I NAME MY PRICE BUT DON'T WANT THE PRIZE: EFFECTS OF SEEMINGLY USEFUL INFORMATION IN THE NAME-YOUR-OWN-PRICE MECHANISM[1]

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ABSTRACT

This study investigates the effects of information provision on decision-making in an e-commerce model, the name-your-own-price mechanism, capitalizing on information asymmetry and quality uncertainty. Despite the potential benefits of this mechanism to both sellers and buyers, evidence suggests that buyers may fall prey to the winner’s curse. Using a controlled experiment, two types of information provision, bid outcomes and bid recommendations, are manipulated to assist buyers’ decisions. Subjects provided with accepted and rejected bid outcomes performed worse than subjects provided with only accepted bid outcomes. Furthermore, subjects provided with bid recommendations initially reacted to the information by bidding higher but subsequently learned to assimilate the information reducing the winner’s curse. The findings provide interesting insights on how a potentially advantageous e-commerce model can be negatively affected by the suboptimal decisions of consumers.

Keywords: Electronic commerce, Auctions, Winner’s curse, Information asymmetry, Quality uncertainty

1. Introduction

The increasing use of the Internet in both business-to-business (B2B) and business-to-consumer (B2C) markets has allowed a new variety of business models to emerge. Many of them are theoretically attractive from a business point of view and have, in fact, been successfully implemented in many physical settings [Fruhling and Digman 2000]. However, their online counterparts are not always as equally well received. An example is the e-commerce model commonly known as the name-your-own-price mechanism (NYOP) and used by several e-commerce vendors such as Expedia™ and Priceline™. In this e-commerce model, consumers commit to prices for products or services with some uncertain attributes in exchange for possibly lower prices. The model is regarded as economically attractive in terms of providing potential extra yields to vendors and savings to consumers [Anonymous 2001]. However, consumers view the model quite differently, as many of them, especially the inexperienced, are often disappointed with the items received given the amount paid and the quality expected[2]. This phenomenon, where buyers enter into loss making purchases, is known as the winner’s curse and has been identified in many physical settings [Akerlof 1970; Ball et al. 1991; Capen et al. 1971; Roll 1986].

Complaints surrounding the NYOP mechanism may not lie with the model itself, but rather with the suboptimal

[1] Financial support for this study was partly provided from the Michael R. and Mary Kay Hallman Fellowship at the University of Michigan Business School.

[2] Priceline™ was kicked out of Connecticut Better Business Bureau in September 2000 after generating about 300 consumer complaints since 1998. About 80% of the complaints were from customers who bought the low-cost airline tickets and "didn't like one aspect of the itinerary" (ZDNet News, 9/21/2000).

decisions of the participating buyers[3]. Therefore, helping the buyers make better decisions, by taking into account the characteristics of the situations they are facing, is important to the long term success of the e-commerce model. Past research into the winner's curse has relied on providing buyers with various levels of information and experience to help them learn to avoid the winner's curse, but the effectiveness of such approaches has been disappointing [Ball et al. 1991; Foreman and Murnighan 1996]. Recent studies have confirmed that the winner's curse exists in electronic auctions such as E-bay.com™ [Metha and Lee 1999] and across various types of electronic auction venues such as C2C and B2C [Oh 2002]. We continue this investigation by looking at the effects of information provision on decision making in situations where buyers face quality uncertainty and information asymmetry. Specifically, we investigate the prevalence of the winner's curse in the NYOP mechanism, and the effectiveness of the information provided by systems that attempt to facilitate decisions from the buyer's perspective.

The rest of the paper is organized as follows. First, the NYOP mechanism is introduced, together with its economic attractiveness. We describe characteristics shared by the NYOP mechanism, i.e. quality uncertainty and information asymmetry, that often result in a behavioral phenomenon known as the winner's curse. Second, past literature is reviewed on the effectiveness of learning to avoid the winner's curse by providing buyers with information and experience. We then look at the effectiveness of two types of information provision that are commonly used in the NYOP mechanism, i.e. bid outcomes and bid recommendations, using a controlled experiment. Finally, the results and the implications of the study are discussed.

2. Name-Your-Own-Price Mechanism

Dynamic pricing mechanisms, in which buyers and sellers actively engage in the price discovery process, have become increasingly popular in online markets [Kaufman and Wang 2001]. Auctions are probably the most commonly known form of dynamic pricing mechanisms. In an auction, resources are allocated based on an explicit set of rules and prices are determined by bids from buyers or sellers [Mcafee and McMillan 1987]. There are many different types of auctions, which we classify into two general categories: seller auctions and buyer auctions. In a seller's auction, the *seller* initiates an auction by listing an item for sale [Chui and Zwick 1999]. Buyers bid against each other for the item, and the winner is the one with the highest bid (or lowest bid in Dutch auctions). Common seller auction formats include the English auction (first-price, ascending-bid auction), Dutch auction (first-price, descending-bid auction), first-price sealed-bid auction, and the Vickrey auction (second-price, sealed-bid auction). Versions of these auctions have become increasingly popular in online business-to-customer (B2C) and customer-to-customer (C2C) markets, with eBay™, Yahoo!™ Auctions and Amazon™ Auctions being the largest online players, generally using the English auction format.

In a buyer's auction, the *buyer* initiates an auction by requesting to purchase an item [Chui and Zwick 1999]. There are two major types of buyer's auctions, one uses the request-for-proposal mechanism and the other uses the NYOP mechanism. The request-for-proposal mechanism has been commonly used in both physical and online business-to-business (B2B) markets for procurement (e.g. Covisint™ and FreeMarkets™). However, it is also used in online business-to-consumer (B2C) markets to trade finance and mortgage services (LendingTree™). In this mechanism, the buyer initiates an auction by requesting to purchase an item. The buyer specifies his requirements and the participating sellers submit their proposals within a defined period. If there are offers that satisfy the buyer's specific requirements, the buyer determines the winning offer, which is usually (but not necessarily) the lowest cost bid.

The NYOP mechanism is similar to the request-for-proposal design, except with the request-for-proposal design, the buyer explicitly defines the desired product(s). With the NYOP mechanism, the buyer places a bid on an item with unknown attributes. Additionally, the buyer does not determine the winning bid; rather, the auctioneer chooses a seller whose offer meets the buyer's criteria. Furthermore, multiple sellers may compete for the sale; consequently, the buyer may achieve significant savings depending on the sellers' willingness to make a sale. However, the buyer is not in control of nor has knowledge of the seller competition. The buyer has no guarantee of avoiding the winner's curse, as one can still experience the winner's curse even when paying less than the value of the product [Bazerman and Samuelson 1983].

Two important characteristics are explicitly implemented and exploited in the NYOP mechanism, information asymmetry and quality uncertainty. This study looks at how a consumer's failure to incorporate these two characteristics in their bid decision results in the winner's curse.

[3] IDC Senior Research Analyst Joshua Friedman commented that "the trouble with Priceline.com is not with the type of services it promotes, but in the sales pitches themselves… Priceline.com customers sometimes overbid and pay more for airline tickets than they would buying directly from an airline." (PC World 10/5/2000)

2.1. Information Asymmetry and Quality Uncertainty

In the NYOP mechanism, the buyer has to predetermine the price she is willing to pay for a product or service. For instance, when an individual wants to purchase an airline ticket and places a bid, she can only be specific on some of the product attributes (date, number of stopovers, etc.) but must be flexible with other aspects of the product or service (time, airlines, etc.). The auctioneer searches among offers from participating sellers that satisfy the buyer's minimum requirements and decides to accept a bid only if a match exists with a value to the seller that is less than the bid amount. Quality uncertainty refers to the buyer's inability to know in advance the exact nature of the good or service in the NYOP mechanism, which fundamentally reduces the value of the good. Information asymmetry is when the seller has more information regarding the value of an item when deciding whether or not to accept the offer and buyers have limited information about an item's value when naming their price. Neither physical inspection to minimize quality uncertainty, nor obtaining complete information about the product or service to minimize information asymmetry is possible prior to the sale. In more traditional auction markets, physical inspection, as well the ability to specify the exact nature of an acceptable product or service reduces some but not all of the quality uncertainty and information asymmetry. Therefore, information asymmetry is likely in the traditional markets, but not to the extent of NYOP mechanisms due to the nature of quality uncertainty built-in to the auction.

The NYOP mechanism is popular among sellers because they can achieve additional yields by not revealing the exact product characteristics thus not directly competing with those same goods sold in the retail market. This approach also allows the seller (or supplier) to conceal its brand so no channel conflict is created. [Fogel 2005]. Buyers are able to achieve savings because the goods and services sold under the NYOP mechanism are considered "damaged" due to the uncertainty of the product or service attributes [Anonymous 2001]. The NYOP mechanism enables the possible sale of goods and services that would not ordinarily be sold through more traditional markets and the sale of inventory that may not be sold otherwise [Fogel 2005]. Due to the nature of the NYOP mechanism buyers tend to be looking for goods with greater discounts and therefore one would expect them to bid less and thus be less inclined to fall prey to the winner's curse. Quality uncertainty and information asymmetry are closely related in the sense that the latter implies the former, but not vice versa, for instance, if the quality is equally uncertain to both the buyers and the sellers. Samuelson [1984] points out that the presence of asymmetric information in a market may preclude a mutually beneficial sale even if the good is worth more to the buyer than to the seller.

