Stability of the Truth-telling Strategy in Multi-unit Option Allocation Auctions: Laboratory Experimentation*

Atsushi Iwasaki and Makoto Yokoo
Graduate School of Information Science
and Electrical Engineering, Kyushu University,
Fukuoka 812-8581, JAPAN,
{iwasaki,yokoo}@is.kyushu-u.ac.jp

Masafumi Matsuda
NTT Corporation,
NTT Communication Science Laboratories,
Kyoto 619-0237, JAPAN,
masafumi@cslab.kecl.ntt.co.jp

Abstract

This paper investigates the performance and bidding behavior in a multi-unit option allocation auction protocol, employing laboratory experiments. In the protocol, truth-telling is a weakly dominant strategy, even if the marginal values of each agent can increase and agents can submit "false-name bids." However, such new protocols have not been widely used so far. One major reason is that people do not trust how well a new protocol might perform in a real-world setting. In the real-world setting, there exist not only computational agents, but also real humans. To fill the gap between theory and the real-world, we focus on laboratory experimentation using real humans to observe how bidders will behave in an environment that includes both real humans and computational agents. Our experimental results propose a segmentation which gives a seller a clue as to which protocol he should choose and also show that there is some over-bidding behavior in our protocol, and the existence of this behavior makes the earnings and efficiency of our protocol worse than the predicted values. Nevertheless, individual data indicate that our protocol leads a considerably larger bidders to take a truth-telling strategy consistently than does a uniform-price auction.

1. Introduction

The Internet has recently provided an excellent infrastructure for executing much cheaper auctions with huge number of buyers and sellers from all over the world. More and more companies and consumers buy and sell various goods on Internet auctions; therefore, Internet auctions have become a popular part of Electronic Commerce [14, 13]. In particular, computational mechanism design has become very popular among computer scientists [7, 4, 5]. Some of these works developed bidding agents to help humans participant in auctions, e.g., [11], while others design a robust auction protocol against frauds that can occur in the Internet, e.g., [15].

However, virtually none of these new protocols[1] has been widely used so far, including the more traditional Vickrey auction protocol and the Vickrey-Clarke-Groves (VCG) mechanism.

One major reason why these new protocols have not been used so far is that people do not trust how well a new protocol might perform in a real-world setting. In the real-world setting, there exist not only computational agents, but also real humans. These real humans can directly participate in the auction as well as indirectly participate via proxy agents.

These humans and computational agents controlled by humans do not necessarily act as anticipated by the designer of a protocol. When designing a mechanism, we often assume that they take an equilibrium strategy. On the other hand, the behavior of them can be rather complicated and difficult to predict. For example, human with wrong valuations and agents with flawed code would make mistake, i.e., non-equilibrium strategies. It may be to the advantages of other participants (experts or sophisticated agents) to play by non-equilibrium strategies. The fact that we don't know how a new protocol would performs in such situations can prevent people from using it and encourage them to stick to more traditionally familiar protocols, although new protocols potentially have various advantages.

To fill the gap between theory and the real-world, we need to examine the performance of a new protocol when it is used among real humans and/or computational agents so that we can use the obtained knowledge to design a better protocol that can achieve desirable properties.

* This research was conducted when the authors (Atsushi Iwasaki and Makoto Yokoo) belonged to NTT Corporation, NTT Communication Science Laboratories.

1 FCC's simultaneous multi-round auction might be a notable exception.

		False-name bids	
		n/a	available
Marginal values	decreasing	VCG/Ausubel	VCG/Ausubel
	general	VCG	Option Allocation

Table 1. Auction protocols where truth-telling or sincere bidding is an equilibrium strategy.

In this paper, we focus on laboratory experimentation using real humans to observe how bidders will behave in an environment that includes both real humans and computational agents. Alternatively, we can use simulations to examine off-equilibrium behaviors. However, this does not meet our current goal of observing what kinds of behaviors appear in such an environment. As Roth [12] pointed out, we believe that mechanism design, laboratory experiments, and simulation must complement each other in designing protocols that can be widely accepted. In fact, many auction experiments have already been conducted [9, 10, 3]. Bichler [3] analyzed multi-attribute auctions to implement his auction in a real-world setting. Kagel and Levine [10] investigated bidding behavior in multi-unit uniform-price and Ausubel auctions.

