

# AN INVESTIGATION OF PREMIUM BIDDING IN ONLINE AUCTIONS

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## ABSTRACT

Although the Internet is useful for transferring information, transactions in Internet auctions can have a greater *information asymmetry* than corresponding transactions in traditional environments because current auction market mechanisms allow the seller to remain anonymous and to easily change identities. Buyers must rely on the seller's description of a product and ability to deliver the product as promised. Internet auction environments make opportunistic behavior more attractive to sellers because the chance of detection and punishment is decreased. In this research, we show how fee structures at eBay, the largest online auction house, motivate shilling behavior. We distinguish between two different types of shilling that exhibit different motivation and behavior: shilling can be used to make the bidders pay more for an item, *competitive shilling*, and shilling that can be used to avoid paying auction house fees, *reserve price shilling*. We then use data on 10,260 eBay auctions during April 2001, with 30,496 bids on 7,071 auctions from 5,304 distinct bidders and 1,385 distinct sellers, to examine reserve price shilling using a probit model. Our results show that with reserve price shilling, bidders tend to repeat their behavior, book value and starting bids are indicative of reserve price shilling.

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**KEYWORDS:** Economic analysis, electronic markets, e-commerce, empirical research, fraud detection, information asymmetry, Internet auctions, opportunism, shilling.

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## INTRODUCTION

Electronic commerce offers a variety of new business models, such as group buying and Internet-based stock trading and investment management, which represent changes in how business can be done with the aid of new technologies. Online auctions have emerged as a result of the changes brought about by Internet technology. Now there are firms such as eBay and Yahoo! that offer auctions of up to ten days, joining millions of sellers to millions of buyers, and increasing the liquidity of the sale goods. However, although online auctions allow consumers to find a wider variety of items and sellers to extend their reach, this technology also has changed or reduced much of the information that is transferred, especially seller-related information.

### **Motivation**

Such changes have allowed opportunistic buyers to more easily victimize unknowing consumers. According to the National Consumers' League (2001), Internet fraud increased over eight times from 1997 to 1999. In addition, the FBI (1999) reported that fraud slightly decreased during that time. E-commerce opportunism is facilitated by an increase in information asymmetry between the online buyer and the online seller, especially in the areas of seller and product inspection, allowing sellers to take advantage of anonymity to act opportunistically. This behavior is illustrated by a Harris Poll Report survey ([www.harrispollonline.com](http://www.harrispollonline.com)), whose statistics we quote below (National Consumer League, 2001). An estimated 35.6 million people participated in online auctions in 2000, with about 83% of bidders making at least one successful bid. These bidders were confident in the ability of online auction transaction to result in eventual receipt of goods. 94% indicated they were "very confident" or "somewhat confident" to receive the items for which they have paid.

Despite this high degree of confidence, however, the Harris survey reports that 41% of

buyers have had problems. 20% indicated that they received items much later than expected. 11% received items different than the seller promised. 10% received damaged items, and another 10% never received the items. Most bidders, about 62%, indicated that they were able to resolve these problems. Another 29% resolved auction transaction-related issues by complaining to the auction site, and achieved no monetary resolution. Still another 10% disputed credit card charges with 80% success, and 5% made insurance claims also with 80% success. Others enlisted assistance from mediation services, the Better Business Bureau, or other consumer groups. The final group, some 21% overall, claimed they took no action to resolve transaction-related problems. Evidently, there is more cause for concern than is popularly believed.

Among the various kinds of fraud that are occurring in this context, one type of auction fraud that is the hardest 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. On its face, shilling also increases any commission that an auction house may receive for an auction. Auction houses like eBay are able to employ statistical techniques to detect the probability of the occurrence of shilling, but auction houses are unable to *explicitly* detect shillers due to the anonymity of sellers and buyers on eBay, and may be reluctant to investigate or punish shills in any case. Just the fact that shilling has the potential to generate more revenue for an auction house because of higher commissions that result from higher sale prices brought about when a seller “runs up the bid”.

Shilling is more difficult in traditional auctions when compared with online auctions. *First*, the bidder often needs to be present, and is readily identified by all other bidders, increasing the likelihood of detection and thus diminishing the incentive to shill. *Second*, the length of the auction is usually only several minutes long. Compared to online auctions, shills do not have as much time to enter a false bid in the hopes that, in the minutes that follow, legitimate bidders

may outbid the shill. *Third*, the number of potential bidders in traditional auctions is relatively limited when compared to online auctions. Thus, there is a larger chance to find a bidder whose private valuation of an item exceeds that of the shill bid in online auctions. While there are isolated examples in traditional auctions where the seller or buyers can remain anonymous, the scope and participation, drawn from millions of participants, is unmatched in online auctions.

### **Research Questions**

Although Information Systems (**IS**) researchers have examined e-commerce buyer behavior (e.g., Lee 1998; Kauffman and Wood, 2003; Vakrat and Siedman, 1999), less work has been done to investigate Internet seller behavior. We propose a model that shows how sellers in Internet auctions are motivated toward a decision to make a shill bid in the absence of identification and personal contact, and ask:

- ❑ Why does the online environment motivate opportunistic decisions like shilling, and how can one characterize the type and extent of shilling that occurs in online auctions?
- ❑ How can we detect and predict when a seller will decide to act opportunistically in online auctions?
- ❑ How can the motivation for opportunistic decisions in online auctions be curtailed through auction design mechanisms?

### **Referent Theory**

We will show how economic theory provides an explanation for the increase of opportunism, such as shilling, among sellers on the Internet. We analyze data on rare coin auctions to show how anonymous sellers react to buyers. We then develop a technique to examine opportunistic behavior as it is occurring in terms of what effect such opportunism would have on an auction's characteristics, and then testing to see if this exists. We identify two forms of shilling, each with its own motivation and different associated behavior and results.

*First, reserve price shilling* is what occurs when a seller shills to avoid paying fees, such as *listing fees* (i.e., charged the seller to list an auction, and increase with the auction's declared starting bid), or *secret reserve fees* (i.e., charged to place a secret reserve on an auction so that the item will not sell until the secret reserve is met). Reserve price shilling can be used to avoid paying such fees, or to get bidders to bid above a seller's secret reserve price.

*Second, competitive shilling* occurs when a seller tries to "run up the bid" by entering bids to make legitimate bidders pay more, and the amount is above the seller's reserve price. 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 (Riley and Samuelson, 1981.) The difference between the actual bid and the bidder's valuation is called the *bidder surplus*. The seller risks both losing the sale and paying a commission fee (by accidentally winning his own auction) in order to receive more of the bidder surplus from an auction item.

### **Overview of the Main Results**

To pursue an in-depth understanding of these issues, we developed an empirical research design that involved the collection of tens of thousands of bid, bidder, seller, auction, and item data records. This approach enables us to analyze on how shills in electronic auctions bid on their own products to drive up the price. We show that their characteristic behaviors may not only be to ensure a higher price, but also this behavior increases the likelihood that the seller can avoid paying a reserve price fee to an auction operator. Following our analysis to develop evidence of shilling, we offer suggestions for how auction houses may eliminate this by incorporating elements into their auction design that are motivated by economic theory.