2.2. Winner's Curse

When bargaining under information asymmetry, Samuelson [1984] argues that the buyer should estimate the item's value conditional on winning the bid. The buyer should account for the fact that the item's value has a different distribution given that the seller accepts the bid, since a bid is only accepted when the product's value to the seller is lower than the bid. Buyers often ignore this last concept. In fact, when facing a situation with quality uncertainty and information asymmetry, a winning buyer often finds that he or she has paid too much for an item of uncertain value or has received something of lower quality than expected, and hence fallen prey to the winner's curse [Bazerman and Samuelson 1983]. The winner's curse has been studied both theoretically [Akerlof 1970; Case 1979; Oren and Williams 1975; Rothkopf 1980; Samuelson 1984; Selten et al. 2005; Winkler and Brooks 1980] and empirically in various settings, such as oil leases [Capen et al. 1971], stock investments [Miller 1977], baseball players [Cassing and Douglas 1980], book publishing [Dessauer 1981], corporate takeovers [Roll 1986], and more recently, NBA basketball players [Eschker et al. 2004]. In all these settings, the winners were "cursed" by paying too much for an item or receiving an item of lower quality than expected [Thaler 1988].

Perhaps the most prominent evidence of the winner's curse in bilateral bargaining with asymmetric information is the study by Samuelson and Bazerman [1985]. In their experiment, the subjects participated in a company acquisition game in which each of them was asked to make an offer to acquire a company from the existing management. The company value was uncertain to the buyer when the offer was made, but the distribution of values was known to range between \$0 and \$100. Furthermore, whatever the company was worth to the seller, it was worth more to the buyer. After the buyer made the offer, the seller, who had much better information about the company's value than the buyer, decided whether or not to accept the offer. The seller would always accept the offer as long as it was equal to or greater than the seller's value. In the experiment a vast majority of the subjects experienced the winner's curse by overestimating the actual value and offering too much for the company. A common strategy adapted by the subjects to account for the value uncertainty was to look at the average value. Therefore, the average value of the item, given the bid is accepted, is below the average (in this case ½ the average).

Studies on the winner's curse in an auction context suggest that it is a persistent behavioral phenomenon under quality uncertainty and information asymmetry [Ball et al. 1991; Samuelson and Bazerman 1985]. With the NYOP mechanism buyers are required to be flexible on exact product characteristics when naming the price for a product whose quality is uncertain. Once again, the seller knows the value of the goods and can choose whether or not to accept the price. The buyer experiences information asymmetry since the only information known to her until receipt of the goods or service are the limited characteristics identified at the beginning of the buy transaction. We claim that because the NYOP model exhibits quality uncertainty and information asymmetry, consumers are vulnerable to the winner's curse. Also, there is anecdotal evidence that the winner's curse exists in the NYOP mechanism, as reflected by consumers' complaints on lower than expected quality of items received.

2.3. Learning to Avoid the Winner's Curse

The NYOP mechanism provides a good example on how an economically attractive e-commerce model can be adversely affected when bidders adjust their bids to account for the quality uncertainty and the information asymmetry inherit in such a mechanism. In fact, experienced bidders in a familiar domain can lose money if they fail to understand the subtleties in the bidding process [Milgrom 1989]. Yet, Kagel and Levine [1986, pg. 917] contend that the winner's curse "is a disequilibrium phenomenon that will correct itself given sufficient time and the right kind of information feedback." But not leaving to chance, helping bidders learn to avoid the winner's curse is critical to the long-term success of the name-your-own-mechanism and similar models. Websites such as Biddingfortravel.com hosted by ezboard® offer advice to educate and improve the bidding experience for Priceline.com's travel products[4].

Past research has provided buyers with additional information and experience to help them learn to avoid the winner's curse. These studies consistently found that the winner's curse is highly resistant to learning even when subjects were given opportunities to learn from their own behavior and the outcomes of others. [Ball et al. 1991; Cifuentes and Sunder 1991; Foreman and Murnighan 1996; Holt and Sherman 1994]. The repeated plays required for learning may be unrealistic in a real world setting as buyers may not continually subject themselves to repeated loss generating buys without choosing an alternative purchase medium. Customers' attitudes and satisfaction are known factors contributing to the success and failure of electronic commerce markets [Schaupp and Belanger 2005; Shergill and Chen 2005]. Online stores also recognize good customer service and support as key to their customer retention [Reibstein 2002], consequently sellers, as well as e-commerce auction websites, should also be concerned with customer satisfaction and retention, as well as profitable sales. This is also evidenced by the fact that in 2000 an NYOP mechanism user, Priceline™, had only 39% of its sales from repeat customers; whereas, a seller auction format user, Amazon.com, had 70% of its sales from repeat customers [Anonymous 2000]. Therefore, it is important to help buyers make decisions that minimize the chances of the winner's curse, especially in online markets when customers are simply a click away from the competitors. We focus on the information a system can provide to assist consumers in formulating better buying decisions.

3. Effects of Irrelevant and Distracting Information

Previous studies on decision making under information asymmetry have provided subjects with what was considered as the "best" information to help make a decision [Ball et al. 1991; Foreman and Murnighan 1996]. However, the subjects still failed to learn to avoid the winner's curse. They noticed something wrong with their bidding strategy but could not identify the causes. Ball et al. [1991] commented that this leaves people ill-equipped when they are in a different environment, even though the same logic applies. The findings of past studies suggest that simply providing people with additional information may not help buyers learn to avoid the winner's curse in the NYOP mechanism, an environment with quality uncertainty and information asymmetry explicitly built in.

Logic, as well as statistical theory, would indicate that one is better off with more information than with less when trying to make a decision. A decision maker should do no worse even if the additional information provided is totally irrelevant and useless. However, humans do not process information as intuitive statisticians and one's accuracy in judgment can be reduced when irrelevant distractor information is present [Hogarth 1982; Reneau and Blanthorne 2001; Tversky and Kahneman 1981, 1986]. There are cognitive limitations of human beings in terms of knowledge and computational capacity, or what Simon [1987] referred as bounded rationality. Additional information, especially if irrelevant, may result in ineffective decisions [Reneau and Blanthorne 2001]. Sometimes information is not always processed as intended, for instance, some information may require less mental effort to process than other information [Smith 1982]. To help sellers and buyers handle information overload, e-commerce websites are using online recommendation agents [Maes 1994].

Decision makers have been found to be poor judges of the usefulness of additional information. While increased information sometimes leads to greater accuracy in judgment [Peterson and Pitz 1988], often, additional information only leads to an increase in confidence with no increase in accuracy [Paese and Sniezek 1991]. Even worse, decision makers may be influenced by information that had the actual effect of degrading performance while still under the

[4] Information on goal of Biddingfortravel.com obtained from http://p070.ezboard.com/fpricelineandexpediabiddingpostingguidelines.showMessage?topicID=55.topic, March 3, 2006.

false impression that it was helpful [Davis et al. 1994].

Information processing has been found to be an important factor in affecting the success of information systems in providing decision and task support [Dennis and Carte 1998; Vessey 1991]. Lack of information processing by the decision-makers in group support systems was related to non-use of information exchanged, even though there was sufficient information available to make the optimal decision [Dennis 1996]. Given the importance of information processing to decision and task support, we argue that learning to avoid the winner's curse in the NYOP mechanism depends, not only on the availability of the information, but also on the relevance of the information.

When naming their prices, buyers in the NYOP mechanism should account, first for the quality uncertainty, *and* second for the information asymmetry between themselves and the sellers [Samuelson 1984]. In order to do that, buyers should determine their bids, first on the distribution of the item value, *and* second on the condition that the bid is accepted. With information asymmetry, the fact that the sellers have better information implies that the possible value of a product to the seller is not symmetric given the bid is accepted. However, buyers often take into consideration only the quality uncertainty (i.e. the value distribution). Using the NYOP mechanism, Priceline™ has a low bid screen and may inform the prospective buyer that their bid is so low there is little chance it will be accepted; and yet often that bid is accepted[5]. Buyers often make naive assumptions that the sellers have the same information as themselves as if there was no information asymmetry [Samuelson and Bazerman 1985]. By ignoring the information asymmetry between the seller and the buyer, a successful buy transaction can result in the winner's curse. In order to overcome the information asymmetry problem so as to avoid or minimize the winner's curse, two types of information provision are generally used in auction formats. They are bid outcomes and bid recommendations.