More specifically, we examine the performance and behavior of an auction protocol for multi-unit auctions, called the OPtion allocation (OP) protocol [8]. In this protocol, truth-telling is a weakly dominant strategy, even if the marginal values of each agent can increase and agents can submit "false-name bids."[2] Table 1 summarizes auction protocols where truth-telling or sincere bidding is an equilibrium strategy. This protocol is the first non-trivial open ascending-price auction protocol that generalizes the Ausubel auction [1] both in terms of the types of value functions and in terms of the robustness against false-name bids. However, this paper mainly explains the results on a sealed-bid version of the OP because they were theoretically equivalent to those on an open ascending-price version of the OP. Furthermore, we compare the OP with a uniform-price auction, which is a representative conventional auction and actually used [6]. Our experimental results show that individual bidding indicates the closer conformity to truth-telling in the OP than the UP, although the aggregate data indicates that the theoretical predictions of the OP fails more than those of the UP because of a certain number of overbidding bidders.

This paper is organized as follows. Section 2 introduces the valuation setting in our experiments and explains the uniform-price and option allocation auctions. Section 3 outlines our experimental design. Section 4 reports the results of the experiments. Section 5 discusses our results and mentions the experimental results of open ascending-price auctions. Section 6 concludes the paper.

2 False-name bids involve a new type of cheating that can be done easily on the Internet. Specifically, there may be some agents with fictitious names, such as multiple e-mail addresses, who can decrease their payments by using false-name bids [16]. However, we excluded false-name bids to make experiments tractable because it is difficult for subjects to understand the procedure itself of the OP.

2. Uniform-price Auction and Option Allocation Auction

This section discusses our valuation setting and two multi-unit auction protocols, the sealed-bid uniform-price (SUP) and the sealed-bid option allocation (SOP) auctions, as well as the game theoretical predictions.

2.1. Valuation Setting

Ausubel and Cramton [2] introduced a flat demands setting where bidder i has a constant marginal value v_i for the good up to the available supply. Kagel and Levine [10] employed the flat demands setting and conducted their experiments on the uniform-price and Ausubel auctions with a supply of two units.

We extend this setting to estimate a situation where the marginal values of bidders can increase. Let us consider the following example: "You are purchasing tickets for you and your child. You demand at least two tickets, thus not settling for one ticket. If the price is cheap enough, you may demand three tickets, with the third for your husband or wife." In general, we can assume that the marginal values tend to diminish if the quantity of units becomes very large. On the other hand, if the quantity of units is relatively small, we assume that the marginal values of bidders can increase.

We investigate bidding in independent private value auctions with $(n + 1)$ bidders and three identical goods. Bidders 1, 2, ..., n demand only one unit, valuing it at v_1, v_2, ..., v_n, respectively. The $(n+1)$th bidder, h, demands three units of the good, valuing them at 0, $2v_h$, $(2+\delta)v_h$, respectively ($\delta \in (0, 1)$). Bidders' values, v_i $(i \in \{1, 2, \ldots, n, h\})$ are drawn *iid* from a uniform distribution on the interval $[0, V]$.

2.2. Sealed-bid Uniform-price Auction

In the sealed-bid uniform-price auction [6] (also called a multi-unit English auction), each bidder simultaneously submits a sealed bid vector $\mathbf{b^i} = \{b_i^1, \ldots, b_i^k, \ldots, b_i^K\}$, in which b_i^k represents a value for k units of an item. However, a bidder is constrained to submit $b_i^{k-1} \leq b_i^k$. The value vector may or may not be true. The auctioneer inverts the bid vector to obtain a demand curve $q_i(p)$ according to Eq. 1.

$$q_i(p) = \arg \max_{k \in [0,K]} \{b_i^k - p \times k\}. \qquad (1)$$

The demand curve represents the demand of the bidder at a price per unit of p. Then the auctioneer aggregates all bidders' demands at each price per unit. All units are sold at the market-clearing price at which the aggregate demand exactly meets the available supply.

For bidders demanding a single-unit, the optimal strategy is bidding their value v_i on one unit. The optimal strategy of the bidder who demands three units against n bidders with single-unit demand is to bid 0 on one unit, $2v_h$ truthfully on two units and $2v_h$ on three units. Notice that the marginal value between the bid on two units and on three units is zero. Ausubel and Cramton [2] define such bidding as "demand reduction" in the SUP. Accordingly, a truth-telling strategy is not an equilibrium strategy in the SUP. For bidder h, the demand reduction (DR-) strategy is a weakly dominant strategy in our setting.

2.3. Sealed-bid Option Allocation Auction

The procedure of the sealed-bid option allocation auction [8] is similar to that of the SUP. However, the auctioneer allocates options to bidders once in the SOP, according to "clinching rule" developed by Ausubel [1]. Each option includes a pair of the number of units a bidder can obtain and the price per unit she pays. She then chooses the number of units per price bidders actually obtains from their allocated options.

Each bidder simultaneously submits a bid vector. The auctioneer then inverts the bid vectors to obtain a demand curve according to Eq. 1. The auctioneer then calculates all bidders' demands at each price per unit. Next, the auctioneer considers a price vector

$$\{p^0, \ldots, p^l, \ldots, p^L\} \text{ for all } l,\ p^{l-1} < p^l. \tag{2}$$

Notice that p^L satisfies $\sum_i q_i(p^l) \leq K < \sum_i q_i(p^{l-1})$.

