Collusion and equilibrium selection in auctions*

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Abstract

We study bidder collusion and test the power of payoff dominance as an equilibrium selection principle in experimental multi-object ascending auctions. In these institutions low-price collusive equilibria exist along with competitive payoff-inferior equilibria. Achieving payoff-superior collusive outcomes requires complex strategies that, depending on the environment, may involve signaling, market splitting, and bid rotation. We provide the first systematic evidence of successful bidder collusion in such complex environments without communication. The results demonstrate that in repeated settings bidders are often able to coordinate on payoff superior outcomes, with the choice of collusive strategies varying systematically with the environment.

Key words: multi-object auctions; experiments; multiple equilibria; coordination; tacit collusion

1 Introduction

Auctions for timber, automobiles, oil drilling rights, and spectrum bandwidth are just a few examples of markets where multiple heterogeneous lots are offered for sale simultaneously. In multi-object ascending auctions, the applied issue of collusion and the theoretical issue of equilibrium selection are closely linked. In these auctions, bidders can profit by splitting the markets. By acting as local monopsonists for a disjoint subset of the objects, the bidders lower the price they must pay. As opposed to the sealed bid auction, the ascending auction format provides bidders with the opportunity to tacitly coordinate on

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dividing markets and to punish non-collusive bidding. Thus, low-price collusive equilibria co-exist along with high-price competitive equilibria even in a non-repeated setting (Brusco and Lopomo, 2002). If there are complementarities in bidder values across objects, and auctions are repeated, bidders may further benefit by splitting the markets over time, and taking turns in buying packages at low prices. These opportunities make the multi-object ascending auction an ideal institution for the study of equilibrium selection. Assuming that communication between the bidders is limited to the bidding, any splitting of the markets must be tacitly coordinated in the early stages of the auction. Thus achieving payoff-superior collusive outcomes requires complex strategies that, depending on the environment, may involve signaling, market splitting, and bid rotation. While such tacit coordination is possible in theory, it is an empirical question of whether it may be achieved in practice.

The tradition in many theoretical models has been to assume that the players will coordinate on payoff superior equilibria (see Tirole 1988, pp. 403-404). Van Huyck, Battalio and Beil (1990, 1991) argue that, due to strategic uncertainty, payoff dominance may not be a salient selection principle in many strategic situations with multiple equilibria. Still, repeated prisoners' dilemma and oligopoly experiments demonstrate that agents are often able to achieve payoff superior cooperative or collusive outcomes in simple settings with a small number of players (Fouraker and Siegel, 1963; Selten, Mitzkewitz and Uhlich, 1997).

We test the power of payoff dominance as an equilibrium selection principle in a much more complex economic setting that is both policy relevant and pushes the boundaries of the current knowledge on agents' abilities to use sophisticated strategies to solve coordination problems. We study bidder behavior in laboratory ascending auctions for multiple objects without communication.

The airwave spectrum sales in Europe, The United States and many other countries brought to the forefront the possibility of collusion in multi-object auctions (Milgrom, 1998; Cramton and Schwartz, 2000; Klemperer, 2000 and 2002). In many cases these sales employed a simultaneous multi-object ascending auction format. Cramton and Schwartz (2000) report that firms bidding for similar licenses in Federal Communications Commission (FCC) spectrum auctions in the U.S. used signaling and bidding at low prices to tacitly coordinate on license allocations across markets; the deviations from tacit agreements were punished with retaliating bids. There is evidence that bidders sometimes used the financially inconsequential portion of the bid (the last three digits) in order to signal their identity or to indicate a market that bidder would retaliate against in the event the current bid was raised. In fact, in 1997, the FCC fined Mercury PCS $650,000 for "placing trailing numbers at the end of its bids that disclosed its bidding strategy in a ... manner that specifically invited collusive behavior" (FCC 1997). Jehiel and Moldovanu (2000) present evidence of bidders dividing markets via bid signaling in the German 1999 GSM spectrum auction.

Empirical analysis of bidder collusion in spectrum and other auctions is difficult to conduct due to the lack of observability of bidders' valuations; it may be hard to distinguish between collusive behavior and low valuations.[1] Therefore, we use the experimental laboratory to study whether bidders are able to coordinate on Pareto superior equilibria in a complex multi-object auction setting.

Previously, outright collusion among bidders has not been reported under standard experimental procedures in auctions without communication (Kagel, 1995).[2] This is not surprising given that, theoretically, collusion in most auction formats requires formation of bidding rings (Graham and Marshall, 1987; McAfee and McMillan, 1992), or repeated play (Milgrom, 1987; Skrzypacz and Hopenhayn, 2002). Multiple object open ascending auctions provide new possibilities for collusion that are non-existent under other auction formats, both because these auctions allow for improved coordination among bidders, and because they facilitate collusion enforcement. Brusco and Lopomo (2002) (BL) demonstrate that, even in a non-repeated setting, there exists a perfect Bayes Nash "signaling" equilibrium where the bidders split the markets and capture a larger portion of the surplus than under the standard non-cooperative or "competitive" bidding equilibrium. Such a collusive equilibrium exists even in the presence of complementarities and is enforced by the threat of reverting to competitive bidding if a deviation occurs. The equilibrium suggested by BL is complex and requires sophisticated tacit coordination among bidders and common beliefs about punishment strategies. Competitive bidding, on the other hand, is straightforward. Repetition expands the possibilities for collusion, with a wider variety of strategies that may be used to achieve collusive outcomes. In this study we investigate whether the bidders are able to coordinate on a collusive equilibrium in such a complex environment, and whether bidder strategies vary systematically with the environment.

Experimental evidence from two closely related areas of study suggests that collusion in multiple object auctions might be successful. First, collusion has been observed in multiple object auctions in the presence of facilitating devices or communication (Sherstyuk, 1999; Kwasnica, 2000). Second, anti-competitive behavior has been observed in multi-unit auctions in the form of demand reduction (Algsemgeest et. al, 1998; Kagel and Levin,

[1]A number of empirical studies provide evidence of bidder collusion under other (simpler) auction formats, including both sealed bid auctions, such as auctions for state highway construction contracts and school milk markets (Feinstein, Block and Nold, 1985; Porter and Zona, 1993 and 1999) and oral ascending bid auctions, such as forest service timber sales (Baldwin, Marshall and Richards, 1997).

[2]Provided that communication is allowed, collusion is known to be quite effective in posted-offer and sealed bid experimental markets (Isaac, Ramey and Williams, 1984; Isaac and Walker, 1985; Kwasnica, 2000).

2001a and 2001b). Demand reduction by a bidder or bidders is closely related to bidder collusion since, like collusion, it attempts to affect market prices by withholding bidder demand. But unlike collusion, it may be caused by behavior of just one bidder who is able to affect market prices by reducing own demand; no coordination among bidders may be necessary. In fact, experiments on demand reduction are often designed to free the environment from strategic uncertainty regarding other bidders' behavior (Kagel and Levin, 2001a and 2001b). Collusion, on the contrary, requires strategic interaction among bidders; the success of collusion fully depends on bidders' ability to coordinate on a low price equilibrium. In this respect, achieving a collusive outcome adds an extra degree of difficulty for the bidders as compared to a demand reduction setting.

We investigate anti-competitive behavior in an auction setting which adds degrees of complexity to earlier studies. To achieve low-price collusive outcomes in a multi-object environment, bidders need to use signaling and coordination across markets in addition to the threat of retaliation.

While this experimental study was initially inspired by the theoretical findings of Brusco and Lopomo (2002), there are important differences between BL and our setting. First, Brusco and Lopomo consider one particular kind of collusive equilibria, while our objective is to study equilibrium selection among many collusive equilibria. While the existence of BL equilibria does not require repetition, we study collusion in a repeated setting. Repetition ensures existence of other collusive equilibria, such as bid rotation, along with BL signaling. It also gives bidders a better chance to achieve coordination and to form consistent beliefs about each others' behavior. It is well established that repetition helps to achieve and sustain collusion in simple two-person markets with complete information (Fouraker and Siegel, 1963). However, it is unknown whether bidders are able to discover collusive strategies, and to select them on the basis on payoff dominance, in complex multi-object environments under incomplete information. The repeated setting is also directly relevant to many real world auctions, such as the recent spectrum license sales.[3]

Another important difference between BL and our study concerns the effect of complementrities on the incidence of collusion. BL consider collusive equilibria in environments with either no complementarities or large complementarities, and do not consider the moderate complementarity case. In some real-world auctions, however, the moderate complementarity case may be most relevant. In addition, including a moderate complementarity

[3]For example, Klemperer (2002) notes that the same firms were likely to be the key players in many European telecom auctions: "...By the time of the Italian sale the situation was dramatically different from the one the UK had faced. Most importantly, firms had learned from the earlier auctions who were the strongest bidders, and hence the likely winners, at least in an ascending auction..." (p. 834).

environment permits a more thorough examination of equilibrium selection. Therefore, we study bidder collusion in moderate complementarity, as well as in no complementarity and in large complementarity environments. Collusion in moderate complementarity environments can be supported by repeated play.