3.1. Bid Outcomes

In previous studies, bid outcomes were provided to subjects in order to help them learn to avoid the winner's curse [Ball et al. 1991; Foreman and Murnighan 1996]. One kind of information provision, referred to as "full outcomes", generally consists of information on both accepted and rejected bids. Subjects are given the outcomes of their bids even if they are rejected, which is not often the case in real life. Instead, people typically receive what are referred to as "acceptance outcomes," which consist of information on accepted bids only and details of rejected bids are never known. Web sites, such as Priceline-Bids.com and Pricelinedeals.com provide searchable databases of other people's bids, but the details of the outcomes are limited to accepted bids only.

Full outcomes provide additional information to the potential buyers than do accepted outcomes and therefore appear to be more desirable. One would expect that buyers would be no worse with the additional information provided by the full outcomes. Web sites, such as Biddingfortravel.com provide the Priceline.com user community a means through discussion boards to list terms and details of successful and rejected bids. They also provide detailed advice on how to make informed bids when provided groundwork information about the intended travel product, e.g., flight plans. However, recall that a buyer should only look at the distribution of the item value *given the condition that the bid is accepted* [Samuelson 1984]. In other words, buyers should not take into consideration the outcomes in which the seller's value is higher than the buyer's bid because the bidders under information symmetry will always reject those bids. In that case, the distribution of the item value to the buyers is actually the distribution of the item value *given the bid is accepted*, which is in fact more directly given by "acceptance outcomes." "Full outcomes" present a distribution of the item value based on both accepted and rejected bids and the additional information, rejected bids, is in fact irrelevant and could possibly distract the bidder. To obtain the conditional distribution of an item's value given the bid is accepted, the bidder would have to cognitively filter out the rejected outcomes. Ball et al. [1991] found that the subjects often misinterpreted the feedback or misanalyzed the information, falling victim to the winner's curse. Reneau and Blanthorne [2001] found that the subjects made more accurate predictions when no irrelevant distractor information was present. And accordingly, bidding guidance (from Biddingfortravel.com) does not guarantee a successful or satisfactory result. Therefore, we argue that acceptance outcomes are more favorable to learning to avoid the winner's curse in the NYOP mechanism than full outcomes because the relevant information required is more directly available with fewer distractions, and therefore require less mental processing. Hence we have the following hypothesis:

H1: Bidders receiving acceptance outcomes learn to avoid the winner's curse better (i.e. bid lower) than bidders receiving the full outcomes in the NYOP mechanism.

3.2. Bid Recommendations

Bid recommendations, another type of information provision, are used in the NYOP mechanism to help buyers make their offer decisions after the buyers submit their initial bids. Advising buyers of the probability that their

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[5] Information obtained from discussion board at Biddingfortravel.com on March 3, 2006 at link http://p070.ezboard.com/fpricelineandexpediabiddingpostingguidelines.showMessage?topicID=27.topic

current bid will be accepted or the probability of winning if the initial bid is increased by a certain amount are typical bid recommendations. While the change in bid amount and its corresponding chance of having the bid accepted is intended to facilitate the offer decision, this kind of feedback can confuse buyers by blurring the difference between the probability of bid acceptance (winning the item) and the probability of value gain (making a monetary gain). And as practiced in the NYOP mechanism, it's the intention to increase the buyer's bid, which will increase the seller's gain. In many situations in which the winner's curse is possible the fact that the item is worth more to the buyer than to the seller creates an illusion that increasing the chance of bid acceptance is equivalent to increasing the chance of value gain. And with information asymmetry, these two seemingly positively related events are in fact negatively related. Due to the distraction created by these kinds of recommendations, we make the following hypothesis:

H2: Bidders receiving no bid recommendations learn to avoid the winner's curse better (i.e. bid lower) than bidders receiving recommendations in the NYOP mechanism.

4. Method

4.1. Subjects

One hundred and thirty four undergraduate and graduate students, recruited from various colleges throughout the campus of a major university, participated in the laboratory experiment. Fifty percent of the subjects were female; the subjects' ages ranged from 18 to 38 with an average age of 21.2 years. Ninety percent of the subjects had purchased online, and 18% had visited or purchased from a NYOP mechanism-type auction, such as Priceline™ before.

4.2. Experimental Design

To test the two hypotheses on bid outcomes and bid recommendations, a controlled experiment based on Ball et al. [1991] was conducted simulating the NYOP mechanism in a web-based environment. In the experiment the subjects were asked to make price offers for 30 different antique coins. The quality and value of each coin was known to the sellers (the system), but unknown to the subjects (the buyers). Certain parameters were made to facilitate the experiment:

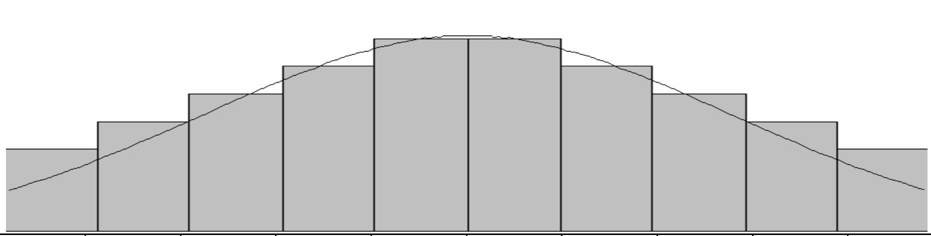
- The subjects began the experiment with a balance of $15,000. The subjects were informed that the value of each coin ranged between $20 and $200, and that whatever the value, each coin was worth 25% more to them than to the seller. Potential buyers using the NYOP mechanism in websites such as Priceline™ typically have an informed opinion of the value of their intended product if they have researched the price. They also know that the intended product is worth more to them, than the seller[6]. Prior bidding studies have been designed with target value range between $0 and some higher dollar value making a bid of zero as the optimal strategy [Ball et al. 1991]. Prior researchers have concerns with a zero-bid solution, therefore, in our experiment the lower bound of the target value was made a non-zero dollar amount of $20 [Cifuentes and Sunder 1991; Samuelson and Bazerman 1985].
- Price offers for each of the 30 coins were to be made in multiples of $20. The sellers would then decide whether or not to accept the offers. The sellers would always accept the offers provided that they were equal to or greater than the seller's reservation price, which were randomly generated based on a discretized normal distribution (Figure 1). Potential buyers using the NYOP mechanism in websites such as Priceline™ may receive a counteroffer and may be informed of a specific minimum re-bid amount[7]. Target value of the coins followed prior research with random number generation by Ball et al. [1991] and uniformly distributed actual value of the target object by Foreman and Murnighan [1996]. The distribution of the values was not explicitly provided to the subjects. The subjects were given feedback on the outcomes of similar transactions from which they could implicitly determine the distribution.

The subjects were told that they would be paid for their participation and on how well they performed. For their participation they were guaranteed a monetary compensation of $10, and as an additional incentive to increase their involvement they would also receive an additional 1/10 of a cent on the dollar at the end of the experiment. For instance, an ending balance of $7,000.00 would result in a payment of $10.00 + ($7,000.00 x 0.001) = $17.00 to the participant. Subjects were given ample time to read the instructions outlining the process entailed in acquiring the antique coins. After all questions were answered, the facilitator reiterated that acquiring a coin was a neutral event and that the only measure of performance was the value of their ending balance at the end of the experiment, which

[6] Bidding guidelines obtained March 3, 2006 from http://p070.ezboard.com/fpricelineandexpediabiddingpostingguidelines.showMessage?topicID=55.topic

[7] Counteroffer and re-bid information obtained March 3, 2006 from http://p070.ezboard.com/fpricelineandexpediabiddingbiddingrelatedquestions.showMessage?topicID=1085.topic

followed prior experimental design [Ball et al. 1991].



Seller's Value (SV)	$20	$40	$60	$80	$100	$120	$140	$160	$180	$200
Buyer's Value	$25	$50	$75	$100	$125	$150	$175	$200	$225	$250
Probability	6%	8%	10%	12%	14%	14%	12%	10%	8%	6%
Cumulative Probability	6%	14%	24%	36%	50%	64%	76%	86%	94%	100%
E(SV) | Accepted	20	31	43	56	68	79	89	97	104	110
E(BV) | Accepted	25	39	54	69	85	99	111	122	130	138
E(Gain/Loss)	5	-1	-6	-11	-15	-21	-29	-38	-50	-63

Figure 1: Discretized Normal Distribution of Seller's and Buyer's Value

Using a 2x2 full factorial design, two types of information provision were manipulated in the experiment: bid outcomes and bid recommendations. The two different levels of bid outcomes - full outcomes (F) or acceptance outcomes (A) were of 250 similar transactions by other bidders, as well as their own previous transactions. The two different levels of bid recommendations - no bid recommendations (R-) or bid recommendations (R+) pertained to the probability that their initial bids being accepted, together with the increase in the probability of winning if the initial bids were increased (R+). Hence, the 2x2 design generated four cells with different levels and combinations of information provision. To control for chance factors the subjects were randomly assigned to one of the four conditions with the opportunity to bid on 30 coins. Each of the 30 rounds started with the initial bid screen as shown in Figure 2.