Let us define the maximum quantity of units that a bidder i can buy at price p^l as c_i^l:

$$c_i^l = \min\left\{q_i(p^l),\ s_{-i}(p^l)\right\}, \tag{3}$$

where $s_{-i}(p)$ represents the residual supply facing bidder i at price p defined as Eq. 4.

$$s_{-i}(p) \equiv \max\{0,\ K - \sum_{j \neq i} q_j(p)\}. \tag{4}$$

The residual supply is always non-negative and a non-decreasing function at the price p. It also indicates the amount of the item that other bidders no longer demand at that price.

The auctioneer allocates options represented by the following ordered pairs,

$$\{(p^0, c_i^0), \ldots, (p^l, c_i^l), \ldots, (p^L, c_i^L)\},$$

where (p^l, c_i^l) means that bidder i can buy $x_i \in [0, c_i^l]$ units of the item at price p^l. From the definition, c_i^l is non-decreasing. Therefore, when bidder i purchases x_i units, the optimal price per unit is given by

$$p(x_i) = \min\{p | c_i(p) \leq x_i\}. \tag{5}$$

Finally, each bidder chooses one of the options she clinched and executes it.

However, when bidder i executes an option that satisfies $c_i^l = q_i(p^l)$, the following restrictions are imposed on the bidder to increase the risk of a stay-high bidding strategy, in which a bidder maintains a high constant demand.

- The bidder is not allowed to choose to buy nothing.
- If the bidder chooses to buy units at price p^l, then she needs to buy the maximum number of units c_i^l.

For bidders demanding a single-unit there is a dominant strategy to bid their value, v_i as in the uniform-price auction. For bidder h the truth-telling (TT-) strategy is a weakly dominant strategy in our setting.

3. Experimental Design and Informal Conjectures

There are three units for sale and one subject competing against three computer agents in each experimental auction ($n = 3$). Valuations v_i ($i \in \{1, 2, 3, h\}$) are drawn *iid* from a uniform distribution with support $[0, ¥400 (\fallingdotseq \$3.60)]$ and $\delta = 0.8$. Computer agents 1, 2 and 3 demand only one unit, and they are programmed to follow the dominant strategy. Each hs know they are bidding against computers, the number of computers, and the computer's bidding strategy. This use of computer agents may seem to be unrealistic. However, this paper is mainly interested in subjects' behavior in the different auctions. Introducing computer agents makes simplifies the strategic environment that a subject faces. Thus, we can concentrate on how subjects respond to auction protocols.

Table 2 shows the results of numerical calculations when bidder h is assumed to take either of two strategies: the TT-strategy or the DR-strategy. These expected values are calculated with 500 sets of simulations in each combination of

Protocol	Uniform-price		Option Allocation	
Strategy	TT	DR*	TT*	DR
Earnings	72.32	122.96	124.84	122.96
Efficiency (%)	96.15	95.57	93.19	95.57
Revenue	483.14	398.72	405.39	398.72

Table 2. Earnings, Efficiency, and Revenue of the TT- or DR-strategy in each protocol. $*$ denotes a dominant strategy in each protocol.

a protocol and a strategy. It also suggests the following conjectures:

Conjecture 1: The expected earnings in the SOP are higher than those in the SUP.

Conjecture 2: The expected efficiency in the SUP is higher than that in the SOP.

Conjecture 3: The expected revenue in the SOP is higher than that in the SUP.

Bidders h were drawn from a wide cross-section by a temporary staff agency. Almost all of them were undergraduate students at universities around Kyoto.[3] Instructions were read out loud with subjects having copies to read as well. In the sealed-bid auctions, subjects submitted three bids b_1, b_2 and b_3 on unit 1, unit 2 and unit 3, respectively. Note that they bid the value itself on each unit, not the marginal value. After submitting bids, the auction outcome immediately appeared on the computer screen. Only in the SOP, each subject then chose one of the options she obtained. At the end of each auction, the number of units she obtained was identified, payments were posted, profit was calculated, and cash balances was updated.

Our sessions began with 3 or 5 dry runs to familiarize subjects with the procedures, followed by 27 auctions played for cash. At the start of each auction both h and computers received new valuations. Subjects were given starting cash balances of ¥300. Positive profits were added to this balance and negative profits subtracted from it. End-of-experiment balances were later paid in subjects' bank accounts. Our sessions lasted between 1.5 and 2 hours. The SUP was conducted in two sessions (20+22=42 subjects) and the SOP used three sessions (22+22+18=62 subjects).