We find that bidders are often able to coordinate on payoff-superior collusive outcomes in ascending auctions for multiple objects both without and with moderate complementarities, as long as the number of bidders in the market is small (2-person markets). To our knowledge, this is the first experimental study to observe stable, tacit collusion under such a complex institution lacking in significant facilitating devices. We further show that collusive strategies vary markedly depending on the environment. While most bidders make extensive use of strategies similar to those described by BL in no complementarity environments, in the presence of complementarities, bidders often adopt higher-payoff bid rotation strategies. We thus provide strong evidence in favor of payoff dominance as an equilibrium selection principle in this institution. Our results also provide new behavioral insights that are not anticipated by the theory. While the theory predicts that collusion can be sustained in environments with large complementarities, we find that there are levels of complementarities that make collusion less likely.

The remainder of the paper is organized as follows. In Section 2, we state the theoretical predictions on competitive and collusive equilibria and illustrate them using simple examples. Section 3 contains the experimental design. Overall results on the presence of collusion are given in Section 4. In Section 5, we examine individual behavior and address the equilibrium selection issue. We conclude in Section 6.

2 Theoretical predictions

There are two objects for sale, A and B, and the set N of bidders, $i = 1, .., n$. The institutional details and the model follow BL closely The institution is the simultaneous ascending bid auction, in which each object is sold in a separate market via an ascending bid auction. The auction is run simultaneously for both objects; the auction ends only after the bidding for both objects has stopped. Let a_i be bidder i's value for object A, and b_i be bidder i's value for object B. Bidder i's value for the package AB is given by $u_i(AB) = a_i + b_i + k$, where k is the common additive complementarity term. It is assumed that values (a_i, b_i) are drawn independently across bidders from the same probability distribution (F) with support $[0, 100]$.[2] When $k = 0$, there is no complementarity. When $k > 100$, there is large complementarity and allocative efficiency dictates that one bidder wins both objects. Moderate complementarity, $0 < k \leq 100$, represents the intermediate case where the individual object valuations can affect the efficient allocation. Competitive outcomes are characterized by BL with the following observation.

Observation 1 (Competitive predictions)

1. *With no complementarity, the Separate English Auction strategy profile (SEA: bid up to your value on each object independently of the other object) forms a perfect Bayesian equilibrium (PBE) in the simultaneous ascending bid auction. The resulting allocation is efficient and the prices are equal to the second highest values for each object.*

2. *With large complementarity, $k > 100$, there exists a (competitive) PBE with the following outcome: the two objects are allocated to the bidder with the highest value for the package, at a price equal to the second highest valuation for the package (the Vickrey price); the allocation is always efficient.*

For the remainder of this paper, we consider collusive outcomes to be those that result from bidders' suppressed price competition and yield significantly lower than competitive revenue for the auctioneer, and higher than competitive expected payoffs for the bidders. BL show that the auction game has a collusive equilibrium that involves the use of signaling. In fact, BL demonstrate that the collusive equilibrium is interim incentive efficient amongst mechanisms that always assign bidders at least one object.

Observation 2 (Collusion via signaling predictions)

1. *If there are two bidders, $n = 2$, then under certain restrictions on the distribution of values F and k, collusive outcomes (prices below the SEA prices) can be supported as PBE in the simultaneous ascending bid auction. These equilibria are sustained using the threat to revert to competitive play if players deviate from their collusive strategies. The above mentioned restrictions hold, in particular, if F is uniform, and if $k = 0$, or $k > 100$.*

2. *Collusion is a low numbers phenomenon. If $n > 2$ and $k = 0$ (no complementarity), the prices under the collusive BL outcome differ less from the competitive outcome. BL collusive signaling strategies prescribe bidding competitively until only two bidders are left bidding; then strategies similar to the $n = 2$ case are employed.*[4]

We refer to the corresponding outcome in Observation 1(1) as the SEA competitive outcome, the outcome in Observation 1(2) as the Vickrey competitive outcome, and the outcome in Observation 2 as the BL collusive, or the BL signaling outcome. We also note

[4] With a positive complementarity and $n > 2$, a collusive equilibrium is not described by BL.

that the competitive PBE outcomes described in Observation 1 have a close correspondence to competitive equilibria (CE) in the neoclassical sense. The following examples illustrate both the competitive predictions, and how signaling works to achieve higher-payoff collusive outcomes. The latter outcomes are supported as equilibria using the threat to revert to competitive bidding (SEA or Vickrey, correspondingly) once a deviation is observed. We assume that a bid of one is the minimum allowable bid as well as the minimum bid increment for future bids.

Example 1 Let there be $n = 2$ bidders, with values drawn from the uniform distribution for both objects. Suppose that $a_1 = 96$, $b_1 = 72$, $a_2 = 6$, and $b_2 = 54$. If $k = 0$ (no complementarity), then the SEA competitive outcome is $p_a = 6$, $p_b = 54$, with both items allocated to bidder 1. The BL collusive signaling strategy prescribes each bidder to signal their most preferred item by bidding on it first. They stop bidding if no one else bids on this item. Hence, the BL collusive signaling strategy in this case yields the following outcome: item A is allocated to bidder 1 at $p_a = 1$, and item B is allocated to bidder 2 at $p_b = 1$. Note that the resulting allocation is inefficient.

If $k = 101$ (large complementarity), then the Vickrey competitive outcome is $p_a + p_b = 6 + 54 + 101 = 161$, with both items allocated to bidder 1. The BL collusive outcome coincides with the one described above (for $k = 0$) in this case.

Example 2 Let there be $n = 2$ bidders, with values drawn from the uniform distribution for both objects. Suppose that $a_1 = 38$, $b_1 = 8$, $a_2 = 36$, and $b_2 = 29$. If $k = 0$ (no complementarity), then the SEA competitive outcome is $p_a = 36$, with item A allocated to bidder 1, and $p_b = 8$, with item B allocated to bidder 2. The BL collusive signaling strategy prescribes each bidder to first bid on their most preferred item, and, if both bidders bid on the same item, keep bidding on it until one of the bidders switches to the other item; then stop. In this case, both bidders will start bidding on item A, until its price reaches 8, at which point bidder 2 will switch to item B. The rationale for bidder 2's switch is that he would prefer to win B at a price of 1 and a potential profit of 28 than to raise the bidding on A to 9 for a maximum potential profit of 27. Once the markets have been split, the bidders discontinue bidding. Hence, the BL collusive signaling strategy yields the following outcome: item A is allocated to bidder 1 at $p_a = 8$, and item B is allocated to bidder 2 at $p_b = 1$.

If $k = 101$ (large complementarity), then the Vickrey competitive outcome is $p_a + p_b = 38 + 8 + 101 = 147$, with both items allocated to bidder 2. If colluding bidders anticipate that the common complementarity term will be competed away under the Vickrey competitive outcome, then the BL collusive signaling strategy and the corresponding outcome are the same as in the no complementarity case: item A is allocated to bidder 1 at $p_a = 8$, and item B is allocated to bidder 2 at $p_b = 1$.

While BL consider only environments with no complementarity or with large complementarity, competitive equilibria (CE) in the neoclassical sense can be also characterized for 2-person markets with a common moderate complementarity (Sherstyuk, 2003). In moderate complementarity case, the minimal (lowest possible) CE price coincides with the Vickrey price whenever efficiency requires that both items be allocated to the same bidder. The strategies described by BL to support the Vickrey competitive equilibrium are quite complex. Our numerical simulations indicate that if the complementarity is common, unsophisticated "honest" bidding (bid on the object or the package that maximizes one's payoff at current prices) in most cases leads to CE outcomes in the simultaneous ascending bid auction, with the prices being the minimal (lowest possible) equilibrium prices. This gives us additional grounds to expect that if the bidders behave competitively in the laboratory setting, the outcomes will converge to the CE predictions for any value of the common complementarity term.

Examples 1 and 2 (continued) Let $k = 50$ (moderate complementarity). When efficiency requires to allocate both items to the same bidder, the minimal CE price coincides with the Vickrey price. For the bidder values given in examples 1 and 2 above, the CE outcome is the following. Example 1: $p_a = 6 + 50 = 56$, $p_b = 54$, thus $p_a + p_b = 6 + 54 + 50 = 110$ (the Vickrey price), with both items allocated to bidder 1. Example 2: $p_a = 38$, $p_b = 8 + 50 = 58$, thus $p_a + p_b = 38 + 8 + 50 = 96$ (the Vickrey price), with both items allocated to bidder 2. It is straightforward to check that honest bidding leads to the competitive outcomes for the cases $k = 0$, $k = 50$ and $k = 101$, in both examples.

BL strategies support collusive outcomes as equilibria even in a one shot auction game. If bidders interact with each other repeatedly and view each auction as part of a repeated game, then possibilities for bidder collusion are much richer than discussed by BL. In particular, collusion can be sustained at minimal prices, and bidders may split markets not only within periods, but also across periods. The latter strategy allows bidders to capture the complementarity term, which cannot be captured under collusion considered by BL, or under any market splitting within a period. These collusive outcomes, along with BL signaling outcomes, can be supported as equilibria in the repeated game using the threat to revert to competitive bidding in later periods if a deviation occurs. Many outcomes can be supported by repeated play. Here we focus on a few that are intuitively appealing and will be shown to correspond well to the data.

