

Ascending Prices and Package Bidding: Further Experimental Analysis

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Abstract

We explore the performance of multi-round, price-guided combinatorial auctions for a previously untested class of value profiles in which synergies arise from shared fixed costs. We find that, in many cases, a simulator that bids straightforwardly does well in predicting auction performance, but exceptions arise because human bidders sometimes rely on cues besides prices to guide their package selection and because they sometimes bid aggressively on items for which they have no value in order to increase payments by bidders seeking complementary packages. In our experiments, this latter behavior not only raises prices, but can also improve efficiency by mitigating the threshold problem. Comparisons between a combinatorial clock auction (CCA) and a simultaneous ascending auction (SAA) are reported.

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Key words: Package auctions, SAA auctions, CCA auctions, threshold problem.

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1. Introduction

In a previous paper, we compared the properties of two price-guided auction mechanisms proposed for radio spectrum licenses when there are synergies among the licenses for sale (Kagel, Lien, and Milgrom, 2010). The two mechanisms were a combinatorial clock auction (CCA),¹ which features package bidding, and a closely matched version of the simultaneous ascending auction (SAA), in which all bidding is on individual items. In our earlier paper we found that, within a certain class of environments exhibiting synergies due to geographic adjacency, simulations with “straightforward bidding” often predicted the conditions under which the CCA would, in the lab, achieve higher efficiency than the SAA.

The present paper expands upon our earlier one in several ways: it reports experiments with a previously untested and empirically important class of valuation profiles; it examines how bids by human bidders differ from those made by the simulator, and investigates the implications of those differences for auction performance; and it refines our previous simulator to provide better predictions about lab outcomes.

In the newly tested valuation profiles, synergies among items purchased in the auctions arise from shared fixed costs that must be incurred to extract value from any or all of the items. Synergies of this sort appear to be very common in business and have been studied in another context by Cantillon and Pesendorfer (2006).² Our earlier experimental paper, like some others examining spectrum-auction rules (Brunner et al., 2010; Goeree and Holt, 2010), instead studied value profiles in which synergies arise from geographic adjacency of acquired licenses.³ According to both the old valuations and the new ones, there is a large (“global”) bidder who wishes to acquire all items and two smaller (“local”) bidders who have positive values for only a subset of the items.

We find that our straightforward simulator continues to have substantial predictive power in the experiments with fixed-cost synergies, just as it did in the experiments with geographic synergies. We identify two sets of environments, however, in which the simulator’s predictions about the efficiency of outcomes are often mistaken. The first set, which we identified in our earlier paper, consists of cases in which the efficient outcome either assigned all items to the global bidder or split them between the two local bidders. CCA outcomes in these cases were consistently efficient, but the simulator sometimes predicted inefficient outcomes. The second set, which arises in our newer experiments testing fixed-cost environments, consists of cases in

¹ This refers to the original “combinatorial clock auction” of Porter, et al. (2003). The same name has subsequently been applied to a related but different auction design that was adopted for radio spectrum sales by governments in various countries, including the UK, Ireland, Austria, Denmark, Switzerland, the Netherlands, Canada, and Australia.

² Those authors used a similar fixed-cost structure to analyze combinatorial auctions for London bus routes, in which a bus company servicing multiple routes uses a common hub for maintaining and storing equipment.

³ Geographic synergies had been regarded as potentially important in the US and Canadian second generation (“2G”) spectrum auctions of the 1990s, when most mobile providers had regional networks and limited roaming. Auctions in the current decade are mostly for licenses to use newly released frequencies in order to expand capacity or offer new services. To take advantage of the additional capacity, a carrier must incur costs to develop and supply phones to its customers with radios and filters tuned to the acquired frequencies. These costs are fixed because once the phones are developed and distributed they add value in every region that the carrier serves.

which the efficient outcome splits the items between the large bidder and at least one of the smaller bidders. The simulator sometimes predicts efficient CCA outcomes for these cases, but in these cases the experimental outcomes are typically inefficient. In this paper, we find that the key to understanding these predictive failures lies in the differences in how the simulated and human bidders deal with the *package selection problem*.

The way bidders select packages to bid on is the key to understanding auction performance. In a combinatorial auction of even moderate size, bidders do not bid on all packages; they select a subset on which to bid actively. Indeed, in some auctions, the rules themselves limit the number of packages bid on in order to limit the complexity of the winner-determination problem.⁴ Although there is no such rule in our experiment, our subjects rarely bid actively on more than a handful of packages during the auction. According to theorems introduced in our previous paper, if each bidder bids sufficiently aggressively on its “efficiency relevant packages,” then the auction outcome will necessarily be efficient, and if, in addition, bidders bid equally aggressively on their other “core relevant packages,” then the auction outcome will be in the core of the associated cooperative game (which is important in part because the core guarantees competitive revenues for the seller). Thus, the likelihood that a dynamic auction will lead to efficient or core outcomes in any particular environment depends on the bidders’ ability to use the feedback and other information in the auction to identify and select the relevant packages.

In both the first paper and this one, we explore the hypothesis that prices alone provide the information that guides human bidders’ package choices. In the first paper, we did that by introducing a simulation in which bidders were programmed to bid in each round only for a *single* bundle – the most profitable one at prevailing prices, and to bid on no bundle when they were holding a provisionally winning bid. We called this “straightforward bidding.” In this paper, we explore that hypothesis more closely.

In our initial experiments involving geographic synergies, the simulator was often successful in predicting when the CCA mechanism would lead to nearly efficient outcomes or perform well relative to the SAA mechanism. We hypothesized that the failures we encountered in particular environments arose because the simulated bidders based their package selections only on prices, while a human bidder solves the package selection problem differently, paying attention to both prices and other cues. In our experiment, the main non-price cue was the bidder’s role in the experiment (“local bidder” or “global bidder,” which also identifies the set of items that held positive value for the bidder). In the cases we identified where the simulator wrongly predicted inefficient CCA outcomes, role-names could have guided the human bidders to bid on the right packages. If role-names actually did guide bidders to bid on the corresponding “named packages” even when other packages were more profitable, then we might expect there to be other environments in which the roles mislead the human bidders, causing them to perform *worse* than the simulated bidders. The new valuation

⁴ For example, the Canadian 700MHz spectrum auction scheduled for 2014 includes such a rule.

profiles with synergies based on fixed costs include environments in which the roles are misleading in that way, allowing a test of this prediction.

Taken as a whole, the efficiency data from the present experiment and the earlier one support the finding that roles act as cues that affect bidding and explain the failures of the straightforward simulator in the way we have just described. When the efficient outcome corresponds to bidders' named packages, CCA auctions achieve high efficiency more often than the SAA and more often than the simulator would predict. But in cases where efficiency requires that items be split between the large bidder and at least one of the smaller bidders, the finding is reversed. Both the improved performance of the CCA in the first set of cases and the diminished performance in the second set would be expected if bidders were using their roles as cues to select packages. In contrast to the CCA, the misleading label "global bidder" does little damage to performance in the SAA, because a bidder who bids for a large named package in the SAA also necessarily bids for all subsets of that package.

While the ability of the original simulator to predict efficiency is interesting, it may also conceal part of the story. Subjects sometimes bid on more than one package and, in our test scenarios, in later auction rounds a bidder's named package is often its second-most-profitable package. Price-guided bidders might place bids on the named package for that reason alone, without relying on their roles. To account for that possibility in the efficiency analysis, we introduce a new simulator that more accurately reflects bidders' propensity to bid on multiple packages: it places bids on just the single most-profitable package 60% of the time and on the two most profitable packages 40% of the time. This alternative simulator leads to more accurate predictions than our original simulator, but it still does not account for the whole of the named-package effect on efficiency.

We also looked for direct evidence that roles and named packages affect subjects' bidding. We found that subjects bid on fewer packages, on average, when the most profitable package is the named one. In addition, bidders are more likely to bid on the second-most-profitable package when it is the named package than when it is not. These findings are what we might expect if bidders were trying to place bids on relevant packages using both profitability and roles as indicators to guide their package selections.

In addition to these findings about non-price cues, we have two other notable findings about how human behavior deviates from our simple simulators and about how that deviation affects auction outcomes. The first concerns a kind of "strategic bidding" behavior that we found in the CCA auctions. Local bidders in our experiment often place bids on packages containing items that have *zero* marginal value to them – something that straightforward bidders never do – but they stop bidding on such packages before these bids win. A local bidder benefits from such bids by driving up the price eventually paid by the other local bidder, helping to resolve the so-called "threshold problem" and thereby enhancing efficiency (and revenues). According to Beck and Ott (2013), in many combinatorial auctions, including the CCA, bids on zero-value items may not only be

part of an undominated strategy, they may actually be a necessary feature of every undominated Nash equilibrium in some environments.

Second, there were a small number of auctions that ended much earlier than others. These early-ending auctions were associated with lower efficiency, lower revenues, and higher bidder profits. In addition, bidders in these auctions usually refrained from bidding on packages with large potential profits at the end of the auction, suggesting collusive-like behavior. When there was strategic bidding on zero-value items, early-ending auctions were less common, contributing to higher efficiency and revenues.

The paper proceeds as follows: Section 2 reviews some of the theoretical results reported in our earlier paper (KLM), which guide the analysis of the experimental outcomes. The experimental design and procedures are reviewed in Section 3, with the experimental results reported in Section 4. Concluding remarks are offered in Section 5.

2. Theoretical Considerations

Blumrosen and Nisan (2005) provide a number of striking examples where price-guided auction procedures fail to achieve even a fraction of the maximum possible (efficient) allocation of resources. Nevertheless, several pioneering theoretical and experimental studies have explored various price-guided auction mechanisms designed to overcome these worst-case outcomes (Kwasnica et al., 2005; Porter et al., 2003; Brunner et al., 2010; Goeree and Holt, 2010). Our previous paper studies the question: Under what conditions does a series of bids in a *combinatorial* auction produce an allocation that is efficient and/or in the core? In doing so it proves two theorems which, stated informally, assert that if bidders bid sufficiently *aggressively* in an auction for the right packages (their “efficiency-relevant” or “core-relevant” packages, respectively), then the outcome of the auction will necessarily be efficient or in the core.⁵ These theorems offer a possible theoretical explanation for how various auctions can lead to good outcomes even in combinatorial environments.

However, the sheer number of possible packages available to bid on, even with a very limited number of items up for auction, ensures that a bidder will bid on only a subset of its profitable packages.⁶ So it becomes important to ask: what might guide bidders even to identify, let alone to bid sufficiently aggressively on, these efficiency-relevant or core-relevant packages? One obvious answer is that if bidders bid exclusively on their most profitable packages, and these packages correspond to the efficiency-relevant or core-relevant packages in

⁵ The reader should consult KLM for a formal statement and proof of these two theorems.

⁶ One way to compensate for this is for the auctioneer to put some structure on the packages. However, this will typically still leave a large numbers of packages to bid on and, as will be shown below, care must be taken as to how packages are structured in relationship to bidder preferences and bid patterns, in order to achieve high efficiency.

an ascending price package auction, this will lead to (near) efficient or core outcomes.⁷ Alternatively, bidders might also find packages to be salient for other reasons. In our experiment, a package could be salient because it corresponds to the subject's named role in the experiment as either a "global" bidder with value for all items, or as a "local" bidder with value for only a limited set of items. Early in the auction, the "named" packages are often also the most profitable packages for the bidders. That can change as the auction progresses, but bidders might continue to bid on the named packages either because they are salient or because of potential strategic advantages arising from the complicated fitting issues inherent in package bidding. If the named packages actually are the efficiency-relevant or core-relevant packages in the auction and if bidders bid mostly on those packages, then the KLM theorem implies that one can expect (near) efficient or core outcomes.