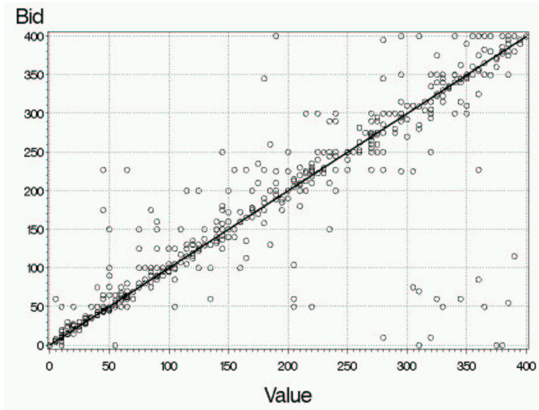
4. Experimental Results

4.1. Sealed-bid Uniform-price Auctions

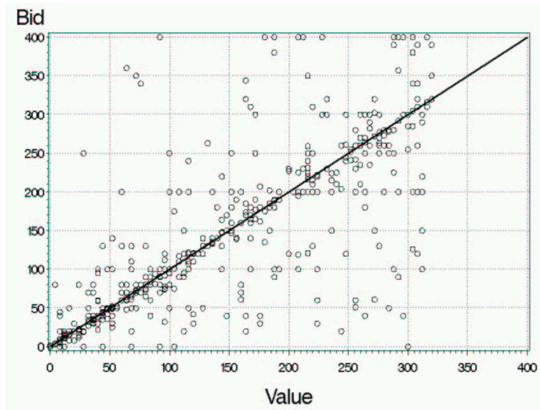
Figure 1 provides scatter diagrams of unit 2 bids and unit 3 bids over the last 12 auctions after subjects have learned the auction rule. Figure 1(a) represents $(b_2 - b_1)/2$ relative to v_h, while Figure 1(b) represents $b_3 - b_2$ relative to δv_h.

Figure 1(a) shows a large number of bids at value for unit 2. Categorizing bids within ¥5 of value as equal to value, about 40% of unit 2 bids were on value and above value. However, bidders do not lose money as a consequence of bidding above value: 82.84% of all unit 2 bids greater than value earned nonnegative profits.

3 We have no data which disciplines subjects are students of. A referee points out that the disciplines of subjects is important because some studies report that whether they study economics may affect their behavior. However, since there is no interaction between subjects in our experiment, we do not have to consider the effect much.



(a) Unit 2 bids



(b) Unit 3 bids

Figure 1. Scatter diagrams of bids relative to value for bidder h in last 12 auctions of the SUP.

Figure 1(b) shows that there is a clear shift in the distribution of unit 3 bids to unit 2 bids in the predicted direction: 38.9% of all unit 3 bids were more than ¥5 below value versus 20.44% of all unit 2 bids. However, 1.79% (9/504) of all unit 3 bids are equal to zero as the DR-equilibrium requires. There are still lots of unit 3 bids above value (33.53%, 169/504). This might be because we did not explicitly advise against bidding above value. Kagel and Levine [10] explicitly advised against bidding above value and successfully led subjects not to bid above value.

Table 3 summarizes the data contained in Figure 1 and our analysis of h's bids compared to the DR-equilibrium predictions.

Table 4 calculates actual and predicted earnings, effi-

Unit 1 bids		Unit 2 bids		Unit 3 bids	
$b_1 < 0$	n/a	$b_2 - b_1 < 2v_h$	20.44% (103/504)	$b_3 - b_2 < \delta v_h$	38.89% (196/504)
$b_1 = 0$	97.62% (492/504)	$2v_h = b_2 - b_1$	39.09% (197/504)	$\delta v_h = b_3 - b_2$	27.58% (139/504)
$0 < b_1$	2.38% (12/504)	$2v_h < b_2 - b_1$	40.48% (204/504)	$\delta v_h < b_3 - b_2$	33.53% (169/504)
Equilibrium Outcome (DR-equilibrium)	$b_1 = 0$	$b_2 - b_1 = 2v_h$		$b_3 - b_2 = 0$	

Table 3. Bidding in SUP (last 12 auctions)

Actual	Predicted	Difference
Earnings		
52.67	114.19	-61.51[a]
(6.55)	(7.43)	(5.94)
Efficiency (Percentage)		
92.62	94.93	-2.30[b]
(6.35)	(3.98)	(0.60)
Revenue		
453.74	379.36	74.38 [a]
(13.17)	(11.02)	(8.71)

a Significantly different from zero at the 0.01% level, 2-tailed Wilcoxon signed rank test.

b Significantly different from zero at the 0.2% level, 2-tailed Wilcoxon signed rank test.

