Market performance and collusion in sequential and simultaneous multi-object auctions: evidence from an ascending auctions experiment

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Abstract

We compare efficiency and susceptibility to collusion of two alternative ways to sell multiple objects in independent private values environments: simultaneous and sequential ascending auctions. Both auctions are common in the real world. With explicit communication among bidders, collusion was more frequent in sequential than in simultaneous auctions. We suggest that it may be due to lower complexity of sequential auctions as compared to simultaneous ones. Complexity considerations may thus be important in auction design. We further consider effects of closing rules on auction performances, and analyze collusive schemes adopted by bidders.

JEL classification code: C92, D44
Key words: multi-object auctions; experiments; collusion

1 Introduction

Multi-object auctions have become a subject of close attention of economic theorists and experimentalists, both due to an academic interest, and to a growing use of multi-object auctions in practice. Government auctions to sell the electro magnetic spectrum are among the most broadly-discussed recent examples of multi-object auctions (e.g., Cramton, 1998,

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Jehiel and Moldovanu, 2003). There are many other real-world examples, however. Multiple procurement contracts, real estate, utility procurement and school milk contracts are offered for sale annually (Pesendorfer, 2000). The auction formats vary from case to case, including both simultaneous and sequential auctions. Spectrum auctions in many countries adopted a simultaneous ascending auction format, with an argument that such format allows better coordination and promotes the efficient aggregation of complementary licenses (McAfee, 1999; Cramton, 1998; Crampton and Schwartz, 2000; Klemperer, 2002). In other cases, multiple objects such as estate, used cars, cattle, fish, vegetables, timber and wine are often allocated in comparable lots at sequential auctions (Phillips et al., 2003; Caillaud and Mezzetti, 2004; Raviv, 2006).

In many cases, such as spectrum license sales, the auction format is chosen by the auctioneer with an objective to meet certain performance criteria, such as efficiency, revenue maximization and collusion-proofness. The laboratory research that compares different auction formats in view of these criteria is therefore of immediate interest. Indeed, several experimental studies have compared efficiency and revenue-raising properties of simultaneous and sequential multi-unit auction. Lunanders and Nilsson (2004) compare bidding behavior for multiple identical contracts in first-price simultaneous, first-price sequential and first-price combinatorial auctions. They report that when bidders have non-linear average costs of winning more than one contract, combinatorial auctions are the most efficient. Goeree et al. (2006) compare the performances of first-price simultaneous, first-price sequential, simultaneous descending and simultaneous ascending auctions in various bidding environments with single-unit demand. They find that simultaneous ascending auctions are the most efficient, but at the same time they yield lower and more variable revenues than other auction formats. While Goeree et al. note that low and variable revenues in uncompetitive situations yield suspicion of collusion, they do not study collusion per se and do not compare susceptibilty to collusion across auction formats. This is what we do in this paper.

In this paper we investigate and compare the performances of simultaneous and sequential ascending multi-object auctions with an emphasis on their susceptibility to collusion. Vulnerability to collusive bidding is indeed a major concern in many real-world multi-unit auctions.[1] Pesendorfer (2000) studies collusive bidding for school milk contracts in Florida in Texas during the 1980s. Cramton and Schwartz (2000) discuss tacit bidder collusion in

[1] If objects sold in the auctions are similar, the simultaneous auction format is also vulnerable to demand reduction incentives; see, e.g., Ausubel and Cramton (2002), Alsemgeest et al. (1998) and Kagel and Levin (2001). We do not discuss the problem of demand reduction in this paper.

spectrum auctions in the U.S.; Jehiel and Moldovanu (2003) present similar evidence for the European spectrum auctions. It is therefore important to study and compare bidder collusive tendencies in different multi-unit auction formats.

We focus on ascending auctions, since the ascending nature has been often argued to enhance efficiency.[2] On the other hand, it has been argued that ascending auctions are more vulnerable to collusion than sealed bid auctions in a repeated framework (Klemperer, 2003).[3] In this sense both simultaneous and sequential ascending price auctions are vulnerable to collusive bidding. However, collusive tendencies may differ between sequential and simultaneous auctions. For example, if bidders ignore repeated game framework and focus on the stage game, then sequential auctions discourage collusion through backwards induction: Collusive agreements cannot be sustained in the final period, possibly unraveling to the earlier periods of the auction.

Theoretical literature offers many insights into the issue of collusion in auctions. McAfee and McMillan (1992) characterize possibilities of collusion in a static single-object auction with communication with and without side payments, focusing on sealed-bid auctions. They show that without side payments, the best collusive scheme a cartel can use is random assignment of the object at the reserve price. Fudenberg, Levine and Maskin (1994) show that in repeated auctions with communication, where players observe all bids, a folk theorem implies that various collusive schemes can be supported as subgame perfect equilibria. Skrzypacz and Hopenhayn (2004) characterize possibilities of implicit collusion in repeated sealed-bid auctions with no communication and no side payments; they show that collusion better than bid rotation of objects is feasible. Aoyagi (2003) also demonstrates that if an auction with communication is repeated, then even without side payments, a dynamic scheme payoff-superior to any static one can be implemented. Such dynamic "splitting objects across time" schemes are somewhat similar to the static ranking mechanism discussed by Pesendorfer (2000) for collusion in multi-object auctions, where bidders submit their preferences for the objects. Due to the absence of side payments, each collusive scheme has to give each bidder a sufficiently high share of objects to insure incentive compatibility. Both the ranking mechanism of Pesendorfer (2000) and collusive mechanism of Skrzypacz and Hopenhayn (2004) and Aoyagi (2003) improve efficiency as compared to the random assignment by assigning each bidder the objects he or she values more with higher probability. Kwasnica (2000) notes that serial dictator

[2]Kwasnica (2000) studies bidder collusion in multi-object sealed bid auctions, as will be discussed below.

[3]This is because the bidding procedure allows for a finer degree of information transmission, decreasing the payoff from defecting from a collusive agreement; see Klemperer (2003).

is another incentive compatible mechanism to allocate multiple objects within a cartel when communication is possible. Brusco and Lopomo (2002) show that in simultaneous ascending price auctions for multiple objects, collusion better than random assignment is possible even in a non-repeated setting without communication. Similar to the collusive schemes discussed above, bidders split the objects among themselves, but they signal their preferences over objects in the process of bidding, rather than through explicit communication. Accordingly, another objective of this paper is to uncover how bidders may collude in multi-object ascending auctions. We consider collusive schemes adopted by bidders in view of the theoretical possibilities discussed above.

The research on collusion in various experimental markets has been extensive, with early contributions including Fouracker and Seigel (1963) and Isaac and Walker (1985). Recently, more studies focus on multi-object auctions. Kwasnica (2000) reports that bidders successfully collude in multi-object sealed bid auctions with communication. He provides evidence that bidders used collusive schemes that were payoff-superior to random assignment; in particular, the ranking mechanism of Pesendorfer (2000) was adopted frequently. Kwasnica and Sherstyuk (2005) study tacit bidder collusion in simultaneous ascending price auctions but do not compare the results with the sequential auction setting. They provide evidence of collusion via signaling consistent with Brusco and Lopomo (2002) in two-person experimental markets. Burns (1985) reports some cases of collusion in sequential auctions. Phillips et al. (2003) give evidence of bidder collusion in sequential multi-unit ascending auctions for homogeneous goods with communication. In their design all bidders had identical demand schedules and therefore did not face a trade-off between efficiency and equity which occurs in heterogeneous bidders environments. The bidders successfully adopted simple bid rotation schemes to split the objects.[4]

In this paper we compare collusion in simultaneous and sequential ascending auctions with heterogeneous objects and bidders. To single out differences in collusive tendencies, if any, in our experimental design we eliminated all features of the environment that would give different across formats predictions if bidders behave competitively: First, there are no complementarities in bidder values across objects. Second, we assume each bidder's values for objects are independent of one another. This is unlike many studies in sequential auctions which assume that bidder valuations for the objects are either perfectly correlated (e.g., Caillaud and Mezzetti, 2004), or they are facing downward-sloping multi-unit demand schedules (e.g., Robert and Montmarquette, 1999; Phillips et al., 2003).

[4] "Our explanation for collusion being successful... is a simple bid sharing plan that lets bidders alternate taking the low bid is *focal*..." (Phillips et al., 2003, p. 977).

In this sense, our sequential auctions setting resembles a repeated auction setting (e.g., Skrzpacz and Hopenhayn, 2004, and Aoyagi, 2003), except in our case, bidders learn their valuations for a series of objects before these objects are auctioned, rather that for one object at a time.

Traditionally, collusion has implied explicit communication (e.g., McAfee and McMillan, 1992; Aoyagi, 2003; Isaac and Walker, 1985; Kwasnica, 2000; Phillips et al., 2003), and we followed this tradition and allowed bidders in our experiment to communicate explicitly between auction series.[5] In line with earlier experiments that studied effects of communication on market outcomes, we studied repeated interactions of subjects in a given auction setting. The repeated game framework is easily justifiable; for example, Aoyagi (2003) argues that "if collusion is a product of frequent interaction,... a more appropriate framework for analysis is that of repeated games..." (p. 80). Caillaud and Mezzetti (2004) also write that "many goods, services and contracts are allocated ... at sequential auctions, to a quite well-established and limited group of potential buyers" (p. 79).

We report a number of interesting findings from our experiments. We find that bidders in our experiments were able to reach and sustain collusive agreements somewhat more often in the sequential than in the simultaneous auctions. We conjecture that the simultaneous auction format was too complex for some bidders and prevented them from realizing the advantages of suppressed price competition. In contrast, sequential auctions allowed bidders to focus on one object at a time, which reduced the complexity of the problem and allowed them to realize the advantages of bidder collusion. We thus suggest a connection between auction complexity and collusive behavior in multi-object settings.

We further take a closer look at collusive schemes adopted by bidders. We find that colluding bidders were often able to allocate object efficiently, and the efficiency of outcomes under collusion was no lower than the efficiency before communication.

Finally, we get another insight from our experiment. By varying auction ending rules in the simultaneous auctions, we observed that the auction ending rule had a noticable effect on outcomes in multi-object auctions, not unlike to what Roth and Ockenfels (2002) observed in single-object auctions. While bidders focusing on end-of-period bidding led to somewhat higher than competitive bidder payoffs in some cases, it distracted bidder

[5]Recently, attention in the literature has been paid also to tacit, or implicit collusion; see, e.g., Brusco and Lopomo, 2002; Skrzpacz and Hopenhayn, 2004; Kwasnica and Sherstyuk, 2005; Li and Plott, 2005. However, experimental evidence shows that bidders have difficulty reaching collusive agreements in multi-object auctions without communication in the markets with more than two bidders, unless a very specific valutions structure is imposed; see Phillips et al., 2003; Kwasnica and Sherstyuk, 2005; Li and Plott, 2005.

attention away from collusion and led to lower than collusive bidder payoffs in other cases.

2 Research questions and experimental design

Research objectives The experiment was designed in view of the following research objectives, as discussed in Section 1 above:

1. (Benchmark) Compare the performances of simultaneous and sequential ascending multi-object auctions without communication, in an environment where, under the competitive behavior assumption, the simultaneous and sequential auctions should yield identical outcomes.

2. Compare the sequential and simultaneous ascending-price multi-object auction formats in terms of their susceptibility to collusion.

3. Study collusive schemes adopted by bidders.

4. Study the effect of auction closing rules on auction outcomes and on occurrences of collusion.

Experimental design The motivation for many elements of experimental design, such as independent across bidders and objects valuations, repeated game framework, and the presence of explicit communication in between auction series in the second part of each session, in view of the above research objectives, was given in Section 1 above.

Groups of four subjects participated in a series (up to 10) of computerized ascending auctions for four objects, labeled A, B, C and D. The group composition stayed the same throughout the session.

