Auctions with Package Bidding: An Experimental Study

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Abstract

This paper reports the results of auction experiments to evaluate auction designs when agents have superadditive values for heterogeneous objects. The first factor of the experimental design is auction choice. We considered generalized Vickrey auctions, simultaneous ascending auctions, and clock-proxy auctions. The second factor is the value structure of agents. In addition to a benchmark case of additive values, we considered superadditive value structures which feature the exposure problem and the coordination problem. The third factor is subject characteristics. We ran experiments with professional traders and university students. We found that clock-proxy auctions outperformed generalized Vickrey auctions. Clock-proxy auctions outperformed simultaneous ascending auctions with the exposure problem value structure, and did statistically equally well with the additive and the coordination problem value structure. The result suggests a trade-off:between efficiency improvements and complexity in package bidding. An ANOVA of outcomes demonstrated that auction designs were significant, and the interaction terms were often significant. We estimated the effect of auction design on efficiency and revenue and found that its magnitude depended on the valuation structure and subject characteristics. The result suggests that market design is not one-size-fits-all but that a successful design builds on an understanding of problem specific issues.

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1 Introduction

The goal of market design is to define trading procedures which improve efficiency and other performance goals. Formally, the market design problem in a given economic environment is

$$\text{maximize } f(x:t) \text{ subject to } x \in X \tag{1}$$

where x is a trading procedure, X is the design space of the possible trading procedures, t is the type profile of agents, and $f(x,t)$ is the performance function. The task of the market design is the characterization of the solution $x^*(t)$.

A standard method in evaluating performance of trading procedures is structural econometrics. In this approach, a researcher first derives an equilibrium strategy of an agent which maps its type to an action in a game induced by the trading procedure. From the observed data, the researcher estimates the types of the agents. Then, a researcher evaluates the performance of an alternative trading procedure from an application of the estimated type. Some recent examples include a comparison between uniform and discriminatory pricing rules in treasury auctions (Hortacsu (2002)) and the choice of auction formats for timber auctions (Athey, Levin, and Seira (2004)).

There are two issues in the application of this approach. First, this approach requires data about the behavior of the agents that are detailed enough to allow a statistical identification of their type. But in many markets, detailed data are proprietary and not usually available. Moreover, the structural approach is based on an assumption that agents play a Bayes-Nash equilibrium. But in a complex environment, it may not be realistic to assume that an agent can correctly compute an equilibrium strategy and outcomes. For example, in a package auction of 16 objects, there are $2^{16}-1$ possible packages, and the evaluation of all bids and packages that maximize the expected payoff can be computationally infeasible. Furthermore, in a setting where there are multiple equilibria, it is not certain which equilibrium a researcher should focus on.

In this paper, we consider an alternative experimental approach to evaluate performances of trading procedures. In this experimental approach, a researcher starts with the experimental design where a researcher controls the levels of factors which may affect performance. Then, a researcher randomly assigns these treatments to experimental units and then observes agents' behavior and performance. An empirical strategy is 'experimentalist': that is, a researcher estimates the causal effect of underlying factors on performance.

A practical justification for the experimental approach may be found in the use of polling in the policy-making process and clinical trials in the drug development process. In the policy-making process, it is common for a policy maker to conduct a poll and focus groups when they form a policy. In the United States, the Food and Drug Administration requires clinical trials to evaluate the safety and effectiveness of a new drug before it is marketed. In a similar way, an economic laboratory test can be an effective way to estimate the strategic response of agents and to check the robustness of performance of a proposed economic and business design before its actual implementation.

In this paper, we conduct laboratory experiments to study designs of trading procedures in an environment where multiple heterogeneous and indivisible objects are going to be allocated among agents with superaddtive values. Here, heterogeneous objects have different characteristics. Consequently, agents can have different values for different objects. Furthermore, with superadditive values, the value of a package of objects can be more than the sum of the values of the objects in the package.

A motivation to study this problem is its practical significance. As a result of recent progress in information technology, the costs of communication and information processing have decreased over the past decades. It is now possible to design and implement innovative and flexible trading procedures. Early examples of package bidding include airport scheduling and space stations (Banks, Ledyard, and Porter (1982)), transportation services (Ledyard, Olson, Swanson, and Torma (2000)), and train scheduling (Brewer and Plott (1996)). In London bus auctions studied in Cantillon and Pesendorfer (2004), the London bus procurement authority allows package bidding. In planned FCC Auctions No. 31 for upper 700 MHz bands, the auction rules allow package bidding (FCC (2002)). Thus it is significant to understand the performance effect of package bidding procedures.