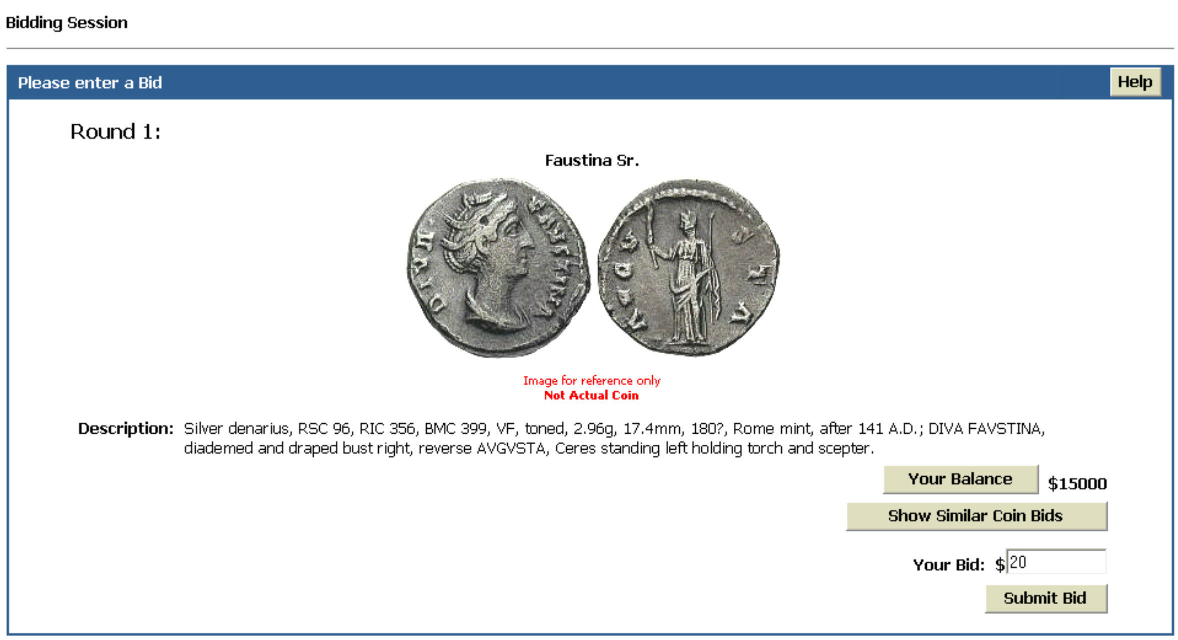
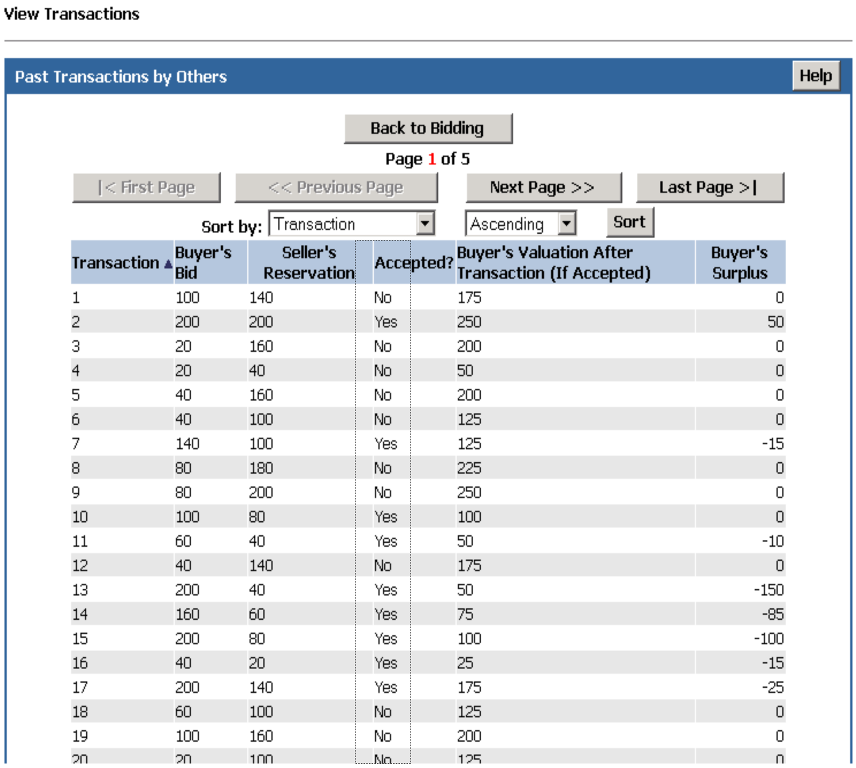


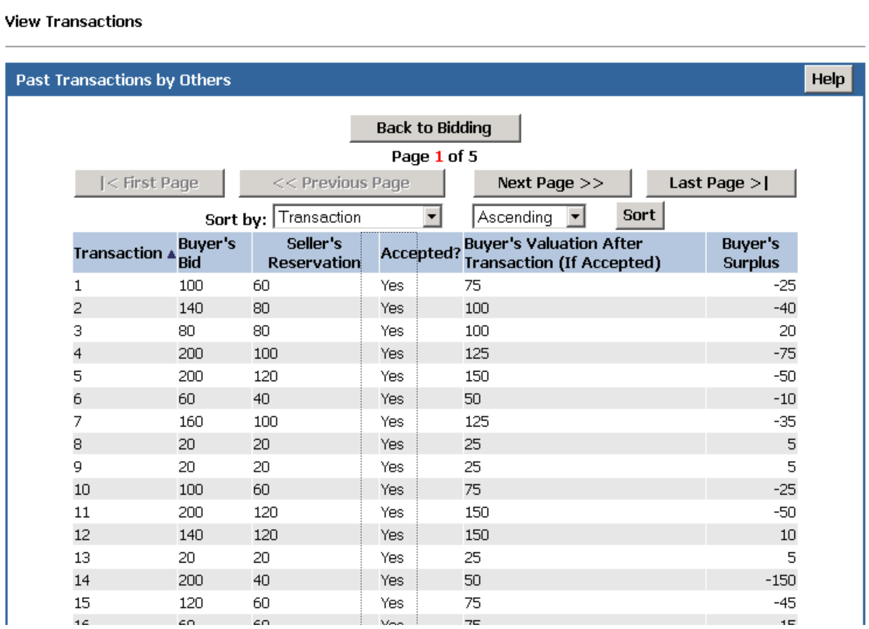
Figure 2: Initial Bid Screen

Subjects were provided with 250 past transactions as well as their own previous bids that included either full outcomes (Figure 3) or acceptance outcomes (Figure 4) depending on their treatment, which they could view prior to placing their bid. The 250 past transactions were randomly created reflecting the seller's value of the coin as depicted in Figure 1



Transaction	Buyer's Bid	Seller's Reservation	Accepted?	Buyer's Valuation After Transaction (If Accepted)	Buyer's Surplus
1	100	140	No	175	0
2	200	200	Yes	250	50
3	20	160	No	200	0
4	20	40	No	50	0
5	40	160	No	200	0
6	40	100	No	125	0
7	140	100	Yes	125	-15
8	80	180	No	225	0
9	80	200	No	250	0
10	100	80	Yes	100	0
11	60	40	Yes	50	-10
12	40	140	No	175	0
13	200	40	Yes	50	-150
14	160	60	Yes	75	-85
15	200	80	Yes	100	-100
16	40	20	Yes	25	-15
17	200	140	Yes	175	-25
18	60	100	No	125	0
19	100	160	No	200	0
20	20	100	No	125	0

Figure 3: Past transactions provided under Full Outcome Information



Transaction	Buyer's Bid	Seller's Reservation	Accepted?	Buyer's Valuation After Transaction (If Accepted)	Buyer's Surplus
1	100	60	Yes	75	-25
2	140	80	Yes	100	-40
3	80	80	Yes	100	20
4	200	100	Yes	125	-75
5	200	120	Yes	150	-50
6	60	40	Yes	50	-10
7	160	100	Yes	125	-35
8	20	20	Yes	25	5
9	20	20	Yes	25	5
10	100	60	Yes	75	-25
11	200	120	Yes	150	-50
12	140	120	Yes	150	10
13	20	20	Yes	25	5
14	200	40	Yes	50	-150
15	120	60	Yes	75	-45

Figure 4: Past transactions provided under Acceptance Outcome Information

A final bid screen was displayed to allow buyers to confirm or increase (or even decrease) their initial bids. The final bid screen in Figure 5 provided the subjects with bid recommendations and showed the probability of their initial bids being accepted, together with the increase in probability of winning if the initial bids were increased by $20 and $40 respectively.