The named packages can be further understood as follows: In many practical auctions, bidders have some idea about what the relevant packages may be, either for themselves or for other bidders or both. Relevant packages are typically well-coordinated ones. In order to increase the chance of winning and keeping prices low, a single bidder who knows what packages other bidders will bid on may bid on the packages that fit well, in the sense that they can win when other bidders' package bids are also winning. If the named packages fit together in this way, then they may become a focal point for bidders. In the experiment, bidders do commonly bid on named packages along with their most profitable package, and that can help achieve near efficient outcomes when the named packages correspond to the efficiency-relevant packages. By the same token, when the efficiency-relevant packages do not correspond to the named packages, bidding more aggressively on named packages than on the actually relevant packages can inhibit an efficient outcome. In our experiment, the items of potential interest to any bidder are known to all bidders: There are two local (or regional) bidders, one with value for items A, B, and C only and the other with value for D, E, and F only, and a global bidder with value for all six items. As revealed by the results reported below, the packages ABC and DEF become focal points that can successfully coordinate bidding, even when price signals alone would be ineffective. The global bidder, in addition to bidding on the global package, can sometimes also strategically bid on subsets of items to promote an early end to the auction, or to ensure getting some items that it values particularly highly.

In addition to exploring when, how, and why bidders achieve high- or low-efficiency outcomes in CCA package auctions, we compare the performance of the CCA to a closely matched version of the simultaneous ascending price auction (SAA), which is a suitable benchmark because it is a non-package auction that is widely used for radio-spectrum sales. We also investigate individual bidder behavior in the CCA auctions and compare revenue and profit outcomes between the CCA and SAA auctions.

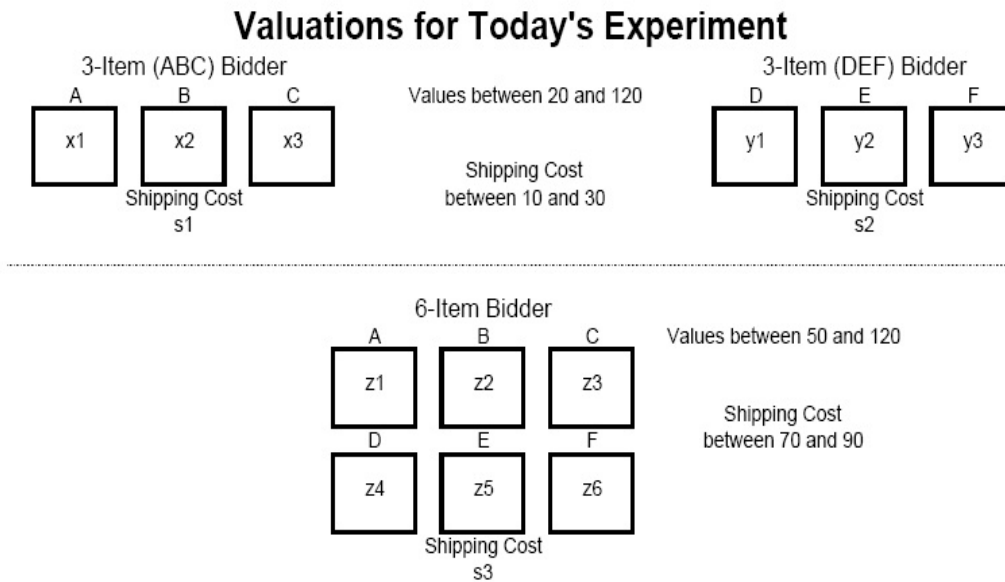
⁷ Near because, with minimum-reasonable-size price increments, one can expect to miss the maximum that can be achieved with sufficiently small price increments.

3. Simulation Outcomes and Experimental Design and Procedures

Auctions were conducted with either four or six items for sale. Since similar value structures and procedures were used in both cases, we only provide a detailed description of the six-item case, as illustrated in Figure 1.

There were three bidders in each auction: two “local” bidders, one with positive value only for items A, B and C, and another with positive value only for items D, E and F. Both local bidders had synergies between all three items as a result of lumpy shipping costs, which were fixed and independent of the number of items purchased for up to three items.⁸ Local bidders wanting to purchase additional items incurred a second fixed shipping cost equal to the shipping cost of the initial three items purchased. The third bidder was a “global” bidder with positive value for all six items, along with a fixed shipping cost for up to six items. As noted, this valuation structure is representative of synergies resulting from lumpy shipping costs or large fixed costs that would result from a common hub servicing a number of trucking or bus routes (as in, e.g., the London bus route system; see Cantillon and Pesendorfer, 2006).

Figure 1



Before any laboratory experiments were run, we first ran a set of simulations in an effort to identify valuation structures for which the CCA auction would be likely to achieve high efficiency, as well as those for which it would be likely to achieve low efficiency. For these, the stand-alone values for local bidders were integer values drawn from the interval [20, 120] and the fixed shipping costs were integer values drawn from the interval [10, 30]. Global bidders’ stand-alone values were integers drawn from the interval [50, 120], and

⁸ In contrast, in KLM, there were pairwise synergies between physically adjacent items with positive value.

the shipping costs were integer draws from the interval [70, 90].⁹ The four-item auctions were the same as the six-item auctions but with standalone items C and F dropped.

The simulations employed three sets of 100 random draws based on this valuation structure, with 100 simulations for each random draw.¹⁰ All of the simulations were for CCA auctions, with simulated bidders bidding in each round on the single package that yielded the highest positive profit, except that provisional winners from the previous round did not bid in the current round. Based on the simulation results, the following four types of valuation profiles were selected for employment in auctions with human agents:¹¹

1. *Easy/Named*: Valuations for which the CCA simulations achieved 100% efficiency and the efficient allocation called for allocating items according to named packages (either splitting the items between the two local bidders or assigning all the items to the global bidder). In the KLM experiment, these valuation profiles achieved very high efficiency in CCA auctions and had significantly higher efficiency than SAA auctions.¹²
2. *Hard/Named*: Valuations for which the CCA simulations achieved relatively low efficiency but the efficient allocation called for items to be allocated according to named packages. In KLM, these profiles achieved somewhat lower efficiency in the CCA auctions than the Easy/Named valuations, but still had substantially higher efficiency than in corresponding SAA auctions.¹³
3. *Hard/Unnamed*: Valuations for which the CCA simulations achieved relatively low efficiency and the efficient allocation did *not* call for items to be allocated according to named packages (items to be split between all three bidders or the between one of the local bidders and the global bidder). In KLM, these profiles achieved relatively low efficiency in CCA auctions and significantly lower efficiency than in the corresponding SAA auctions.¹⁴
4. *Easy/Unnamed*: Valuations for which the straightforward CCA simulator achieved 100% efficiency and the efficient allocation did *not* call for items to be allocated according to named packages. There were no profiles of this sort in KLM: they did not show up in the simulations with any consistency, due to the synergy structure and parameter values employed there.

⁹ The full set of instructions along with a number of screen shots can be found at http://www.econ.ohio-state.edu/kagel/KLM_trucking_insts.pdf.

¹⁰ Repeated simulations are needed as different outcomes may result due to ties for the provisionally winning bidders in each round, which were resolved randomly in the simulations and in the auction software.

¹¹ The full set of profiles used and the simulation results are contained in the online data appendix.

¹² These valuation profiles were simply referred to as “Easy” in KLM.

¹³ Average predicted efficiency under the straightforward simulator for these profiles is 78.3% (max 80.4%) for CCA6 auctions; 82.1% (max 95.5%) for CCA4 auctions (max is the maximum efficiency for any profile in this category). These valuation profiles were referred to as “Medium Hard” in KLM.

¹⁴ Average predicted efficiency under the straightforward simulator for these profiles is 69.4% (max 73.9%) for CCA6 auctions; 78.8% (max 84.2%) for CCA4 auctions (max is the maximum efficiency for any profile in this category). In KLM these profiles were simply referred to as “Hard”.

Subjects in the laboratory experiments were provided with copies of Figure 1 as well as a detailed description of the possible synergy relationships and stand-alone values. In any particular auction, they got to see only their own valuations. Regarding the other participants, subjects were told that “Item values and shipping costs will be selected so that we can explore what happens under a number of different valuation profiles, while providing you with what we anticipate will be respectable earnings when *averaged* over all the auctions within a given experimental session.”

The auctions’ rules were essentially the same as those reported in KLM and are briefly summarized below.

3.1. CCA Auctions

The CCA auctions used a variant of the package-auction rules in Porter et al. (2003). Participants could bid on as many packages as they wanted under XOR bid rules, so that only one of the bids was a provisional winner in any given round, and players got *all* the items in that package. Package bids eliminate the *exposure problem*, thereby allowing a bidder to bid nearly up to its values for a set of items without the risk of getting stuck winning only a low-value subset.

In each round, bidders observed the prices for each item and decided which packages to bid on. Each package bid consists of a set of items along with a single package price equal to the sum of the current round prices of the included items. At the end of each round, provisionally winning bids were determined from among all current and past bids by finding the feasible combination that maximized seller revenue. Ties among multiple sets of packages that maximized seller revenue were broken randomly. Prices associated with past bids were based on prices in the round in which the bids were originally placed.

Prices for all items started at 5 ECUs (experimental currency units), and were raised according to the following rules: From the set of provisionally winning bids in the previous round and the set of new bids in the current round, if an item attracted two or more bids, or if it was included in a provisionally winning bid and a new bid, then its price increased by 5 ECUs. Otherwise, the item’s price remained the same.¹⁵ Thus, those items with price increases in the current round were easily identifiable as items for which two or more bidders were actively competing.¹⁶

Following each round, bidders were privately informed about which, if any, of their bids was a provisionally winning bid.¹⁷ This was done so that subjects could avoid competing against themselves.

Subjects were encouraged to place bids on multiple potentially profitable packages, particularly early on, as “... the opportunity to make profitable bids on individual items or packages with low synergies, which

¹⁵ Prices were thus weakly increasing from round to round, unlike RAD (Kwasnica et al. (2005)) or the FCC’s Modified Package Bidding.

¹⁶ If a provisional winner bids on a new package with overlap with any item previously bid on, the price of that item will increase.

¹⁷ Tentative winning bids were *not* announced in either Porter et al. (2003) or in Brunner et al. (2010).

may become provisional winners later in the auction, will only be present early in the auction.”¹⁸ There were no activity rules restricting the items subjects could bid on.

An auction ended after two consecutive rounds of no new bids or, what amounts to the same thing, no price increases. Two rounds were used to give everyone a chance to determine whether they were satisfied, given current prices, with their provisionally winning allocations.

3.2. SAA Auctions

The SAA screen was designed to look the same as the CCA screen, so that differences in comparative performance could not be attributed to differences in presentation. The rules were also designed to be as similar as possible, with the auction proceeding in a series of rounds with automatic 5 ECU increases in prices for items with excess demand. Just as in the CCA, a subject only had to click “set” next to any set of items to place a bid on those items (see below). However, unlike in the CCA, an SAA bidder could only make one bid in each round, and that bid was interpreted and processed as a collection of independent item bids rather than as a package bid.

The auction ended once there was no longer excess demand for any item, with each item sold at the current price. Thus, a bidder who bid more than his or her standalone value for an individual item in order to capture the synergy payoff was exposed to a possible loss from winning only a subset of those items and paying more than that subset’s value. Our version of the SAA also had a number of rules and features not present in the CCA.

1. *Activity requirement*: Each auction started with bidders eligible to bid on all items. In subsequent rounds the total number of items a bidder was eligible to bid on could not exceed the number bid on in the previous round. This *activity rule*, which resembles the rule used in spectrum auctions, was explained to bidders as necessary to have the auction close in a timely manner.
2. *Default bids*: Each round of the auction started with a default bid labeled “currently demanded bid,” which was the previous round’s bid (or a bid on all items in the first round of bidding). Any time a new bid was entered that reduced eligibility, the bidder was notified and required to reconfirm the bid.¹⁹
3. *Minimum bid requirement*: Once there was no longer any excess demand for an item, the current high bidder for each item could not withdraw its provisionally winning bid and remained committed to that bid until someone else bid higher.
4. *Price rollback rule*: Near the end of an auction, it was possible to go from excess demand for an item to zero demand if all those bidding on that item dropped their demand at the same time. This could result in

¹⁸ In a mechanism-design experiment, the instructions are an important part of the treatment, as bidders are informed of the favorable properties and operation of what will typically be a novel institution.