Table 4. Earnings, Efficiency and Revenue in the SUP (mean values with standard error of the mean in parentheses)

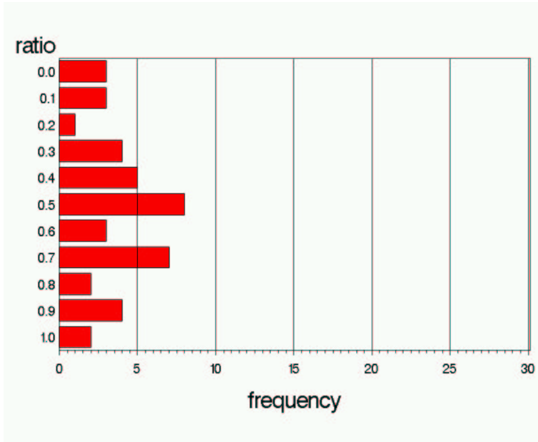


Figure 2. Distribution of the individual ratio of actual earnings relative to predicted earnings of the DR-strategy in the SUP.

ciency and revenue over the last 12 auctions. Predicted values are based on the DR-equilibrium predictions. Actual earnings are about half of predicted earnings. The earnings are closer to the TT-equilibrium predictions (¥68.70) than to the DR-equilibrium predictions.

As Table 3 shows, most subjects bid on value. Thus, they seemed to bid according to the TT-strategy. However, since the aggregate data does not always capture individual bid patterns, we focus on the individual ratio of the actual earnings relative to the predicted earnings averaged over the last 12 auctions. Figure 2 represents the distribution of the ratio. We classify the bid patterns into the following three types.

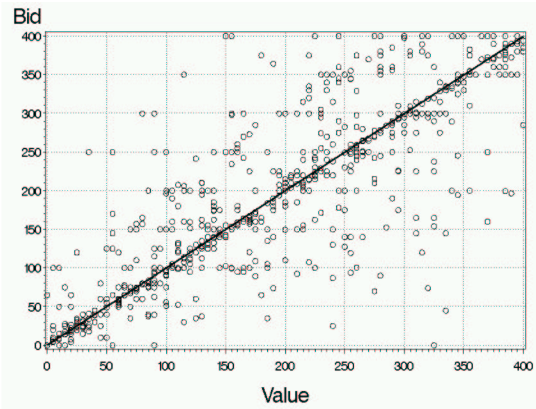
1. A small percentage of all bidders (14.2%; 6/42) bid sub-optimally, bidding close to value on unit 1 and unit 2. The bidders often bid below value on unit 3, and there is no bids above value. They obtained earnings of 95% or more of maximum possible earnings over the last 12 auctions.

2. Over half of the bidders (59.5%; 25/42) consistently bid close to their values on unit 2 and unit 3. However, bids above or below value on unit 3 were occasionally observed. Therefore, their bids are widely dispersed, and the bidders obtained the 35-85% of maximum predicted earnings.

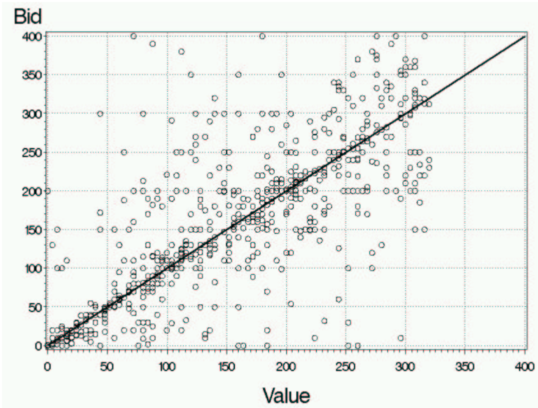
3. The remaining bidders (11/42; 26.3%) bid above value on both unit 2 and unit 3, with very little or no demand reduction on unit 3. They earned at most 30% of maximum possible earnings or non-positive earnings.

Consequently, the distribution of the ratio of the earnings suggests that bidders try to manipulate auction outcomes and they may change their bidding policy in each auction.

Efficiency is defined as the average ratio of the social surplus to the Pareto efficient social surplus. Actual efficiency is very close to the predicted efficiency. The efficiency losses resulting from bidding above value on both unit 2 and unit 3 only offset the efficiency gains resulting from over-revelation (very little demand reduction) of unit 3. Dropping subjects who often bid above value on both



(a) Unit 2 bids



(b) Unit 3 bids

Figure 3. Scatter diagrams of bids relative to value for bidder h in last 12 auctions of the SOP.

units (11/42 subjects), the efficiency improves up to 94.41% and the efficiency losses decrease.

Actual revenue is consistently above the predicted revenue. By dropping subjects who often bid above value, although the actual revenue (¥421.00) comes close to the predicted revenue (¥379.36), the difference is still large. This results from over-revelation (truth-telling) of demand on unit 3 in addition to many bids above value.

These results for efficiency and revenue are consistent with the earlier experiments by Kagel and Levine [10].