Bidding Session

Please confirm your Bid Help

Round 1:

Faustina Sr.

Description: Silver denarius, RSC 96, RIC 356, BMC 399, VF, toned, 2.96g, 17.4mm, 180?, Rome mint, after 141 A.D.; DIVA FAVSTINA, diademed and draped bust right, reverse AVGVSTA, Ceres standing left holding torch and scepter.

Your Current Bid is:	$20
Your chance of being accepted by seller is:	6%
If you increase your bid to:	$40
Your chance of being accepted by seller is:	14%
If you increase your bid to:	$60
Your chance of being accepted by seller is:	24%
To confirm this bid hit submit. To change your bid, enter new amount and press submit.	$ 20

Submit Bid

Figure 5: Recommendation Screen

After each final bid was entered, subjects were provided the outcome of their bid. Subjects provided with full outcomes were given details of their bid regardless of the whether the bid was accepted (Figure 6).

Round Result

Your Current Transaction

Your bid is:	$80
The seller's reservation is:	$100
Your bid was:	NOT Accepted
You bid valuation would have been:	$125
Your original balance is:	$14980
Your new balance is:	$14980

Your Previous Transactions

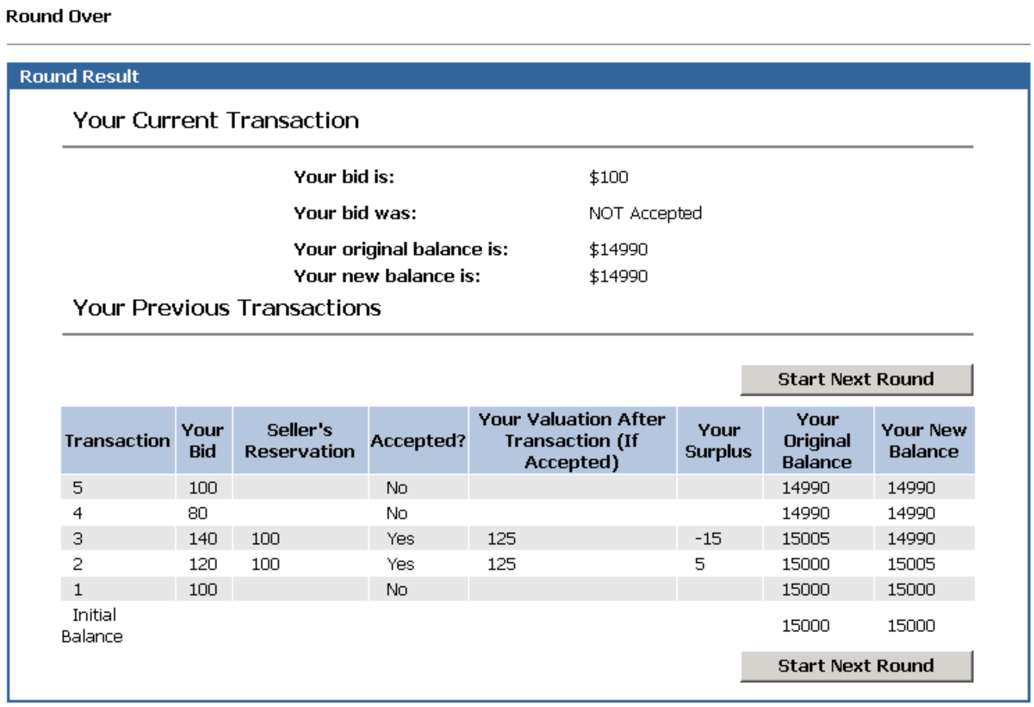
Start Next Round

Transaction	Your Bid	Seller's Reservation	Accepted?	Your Valuation After Transaction (If Accepted)	Your Surplus	Your Original Balance	Your New Balance
5	80	100	No	125	0	14980	14980
4	160	100	Yes	125	-35	15015	14980
3	140	120	Yes	150	10	15005	15015
2	120	100	Yes	125	5	15000	15005
1	100	140	No	175	0	15000	15000
Initial Balance						15000	15000

Start Next Round

Figure 6: Bid outcomes provided under Full Outcome Conditions

Subjects provided with acceptance outcomes were given details of their accepted bids or simply notified that their bids were rejected (Figure 7).



Transaction	Your Bid	Seller's Reservation	Accepted?	Your Valuation After Transaction (If Accepted)	Your Surplus	Your Original Balance	Your New Balance
5	100		No			14990	14990
4	80		No			14990	14990
3	140	100	Yes	125	-15	15005	14990
2	120	100	Yes	125	5	15000	15005
1	100		No			15000	15000
Initial Balance						15000	15000

Figure 7: Bid outcomes provided under Acceptance Outcome Conditions

The questions outlined in the Appendix were administered to the participants at the conclusion of the experiment to obtain information regarding their experience and bidding behavior.

5. Results

The subjects were randomly assigned to the four conditions: full outcomes without recommendations (F/R-, N_1=33); full outcomes with recommendations (F/R+, N_2=34); acceptance outcomes without recommendations (A/R-, N_3=31); and acceptance outcomes with recommendations (A/R+, N_4=33). The imbalanced number of subjects across the four conditions was due to unexpected technical problems during the experiment, and the incomplete data corresponding to the subjects was rendered unusable. The remaining responses (N = 131) were analyzed in terms of the frequencies of gains and losses in each condition using the table analysis. Also, the average dollar amounts of gains and losses were analyzed using repeated measures ANOVA with bid outcomes and bid recommendations modeled as between-subjects effects and rounds (1-30) and bid types (initial vs. final) modeled as within-subjects effects.

The descriptive statistics for each treatment group, full outcomes with recommendations (F/R+); full outcomes without recommendations (F/R-); acceptance outcomes with recommendations (A/R+); and acceptance outcomes without recommendations (A/R-) are shown in Tables 1-4.

Table 1: Descriptive statistics for Full Outcomes with Recommendations Condition (F/R+)

	Initial Bid					Final Bid				
Round	Mean	S.D.	Min	Med	Max	Mean	S.D.	Min	Med	Max
1	76	32	20	80	140	91	33	40	80	160
2	82	39	20	80	180	94	38	20	100	160
3	92	45	20	80	200	101	45	20	100	220
4	97	38	40	100	200	105	28	60	100	200
5	99	34	40	100	200	110	36	40	100	220
6	102	37	40	100	200	110	46	40	100	280
7	98	39	20	100	180	98	34	20	100	180
8	97	31	40	100	180	104	31	40	100	180
9	100	31	40	100	160	99	33	40	100	160
10	96	36	20	100	200	98	31	40	100	160
11	94	35	20	100	160	98	31	20	100	160
12	102	41	40	100	200	103	36	40	100	200
13	91	33	20	100	160	92	31	20	100	140
14	99	47	20	80	200	96	43	20	80	200
15	95	34	20	100	160	98	35	20	100	160
16	97	38	20	100	180	94	33	20	100	180
17	91	40	20	100	180	93	39	20	100	180
18	94	43	20	100	200	93	41	20	80	200
19	91	46	20	80	220	95	45	20	80	220
20	87	34	20	100	180	91	32	20	100	160
21	91	35	20	100	200	94	31	40	100	180
22	93	44	20	100	200	93	39	20	100	200
23	91	37	20	80	160	98	39	20	100	180
24	103	44	40	100	200	101	42	40	100	200
25	101	43	20	100	200	105	37	40	100	200
26	95	44	20	100	200	98	41	20	100	200
27	95	39	40	100	200	97	37	40	100	200
28	101	42	40	100	200	107	39	40	100	200
29	94	34	40	100	200	96	32	40	100	200
30	94	43	20	90	200	97	41	20	100	200

Table 2: Descriptive statistics for Full Outcomes without Recommendations Condition (F/R-)

	Initial Bid					Final Bid				
Round	Mean	S.D.	Min	Med	Max	Mean	S.D.	Min	Med	Max
1	82	31	20	80	140	82	31	20	80	140
2	94	34	20	100	180	94	34	20	100	180
3	95	37	20	100	160	96	37	20	100	160
4	97	41	40	100	200	97	40	40	100	180
5	97	35	40	100	160	97	35	40	100	160
6	102	35	40	100	180	102	35	40	100	180
7	91	37	20	80	160	91	37	20	80	160
8	97	34	20	100	160	97	34	20	100	160
9	92	38	20	80	160	92	38	20	80	160
10	88	31	20	80	160	88	31	20	80	160
11	93	41	20	100	180	93	41	20	100	180
12	92	31	20	100	160	92	31	20	100	160