### **THEORETICAL BACKGROUND**

Four areas in the literature offer useful theoretical insights for modeling and understanding

deception and information asymmetry problems in buyer-seller interactions on the World Wide Web. *First*, IS and Marketing researchers are investigating shilling from a theoretical and analytical modeling viewpoint, to understand how shilling is motivated within online auctions. *Second*, Economics researchers investigate problems of how *information asymmetries* can affect seller behavior within a transaction, especially in the area of motivation and disincentives for opportunistic behavior. *Third*, this research uses some methods described in Cognitive Science research that discusses deception and the techniques that are required to detect it. *Fourth*, several recent IS articles discuss online auctions, and other auction economics works are useful, including work by Vickery (1961), Milgrom (1989), and Riley and Samuelson (1981).

### **IT and the Facilitation of Shilling**

Wang, Hidvegi and Whinston (2001) point out how traditional auction theory assumes a small number of identifiable bidders that bid in a single isolated auction that cannot be repeated. Moreover, the auction literature typically makes a number of other relatively strong assumptions about the manner in which transaction-making ensues. The transactions are costless. Buyers and sellers possess perfect information to inform their transaction-making, do not collude. This contrasts with online auctions where there are many repeated auctions and many bidders. Also, the identities of the bidders and of the sellers are often masked behind a “handle,” and there may be no disclosure of a person’s real identity. The authors developed analytical models of the ways that reserve price fees can be used to limit the occurrence of shilling in online auctions.

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. We will examine shilling as it occurs. We propose no new models for assessing performance. Instead, we theorize and analyze about why IT facilitates opportunistic seller

behavior, how to detect and predict such behavior, and how to prevent it in the future.

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

Many 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 do not believe that sellers will not 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. Hence, sellers of high quality cars will not be able to transact at a price that reflects value. At the limit, they will not transact. The result is market failure. 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 (as with a monopoly), product quality is reduced if buyers cannot be fully and accurately evaluated before the purchase. Shapiro (1983) extended Klein and Leffler's model to incorporate imperfect communication between customers.

Central to these papers' models is the *punishment* 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 Internet sellers to mask their identities, increasing information asymmetry and reducing chances of detection and punishment. We will show how the reduced chance of punishment can lead to more opportunistic behavior.

There has been much discussion on reputation systems in online auctions that arises from seller opportunism. Recent research suggests that Internet technology can reduce seller opportunism with respect to prices, since search costs are reduced, leading to a reduction in a vendor's ability to charge higher prices than its competitors. However, in other areas of

information, such as product or vendor inspection, the anonymous and translocational nature of the Internet can increase information asymmetry, which can result in seller opportunism. This is pointed out in much of the online auction reputation systems literature. Wood, Fan, and Tan (2002) show how eBay-like reputation systems can lead to opportunistic behavior once a seller's reputation has been established. This effect is exacerbated by the reluctance of sellers to leave negative comments. Dellarocas (2003) discusses how eBay-like environments contain *moral hazard* where sellers are motivated to profit from information asymmetry inherent within the online auction environment. Resnick and Zeckhauser (2002) describe how there is a disincentive to provide negative feedback, thus promoting opportunistic behavior. We examine a specific opportunistic behavior, shilling, and analyze how the design of the eBay fee structure can motivate such opportunism among eBay sellers.

### **Detecting Deception**

The Cognitive Science literature also discusses deception. DePaulo and Pfeifer (1986), and Johnson, et. al. (2001), discuss how deception detection has a low rate of feedback—occurrences of successful deception detection are so few that individuals do not get feedback to improve how they detect it. With the low rate of feedback, people who are experienced at auditing tasks cannot outperform novices. This is true when auditors' judgments are confirmed or disconfirmed, and auditors are unsure what cues and rules lead to success at detection.

DePaulo, Stone and Lassiter (1985) note that receivers tend to accept what is told to them, with little thought of deception, making deception detection more problematic. The Internet further exacerbates this problem. Internet sellers can assume many identities (e.g., Bunker, 2001; Clemons, Hann and Hitt, 2001), and thus decreasing the rate of detection to an even lower level. This can motivate fraudulent behavior.

Johnson et al. (2001) describe how deceptive behavior can be detected. In their study, auditors who are continuously successful appear to employ a heuristic that detects inconsistencies in light of the deceiver's goals in possible actions. Successful auditors appear to learn to identify the effects of fraud in comparison with situations where none is occurring, and then examine that effect more closely. We use this general method and will determine how the outcome and bidding behavior observed in an auction containing a shill bidder will differ from auctions containing no shill bidder, and then we examine those auctions more carefully in comparison to the other auctions.

The Finance literature has long since accepted this technique, as similar papers employ this technique where participants deliberately hide their fraudulent or opportunistic behavior. For example, Christie and Shultz (1994a) in an award-winning *Journal of Finance* paper, note how NASDAQ dealers acted collusively in avoiding odd-eighth stock quotes, thereby increasing the spread 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. This work made a significant impact in the industry. Soon after it appeared as a working paper, the practice all but ceased (Christie and Shultz, 1994b). A subsequent related impact was a \$1.03 billion settlement payment by the market makers related to instances in which explicit collusion was shown to have occurred (DeGraw, 1999). Chen (2000) used similar techniques and found evidence for similar tacit collusion in the spreads for initial public offerings of stock, where the spread clustered around 7% over a 14-year period regardless of the size of the issue.

### **Other Relevant Perspectives on Bidding Behavior in Auctions**

The IS auction literature has concentrated on auction characteristics and bidder behavior in

Internet auctions, not seller behavior (e.g., Bapna, Goes and Gupta, 2001; Ba and Pavlou 2002; Easley and Tenorio 2002). Vakrat and Seidmann (1999) compare online catalog prices with online auction prices. They obtained data from 473 online auctions, such as SurplusAuction and OnSale.com. They compared prices received in these auctions with prices from Internet catalog sellers, such as PriceScan.com, and the now-acquired Egghead.com. They showed that sellers should expect to make less for items sold online, and that price discounts increase as items become more expensive. We extend by examining how sellers try to boost the amount they receive in online auctions through opportunistic behavior.

Auction theory in Economics stresses the importance of a bidder's value of an item. Some 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, Crook and Froeb, 2000), where each bidder can have a unique valuation. Feldman and Mehra (1993) suggest that the independent private value assumption is valid for collectors. But resellers who purchase an auction item for later resale use common value as an estimate of the value of the auction item to be sold on the secondary market. Since we are examining seller shilling, we assume common values because, if the bidders are actually sellers using a secret identity, then they would expect to be able to obtain the market value for a collectible (Feldman and Mehra, 1993). In rare coin auctions, we can use *book value* listings from *Coin World* (Gibbs, 2000), the "industry bible," as a proxy for common value. Most coin dealers agree that this book value listing represents how much a coin is worth to the final collector, and thus is a good representation of a coin's common value in an auction.

### **WHY ARE SELLERS MOTIVATED TO DO RESERVE PRICE SHILLING?**

To predict the motivation for a seller's decision to shill, we must first understand two

situations. *First*, auction houses charge fees that may impact a seller's behavior. *Second*, auction houses may have little incentive to strictly police shilling behavior. We next discuss how the decision for shilling behavior can result from the environment and fee structure imposed by the online auction house.