Let us pause for a moment to understand the auctioneer's maximization problem. In this setting, a designer is primarily interested in the efficiency of an allocation. The revenue is an additional interest. There are two constraints on the response of the agents. The first issue is incentive compatibility. Since the valuations are private, the agents may choose not to reveal their true valuations, but rather tell careful lies. The second issue is complexity. Real world agents have limited resources for communication and cognition. Thus a mechanism needs to be simple and transparent.

Before going into the case of multiple heterogeneous objects, let us review the simplest case of an allocation of a single object. In this case, ascending auctions are a reasonable candidate in a symmetric private value environment with risk-neutral agents. First, they satisfy incentive compatibility: ascending auctions are truthful. Second, a truthful equilibrium in ascending auctions is efficient. Third, by a revenue equivalence theorem, the seller expected revenue will be the same other standard auction mechanisms. Fourth, ascending auctions are simple to work with. Communication complexity is low since the decision problem is solely to decide a bid or the drop out price. Furthermore, cognitive complexity is also low since the price to be paid is transparent. Indeed, in experiments (Kagel, Harstad, and Levin (1987)), the bids at the first price auctions were well above the equilibrium predictions. In 80% of the second price auctions, prices exceeded the dominant strategy price by more than one minimum increment. In contrast, in 70% of the ascending auctions, the difference between the actual and the predicted price was less than one minimum increment.

But in the allocation of heterogeneous objects, theoretical analysis is difficult because incentive compatibility and complexity constraints are much tighter and there are trade-offs between the two. When agents have superadditive values, an ascending auction with or without package bidding can suffer from inefficiencies due to strategic bidding (Milgrom (2004)). In addition, a mechanism is needed to discover not only a market price for each object but also the prices for all the packages (Nisan and Segal (2004), for example).

An issue about ascending auctions without package bidding is the *exposure problem*. Consider an agent who is interested in a package. In order to win the package, the agent needs to outbid other agents who are only interested in the subsets. If package bidding is allowed, then the agent can directly express valuations following the procedure. Otherwise, the agent needs to compete for each object. The agent may be exposed to a loss if the superadditive values are not realized. Given this risk, the agent might bid lower, causing inefficiencies. In other words, without package bidding, package prices may not be discovered correctly.

Another issue about ascending auctions with package bidding is called the *coordination problem* (or the threshold problem). Consider agents who are interested only in smaller packages. If there is no package bidding procedure, then it is sufficient that these agents can express their valuations in an auction for each object. But if a package bidding procedure is allowed, there might be some other agents who use the procedure to bid for the whole package. Here, agents interested in smaller packages have an incentive to bid low in order to free-ride the bids by other bidders to decrease the payment.

Consequently, with package bidding, agents may fail to coordinate to beat a package bid. That is, object prices may not be discovered correctly.

The other problem is communication complexity. With superadditive values, the mechanism may need to determine a supporting price for each package in order to find an efficient allocation. For example, for an allocation of N objects, $2^N - 1$ prices need to be discovered. This requirement imposes a heavy communication burden for agents.

As a result, the theoretical research has not yet identified a mechanism which can deal with these issues successfully, in spite of remarkable progress (Ausubel, Cramton, Milgrom (2004), Ausubel and Milgrom (2002,2004), Kwasnica, Ledyard, Porter, and DeMartini (2002), Milgrom (2000), Parkes (2004)).

This problem seems to call for an experimental approach. First, an equilibrium analysis of these mechanisms is not well developed, and the mapping from agents' types to an equilibrium performance of the mechanisms is not known. Second, with the package bidding procedure, the strategic decision problem of an agent is complex since it involves a large number of possible packages. Thus, an auctioneer may need to be concerned about the implication of these complexities on the auction performance instead of simply applying a standard equilibrium analysis.

In our experiment, we control three factors. These three factors are auction design, value structure, and subject characteristics. We rewrite (1) to

$$\text{maximize } f(x : t_1, t_2) \text{ subject to } x \in X$$

where x is the auction design, t_1 is the value profile of agents, and t_2 is the subject characteristics. We implement a factorial design rather than a sequential design in order to account for possible nonlinear treatment effects.