Observation 3 (Collusion based on repeated play) *The following collusive outcomes can be supported as Nash equilibria in the infinitely repeated auction game, provided that the bidders are patient enough:*

1. *(Minimal bid) The two items are allocated to two bidders, chosen at random in every period, at the minimal (seller reservation) prices.*
2. *(Bid rotation) Bidders take turns across periods in buying both items at the minimal prices, thus capturing the complementarity term.*

For examples 1 and 2 above, these predictions say that the items will be allocated at minimal prices $p_a = p_b = 1$, to either different bidders (minimal bid), or to the same bidder (bid rotation).

The variety of collusive equilibria in the repeated multiple object simultaneous ascending auction allows us to test the power of payoff dominance as an equilibrium selection criterion. Since there is asymmetric information concerning bidder valuations, we focus on the payoff relationships of different equilibria from an ex ante perspective. In other words, we compare collusive strategies in terms of each bidder's expected profits from the auction prior to observing their valuation draws. This approach is also necessary to generate advantages for strategies that rely on the repeated game for support. Observe that in the case of a strong common complementarity ($k > 100$), payoff-superiority predicts that bidders will prefer the bid rotation strategy ("Rotation") to the BL signaling strategy ("BL") since it allows them to capture the extra payoff. However, when there is no complementarity (or k is small), the BL signaling strategy will yield higher expected payoffs for the bidders than either rotation or minimal bid ("MinBid") strategy.

Observation 4 (Payoff ranking of equilibria with two bidders) *Suppose there are two bidders, $n = 2$, and the conditions on F for the existence on BL signaling equilibria are met.*

1. *If $k = 0$, then the expected value to the bidders of the BL strategy is strictly greater than the expected value of the minimal bid and bid rotation strategies. Hence, in terms of bidder ex ante expected payoffs, the equilibria can be ranked as follows:*

$$\text{BL} > \text{Rotation} \sim \text{MinBid} > \text{SEA}.$$

2. *If the complementarity term is moderate, $0 < k \leq 100$, then the ex ante expected value to the bidders of the bid rotation strategy is greater than the ex ante expected*

value of the minimal bid strategy:[5]

$$\text{Rotation} > \text{MinBid} > \text{Competitive}.$$

3. *If the complementarity term is large, $k > 100$, then the ex ante expected value to the bidders of the bid rotation strategy is greater than the ex ante expected value of the BL and minimal bid strategies. Hence,*

$$\text{Rotation} > \text{BL} > \text{MinBid} > \text{Vickrey}.$$

BL collusive signaling equilibria can be also supported when there are more than two bidders. However, BL equilibria offer less advantages to the bidders relative to the competitive outcome as the number of bidders increases. While the profitability of bid rotation and minimal bid decrease as well (since each individual bidder is less likely to be allocated the objects), the low (minimal) prices of these strategies continue to benefit the bidders. When the number of bidders is large, bid rotation and minimal bid payoff dominate BL even in the case of no complementarities.

Observation 5 (Payoff ranking of equilibria with large n) *Suppose the conditions on F for the existence of the BL equilibria are met and $k = 0$. Then, there exists an $\overline{N}$ such that for all $n > \overline{N}$, the equilibria can be ranked in terms of bidder ex ante expected payoffs as follows:*

$$\text{Rotation} \sim \text{MinBid} > \text{BL} > \text{SEA}.$$

If F is the uniform distribution, then rotation and minimal bid yield higher expected payoffs than BL strategy for all $n > 2$.

The experiments discussed below allow us to assess whether bidders are able to collude at all in such complex institutions, and whether they tend to select higher-payoff collusive strategies. Rather then testing a specific one-shot or repeated game equilibrium prediction, we consider subjects' ability to solve complex coordination problems and to achieve payoff-superior outcomes.

3 Experimental design

Groups of subjects participated in a series (up to 25) of computerized ascending auctions for two fictitious objects labeled A and B.[6] The group composition stayed the same throughout the session, and the ending period was not announced. The repeated game

[5] Following BL, we do not define collusive signaling strategies for moderate complementarity cases.

[6] Experimental instructions are available from the authors upon request.

setting served two purposes: (1) it allowed bidders to form consistent beliefs about each others' behavior, which was necessary for the collusive strategies discussed in the previous section, and (2) it augmented the set of collusive equilibria and allowed us to study payoff-dominance as equilibrium selection principle. Within an auction period, each object was sold in a separate auction run simultaneously for both objects. 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.[7] Both auctions ended only when no new bids had been placed on either object for a number of seconds.

Bidders' valuations for each object were integers between 1 and 100. Valuations were independently drawn from the discrete uniform distribution for each bidder, object and period. In some sessions bidders faced a complementarity for the two objects. This complementarity term was common to all bidders and announced at the beginning of the experiment.

Three treatment variables were considered: market size, complementarity, and experience. To test the effect of market size on the incidence of collusion, we conducted experimental auctions with two and five bidders. Van Huyck, Battalio and Beil (1990) (VBB) suggest that groups of size two can more easily coordinate on Pareto dominant Nash equilibria than can larger groups.[8] Thus, a larger group size may lead to less collusion for two reasons: less theoretical possibilities for collusion, as discussed in Section 2, and coordination failure, as observed by VBB. There is, however, a difference in the coordination problem faced by bidders in these auctions and the coordination games of VBB. In the pure coordination game, participants can avoid the risk of lower payoffs by selecting Pareto inferior outcomes. With larger group sizes risk dominance, due to strategic uncertainty, may be a more salient equilibrium selection criterion. In multi-object ascending auctions, however, a collusive, payoff superior, outcome is just as low risk as the competitive outcome; upon observed deviation, all bidders have the opportunity to revert to the competitive equilibrium. Even collusive strategies that are supported only by repeated play are relatively low risk since the bidders can revert to the competitive equilibrium in subsequent periods (or even in the same period). Therefore, our experiments test the ability of large groups to uncover complex strategies and solve coordination problems when

[7] In BL, the auction is assumed to proceed in a series of discrete rounds (or iterations) with a minimum bid increment, but the increment has to be arbitrarily small. Thus, the auction appears to be very much like a continuous ascending auction. We chose the continuous setting to allow experimental auctions to proceed at a reasonable rate. Importantly, the continuous nature of bidding does not shrink the equilibrium set of the BL model.

[8] Dufwenberg and Gneezy (2000) also found that experimental price competition markets with two firms tended to charge prices above the Bertrand prediction whereas markets with three or more competitors tended to closely resemble Bertrand competition.

the riskiness of playing a collusive strategy is relatively low, and risk dominance is not expected to be a salient factor.

To examine the effect of complementarities, we conducted sessions with either no complementarity, $k = 0$, a moderate complementarity, $k = 50$, or a strong complementarity, $k = 101$. BL show the existence of collusive signaling equilibria for no complementarity and strong complementarity cases in a non-repeated setting. As we discussed in Section 2, in a repeated setting there are a variety of collusive equilibria in both no complementarity and positive complementarity cases, but payoff rankings of various collusive strategies differ across complementarity treatments. Thus, addition of the moderate complementarity treatment allows us to better study how the presence and size of complementarity affects collusive equilibrium selection, and whether payoff dominance is in fact a salient equilibrium selection criterion.[9]

Previous studies have found that experience can greatly improve the ability of subjects to coordinate their behavior (Meyer et al. 1992). We considered previous experience with the auction institution as a treatment variable. Each session employed either all inexperienced subjects, who had not previously participated in any of these auctions, or all experienced subjects, who each had participated in one previous session. In no session did experienced and inexperienced subjects participate together in one market. In a number of early experimental sessions, we conducted experiments with groups of subjects who had participated in an earlier session under some treatment ("mixed" experience). In later sessions, experienced subjects were asked to participate in an identical auction institution in terms of the group size variable ("sorted" experience). Given the sophisticated nature of collusive strategies, experience may be necessary for the subjects to successfully coordinate on these strategies. Table 1 lists the number of experiments completed under each treatment variable combination.

TABLE 1 AROUND HERE

A total of 40 experimental sessions were completed using students, primarily undergraduates, at the University of Arizona (UArizona), California Institute of Technology (CIT), University of Hawaii (UH), University of Melbourne (Mel), and Pennsylvania State University (PSU). Up to five 2-person markets, or up to three 5-person markets were run independently in each session. A total of 120 independent markets were observed. Each session lasted no more than three hours, including about one hour for instructions and

[9] As will be shown in Section 4 below, collusion was rarely observed in the large complementarity treatment. Thus, not having a moderate complementarity treatment would have precluded us from studying the issue of collusive equilibrium selection, i.e., how bidder collusive strategies varied across the environments where collusion occurred.

practice. Typically, there was one practice period, but an additional practice was offered if subjects indicated that they were not ready to start. Depending upon the speed at which the auctions progressed, subjects completed between 6 and 25 auction periods in a session. For inexperienced subjects, an average of 17.1 and 13.4 periods were completed in the 2-person and 5-person markets respectively; the experienced sessions averaged 22.6 and 17.0 periods. Subject payments ranged between 7 and 43 dollars, with 5 dollars show-up fee.