### **How 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 non-refundable *listing fee*. The listing fee is based upon the amount of the starting bid, set by the seller. Higher starting bids require higher the listing fees. During listing, the seller can select other options that are also available for an additional fee. Specifically, in the context of this research, the seller can declare a *secret reserve amount* which the bidders must exceed if they are to win an item. Starting bid amounts and the existence of a secret reserve (whether the secret reserve is met or not) are available to bidders on an item screen that lists the auction information. If the seller opts for a secret reserve amount, then he is charged a *secret reserve fee*. If the item is successfully sold (i.e., the item receives at least one bid that is above the secret reserve amount, if a secret reserve amount is declared by the seller), eBay charges a *closing fee*, which is a decreasing percentage commission of the sale price (the *commission rate*), 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. (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 flat at 5%. 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**

TRANSACTION AMOUNT	CLOSING FEE (FIXED FEE + COMMISSION RATE ON SALE AMOUNT)	LISTING FEE ON STARTING AMOUNT	SECRET RESERVE FEE ON RESERVE AMOUNT
\$0.01 - \$9.99	5%	\$0.30	\$0.50
\$10.00 - \$24.99	5%	\$0.55	\$0.50
\$25.00 - \$49.99	\$0.625 + 2.5%	\$1.10	\$1.00
\$50.00 - 199.99	\$0.625 + 2.5%	\$2.20	\$1.00
\$200 - \$1000	\$0.625 + 2.5%	\$3.30	\$1.00
> \$1000	\$12.50 + 1.25%	\$3.30	\$1.00

**Note:** Other auctions show some similarities with their fee schedules. During this period, Amazon and Yahoo employed graduated closing fee structures similar to eBay. Amazon charged the same listing fee (\$.10) for every item while Yahoo employed a graduated listing fee structure similar to eBay. Neither Amazon nor Yahoo charged for secret reserve prices, although Yahoo would raise the listing fee to be the fee that should be charged for the secret reserve price. But, Amazon and Yahoo do not have enough market share to generate sufficient data needed for this analysis, and thus eBay, which controlled over 80% of the online auction market at that time, is the only auction house used in this study.

To illustrate how the fee structure at eBay motivates reserve price shilling, if the seller sets the auction's starting bid at less than \$10, the listing fee is \$.30. If the seller sets the auction's starting bid at greater than \$200, the listing fee is \$3.30. Thus, a seller who wants to ensure that an item is sold for at least \$200 can set the auction's starting bid at an amount of less than \$10 and then enter a shill bid for \$199.99. This bid can be lower if the shill uses agents to bid higher, when another bidder makes a bid below \$200. If another bidder bids more than \$200, the seller will save \$3.00 in listing fees, but risks inadvertently winning the auction, thus forgoing any sale and also forcing the seller to pay a commission.

eBay charges a *secret reserve fee* of \$.50 or \$1.00, refunded if the item is sold at a higher price higher than the reserve price. eBay discourages 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 prevent such behavior, eBay sellers who are inclined to shill will prefer shilling to setting a secret reserve price until the shill bid reaches \$10. Why? A seller can win his own auctions, but still owe less than the \$.50 or \$1 fee charged for setting a secret reserve price:

$$\text{Break-Even Shill} = \text{Secret Reserve Fee} / \text{Commission Rate} = \$.50 / 5\% = \$10.$$

There is a chance on any bid over \$10 that the seller can shill and not pay because a legitimate bidder will outbid the shill seller. Consider that eBay charges a 2.5% commission plus \$0.625, and charges a \$1 for a secret reserve price. Given these parameters, if a seller has a 25% probability of winning an auction, then the seller will save 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:

$$\begin{aligned} \text{Expected \$1 Reserve Fee} &= ((\text{Reserve Fee} / \text{Probability of Winning}) - \text{Fixed Fee}) / \text{Commission Rate} \\ &= ((\$1 / 25\%) - \$0.625) / 2.5\% = \$135. \end{aligned}$$

So with eBay's fee structure for secret reserve fees and a 25% probability of winning, a bidder is more inclined to shill than pay for a secret reserve price until the shill bid for the auction exceeds \$135. This assumes that only the reserve fee is considered. Using eBay's fee schedule, 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 Fee, April 2001**

PROBABILITY OF WINNING A SHILL BID	BID AMOUNT FOR WHICH SHILLING COST > MINIMUM OF RESERVE FEE AND LISTING FEE
10%	> \$375.00
20%	> \$175.00
25%	> \$135.00
30%	> \$108.33
40%	> \$75.00
50%	> \$55.00

The expected cost of shilling decreases when the probability of winning decreases. So sellers will try to reduce the probability of winning, and one can see how an auction house's fee structure can motivate shilling behavior. For eBay, the secret reserve insertion and commission rate fees all motivate shilling behavior up to a fairly high-priced auction item.

Setting up a new identity with online auction houses like eBay is relatively simple, quick,

and has no monetary cost. It only requires a credit card. New users are allowed to bid on any item, and are not excluded from online auctions until their reputation score goes to  $-3$ , or unless they are disciplined for violating eBay online auction rules. Thus, we do not consider the time costs for setting up a new identity to be a detriment for users who wish to use multiple identities.

### **How Do the Internet Environment and Auction House Behavior Motivate Shilling?**

Shilling is not socially accepted behavior. eBay no longer permits it, for example. To shill, a seller assumes a different identity to profit at the expense of the high bidder or the auction house. In the United States and other countries, shilling is considered criminally fraudulent behavior, punishable by both fines and/or jail terms. For example, Mahoney (2001) reports how a man was charged with sixteen counts of fraud resulting from shilling. Additionally, most auction houses suggest the possibility of severe reactions if shilling occurs. Evidently, since the perceptions of the potential conflict of interest are strong, sellers must abide by set of rules of operation that minimize the likelihood of shilling. Moreover, Bunker (2001) reports that there are groups that are dedicated to the removal of shilling from online auctions. Thus, the seller also ought only to shill if the sale item has a high valuation to warrant the increased risk and time spent to track and enter shill bids.

The possibility of detection of shilling is reduced online because Internet auction sellers and bidders can set up identity-masking “handles,” thus hiding the identities of buyers and sellers. 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 e-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 effect on the information asymmetry. Shilling results in higher bids, which results in additional profit for any auction house that makes a commission from total sale price. The houses, then, may be reluctant to make efforts to detect opportunistic sellers whose actions are profitable for the house, even if they declare adherence to an anti-shilling code of ethics, and require participants to do the same. Bunker (2001) notes how online consumers speculated that eBay ignores shilling because it involves some of their biggest clients, and they generate substantial income for eBay. Bunker notes that the punishments meted out to transgressors are light, involving first a warning and then a 30-day suspension from the site. The detection costs for the shill, thus, are not very high.

If the auction house is unwilling to reduce the effects of the increase in information asymmetry brought about by anonymity intrinsic to the online environment, then the probability of detection is reduced even further. This may motivate more sellers to adopt shilling as a viable strategy to achieve the goal of selling at the highest price that can be achieved in the market, while minimizing the associated operational costs assessed by the auction market provider.

