Zavoina W., and McKelvey, R. D. "A Statistical Model for the Analysis of Ordinal Level Dependent Variables," *Journal of Mathematical Sociology 4*(3), 1975, 103-120.