Four objects were offered for sale in every series. Two main experimental treatments are considered: sequential and simultaneous auctions. Under the sequential format, the objects in a given series were auctioned off one after another, with a 30 second pause between auctions. Under the simultaneous format, the auctions for all objects were run simultaneously, with each object being sold in a separate market.[6] When an auction opened for bidding, bidders were free to place, at any time, as many bids as they desired as long as the bid was at least as great as the reservation price (equal to one experimental dollar), and the bid was strictly greater than previous bids on that object. In sequential

[6]Thus an auction series corresponds to an interval within the session when all four objects are auctioned off. In the sequential treatment, the series consisted of four auction periods in which four objects were auctioned off one at a time. In the simultaneous treatments, a series corresponds to one auction period in which all four objects were auctioned off simultaneously.

auctions, bidders could only bid on one object at a time; in simultaneous auctions, the bidders could bid on any or all four objects. All incoming bids (but not bidder ID's) were observable to all bidders in the market through the computer. The bids were colour coded, with bidder own bids shown in blue, and others' bids shown in black. Thus, bidders could easily see at any time during bidding whether they or someone else were the highest bidder on a given object. When an auction closed, the object was allocated to the bidder with the highest bid for that object.

Initially, both simultaneous and sequential auctions were operated under the hard closing rule. Each auction was open for bidding for a fixed number of seconds: 240 seconds in the simultaneous auctions and 140 seconds in the sequential auctions. We allowed a longer period duration in the simultaneous auctions since subjects bidding on four objects at the same time could require more time to make bidding decisions, enter bids, and keep track of others' bids. We will call the corresponding treatments SEQH (sequential auctions - hard closing rule) and SIMH (simultaneous auctions - hard closing rule). While conducting the experiments, we observed a significant amount of end-of-period bidding under the hard closing rule, especially in the SIMH treatment. To consider a possible effect of the closing rule, we added the third treatment SIMS: simultaneous auction with the soft closing rule. Under the latter, the auctions ended when no new bids were placed on any of the four objects for 30 seconds.

Bidder valuations for the objects were integers between 1 and 100. Valuations were independently pre-drawn from the discrete uniform distribution for each period. At the beginning of each auction series, the bidders were given out slips of papers with their private valuations. Bidder own valuations were also shown on their computer screens when the bidding was open.[7]

The auctions were run without communication for the first few periods to allow the auctions to converge to competitive outcomes. The auctions were typically run without communication in the first three series (12 sequential auctions) in the SEQ treatment, and the first four series (4 series of 4 simultaneous auctions) in the SIM treatments.[8,9]

[7]See Appendix A for the experimental instructions.

[8]We chose to start communication "earlier" in terms of the the number of one-object auctions completed before communication in SEQ auctions as compared to SIM for two reasons. First, we felt that going through twelve separate auctions, one at a time, would allow bidders to understand the environment better than if they went through three simultaneous four-object auctions. Second, we were concerned that SEQ auctions would run overtime and would have to end before all 40 auction periods were completed. We wanted to give bidders a comparable with the SIM treatment number of communication sessions.

[9]Communication started after series 2 (auction period 8), instead of 3 (auction period 12), in SEQH-5 session by mistake. Communication started after series 5, instead of 4, in SIMH-5 session since series 1 in this session had to be disregarded due to bidding errors.

After that, it was announced, using the standard language of communication instructions, that bidders would be allowed to communicate in between auction series. The bidders were informed about their bidder values in a given auction series before each communication session started, but they were not allowed to disclose their values to anyone.

Procedures A total of 15 independent four-person groups participated in the experiments, with 5 groups per each treatment. The subjects were all undergraduates students at the University of Hawaii at Manoa, mostly from the College of Social Sciences. One or two four-person groups were run independently in each session.[10] The sessions were run for the maximum of 2.5-3 hours. All 10 auction series were completed in all SIM sessions; between 6 to 9 series were completed in each SEQ session. At the end of each session, the subjects were paid $5 show-up fee, plus their earnings, in private.

3 Results

The data from the experimental sessions are summarized in tables 1- 3 and 5- 7 and figures 1-4. Tables 1- 3 present descriptive statistics on market prices, efficiencies, and bidder payoffs per auction, pooled by treatment; tables 5- 7 (in Appendix B) give more detailed statistics for each session. Since the hard closing rule was used in two of the three treatments, we compare the actual data with the sealed bid (SB) auction predictions as well as with the ascending English auction (EA) predictions (see Roth and Ockenfels, 2002).[11] Figure 1 gives the dynamics of average price deviations from the English auction and sealed bid competitive equilibrium predictions, pooled by treatment. Figures 2-4 present market price dynamics for each session by treatment. For expositional convenience, each auction in both SEQ and SIM treatments is represented as a separate period in the figures. For example, periods 1,2,3,4 in the figures correspond to auctions for goods A, B, C, D in series 1. In Figure 1, auction series are separated by vertical lines.

Market efficiency, reported in tables 2 and 6, is defined in the usual way, as the share of gains from trade captured. Tables 2 and 6 also report the share of auctions in which efficient allocations were achieved.

Bidder payoffs (gains), reported in tables 3 and 7, are the differences between the highest bidder's value and the price they paid in a given auction (in experimental dollars).

[10] Since all groups were run independently from each other, we will refer to individual groups as "sessions" below.

[11] Theoretical predictions listed in the tables differ across sessions slightly since they are computed based on the specific bidder values drawn. The auctions in which bidding errors occurred are excluded.

TABLES 1- 3 AND FIGURES 1-4 AROUND HERE

3.1 Comparison across treatments before communication

To provide a benchmark for auctions with communication, we first compare auction performances in series before communication. For statistical comparisons across treatments, we use per session averages in auction series before communication. These are per session averages for periods 1-16 for SIMH and SIMS treatments (excluding periods 1-4 in session SIMH-5), and per session averages in periods 1-12 for SEQH treatment (excluding periods 9-12 for session SEQH-5); see footnote 8.

Result 1 *Prices before communication closely followed the English Auction competitive predictions in SIMS treatment only. In SIMH and SEQH treatments, average prices before communication were similar to each other and below the SIMS prices. They were below both competitive predictions, but closer to the Sealed Bid than to the English Auction prediction.*

Support: Figures 1-4, Tables 1, 5. Figure 1 displays average price deviations from the EA and SB predictions, by treatment. It is apparent from the figure that the SIMS prices closely traced the EA predictions before communication (until period 16 on the figure). The average price deviation from the EA prediction in SIMS sessions was only 2.57 experimental dollars; in comparison, the average deviation from the SB prediction was 9.84 experimental dollars. Figure 4 and table 5 indicate that SIMS prices closely followed the EA predictions before communication not just on average but also for every session.[12] For SIMH and SEQH treatments before communication (up to period 16 for SIMH and up to period 12 for SEQH on figure 1), the average price deviations from the EA are -12.56 and -14.09 experimental dollars (SIMH and SEQH treatments, respectively), and the price deviations from the SB predictions are -6.17 and -6.82 experimental dollars (SIMH and SEQH treatments, respectively). The null hypothesis of no price differences between the SIMH and SEQH treatments before communication cannot be rejected according to Wicoxon Mann-Whitney rank-sum test (p-value is 0.917); the hypotheses of no price differences between SIMH and SIMS, and SEQH and SIMS are both rejected (the corresponding p-values are 0.028 and 0.009, respectively).[13] □

[12] From figure 4 and table 5 we also note that prices stayed close to the EA prediction after communication in sessions SIMS-3 and SIMS-5, which will be classified as non-collusive below.

[13] Because per session averages included aggregation across different ranges of periods, here we used per session average price deviations from the EA predictions as units of observations for statistical comparisons.

Result 2 *The percentage of auctions resulting in efficient allocations was higher under the SIMS treatment than under either SIMH or SEQH treatment before communication. The average efficiencies of allocations were not significantly different across treatments.*

Support: Tables 2, 6. Although efficiencies of allocations, measured as percentages of gains from trade captured, were similar across treatments before communication (the null hypotheses of no differences between any two treatments cannot be rejected at any conventional confidence level according to Mann-Whitney rank-sum test), the share of auctions resulting in efficient allocations was higher under SIMS treatment. Under SIMS treatment before communication, 89% of all auctions resulted in efficient allocations, as compared to 56% for SIMH and 62% for SEQH; the differences in per session averages across treatments are significant between the SIMH and SIMS treatments (p-value is 0.0117) and between SEQH and SIMS treatments (p-value is 0.0147), but not between SIMH and SEQH treatments (p-value is 0.5245).[14] □

Result 3 *In auction series before communication, average bidder payoffs were higher in SIMH and SEQH treatments than in the SIMS treatment.*

Support: Tables 3, 7. The average payoff of a winning bidder in a SIMS auction before communication was 8.07 experimental dollars, as compared to 21.51 experimental dollars in SIMH and 21.31 experimental dollars in SEQH. The p-values for the differences in per session payoffs between SIMH and SEQH, SIMH and SIMS, and SEQH and SIMS, and are 0.754, 0.009, and 0.1172, respectively. □

To complete the comparison across treatments before communication, we compare time-effectiveness of simultaneous and sequential auction. Since SIMH and SEQH auctions had pre-set period durations, we compare duration of bidding activity, rather than period duration, across treatments. For each period, the duration of bidding activity is defined as the time between the earliest and the latest bid in the period; this also allows for a comparison between SIMH and SIMS treatments.

Result 4 *SIMH auctions before communication were the most time-effective among the three treatments, followed by SIMS. SEQH auctions had the longest duration of bidding activity per four-object auction series.*

[14]Efficiency of allocations stayed high in SIMS treatment even after communication. 77% of SIMS auctions in series with communication resulted in efficient allocations, as compared to 52% for SIMH and 57% for SEQH. Efficiencies of allocations in collusive auctions will be discussed below.

Support: The average bidding activity time in periods before communication in SIMH was 205.67 second, as compared to 379.92 seconds for SIMS treatment. The average duration of the bidding activity in SEQH treatment was 105.60 seconds per period, corresponding to 422.40 seconds per four-object auction series.[15] □

In sum, we observed no significant differences, other than in duration of bidding, between the simultaneous and sequential auctions SIMH and SIMH before communication. It appears that the biggest difference in performance measures was not between the simultaneous and the sequential auction formats, but between the auctions with the hard and the soft closing rule. The SIMS treatment that employed the soft closing rule was the one that resulted in closer to the competitive (English Auction) prediction prices and allocations, and in lower bidder gains, as compared to the two treatments with the hard stopping rule.

One possible explanation of the observed performance differences between SIMS and the other two treatments lies in the effect of the closing rule itself. Roth and Ockenfels (2002) argue that the hard closing rule may have a significant effect on auction outcome by creating incentives for bidders to hold off their bidding activity till late in the auction period and then engage in end-of-period bidding behavior; the soft closing rule eliminates possibilities for such "sniping." Our data support their argument in application to simultaneous multi-object auctions. In the part of our experiment before communication, there were, on average, 25.05 bids made per period (equivalent to a series) in SIMH treatment, with an average time interval of 9.7 seconds between any two bids. However, 22.5% of all per period bids were made within the last 10% of the bidding activity time,[16] and the average time interval between any two bids at this time was only 2.7 seconds (with a minimum of 0 and the maximum of 6 seconds). (As we will see later, in several sessions in SIMH treatment auctions, this effect carried over into the series with communication.) In comparison, there were, on average, 67.08 bids per period (series) in SIMS auctions with no communication, with an average time interval of 6.44 seconds between the bids in a period. Only 8.09% of per period bids were made within the last 10% of the bidding activity time interval, and the average time interval between any two bids at this time was 8.09 seconds (with a minimum of 2 and the maximum of 13 seconds).[17] For the SEQH

[15]This excludes periods where the bidding activity had to be halted during the period due to technical difficulties.

[16]By definition of the bidding activity time, at least one bid is made at the very beginning, and at least one bid is made at the very end of the bidding activity time interval.

[17]For the SIMS treatment, the data on the timing of bids was lost for the last two sessions, and the statistics regarding the timing refer to sessions SIMS-1, SIMS-2 and SIMS-3 only.

treatment, the evidence for the end-of-period bidding is not as pronounced as for the SIMH treatment: in the SEQH treatment before communication, there were only 7.80 bids per period on average (to compare with the simultaneous auction treatments, this corresponds to the average of 31.21 bids per four-object series), but in 31 out of 55 periods only one bid was made within the last 10% of the bidding activity time interval.