¹⁹ KLM reports that, in a previous set of SAA auctions without default bids, a number of subjects let their eligibility lapse well before it was profitable to do so. These procedures were implemented to prevent this from happening inadvertently.

unsold items with a potentially large, negative impact on efficiency. The price rollback rule deals with this situation.²⁰ In the event that demand for an item falls to zero, the round outcome is cancelled and the price of the item with zero demand is rolled back to the level of the preceding round. In addition, one of the bidders with positive demand for that item in the previous round is selected at random and a minimum bid requirement is imposed on that bidder for those items at the previous round's price. The round is then rebid, with the revised prices and constraints binding.

3.3. Computer Interface and Aids for Subjects

Auctions with multiple items and synergies among them are quite complicated, so the nature of the bidder interface and any analytic tools it includes can affect bidder behavior. Since the experiment was intended to be representative of a high-quality field implementation, subjects were provided with computational aids they might expect to have from support staff in a field setting. These consisted of a table listing *all* possible bids, with corresponding analytic information, so that subjects could bid on items by simply clicking on the “add” or “set” space next to packages they were interested in (see Figure 2 for a sample screen shot). To make it easy for bidders to compare alternative packages, the table could be sorted using a number of potentially relevant criteria, e.g., current cost, current profit, etc.²¹ A *double-criterion sort* routine was employed so that a bidder interested in comparing a particular group of bids could easily do so by checking a box designated for that purpose next to each package. Checked packages were sorted first, followed by unchecked packages. Check marks were automatically put in place for packages containing only those items with positive values for local bidders, so as to minimize any potential confusion, as well as next to any package bid on after the first round, as these were presumably packages of interest. Bidders could easily uncheck any packages they were no longer interested in. The same set of sort routines and calculations were provided for both SAA and CCA auctions. Based on the training sessions, it seemed clear that we had provided bidders with too many sort options, so we emphasized the need to use the “current profit” sort to help in deciding which items to bid on, after which they might find one of the other sort options useful.

[Insert figure 2 here]

3.4. Experimental Procedures

Subjects were recruited to participate in a series of three sessions taking place within a two-week period, with each session lasting for approximately two and a half hours. Within each series, all of the auctions had the same auction mechanism (SAA or CCA) and the same number of items (four or six). The first meeting was a training session where subjects were introduced to the experimental procedures and computer interface, followed by several dry runs, which were all that could be completed in the allotted time period. To ensure a high return rate, subjects were offered a \$30 participation fee, to be paid after the completion of all three

²⁰ The minimum bid requirement would not apply in this case, as there would be no current high bidder for the item in question.

²¹ See the online instructions for complete details regarding this and the rest of the bidder aids provided.

sessions, with half of session two's auction profits withheld until completion of all three sessions. In addition, subjects were paid a flat \$15 at the end of the initial training session in lieu of any earnings from the dry runs. Given the complicated nature of the auctions, subjects were provided with summary instructions which they could take home to study. Sessions 2 and 3 began with asking if subjects had any questions, answering the questions posed, and then proceeding directly to play for cash.

Earnings in sessions 2 and 3 were advertised to range between \$10 and \$60 or more per person with average earnings of \$30-\$50 per person. Payoffs were denominated in experimental currency units (ECUs), with a minimum conversion rate of 1 ECU = \$0.10.²² Subjects were provided with starting capital balances of 150 ECUs. Any profits earned in an auction were added to these starting capital balances, and losses subtracted from it, with total earnings for a session consisting of a subject's end-of-session balance, less 130 ECUs, but not less than zero.

Each subject's role as a local or global bidder was randomly assigned prior to each auction, with bidders in each auction group randomly re-assigned following each auction. Each experimental session was designed to have five or more auctions (all with the same valuations) running at the same time. In case the number of subjects was not a multiple of three, the extras became bystanders for that auction, and were guaranteed to be active in the next auction.²³ Subjects' computer screens reported only their own outcome until the end of the auction, when the full allocation of units to all bidders in their auction was reported along with a final analytics screen that they could manipulate. The latter was designed to give bidders a chance to see what profitable packages they might have missed out on.

Each auction began with subjects given a couple of minutes to look at their valuations, to sort packages, and to check any items/packages they might be particularly interested in. All auctions started with each auction round lasting 25 seconds. After round 6 or 7, the round time was reduced to 20 seconds, and was reduced to 15 seconds after round 12 or so, to speed things up.²⁴ Once these shorter round times went into effect, the auctioneer announced "round ending" a second or two prior to the round actually ending.

[Insert Table 1 here]

Table 1 lists the auction sessions conducted, along with the number of subjects and the number of auction profiles employed in each session. With minor exceptions, the same auction profiles were employed in

²² In sessions where average earnings were lower than advertised, the conversion rate was increased at the end of the session. The instructions explicitly stated that these were *minimum* conversion rates (emphasis in the instructions).

²³ Bystanders had the final payoff screen from the last auction they participated in frozen on their screen.

²⁴ Times for round completion were determined based on the training sessions, during which we asked subjects whether or not they had enough time. The few complaints we had were requests for shorter round times. There is a tradeoff here between allowing too much time, so that subjects get bored and distracted from the issue at hand, versus having enough time to make reasoned choices. Our software was developed with this in mind, so that we could shorten bidding time in later rounds in view of the pace with which new bids were submitted.

the CCA4 and SAA4 auctions, as well as in the six-item auctions.²⁵ Two sets of six-item CCA auctions were conducted since, in many ways, these yielded the most informative outcomes under the different CCA auction profiles, and we were unable to complete the full set of profiles planned in CCA6-Series 1 within the 2.5 hour time-frame.

Subjects were recruited through e-mail lists of students taking economics classes at Ohio State University in the current and previous quarters. No subject participated in more than one auction series. For subjects completing all three sessions, average earnings for the six-item auctions were \$119, with minimum earnings of \$59 and maximum earnings of \$196, including the \$30 show-up fee and the \$15 payment for the first session. Average earnings for the four-item auctions were \$108, with minimum earnings of \$64 and maximum earnings of \$171, including the \$30 show-up fee and the \$15 payment for the first session.

4. Experimental Results

4.1. Early-Ending/ Collusive-Like Auctions

Before discussing bidding in detail, we briefly report on a number of auctions which ended much sooner than the vast majority of auctions. These early-ending auctions typically ended with bidders earning substantially greater profits than in the remaining auctions and with all bidders earning positive profits (or with two of the three bidders earning positive profits, the remaining bidder typically priced out of the market). As such, we consider them to be “collusive-like” auctions, involving tacit collusion of one sort or another.

We define auctions as collusive-like if the bidding lasted for 10 rounds or less. Although this is a somewhat arbitrary cutoff, 10 rounds for the CCA auctions includes 2 rounds with no price changes at the end, with a number of the auctions in question ending well before 10 rounds. Table 2 reports the mean number of rounds to auction completion for all CCA and SAA auctions, along with the mean number of rounds to completion for the early-ending auctions. The frequency of early-ending/collusive-like auctions is also reported. The early-ending auctions were typically ones in which all three bidders made substantial profits, or in which two out of the three bidders earned substantial profits, with one of the local bidders priced out of the market, and the remaining local bidder and the global bidder no longer competing.

[Insert Table 2 here]

One might be tempted to argue that collusive-like outcomes in the CCA auctions were a result of providing bidders with information about provisional winners following each round of bidding. While this may be a facilitating factor, the fact that collusive-like outcomes are also reported in the SAA auctions, where

²⁵ These exceptions resulted from differences in the number of auctions we were able to complete within the time frame sessions were scheduled for, along with one incorrectly programmed profile in one of the sessions.

provisional winners are not announced, indicates that this is not a necessary condition for collusive-like results.²⁶

CCA6-Series 1 had an unusually large number of auctions (18 out of 96) that ended early with bidders earning very large profits. In six of the first eight of these, the global bidder dropped out and earned zero profits, but global bidders in the other auction groups with the same profiles competed for a large number of rounds and earned reasonably high profits (between 30 and 77 ECUs per auction profile). So these auctions did not end early because of unusually low-value draws for global bidders. In eight out of the ten remaining early-ending auctions, either all three bidders earned substantial profits or two earned substantial profits and one of the local bidders was priced out of the market.

The unusually large number of auctions that ended early in this series was, we believe, the result of one subject near the end of the training period announcing (to paraphrase) “If a bidder has low valuations they cannot make much money and might as well drop out early to help the others.” That the initial auctions that ended early were largely the result of early dropouts by global bidders suggests that this subject’s statement precipitated these early global dropouts. This, in turn, established a paradigm for the more sustainable collusive pattern observed in later auctions, in which all three bidders held back from stiff competition, or the two remaining bidders held back once one of the local bidders was priced out of the market.²⁷

The analysis that follows includes all the early-ending/collusive-like auctions. The results show that early-ending auctions have a large negative impact on efficiency and revenue, while substantially increasing bidder profits.

4.2. Patterns of Individual Bidding

Subjects’ bidding behavior in the CCA auctions exhibits a number of consistent characteristics that are consequential for auction outcomes. First, consistent with previous results, subjects bid on only a small number of profitable packages, with the most profitable package attracting the most attention. This is of considerable importance, since a sufficient condition for auction outcomes to be fully efficient is that subjects bid sufficiently

²⁶ Within the SAA, the closest thing to a provisional winner being announced is when the minimum bid requirement takes effect, which would indicate that no one else is bidding on that item. However, Brusco and Lopomo (2002) identify the existence of low-revenue, tacit collusive equilibria in SAA type auctions, and Cramton and Schwartz (2002) report evidence to this effect in some of the FCC radio spectrum auctions. Beside setting reserve prices, collusive-type outcomes within the CCA can be mitigated, in the case of ties for provisional winners, by allocating items to the smallest number of bidders (as opposed to the random allocation employed in the experimental design), so as to keep the maximum number of bidders “out of the money.”

²⁷ Interestingly, the subject making the announcement was the first global bidder to drop out early, but did not do so later as either a global or a local bidder. This suggests either that his announcement was designed to get others to do so or that, after his first experience, he recognized that there was actually little personal gain to this strategy as a global bidder, given that the group composition changed randomly between auctions.

aggressively on the relevant packages (KLM, 2010).²⁸ If bidders bid on only a small number of packages, they may miss the relevant packages or not bid sufficiently aggressively on them.²⁹

Table 3, columns 2 and 5, report the percentage of profitable packages subjects bid on in each round for global and local bidders, respectively, with the average number of profitable packages available to bid on reported in parentheses. The columns following these show where the bids were directed in terms of the percentage of times bids were placed on the most profitable and the second-most-profitable packages.³⁰ Data are excluded for the last two rounds of each auction where, by definition, there are no new bids, as well as rounds in which the bidder is a provisional winner. For example, in rounds 1-5 in the CCA6 auctions, global players bid on 11.9% of the profitable packages available to bid on (7.2 out of 59.5 profitable packages), with bidders bidding on their most profitable package 63.5% of the time, and their second-most-profitable package 49.0% of the time. Bidding on only a small proportion of the profitable packages occurred even in later rounds where there were relatively few profitable packages available to bid on: e.g., local bidders in rounds 11-15 in the CCA6 auctions bid on less than half of the profitable packages available, with the average number of profitable packages as little as 4.8.³¹ With the exception of global bidders in the six-item auctions, there was very limited bidding on lower-valued packages, in favor of the first- and second-highest-valued packages.³²

[Insert table 3 here]

If CCA prices fail to guide bidders to the relevant packages in each round, the theoretical conditions required to achieve (near) fully efficient and core outcomes could still be satisfied if bidders vary the packages they bid on during the auction, and bid sufficiently aggressively on all of these packages at appropriate times. But this is not what we find: bidders typically failed to place any bid on some of the packages. For example, in the CCA4 auctions, a global bidder on average bids at least once on only 6.3 distinct packages out of the 15 packages they could bid on, so that on average over 8 packages never receive any bid at all from the global bidder during the auction. Local bidders come closer to bidding on all packages at least once during the auction;

²⁸ If the efficient outcome is unique, this condition is also necessary for full efficiency. By “sufficiently aggressively,” we mean there are no profitable packages for losing bidders to bid on at the end of the auction; for winning bidders we mean there are no packages with (potentially) higher profit than the winning package.