4 Overall results: when does collusion occur?

The data on the overall performance of experimental auctions are summarized in Tables 2-4 and Figures 1 and 2. Table 2 summarizes experimental sessions by treatment and classifies experimental outcomes according to criteria to be described below. Tables 3-4 present descriptive statistics on market prices, efficiencies, and bidder gains, pooled by treatment. Examples of market price dynamics by treatment are provided in Figures 1 and 2. For expositional convenience, the prices we report are the sums of prices for both objects. Market efficiency, reported in Table 4, is defined as the ratio between the realized and maximal attainable social surplus. Table 4 also reports relative bidder gains, which is the proportion of the maximal attainable social surplus captured by bidders. Relative gains can be considered a measure of collusive effectiveness and coincide with the index of monopoly effectiveness as employed by Isaac and Walker (1985). The greatest profits a collusive group can hope to obtain is by achieving the efficient outcome and paying the auctioneer the minimal prices. This level of profits cannot, however, be supported as an equilibrium in either the single shot or infinitely repeated game.

TABLES 2-4 AND FIGURES 1-2 AROUND HERE

We compare the actual market performance with the following theoretical predictions, discussed in Section 2:

- **SEA competitive** outcome is the only competitive prediction for the 2N and 5N treatment, but it may also have some predictive power for markets with complementarities if bidders do not fully take the complementarity term into account.

- **Vickrey competitive equilibrium** outcome is the CE prediction for the positive complementarity treatments; we use this term to denote the corresponding CE prediction for both $k = 50$ and $k = 101$ cases.[10]

[10] For the moderate complementarity case, $k = 50$, depending on bidder value draws, competitive equilibrium outcomes may involve either allocating both objects to the same bidder, in which case the CE price is the “true” Vickrey price, or splitting the objects among bidders, in which case the CE price is

- **BL collusive signaling equilibrium** outcome is only characterized for 2N, 2Y101, and 5N treatments.[11]

- **Minimal bid** outcome allocates the objects randomly between bidders at the minimal price in every period.

- **Bid rotation** outcome allocates both objects to the same bidder at the minimal prices. The winning bidder varies across periods.

Based on average prices in each market, we classified market outcomes into collusive and competitive categories in the following way. Generally, we call a market COLLUSIVE if the average market price is below 50% of the SEA competitive prediction; we call a market COMPETITIVE otherwise. The collusive classification is based upon observed prices and, therefore, low seller revenue rather than any specific model of collusion. The motivation for using such a standard is that it allows us to identify situations where bidder strategies and outcomes differed significantly from the competitive outcome. Analysis of bidder strategies in the markets classified as collusive will be given in Section 5 below.

Even though theoretical competitive predictions differ between the no complementarity and positive complementarity cases (SEA and Vickrey outcomes, respectively), we choose the SEA benchmark to separate collusive from competitive outcomes in all cases. The reason is that in the presence of complementarities, observed prices may be below the Vickrey level due to phenomena other than anti-competitive behavior, such as bidder bounded rationality or the "exposure problem" (Bykowsky et al, 2000; Kagel and Levin, 2001b). We classify a market as collusive only if its low price level is unlikely to be attributed to other behavioral phenomena.

The COMPETITIVE markets are further classified into *competitive-SEA* category (if the average market price was within 15% of the SEA competitive prediction); *competitive-mixed* category (if the average market price was more than 15% above the SEA competitive prediction, but more than 15% below the Vickrey competitive prediction); or *competitive-Vickrey* category (if the average market price was within 15% of the Vickrey competitive prediction). Obviously, competitive-mixed and competitive-Vickrey categories only apply to positive complementarity treatments. Finally, the markets where the average market prices did not reach the SEA prediction, but were "too high" to be considered collusive

different from the Vickrey price. For the value draws used in the experiment, the CE price differed from the Vickrey price in at most 2 out of 25 periods in each market. For the sake of convenience, we therefore use the term "Vickrey outcome" to denote the CE outcome in all treatments with complementarities.

[11]For presentation clarity, collusive BL prices are displayed in the figures for the 2N treatment only (Figure 1). For the 2Y101 treatment, it is obvious that the BL prediction is out-performed by one of the alternative predictions for the markets displayed. In the 5N treatment, collusive BL prices coincide with the SEA competitive prices in 23 out of 25 periods.

(between 50% and 85% of the SEA competitive price), are classified into the *competitive-other* category.[12]

Classification results are given in Table 2. These results are robust to variations in threshold price levels used to distinguish between categories. Based on the data in the tables and the figures, we obtain the following conclusions. All statistical comparisons of proportions used to support the results utilize p-values generated by one-tailed Fisher exact tests.

Result 1 (Collusion in small size markets) *There was a significant amount of collusion in 2N and 2Y50 markets. Collusion does occur in small markets, and the presence of a common moderate complementarity does not hinder collusion.*

Support: Tables 2-4 and Figures 1-2. From Table 2, in the 2N treatment with inexperienced subjects, 3 out of 30 independent 2-person markets (10%) were collusive. For experienced subjects, 10 out of 18 markets (55%) were collusive. From Table 3, the prices, on average, were significantly below the SEA predictions at 5% confidence level for both experienced and inexperienced subjects. For experienced subjects, the average prices were 36.01% below the SEA predictions; the average bidder gains were 63.21%, as compared to 49.34% under the SEA prediction; the difference is significant at 2% confidence level (t-test, one-sided).

In the 2Y50 treatment, 5 out of 16 independent markets with inexperienced subjects (31%) were collusive. On average the actual prices were 47.48% below the Vickrey price and 1.88% below the SEA prediction; the standard deviation of 58.74 percentage points on the latter difference indicates significant heterogeneity in prices across markets (Table 3). □

Result 2 (Collusion with large numbers) *Collusion is a small numbers phenomenon: no collusion was observed in 5-person markets.*

Support: Tables 2-4 and Figures 1-2. All markets in 5N and 5Y treatments are classified as competitive (Table 2). The mean market price in the 5N treatment is 1.63% percent above the SEA competitive prediction, with a standard deviation of only 7.5 percentage points; market efficiency is at 98.25% (with a standard deviation of 1.93% only), and relative bidder gains are at 15.27%, as compared to the SEA prediction of 18.84%. In 5Y50 and

[12] The markets in this "other" category may be characterized by the lack of convergence to either competitive or collusive outcomes, or may hide some forms of "learning to collude." For example, in 2N Market 1-201 CIT, observed market price switched from the competitive to BL levels after period 14 (see Figure 1). We take a conservative approach in detecting collusion and classify markets as collusive only if the overall average price was far below the SEA prediction. We are grateful to an anonymous referee for this observation.

5Y101 treatments, the average market prices, market efficiencies and bidder gains are all in the range between the SEA and Vickrey competitive predictions, and a distance from any of the collusive predictions (Tables 2-4); for experienced markets in 5Y101, the average price is only 1.7% below the Vickrey prediction. In principle, the lack of collusive outcomes in 5-person markets could be due either to fewer theoretical possibilities for collusion, as stated in Observation 2(2), or because bidders did not play a collusive equilibrium at all. To discriminate between these possibilities we considered whether collusion occurred when it was theoretically possible according to BL. In all 13 periods under the 5N treatment where the SEA and BL predictions differed,[13] the market prices were at or above the SEA prediction and away from the BL prediction. Therefore, with some confidence, we can say that play in 5-person markets is most closely characterized as competitive. Pooling across experience treatments, the difference in proportions of collusive markets between 2N and 5N treatments is highly significant (p-value = 0.048). □

Result 3 (Effect of experience) *Experience in the same size market ("sorted") increases the incidence of collusion in 2-person markets. Experience in any size market ("mixed") does not always increase the incidence of collusion. That is, experience is market-size specific.*

Support: Table 2. In 2N markets, the percentage of collusive markets increased from 10% among inexperienced subjects (3 out of 30 markets) to 58.3% among subjects experienced in the same size market (7 out of 12 markets); the difference in proportions is highly significant (p-value=0.0023). In 2Y101 markets, all 16 markets with inexperienced subjects were competitive, but 2 out of 11 markets with experienced (sorted) subjects were collusive. In 2Y50 markets, 31.25% of markets (5 out of 16) with inexperienced subjects were collusive, but all 5 markets which employed "mixed" experienced subjects were all competitive. □

It is known from other experiments on cooperation that previous experiences may affect how subjects behave in the future (e.g., Davis and Holt, 1993). A possible explanation of why experience was market-size specific in our experiments may be based on subjects' bounded rationality. Suppose an inexperienced subject first experiments with various collusive and non-collusive strategies in the auctions, but by the end of the session converges to a certain strategy which she considers optimal given her experience. This experience

[13] BL show that in 5-person markets with no complementarity, signaling collusive outcomes will differ from SEA competitive outcomes only in about 5% of the cases, depending on bidder value draws. For the value draws used in our experiment, BL and SEA outcomes differed only in periods 15 and 18. Since some 5N markets with inexperienced subjects were repeated for less than 18 periods, we have only 13 such observations in total.

may then carry over into the next auction session in which she participates. Since a subject with a previous experience in a 2-person market was more likely to see collusion attempts and consider their benefits, she would be more likely to try to collude again. A subject with a previous experience in a 5-person market, having observed overwhelmingly competitive behavior there, may be less likely to collude even in a smaller size market.