A curious observation is that the hard stopping rule appeared beneficial for the bidders in this part of the experiment. Even without explicit collusion, it led to higher bidder gains in SIMH and SEQH auctions than in the SIMS auction.

3.2 Effect of communication

We now consider the effect of communication on the performances of the auctions, with the emphasis on its effect on the emergence of collusive tendenices. While we observed some evidence of lower than competitive prices in SIMH and SEQH auction series before communication, the downward price deviations from the competitive prediction were relatively moderate. The next step is to see whether these deviations became more pronounced after communication was allowed.

Result 5 *Per treatment average prices declined, and per treatment average bidder payoffs increased after communication as compared to before communication in all treatments. However, due to large variations in price dynamics across sessions, the effect of communication on the actual price and bidder gains deviations from the EA competitive predictions is significant for SIMS treatment only.*

Support: Figures 1-4, tables 1, 3, 5, 7. Tables 1, 3 and figure 1 indicate that in all treatments, average prices declined, and bidder payoffs increased after communication as compared to before communication. This may be partly due to lower predicted prices after communication (see tables 1, 5). To adjust for this factor, we consider the deviations of actual prices from the EA predictions. The gap between the competitive equilibrium EA predictions and the actual average prices increased in the periods after communication in all treatments. However, this was not true for every session. According to Wilcoxon signed rank test based on per session averages, the effect of communication on the price deviations from the EA competitive predictions is significant for SIMS treatment only; the corresponding p-values for the differences before and after communication are 0.6858 for SIMH treatment, 0.1380 for SEQH treatment, and 0.0431 for SIMS treatment. Similarly, the p-values for the differences in bidder gains deviations from the EA predictions before and after communication are 0.6858 for SIMH treatment, 0.2249 for SEQH treatment, and 0.0431 for SIMS treatment (Wilcoxon signed rank test). □

We also note that communication did not have a significant effect on overall efficiencies of allocations.

Result 6 *Over all sessions, the effect of communication on auction efficiencies is insignificant for all treatments.*

Support: Wilcoxon's signed rank test of auction's efficiencies and percentages of efficient allocations before and after communication gives the following results. For efficiencies, the p-values are: 0.5002 (SIMH), 0.3452 (SEQH), 0.3452 (SIMS); for percentages of auctio series resulting in efficient allocations, the p-values are: 0.7865 (SIMH), 0. 5868 (SEQH), 0.4982 (SIMS). □

Even though the results above show that many differences were insignificant overall, there were some sessions where communication clearly had an effect on prices and auction outcomes. Let us now look for more pronounced cases of suppressed price competition, which we will call bidder collusion. We will call a market collusive if it is characterized by the prices close to the minimal (seller reserve) price of 1 experimental dollar, and by high bidder gains. We will call a given auction series collusive if the average price for the four goods (A, B, C and D) was no higher than 20 experimental dollars in this series.[18] As it is evident from the analysis above, no auction series before communication displayed such collusive characteristics. We now consider auction series with communication.

Result 7 *There were no collusive auction series in any treatment before communication. After communication, collusion was attempted under all treatments. Yet in every treatment there were sessions where collusion was not observed.*

Support: Figures 1-4, tables 1, 3, 5, 7. As discussed above, average prices declined, and bidder payoffs increased after communication as compared to before communication. However, under every treatment there were sessions (SIMH-1, SIMH-2, SIMH-3, SEQH-2, SIMS-3, SIMS-5) where there were no collusive auction series, and the prices did not fall, and bidder payoffs did not increase after communication as compared to before communication (tables 5, 7, and figures 2-4). The average price deviations from the competitive

[18]The threshold level of 20 dollars that defines a collusive auction series is chosen rather ad-hoc but it does not affect our conclusions. In most collusive auction series, the objects were sold at the reserve price of 1 dollar.

EA prediction did not change, or became significantly smaller after communication as compared to before communication in the sessions SIMH-1, SIMH-2, SIMH-3, SEQH-2, SEQH-3, SIMS-3 and SIMS-5. □

This indicates that collusion was not a trivial task to achieve. From observing communication sessions, we note that discussions of collusion did not even arise in some of the sessions.

We next look at the comparison across treatments. We will say that collusion was observed in a given session if at least one auction series in this session was collusive.

Result 8 *According to the number of sessions where collusion was observed, the treatments can be ranked as follows: SEQH>SIMS>SIMH.*

Support: Figures 1-4, tables 1- 3, 5- 7. After communication, average prices under SEQH treatment were 20.70, as compared to 28.16 under SIMS, and 36.48 under SIMH. Bidder payoffs were 46.31, 42.93, and 28.26, correspondingly (tables 1 and 3). From table 5 and figures 2-4, collusion was observed in 4 out of 5 sessions in SEQH (all sessions except SEQH-2), 3 out of 5 sessions in SIMS (SIMS-1, SIMS-2 and SIMS-4), and 2 out of 5 sessions in SIMH (SIMH-4 and SIMH-5). However, the differences in proportions of collusive sessions between any two treatments is not statistically significant (Fisher exact test, two-sided). □

Thus with communication, collusion was observed in more sessions in the sequential auctions than in the simultaneous auctions treatments. Even though the differences between treatments are not statistically significant, two points are worth noting. First, we obtain no evidence that sequential auctions, at least in our design, were less susceptible to collusion than simultaneous auctions. Apparently, there was no unraveling within sequential auction series that would break collusive outcomes. One possible explanation for why this may be the case has to do with auction complexity. From observations, the simultaneous auctions appeared as a rather complex institution for some bidders, and this complexity prevented them from realizing the advantages of suppressed price competition. Sequential auctions allowed bidders to focus on one object at a time, which was a less complex task and often helped the bidders to consider collusive possibilities.[19] In section 5 below, we discuss how one could evaluate and compare strategic complexities of each auction institution, and how auction complexity may affect bidder collusion.

[19] Isaac and Schnier (2005) note that in multiple good silent auctions that follow the simultaneous ascending auctions format, it may be costly for bidders to switch bidding attention from one item to another due to geographic dispersion of the items in a room. These costs can also be thought of more generally as costs of participating in several bidding processes at the same time.

Another observation concerns the simultaneous auctions with the hard closing rule (SIMH treatment). Apparently, while the hard closing rule in SIMH auctions before communication caused lower than competitive pricing, the same treatment was characterized by the smallest number (2 out of 5) of collusive low-price sessions after communication. From listening to communication sessions and observing bidding behavior, this again may be explained by the effect of the closing rule. As discussed above, we observed a large amount of end-of-period bids under this treatment before communication, with this behavior having a significant effect on auction outcomes. In several sessions in SIMH auctions, this effect carried over into the series with communication. The non-collusive sessions SIMH-1, SIMH-2, and SIMH-3 after communication were still characterized by a large proportion of end-of-period bids: out of 30.16 bids submitted on average per period after communication, 5.55 bids were end-of-period bids (submitted within the last ten percent of the bidding activity time). This is indistinguishable with the bidding activity before communication, where on average 28.5 bids submitted per auction series, and an average of 5.5 of them were end-of-period bids. From observation of communication sessions, the bidders were so focused on the competitive spirit of the end-of-period bidding that discussions during communication sessions never turned to the possibility of collusion. It appeared that some bidders in simultaneous auctions chose "sniping," rather than collusion, as their preferred strategy.

We note that the bidding activity was quite different in collusive sessions SIMH-4 and SIMH-5: Before communication, an average of 20.44 of bids were submitted per auction series, with an average of 4.78 of them being end-of-period bids; after communication, an average of only 9.73 bids were submitted per auction series, and only 2.27 of those were end-of-period bids.[20]

4 Analysis of collusive auctions

Our next objective is to take a closer look at collusive auction series. Table 4 summarizes observations from communication sessions and characteristics of collusive auction series (where the average prices per object were no higher than 20 experimental dollars). Apart from reporting prices and efficiencies of collusive auction series, we also report the index of collusive effectiveness. Collusive effectiveness is defined as the share of actual bidder gains to the maximal bidder gains possible. Collusive effectiveness would be 100% if all objects in a series were allocated efficiently at minimal prices.

[20]Due to a very low number of bids in many auction series, it is more instructive here to report the actual number, rather than the share, of end-of-period bids.

We are interested in the types of collusion schemes discussed and adopted by bidders, and the effects of mechanisms adopted on price levels and efficiency of allocations. Most broadly, there are two types of collusive schemes that may be adopted by bidders in auctions with communication: (i) Either a splitting markets agreement, where during communication session the bidders explicitly agree on which bidder is to get what object; or (ii) allocations though bidding agreements, under which the objects allocations across bidders are not agreed upon in advance but are decided in the process of bidding. Three well-known collusive schemes of the first type are random assignment (RANDOM), serial dictatorship (SD), and ranking mechanism of Pesendorfer (2000) (RANKING). These schemes allocate objects so that each bidder gets exactly one object in each auction series. Bid rotation scheme is similar to the above schemes but involves splitting objects across, instead of within, auction series. Examples of the second type of schemes include bid reduction (bidding a certain percentage of object value, or bidding object value minus an agreed amount), and code bidding (e.g., using decimal points to signal own value to others).

Among the above schemes, code bidding and linear bid reduction yield the highest efficiency of allocations (since they imply that the bidder with the highest value should buy the object), provided that bidders do not misrepresent their values for objects. However, these schemes do not guarantee that each bidder will buy an object, and for this reason they are not incentive compatible (i.e., they create incentives for bidders to misrepresent their true valuations for the objects). The random assignment scheme guarantees that each bidder gets an object, creates no incentives to misrepresent, but is characterized by low efficiency of allocations. Serial dictatorship and ranking schemes guarantee that each bidder gets an object and therefore they do not generally result in fully efficient allocations of object to bidders, but since they take bidder's ordinal preferences for objects into account, their expected efficiency is higher than the efficiency of the random assignment scheme. A big advantage of these mechanisms is that they are incentive compatible (see Pesendorfer, 2000; Kwasnica, 2000). Thus SD and ranking schemes present a trade-off between "fairness" (everyone gets an object) and efficiency considerations. The ranking mechanism yields higher efficiency than SD.

TABLE 4 HERE

As evident from table 4, the most common type of collusive scheme discussed was an agreement to split markets. From observation, each bidder typically stated which object (A, B, C or D) was their most preferred; then conflicts of interest were resolved through negotiations. Apparently, the bidders were trying to achieve higher efficiency of allocations than would be achieved under random assignment of objects to bidders. We analyzed object allocations among bidders to infer if these allocations were consistent with SD or ranking schemes. Table 4 shows that it was overwhelmingly so. Bid reduction (bidding at 10% of object value), and code bidding (using decimal points to signal own value to others) were adopted in one session each (sessions SIMS-2 and SEQH-4, respectively).

Result 9 *Serial Dictatorship (SD) was the most common collusive scheme adopted by bidders. The allocations consistent with SD were, in most cases, also consistent with RANKING. Objects allocated through these schemes were sold at minimal prices, with each bidder buying one object in a series. Two collusive markets that used code bidding and bid reduction were characterized by slightly higher prices and higher efficiency than the markets where the SD/ranking scheme was adopted. One collusive session that did not have a well-defined collusive scheme was characterized by low efficiency and low bidder gains.*

Support: Table 4. In 5 out 9 sessions where collusion was observed after communication, allocations were consistent with Serial Dictatorship scheme in 100% of collusive series. In one other session (SIMS-1), the allocations were consistent with SD in 80% of collusive series. In 5 out of these 6 collusive sessions, the allocations were also consistent with RANKING in all, or all but one, collusive series. The average prices were below 2 experimental dollars in all of these 6 sessions, and in 4 out of these 6 sessions the prices were exactly equal to the minimal acceptable price of 1 experimental dollar for every object. Both efficiency and collusive effectiveness across these six collusive auction series ranged between 81% and 100%, with an average of 87.17%.[21] Each bidder was assigned one object in every collusive series in all but one of these six sessions, and the average rank of the assigned object was between 1.5 and 1.55 (compared to the theoretical predictions of 1.604 for SD, 1.57 for RANKING, and 2.5 for RANDOM).