²⁹ Scheffel et al. (2012) also make this point. They find that the limited number of packages bidders evaluate is the biggest barrier to full efficiency in combinatorial auctions. They also find that, on average, bidders select the same number of packages to bid on, independent of the number of packages a bidder is interested in. While we do not have any measure of the number of packages bidders are interested in, we do find that the number bid on increases with increases in the number of profitable packages available to bid on.

³⁰ These percentages are independent of each other in that a bid on the second-most-profitable package is counted regardless of whether or not a bid was placed on the most profitable package. With the exception of global bidders in the six-item auctions, there was very limited bidding on lower-profit packages, in favor of the most- and second-most profitable packages: For auctions in rounds 11 and higher these percentages ranged from 2%-6% (1% or less) for global (local) bidders in the four-item auctions; and between 23-26% (8-11%) for global (local) bidders in the six-item auctions.

³¹ Subjects reported that they had more than enough time to bid on all the packages they wanted, so the limited bidding is not driven by round duration.

³² For auctions in rounds 11 and higher these percentages ranged from 2%-6% (1% or less) for global (local) bidders in the 4 item auctions; and between 23-26% (8-11%) for global (local) bidders in the 6 item auctions.

e.g., on average in the CCA4 auctions they bid at least once on 2.4 out of the 3 available packages containing only positively-valued items. For CCA6 auctions, global bidders bid, on average, on 11.7 out of the 63 possible (profitable) packages they could bid on, with local bidders bidding on 4.9 out of the 7 possible (profitable) packages containing only positively-valued items.

To summarize: (i) bidders bid on only a small percentage of the profitable packages in each round and omit some packages entirely from their bidding during the auction and (ii) the most profitable packages were consistently bid on most often.

While the fact that bidders tend to bid much more often on their most profitable package than on their less profitable packages is consistent with the possibility that bidders' package choices are guided primarily by prices and profits, it is also possible that these same packages might be selected by other criteria. In many cases, particularly early in each auction, the most profitable packages and the "named" packages – the ones consisting of all items for the global bidder and all positively-valued items for the regional bidders – coincide. To establish the degree to which prices and profits guide bidding, Table 4 reports data for those auction rounds in which the most profitable packages did *not* coincide with the named packages. As shown, when the named package did not coincide with the most profitable package, and bidders chose to bid on only one of the two, the most profitable package attracted substantially more attention. Pooling over all the data reported in Table 4, bids on the most profitable package alone, in conjunction with bids on both the named package *and* the most profitable package, accounted for a bit more than three quarters of all bids on average: The most profitable package alone accounted for 53.1% of all bids, with bids on both the most profitable package *and* the named package attracting an additional 27.5% of all bids. This helps explain some of the differences between bidding by human subjects and the straightforward simulator in the data reported below.

[Insert Table 4 here]

Some of the additional bidding on named packages can be attributed to the fact that those packages are often the second-most-profitable packages. For rounds with at least one bid, a bidder bids on the second-most-profitable package 50.5% of the time, while bidding on the most profitable packages 79.1% of the time. Still, a closer look shows that this fails to explain the whole effect: consider the rounds in which the named package is profitable but not most profitable. In those rounds, when the second-most-profitable package is the named one, a local bidder in CCA6 bids on it 62.7% of the time; when it is not the named package, the second-most-profitable package is bid on 37.5% of the time. In contrast, for the global bidder in CCA6, the names do not affect the frequencies of bidding on the second-most-profitable package.³³

³³ When the second-most-profitable package is the named package, a global bidder in CCA6 bids on it 44.4% of the time; and when the second-most-profitable package is not the named package, it is bid on 42.5% of the time. For the global bidder in CCA4, the corresponding numbers are 33.3% and 37.5%, respectively. For the local bidder in CCA4, when the named package is not the most profitable, it is always the second most profitable.

Another effect of the roles on bidding is that local bidders bid on fewer packages when the most profitable package is the named one. Consider local bidders in CCA6. In the rounds where a bidder made at least one bid, the average number of packages bid on was 2.60 out of 5.64 profitable packages. A simple linear regression shows that a subject bids on 0.288 fewer packages when the most profitable package is the named one ($p < 0.01$).³⁴ A global bidder also bids on 1.15 fewer packages when the most profitable package is not the named package, but the result is not significant ($p = 0.182$).

Subjects typically did *not* place bids in rounds in which they were provisional winners. This effect was most pronounced in later rounds, when the auction had a greater chance of ending. In auction rounds 11 and above, global (local) bidders failed to submit new bids in 86.9% (77.0%) of all rounds in which they were provisional winners in CCA4 auctions, and in 79.2% (75.6%) in CCA6 auctions.³⁵ The reasons for these high frequencies are threefold: (i) subjects do not bid in every round even when they are *not* provisional winners (see below), (ii) bidding on packages as a provisional winner can extend the auction and/or raise prices on provisionally winning bids with unknown consequences, so that provisional winners were willing to settle for what they already had, and (iii) more often than not, the profit on the provisionally winning package was greater than or equal to the potential profit from any other package.

In cases where a provisional winner's profits were greater than or equal to their highest potential profit, new bids were not submitted in 88.9% (84.3%) of all cases for global (local) bidders in CCA4 auctions and in 84.3% (85.8%) of all cases for global (local) bidders in CCA6 auctions. Provisional winners were much less likely to stand pat when their provisional profits were lower than their highest potential profits, with no new bids submitted in 58.5% (28.6%) of all such cases for global (local) bidders in the CCA4 auctions, and 56.2% (53.2%) of all such cases in the CCA6 auctions. Bidders were substantially more likely to bid following a round in which they had not secured a provisionally-winning bid (and there were positive profits to be had), bidding on at least one package in 75.3% (67.2%) of all such cases for global (local) bidders in the CCA4 auctions and in 78.1% (74.4%) of all cases for global (local) bidders for CCA6 auctions. Finally, looking at those cases in which a provisionally winning bidder did not bid and was not winning on her most profitable package, the profit difference compared to their best alternative averaged 20.6 (16.3) ECUs for global (local) bidders in the CCA4 auctions, and 61.1 (34.0) ECUs for global (local) bidders in the CCA6 auctions.

[Insert Table 5 here]

³⁴ The dependent variable in the regression is the number of packages bid. The right-hand-side variables are the number of profitable packages, a dummy variable with 1 indicating that the most profitable package is the named package, and the round. All the coefficients are significant with $p < 0.01$. Clustering at the subject level, the coefficients remain still significant with $p < 0.01$ except for the dummy variable ($p = 0.021$). For this regression, we exclude the observations with 7 profitable packages because when the most profitable package is not the named package, the number of profitable packages is at most 6.

³⁵ For rounds 1-10, the corresponding percentages are 81.1% and 88.0% for global and regional bidders in CCA4 auctions and 63.6% and 71.1% for global and regional bidders in CCA6 auctions, respectively.

Table 5 reports the scope of potential profits available at the end of the auction, distinguishing between losing and winning bidders. Most losing bidders had fully exhausted any potential profit opportunities by the last bidding round. This behavior is part of the theoretical sufficient conditions for achieving close to efficient and/or core outcomes in package auctions. However, what is particularly striking is the large size of the forgone profit opportunities for losing global bidders in the CCA6 auctions.³⁶ The standard error of the mean is quite large here (23.4), which, given the small number of observations in this category, indicates that these large forgone profit opportunities are largely driven by a few outliers.³⁷ Relatively large forgone profit opportunities for winning bidders are much easier to understand, as the complicated nature of the auction is such that with reasonable profits in hand, a potential winner might well not want to extend the auction, as these profits might be jeopardized by setting off new rounds of competition.

The *threshold problem* is an inefficiency that arises when local bidders withhold profitable bids on their packages, hoping that the other local bidder will raise its bid sufficiently for the combination to defeat the global bidder. If this effect were significant in our experiment, then we should find that local bidders, when *losing* the auction, would have greater scope for increased profit opportunities than global bidders. There is no evidence of such a threshold problem in Table 5 for either the four- or six-item CCA auctions, as the frequency with which higher profits were available for losing local bidders is smaller, in both cases, than for global bidders.

The traditional analysis of the threshold problem omits the possibility that local bidders might adopt alternative strategies to encourage higher bids by the other local bidder. What helps mitigate the threshold problem here is that, in a number of cases, local bidders bid on packages containing items with *zero value* to them; i.e., a local bidder with positive values for A, B and C, bids on a package containing one or more items D, E and F.³⁸ This is especially common in early auction rounds: overall, in the CCA auctions, 37.0% of all local bids consisted of packages with one or more zero-value items. This decreased to 8.6% of all local bids in rounds 11 and higher, when the auction had a reasonable chance of ending. In a number of cases, this resulted in local bidders being provisional winners on packages containing one or more of these zero-value items (10.5% of local bidders' provisionally winning bids). But they rarely got caught winning packages of this sort, as in only 3 out of 572 cases did a local bidder's winning package contain one or more zero-value items. Bidders varied greatly in terms of strategic bidding of this sort: 25.9% (15 out of 58) made these bids 40% of the time or more, versus 32.8% who made these bids 5% of the time or less (with 11 of these 19 never making a bid of this sort). We discuss the impact of this zero-value item bidding strategy in some detail in Section 4.7 below. For the

³⁶ All calculations here are conditional on bidders not having exhausted their profit opportunities.

³⁷ The standard error, as opposed to the standard error of the mean, is 84.2, almost the same as the average foregone profits.

³⁸ To drive up the prices for other bidders and at the same time avoid becoming the provisional winner of a package containing zero-value items, it is important to know about the other bidders' demands. For example, an ABC bidder may bid on single items D, E, or F to drive up the prices for those items, knowing that the other bidders are less likely to bid on packages ABCEF, ABCDF, or ABCDE.

moment, we simply point out that bidding on zero-value items results in a significant reduction in early-ending auctions, which in turn plays a major role in improving economic efficiency. It also results in a modest increase in profits for the local bidder doing the zero-value bidding, primarily as a result of obtaining positive items that they would not otherwise have won.

4.3. Efficiency

Efficiency is calculated as $(S_{actual} - S_{random}) / (S_{max} - S_{random}) \times 100\%$, where S_{actual} is the realized surplus from the auction, S_{random} is the mean surplus resulting from a random allocation of items, and S_{max} is the maximum possible surplus.³⁹ This normalized efficiency measure yields a mean efficiency of 0% with random assignment of the items, versus 100% for the surplus-maximizing assignment. Table 6 reports mean efficiency for each of the four types of auction profiles, along with the frequency of achieving 100% efficiency. Non-parametric tests for differences between the CCA and SAA auctions within each type of profile, using each auction as the unit of observation, are reported in the rightmost columns.