4.2. Sealed-bid Option Allocation Auctions

Figure 3 provides scatter diagrams of unit 2 bids and unit 3 bids over the last 12 auctions. It shows that bids are more widespread than those in the SUP. As observed in the SUP, there is a small shift in the distribution of unit 3 bids to unit 2 bids in an unpredicted direction: about 30% (225/744) of all unit 2 bids and about 38% (284/744) of all unit 3 bids below value are distributed over a wide range of value.

However, it is natural that there is little incentive to avoid reducing demand on unit 3 in the SOP. This demand reduction of unit 3 does not always hurt the bidders' earnings. If they bid truthfully and obtain options with which they can buy a certain number of units, they would only reduce the number of units that they actually buy to increase their profits.

There is a large number of bidders who bid above value: about 40% of all bids on unit 2 and unit 3 are greater than value. However, bidders do not lose money as a consequence of bidding above value: 76.04% of all unit 2 bids greater than value earned nonnegative profits, while 80.68% of all unit 3 bids greater than value earned nonnegative profits. Table 5 summarizes the data contained in Figure 3 and our analysis of h's bids compared to the TT-equilibrium predictions.

Table 6 calculates actual and predicted earnings, efficiency and revenue over the last 12 auctions. Predicted values are based on the TT-equilibrium predictions.

Actual earnings are significantly lower than the predicted earnings. This results from widespread bids above or below value. However, when categorizing the individual data by the ratio of actual earnings relative to predicted earnings averaged over the last 12 auctions, the consistency of bidders' strategies is more apparent in the SOP than in the SUP. Let us explain the bid patterns in the SOP.

1. Over the half of all bidders (58.06%; 36/62) consistently bid on value on unit 2 and bid on or occasionally below value on unit 3. They earned 95% or more of maximum possible earnings.

2. A third of bidders (30.64%; 19/62) consistently bid on value on unit 2 but bid occasionally above or below value on unit 3. They obtained 45-85% of maximum predicted earnings.

3. The remaining small percentage of bidders (11.29%; 7/62) consistently bid above or on value on unit 2 and bid often above value on unit 3. All of them obtained non-positive earnings.

Figure 4 shows that the distribution of the individual earnings ratio of the SOP appears to be bimodal and has two peaks, one at 0 and the other at 1, although the frequency at 0 might be outliers. In contrast, the distribution of the SUP

Unit 1 bids		Unit 2 bids		Unit 3 bids	
$b_1 < 0$	n/a	$b_2 - b_1 < 2v_h$	30.24% (225/744)	$b_3 - b_2 < \delta v_h$	38.17% (284/744)
$b_1 = 0$	92.34% (687/744)	$2v_h = b_2 - b_1$	27.69% (206/744)	$\delta v_h = b_3 - b_2$	22.18% (165/744)
$0 < b_1$	7.66% (57/744)	$2v_h < b_2 - b_1$	40.07% (313/744)	$\delta v_h < b_3 - b_2$	39.65% (295/744)
Equilibrium Outcome (TT-equilibrium)	$b_1 = 0$	$b_2 - b_1 = 2v_h$		$b_3 - b_2 = \delta v_h$	

Table 5. Bidding in the SOP (last 12 auctions)

Actual	Predicted	Difference
Earnings		
91.85	120.99	-29.14[a]
(7.08)	(6.50)	(3.42)
Efficiency (Percentage)		
87.59	93.57	-5.98[a]
(6.35)	(0.38)	(0.75)
Revenue		
400.26	398.19	2.07
(8.86)	(8.55)	(6.17)

a Significantly different from zero at the 0.01% level, 2-tailed Wilcoxon signed rank test.

Table 6. Earnings, Efficiency and Revenue in the SOP (mean values with standard error of the mean in parentheses)

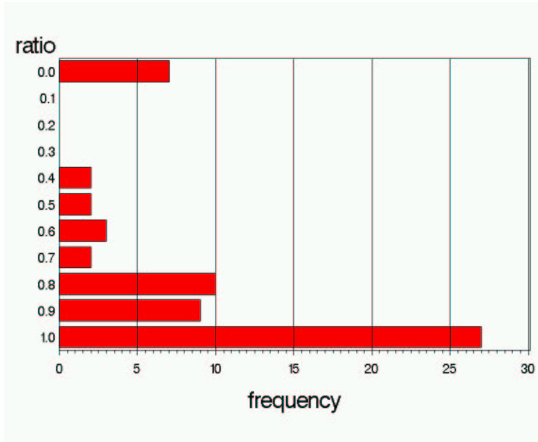


Figure 4. Distribution of the individual ratio of actual earnings relative to predicted earnings of the TT-strategy in the SOP.

in Figure 2 is unimodal and has one peak at 0.5. The difference between these distributions suggests that the larger number of bidders acquire the TT-strategy consistently in the SOP than those in the SUP.