13	94	35	20	80	160	94	35	20	80	160
14	99	37	20	100	200	99	37	20	100	200
15	94	32	20	100	160	94	33	20	100	160
16	104	35	40	100	200	104	35	40	100	200
17	94	36	40	100	180	93	37	40	100	180
18	86	41	20	80	180	86	40	20	80	180
19	86	43	20	90	200	86	43	20	90	200
20	96	39	20	100	160	96	39	20	100	160
21	91	37	20	100	180	91	37	20	100	180
22	93	43	20	100	200	93	43	20	100	200
23	98	41	20	80	200	98	41	20	80	200
24	104	41	20	100	200	104	41	20	100	200
25	85	34	20	80	140	85	34	20	80	140
26	90	34	20	80	160	90	34	20	80	160
27	93	43	20	100	200	93	43	20	100	200
28	90	43	20	100	180	90	43	20	100	180
29	92	43	20	80	200	92	43	20	80	200
30	95	47	20	80	200	95	47	20	80	200

Table 3: Descriptive statistics for Accepted Outcomes with Recommendations Condition

	Initial Bid					Final Bid				
Round	Mean	S.D.	Min	Med	Max	Mean	S.D.	Min	Med	Max
1	64	43	20	60	220	74	48	20	60	220
2	70	39	20	60	220	78	43	20	60	220
3	77	36	20	80	160	84	34	20	100	160
4	83	39	20	80	180	90	44	20	100	220
5	90	42	20	80	200	87	34	20	100	160
6	76	33	20	80	140	82	35	20	80	160
7	79	33	20	80	160	83	36	20	80	160
8	81	38	20	80	180	81	40	20	80	180
9	81	42	20	80	180	87	42	20	80	180
10	84	43	20	80	180	84	39	20	80	160
11	75	36	20	80	140	79	39	20	80	160
12	81	41	20	80	200	79	36	20	80	160
13	82	40	20	80	180	83	38	20	80	160
14	80	39	20	80	180	85	38	20	100	180
15	76	34	20	80	140	80	35	20	80	140
16	78	39	20	80	160	80	42	20	80	180
17	72	36	20	80	140	73	36	20	80	140
18	75	42	20	80	200	73	36	20	80	160
19	71	34	20	60	160	73	32	20	60	140
20	67	35	20	60	140	69	34	20	60	140
21	78	46	20	60	200	76	41	20	60	140
22	68	35	20	80	120	73	36	20	80	140
23	75	38	20	60	160	74	36	20	60	140
24	73	38	20	80	160	72	34	20	80	120
25	75	41	20	60	160	78	41	20	80	160
26	76	47	20	80	200	76	43	20	80	200
27	84	44	20	80	200	85	43	20	80	200

28	69	32	20	60	140	73	33	20	80	140
29	77	39	20	80	160	77	37	20	80	160
30	87	44	20	80	200	88	43	20	80	200

Table 4: Descriptive statistics for Accepted Outcomes without Recommendations Condition

	Initial Bid					Final Bid				
Round	Mean	S.D.	Min	Med	Max	Mean	S.D.	Min	Med	Max
1	60	31	20	60	160	60	31	20	60	160
2	73	31	20	80	120	73	31	20	80	120
3	77	33	20	80	160	77	33	20	80	160
4	83	35	20	80	140	83	35	20	80	140
5	81	39	20	80	160	81	39	20	80	160
6	77	43	20	60	160	77	43	20	60	160
7	74	35	20	80	140	74	35	20	80	140
8	70	33	20	80	140	70	33	20	80	140
9	72	31	20	80	140	72	32	20	80	140
10	81	41	20	80	180	81	41	20	80	180
11	78	32	20	80	180	78	32	20	80	180
12	83	40	20	80	140	83	41	20	80	160
13	88	39	20	80	160	88	39	20	80	160
14	88	38	20	80	140	89	40	20	80	180
15	81	38	20	80	180	81	38	20	80	180
16	92	42	20	100	180	92	42	20	100	180
17	81	45	20	60	200	81	45	20	60	200
18	89	40	20	80	180	90	41	20	80	180
19	90	53	20	100	300	84	37	20	100	180
20	91	44	20	100	180	91	44	20	100	180
21	83	34	20	100	160	83	34	20	100	160
22	75	37	20	80	180	75	37	20	80	180
23	75	40	20	60	140	75	39	20	60	140
24	86	38	20	80	160	86	38	20	80	160
25	81	40	20	80	200	81	40	20	80	200
26	88	43	20	80	200	88	43	20	80	200
27	86	37	20	100	160	87	37	20	100	160
28	85	40	20	80	200	85	40	20	80	200
29	86	38	20	80	220	86	38	20	80	220
30	92	58	20	80	300	92	58	20	80	300

5.1. Bidding Behavior across Conditions

The transaction outcomes were analyzed in terms of frequencies of gains and loss transactions under each condition:

- For those under full outcomes, 72% (2980) of the transactions resulted in gains, and 28% (1146) of the transactions resulted in losses.
- For those under acceptance outcomes, 77% (2982) of the transactions resulted in gains, and 23% (858) of the transactions resulted in losses. There are a significantly fewer number of loss transactions under the acceptance outcomes condition (chi-square=31.162, d.f.=1, $p<0.001$).
- For those provided with recommendations, 75% (3064) of the transactions resulted in gains, and 25% (1014) of the transactions resulted in losses.
- For those provided no recommendations, 74% (2898) of the transactions resulted in gains and 26% (990) of the transactions resulted in losses. There is no significant difference between those receiving

recommendations and no recommendations in terms of the number of gain and loss transactions (chi-square=0.378, d.f.=1, p=0.5).

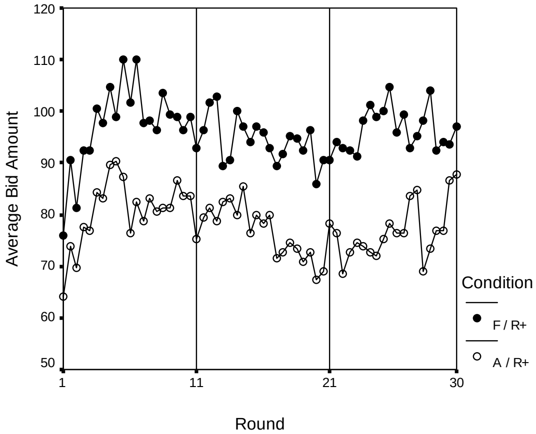


Figure 8. Average bids over 30 rounds: F/R+ & A/R+

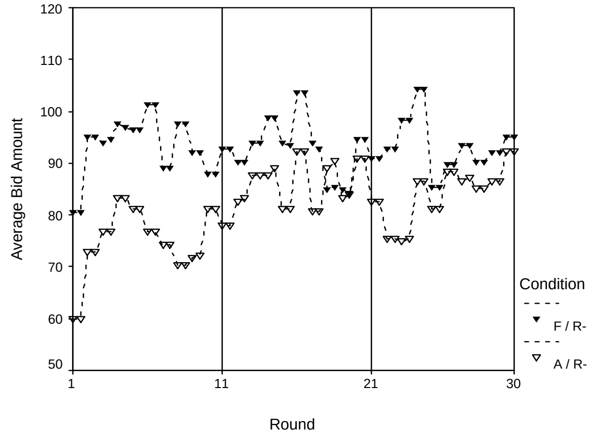


Figure 9. Average bid over 30 rounds: F/R- & A/R-

The average initial and final bid amounts for each of the four conditions over the 30 rounds are depicted in Figures 8-11. The average payoff amounts for each of the four conditions over the 30 rounds are depicted in Figure 12.

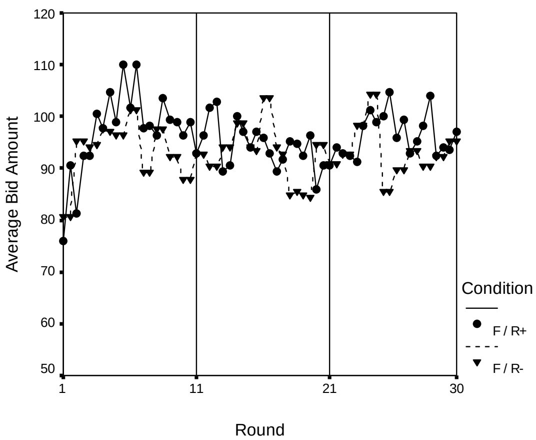


Figure 10. Average bids over 30 rounds: F/R+ & F/R-

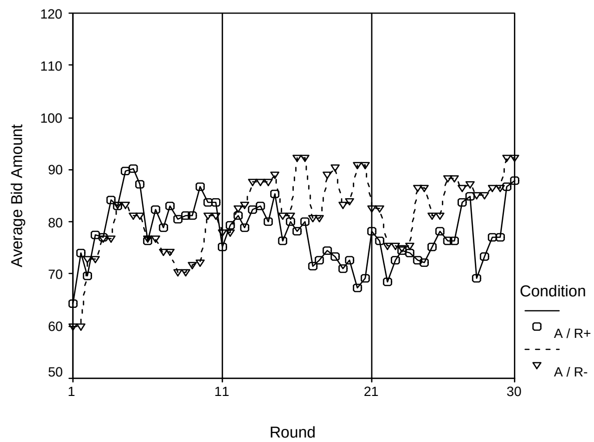


Figure 11. Average bids over 30 rounds: A/R+ & A/R-

The transaction outcomes were also analyzed in terms of average amount of gains and losses. The test results of between-subject effects are summarized in Table 5. The main effects of bid outcomes were significant on both bid amount and payoff. Subjects receiving acceptance outcomes performed significantly better than subjects receiving full outcomes over the 30 rounds ($F=5.469$, $p<0.05$). Consistent with past studies, we also looked at bid amount (Table 6), which provides a better indication of the decision quality, which is not always reflected on payoff due to random chance in a specific round.