Result 4 (Collusion with large complementarities) *The presence of a large complementarity was detrimental for collusion: there was very little collusion in 2-person markets with large complementarities.*

Support: Table 2. All 16 independent markets in 2Y101 treatment with inexperienced subjects were competitive. The difference in proportions of collusive markets between 2Y101 inexperienced markets and all other 2-person inexperienced markets is significant at 7.71% level. The proportion of collusive markets in the 2Y101 experienced (sorted) treatment was only 18.2% (2 out of 11 markets), which is significantly below the proportion of collusive markets in 2N and 2Y50 experienced (sorted) treatments (p-value=0.041).□

The approach adopted for detecting collusion in positive complementarity treatments is rather conservative. A market is considered collusive only if the average prices are far below the SEA level, even though the theory prescribes using the Vickrey competitive benchmark. In fact, as it is evident from Tables 2-4, the average prices and bidder gains in inexperienced and experienced (mixed) competitive markets with complementarities were half-way between the SEA and the Vickrey predictions, and many markets fell into the *competitive-mixed* category. A natural question is then whether these lower prices in small markets with positive complementarities were due to some non-collusive factors, such as bidder bounded rationality[14] and the exposure problem, or to subjects' attempts to suppress price competition in order to achieve higher bidder gains. The following evidence argues against attributing prices below Vickrey levels in 2Y101 markets to subjects' attempts to suppress price competition. First, these markets were rarely successful in achieving collusive price levels (Result 4). Second, the proportion of *competitive-Vickrey* markets among all markets classified as competitive increased significantly with experience (Table 2). Finally, deviations from the Vickrey outcome towards the SEA outcome were observed also in 5Y treatments, where we know, from the 5N treatment, that competition was the only outcome. Therefore it is likely that most of the price deviation from the Vickrey prediction in 2Y101 markets were due to non-collusive factors, rather than attempts to suppress price competition.

[14]From casual observations of bidder behavior during the experiments, we know that some bidders had difficulties realizing that they should bid above their separate item valuations in treatments with complementarities, both in 5-person and 2-person markets.

5 Individual behavior and equilibrium selection

The pooled data indicate that collusion does occur in small size markets with multiple objects. This provides a partial understanding of the equilibrium selection issue; in some cases bidders select an equilibrium that is payoff superior to the competitive outcome. The final step is to address the equilibrium selection issue when bidders did collude. We consider whether bidders in collusive markets were able to coordinate on payoff superior collusive equilibria. In order to discriminate among different collusive theories, we take a closer look at individual strategies employed by the bidders.

For the purposes of this analysis we focus on the markets classified as COLLUSIVE (average market price is less than 50% of the SEA prediction; 21 markets total). While there may be interesting equilibrium selection issues in the COMPETITIVE observations, the small differences in prices and allocations observed in these situations makes formal identification of likely strategies difficult. As an example, in the 5N treatment, the BL and SEA predictions are almost always the same.

Each collusive strategy described in Section 2 has two essential aspects: (1) prescriptions for bidding and the resulting allocations and prices on the equilibrium path; (2) specification of how collusive outcomes are enforced as equilibria (i.e., out of equilibrium play). While the theories we consider differ in the predictions on the equilibrium play (signaling, bid rotation or minimal bid), they suggest a similar enforcement strategy (threat of retaliation, either immediately after a deviation or in the future periods). To discriminate among theories, we first focus on how allocation and pricing decisions are achieved in successful collusive markets. We will turn to the enforcement issue at the end of this section.

We begin by looking at the qualitative predictions of the signaling model of tacit collusion. Observations of real world auctions and the BL theory predict signaling of preferred markets in early bids. We consider a bidder to be signaling in a given period if one of the following conditions is met: (1) they bid on their highest valued object first, (2) they bid on both objects at the same time but placed a strictly higher bid on their highest valued object, or (3) they had the same valuation for both objects.[15] Table 5 lists the proportion of initial bids that are consistent with signaling, by treatment.

TABLE 5 AROUND HERE

Result 5 (Signaling in markets with no complementarities) *There was a significant amount of signaling in 2-person markets without complementarities. More signaling*

[15] When a bidder has identical valuations across markets, it is impossible to reject the possibility that the bidder is signaling.

was observed in markets classified as collusive.

Support: The mean proportions of initial bids that can be classified as signaling are listed in Table 5. Since a bidder who is randomly selecting an initial object to bid on will appear to be signaling half of the time, we compare the mean signaling proportion under each treatment to 50%. In the 2N collusive markets (both inexperienced and experienced), the level of signaling is significantly greater than 50%. In the 2N treatment overall, 34 out of 96 (35%) subjects placed signaling bids at least 75% of the time. Further, we find that the level of signaling is highly related to the success of collusion. In the no complementarity treatment, 20 out of 26 (77%) subjects in 2N markets that were classified as collusive placed signaling bids at least 75% of the time compared to only 14 out of 70 (20%) for markets classified as competitive. This difference is significant at any reasonable level (p-value = 0.000). In both the 2N inexperienced and 2N experienced treatments, the mean level of signaling when collusion was observed was significantly greater than under the competitive outcomes (Table 5). □

While Table 5 indicates that there is significant signaling in no complementarity treatments, the particularly low levels of observed signaling in some of the complementarity treatments suggests that a signaling strategy alone cannot explain all data well. For example, in the 2Y101 treatments, markets classified as collusive only appeared to be signaling 30% of the time. In Tables 6 and 7 we examine how well various strategies discussed in Section 2 fit the data. We first compare the observed final allocations in each period with four possible strategies:

1. Rotation – one bidder is allocated both objects.
2. Split – each bidder is allocated one object (consistent with minimal bid and BL).
3. BL – the bidder predicted by the BL signaling outcome is allocated each object.
4. Efficient – the objects are allocated to the bidders required to obtain the maximal social surplus (usually consistent with competitive models).

In Table 6 we report the mean (across markets) of the proportion of periods in which the allocation is consistent with each strategy. Different strategies also predict different prices for the objects. A stricter standard is to require that the allocation and prices match those predicted by the strategy. Since bidders often started with bids that were somewhat greater than the minimal bid and placed bids in quite large increments (one experimental dollar or greater), we classified a price realization as being consistent with a particular strategy if the sum of the winning bids on the two objects were within 10 experimental dollars of the prediction. We compare the five theoretical predictions identified in Section 2 to the observed allocations and prices. The mean proportion of periods in each market consistent with these strategies are listed in Table 7.

TABLES 6-7 AROUND HERE

Result 6 (Bidder behavior in markets with complementarities) *Among 2Y markets classified as collusive, bid rotation dominates all other descriptions of bidder behavior.*

Support: Tables 6-7. Across the eight 2Y50 and 2Y101 experiments classified as collusive, more than 70% of the observed allocations have one bidder winning both objects (Table 6). This is strong evidence against the BL signaling and minimal bid strategies, which require splitting of the markets in all periods. However, the Vickrey competitive outcome would also predict winning both objects in all 2Y101 periods and the vast majority of the 2Y50 periods. When the price information is also considered (Table 7), none of the data are consistent with the Vickrey prices. The proportion of the data consistent with rotation also drops when the price information is added, but rotation remains the strategy that is consistent with the data the greatest proportion of the time. □

It is clear that in 2Y experiments bidders coordinate on the more profitable rotation strategy that enables them to capture the complementarity term; the complementarity would be lost under any splitting arrangement such as minimal bid or BL. However, in 2N experiments, bid rotation no longer has this advantage; the BL signaling strategy yields higher expected payoffs.

Result 7 (Bidder behavior in markets with no complementarity) *Among 2N markets classified as collusive, the allocation of objects is often consistent with the BL signaling strategy.*

Support: Tables 6-7. In the 13 2N markets classified as collusive, bidders split markets in over 80% of the periods (Table 6). While this is a strong rejection of bid rotation, a number of collusive strategies, such as minimal bid and BL signaling, are consistent with these allocations. Since the BL predicted allocation is a proper subset of the split prediction it is not surprising that more allocations are consistent with the split classification. If bidders were actually utilizing a random minimal bid strategy, we would expect that half of the time the split classification will be consistent with the BL signaling strategy as well. In 12 out of 13 markets, the proportion of splitting observations that are consistent with the BL signaling strategy as well is far greater than half. The introduction of prices drives a wedge between the minimal bid and BL strategies; minimal bid always predicts the minimum bid level, but BL signaling predicts higher bids in the case of conflict (about half the time). Not surprisingly, the performance of both strategies declines with the inclusion of prices. The relative performance of each of the two market splitting strategies does not change markedly. Pooling across collusive 2N experiments, the null hypothesis that the mean difference of observed prices and the BL prices is zero cannot be rejected at a 5% level; the same hypothesis can be rejected for the mean difference between observed prices and minimal bid prices. In all collusive experiments, the average price is considerably higher than the minimal bid prediction. □

The above results allow us to discriminate among collusive theories and discuss the power of payoff dominance as an equilibrium selection principle. The relative strength of the BL strategy in the 2N treatment suggests that bidders, when they successfully collude, are strategically splitting markets. When considered along with the high coincidence of signaling and collusion (Result 5), this result is strong evidence that bidders can coordinate on payoff superior collusive outcomes solely through the bidding process. We speculate that it is this ability to increase expected profits that enables successful tacit collusion. When combined with the observation that bidders utilize a rotation strategy in positive complementarity experiments (Result 6), these results provide evidence in favor of payoff dominance as a selection principle. In the no complementarity treatments, when the BL signaling strategy is the best strategy for the bidders, bidders follow it, and in the complementarity treatments, when the expected profit of the rotation strategy dominates the BL signaling strategy, bidders favor rotation. In 7 out of 8 of the collusive markets with a positive complementarity, relative bidder gains - a measure of bidder profitability - were greater than those predicted by the BL strategy.[16]

Finally, we turn to the issue of collusion enforcement. When collusive agreements are broken, bidders must be willing to punish deviant bidders by reverting to the competitive bidding. It is difficult to distinguish retaliatory moves to the competitive equilibrium from purely competitive bidding. However, a clue into the willingness of some bidders to punish defectors is provided in the data.