To analyze efficiency more formally, we ran one-sided Tobit regressions, accounting for the corner solution at 100% efficiency, where the dependent variable is our normalized efficiency measure.⁴⁰ The Tobits pool the data for all CCA and SAA auctions, with the Easy/Named auction profiles as the omitted variable, along with dummy variables for each of the other auction profiles. Additional right-hand-side variables consist of a dummy variable for the early-ending auctions, a dummy for the four-item auctions, a dummy for the SAA auctions, and three additional dummy variables, one each to account for interaction effects between the SAA auctions and the Hard/Named, Hard/Unnamed and Easy/Unnamed auctions.⁴¹ We employed two different error specifications, one with errors clustered by auction profile, and one with clustering at the session level, both of which yield essentially the same results. Results reported here are with errors clustered by auction profile, as there are many more of these than sessions (40 versus 10), and the cluster-robust standard error estimator is sensitive to having a sufficiently large numbers of clusters. The regression results themselves are reported in the Appendix to the paper, with the analysis here focusing on the marginal effects of the different explanatory variables.

Average overall efficiency calculated from the Tobit index function is 91.8%. Auctions that end early, in 10 rounds or less, *reduce* average efficiency by 9.9% to 81.9%, while four-item auctions average 5.3% higher efficiency. Table 7 reports mean differences in efficiency between the different CCA auctions based on the

³⁹ The value of the random allocation is computed by taking the average of the surplus over all possible allocations – 3^4 and 3^6 respectively – assuming all items are sold in each auction.

⁴⁰ We also ran probits, similar to the Tobits, where the dependent variable is set to 1 in cases where 100% efficiency is achieved, and to 0 otherwise. They yield similar results to those reported for the Tobits, and are thus omitted.

⁴¹ We also ran a specification checking for interaction effects between the four-item auction dummy and the SAA dummy. This interaction effect was not significant at conventional levels ($p > 0.10$), so it was dropped from the regressions.

Tobit index function, along with mean efficiency differences from the corresponding SAA auctions. The statistical significance of the efficiency differences is also reported. Looking at the first column of numbers in Table 7, the Hard/Named CCA auction profiles have 3.2% lower average efficiency than the Easy/Named CCA profiles, with this difference statistically significant at the 5% level. Efficiency drops even further for the Easy/ and Hard/Unnamed CCA auctions compared to the Easy/Named CCA auctions. There are no significant differences in efficiency between the Easy/ and Hard/Unnamed auctions. The bottom row of Table 7 compares efficiency in the SAA auctions to the corresponding CCA auctions at the top of the table. The important thing to note here is that whereas the CCA versions of both the Easy/ and Hard/Named auction profiles achieved significantly *higher* efficiency than their SAA counterparts, both the Easy/ and Hard/Unnamed CCA profiles had *lower* efficiency than their SAA counterparts.

[Insert Tables 6 and 7 here]

Tables 6 and 7 show that, in terms of comparing CCA with SAA auctions, which is a prime purpose of the present paper, we don't miss much by collapsing the four auction profiles into the two main categories - Named versus Unnamed auctions. Table 8 reports mean efficiency values and frequency of achieving 100% efficiency in terms of Named versus Unnamed auction profiles, with Table 9 reporting the corresponding Tobits. Both the Tobits and the non-parametric Mann-Whitney tests show that for Named auctions the CCA achieves significantly higher efficiency than the SAA, whereas for Unnamed auctions the reverse pattern holds.

[Insert Tables 8 and 9 here]

The mechanism behind the fact that named packages and their relationship to the efficient outcome serve as a better predictor of efficiency than the straightforward simulator in the CCA auctions is as follows: First, as Table 4 showed, for both local and global bidders, when the named package no longer corresponds to the most profitable package, named packages still attract a considerable amount of attention, either in terms of bidding on the named package only, or more often, bidding on *both* the named package and the most profitable package. Further, when the named package is no longer the most profitable package, the amount bid on the named package must be greater than the bid on the most profitable package, since the latter contains fewer items. This, in conjunction with the CCA auction's assigning packages so as to maximize seller revenue, means that, other things equal, the CCA algorithm would pick a bidder's named package over the bidder's most profitable package to include as the winning package when both are bid on, and in general would tend to pick named packages over more profitable packages as provisional winners.⁴² The net result is that, in the CCA auctions with Hard/Named profiles, bidding on Named packages in addition to or in favor of the most profitable packages helps to promote auction efficiency. In contrast, in the Easy/Unnamed CCA auctions, bidding on

⁴² One important reservation to this conclusion could result from sufficiently thick competition so that smaller (unnamed) packages are aggressively bid on in later auction rounds. However, with strong complementarities between individual items this is not very likely, even with reasonably strong competition.

Named packages tends to reduce auction efficiency compared to bidding exclusively on the most profitable packages.

Closely related to this is the fact that the four-item CCA auctions achieve higher efficiency than the six-item CCA auctions (5.3% higher according to the Tobit index function). This reflects the fact that, although both global and local bidders are bidding on more packages in the six-item auctions (recall Table 3), they are bidding on a substantially smaller percentage of the profitable packages, so it is that much less likely that they will be bidding on those packages that constitute the efficient outcome compared to the CCA4 auctions.

4.4. Revenue Effects

Following Milgrom (2007), we use the minimum revenue in the core as the standard against which to judge revenue from the package auctions. The core for package-allocation problems has a competitive-revenue interpretation: An individually rational allocation is in the core if there is no group of bidders who could all do better for themselves and for the seller by raising some of their losing bids. Hence our analysis focuses on revenue as a percentage of the minimum revenue in the core. Note that the selection of auction profiles paid little, if any, attention to revenue or profits, being mainly concerned with auction efficiency. However, as a practical matter revenue and bidders' profits are important factors to take into account in choosing between auction mechanisms.

Tables 10 and 11 report revenue effects: First the raw data with non-parametric Mann-Whitney tests, then with regressions similar to those used to analyze efficiency. In both tables revenue is measured as a percentage of minimum revenue in the core. For treatment effects we focus on the collapsed categories reported in Table 8, based on the clear and striking differences between auctions in which the efficient outcome corresponds to Named versus Unnamed packages. The regression specification is similar to the one employed for efficiency, with errors clustered by auction profile (details provided in the Appendix). An unrestricted linear regression is employed since revenue as a percentage of minimum revenue in the core can exceed 100%.

[Insert Tables 10 and 11 here]

Revenue as a percentage of minimum revenue in the core is predicted to average 93.8% based on the regression. The most striking impact on revenue results from early-ending auctions where the marginal effect is a 52.1% reduction in revenue. The early-ending auctions have a particularly strong impact on the raw data reported in Table 10. As such, we look to Table 11 for treatment effects. Within the CCA auctions, at the margin revenue increased 4.8% in Unnamed compared to Named auction profiles ($p < 0.10$). So although efficiency is higher within the CCA auctions when the efficient outcome corresponds to the Named auctions, revenue is lower. The SAA auctions generate significantly more revenue than the CCA auctions for the Named auction profiles, which is reflected in the raw data as well.

4.5. Bidder Profits

Tables 10 and 11 also report profits based on a regression specification that is identical to the one used for revenue, except that the dependent variable is total bidder profits, measured as a percentage of the efficient allocation. Total profits predicted from the regression average 21.0% of the efficient allocation. As with revenue, the biggest impact on profits comes from early-ending auctions, as profits there have essentially tripled (62.0% of the efficient allocation) compared to the overall average.⁴³

Profit patterns between treatments are the mirror image of those reported with respect to revenue. Total profits are 7.6% lower in SAA compared to CCA auctions when Named packages correspond to the efficient outcome ($p < 0.01$), with no significant differences between the two for Unnamed packages. Within the CCA auctions, total profits are a bit lower when Unnamed packages correspond to the efficient allocation compared to when Named packages do.

4.6. Distance from the Core

Distance from the core is measured in terms of the scaled distance from the core, with the latter defined as the maximum violation of one of the inequalities defining the core, divided by the difference between full efficiency and efficiency resulting from randomly allocating items to bidders.⁴⁴ Here too we report the raw data as well as one-sided Tobits (with the corner solution zero distance from the core) in terms of the collapsed auction profiles. In this one case the interaction effect between the 4-item auctions and the SAA dummy is significant at conventional levels ($p < 0.10$), so that the results, reported in Table 13, account for this interaction effect.

[Insert Tables 12 and 13 here]

The overall scaled distance from the core according to the Tobit index function is 22.0%. Early-ending auctions have a large impact here as well, with the marginal impact being a 56.0% increase in the scaled distance from the core, with *none* of the early-ending auctions having zero distance from the core. The Tobits show that the marginal effect for the CCA4 auctions compared the CCA6 auctions is to reduce the scaled distance from the core by 11.7% ($p < 0.01$). The Tobits show no significant differences between Named and Unnamed CCA auctions with respect to distance from the core. Named CCA4 auctions come closer to core outcomes than their SAA counterparts, with Unnamed CCA6 auctions tending in the opposite direction.

⁴³ Obtained by adding the dummy for early ending to the constant in Table A1.

⁴⁴ This is $D_{max}/(S_{max} - S_{random}) \times 100\%$ where D_{max} is the maximum violation of one of the inequalities defining the core and S_{max} and S_{random} are the same as were used to define efficiency. The normalization is based on the fact that in calculating the core, efficiency is used as one of the core constraints, the one for the grand coalition involving all bidders and the auctioneer. This normalization enables us to compare the distance from the core across different auction profiles and to compare it to normalized efficiency as well.

To sum up, outcomes are closer to the core (the core embeds both efficiency and competitive pricing) under CCA than SAA auctions when Named packages correspond to the efficient outcome, but this pattern reverses when Unnamed packages correspond to the efficient outcome.

4.7. Impact of Bidding on Zero-Value Items

Local bidders' bidding on zero value items strongly impacts the auction process. First, early-ending auctions have a substantially lower frequency of zero-value bidding than later-ending auctions – 46.4% of early-ending auctions had at least one zero-value bid in the first ten auction rounds compared to 76.4% of non-early-ending auctions. Further, a probit shows that the marginal effect of a zero-value bid in the first ten rounds is a reduction of 0.10 ($p < 0.01$) in the probability of the auction ending early.⁴⁵ Given the large negative impact of early-ending auctions on revenue and efficiency, zero-value bidding indirectly promotes increased auction revenue and improved efficiency.

To investigate the impact of zero-value bidding on profits, we ran separate Tobits for global and local bidders, employing the same specification as in the regressions for profits as a whole, but adding a BidZero dummy (value = 1 if either local bidder bids on a package containing zero-value items; 0 otherwise) for the global-bidder Tobit, and separate BidZero dummies for each of the local bidders for the local-bidder Tobit.⁴⁶ There is a negative effect on global bidders' profits from zero-value bidding which just misses being statistically significant at the 10% level ($p = 0.11$). A local bidder who bids on zero-value items generates a positive increase in its own profits of 1.4% ($p < 0.05$), which, although modest in absolute value, is substantial compared to the average normalized local-bidder profit of 5.7%. Zero-value bidding by one local bidder has no significant effect on the other local bidder's profits ($p = 0.67$). Running a probit on the frequency of winning suggests that much of the increase in a local bidder's profits resulting from its own zero-value bidding can be attributed to an increase in the probability of winning ($p < 0.01$).⁴⁷ This, taken together with the negative impact on the global bidders' profits, indicates that local bidders' zero-value bidding helps to overcome the threshold problem.

⁴⁵ Right-hand side variables in this case consisted of dummy variables for the CCA4 auctions and the Unnamed auctions, and a BidZero dummy set equal to 1 if any zero-value items were bid on in the first 10 auctions (and 0 otherwise), with the omitted treatment variable consisting of Named CCA6 auctions. Note that there are clearly alternative ways to characterize bidding on zero-value items than the one employed here. We adopt this parameterization because it is straightforward to implement and, as noted earlier, the bidding on zero-value items tends to be concentrated in a subset of the bidders.

⁴⁶ Tobits need to be employed here since there are many cases where no local bidder gets an item, as well as many cases where the global bidder gets no items. The BidZero dummies in these regressions take on a value of 1 if zero-value items were bid in any auction period.