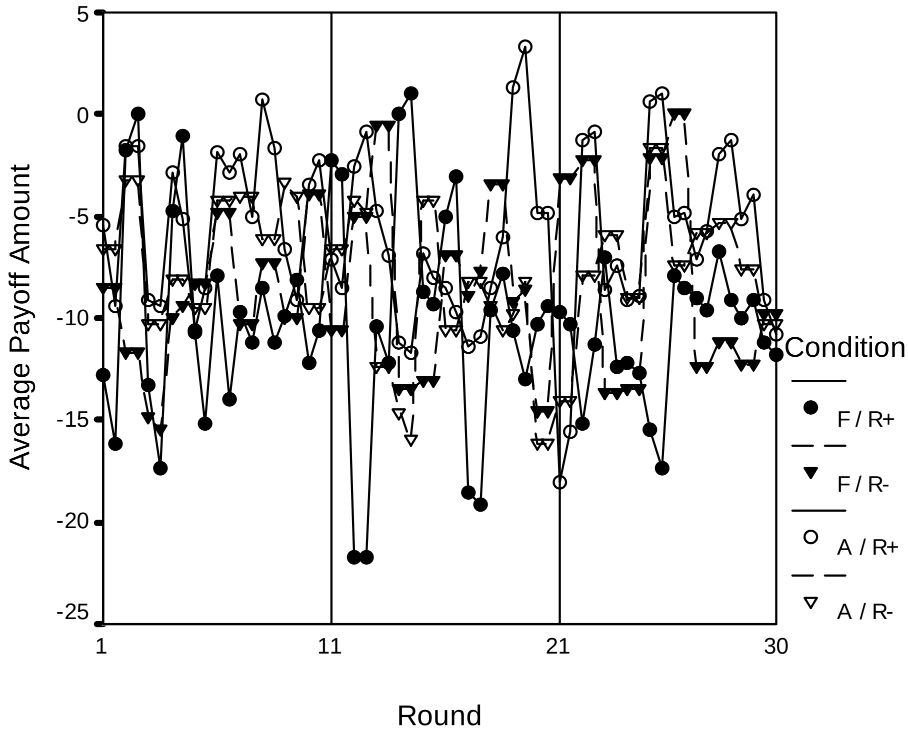


Figure 12. Average payoff amounts over 30 rounds

Table 5: Tests of between-subject effects on payoff amount

Independent Variable(s)	**F-stat**	**p-value**
Recommendations	0.053	0.819
Full Outcomes	5.469	0.021*
Recommendations * Full Outcomes	3.146	0.079

* p < 0.05

Table 6: Tests of between-subject effects of bid amount

Independent Variable(s)	**F-stat**	**p-value**
Recommendations	0.006	0.937
Full Outcomes	15.492	0.000***
Recommendations * Full Outcomes	0.702	0.404

*** p < 0.001

Hypothesis 1 was supported. Subjects receiving acceptance outcomes (accepted bids only) bid significantly lower than subjects receiving full outcomes (accepted and rejected bids) over the 30 rounds ($F=15.492$, $p<0.01$). Subjects receiving acceptance outcomes learned to avoid the winner’s curse better than bidders receiving full outcomes, as indicated by their lower bids.

Hypothesis 2 was not supported. The main effects of bid recommendations were not significant ($F=0.006$, $p>0.05$). There is no evidence that subjects receiving bid recommendations bid significantly higher than subjects receiving no bid recommendations over the 30 rounds.

5.2 Bidding Behavior over Time

To investigate the bidding behavior of individual subjects over the course of the experiment, tests of within-subject effects were performed and are summarized in Table 7. The following tests were significant: main effects of rounds and bid types (initial vs. final), the 2-way interaction between rounds and final bid types, and the 3-way interaction between rounds, bid types and recommendations. The initial bid and final bid for subjects receiving recommendations or no recommendations were significantly different across the 30 rounds.

Table 7: Tests of within-subject effects

Independent Variables(s)	**F-stat**	**p-value**
Round	2.000	0.001**
Final Bid	9.747	0.002**
Round * Final Bid	2.475	0.000***
Round * Full Outcomes	0.754	0.825
Round * Recommendations	1.082	0.349
Final Bid * Full Outcomes	0.288	0.593
Final Bid * Recommendations	8.944	0.003**
Round * Final Bid * Full Outcomes	1.345	0.103
Round * Final Bid * Recommendations	2.688	0.000***
Round * Full Outcomes * Recommendations	0.732	0.850
Final Bid * Full Outcomes * Recommendations	0.620	0.432
Round * Final Bid * Full Outcomes * Recommendations	1.225	0.189

** p < 0.01 *** p < 0.001

The average initial and final bid amounts for subjects receiving recommendations and no recommendations are depicted in Figures 13 and 14. In general, subjects receiving recommendations significantly increased their final bid amounts over the initial bid amounts for the first 10 rounds (t=4.03, p<0.001). However, their final bid amounts were significantly lower in round 11-20 (t=-2.429, p<0.05). Subjects receiving no recommendations did not significantly increase their final bid amounts over the initial bid amounts for the first 10 rounds. However, their final bid amounts were significantly higher in round 11-20 (t=2.108, p<0.05). The results could suggest the frustration from their low bids being frequently rejected emphasizing the confusion between a winning and gaining bid.

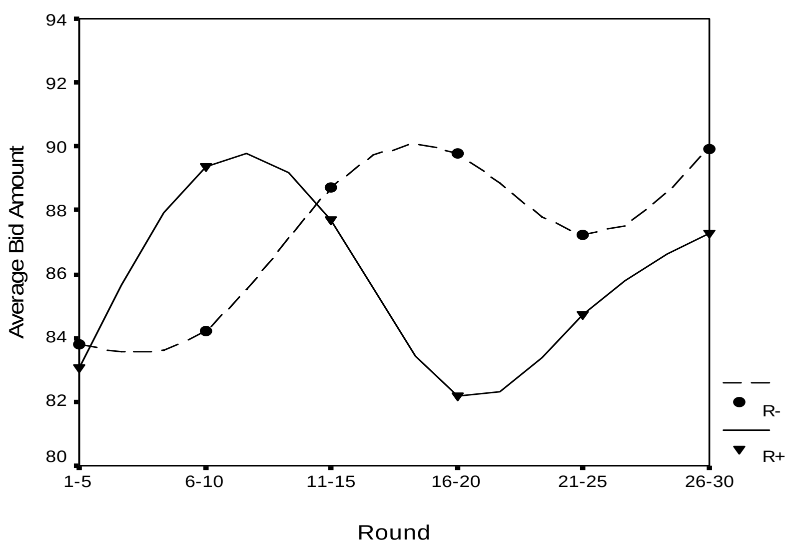


Figure 13: Average initial bid amounts for Recommendation Conditions

The objective of the study was to examine the effects of providing additional information that is seemingly useful for decision-making, and specifically learning to avoid the winner's curse. The findings of the study contribute to the objective in several ways. Consistent with previous studies, we found that buyers using the NYOP mechanism continue to be vulnerable to the winner's curse. The subjects anchored their initial bids around the (unconditional) average seller's value (i.e. $100) and adjusted upwards and downwards depending on their near term outcomes. The anchoring and adjustment heuristic is a common strategy found in decision-making literature [Tversky and Kahneman 1974]. However, anchoring and adjusting the bids around the unconditional average seller's value suggests that the subjects may not have fully understood the implications of quality uncertainty and information asymmetry.