Actual efficiency is farther from the predicted efficiency than in the SUP. The efficiency losses result from bidding above value on both unit 2 and unit 3. Dropping subjects who never earned positive profits (7/62 subjects), the efficiency improves up to 91.12%.

Actual revenue is very close to the predicted revenue. Here, revenue gains resulting from bidding above value on both units offset revenue losses resulting from bidding below value or choosing the smaller option.

Bidders who do not choose their optimal option may explain the differences between actual and predicted values. However, there were few bidders who did not choose their optimal options (6.99%; 52/744). On the other hand, when bidders chose their optimal options (93.01%; 692/744), a third of them (33.2%; 247/744) chose the smaller option and bought fewer units than they could have bought. This includes the following two cases: bidders who obtain options with which they can buy three units at maximum choose to buy two units to maximize their profits (31.72%; 236/744); the other bidders who obtain options with which they can buy two units at maximum choose to buy nothing because the price of the option is so high that they face a loss (1.48%; 11/744). As a result, in the third of the SOP, one or two units remain unsold. These unsold units theoretically and experimentally reduces efficiency of the SOP even more than that of the SUP.

5. Discussions

5.1. Segmentation

Tables 4 and 6 show that Conjectures 1 and 2 hold. The differences are significant; $t(1229)$=4.06, $p < 0.0001$ for Conjecture 1, and $t(1245)$=-5.13, $p < 0.0001$ for Conjecture 2. However, they also indicate that Conjecture 3 is rejected and the difference is significant; $t(932)$=-3.37, $p < 0.0008$.

A possible reason why Conjecture 3 is rejected is that the outcomes in the SUP are closer to the TT-equilibrium than to the DR-equilibrium. Table 2 shows the revenue in the SUP with the TT-strategy is even greater than that in the SOP. Furthermore, bids above value on both unit 2 and unit 3 increase bidders' payment easily because a bidder's outcome depends directly on her own bid in the SUP. After all, only few subjects could find that the DR-strategy is optimal in the SUP. Thus, the results in the SUP comes close to the predicted results from the TT-strategy.

These results suggest that a seller would use the SUP to increase efficiency and revenue, while using the SOP to increase buyers' earnings, say customer satisfaction. This segmentation gives the seller a clue as to which protocol he should choose. However, we should note that the higher revenue in the SUP might not always realize considering agent-mediated markets. In other words, sophisticated agents would easily find the DR-strategy to increase their earnings though subjects in our experiments could not find it.

5.2. Stability of the TT-strategy in the SOP

Bids in the SOP are dispersed much more than in the SUP. In particular, over-bidding behavior prevents the theory from predicting results correctly. Therefore, the earnings and efficiency become much worse than predicted in the SOP because some of the bidders tend to over-bid.

Nevertheless, the revenue is more consistent with the theoretical predictions in the SOP than in the SUP. Thus, we can say that the SOP would lead sellers to predict their revenue more correctly. In addition, as the theory predicts, under-bidding behavior does not make the performance worse so much and it is difficult for agents to increase their earnings by deviating from the strategy, since the TT-strategy is optimal in the SOP.

Alternatively, the ratio of earnings to the predicted ones reveals that there are bidders who earn approximately predicted profits in the SOP more consistently than in the SUP. In contrast, the ratio in the SUP is uniformly distributed, so each of the bidders changes between the various bidding policies. Accordingly, we can say that the TT-strategy in the SOP is more stable than the DR-strategy in the SUP, though there are a certain number of bidders who could not earn non-negative profits in the SOP.

5.3. Open Ascending-price Auctions

It is more important to explore bidding behavior in an open ascending-price version of the OP (AOP), since it has developed as the first non-trivial open auction in which sincere bidding by all bidders is an ex post perfect equilibrium, even if the marginal values of bidders can increase. This is one of the most salient theoretical characteristic of the OP. Thus, we also conducted the experiments on the AOP. In the auctions, bidders obtain feedback regarding rivals' drop-out price so that they can change their bidding strategies.

In the AOP, bidders conceal their demands on unit 3 more likely than those in the SOP, although they also tend to bid above value on unit 2. At the same time, there is a significant number of bids extremely above value on unit 3, i.e., declaring three units until the end of the auction. This bidding behavior may be observed because there is a strategy that provides the same outcome as the TT-strategy, e.g., adaptive bidding strategies in which a bidder changes her bidding strategy during an auction. She can observe the aggregate demands, which tells her the options she gets. Then, if she observes that she cannot further improve her utility, she may maintain her current bid due to laziness or the desire to hide her true valuations.

Actual earnings and efficiency become worse than in the SOP, while revenue remains approximately the same. Nevertheless, the TT-strategy in the AOP is still more stable than the open ascending-price version of the UP.