⁴⁷ The increased probability of winning is equal to 0.11. Employing Heckman's (1979) two-stage estimator to correct for sample-selection bias confirms these results, showing that a local bidder's own zero-value bidding has no impact on its profits when it wins, but does result in a statistically significant increase in its probability of winning ($p < 0.01$).

4.8. Predictive Power of an Alternative Simulator

Results from pilot CCA4 auctions showed that predictions for the straightforward bidding simulator failed rather dramatically for the Easy/Unnamed CCA auctions where the simulator predicted 100% (or near 100%) efficiency. At the same time, it was clear from the individual bid data that subjects consistently bid on more than their most profitable package in the CCA auctions (recall Tables 3 and 4), and our theory suggests that this could have an important effect on efficiency. To account for this, we looked for a simple alternative that might better track the four item data, settling on one in which subjects always bid on their most profitable package, while also randomly bidding on their second most profitable package 40% of the time.⁴⁸ While this alternative simulator is still just a rough approximation to bidder behavior, looking at its predictions relative to the straightforward simulator indicates it is a significant step in the right direction, without being so detailed as to be inapplicable to other settings.

In an effort to test this alternative simulator, the CCA6 profiles were selected so that in about half of all cases predicted efficiency was essentially the same under the two simulators, with the other half selected so that the two simulators gave very different predictions (e.g., about half of the Easy/Unnamed auctions profiles were chosen so that the second simulator predicted relatively low efficiency in contrast to the high efficiency predicted with straightforward bidding, with the other half chosen so that both simulators predicted relatively high efficiency). This strategy was employed for all four categories, and was reasonably successful in all but the Easy/Named category where both simulators came back with very high efficiency for all of the 300 randomly drawn profiles that we explored.

[Insert Table 14 here]

Table 14 reports mean absolute differences between predicted and actual efficiency under the two simulators distinguishing between Named and Unnamed auction profiles. For both the four- and six-item CCA auctions, the alternative simulator is significantly more accurate ($p < 0.01$). If we break out the early-ending CCA auctions, there are no significant differences between the predictive accuracy of the two simulators ($p = 0.31$), which is not surprising given the low efficiency in these auctions and the collusive-like behaviors adopted by bidders in these cases. Further, focusing on the Easy/Named auctions, neither simulator predicts efficiency significantly better than the other ($p = 0.30$), as we had expected because of the coincidence of named and most profitable packages in this case. One difference is that the alternative simulator tends to predict a wider distribution of outcomes, which more accurately matches findings in the lab. For example, consider the Hard/Unnamed CCA4 auction profiles, for which full efficiency calls for the following allocation (A, D, BC),

⁴⁸ Consistent with the data, neither simulator placed a new bid when it was a provisional winner in the previous auction round. It should be noted that when the named package is not the most profitable package, bidding on the most profitable package and the second-most profitable package, where the latter corresponds to the named package, averaged 29.7% and 13.8% of all bids for local and global bidders respectively.

where A and D represent allocations to the two local bidders, with the global bidder getting B and C. For these cases, the straightforward simulator predicts the same allocation (0, D, ABC) in all 100 replications, with a normalized efficiency value of 84%, while the alternative simulator predicts a distribution of allocations as follows: (0, D, ABC; 51), (A, D, BC; 41), (A, 0, BCD; 6) and (0, 0, ABCD; 2) (where the numbers following the semi-colon indicate the predicted number of times for each allocation) resulting in an average efficiency of 91%. Of the six auctions involving this particular profile, four achieved the fully efficient outcome (A, D, BC), with one each achieving (0, 0, ABCD) and (0, D, ABC) for an average realized efficiency of 94%.

Alternatively, take the following Hard/Named CCA6 auction profile where full efficiency calls for the global bidder to get all six items. In this case, the straightforward simulator predicts the fully efficient outcome 45 times, along with the inefficient outcome (0, 0, ABD) for the remaining times, for an average efficiency of 78%. The alternative simulator, on the other hand, predicts the fully efficient outcome 33 times along with a close to fully efficient outcome (C, 0, ABD) for the remaining times, for a predicted efficiency of 97%. This compares with the experimental outcomes which yield the fully efficient outcome 4 times and the (C, 0, ABD) outcome the remaining 2 times, for an average efficiency of 99.1%.

In short, by having subjects bid on their second-most profitable package 40% of the time (in addition to bidding on their most profitable package), the alternative simulator (i) comes closer to bidders' actual behavior and (ii) identifies some allocations that the straightforward simulator misses. As such, the relatively simple alternative simulator predicts auction efficiency more accurately in our experiments.

5. Conclusions

According to the theory articulated in our earlier paper, combinatorial auctions lead to efficient or core allocations when bidders, during the auction, bid sufficiently aggressively on certain "relevant" packages. This would be trivially satisfied if bidders could bid equally aggressively for all profitable packages, but that is infeasible in large auctions. Compounding the difficulty is that, in experiments, bidders bid on relatively few packages, even when the number of items is so small that bidding on all packages would at least be conceivable. Consequently, bidders face a *package selection problem*.

In auctions like the SAA, in which bidders bid separately for individual items, bidding for any package necessarily implies bids on all subsets of that package, so the package selection problem is less important. Instead, when synergy values are high, the SAA faces an *exposure problem*: as prices rise, a bidder may have to choose between continuing to bid for its large package or accepting a smaller package at a time when both options involve losses. To avoid such a risk, a bidder could drop out of the auction when prices are lower, but doing so reduces clearing prices and threatens efficiency.

One might theorize that the relative magnitudes of the package selection problem and the exposure problem can determine the relative performance of the SAA and the CCA. Because we have no good measure

to control for the magnitude of the exposure problem, our experimental findings, while interesting, cannot be conclusive about that. In our experiment, a surrogate for the magnitude of selection problem is the simulation outcome: our simulated bidders rely straightforwardly on provisional prices and profits to guide the choice of packages on which to bid. When that guidance is good, meaning that the simulator efficiency is high and the package names are not misleading, the CCA displays higher efficiency in experiments than the traditional SAA. But when the guidance is poor or the package names are misleading, the outcomes can be less efficient than the SAA.

In the outside world, bidders sometimes have access to better cues and more information than the auctioneer. For example, in auctions for stands of timber, a bidder may know the locations of all the mills and perhaps something about their supply situations, which helps to identify the relevant packages. In the London bus routes auction, knowledge about the location and capacity of existing facilities can be an important clue to the relevant packages. Or consider a radio spectrum auction with nine licenses for sale in a band. If bidders determine that high-speed broadband requires acquiring at least four licenses, they may guess that the only relevant packages are ones with four, five, or nine licenses.

In our experiment, the bidders' roles ("global" or "local") provided a non-price cue about which packages were most likely to be relevant. Our straightforward simulator for predicting outcomes omitted this cue, but the subjects in the experiment did not: lab outcomes tended to be more efficient than predicted by the simulator when the efficiency-relevant packages were the named ones and less efficient otherwise.

The variety of experimental outcomes reported here also highlights another of our themes: that the comparative outcomes of different mechanisms depend on the environment and that the set of possible environments is too vast to permit sweeping statements about comparative performance based just on experiments: there is an "experiment selection problem." To make useful progress, emphasis needs to be placed on improving our understanding of the behavior of individual subjects, and then supplementing experimental findings by theory and simulations to deduce how that behavior will play out in a wide class of environments.

One encouraging finding for our approach is that the theory we had devised and tested for environments with geographic synergies has also performed well using the previously untested class of valuation profiles with synergies based on fixed costs. The common findings across both classes increase our confidence that the simulator may succeed for a variety of environments. The failures of the simulator based on non-price cues ("roles") in the two environments, as described above, are also consistent with a single theory, which also raises our confidence in the findings.

Another new and surprising finding concerned aggressive bidding tactics by local bidders, who bid on valueless items to drive up their prices to other bidders, thereby mitigating the threshold problem. This opens

up a potential line of study of bidder behavior to explain why the threshold problem, which in theory can interfere with efficiency, has been found not to interfere with efficiency in many experiments.

Although there are reasons to be optimistic that some of our findings may extend to other environments, both sets of our experiments do include special features that could be important for our findings. What happens if the local bidders' package demands don't line up so neatly? What happens if there are many more items? What happens if the auction rules are slightly different; for example, if we introduced a new activity rule into our CCA? The theory we have used has important limits, too. When efficiency is too difficult to achieve by any mechanism, how do these mechanisms compare? All of these questions are susceptible to further experiments, and we are hopeful that theories of individual behavior and mechanism performance can be combined with simulations to extend our findings to a much wider set of environments.

Even if the current theories and simulators can be extended, there is another daunting challenge: comparisons between the CCA and the SAA will require developing a simulator for the SAA. Unlike the CCA, in which the important decision is package selection, the most important decision for determining profits in an SAA with synergies is often the exit decision. A bidder who is confident that final auction prices will not exceed its package value should continue bidding even if prices of individual items exceed their standalone values, but a bidder with identical current prices and values but a different expectation of final prices may find it optimal to withdraw from the auction to avoid winning an unprofitable package. To capture exit decisions, a successful simulator will likely need to include one or more terms for bidder expectations about future prices, which is a considerable challenge, but one that needs to be solved to make any useful prediction about the comparative performance of the SAA and the CCA.

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Appendix: Regression Results

Table A1

Regressions: Named-Unnamed Auction Profiles
(standard errors of the estimates in parentheses)

| Variables | Efficiency | Revenue | Total Profit | Dist. from Core |
|-----------------------|-------------------|-------------------|-------------------|-------------------|
| Constant | 1.02** (0.03) | 0.90** (0.02) | 0.21** (0.02) | 0.18** (0.04) |
| Early | -0.14** (0.04) | -0.52** (0.05) | 0.41** (0.03) | 0.56** (0.09) |
| 4Item | 0.10** (0.02) | 0.10** (0.02) | 0.00 (0.02) | -0.12** (0.03) |
| SAA | -0.13** (0.03) | 0.05* (0.03) | -0.08** (0.03) | 0.03 (0.03) |
| Unnamed | -0.11** (0.03) | 0.05 (0.03) | -0.03 (0.02) | 0.03 (0.04) |
| SAA*Unnamed | 0.21** (0.04) | -0.06* (0.03) | 0.09** (0.03) | -0.07 (0.04) |
| Pseudo R ² | 0.33 | 0.38 | 0.33 | 0.46 |
| Sigma/Root MSE | 0.19 | 0.18 | 0.15 | 0.25 |

* Coefficient value significantly different form 0 at the 5% level or better, two-tailed test.

**Coefficient value significantly different form 0 at the 1% level or better, two-tailed test

Tobits – Efficiency and Distance from the Core.

Linear Regressions – Revenue and profits.

Variables:

Early = 1 if auction ended in 10 rounds or less; 0 otherwise.

4item = 1 if 4 item auctions; 0 otherwise.

SAA = 1 if SAA auction; 0 otherwise.

Unnamed = 1 if Unnamed auction profiles; 0 otherwise.

Table A2
 Efficiency Tobit: Detailed Auction Categories
 (standard error of the estimate in parentheses)

| Variable | Efficiency |
|-----------------------|-------------------|
| Constant | 1.05** (0.04) |
| Early | -0.15** (0.03) |
| 4Item | 0.11** (0.02) |
| SAA | -0.11** (0.03) |
| Hard Named | -0.08* (0.04) |
| Hard Unnamed | -0.16** (0.05) |
| Easy Unnamed | -0.14** (0.04) |
| SAA*Hard Named | -0.02 (0.06) |
| SAA*Hard Unnamed | 0.15** (0.04) |
| SAA*Easy Unnamed | 0.27** (0.06) |
| Pseudo R ² | 0.42 |
| Sigma | 0.19 |

** Coefficient value significantly different form 0 at the 1% level or better, two-tailed test.

Variables:

Early = 1 if auction ended in 10 rounds or less; 0 otherwise.

4item = 1 if 4 item auctions; 0 otherwise.