Result 8 (Overbidding) *Some bidders are willing to bid above their values. The persistence of this behavior amongst experienced bidders suggests that bidders are punishing non-collusive behavior.*

Support: In the 2N and 5N treatments, 45 out of 151 (30%) bidders placed bids in two or more periods that were above their valuations for an object. In the complementarity

[16]In 6 out of 8 of the observations, relative gains are closest to the expected relative gains under the rotation strategy.

treatments, 34 out of 152 (22%) bidders placed at least two combined bids that exceeded their valuations with the added payoff. Some of these bids might be attributed to mistakes, but we would then expect overbidding to decline as bidders gained experience. Overbidding actually increased with experienced subject. In the no complementarity case, 15 out of 46 (33%) experienced bidders overbid at least twice and, in the complementarity case, 16 out of 52 (31%) of experienced bidders overbid. The difference in proportion of overbidding in experienced and inexperienced groups is not significant for the no complementarity treatment but is significant for complementarity treatment (p-value = 0.020). □

While we are unaware of theories which would propose bidding at a loss in order to punish non-collusive bidders, we observe such behavior at times. Such behavior may be rationalized by the repeated nature of our auction. It may also be attributed to bidder bounded rationality, where one bids above their value just to make a point that they are dissatisfied with the other bidder's non-cooperative behavior. Even so, overbidding is only suggestive of punishment behavior. If bidders are using such a strategy, we should expect to not see overbidding when both bidders are coordinating their behavior. Of the 79 bidders across all treatments who placed above value bid at least twice, only one was in a market that was classified as collusive. On the other hand, bidders should only be willing to punish when the opposing bidders have already deviated from the collusive strategy. We classify bidders as having deviated from a collusive strategy if in the current period they have placed bids in excess of five experimental dollars on both objects. [17] In the no complementarity treatment, above value bidding follows a deviation by the other bidder(s) 83% of the time, and in the complementarity treatments, overbidding ocurrs subsequent to a deviation 99.6% of the time. The willingness of the bidders to respond to a deviation *within* a period is noteworthy since it suggests that the use of punishment at times is not inconsistent with one shot BL theory. Finally, if bidders were making errors, we would not expect them to repeat their mistakes. Contingent upon making an above value bid, bidders averaged placing 1.8 above value bids per period in the no complementarity treatments and 1.4 above value bids per period in the complementarity treatments. In the no complementarity treatment, one bidder averaged as high as 6 over value bids per period. Overbidding, therefore, appears to be consistent with the utilization of punishment strategies by at least some bidders.

[17] Observation of prices above five on both units is clearly inconsistent with an efficient bid rotation scheme, and the BL strategy with two bidders. These prices, however, may not be inconsistent with the BL strategy with five bidders.

6 Conclusions

We found that collusion occurs in experimental auctions for multiple objects as long as the number of bidders is small. The presence of a common moderate complementarity does not eliminate collusion. The incidence of collusion increases with bidder experience in small size markets.

A closer examination of the individual data provides insights into the behavior supporting collusive outcomes. Especially in the no complementarity treatments, signaling and retaliatory bidding are recognized by bidders as tools to support collusive play. Thus, outcomes of these auctions, when classified as collusive, often match the BL signaling model quite well. However, when there is a positive complementarity, there is the added concern of "leaving money on the table" in the form of an uncaptured complementarity term. Successful collusive bidders appear to avoid this by utilizing a bid rotation strategy.

These results provide additional insights into the experimental equilibrium selection literature. In this literature, small groups of experimental subjects are often capable of coordinating on Pareto superior Nash equilibria. Here we demonstrate that small groups of bidders sometimes coordinate on ex ante Pareto improving perfect Bayes Nash equilibria in an environment where the strategy space is significantly richer and there is private information. This coordination, however, is more difficult to obtain than in the simpler settings previously studied. Few groups coordinate on something other than the competitive outcome; only about 20% of all 2-person markets were classified as collusive. In addition, previous experience appears to be a significant factor in driving selection of an outcome that dominates competition. Finally, the complementarity treatment condition allowed us to examine whether bidders, when colluding, select payoff superior strategies. Remarkably, we found that collusive strategies appear to vary systematically with the complementarity treatment, as predicted by payoff dominance as a selection principle.

We also provide evidence on the failure of large groups of bidders to coordinate on payoff-superior outcomes. In our setting, this coordination failure cannot be fully attributed to a higher riskiness of collusive outcomes, as in the other studies. An ascending auction format allows each bidder to observe a deviation from a collusive strategy and to immediately retaliate in return; hence collusion attempts are relatively low-risk in any size group. Yet, we find that large groups gravitate towards the payoff-inferior competitive prediction. This indicates that in our context the failure of 5-person markets to coordinate on a collusive outcome cannot be fully attributed to strategic uncertainty and may be due to other factors, such as lower gains from collusion or other coordination problems that emerge in large groups.

These results suggest two future avenues of research on collusion in auctions. First, given enough time, some groups manage to collude while others do not. The information on why some groups are successful must be contained in the dynamics of the bidding process. Was the collusive outcomes the result of well planned behavior by a few insightful bidders, or was it the result of some fortuitous event? Would all groups end up colluding if given enough time? Second, the simultaneous ascending bid auction is one particular institution for the sale of multiple objects; other institutions might be more or less susceptible to collusion. For example, in a first-price sealed bid auction, bidders can no longer use the BL signaling strategy. Would collusion be observed experimentally? While Kwasnica (2000) tells us that we should expect collusion when communication is allowed, we are not aware of any studies that look for the formation of tacit collusion under this institution. An English clock auction for multiple objects may also decrease collusion by making coordination among bidders more difficult; yet, Grimm and Englemann (2001) report some tacit collusion in experimental ascending clock auctions for homogeneous objects. Increased experimental and theoretical work along these lines could provide us with a thorough understanding of relative likelihood of collusion under different multi-object auction formats. An understanding of how collusive strategies are manifested in the lab may also help to recognize collusive activities of real bidders in the field.

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No. of bidders	Complementarity	Notation	Subject pools	No.of independent markets	
				Inexperienced	Experienced
2	None	2N	Mel,CIT,PSU,UH	30	18
2	50	2Y50	Mel,CIT	16	6
2	101	2Y101	PSU,UH	16	11
5	None	5N	Mel,CIT,PSU	9	2
5	50	5Y50	Mel	3	0
5[a]	101	5Y101	UArizona	5	4

[a]Two inexperienced markets and one experienced market in 5Y101 treatment had only 3 bidders due to no-shows. All predictions below are adjusted accordingly.

Table 1: Number of experimental markets by treatment

Treatment	Subject pool	No. of indep. markets	No. of periods	No. of markets by outcome				
				compet-SEA	compet-mixed	compet-Vickrey	compet-other	collusive
2N	Mel,CIT,PSU,UH	30	6 -- 22	21	n/a	n/a	6	3
2N exp (mixed)	Mel	6	17 -- 25	3	n/a	n/a	--	3
2N exp (sorted)	CIT,PSU,UH	12	16 -- 25	5	n/a	n/a	--	7
2Y50	Mel,CIT	16	9 -- 25	1	7	2	1	5
2Y50 exp (mixed)	Mel	5	12 -- 25	--	4	1	--	--
2Y50 exp (sorted)	CIT	1	25	--	--	--	--	1
2Y101	PSU,UH	16	15 -- 25	--	11	5	--	--
2Y101 exp (sorted)	PSU,UH	11	12 -- 25	--	3	6	--	2
5N	Mel,CIT,PSU	9	6 -- 25	9	n/a	n/a	--	--
5N exp (mixed)	Mel	1	15	1	n/a	n/a	--	--
5N exp (sorted)	PSU	1	22	1	n/a	n/a	--	--
5Y50	Mel	3	7 -- 12	--	1	2	--	--
5Y101	U Arizona	5	9 -- 12	--	3	2	--	--
5Y101 exp (sorted)	U Arizona	4	10 -- 21	--	0	4	--	--

"**exp (mixed)**": all subjects have participated in an earlier session

"**exp (sorted)**": all subjects have participated in an earlier session with the same size market