The other three collusive sessions employed different variants of allocations though bidding arrangements. Session SEQH-4 adopted a code bidding arrangement, with the resulting average price of 6.29 experimental dollars. Session SIMS-2 adopted a linear bid reduction (to 10% value) agreement, with the resulting average price of 7.49 experimental dollars. The number of winning bidders per series was 3 and 2.6 respectively. In SIMS-2

[21] In general, there may be two sources of losses of bidder gains: higher than minimal prices, and inefficiency of allocations. If objects are allocated at minimal prices, as it was in the case of these 6 collusive sessions, then the index of collusive effectiveness becomes identical to the index of efficiency.

session, the bidders apparently did not misrepresent their values, achieving 100% efficiency; the amount of misrepresentation was also low in SEQH-4, as shown by the efficiency level of 95%. While the efficiency was somewhat higher, the average prices in these two sessions were also higher than in the SD/ranking sessions, resulting in collusive effectivness of 85% and 91% (SEQH-4 and SIMS-2, respectively), indistinguishable from the average of 87.17% for SD/ranking sessions. One other session, SIMH-5, employed a loosely defined "bid on favorite market" bidding agreement, which resulted in low efficiency of 53% and low collusive effectiveness of 36%, with the average price of 10.1 experimental dollars. □

Because of a small number of collusive sessions in each treatment, we cannot sensibly look for differences in collusive schemes and their characteristics across auction formats. Consideration of Table 4 suggests, however, that there were no differences in collusive schemes adopted in different treatments: the SD/RANKING schemes were observed in all three treatments. Since other schemes (bid reduction and code bidding) were only observed in one session each, we cannot judge if these schemes were more "typical" to one, than to another, auction format.

Result 10 *Efficiency of allocations in collusive series were no lower, and in some sessions higher, than efficiency in non-collusive series. Bidder gains were significantly higher in the collusive than in non-collusive series.*

Support: For each session where collusion was observed, we compare the average efficiency and bidder gains in non-collusive and collusive series. Overall, the average efficiency was slightly lower in collusive series (85.67%) than in non-collusive series (92.88%). However, in 3 out of 9 collusive sessions (SEQH-3, SEQH-4 and SIMS-2), efficiency was higher in the collusive series than in non-collusive series. Wilcoxon sign-rank tests on efficiencies in collusive non-collusive auction series indicates that the null hypothesis of no differences in efficiencies between collusive and non-collusive sessions cannot be rejected (p-value is 0.213). The average bidder gains for collusive series were 60.41 experimental dollars, as compared to 17.78 experimental dollars in non-collusive series. The difference between bidder gains in collusive and non-collusive sessions is highly significant (Wilcoxon sign-rank test, p-value is 0.008). □

Interestingly, these results are very consistent with Kwasnica's (2000) findings on collusive schemes adopted by bidders in multi-object sealed bid auctions. Similar to Kwasnica, we find that the SD/RANKING was the most widely adopted collusive arrangement, and that linear bid reduction was also used in some sessions. Further, like Kwasnica, we find that collusive schemes yielded highly efficient allocations, and bidders did not always misrepresent their values even when they had incentives to do so (as under the linear bid reduction agreement).

5 Considerations of auction complexity and collusion

In section 3.2 above we suggested that a relatively infrequent occurrence of collusion in simultaneous multi-unit auctions may be due to a more complex nature of simultaneous auctions as compared to sequential auctions. In this section we briefly elaborate on this idea. Our thoughts here are preliminary and are offered mainly for discussion. This is both because the observed differences in collusive tendencies between simultaneous and sequential auctions were not statistically significant, and because the literature on measuring complexity in auctions is somewhat scarce. We briefly discuss how one may compare complexities of simultaneous and sequential auctions, and how auction complexity may affect collusive tendencies.

Comparing complexities of simultaneous and sequential auctions Although it may be intuitively clear that simultaneous auctions are more complex than sequential ones because the former require a bidder to operate in many markets simultaneously, it is instructive to formalize this idea. In economic and game theoretic literature, the issue of complexity was, among the first, raised in context of the theory of repeated games (e.g., Abreu and Rubinstein, 1988; Kalai and Stanford, 1988). In this literature, complexity of a strategy is measured by the number of finite states in the machine (automaton) that implements this strategy. Mostly relevant to our study, Fershtman and Kalai (1993) use the tools of finite automata to study strategic complexity of multi-market competition between firms. They consider two aspects of complexity that are both relevant to the issue of collusion in multi-unit auctions: the complexity of operating simultaneously in different markets (in our case, bidding for different objects), and the complexity of competing with other firms (in our case, with other bidders). They demonstrate that multi-market decision making is more complex then single-market decision making; and that collusion is more complex then competition (the latter is due to the necessity to account for punishment states). Although the finite automaton approach to measure complexity cannot be directly applied to our ascending auction games because these auctions have continuous strategy spaces, in Appendix C we suggest a way to extend this approach to ascending auctions. Using this approach, we can show that the simultaneous ascending auction is more complex than its sequential version. Further, we show that collusive strategies are more complex than simple competitive bid-according-to-your-value strategies. Together, these two arguments imply that, within a certain bounds of bidders' complexity parameter, collusion may occur in the sequential but not in in the simultaneous auction.

How can auction complexity affect collusive tendencies? An alternative (and a complementary) approach to explaining why collusion may occur less frequently in simultaneous than in sequential auctions, assuming collusion in the sequential auctions is supported by repeated play, would be to suppose that operating in simultaneous markets decreases the quality of monitoring of each others' behavior (e.g., due to each bidder's limited capacity to watch all markets at the same time). Thus, a deviation form a collusive scheme would be more likely to go undetected in a multi-market, than in a single-market setting. This would create incentives for bidders to deviate from collusive schemes more often in the simultaneous auctions as compared to the sequential ones. Since such deviations would nevertheless be detected with some probability, and would then trigger competition, this may lead to less collusion in simultaneous than in sequential auctions.

6 Discussion

This study suggests some interesting insights into the nature of bidder collusion in multi-object auctions, and provides a comparison between simultaneous and sequential ascending auctions. From our laboratory experiments on multi-object auctions with communication, we observed no evidence that the sequential format makes collusion harder to achieve. On the contrary, auctioning one good at a time instead of simultaneously appears to have an opposite effect for inexperienced bidders. It allows them to better focus on each object and makes their decision problem easier, possibly helping bidders to realize low payoffs from competition and potential benefits from collusion. We observed no unraveling due to the end-game effects in sequential auctions, possibly because of the repeated nature of our auctions.

We observed that auction stopping rules had a significant effect on market efficiency and market prices in multi-object auctions, with the soft closing rule treatment resulting in more efficient allocations. Before communication, sessions conducted under the hard closing rule were characterized by lower prices than those conducted under the soft closing rule. After communication, collusion was somewhat more frequent in the simultaneous auctions with the soft closing rule than those with the hard closing rule. It is possible that the hard closing rule focused some bidders' attention on the end-of-period bids and away from collusion, especially in the simultaneous auctions. Another possibility is that the soft closing rule brought in the possibility to retaliate against defectors, thus helping collusion enforcement. Still, our data demonstrate that the closing rule was not the only factor preventing bidders from colluding in the multi-object auctions. In all three treatments, there were sessions where collusion never occurred. This suggests that collusion in multi-object environment was indeed a complex task to achieve.

We thus may reasonably claim that auction complexity can be an important factor in reducing bidder collusive tendencies. Simultaneous auctions, therefore, may have advantages over their sequential analogs even in the environments where there are no complementarities or other interdependencies in bidder valuations across objects. First, they are more time-efficient than sequential auctions. Further, they are no more, and may be less susceptible to collusion among bidders, even when bidders find ways to communicate with each other. Complexity considerations are thus important in auction design.

A closer consideration of collusive markets revealed that bidders are able to allocate objects in ways that balance efficiency and equity considerations, so that efficiencies of allocations do not necessarily decrease as compared to non-collusive series. Specifically, splitting markets across bidders through Serial Dictatorship and Ranking were the most commonly adopted collusive schemes. These schemes have an advantage of being "fair", in the sense that each bidder gets one object at a minimal price, and they are also more efficient than random assignments. Alternative collusive schemes, such as code bidding and bid reduction, were less frequent, possibly due to the lack of "fairness" and incentive compatibility. This suggests that although collusion is always detrimental for the auctioneer's revenue, it does not always reduce auction's efficiency.

Appendix A

Experiment Instructions[22]

Introduction

You are about to participate in an experiment in the economics of market decision making in which you will earn money based on the decisions you make. All earnings you make are yours to keep and will be paid to you IN CASH at the end of the experiment. During

[22] The instructions given here are for SIMH treatment. Instructions for the other two treatments differ slightly from these in the market organization part (SEQH) and in the description of the closing rule (SIMS). All instructions are available from the corresponding author upon request.

the experiment all units of account will be in experimental dollars. Upon concluding the experiment the amount of experimental dollars you earn will be converted into dollars at the conversion rate of ______ dollars per experimental dollar. Your earnings plus a lump sum amount of 5 dollars will be paid to you in private.

In this experiment you are going to participate in a market in which you will be buying units of fictitious assets. At the beginning of the experiment, you will be assigned to a market with 3 other participant(s). *What happens in your market has no effect on the participants in other markets and vice versa.*

From this point forward, you will be referred to by your bidder number. You are bidder number ________ in this experiment.

Resale Values and Earnings

Trading in your market will occur in a sequence of independent market days or trading periods. Four assets (labeled A, B, C and D) will be for sale in the market in each period. During each market period, you are free to purchase from the computer one unit of each of the four assets if you want. The value to you of any decisions you might make will depend on your "resale values" for the assets which will be assigned to you for each trading period. Resale values may differ among individuals. *You are not to reveal your resale values to anyone. It is your own private information.*

At the beginning of every trading period, you will be informed about your resale values for the assets for this period. For example, you may receive a value sheet that looks like this:

Period	Asset	Resale Value
1	A	52
	B	13
	C	90
	D	71

If you purchase an asset, your earnings from the asset purchase, which are yours to keep, are equal to the difference between your resale value for that asset in that period and the price you paid for the asset. That is:

YOUR EARNINGS = RESALE VALUE - PURCHASE PRICE.

Suppose for example that you buy asset A, and that your resale value for A is 52 in this period. If you pay 30 for the asset then your earnings are

EARNINGS FROM THE ASSET = 52 - 30 = 22 experimental dollars.

You can calculate your earnings on your accounting sheet at the end of each period.

Your total earnings in any period are given by the sum of your earnings for each asset. Suppose, for example, that you purchased asset A for earnings of 50 and asset B for earnings of 80, but did not purchase assets C or D. Then your total earnings in that period would be

$$\text{TOTAL EARNINGS} = 50 + 80.$$

Remember, if you purchase a unit of a particular asset, you must use the resale value for that asset for that period. Your earnings from the asset are zero if you do not buy the asset in this period.

Market Organization

Four assets (labeled A, B, C and D) will be for sale in the market in each period. There will be four participants in the market. Each period opens for bidding for ______ seconds. Participants may then submit bids for assets by entering bids into the computer. Any bidder is free at any time during the period to place bids to buy one unit of any or all asset at specified prices. Any bid at least as high as one experimental dollar is allowed. Each subsequent bid for an asset in the period must be higher than the existing bids for that asset. For example, if the current highest bid for asset A in a given period is 31, you must bid more than 31 for asset A. As long as the period is open, you are free to make as many bids as you like.

After the period is closed, each asset is sold to the bidder with the highest bid for that asset. Only one unit of each asset may be sold in a period. The asset is not sold if no bids are placed for the asset, or if all bids are below one experimental dollar.