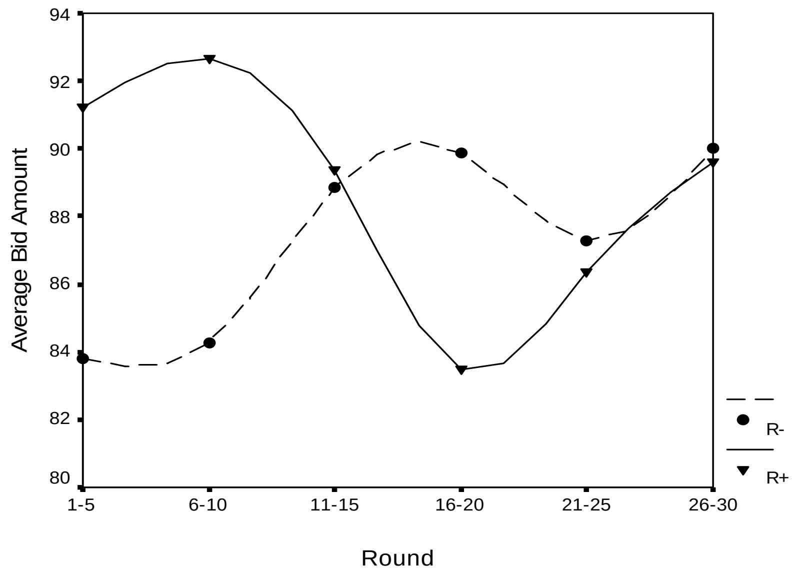


Figure 14: Average final bid amounts for Recommendation Conditions

Providing subjects with different additional information, bid outcomes and bid recommendations, affected their behavior. Our experiment found that subjects provided with acceptance outcomes bid significantly lower than subjects provided with full outcomes, which contained both the accepted and rejected bids. As Samuelson [1984] pointed out, buyers should estimate the value based on the condition that the intended bid is accepted. Subjects provided with full outcomes considered information (rejected bids) that was irrelevant to their decisions and consequently bid at higher levels, supporting research using irrelevant distractor information [Reneau and Blanthorne 2001]. Conversely, subjects provided with only acceptance outcomes learned to bid at lower levels.

Bid recommendations can provide additional information as to the distribution of the bid values and hence should, if used properly, help people learn to avoid the winner's curse. However, bid recommendations were found to create confusion between increasing the chance of winning the items. As one subject commented in the post-experiment evaluation, "at first the recommendations made me think, I want my bid to be accepted! Then I realized that acceptance doesn't guarantee a reward." Bid recommendations could have hurt the subjects in the beginning of the experiment as they were induced to bid higher. Many subjects learned to make use of the information provided by the recommendations, and bid lower. Instead of interpreting a low chance of being accepted as an indication for the need to bid higher, they made use of a high chance of being accepted to alert them of the need to bid lower. In practice, recommendations are only provided to the buyers when their bids are too low, but not vice versa. In reality, it is unlikely that consumers will be alerted that their bids may be too high, but they are provided recommendations when their bids are too low. Also, subjects in this experiment were asked to name their prices for 30 auctions regardless of the whether they were happy with the previous outcomes. In reality, consumers are unlikely to allow themselves to keep suffering losses over 30 exchanges before terminating the business relationship.

6. Limitations

Subjects in this study were purposely introduced to an unfamiliar domain (i.e. acquiring antique coins) in order to control for the introduction of personal experience into the experiment. Even so, using antique coins as the objective may have diminished the full capabilities characteristic in the NYOP mechanism. This research used a controlled lab experiment, which is the simplest possible setting with minimal risk to empirically study the behavior of subjects using an on-line auction mechanism. However, generalizing these findings to other empirical settings should be done with care. We recommend future studies investigate more fully the characteristics of the NYOP mechanism. Obtaining real world data on bidder's actual behavior in NYOP settings could extend the current work.

Bidding guidance from Biddingfortravel.com and counteroffers and minimum re-bids in the NYOP mechanism of Priceline™ were actualized in the design of the controlled experiment. In the NYOP mechanism, the failure to understand the implications of quality uncertainty and information asymmetry may have resulted in some subjects falling victim to the winner's curse. Though the words "winner's curse" were not used by Glenn Fogel, senior vice president – corporate development Priceline.com, he indicated "there is a bit of uncertainty and insecurity about buying online"[Fogel 2005]. Subjects remarked on the quality and condition of the coin even though they were informed verbally and in written form during the introduction and on the screen of every bidding session that the image of the coin was for reference only and not the actual coin. Removing these subjects from the analysis did not alter the results.

Some may argue that a buyer may be satisfied as long as she can close a deal at a reasonable cost and that imposing an experimental environment where obtaining a product is a neutral event is unrealistic. Although this may indeed be true in practice, the distinction between a satisficing and positive value outcome for the buyer is not the focus of this paper. The experiment undertaken in this study was to ascertain the influence of information provision on the subjects' bids and any resulting presence of the winner's curse. We adopted aspects of previous experiments within the winner's curse domain where possible.

Subjects in this study were to base their decisions solely on the monetary value of the item, and the experimental design restricted bidding to $20 increments. Realistically, subjects may not be restricted to such increments; however, traditional auction houses often devise increments of bidding in order to speed the process. Therefore, placing restrictions was not necessarily unrealistic.

7. Implications and Conclusions

The NYOP mechanism provides an example of how a theoretically attractive e-commerce model may be jeopardized by the suboptimal behavior of the consumers. Consumer goodwill is jeopardized by the winner's curse and may manifest itself in a lower customer return rate. Yet for those who understand its nuances, the NYOP mechanism can provide savings to buyers, as well as extra yield for sellers, even though the seller's view was not a focus of this study. Buyers in the real world are likely to be familiar with the domain when they participate in auctions; however, even an experienced buyer in a familiar domain can lose money if she fails to understand the subtleties in the underlying mechanism [Milgrom 1989], and as evidenced by the discussion thread postings on Biddingfortravel.com. And even so, when using the NYOP mechanism, a buyer bidding for a particular flight may not know the actual airline and flight times until she pays for the ticket and still be subject to the winner's curse not because of the price, but because of some other relevant information related to the quality of the flight. The success of an e-commerce model depends not only on its technical and economic aspects, but also on its behavioral impact on users. In general, in order for an information system to effectively support buyer's decisions towards desirable outcomes, it is important for the information provided by the system be relevant to help facilitate the decision making process.

The findings of this study shed some light on how information systems can better support bidders' decisions. Providing bidders with both accepted and rejected bids may seem logical since bidders are provided with what is conceivably more complete information. The rejected outcomes should have provided important information that could have helped the subjects learn to avoid the winner's curse in the next round. However, the results show that lower quality decisions came from being provided both accepted and rejected bid information, whereas higher quality decisions resulted from being provided only accepted bid information. The study showed that irrelevant information did not improve outcomes. In practice, rejected bid information could be provided as an option, and the bidder could request this information separately. Future research could investigate the manipulation of information provisioning as an additional link to see if and when used, and effects in decisions and existence of winner's curse.

Similarly, properly interpreted, recommendations can provide additional information regarding the value of the item. Recommendations used by the NYOP mechanism created confusion between the chance of winning an item and making a profitable deal. Yet, with repeated use, the recommendation information was shown to be useful and interpretable. Information systems designed to support decision-making should extend and overcome the limitations of decision makers [Silver 1988, 1991; Todd and Benbasat 1999]. E-commerce vendors often focus mainly on the amount the information provided to the users but less on how it will be used. This study shows that attention should be given to the human processing capabilities of potential e-commerce auction users and systems' design might consider better aids for acquiring and processing the information.

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Appendix A. Post-experiment Questionnaire

1. In general, describe how you determined your bid amount for an item.
2. You bid $XXX in the first round, why did you bid that amount and how did you determine the bid amount? (Note: the amount of their bid in the first round was inserted (auto-generated) in the question, replacing XXX.)
3. You bid $MAX in round ZZZ, why did you bid that amount and how did you determine the bid amount? (Note: the maximum dollar amount and the round of that bid were inserted (auto-generated) in the question, replacing the $MAX and ZZZ.)
4. You bid $MIN in round ZZZ, why did you bid that amount and how did you determine the bid amount? (Note: the minimum dollar amount and the round of that bid were inserted (auto-generated) in the question, replacing the $MIN and ZZZ.)
5. What have you learned about this game in general?
6. If an expert appraisal were available that would tell you the exact value of the coin, how much would you be willing to pay for the appraisal? Why?
7. If you could play the game again but can only bid the same price for all of the 40 coins, what would you bid? Why?
8. Did you try to maximize the payoff or the number of coins won? (3 point scale)
   Mainly maximize the number of coins won – Both – Mainly maximize the payoff
9. How would you describe your on-line purchasing experience?
10. How useful do you find the past transactions in helping you to determine your bids?
    Not useful at all -– Somewhat useful – Useful – Very useful – Extremely useful
11. If the past transactions were not available, your performance (in terms of the money you made) would have been: (5 point scale)
    Much worse – Slightly worse – About the same – Slightly better – Much better
12. If the past transactions were not available, would you have bid a different amount in the first round? If yes, what would that amount have been? Why?
13. How useful do you find the recommendations in helping you to determine your bids? (5 point scale)
    Not useful at all -– Somewhat useful – Useful – Very useful – Extremely useful
14. If the recommendations before you confirmed your bid were not available, your performance (in terms of the money you made) would have been: (5 point scale)
    Much worse – Slightly worse – About the same – Slightly better – Much better
15. If the recommendations were not available, would you have bid a different amount in the first round? If yes, what would that be? Why?