### **Research Hypotheses**

As we have argued, auction sellers who decide to shill accept risks and ignore the social mores against this behavior. Thus, it is reasonable to suggest that if a seller has exhibited shilling behavior in the past, he has already justified the practice of shilling to themselves, both in terms of risk and ethics, and hence, is prone to decide to shill again. This leads to our first hypothesis:

- **REPEATABLE SHILLING BEHAVIOR HYPOTHESIS (H1).** *Sellers that have shilled before are more likely to shill again.*

Similarly, we propose that sellers with a reputation for opportunistic behavior risk little by behaving in the same manner. 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, we propose that experienced sellers and sellers with stronger reputations are motivated against deciding to shill because detection could result in a greater loss.

- **HYPOTHESIS 2A (THE EXPERIENCED SELLER HYPOTHESIS).** *Experienced sellers will be less likely to shill.*
- **HYPOTHESIS 2B (THE SELLER REPUTATION HYPOTHESIS).** *Sellers with a good reputation will be less likely to shill.*

Shilling can also be motivated by auction rules that permit a lower starting bid. Thus, sellers can save money by setting a relatively low starting bid for an auction and then, after bidders start bidding, sellers can shill to ensure that they do not receive a final bid below their own valuation:

- **HYPOTHESIS 3 (THE LOW STARTING BID HYPOTHESIS).** *A low starting bid is associated with future reserve price shilling.*

Sellers will want to minimize the probability of winning a shill bid because, as shown in Table 2, the lower the probability of winning a shill bid, the lower the expected cost. Thus, they will want to shill early in the auction cycle to increase the number of bidders who will view the auction and increase the chance that some bidder will bid higher. So longer length auctions are desirable to reserve price shills:

- **HYPOTHESIS 4 (THE AUCTION LENGTH HYPOTHESIS).** *Reserve price shills are more likely to have longer-running auctions than sellers who do not shill.*

As we stated earlier, the price the item is expected to command in an auction (e.g., common value) will have an effect on reserve price shilling. At lower common values, the risk and the value of the seller's time may make shilling unprofitable. At higher values, the seller's risk of

financial loss is greater, and the motivation for shilling is thus increased:

- **HYPOTHESIS 5 (THE COMMON VALUE HYPOTHESIS).** *There is a positive relationship between the common valuation of an auction item and the existence of reserve price shilling behavior.*

Finally, as reserve price shilling replaces paying a fee to set a reserve price, the existence of a reserve price may affect the motivation to shill. That effect, if it does exist, could be counter-intuitive. If the seller feels no need to shill because a secret reserve price protects him from risk, then the existence of a secret reserve price should reduce the likelihood of reserve price shilling. However, the opposite is also possible. If a secret reserve price is set, then the seller will absorb no risk by shilling below the secret reserve price. In this case, the seller benefits by bidding on his own auction to force the bid to a higher level above the reserve price, thus using shilling as a type of communication vehicle to indicate that other bidders are not bidding high enough. Otherwise, a seller's product will not sell, and so will be forced to pay the reserve price fee.

If a seller can force other bidders to bid above the secret reserve price by bidding up to it, the seller will profit from doing this with very little risk. Furthermore, the seller may feel less ethical concern about reserve price shilling when the fraudulent bids are below the reserve amount. Such a bid is not fraudulent, and thus not illegal, since financial damages, one of the elements necessary for fraud, are not possible. Legitimate bidders will never win the auction until they bid above the reserve price, and since they cannot win an auction below the reserve price, a shill bid will simply raise bids to the point where winning the auction is possible. Sellers can “communicate” with bidders through a bidder who will bid up to the reserve amount, thereby forcing bidders to bid up to that point where the auction item can be sold.

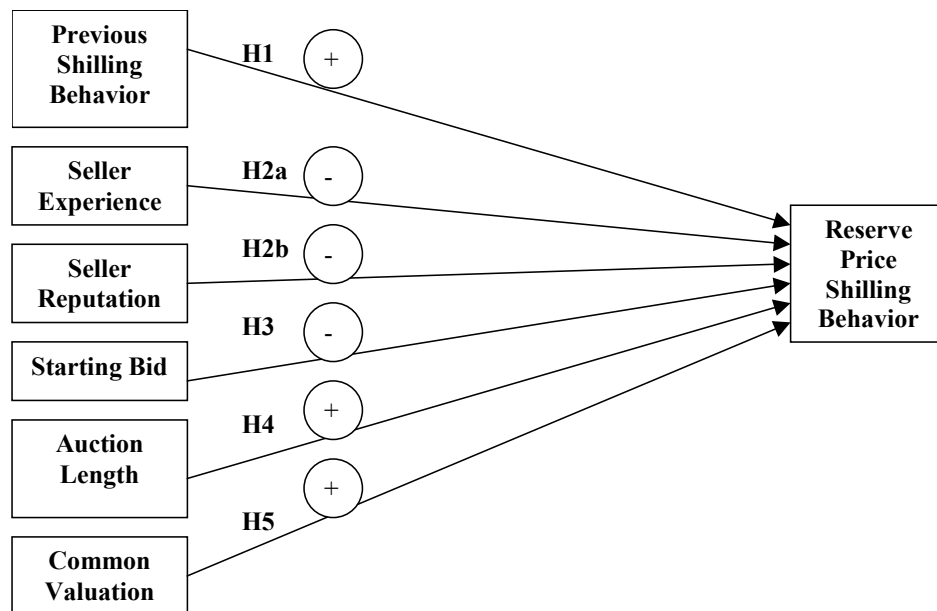
## A Conceptual Model for Reserve Price Shilling

Even though we cannot formulate a specific hypothesis about the role of a secret reserve price, we nevertheless recognize that it is a potential factor that needs to be considered as a control variable as we attempt to explain reserve price shilling. Also, we should consider other control variables, such as competition in other auctions, to shed light on our empirical model. Overall, the hypotheses that we discuss give rise to our specification of a general model.

$$\text{Reserve Price Shilling Behavior} = f(\text{Previous Shilling Behavior, Seller Experience, Seller Reputation, Starting Bid, Previous Bid, Time Left in Auction, Common Value})$$

We next present a conceptual model for the hypothesized shilling behavior. (See Figure 1.)

**Figure 1. Overview of Hypotheses Tested in the Empirical Model**



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. Reputation researchers point out that, in Internet-based auctions, the amount of information transferred between the seller and the buyer is especially incomplete (e.g., Resnick

and Zeckhauser, 2002; Wood, Fan, and Tan, 2003). Often, sellers and competing bidders are anonymous or unknown.

## DATA

We used an Internet agent to gather data for this study from eBay. It gathered user-specified auction information from eBay, including auction characteristics, item characteristics, seller characteristics, bidder characteristics, and bid characteristics. It uses a set of categories and examines archival data that eBay provides to users. It then examines each category archive for each day of the previous month's data. This, in turn, contains several Web pages of archived auction data. Auctions are "drilled" for item and bid information.

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 description of 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.

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* (Gibbs, 2001). *Coin World's* book values are typically what are charged by dealers at stores. They represent market prices for collectors with a small 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 whose book values ranged from \$1.30 to \$5,750.