Example 1 Suppose that, in a given period, the following bids are entered:

Bids on A:

buyer 2 bids 41 on A

buyer 3 bids 50 on A

Bids on B:

buyer 1 bids 36 on B

buyer 3 bids 42 on B

Bids on C:

buyer 4 bids 15 on C

Bids on D: none

Then asset A is sold to buyer 3 for 50 experimental dollars, asset B is sold to buyer 3 for 42 experimental dollars, and asset C is sold to buyer 4 for 15 experimental dollars. Asset D is not sold since there were no bids placed on that asset.

After the asset allocations and prices are announced, you are required to record your earnings on your record sheet. There will be a 40 second pause between periods to allow you to record your earnings.

This will continue for a number of periods. At the end of the experiment, you will be asked to calculate your total profits and record them on the record sheet enclosed.

Submitting Bids and the Bidbook

When the period is open, on your screen you will see a button called, 'Bidbook'. If you press that button, a new window will appear titled, 'Player Bid Page'. Your bidbook may look something like this:

Market 1 Period 1

Asset	Price	Minimal Price	Quantity	Value
A		1	1	52
B		1	1	13
C		1	1	90
D		1	1	71

Your resale values for the assets in this period are displayed in the "Value" column. The "Quantity" column shows that there is one unit of each asset for sale in the period. The "Minimal Price" column shows that the minimal bid of one experimental dollar is allowed for each asset. In the hypothetical example above, the resale values are: 52 for A, 13 for B, 90 for C and 71 for D. This indicates that you would receive a value of 52 for asset A if you place the highest bid for that asset. Likewise, your value for asset B would be 13, value for C would be 90, and value for D would be 71. These numbers may change from period to period.

You may submit a bid by typing a bid price for either asset in the 'Price' column, and then selecting the 'Submit' button. Notice that you can place bids for assets A, B, C or D either individually or simultaneously. If you place a bid for different assets at the same time, the computer will treat them just as if you had placed them in separate bids. If your bid is above the current highest bid for the asset, it will appear in the the bottom portion of the main ('Asset Market Experiments') window. This window displays current bids in the period. Your bids are indicated in blue while the bids of others are colored black. You may view previous periods' results by selecting the 'Result' button on your main screen.

Determination of Resale Values

For each buyer the resale value for each assets in each period will be between 1 and 100. For each asset, each number from 1 to 100 has equal chance of appearing. It is as if each number between 1 and 100 is stamped on a single ball and placed in an urn. A draw from the urn determines the resale value of an asset for an individual. The ball is replaced and a second draw determines the resale value for another participant. The procedure is then repeated to determine the values of other assets. The resale values each period are determined the same way. The following is a table in which the probability of getting a value in a certain range is listed: (It is for your reference)

Range of Resale Value	Probability of a value in this range
1-10	10%
1-20	20%
1-30	30%
1-40	40%
1-50	50%
1-60	60%
1-70	70%
1-80	80%
1-90	90%
1-100	100%

Period zero will be practice. You will receive no earnings for this period. If you have a question, please raise your hand and I will come by to answer your question.

Are there any questions?

Exercise 1 Suppose that buyers' resale values in a given period are:

Buyer 1		Buyer 2		Buyer 3		Buyer 4	
Asset	Value	Asset	Value	Asset	Value	Asset	Value
A	76	A	63	A	52	A	41
B	59	B	6	B	13	B	20
C	86	C	29	C	90	C	71
D	94	D	20	D	71	D	90

The end-of-the period bids are the following:

Bids on A:

buyer 2 bids 11 on A

buyer 3 bids 20 on A

Bids on B:

buyer 4 bids 15 on B

buyer 1 bids 32 on B

Bids on C:

buyer 2 bids 15 on C

Bids on D:

buyer 1 bids 46 on D

buyer 3 bids 61 on D

(1) Which assets are sold? ______________

(2) What did buyer 1 buy? _______ At what price(s)? _______

What is his (her) profit? _______

(3) What did buyer 2 buy? _______ At what price(s)? _______

What is his (her) profit? _______

(3) What did buyer 3 buy? _______ At what price(s)? _______

What is his (her) profit? _______

(3) What did buyer 4 buy? _______ At what price(s)? _______

What is his (her) profit? _______

Communication with Other Participants[23]

Sometimes in the previous experiments, participants have found it useful when the opportunity arose, to communicate with one another. You are going to be allowed this opportunity in between periods. There will be some restrictions. You are free to discuss any aspect of the experiment (or the market) that you wish, except that:

- You may not discuss any quantitative aspects of the private information on your value sheets;
- You are not allowed to discuss side payments or use physical threats.

[23]This part was distributed and read to subjects after series 4 in SIM sessions, and after series 3 in SEQ sessions.

Since there are some restrictions on your communication with one another, an experimenter will monitor your discussion between periods. Remember, after the experiment has been restarted there will be no discussion until after the end of the next period. We allow a maximum of 4 minutes in any one discussion session.

Appendix B

TABLES 5- 7 HERE

Appendix C. Comparing auctions' complexities

In the theory of repeated games, complexity of a strategy is measured by the number of states in the machine (automaton) that implements this strategy (e.g., Abreu and Rubinstein, 1988; Kalai and Stanford, 1988). It is assumed that the stage game of a repeated game has a finite number of actions, and therefore any strategy in a repeated game can be represented by a finite automaton. Our approach to measure complexities in auctions builds on the finite automata approach but allows for continuous action spaces. The idea is to measure complexity not by the number of distinct *states* of an automaton, but by the number of distinct simple bidding *rules* that the automaton prescribes.

To evaluate complexities of multi-object ascending auctions, let $K = \{1, .., k\}$ be the set of objects offered for sale to the set $I = \{0, 1, .., n\}$ of bidders, where $i = 0$ refers to the auctioneer. Let $v_{ij} \geq 0$ denote bidder's i value for object j. From the viewpoint of any bidder $i \in I$, all the relevant information about the auction is summarized by: (i) a k-dimensional vector of current prices p (equal to current outstanding bids for the corresponding objects), with p_j being the current price for object j; and (ii) a $(n+1) \times k$ objects-to-bidders assignment matrix x, where $x_{ij} = 1$ if object j is currently assigned to bidder i, and $x_{ij} = 0$ otherwise. Feasibility requires that $\sum_{i=0}^{n} x_{ij} = 1$ for each $j \in K$. Let $P \subseteq R_{+}^{k}$ be the set of all possible prices, and X be the set of all possible object-to-bidder assignments. Let $Q \equiv R_{k}^{+}$ be the set of all possible bid vectors. A strategy for bidder i is a function $S_i : P \times X \to Q$ that specifies a bid vector for each possible price vector and object assignment matrix. Because this vector-valued function may be quite complex and include many contingencies, our idea is to decompose it, whenever possible, into a finite number of simpler bidding rules, each of which is continuous in the current price.

A finite rule automaton for player i is a four tuple (M_i, m_i^0, B_i, T_i). M_i is a finite set of rule states, and $m_i^0 \in M_i$ is the initial rule state. $B_i : M_i \times P \to Q$ is the bidding function, and $b_i(p; m_i)$ is the k-dimensional bid vector that the machine submits, as a function of the current price p, whenever it is in the rule state $m_i \in M_i$. To obtain a clear "partition" of any strategy into simple rule states, we require that for each rule state $m_i \in M_i$, the function $b_i(p; m_i)$ is continuous in p. The transition function $T_i : M_i \times P \times X \rightarrow M_i$ governs the transition of the machine from one state to another.

Analogously to the previous literature (e.g., Kalai and Stanford, 1988) we can show that any bidder strategy that can be decomposed into a finite number of simple bidding rules can be represented by such a finite rule automaton. Therefore, we can define the complexity of such a strategy to be the number of rule states in the (smallest) finite rule automaton describing it.[24] Essentially, the strategy's complexity will be then equal the number of different contingencies in which qualitatively different behaviors are prescribed.

We now evaluate and compare complexities of competitive and collusive strategies in simultaneous and sequential ascending auctions. Consider first the rule complexity of the simple bid-according-to-your-value competitive strategy. (It is well-known that all players playing this strategy constitutes a Nash equilibrium.) For simplicity, assume there is a minimal bid increment $\delta \in R_{++}$ for bidding on any object in the auction. For each object $j \in K$, the strategy has two distinct rule states, one in which the bidder should bid, and the other – in which the bidder should not bid. Formally, for a given player $i \in I \setminus \{0\}$, the automaton is in the "bidding" state m_j^1 for object j if $x_{ij} = 0$ and $p_j \leq v_{ij} - \delta$ (this is also the initial state); the automaton is in the "non-bidding" state m_j^2 otherwise (i.e., if $x_{ij} = 1$ or $p_j > v_{ij} - \delta$).[25] The corresponding (continuous in current price) bidding rules are given by $b_{ij}(p_j; m_j^1) = p_j + \delta$, and $b_{ij}(p_j; m_j^2) = \emptyset$. If there is only one object, $k = 1$, then the rule complexity of this competitive strategy is equal to 2.[26] Since there are two distinct rule states per market in k markets, and the rule states may change in each market independently from each other, then the rule complexity is equal to the number of distinct rule state combinations across markets, that is, 2^k.[27] We also note that this strategy is the least complex among all strategies that prescribe independent actions across markets and allow for at least two distinct types of actions in each market:

[24]Of course, some strategies may prescribe a qualitatively different way of bidding for each possible price level. If there is an infinite number of price levels, such strategy's complexity will be infinite, according to our measure. However, if we assume discrete and bounded action spaces, which would be the case if bidding is allowed to proceed in (multiples of) certain minimal bid increments only, and if prices are bounded from above by some arbitrarily large number, then any strategy can be represented by a finite rule automaton.

[25]For notational convenience, here we drop bidder's i index and add object's j index in the notation for the rule state; e.g., m_j^l denotes the l-th rule state for object $j \in K$.

[26]Note the analogy with the English clock auction, where a strategy (when to "stay in" or "drop out") can be represented by a "traditional" finite automaton.

[27]See Fershtman and Kalai (1993) for a detailed justifications of this approach.

Observation 1 *The rule complexity of the competitive bid-according-to-your-value bidding strategy in the k-object simultaneous auction is 2^k. This strategy is the least complex among all bidding strategies that: (i) prescribe actions that are independent across markets, and (ii) allow for at least two qualitatively different actions per market.*

Now let us evaluate the complexity of the collusive market splitting strategy, where the bidders split the objects among each other, with each buying their "designated" object(s) at the minimal (reserve) prices $\underline{p}$. Deviations are deterred by the threat to revert to the described above competitive strategy: a deviation in any market triggers competitive behavior in all market (Brusco and Lopomo (2002) give conditions under which such strategy constitutes a perfect equilibrium in the ascending auctions game). As Fershtman and Kalai (1993) point out, collusive trigger-type strategies are more complex than competitive ones, because they include both collusive states and punishment states. Let our collusive market splitting strategy prescribe bidder i to submit the minimal bid for his "designated" objects (let us denote the set of such objects by $K_i \subseteq K$), and not to bid on the other objects (let us denote the set of these objects by $K_{-i} \equiv K \setminus K_i$). Hence for each designated object $j \in K_i$, there are four rule states:

1. State m_j^1 (collusive), which prescribes to bid the minimal allowed amount, $b_{ij} = \underline{p}_j$ (this is the initial state for this object);
2. State m_j^2 (collusive), which prescribes not to bid, $b_{ij} = \emptyset$ (if no deviations have been observed, and i the holder of the highest outstanding bid in this market, $i = j(p)$.
3. State m_j^3 (competitive), which prescribes to bid $b_{ij} = p_j + \delta$, and corresponds to the "bidding" state in the competitive strategy; and
4. State m_j^4 (competitive) which prescribes not to bid, $b_{ij} = \emptyset$, and corresponds to the "non-bidding" state in the competitive strategy.

For each "non-designated" object $j' \in K_{-i}$, there are three rule states: One collusive state $m_{j'}^1$, which prescribes not to bid for this object (the initial state), and two competitive states, one bidding and one non-bidding.