Table 2: Summary of experimental sessions

			Price AB, francs					% deviation	% deviation
Markets	No. of mkts		actual	SEA	Vickrey	BL	MinBid	from SEA	from Vickrey
2N markets									
Inexperienced	30	mean	58.95*	64.52	n/a	14.28	2	-7.98	n/a
subjects		stddv	16.58	8.44	n/a	2.5	0	24.39	n/a
Experienced, all	18	mean	41.96*	66.74	n/a	13.66	2	-36.01	n/a
		stddv	30.97	4.8	n/a	2.45	0	48.93	n/a
2Y50 markets									
Inexperienced	16	mean	62.72	64.07	120.51	n/a	2	-1.88	-47.48
subjects		stddv	41.25	11.17	15.52	n/a	0	58.74	33.47
Experienced, all	6	mean	75.51	64.97	124.72	n/a	2	15.74	-39.58
		stddv	34.73	5.39	8.61	n/a	0	50.62	27.05
2Y101 markets									
Inexperienced	16	mean	128.53	66.31	176.57	14.48	2	93.69	-27.32
subjects		stddv	31.71	5.93	5.38	2.16	0	44.24	17.26
Experienced,	11	mean	130.71	66	177.06	13.092	2	98.34	-26.35
all sorted		stddv	68.68	3.63	3.9	2.0616	0	103.88	38.52
5N markets									
Inexperienced	9	mean	133.48	131.21	n/a	129.43	2	1.63	n/a
subjects		stddv	12.49	4.22	n/a	2.59	0	7.5	n/a
Experienced, all	2	mean	134.99	131.78	n/a	128.86	2	2.44	n/a
		stddv	1.15	0.13	n/a	0.76	0	0.76	n/a
5Y50 markets									
Inexperienced	3	mean	155.87	129.42	167.28	n/a	2	20.43	-6.83
subjects		stddv	9.86	2.31	3.71	n/a	0	6.83	5.21
5Y101 markets									
Inexperienced	5	mean	170.96	114.01	203.44	n/a	2	50.87	-16.15
subjects		stddv	19.99	17.64	13.98	n/a	0	9.38	4.91
Experienced,	4	mean	210.23	124.11	213.29	n/a	2	69.69	-1.7
all sorted		stddv	25.02	16.68	11.94	n/a	0	3.43	6.68

Theoretical predictions differ slighly across sessions since they are based on the actual bidder values drawn.
*Significantly below SEA prediction at 5% level.

Table 3: Market prices by treatment

			Efficiency, percent						Relative gains, percent					
Treatment	No. mkts		Actual	Vickrey	SEA	BL	MinBid	Rotation	Actual	Vickrey	SEA	BL	MinBid	Rotation
2N treatment														
Inexperienced	30	mean	94.63	n/a	100	92.74	74.18	74.18	47.49	n/a	49.71	80.94	73.71	73.71
subjects		stddv	4.99	n/a	0	2.04	6.41	6.41	12.29	n/a	5.91	2.72	6.49	6.49
Experienced,	6	mean	97.28	n/a	100	93.08	75.27	75.27	61.39	n/a	48.7	82.3	74.83	74.83
mixed		stddv	3.14	n/a	0	1.93	6.54	6.54	22.08	n/a	6.23	2.63	6.64	6.64
Experienced,	12	mean	93.74	n/a	100	92.66	75.04	75.04	63.21	n/a	49.34	81.21	74.61	74.61
sorted		stddv	4.48	n/a	0	2.16	4.07	4.07	22.89	n/a	3.45	2.78	4.15	4.15
2Y50 treatment														
Inexperienced	16	mean	91.17	100	89.26	n/a	54.7	87.21	55.37	25.91	53.05	n/a	54.09	87.05
subjects		stddv	4.49	0	1.91	n/a	5.89	4.95	21.63	3.77	5.83	n/a	5.96	5
Experienced, all	6	mean	93.31	100	89.14	n/a	54.37	88.53	49.05	25.66	52.4	n/a	53.79	88.4
		stddv	3.03	0	0.92	n/a	6.02	4.34	20.1	4.63	3.42	n/a	6.1	4.38
2Y101 treatment														
Inexperienced	16	mean	90.35	100	79.61	53.46	43.33	90.58	32.71	19.26	50.83	46.95	42.78	90.5
subjects		stddv	6.51	0	1.51	1.86	3.48	3.15	13.63	2.08	3.77	2.28	3.51	3.18
Experienced,	11	mean	94.34	100	80.01	53.9	42.71	91.62	35.68	19.87	51.77	48.05	42.17	91.55
all sorted		stddv	5.34	0	0.92	1.73	2.11	2.32	26.76	2.05	1.52	1.5	2.13	2.35
5N treatment														
Inexperienced	9	mean	98.25	n/a	100	100	59.99	59.99	15.27	n/a	18.84	20.02	59.47	59.47
subjects		stddv	1.93	n/a	0	0	0.46	0.46	5.62	n/a	1.11	1.65	0.47	0.47
Experienced, all	2	mean	99.64	n/a	100	100	59.72	59.72	16.78	n/a	19.19	21.16	59.21	59.21
		stddv	0.16	n/a	0	0	0.16	0.16	1.78	n/a	0.85	1.24	0.16	0.16
5Y50 treatment														
Inexperienced	3	mean	96.18	100	85.46	n/a	47.51	73.06	17.9	15.64	20.91	n/a	46.97	72.79
subjects		stddv	3.52	0	0.11	n/a	0	0.47	0.65	0.33	0.01	n/a	0.02	0.47
5Y101 treatment														
Inexperienced	5	mean	91.35	100	76.39	n/a	37.96	80.85	20.21	14.65	29.58	n/a	37.67	80.93
subjects		stddv	5.5	0	6.63	n/a	0.83	2.41	5.85	2.88	11.44	n/a	1.07	2.75
Experienced,	4	mean	97.16	100	73	n/a	38.94	79.74	13.33	14.71	24.08	n/a	38.59	79.72
all sorted		stddv	2.11	0	2.24	n/a	1.61	2.74	8.39	2.35	7.38	n/a	1.87	3.03

* Theoretical predictions differ slighly across sessions since they are based on the actual bidder values drawn

Table 4: Efficiency and bidder gains by treatment

Treatment	No of Individuals	Outcome		Average
2N inexperienced	54	COMPETITIVE	mean	0.50
			stddv	0.27
	6	COLLUSIVE	mean	0.69*
			stddv	0.22
2N experienced	16	COMPETITIVE	mean	0.38
			stddv	0.22
	20	COLLUSIVE	mean	0.82*
			stddv	0.15
2Y50 inexperienced	22	COMPETITIVE	mean	0.43
			stddv	0.24
	10	COLLUSIVE	mean	0.41
			stddv	0.28
2Y50 experienced	10	COMPETITIVE	mean	0.36
			stddv	0.25
	2	COLLUSIVE	mean	0.73
			stddv	0.21
2Y101 inexperienced	32	COMPETITIVE	mean	0.48
			stddv	0.27
2Y101 experienced	18	COMPETITIVE	mean	0.26*
			stddv	0.22
	4	COLLUSIVE	mean	0.30
			stddv	0.28

Table 5: Mean (across individuals) proportion of initial bids that are consistent with signaling. * – significantly different than 0.5 at the 5% level.

Treatment	No of Markets	Outcome		Rotation	Split	BL	Efficient
2N inexperienced	27	COMPETITIVE	mean	0.50	0.49	0.48	0.74
			stddv	0.15	0.15	0.14	0.15
	3	COLLUSIVE	mean	0.16	0.84	0.63	0.31
			stddv	0.17	0.17	0.25	0.13
2N experienced	8	COMPETITIVE	mean	0.53	0.47	0.46	0.88
			stddv	0.04	0.04	0.03	0.08
	10	COLLUSIVE	mean	0.11	0.88	0.78	0.53
			stddv	0.13	0.12	0.12	0.17
2Y50 inexperienced	11	COMPETITIVE	mean	0.81	0.19	NA	0.64
			stddv	0.16	0.16	NA	0.15
	5	COLLUSIVE	mean	0.76	0.22	NA	0.54
			stddv	0.19	0.16	NA	0.07
2Y50 experienced	5	COMPETITIVE	mean	0.77	0.23	NA	0.65
			stddv	0.07	0.07	NA	0.11
	1	COLLUSIVE	mean	1.00	0.00	NA	0.56
2Y101 inexperienced	16	COMPETITIVE	mean	0.83	0.16	0.15	0.64
			stddv	0.16	0.16	0.15	0.12
2Y101 experienced	9	COMPETITIVE	mean	0.95	0.05	0.04	0.79
			stddv	0.06	0.06	0.06	0.18
	2	COLLUSIVE	mean	0.92	0.08	0.06	0.54
			stddv	0.06	0.06	0.03	0.14

Table 6: Mean of the proportion of period allocations for each market consistent with models.