We only considered rare coins minted predominantly in the 1800s. These include 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. They also 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. All auctions containing multiple items (e.g., “a roll of Indian Head pennies,” or “a 1857 Flying Eagle with an 1857 Braided Hair large cent,” etc.) were not considered. All auction items that were not coins in these categories (e.g., “gray sheet” coin prices, coin cleaning kits, etc.), as well as those that did not list a year or indicate a grade were not considered. A further complexity for coin pricing involves coins with two different grades for the obverse (i.e., the head of the coin) and the reverse (i.e., the tail of the coin), and thus we did not consider coins with multiple grades. The resulting data include 10,260 eBay auctions during April 2001, with 30,496 bids on 7,071 auctions from 5,304 distinct bidders and 1,385 distinct sellers.

## **MODELING ISSUES AND EMPIRICAL MODEL**

We now analyze the data to gain insights on shilling. We discuss how to detect it, and also distinguish among the kinds of observed bidder behavior, as a means to understand fraudulent bidding. Finally, we outline how our shilling propositions translate into testable hypotheses.

### **Detecting Shilling Behavior**

Detecting shilling behavior is hard. *First*, opportunistic sellers try to remain anonymous and

undetected. *Second*, it is difficult to track multiple Internet auction identities and tie them together. *Third*, opportunistic behavior needs to be viewed in sum, not in isolation. So it is difficult to build a convincing case for it. For instance, bidders may bid too high a price on an auction item that they should not have bid upon. But such behavior needs to be viewed in the context of other behavior and other bids before the opportunistic seller can be identified.

From anecdotal evidence, we know that sellers can easily set up multiple eBay identities. The sellers are also anonymous too. They can easily be opportunistic in a way that is difficult to detect. For example, they can establish new handles or work in collusion with certain buyers to bid on their own items. With less chance of detection, the seller's benefit from opportunistic behavior may be greater than the expected lost profit from future transactions, since changing a handle can mask a seller's identity and reduce the chance of punishment.

We utilize an operational definition of opportunistic bidding. Figure 2 shows a database form that illustrates an instance of *Premium bidding*. Premium bidding is: (1) bidding on an auction, (2) when the same or lower bid could have been made on the exact same item in a concurrent auction, (3) when the auction bid upon ends after the other concurrent auction, and (4) where the bidder did not bid on both auctions. (See Figure 2.)

Figure 2. Premium Bidding

1230258003   1802 DRAPED BUST LARGE CENT AG-3			1230179045   1802 DRAPED BUST LG.CT. ANACS AG-3. NO RE		
Bidder:	seasroot	Start1:	4/14/2001 3:47:02 PM	Bidder2:	hole50
# of Bids 1:	5	End1:	4/21/2001 3:47:02 PM	# of Bids 2:	5
Bid1:	\$13.00	Seller1:	pennyman23	Bid2:	\$9.01
		StartBid1:	\$9.99	startbid2:	\$8.95
Coin: 1802 Draped Bust in condition 3					
Bidder	BidTime	Amount	Bidder	BidTime	Amount
jsents@servtech.com	4/21/2001 3:46:47 PM	\$21.50	pennymancoins	4/20/2001 3:08:36 PM	\$15.76
felixv11@home.com	4/21/2001 3:46:32 PM	\$21.00	mwatson42	4/20/2001 12:48:42 F	\$14.75
crhine1	4/21/2001 3:43:58 PM	\$18.05	larryaiken	4/20/2001 9:15:21 AM	\$16.26
milneleslie	4/21/2001 10:39:25 A	\$15.01	pennymancoins	4/19/2001 2:46:06 PM	\$10.15
▶ seasroot	4/15/2001 7:11:33 AM	\$13.00	▶ hole50	4/14/2001 8:36:19 PM	\$9.01
* [ ]		\$0.00	* [ ]		\$0.00

We define two coins as “the same coin” when they share the same mint year, denomination, mint marks, and condition, as per the coin collecting literature (e.g., Gibbs, 2000). An auction bidder, *seasroot*, bid on an “1802 Draped Bust large cent” in almost good condition. At this time, *seasroot* (1) bid \$13.00 on an auction hosted by seller *pennyman23*. (2) *seasroot* also could have made the same or a lower bid on the same coin from another seller, *collector@ka.net*, in a different auction where the current bid for the same coin was only at \$9.01. (3) *seasroot* also could have done this even though the auction for *collector@ka.net* ended six hours earlier than the auction from *pennyman23*. Finally, (4) *seasroot* did not bid in both auctions.

On its face, and without deeper investigation, premium bidding can be considered to be irrational. The buyer should have a greater level of utility if she were to bid on another auction containing an identical item for the same or for a lower cost. Bakos (1997) showed that, for

commodity items, rational buyers will buy the lowest priced item when search costs are low. However, we provide several possible theoretical explanations for premium bidding.

*First*, bidders may be *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. They also may ignore received information. This is doubtful for two reasons: (a) eBay search capabilities show all items that fit a search criteria and (b) auctions that end early appear towards the top in eBay screens and should be found first. Most auctions support search, so there is no reason why rational bidders would ignore salient information that is easily available.

*Second*, premium bidders seem to prefer certain sellers, and may be willing to pay more, in the absence of countervailing positive reputations. We suspect this is primarily not the case as well. Consumer e-auctions do not have a large, continuous selection of items, so sellers cannot build brand loyalty. The auctions are so numerous that there is one seller for approximately every four buyers.

*Third*, bidders may have a vested interest in making sure a high price is received for a particular item, either because of collusion with the seller or because the buyer handle is used by the seller as a second identity to run up the bid. We believe sellers who wish to avoid paying the \$2 fee charged by eBay for setting a reserve price may be motivated to enter under a pseudonym or to make a fraudulent bid. Thus, they ensure that a higher price is received for the item. The same motivation may occur with sellers who, after bidding is started, would like to receive higher bids. Thus, we contend that premium bidders can be viewed as reserve price shills. To make the case, we use a generalized technique to detect inconsistencies following Johnson, et al. (2001) and we further investigate these three possibilities with the analysis in the next section.

### Characteristics of Premium Bids

All reserve price shills in eBay coin auctions will have five characteristics. *First*, shills will bid regardless of the existence of similar auctions. Shills will show premium bidding. This is how we will separate the two groups of bidders. *Second*, shills will tend to concentrate on fewer sellers than other bidders. *Third*, shills will tend to more often bid early (to set an early reserve price). *Fourth*, shills will bid in larger increments to run up the bid. *Fifth*, shills generally will not try to win. They would rather have a legitimate bidder win.

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 10,260 coin auctions, 622 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. There were 2,069 bids from 1,169 distinct bidders and 237 sellers. Table 3 describes the characteristics that compare auctions containing premium bids with those that do not at both the bid and the bidder levels of analysis. Non-parametric t-test results compare the difference between auctions with and without premium bids. (See Table 3.)

**Table 3. Premium Bidding Descriptive Statistics**

VARIABLES	AUCTIONS WITH PREMIUM BIDS			AUCTIONS WITHOUT PREMIUM BIDS			t-STAT
	Mean	Variance	N	Mean	Variance	N	
<i>Auctions per Seller</i>	1.24	1.01	264	1.08	0.67	905	2.3**
<i>Days Left in Auction</i>	2.74	8.69	866	1.48	5.20	1,203	10.4***
<i>Bid Increment</i>	62%	5.50	866	38%	2.75	1,203	2.6***
<i>Amount of Wins</i>	23%	0.18	866	35%	0.23	1,203	-6.1***
<b>Note:</b> ** = $p < .05$ ; *** = $p < .01$ . Analyses of <i>Auctions per Seller</i> and <i>Days Left in Auction</i> were at the bidder level. <i>Bid Increment</i> and <i>Amount of Wins</i> were analyzed at the bid level.							