6. Conclusions

We examine multi-unit option allocation auction protocol employing laboratory experimentation and explored the performances and behavior in the auctions when bidders have their marginal values that can increase for identical units. We do not assert that the same results would be observed in environments where some bidders are human and others are more sophisticated agents. We believe that our data provide an important first step and are suggestive of what might be observed in real-world settings.

The experimental results first propose a clue for a seller to choose a protocol in his business. Second, the results in the SUP is closer to the ones with the TT-strategy than those with the DR-strategy. The aggregate data seems to indicated that the performance in the SUP are better than that in the SOP. The individual bidding tells us that the stability of the revenue and the TT-strategy in the SOP.

Alternatively, the aggregate data indicate that the theoretical predictions relatively fail due to slightly few bidders in the SOP. Therefore, these results suggest that the outcomes of the SOP are sensitive to bids above value and that preventing bidders from such over-bidding is an important issue in implementing the OP in a real-world setting.

We would like to add an analysis of the AOP in order to further clarify the potential advantages and disadvantages of the OP compared to other protocols in future works. Moreover, we would like to construct bounded rational agents to reproduce experimental results. We believe that developing such agents would accelerate the design and evaluation of bidding agents and feasible mechanisms.

Acknowledgments

We would like to thank Shigeo Matsubara for helpful discussions and comments.

References

[1] L. M. Ausubel. An Efficient Ascending-Bid Auction for Multiple Objects. *American Economic Review*, forthcoming, 2003. http://www.ausubel.com/auction-papers/efficient-ascending-auction-r.pdf.

[2] L. M. Ausubel and P. Cramton. Demand Reduction and Inefficiency in Multi-Unit Auctions. http://www.ausubel.com/auction-papers/demand-reduction-r.pdf, 2002.

[3] M. Bichler. An experimental analysis of multi-attribute auctions. *Decision Support Systems*, 29:249–268, 2000.

[4] V. Conitzer and T. Sandholm. Automated Mechanism Design: Complexity Results Stemming from the Single-Agent Setting. In *Proceedings of the 5th International Conference on Electronic Commerce (ICEC-03)*, pages 17–24, Pittsburgh, PA, USA, 2003.

[5] R. K. Dash, N. R. Jennings, and D. C. Parkes. Computational-Mechanism Design: A Call to Arms. *IEEE Intelligent Systems*, 18(6):40–47, 2003.

[6] M. Friedman. *A Program for Monetary Stability*. NY: Fordham University Press, New York, 1960.

[7] P. Huang, A. Scheller-Wolf, and K. Sycara. Design of a Multi-unit Double Auction E-market. *Computational Intelligence*, 18(4):596–617, 2002. Special issue on agent technology for electronic commerce.

[8] A. Iwasaki, M. Yokoo, and K. Terada. A Robust Open Ascending-price Multi-unit Auction Protocol against False-name bids. In *Proceedings of the 4th ACM conference on Electronic commerce*, pages 85–92. ACM Press, 2003.

[9] J. H. Kagel. *Handbook of Experimental Economics*, chapter Auctions: A Survey of Experimental Research, pages 501–585. Princeton University Press, 1995.

[10] J. H. Kagel and D. Levin. Behavior in Multi-Unit Demand Auctions: Experiments with Uniform Price and Dynamic Vickrey Auctions. *Econometrica*, 69(2):413–454, 2001.

[11] D. C. Parkes and L. Ungar. Preventing Strategic Manipulation in Iterative Auctions: Proxy Agents and Price Adjustment. In *Proceedings of the 17th National Conference on Artificial Intelligence*, pages 82–89, 2000.

[12] A. E. Roth. The Economist as Engineer: Game Theory, Experimentation, and Computation as Tools for Design Economics. *Econometrica*, 70(4):1341–1378, July 2002. Fisher-Schultz Lecture.

[13] S. van Hoesel and R. Müller. Optimization in Electronic Markets: Examples from Combinatorial Auctions. *Netnomics*, 3:23–33, 2001.

[14] P. R. Wurman, W. E. Walsh, and M. P. Wellman. Flexible Double Auctions for Electric Commerce: Theory and Implementation. *Decision Support Systems*, 24:17–27, 1998.

[15] M. Yokoo, Y. Sakurai, and S. Matsubara. Robust Multi-unit Auction Protocol against False-name Bids. In *Proceedings of 17th International Joint Conference on Artificial Intelligence (IJCAI-2001)*, pages 1089–1094, 2001.

[16] M. Yokoo, Y. Sakurai, and S. Matsubara. The Effect of False-name Bids in Combinatorial Auctions: New Fraud in Internet Auctions. *Games and Economic Behavior*, 46(1):174–188, January 2004.