SAA = 1 if SAA auction; 0 otherwise.

Hard Named = 1 if Hard Named auction profiles; 0 otherwise.

Hard Unnamed = 1 if hard Unnamed auction profiles; 0 otherwise.

Easy Unnamed = 1 if Easy Unnamed auction profiles; 0 otherwise.

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Figure 2

Layout of Computer Interface for CCA Auctions

| | | | | | | | | | | | | |
|--------------------------|-------------------------------------|-----------------------------|-------|-----------------------|----------------------|--------------------------|----------------------|---------------------|-------------|-----------------|-------------|-------------------------|
| Experiment: 0044 | | Design: Combinatorial Clock | | Valuation: Capacities | | Date Started: | | | | | | |
| Period | Round | Experiment Status | | Round Duration | Round Time Remaining | Experiment Starting (\$) | Current Balance (\$) | Profit / Loss (\$) | | | | |
| 1 | 1 | Ready to start round | | 25 | 25 | 100.0 | 100.0 | 0.0 | | | | |
| Current auctioneer offer | | | | | | | | | | | | |
| Item: | A | B | C | D | E | F | | | | | | |
| Offer quantity: | 1 | 1 | 1 | 1 | 1 | 1 | | | | | | |
| Current round price: | 5 | 5 | 5 | 5 | 5 | 5 | | | | | | |
| Price increment: | --- | --- | --- | --- | --- | --- | | | | | | |
| Currently demanded bids | | | | | | | | | | | | |
| Package | | | Value | Cost | Potential Profit | | | | | | | |
| 0, 0, 0, 0, 0, 0 | | | 0.0 | 0.0 | 0.0 | | | | | | | |
| This period's valuation | | | | | | | | | | | | |
| ItemA | ItemB | ItemC | ItemD | ItemE | ItemF | Preowned Items | Container Capacity | Container Unit Cost | | | | |
| 87.0 | 74.0 | 77.0 | 0.0 | 0.0 | 0.0 | 0 | 3 | 11.0 | | | | |
| Analytics | Previous period results | | | | | | | | | | | |
| | | Package | Value | Current cost | Current profit | Profit/ value | Last round submitted | Past cost | Past profit | Decrease profit | Empty slots | Fixed cost/ gross value |
| add | <input checked="" type="checkbox"/> | 1, 1, 1, 0, 0, 0 | 227.0 | 15.0 | 212.0 | 0.934 | none | 0.0 | 0.0 | 0.0 | 0 | 0.048 |
| add | <input checked="" type="checkbox"/> | 1, 0, 1, 0, 0, 0 | 153.0 | 10.0 | 143.0 | 0.935 | none | 0.0 | 0.0 | 0.0 | 1 | 0.072 |
| add | <input checked="" type="checkbox"/> | 1, 1, 0, 0, 0, 0 | 150.0 | 10.0 | 140.0 | 0.933 | none | 0.0 | 0.0 | 0.0 | 1 | 0.073 |
| add | <input checked="" type="checkbox"/> | 0, 1, 1, 0, 0, 0 | 140.0 | 10.0 | 130.0 | 0.929 | none | 0.0 | 0.0 | 0.0 | 1 | 0.079 |
| add | <input checked="" type="checkbox"/> | 1, 0, 0, 0, 0, 0 | 76.0 | 5.0 | 71.0 | 0.934 | none | 0.0 | 0.0 | 0.0 | 2 | 0.145 |
| add | <input checked="" type="checkbox"/> | 0, 0, 1, 0, 0, 0 | 66.0 | 5.0 | 61.0 | 0.924 | none | 0.0 | 0.0 | 0.0 | 2 | 0.167 |
| add | <input checked="" type="checkbox"/> | 0, 1, 0, 0, 0, 0 | 63.0 | 5.0 | 58.0 | 0.921 | none | 0.0 | 0.0 | 0.0 | 2 | 0.175 |
| add | <input type="checkbox"/> | 1, 1, 1, 1, 0, 0 | 216.0 | 20.0 | 196.0 | 0.907 | none | 0.0 | 0.0 | 0.0 | 2 | 0.102 |
| add | <input type="checkbox"/> | 1, 1, 1, 0, 1, 0 | 216.0 | 20.0 | 196.0 | 0.907 | none | 0.0 | 0.0 | 0.0 | 2 | 0.102 |
| add | <input type="checkbox"/> | 1, 1, 1, 0, 0, 1 | 216.0 | 20.0 | 196.0 | 0.907 | none | 0.0 | 0.0 | 0.0 | 2 | 0.102 |
| add | <input type="checkbox"/> | 1, 1, 1, 1, 1, 0 | 216.0 | 25.0 | 191.0 | 0.884 | none | 0.0 | 0.0 | 0.0 | 1 | 0.102 |
| add | <input type="checkbox"/> | 1, 1, 1, 1, 0, 1 | 216.0 | 25.0 | 191.0 | 0.884 | none | 0.0 | 0.0 | 0.0 | 1 | 0.102 |
| add | <input type="checkbox"/> | 1, 1, 1, 0, 1, 1 | 216.0 | 25.0 | 191.0 | 0.884 | none | 0.0 | 0.0 | 0.0 | 1 | 0.102 |
| add | <input type="checkbox"/> | 1, 1, 1, 1, 1, 1 | 216.0 | 30.0 | 186.0 | 0.861 | none | 0.0 | 0.0 | 0.0 | 0 | 0.102 |
| add | <input type="checkbox"/> | 1, 0, 1, 1, 0, 0 | 153.0 | 15.0 | 138.0 | 0.902 | none | 0.0 | 0.0 | 0.0 | 0 | 0.072 |
| add | <input type="checkbox"/> | 1, 0, 1, 0, 1, 0 | 153.0 | 15.0 | 138.0 | 0.902 | none | 0.0 | 0.0 | 0.0 | 0 | 0.072 |
| add | <input type="checkbox"/> | 1, 0, 1, 0, 0, 1 | 153.0 | 15.0 | 138.0 | 0.902 | none | 0.0 | 0.0 | 0.0 | 0 | 0.072 |
| add | <input type="checkbox"/> | 1, 1, 0, 1, 0, 0 | 150.0 | 15.0 | 135.0 | 0.900 | none | 0.0 | 0.0 | 0.0 | 0 | 0.073 |
| add | <input type="checkbox"/> | 1, 1, 0, 0, 1, 0 | 150.0 | 15.0 | 135.0 | 0.900 | none | 0.0 | 0.0 | 0.0 | 0 | 0.073 |
| add | <input type="checkbox"/> | 1, 1, 0, 0, 0, 1 | 150.0 | 15.0 | 135.0 | 0.900 | none | 0.0 | 0.0 | 0.0 | 0 | 0.073 |
| add | <input type="checkbox"/> | 0, 1, 1, 1, 0, 0 | 140.0 | 15.0 | 125.0 | 0.893 | none | 0.0 | 0.0 | 0.0 | 0 | 0.079 |

Table 1
Experimental Treatments

| Session | Number of subjects ^a (number of auction profiles in a session) | | |
|---|--|------------|------------|
| | Session 1 ^b | Session 2 | Session 3 |
| <i>Combinatorial clock auction (CCA)</i> | | | |
| 4-items | 19 (2) | 18 (10) | 18 (12) |
| 6-items (Series 1) | 25 (2) | 19 (8) | 20 (8) |
| 6-items (Series 2) | 26 (3) | 21 (10) | 19 (10) |
| <i>Simultaneous ascending auction (SAA)</i> | | | |
| 4-items | 18 (2) | 17 (10) | 16 (11) |
| 6-items | 28 (3) | 23 (10) | 23 (10) |

^a Same subjects participated in a given series. Number of subjects varies due to attrition.

^b Numbers in parentheses were dry runs.

Table 2
Early Ending/Collusive Like Auctions

| | 4-Item Auctions | | | 6-Item Auctions | | |
|-----|--|--------------|--|--|--------------|--|
| | Mean Rounds to Completion ^a | | Percentage of Auctions Ending Early ^b | Mean Rounds to Completion ^a | | Percentage of Auctions Ending Early ^b |
| | All | Early Ending | | All | Early Ending | |
| CCA | 18.1 (5.1) | 7.8 (2.2) | 3.0% (4/132) | 20.2 (7.5) | 7.2 (2.4) | 10.6% (24/226) |
| SAA | 17.1 (7.9) | 9.1 (1.4) | 9.5% (10/105) | 23.8 (7.0) | 9.5 (0.6) | 2.9% (4/140) |

^a Standard deviation reported in parentheses.

^b Number of early ending auctions divided by the total number of auctions in parentheses.

Table 3
 Percent of Profitable Packages Bid on, and Package Profitability, in CCA Auctions^a
 (Average number of profitable packages available to bid on in parentheses)

| | Global bidders | | | Local bidders ^b | | |
|---|---------------------------------------|---|---|---------------------------------------|---|------|
| | Percent of profitable packages bid On | Distribution of bids ^c | | Percent of profitable packages bid On | Distribution of bids ^c | |
| Percent most profitable packages bid on | | Percent 2 nd most profitable packages bid on | Percent most profitable packages bid on | | Percent 2 nd most profitable packages bid on | |
| <i>CCA4 Auctions</i> | | | | | | |
| Rounds 1-5 | 30.8 (13.0) | 73.8 | 64.6 | 64.3 (2.8) | 90.8 | 59.8 |
| Rounds 6-10 | 23.5 (9.8) | 74.8 | 49.1 | 58.3 (2.4) | 89.2 | 41.7 |
| Rounds 11-15 | 23.0 (7.4) | 79.6 | 43.0 | 59.1 (2.2) | 90.3 | 31.3 |
| Rounds > 15 | 28.6 (4.9) | 86.7 | 23.9 | 55.0 (2.0) | 95.8 | 14.3 |
| <i>CCA6 Auctions</i> | | | | | | |
| Rounds 1-5 | 11.9 (59.5) | 63.5 | 49.0 | 50.0 (6.6) | 79.1 | 64.1 |
| Rounds 6-10 | 7.2 (54.2) | 56.7 | 37.8 | 46.6 (5.8) | 80.3 | 61.3 |
| Rounds 11-15 | 7.6 (40.9) | 65.4 | 46.1 | 43.8 (4.8) | 81.7 | 52.5 |
| Rounds > 15 | 6.9 (26.0) | 64.5 | 30.6 | 34.1 (4.4) | 77.2 | 39.7 |

^a Rounds are dropped for provisional winners, if there were no profitable packages to bid on, and when there were no bids.

^b Only includes packages that had positive value for all items for regional bidders.

^c Percentages can add up to more than 100% as subjects often bid on the most profitable package as well as the second most profitable package.

Table 4

Package Bids in CCA Auctions when Named Package is No Longer the Most Profitable Package^a

| | Local bidders | | | | Global bidders | | | |
|----------------------|-----------------|------------------------------|--------------------|-----------------------------------|-----------------|------------------------------|--------------------|-----------------------------------|
| | Number of cases | Percent most profitable only | Percent named only | Percent most profitable and named | Number of cases | Percent most profitable only | Percent named only | Percent most profitable and named |
| <i>CCA4 Auctions</i> | | | | | | | | |
| Rounds 1-5 | 6 | 50.0 | 0 | 50.0 | 0 | -- | -- | -- |
| Rounds 6-10 | 68 | 66.2 | 2.9 | 30.9 | 12 | 33.3 | 16.7 | 25.0 |
| Rounds 11-15 | 68 | 73.5 | 5.9 | 20.6 | 29 | 65.5 | 17.2 | 13.8 |
| Rounds 16-20 | 24 | 91.7 | 4.2 | 4.2 | 15 | 73.3 | 6.7 | 6.7 |
| Rounds > 20 | 4 | 50.0 | 0 | 50.0 | 4 | 100 | 0 | 0 |
| <i>CCA6 Auctions</i> | | | | | | | | |
| Rounds 1-5 | 8 | 25.0 | 12.5 | 62.5 | 0 | -- | -- | -- |
| Rounds 6-10 | 240 | 25.8 | 9.2 | 58.8 | 0 | -- | -- | -- |
| Rounds 11-15 | 203 | 30.0 | 14.3 | 45.3 | 119 | 31.9 | 13.4 | 36.1 |
| Rounds 16-20 | 157 | 39.5 | 19.1 | 29.9 | 57 | 40.4 | 17.5 | 12.3 |
| Rounds > 20 | 67 | 53.7 | 20.9 | 11.9 | 46 | 52.2 | 21.7 | 8.7 |

^a Observations are dropped when a named package is not profitable, a provisional winner does not bid, and in the last round of the auction when there are no bids.