Table 3 provides different measures of how auctions with and without premium bids compare. *Auctions per Seller* determines whether those who enter premium bids typically bid on fewer sellers, as shills probably do. *Auctions per Seller* is the number of auctions bid upon

divided by the number of sellers on whose auctions a bidder bids. A higher ratio means a bidder concentrates on fewer sellers; a lower ratio means a bidder considers more sellers. Bidders who make premium bids are more likely to concentrate on fewer sellers, just as we predict shills will do. *Days Left in Auction* compares the number of days left in the auction when a premium bid is detected with how many days are left in an auction when a non-premium bid is detected. The descriptive statistics indicate that premium bidders tend to drop out early.

*Bid Increment* compares the average percentage increase over the previous bid. Premium bids appear to have a larger percentage included in the bid increment (62%) when compared with other bids (38%). *Amount of Wins* shows how likely a bid is to succeed. We show that premium bids (23% of the time) are less likely to win than other bids (35% of the time). This would be surprising in that premium bids are, by definition, higher than other bids and would be expected to win more often. However, this corresponds to shills' desire to avoid winning.

These statistics offer evidence that premium bidding is likely to be shilling. Whenever we detect that a bidder is bidding in an auction that is not optimal, that bidder's behavior mirrors that of a shill. Thus, with sufficient data, we can test for the existence of opportunistic behavior by describing the effect of that opportunistic behavior and then using this large sample to investigate whether this opportunistic behavior exists. With this evidence to establish, hereafter we will use premium bidding and shilling interchangeably. Indeed, we have shown that premium bidding is a good proxy for shilling behavior based on the statistical similarity of the characteristics of premium bidding and the characteristics of shilling.

### **A Probit Model to Predict Premium Bidding in Auctions**

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, 1998).

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 appears to be statistically identical to reserve price shilling, there are characteristics that can make shilling more attractive to the seller. We show when to expect shilling, and give e-auction houses ways to detect it.

**Nonlinearity of Binary Choice.** Because of the binary dependent variable (i.e., a bidder enters a premium bid or a normal bid), a linear model is inappropriate. Using one might cause the estimates of the dependent variable fall outside the appropriate range limits, a *logical misspecification* (Greene, 2002; Kennedy, 1998). The normalized probability of a bidder entering a premium bid must be between 0 and 1. OLS regression can lead to an estimated dependent variable exceeding the logical max and min values. *Probit* models resolve this problem by forcing the estimated value of the dependent value to be in [0, 1].

## AN EMPIRICAL MODEL FOR DETECTING SHILLING BEHAVIOR

The initial form of our empirical model to detect shilling behavior in Internet auctions is:

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

The definitions of the variables in the model are shown in the accompanying table, which also offers a number of comments about their specification. (See Table 4.) If it is true that a

large portion of premium bidding results from shilling, then we should be able to use variables in the table to predict auctions that are bid upon by premium bidders.

**Table 4. Variables Used in the Generalized Shilling Model**

VARIABLE	DESCRIPTION
$Prob[y_{PB}=1]$	Auction-level dependent binary variable; $y=1$ if auction receives premium bid, $y=0$ if not.
$\alpha$	The intercept.
<i>SellerPB Propensity</i>	This is the ratio of number of auctions with premium bids compared to the total number of auctions held, not including the auction currently being examined. This variable measures how often a seller has a propensity for attracting (or, if shilling, participating in) premium bidding. If premium bidding is a bidder characteristic (due to lack of experience, for example), and thus not evidence of shilling, this variable should not be significant. Seller preferences or If a seller often questionably bids on his or her own auctions, then this variable should be positive and significant.
<i>SellerExperience</i>	Experience level of the seller within eBay's auctions, even though the auction operator refers to it as a "reputation" score.
<i>SellerReputation Ratio</i>	Ratio of positive comments to negative comments, used to measure how a seller's reputation affects the ability to attract premium bids.*
<i>StartingBidBook ValueRatio</i>	<i>StartingBid</i> in the auction, as a measure of the stated reserve price, as a ratio to <i>BookValue</i> . If there is a high <i>StartingBid</i> relative to <i>BookValue</i> , then it is presumed that the seller has no need to shill. Conversely, if a seller enters a high <i>StartingBid</i> , it may show a high valuation of an auction item.
<i>TimeLength</i>	Length of time that an auction, as a measure of the risk of an auction drawing a premium bid. eBay allows auctions in one, three, five, seven, and ten-day increments; seven-day auctions are most popular.
<i>BookValue</i>	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.
<i>ReserveExists</i>	Binary variable set to one if the seller sets a secret reserve, and zero if not.
<i>OtherAuction BidAmount</i>	The lowest amount that can be bid for an identical item in different concurrent auction when this auction starts.
<p><b>Note:</b> * The percentage of negative comments is used in other research (e.g., Kauffman and Wood, forthcoming) to capture the effect of negative comments. Surprisingly, the number of negative comments is significantly positively correlated with the number of positive comments and with the reputation score. This is understandable if you view the reputation score as a proxy for experience, as we do in this research. The more experienced a seller is (i.e., the seller has a higher score), then the higher probability of both positive and negative comments.</p>	

**Resolving Specification Issues for Model Variables.** The ratios in our econometric model give rise to specification problems that must be addressed. One such issue arises with the ratio between *StartingBid* and *BookValue*, in which large ratios are disproportionately larger than small ratios. To illustrate this, we use the following example. If *StartingBid* is \$20 and *BookValue* is \$100, then *StartingBid-BookValueRatio* is 0.2 (\$20/\$100). If the values are reversed, *StartingBid* is \$100 and *BookValue* is \$20, 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  $\ln(\text{StartingBid} / \text{BookValue})$ . 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. Other ratios that we will use in our estimation are also transformed as follows:

$\ln(\text{SellerReputationRatio})$ ,  $\ln(\text{SellerPBPropensity})$  and  $\ln(\text{OtherAuctionBidAmount} / \text{BookValue})$ .

We expect that the effect of the variable, *BookValue*, on shilling is non-linear since bidders may not shill on extremely low-priced items but may quickly adjust their shilling behavior as items have a higher book value. Thus, we add a reciprocal term to our probit model to capture the expected effect of *BookValue* on premium bidding:  $1 / \text{BookValue}$ . If the *BookValue* positively affects premium bidding (i.e., *BookValue* increases implies that the probability of premium bidding increases), then we should see a negative relationship between  $1 / \text{BookValue}$  and premium bidding. Furthermore, we note that  $1 / \text{BookValue}$  decreases quickly as *BookValue* increases, and therefore is useful to predict when a variable's effect increases dramatically at lower values and then levels out asymptotically at higher levels. High *SellerExperience* scores are less distinguishable to the buyer than low *SellerExperience* scores. We specify a logged variable to adjust for the non-linearity:  $\ln(\text{SellerExperience})$ .