Treatment	No of Markets	Outcome		Rotation	MinBid	BL	SEA	Vick
	27	COMPETITIVE	mean	0.04	0.04	0.05	0.45	NA
2N			stddv	0.08	0.08	0.09	0.22	NA
inexperienced	3	COLLUSIVE	mean	0.04	0.58	0.42	0.08	NA
			stddv	0.08	0.33	0.17	0.04	NA
	8	COMPETITIVE	mean	0.05	0.01	0.01	0.60	NA
2N			stddv	0.03	0.03	0.01	0.23	NA
experienced	10	COLLUSIVE	mean	0.02	0.66	0.50	0.11	NA
			stddv	0.04	0.19	0.14	0.09	NA
	11	COMPETITIVE	mean	0.09	0.02	NA	0.17	0.18
2Y50			stddv	0.12	0.05	NA	0.15	0.18
inexperienced	5	COLLUSIVE	mean	0.54	0.16	NA	0.04	0.00
			stddv	0.37	0.15	NA	0.04	0.00
2Y50	5	COMPETITIVE	mean	0.03	0.00	NA	0.17	0.14
experienced			stddv	0.04	0.00	NA	0.16	0.08
	1	COLLUSIVE	mean	0.68	0.00	NA	0.00	0.00
2Y101	16	COMPETITIVE	mean	0.04	0.00	0.01	0.08	0.20
inexperienced			stddv	0.13	0.01	0.03	0.13	0.18
	9	COMPETITIVE	mean	0.05	0.02	0.02	0.02	0.43
2Y101			stddv	0.07	0.05	0.05	0.07	0.26
experienced	2	COLLUSIVE	mean	0.90	0.06	0.04	0.02	0.00
			stddv	0.03	0.08	0.06	0.03	0.00

Table 7: Mean of the proportion of period allocations and prices for each market consistent with different models.

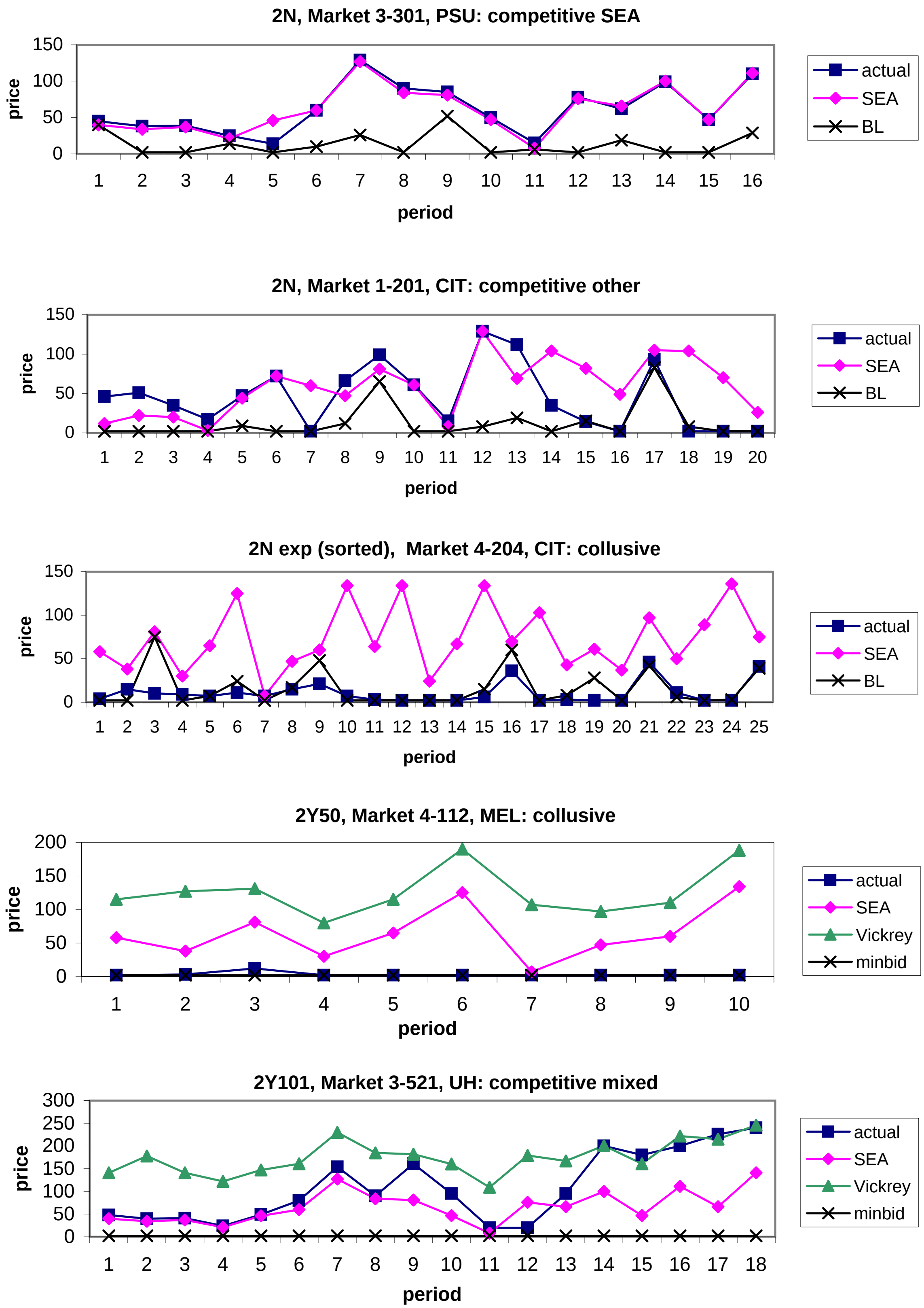

Figure 1: Examples of market price dynamics in 2-person markets.

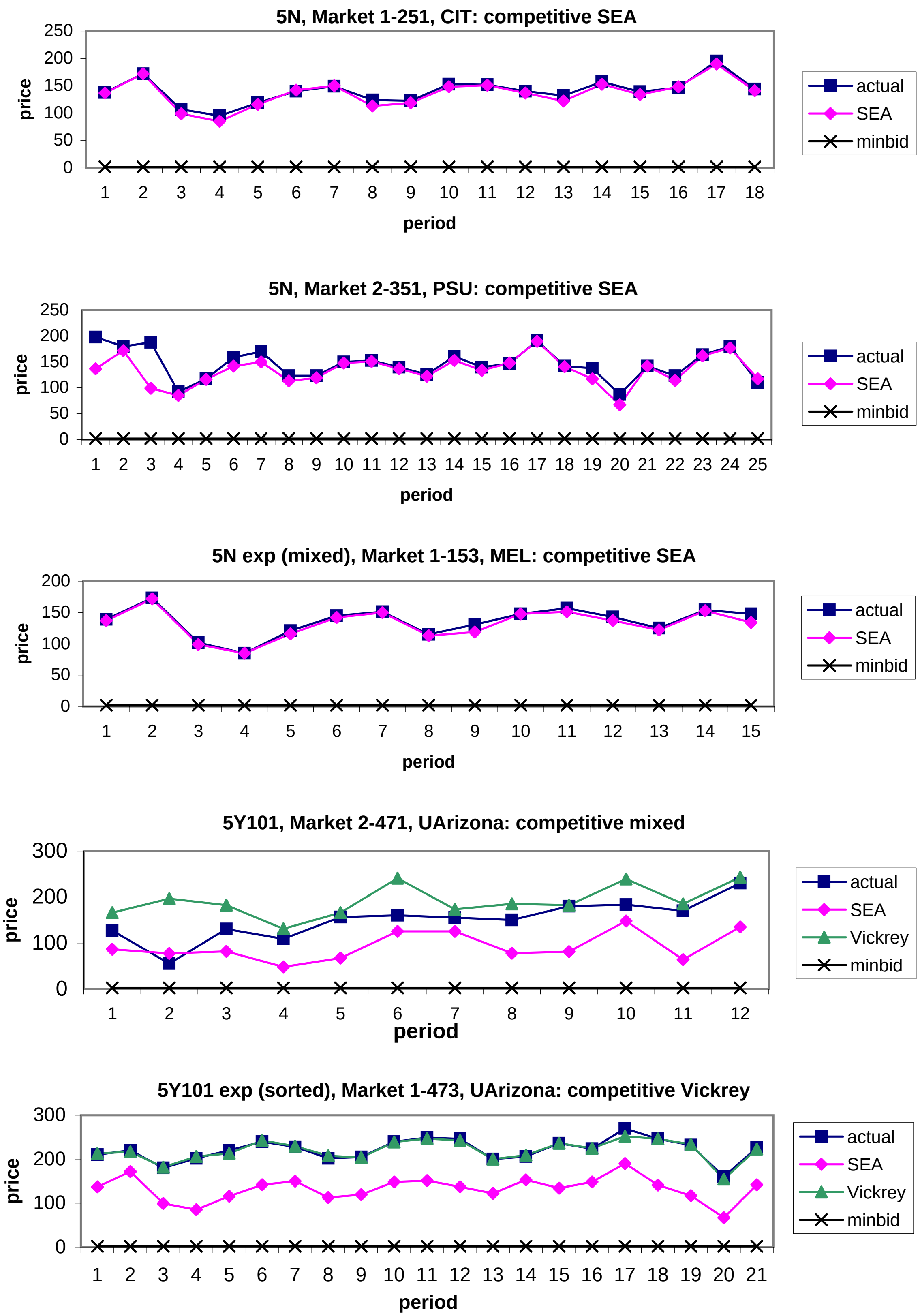

Figure 2: Examples of market price dynamics in 5-person markets.