Collusive states are part of the collusive phase, while competitive states are part of the punishment phase. Therefore, these states are not independent across markets; the automaton is either in a collusive in all markets state, or in a competitive in all markets state. If the strategy prescribes bidder i to get $m \leq k$ "designated" objects, then the number of distinct rule states in the collusive phase is 2^m, while the number of rule states in the punishment phase is 2^k. Hence,

Observation 2 *In k-object simultaneous auction, the rule complexity of the collusive market splitting strategy that prescribes the bidder to get $m \leq K$ objects is $2^m + 2^k$. In particular, if a bidder is prescribed to get exactly one object, then the rule complexity of such strategy is $2^k + 2$.*

We next show that sequential auctions are less complex. Suppose now that the objects are auctioned off one at a time, in a k-period sequential auction; without loss of generality, assume that object $j \in K$ is offered for sale in period j. Here we make an important assumption that in each period, the bidder can focus on this object only, and therefore does not have to take into account his bidding behaviors in the previous and future periods (although the past history may determine the initial rule state for this period's automaton). Thus, a period's automaton needs to represent the play in the current period's single-object auction only. We assume that in between periods, the bidder can switch between rule automata, and is also able to "upload to his memory" period-specific external parameters, such as his own value v_{ij} for the object j, and, for the collusive strategy, whether the current object j is this bidder's "designated" object. Then, for a competitive bid-according-to-your-value strategy, the complexity of any period's rule automaton is just equal to the complexity of the automaton in a single-unit auction, that is, $r = 2$. As before, the first ("bidding") rule state prescribes bidding a minimal increment among the outstanding bid (or the auctioneer's reserve price), and the second rule state ("non-bidding") prescribes not to bid. To summarize:

Observation 3 *In k-object sequential auction, the rule complexity of the competitive bid-according-to-your-value strategy in any single period is equal to 2.*

Now consider the collusive market splitting strategy where, as before, any deviation from collusive behavior triggers a switch to the punishment phase which prescribes the competitive play. Since the number of periods is finite, and it is a dominant strategy to bid competitively in the final period k for all bidders (except the one who is prescribed by the collusive scheme to get the object in this period), and therefore such strategy is not an equilibrium strategy. Hence, as noted in the introduction, there are less game-theoretic reasons to expect collusion in the sequential setting. However, since our experimental evidence shows that subjects have successfully followed this collusive scheme (possibly due to the repeated nature of the sequential auctions supergame), it is still of interest to evaluate the collusive strategy's complexity.

Analogously to the discussion of the simultaneous auction, for each object, there are three or four rule states for the collusive rule automaton: four states for "designated" objects, and three states for "non-designated" objects. (We also note for the sequential auction, the initial state in each period will vary depending upon whether a previous deviation was observed: if the deviation was observed, then the initial state is the competitive bidding state, and if not, then the initial state is one of the collusive states.) What is important for our purposes, then, is the following:

Observation 4 *In k-object sequential auction, the rule complexity of the collusive market-splitting strategy in any single period is at most 4.*

Hence, we obtain two important corollaries (the latter one is already noted in Ferthtman and Kalai, 1993):

Corollary 1 *For both competitive bid-according-to-your-value strategy and collusive market splitting strategy, the level of rule complexity required to implement them is higher in the simultaneous auctions than in the sequential auctions. That is, simultaneous auctions are more complex than sequential auctions.*

Corollary 2 *In both simultaneous and sequential multi-unit auctions, collusive market splitting strategy is more complex then the competitive bid-according-to-your-value strategy. That is, collusion is more complex than competition.*

The above may possibly explain why bidders were able to collude more successfully in the sequential then in the simultaneous auctions: while the complexity of collusive strategy was at most 4 in any single period of the sequential auction, it was $2^4 + 2 = 18$ in the simultaneous auction.[28]

[28] We note that, according to this approach, the multi-object aspect of the auction has a much bigger impact on the measure of a strategy's complexity than the collusive behavior aspect. In particular, if a market-splitting collusive scheme prescribes each agent to get exactly one object, then the difference in the complexity measure between the collusive and the competitive strategies, in both simultaneous and sequential auctions, is at most 2. This does not capture very well the intuition that, even though collusive strategy itself is quite simple, it may not be trivial for bidders to discover it. To capture this feature, we would need to account for how long it takes players to learn a strategy; this is similar to what Gell-Mann (1995) calls "logical depth." Obviously, the competitive bid-according-to-your-value strategy is very intuitive and has the minimal logical depth, whereas collusive strategies are somewhat more difficult to understand. It appears that one would need to turn to the theory of learning in games (e.g., Fudenberg and Levine, 1998) to measure this aspect of a given strategy. However, it goes beyond the scope of this paper.

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LIST OF FIGURES

mean (stddv)	Average Prices								
	ACTUAL			EA PREDICTION			SB PREDICTION		
	All	**BeforeComm**	**AfterComm**	**All**	**BeforeComm**	**AfterComm**	**All**	**BeforeComm**	**AfterComm**
SIMH --	43.56	53.00	35.78	59.95	67.56	54.88	58.31	60.42	56.91
all	(14.36)	(7.03)	(27.82)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SEQH --	34.00	54.28	25.01	58.00	67.33	53.33	57.00	60.06	55.47
all	(12.73)	(8.35)	(17.05)	(22.13)	(20.11)	(21.99)	(14.81)	(16.13)	(14.21)
SIMS --	44.86	69.90	28.16	59.95	67.56	54.88	58.31	60.42	56.91
all	(17.45)	(2.13)	(27.83)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)

Table 1: Mean prices per treatment.

mean (stddv)	% gains from trade captured			% efficient allocations		
	All	**BeforeComm**	**BeforeComm**	**All**	**BeforeComm**	**AfterComm**
SIMH -- all	0.89 (0.09)	0.94 (0.03)	0.85 (0.18)	0.54 (0.13)	0.56 (0.14)	0.52 (0.28)
SEQH -- all	0.89 (0.04)	0.91 (0.08)	0.88 (0.06)	0.60 (0.11)	0.61 (0.16)	0.66 (0.15)
SIMS -- all	0.94 (0.05)	0.96 (0.03)	0.94 (0.07)	0.81 (0.12)	0.89 (0.09)	0.76 (0.20)

Table 2: Mean efficiency and the share of efficient allocations per treatment.

Average Bidder Gains									
mean (stddv)	ACTUAL			EA PREDICTION			SB PREDICTION		
	All	**BeforeComm**	**AfterComm**	**All**	**BeforeComm**	**AfterComm**	**All**	**BeforeComm**	**AfterComm**
SIMH --	25.39	21.27	27.82	17.81	12.44	21.17	19.36	20.07	18.92
all	(11.62)	(5.86)	(21.11)	(0.26)	(0.79)	(0.37)	(0.07)	(0.10)	(0.12)
SEQH --	36.65	25.12	47.11	17.74	13.05	23.72	19.43	20.11	18.84
all	(10.51)	(12.48)	(13.63)	(0.62)	(0.12)	(2.47)	(0.58)	(0.07)	(0.97)
SIMS --	28.98	8.07	42.93	17.80	13.00	21.00	19.44	20.14	18.97
all	(15.99)	(3.13)	(24.80)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 3: Mean biddder gains per treatment.

Session	Communication sessions		No. of auction series after communitation		Characteristics of collusive auction series							
	Collusion discussed?	Collusive scheme discussed	total	No. of collusive series	Price: Mean (stddv)	Efficiency: Mean (stddv)	Collusive Effectiveness: Mean (stddv)	% of allocations consistent with Serial Dictator	% of allocations consistent with RANKING	Avg Rank of assigned object	Avg No. of winning bidders	Prevailing collusive scheme
SIMH-1	no	n/a	6	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
SIMH-2	yes	splitting markets	6	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
SIMH-3	no	n/a	6	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
SIMH-4	yes	linear bid reduction, splitting markets, bid rotation	6	6	1.00 (0.00)	0.86 (0.24)	0.86 (0.24)	100	83.33	1.5	4	SD/ ranking
SIMH-5	yes	bid on favorite market	5	5	10.1 (11.9)	0.53 (0.31)	0.36 (0.47)	0	0	2.82	3	bid on favorite
SEQH-1	yes	splitting markets	6	5	1.00 (0.00)	0.81 (0.25)	0.81 (0.25)	100	80	1.55	4	SD/ ranking
SEQH-2	no	n/a	3	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
SEQH-3	yes	splitting markets	3	1	1.00 (0.00)	1.00 (n/a)	1.00 (0.00)	100	100	1.5	4	SD/ ranking
SEQH-4	yes	code bidding, bid on favorite market	6	2	6.29 (2.36)	0.95 (0.13)	0.85 (0.13)	0	0	1.75	3	code bidding
SEQH-5	yes	splitting markets	7	6	1.00 (0.00)	0.84 (0.22)	0.84 (0.22)	100	83.33	1.51	4	SD/ ranking
SIMS-1	yes	linear bid reduction, splitting markets	6	5	1.05 (0.22)	0.83 (0.24)	0.83 (0.24)	80	80	1.55	4	SD/ ranking
SIMS-2	yes	linear bid reduction, splitting markets	6	5	7.49 (2.04)	1.00 (0.0)	0.91 (0.01)	20	20	1.7	2.6	bid reduction
SIMS-3	yes	splitting markets	6	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
SIMS-4	yes	splitting markets	6	5	1.9 (2.17)	0.89 (0.17)	0.88 (0.17)	100	40	1.5	3.8	SD
SIMS-5	no	n/a	6	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Table 4. Summary of collusive auction series

mean (stddv)	ACTUAL			EA PREDICTION			SB PREDICTION		
	All	BeforeComm	AfterComm	All	BeforeComm	AfterComm	All	BeforeComm	AfterComm
SIMH -- all	43.56	53.00	35.78	59.95	67.56	54.88	58.31	60.42	56.91
	(14.36)	(7.03)	(27.82)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SIMH-1	56.54	54.38	58.04	58.97	67.56	53.00	57.88	60.42	56.12
	(15.75)	(14.25)	(16.86)	(21.79)	(22.07)	(19.93)	(14.64)	(15.51)	(14.07)
SIMH-2	51.05	46.40	53.96	59.95	68.07	54.88	58.08	59.95	56.91
	(16.41)	(16.57)	(15.96)	(22.67)	(22.75)	(21.55)	(14.81)	(15.94)	(14.29)
SIMH-3	53.03	48.88	55.79	59.95	67.56	54.88	58.31	60.42	56.91
	(17.30)	(16.56)	(17.58)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SIMH-4	22.93	55.81	1.00	59.95	67.56	54.88	58.31	60.42	56.91
	(29.12)	(16.79)	(0.00)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SIMH-5	34.28	64.50	10.10	59.39	62.56	56.85	57.88	60.05	56.14
	(31.73)	(20.39)	(11.92)	(23.15)	(24.00)	(22.75)	(14.83)	(14.45)	(15.28)
SEQH -- all	34.00	54.28	25.01	58.00	67.33	53.33	57.00	60.06	55.47
	(12.73)	(8.35)	(17.05)	(22.13)	(20.11)	(21.99)	(14.81)	(16.13)	(14.21)
SEQH-1	23.42	52.67	8.79	58.00	67.33	53.33	57.00	60.06	55.47
	(27.73)	(16.08)	(19.42)	(22.13)	(20.11)	(21.99)	(14.81)	(16.13)	(14.21)
SEQH-2	41.94	46.33	37.14	63.35	67.33	59.00	60.00	60.06	59.93
	(13.87)	(15.42)	(10.63)	(22.93)	(20.11)	(25.92)	(13.88)	(16.13)	(11.74)
SEQH-3	42.79	46.42	39.17	62.67	67.33	58.00	60.38	60.06	60.69
	(22.72)	(12.21)	(30.02)	(22.67)	(20.11)	(24.96)	(13.70)	(16.13)	(11.49)
SEQH-4	44.63	63.09	35.80	57.82	66.09	53.87	57.02	59.39	55.89
	(32.81)	(21.87)	(33.85)	(22.24)	(20.60)	(22.32)	(15.01)	(16.74)	(14.38)
SEQH-5	17.19	62.88	4.14	58.00	70.75	54.36	57.00	62.72	55.37
	(27.10)	(12.38)	(10.85)	(22.13)	(15.21)	(22.64)	(14.81)	(11.65)	(15.38)
SIMS -- all	44.86	69.90	28.16	59.95	67.56	54.88	58.31	60.42	56.91
	(17.45)	(2.13)	(27.83)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SIMS-1	29.58	67.07	4.59	59.95	67.56	54.88	58.31	60.42	56.91
	(33.96)	(19.51)	(8.83)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SIMS-2	35.27	68.63	13.03	59.95	67.56	54.88	58.31	60.42	56.91
	(32.48)	(22.57)	(12.89)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SIMS-3	63.18	71.63	57.54	59.95	67.56	54.88	58.31	60.42	56.91
	(21.85)	(23.07)	(19.49)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SIMS-4	31.75	69.94	6.29	59.95	67.56	54.88	58.31	60.42	56.91
	(36.42)	(22.83)	(14.78)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)
SIMS-5	64.50	72.25	59.33	59.95	67.56	54.88	58.31	60.42	56.91
	(22.60)	(22.78)	(21.41)	(22.38)	(22.07)	(21.55)	(14.70)	(15.51)	(14.29)