**Collinearity, Multicollinearity and Interactions.** Kennedy (1998) points out that strong *pairwise correlation* between independent variables can lead to severe estimation problems of

coefficients, and *perfect collinearity* or *multicollinearity* among multiple variables will cause any regression routine to fail. We examined the correlation matrix from each model and found that the highest correlation had an absolute value of only about 16%. Since a simple 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, we also employed a *condition number test* (Belsley, Kuh and Welsch, 1980; Greene, 2002). No multicollinearity irregularities were present in the data. Greene (2002) describes the condition number of a square matrix as the square root of the largest and smallest matrix roots of the normalized  $X'X$  matrix that is formed in regression analysis. A condition number of 20 or greater may indicate the presence of collinearity between one independent variable and a linear combination of other independent variables. We performed this test with our data, and derived a condition number of 14.3. Thus, with such a low condition number, we are assured that multicollinearity does not exist in our data set. We also tested for interactions using a multiplicative terms method suggested by Neter, et al., (1996), but found no significant interaction among independent variables.

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

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

We hypothesize that we should see a positive relationship for  $\ln(SellerPBPropensity)$  (i.e.,  $\beta_1$  positive and significant, etc.), a negative relationship for  $\ln(SellerExperience)$ , a negative

relationship for  $\ln(\text{StartingBidBookValueRatio})$ , a positive relationship for *Time Length*, and a negative relationship for  $1/\text{BookValue}$ .

## RESULTS

The results from the model shed some light on some interesting phenomena that indicate that premium bidding is, in fact, reserve price shilling. As such, we are able to predict instances of auctions for which there are premium bids, and when premium bids will be made.

### Estimation Results

The results of the adjusted probit model estimation are shown in Table 5. (See Table 5.)

**Table 5. Shilling Model Parameter Estimates**

VARIABLE	HYPOTHESIS	COEFFICIENT	STD ERROR	MARGINAL EFFECTS	STD ERROR	t-STAT
$\alpha$ (Intercept)		-1.039	0.305	-0.358	0.103	-3.47***
$\ln(\text{SellerPBPropensity})$	H1	2.611	0.480	0.900	0.166	5.42***
$\ln(\text{SellerExperience})$	H2a	0.000	0.000	0.000	0.000	-0.20
$\ln(\text{SellerReputationRatio})$	H2b	-5.125	12.685	-1.767	4.373	-0.40
$\ln(\text{StartingBidBookValueRatio})$	H3	-0.132	0.032	-0.045	0.011	-4.13***
<i>Time Length</i>	H4	0.085	0.035	0.029	0.012	2.43**
$1 / \text{BookValue}$	H5	0.000	0.000	0.000	0.000	-1.98**
<i>Reserve Exists</i>	Control	-0.284	0.268	-0.098	0.092	-1.06
$\ln(\text{CurrentOtherAmount} / \text{BookValue})$	Control	-1.102	0.343	-0.380	0.118	-3.22***

**Note:** \*\*\*=significant at  $p < 1\%$ ; \*\*=significant at  $p < 5\%$ . Analysis is at the *auction* level and contains 622 observations of rare coin auctions, with 2,069 bids from 1,169 distinct bidders and 237 distinct sellers.

In our shilling model, we used a binary dependent variable to indicate whether an auction contains a premium bid. We coded auctions with premium bids as 1 and auctions with no premium bids as 0. Hence, positive coefficients indicate that an increase in the variable causes a tendency toward more premium bidding (i.e., reserve price shilling), while negative coefficients indicate that an increase in the variable creates a tendency toward more auctions with no premium bidding (i.e., no reserve price shilling).

In Table 5, we show that 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, we find evidence to support the *Repeatable Shilling Behavior Hypothesis (H1)*. We also show that the higher the starting bid in relation to the published book value, the less likely that premium bidding occurs, thus supporting our *Low Starting Bid Hypothesis (H3)*. We show that the longer auctions also lend themselves to premium bidding, thus supporting our *Auction Length Hypothesis (H4)*. We find that the *BookValue* does have a positive effect on the existence of premium bidding (i.e.,  $1 / \text{BookValue}$  has a significant negative effect), as expected in our *Common Value Hypothesis (H5)*. It should be noted that all of these hypotheses are at the *seller* level or based on auction characteristics *set by the seller*. None of them are at the bidder level. We find strong evidence that premium bidding is a *seller characteristic*, and not solely a bidder characteristic brought on by seller preference or bounded rationality. Thus, we find even more support showing that premium bidding is a well-suited proxy for reserve price shilling.

Note, however, that we did not find support for two other hypotheses, the *Experienced Seller Hypothesis (H2a)* and the *Reputation Hypothesis (H2b)*. We have argued that we will observe increased opportunistic bidder behavior because Internet transactions reduce the chance of detection of shilling, and thus, the likelihood of punishment. It is difficult to catch shills. The likelihood of punishment is remote, so experienced and reputable sellers are not that concerned. With no support for these hypotheses, other possible explanations require more investigation.

We also could not find a relationship between the existence of a secret reserve price and the existence of premium bidding, although we find a slightly negative, though insignificant, relationship between the two. Although this finding is largely inconclusive, we believe that a secret reserve price probably reduces the financial risk of selling an auction item for too little,

causing sellers to avoid shilling because the secret reserve price reduces the necessity for reserve price shilling. Also, conversely, a secret reserve price tends to eliminate all financial risk for a reserve price shilling bid below the reserve amount, since such a bid will not win the auction, and the seller will avoid paying commissions, and *sellers will shill* to communicate with legitimate bidders to a point where they meet the secret reserve price.

Thus, there are opposing forces. If there is one between the existence of a secret reserve price (via *ReserveExists*) and the existence of a reserve price shilling bid, the relationship is too small to be detected by this study. We also could not find a statistically significant relationship between auction *TimeLength* and the existence of a premium bid, indicating that auction length does not seem to affect motivation for reserve price shilling.

**Marginal Effects.** Liao (1994) and Greene (1996) describe how the magnitudes of coefficients in a binary choice model like probit 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 a correlated response of the dependent variable in a probit model. Greene (1996) develops a *marginal effects* measure of coefficients that can be used for probit models. He shows that, in order to determine the marginal effect of a variable, the independent variables must be scaled using a variable,  $z$ , derived from the  $Z$  distribution, on which the probit model is based. For instance, in our binary probit model, the effect of a change in  $\ln(\text{SellerPBPropensity})$  on the modeled likelihood of a premium bid, when all other independent variables are held constant, can be represented (in simple terms) by measuring an increase that a one unit change in an independent variable has on the dependent variable. However, this impact is calculated over the continuous variable  $z$ , as shown below:

$$\begin{aligned} \text{Effect on } E [\text{Prob}[y_{PB}=1]_i | \ln(\text{SellerPBPropensity}_i)] = \\ E [\text{Prob}[y_{PB}=1]_i | z * \ln(\text{SellerPBPropensity}_i) = 1] \\ - E[\text{Prob}[y_{PB}=1]_i | z * \ln(\text{SellerPBPropensity}_i) = 0] \end{aligned}$$

Marginal effects mimic the role of coefficients in OLS regression. In probit models, independent variables do not have a linear effect. The effect of the independent variables on the dependent variable changes, depending on the value of the independent variable. This prevents a simple interpretation of coefficient values as with OLS regression. Marginal effects are used to estimate the effects by figuring out the impact for one unit of change in an independent variable when all other independent variables are held fixed at their mean values.