Table 5
Scope for Increased Profit at End of Auction^a

| | Bidder type | Frequency higher profits available ^b | Average forgone potential profits in ECUs ^c |
|--|-------------|---|--|
| <i>CCA4 Auctions</i> Losing bidders | Global | 17.7% (9/51) | 32.1 (12.4) |
| | Local | 9.7% (10/103) | 25.1 (11.4) |
| Winning bidders | Global | 4.9% (4/81) | 35.0 (26.4) |
| | Local | 1.2% (2/161) | 7.0 (5.0) |
| <i>CCA6 Auctions</i> Losing bidders | Global | 36.5% (19/52) | 165.6 (31.4) |
| | Local | 21.4% (46/215) | 27.4 (5.2) |
| Winning bidders | Global | 26.4% (46/174) | 79.2 (10.2) |
| | Local | 30.0% (71/237) | 48.0 (6.0) |

^a Excludes handful of cases (6 in CCA6, 2 in CCA4) where bidders earned negative profits.

^b Raw data in parentheses.

^c Averaged over those cases with scope for increased profit. Standard error of the mean in parentheses.

Table 6
Raw Efficiency Data by Auction Type

| | Simulation Profile ^a | CCA Efficiency | | SAA Efficiency | | Differences (CCA-SAA) | |
|-----------------|---------------------------------|----------------------|------------------------|----------------------|------------------------|-----------------------|-------------------------------------|
| | | Average ^b | Percent 100% Efficient | Average ^b | Percent 100% Efficient | Average ^c | Percent 100% Efficient ^d |
| 4 item auctions | Easy/Named (5) | 98.7% (1.3) | 97.2% | 91.5% (3.1) | 72.0% | 7.2% (2.78)*** | 25.2% (2.87)*** |
| | Hard/Named (5) | 96.9% (1.2) | 73.3% | 84.1% (2.5) | 20.0% | 12.8% (4.15)*** | 53.3% (3.70)*** |
| | Hard/Unnamed (6) | 91.4% (1.9) | 36.1% | 90.3% (5.0) | 66.7% | 1.1% (-1.88)* | -30.6% (-2.47)** |
| | Easy/Unnamed (5) | 93.3% (2.0) | 60.0% | 97.2% (1.6) | 50.0% | -3.9% (-1.07) | 10.0% (0.78) |
| 6 item auctions | Easy/Named (5) | 92.1% (1.4) | 50.0% | 90.0% (2.1) | 25.7% | 2.1% (1.68)* | 24.3% (2.37)** |
| | Hard/Named (4) | 88.9% (2.3) | 36.4% | 87.4% (2.0) | 0.0% | 1.5% (1.98)** | 36.4% (3.62)*** |
| | Hard/Unnamed (5) | 89.6% (1.5) | 10.5% | 89.9% (2.2) | 31.0% | -0.3% (-1.06) | -20.5% (-2.55)** |
| | Easy/Unnamed (4) | 86.8% (1.8) | 14.0% | 97.1% (1.2) | 60.0% | -10.3% (-4.95)*** | -46.0% (-4.61)*** |

- ^a Number of different CCA auction profiles in parentheses. *Significant at 10% level, two-tailed test.
^b Standard error of the mean in parentheses. ** Significant at 5% level, two-tailed test.
^c Mann-Whitney test statistic in parentheses. *** Significant at 1% level, two-tailed test.
^d Binomial test statistic in parentheses.

Table 7
Efficiency Differences Between Auction Profiles: Tobit Index Function^a

| | Easy/Named | Hard/Named | Easy/Unnamed | Hard/Unnamed |
|--------------|------------|------------|--------------|--------------|
| Hard/Named | -3.2% ** | | | |
| Easy/Unnamed | -6.5% *** | -3.3% ** | | |
| Hard/Unnamed | -7.6% *** | -4.4% ** | -1.1% | |
| SAA | -5.0% *** | -8.0% *** | 7.2% *** | 2.1% |

- ^a Colum effects are relative to respective auction profiles listed in top row.
** Significantly different from 0 at the 5% level, two-tailed test.
*** Significantly different from 0 at the 1% level, two-tailed test.

Table 8

Raw Efficiency Data when Efficient Outcome Corresponds to Named versus Unnamed Packages

| | Simulation Profile ^a | CCA Efficiency | | SAA Efficiency | | Differences (CCA-SAA) | |
|--------------------|--|----------------------|------------------------------|----------------------|------------------------------|--------------------------|---|
| | | Average ^b | Percent 100% Efficient | Average ^b | Percent 100% Efficient | Average ^c | Percent 100% Efficient ^d |
| 4 item auctions | Efficient = Named Package (10) | 97.9% (0.9) | 86.4% | 88.2% (2.1) | 48.9% | 9.7% (4.52)*** | 37.5% (4.28)*** |
| | Efficient = Unnamed Package (11) | 92.3% (1.3) | 47.0% | 93.8% (2.7) | 58.3% | -1.5% (-2.12)** | -11.3% (-1.28) |
| 6 item auctions | Efficient = Named Package (9) | 90.8% (1.3) | 44.6% | 88.9% (1.5) | 14.3% | 1.90% (2.71)*** | 30.3% (4.08)*** |
| | Efficient = Unnamed Package (9) | 88.2% (1.2) | 12.3% | 93.2% (1.4) | 44.2% | -5.0% (-4.49)*** | -31.9% (-4.98)*** |

^a Number of different CCA auction profiles in parentheses.^b Standard error of the mean in parentheses.^c Mann-Whitney test statistic in parentheses.^d Binomial test statistic in parentheses.

*** Statistically significant at the 1% level, two-tailed test.

Table 9

Efficiency Differences Between Auction Profiles for Named versus Unnamed Auction Profiles:

Tobit Index Function

| | Tobits ^a | |
|---------|---------------------|---------|
| | Named | Unnamed |
| Unnamed | -5.8%*** | |
| SAA | -6.6%*** | 4.7%*** |

^a Mean percentage difference in efficiency calculated from Tobit index function.^b Mean change in probability of achieving 100% efficiency from the probit regressions.

*** Significantly different from 0 at the 1% level, two-tailed test.

Table 10
Raw Revenue and Profit Data
(standard error of the mean in parentheses)

| | Revenue ^a | | | Total Profit ^b | | |
|-----------------------------|----------------------|-----------------|-------------------------|---------------------------|----------------|-------------------------|
| | CCA | SAA | Difference ^c | CCA | SAA | Difference ^c |
| <i>4-item auctions</i> | | | | | | |
| Efficient = Named Package | 97.8% (2.3) | 102.6% (2.1) | -4.8% (-1.52) | 23.3% (1.4) | 13.5% (2.7) | 9.8% (2.30)** |
| Efficient = Unnamed Package | 103.1% (2.7) | 97.8% (2.8) | 5.3% (0.87) | 19.7% (1.9) | 24.0% (3.4) | -4.3% (-1.95)* |
| <i>6-item auctions</i> | | | | | | |
| Efficient = Named Package | 85.1% (2.6) | 92.7% (2.3) | -7.6% (-1.87)* | 24.1% (1.9) | 15.7% (2.2) | 8.4% (2.04)** |
| Efficient = Unnamed Package | 89.7% (2.6) | 93.5% (2.1) | -3.8% (-0.57) | 21.9% (1.9) | 20.7% (1.7) | 1.2% (0.86) |

^a Measured as a percentage of minimum revenue in the core.

^b Measured as a percentage of the efficient allocation.

^c Mann-Whitney test statistic in parentheses.

* Statistically significant at the 10% level, two-tailed test.

** Statistically significant at the 5% level, two-tailed test.

Table 11
Revenue and Profit Differences Between CCA and SAA Auctions

| | Revenue ^a | | Total Profit ^b | |
|---------|----------------------|---------|---------------------------|---------|
| | Named | Unnamed | Named | Unnamed |
| Unnamed | 4.8%* | | -2.8%* | |
| SAA | 5.3%** | -0.1% | -7.6%*** | 1.5% |

^a Measured as a percentage of minimum revenue in the core.

^b Measured as a percentage of the efficient allocation.

^c Average of the two local bidders' profits.

*Significantly different from zero at the 10% level, two-tailed test.

**Significantly different from zero at the 5% level, two-tailed test.

***Significantly different from zero at the 1% level, two-tailed test.

Table 12
Raw Data for Scaled Distance from the Core

| | Simulation Profile ^a | CCA Distance from the Core | | SAA Distance from the Core | | Differences (CCA-SAA) | |
|-----------------|----------------------------------|----------------------------|-----------------------|----------------------------|-----------------------|-----------------------|------------------------------------|
| | | Average ^b | Percent Zero Distance | Average ^b | Percent Zero Distance | Average ^c | Percent Zero Distance ^d |
| 4 item auctions | Efficient = Named Package (10) | 11.5% (2.2) | 42.4% | 18.7% (2.3) | 17.8% | -7.2% (-3.23)*** | 24.6% (2.72)*** |
| | Efficient = Unnamed Package (11) | 14.7% (1.9) | 27.3% | 18.3% (3.6) | 13.3% | -3.6% (-0.30) | 14.0% (1.93)* |
| 6 item auctions | Efficient = Named Package (9) | 28.9% (3.2) | 17.9% | 23.5% (2.8) | 7.9% | 5.4% (0.13) | 10.0% (1.80)* |
| | Efficient = Unnamed Package (9) | 28.1% (2.9) | 3.5% | 17.5% (2.4) | 10.4% | 10.6% (2.96)*** | -6.9% (-1.92)* |

^a Number of different CCA auction profiles in parentheses.

^b Standard error of the mean in parentheses.

^c Mann-Whitney test statistic in parentheses.

^d Binomial test statistic in parentheses.

* Statistically significant at the 10% level, two-tailed test.

** Statistically significant at the 5% level, two-tailed test.

*** Statistically significant at the 1% level, two-tailed test.

Table 13
Differences in Scaled Distance from the Core: Tobit Index Function

| | Tobits ^a | |
|------------|---------------------|----------|
| | Named | Unnamed |
| Unnamed | 2.5% | |
| 4-Item SAA | 6.2%* | 0.9% |
| 6-Item SAA | 0.1% | -5.5%*** |

^a Mean percentage difference in efficiency calculated from Tobit index function.

* Significantly different from 0 at the 10% level, two-tailed test.

*** Significantly different from 0 at the 1% level, two-tailed test.

Table 14
 Comparing the Straight Forward Simulator with the Alternative Simulator:
 Mean Absolute Differences Between Predicted and Actual Efficiency
 (standard errors in parentheses)

| | Straight Forward Simulator | Alternative Simulator | Difference: Straight Forward less Alternative Simulator |
|----------------------|----------------------------|-----------------------|---|
| All Auction Profiles | 0.124 (0.006) | 0.086 (0.005) | 0.037*** (0.005) |
| Named Auctions | 0.100 (0.008) | 0.070 (0.007) | 0.030*** (0.006) |
| Unnamed Auctions | 0.145 (0.009) | 0.101 (0.007) | 0.044*** (0.008) |

*** Significantly different from 0 at the 1% level or better, two-tailed paired t-test