Table 5. Mean prices per session

Average Efficiency						
mean (stddv)	% gains from trade captured			% efficient allocations		
	All	BeforeComm	BeforeComm	All	BeforeComm	AfterComm
SIMH -- all	0.89 (0.09)	0.94 (0.03)	0.85 (0.18)	0.54 (0.13)	0.56 (0.14)	0.52 (0.28)
SIMH-1	0.97 (0.05)	0.97 (0.07)	0.98 (0.04)	0.69	0.63	0.74
SIMH-2	0.93 (0.13)	0.91 (0.11)	0.95 (0.14)	0.62	0.4	0.75
SIMH-3	0.93 (0.09)	0.93 (0.08)	0.93 (0.10)	0.48	0.44	0.5
SIMH-4	0.89 (0.20)	0.92 (0.13)	0.86 (0.23)	0.53	0.56	0.56
SIMH-5	0.73 (0.33)	0.98 (0.03)	0.53 (0.31)	0.36	0.75	0.05
SEQH -- all	0.89 (0.04)	0.91 (0.08)	0.88 (0.06)	0.60 (0.11)	0.61 (0.16)	0.66 (0.15)
SEQH-1	0.87 (0.20)	0.96 (0.07)	0.82 (0.24)	0.5	0.58	0.46
SEQH-2	0.90 (0.22)	0.90 (0.24)	0.90 (0.21)	0.65	0.75	0.55
SEQH-3	0.97 (0.07)	0.98 (0.04)	0.96 (0.10)	0.75	0.75	0.75
SEQH-4	0.88 (0.21)	0.79 (0.27)	0.92 (0.17)	0.62	0.36	0.74
SEQH-5	0.85 (0.22)	0.94 (0.09)	0.82 (0.24)	0.5	0.63	0.46
SIMS -- all	0.94 (0.05)	0.96 (0.03)	0.94 (0.07)	0.81 (0.12)	0.89 (0.09)	0.76 (0.20)
SIMS-1	0.86 (0.25)	0.91 (0.26)	0.83 (0.25)	0.65	0.88	0.5
SIMS-2	0.99 (0.06)	1.00 (0.00)	0.98 (0.08)	0.93	0.94	0.92
SIMS-3	0.95 (0.11)	0.94 (0.13)	0.96 (0.13)	0.78	0.75	0.75
SIMS-4	0.94 (0.12)	1.00 (0.00)	0.91 (0.15)	0.78	1	0.63
SIMS-5	0.98 (0.09)	0.96 (0.15)	1.00 (0.00)	0.95	0.88	1

Table 6. Efficiency and the share of efficient allocations per session

	Average Bidder Gain								
mean (stddv)	ACTUAL			EA PREDICTION			SB PREDICTION		
	All	BeforeComm	AfterComm	All	BeforeComm	AfterComm	All	BeforeComm	AfterComm
SIMH --	25.39	21.27	27.82	17.81	12.44	21.17	19.36	20.07	18.92
all	(11.62)	(5.86)	(21.11)	(0.26)	(0.79)	(0.37)	(0.07)	(0.10)	(0.12)
	18.26	23.00	14.96	18.21	13.00	21.83	19.29	20.14	18.71
SIMH-1	(11.35)	(15.14)	(6.21)	(15.09)	(8.85)	(17.51)	(4.88)	(5.17)	(4.69)
	21.13	26.27	17.92	17.49	11.87	21.00	19.36	19.98	18.97
SIMH-2	(13.69)	(18.56)	(8.50)	(15.18)	(7.87)	(17.60)	(4.94)	(5.31)	(4.76)
	19.23	26.25	14.54	17.80	13.00	21.00	19.44	20.14	18.97
SIMH-3	(14.41)	(15.28)	(11.94)	(15.12)	(8.85)	(17.60)	(4.90)	(5.17)	(4.76)
	45.98	18.25	64.46	17.80	13.00	21.00	19.44	20.14	18.97
SIMH-4	(30.65)	(10.87)	(24.99)	(15.12)	(8.85)	(17.60)	(4.90)	(5.17)	(4.76)
	22.36	12.58	27.25	17.78	11.33	21.00	19.29	19.94	18.97
SIMH-5	(26.14)	(5.84)	(30.81)	(15.59)	(7.58)	(17.60)	(4.94)	(5.45)	(4.76)
SEQH --	36.65	25.12	47.11	17.74	13.05	23.72	19.43	20.11	18.84
all	(10.51)	(12.48)	(13.63)	(0.62)	(0.12)	(2.47)	(0.58)	(0.07)	(0.97)
	44.22	24.88	59.70	18.00	13.00	22.00	19.00	20.14	18.09
SEQH-1	(27.60)	(13.29)	(26.39)	(14.71)	(8.85)	(17.29)	(4.94)	(5.17)	(4.67)
	32.06	33.00	29.93	16.65	13.00	25.00	20.00	20.14	19.68
SEQH-2	(19.01)	(20.30)	(16.95)	(14.75)	(8.85)	(22.02)	(4.63)	(5.17)	(3.39)
	35.50	29.06	48.38	17.83	13.00	27.50	20.13	20.14	20.09
SEQH-3	(24.17)	(14.36)	(34.54)	(15.54)	(8.85)	(21.57)	(4.57)	(5.17)	(3.35)
	22.31	3.87	36.88	18.21	13.27	22.11	19.01	19.98	18.24
SEQH-4	(28.03)	(15.00)	(27.52)	(15.06)	(9.10)	(17.75)	(5.00)	(5.31)	(4.75)
	49.17	34.81	60.65	18.00	13.00	22.00	19.00	20.14	18.09
SEQH-5	(31.28)	(34.77)	(23.14)	(14.71)	(8.85)	(17.29)	(4.94)	(5.17)	(4.67)
SIMS --	28.98	8.07	42.93	17.80	13.00	21.00	19.44	20.14	18.97
all	(15.99)	(3.13)	(24.80)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	38.27	7.56	58.74	17.80	13.00	21.00	19.44	20.14	18.97
SIMS-1	(34.57)	(19.55)	(26.15)	(15.12)	(8.85)	(17.60)	(4.90)	(5.17)	(4.76)
	41.43	11.88	61.14	17.80	13.00	21.00	19.44	20.14	18.97
SIMS-2	(30.50)	(8.04)	(22.85)	(15.12)	(8.85)	(17.60)	(4.90)	(5.17)	(4.76)
	10.85	4.50	15.08	17.80	13.00	21.00	19.44	20.14	18.97
SIMS-3	(19.37)	(12.65)	(22.02)	(15.12)	(8.85)	(17.60)	(4.90)	(5.17)	(4.76)
	42.13	10.63	63.13	17.80	13.00	21.00	19.44	20.14	18.97
SIMS-4	(31.71)	(7.33)	(22.80)	(15.12)	(8.85)	(17.60)	(4.90)	(5.17)	(4.76)
	12.25	5.81	16.54	17.80	13.00	21.00	19.44	20.14	18.97
SIMS-5	(13.73)	(12.52)	(13.01)	(15.12)	(8.85)	(17.60)	(4.90)	(5.17)	(4.76)

Table 7. Mean bidder gains per session.

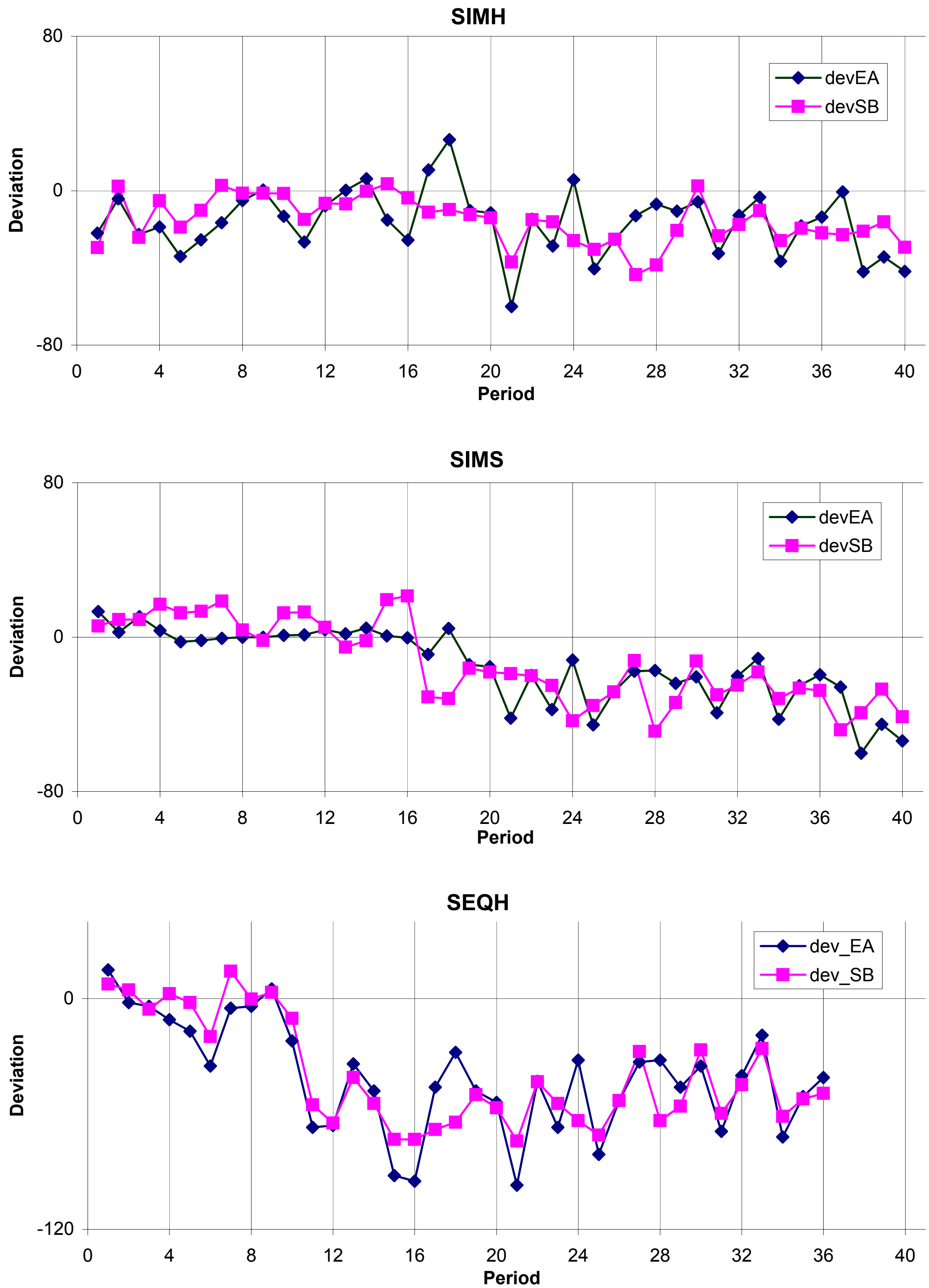

Figure 1: Average price deviations from competitive predictions, in experimental dollars, by treatment