The actual derivation for all variables to determine marginal effects is complicated and its complexity increases geometrically as more variables are considered. LIMDEP 7.0 (Greene, 1995) calculates marginal effects of probit coefficients, following Greene (1996). The marginal effect coefficients allow for clearer understanding of the impact a variable has on the probability of an observed behavior. We believe that the standard errors of the marginal effects offer similarly useful interpretative power. So both columns are included in our results.

**Shilling Model Fit and Prediction Capabilities.** There is no universally accepted *goodness of fit measure*, such as  $R^2$  for linear regression, for binary choice models such as probit (Kennedy, 1998). However, there are several methods advocated by econometricians that we will use to investigate our model fit. One of the most conservative tests is advocated by Veall and Zimmermann (1996), who argue in favor of the pseudo- $R^2$  test of McKelvey and Zavoina (1975). This test helps to avoid overstating model fit. This test yielded a pseudo- $R^2 = 24\%$ , indicating a reasonable predictive capability for our model. Another relevant statistic is the chi-squared value

of our overall model ( $\chi^2 = 79.3; p = .001$ ). Table 6 shows a concordance analysis of actual and predicted values of auctions that contain or do not contain a premium bid. (See Table 6.)

**Table 6. Frequencies of Actual and Predicted Outcomes for the Shilling Model**

ACTUAL OUTCOMES	PREDICTED OUTCOMES		
	Auction Has No Premium Bids	Auction Has Premium Bids	Total
Auction Has No Premium Bids	400	27	427
Auction Has Premium Bids	148	47	195
Total	548	74	622

Our model's predictions of premium behavior are correct 64% of the time (i.e.,  $47/74 = 64\%$ ). This is quite high considering that shills will attempt to hide their actions, and that auctions containing premium bids were only detected in 12% of the observations. We predict actual acceptable bids 94% of the time ( $400/427$ ) while the premium bid predictions are correct 24% of the time ( $47/195$ ). McIntosh and Dorfman (1992) advocate using the sum of the percentages of correct predictions in each category and comparing the result to 100%. The sum of the percentage correct predictions of auctions not containing a premium bid (94%) plus the sum of the percentage correct predictions of auctions that do contain a premium bid (24%) is 118%, which is above their 100% threshold.

Typically, in binary choice models like probit, when one choice grossly outnumbers another choice (as with 69% to 31%), these models skew toward the most popular choice in the analysis of concordant pairs. While this does affect our model, overall, it still performs very well, as we justify with a 24% pseudo- $R^2$ , and the McIntosh and Dorfman statistics. When also considering that sellers are trying to hide any shilling behavior, and that we're trying to predict premium bidding before any bid is placed, our model is quite successful. Our model predicts both types of behavior fairly well, especially when we recognize that detection of such behavior can have legal

ramifications. Why? Because shilling is considered fraudulent, or can drive customers away if detected, and, therefore, will be masked by the seller.

## **IMPLICATIONS**

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 (Bunker, 2000). However, the reserve price shilling that we detect hurts the auction house since seller uses shilling to avoid paying auction fees. Also, any type of shilling can be detrimental to the e-auction in the long run. Pressure will build on e-markets with increased risk of opportunism, forcing prices down (Akerlof, 1970). Akerlof (1970) points out that, in a market with opportunistic sellers, honest sellers will not be able to sell products for their proper market value because consumers will factor opportunism into the prices they are willing to pay, reducing their valuation of the auctioned items. A side effect is that the auction house itself will gather less commission-based fees because the products are being sold at a reduced value. Thus, auction houses need to motivate reputable behavior on the part of their participants and aggressively pursue those who decide to profit at the expense of the best interests of the market.

To avoid reserve price shilling, auction houses can impose a fee structure that more closely motivates proper auction behavior. By doing so, auction houses can reduce the motivation for shilling behavior. In addition, auction houses can develop capabilities that can catch those sellers that engage in shilling. By doing so, auction houses increase the risk of shilling detection, and reduce motivation to shill, bringing the willingness-to-pay on the part of potential buyers of auctioned items more closely in line with their common values in a fair market setting.

Although we specifically studied auctions in this research, our results generalized to other kinds of auctions and 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. The relatively low costs of entry permit new sellers to participate, and they can effectively mask their identities. Our research shows that many sellers use the increased information asymmetry brought about by anonymity intrinsic to the Internet environment to take advantage of consumers.

## **CONCLUSION**

We examined shilling in online rare coin auctions by detecting premium bidding when a bid for the same item in a different auction would be more rational. We show that we can predict a seller's decision to shill based on a seller's previous behavior before the auction begins. We highlight the contributions and limitations of this work, and our thoughts about future research.

### **Contributions**

This research makes two major contributions. *First*, we show how to empirically detect opportunistic behavior by first examining how the effects of a market would look if such behavior exists, and then to empirically test for that behavior. To understand this phenomenon, we examine four aspects: bidders who bid on “the wrong” auction, concentrate on fewer sellers, bid in higher increments, and drop out early. By concentrating on those whose bid in an auction is premium, we are able to show how such bidders behave identically to reserve price shills. This detection technique can be applied to detect opportunistic behavior as it happens, and should be useful to other researchers, policymakers, consumers, and firms. *Second*, we show how to predict when a seller will decide to shill. Auction designers can use such information to detect shilling and design fee structures to minimize the likelihood of shilling while maximizing profit from appropriate use of insertion and secret reserve fees.

It is important to investigate shilling in light of recent news. The Federal Bureau of Investigation is actively investigating shill bids to punish such behavior (Mahoney, 2001). A United States House of Representatives subcommittee is investigating shilling at the industry level, asking representatives from eBay, Yahoo!, and Amazon how they are managing the shilling rate (Hopper, 2001). There are groups that are being formed specifically to combat shilling, even though they claim to be thwarted by the auction house (Bunker 2001). Although traditional auctions have been with us for many years, shilling is receiving more attention than previously because the Internet environment is more conducive to information asymmetries due to the larger, translocational nature of online auctions and the anonymity of online auction sellers and buyers.

### **Limitations and Future Research**

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. However, tests on other auctions are required before such statements can be shown to be true. *Second*, we have shown that our operationalization for premium bidding to proxy for reserve price shilling is 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) and 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. Thus we believe the results would actually be stronger than indicated by this study if we had definitive data indicating whether each seller was a shill. 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 moments of an auction. Thus, a different empirical methodology should be used to examine competitive shilling that occurs in the final minutes of an online auction.

This paper is one of the few that empirically examines opportunism in a market with current data. Not only do we show how to detect shilling behavior, but we also show that such behavior can be predicted based on seller actions. We also show that the intended victim of shilling is not necessarily the bidder, but also could be the auction house, because the seller can avoid fees that the auction house has set. As such, this paper is relevant for several groups of people. Auction houses can learn to set fee structures that do not motivate such behavior. Bidders can use our technique to better examine an auction for possible shillers. Finally, researchers can use our technique of determining the results of opportunistic behavior and seeing if those results are present to test for other opportunistic behavior.

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