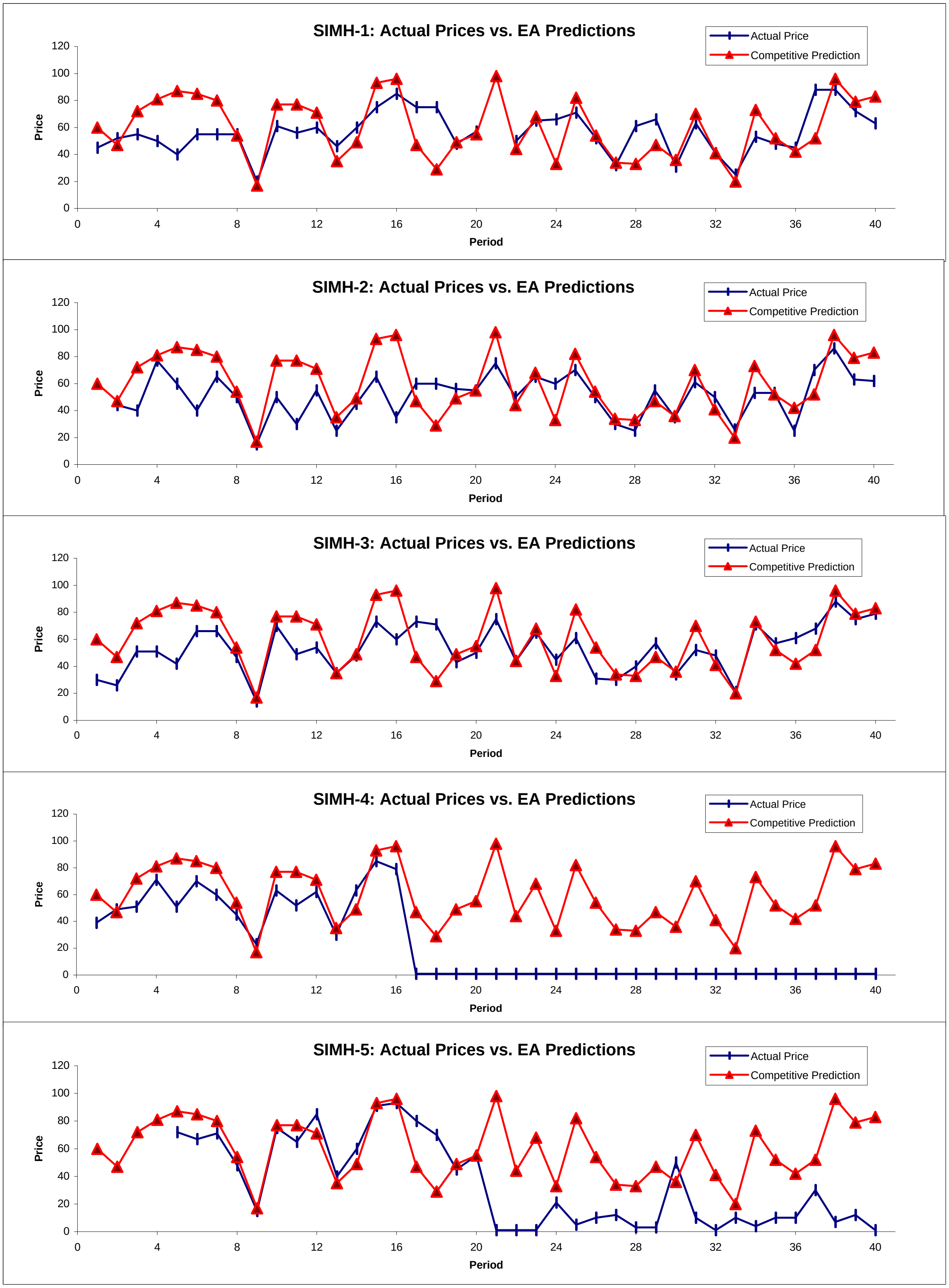

Figure 2: Price dynamics in SIMH treatment, by session. Communication started after series 4 (period 16 on the graphs) in all sessions except SIMH-5, where it started after series 5 (period 20).

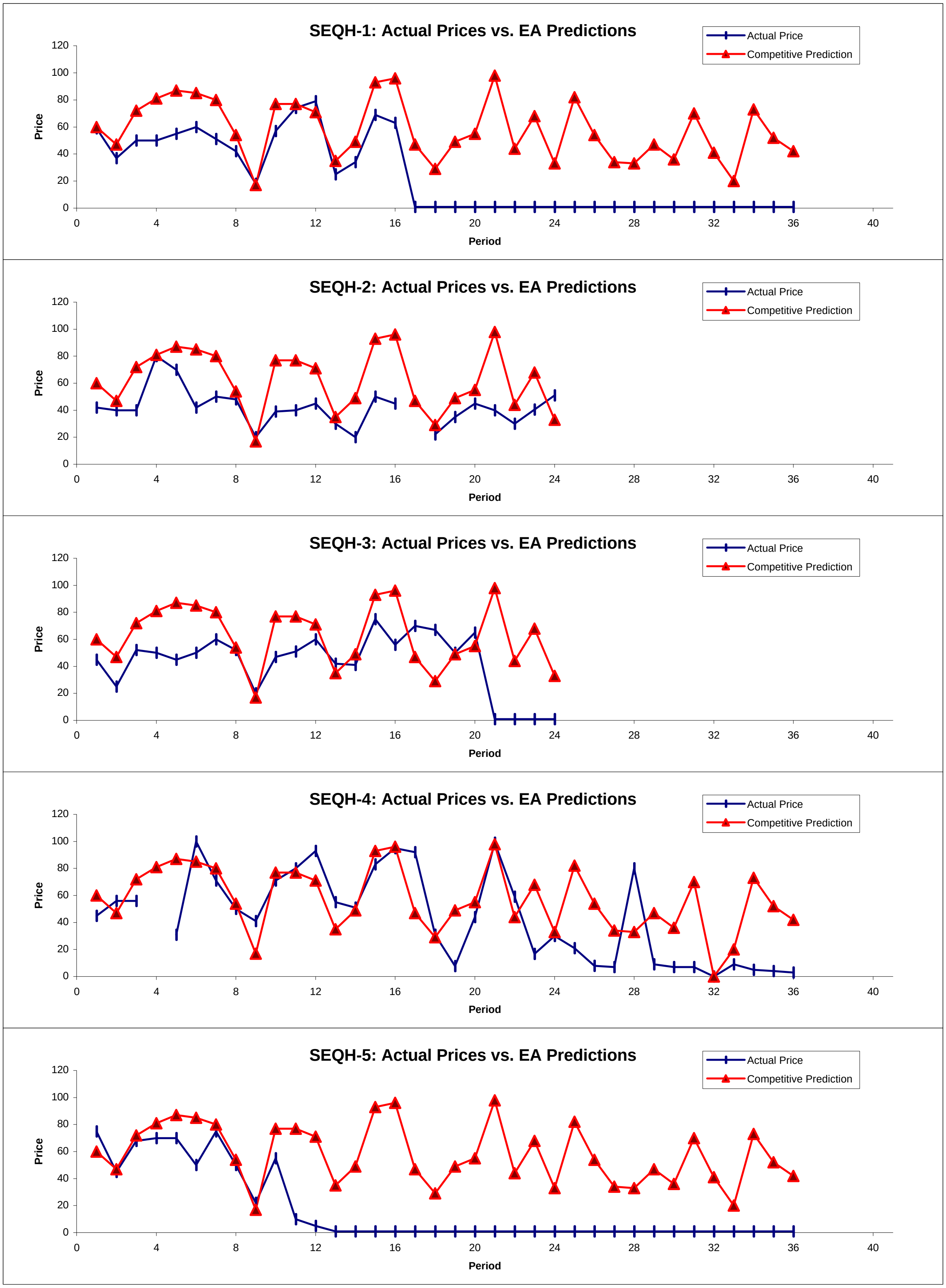

Figure 3: Price dynamics in SEQH treatment, by session. Communication started after period 12 in all sessions except SEQH-5, where it started after period 8.

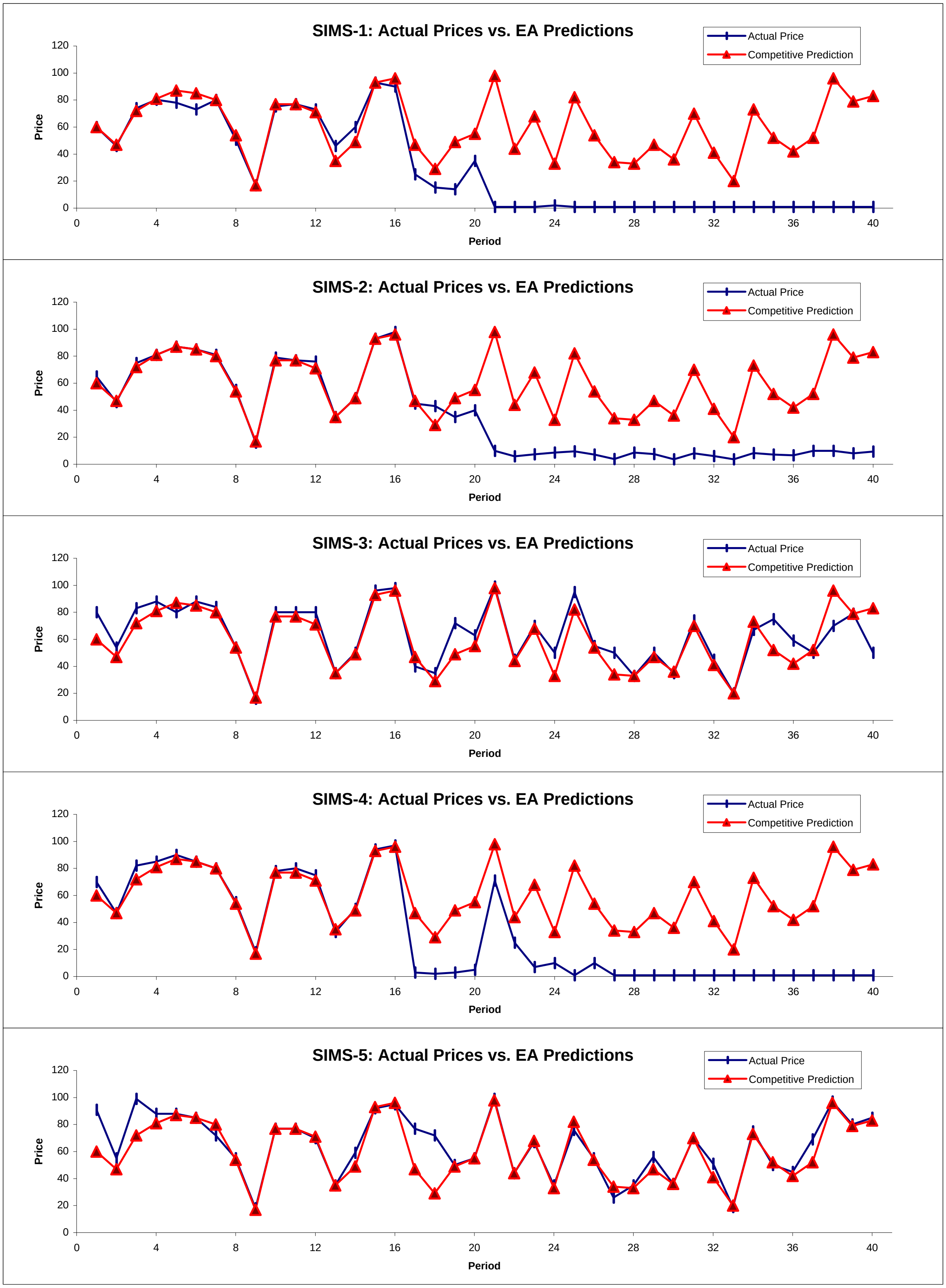

Figure 4: Price dynamics in SIMS treatment, by session. Communication started after series 4 (period 16 on the graphs) in all sessions.