In this experiment, we consider three representative auction mechanisms: generalized Vickrey auctions, simultaneous ascending auctions, and clock-proxy auctions. The first mechanism is generalized Vickrey auctions, in which each agent bids not only on objects but also on packages. Then the auctioneer selects the value-maximizing allocation. Each agent then pays the amount which is equal to the minimum amount required to win the package. Notably, generalized Vickrey auctions are sealed-bid auctions.

Generalized Vickrey auctions satisfy incentive compatibility. First, they are truthful: it is always for the agent's benefit to report the true valuations. Furthermore, any efficient mechanism where sincere bidding is a dominant strategy and losers have zero payoffs is payoff-equivalent to generalized Vickrey auctions. However, Generalized Vickrey auctions suffer from complexity issues, since each agent is required to report the values for all possible packages.

The second mechanism is simultaneous ascending auctions. Simultaneous ascending auctions have been used in U.S. spectrum auctions since 1994. Simultaneous ascending auctions proceed in rounds. At the beginning of each round, the auctioneer sets the current standing price. Then, each agent bids on objects. In simultaneous ascending auctions, there are no package bidding procedures. At the end of the round, the auctioneer chooses the new standing high bid. The auction ends when there are no new bids on any auction. The agent with the standing high bid wins the object. In contrast to generalized Vickrey auctions, simultaneous ascending auctions ensure that the market clears for each object.

Simultaneous ascending auctions are simple. Each agent needs to bid only on individual objects. The agents are always clear about whether a bid is winning and its price. Secondly, the simultaneous ascending auction works well when objects are substitutes, as straightforward bidding will lead to a competitive equilibrium. However, simultaneous ascending auctions suffer from the exposure problem whenever values are superadditive.

The third mechanism is the clock-proxy auction (Ausubel, Cramton, and Milgrom (2004)). Clock-proxy auctions are a two-stage mechanism consisting of clock auctions and proxy auctions. In a first stage clock auction, the auctioneer sets the price for each object. Each agent responds by choosing to stay or to drop out. The auctioneer increases the price for any objects having excess demand. An auction ends when the market clears for each object. In the second stage of proxy auctions, each agent sends their values to a proxy agent. Then proxy agents bid straightforwardly in hypothetical ascending auctions. Straightforward bidding means bidding for the package which is most profitable at the current price. The auctioneer then chooses the value-maximizing allocation based on submitted bids. An economic rational for clock-proxy auctions is that the clock stage will lead to a better price discovery and the outcome of an ascending package auction is primarily driven by the reported bids.

We consider the valuation structures of the agents as the second factor of the experiment. We choose three different valuation structures to quantity the advantages and disadvantages of these auction mechanisms.

First of all, let us define the basic structure of objects and values. In our experiment, there are 16 objects arranged in a rectangle. Five agents are depicted in such a rectangle as in Figure 1. Each agent has a 'base value' for each object.

Figure 1: A Geometric Representation of Objects and Agents

In the benchmark case, each agent has an additive value function. That is, for each agent, the value of the package is simply the sum of the values of the individual contained in the package.

The second case focuses on the exposure problem. In this case, each agent has a high level of interest for those objects closest to their location. For example, agent 1 has the strongest interest in objects 1, 2, 5, and 6. Moreover, Agent 1 has a higher interest in objects 1, 2, and 5 than in object 6. In this case, the efficient allocation is that Agent 3 is going to win the objects 6, 7, 10, and 11, since these objects are closer to agent 3 than to any other agent. But, agent 3 is going to face the exposure problem: without a package bidding procedure, it might be difficult for agent 3 to beat each of the other agents, even though their interest in these objects is weaker. Thus this second case is going to measure the impact of these exposure problems on the performance of auction mechanisms.

In the third case, we consider the coordination problem, where the level of interest is identical among objects close to an agent. Consequently, in an efficient allocation, agent 3 is not going to win any objects, and it will be agents 1, 2, 4, and 5 who will face the coordination problem.

Lastly, we examine the impact of subject characteristics. In standard experiments, the subjects of the experiments are university students. There have been concerns since these students are less knowledgeable and experienced than actual participants in the market. That is, university students may not be representative of the targeted population. If true, it may bias the estimate. To investigate this issue, we ran one session with professional traders who make their living in stock trading and internet auctions.

Given the experimental data, we move to the next step of empirically investigating the optimization problem (2). The advantage of this experimental approach over the 'social experiment' type of study is (1) a researcher has control over the variation in the factors and (2) the assignment of the experimental unit to treatment is random. In contrast, in a 'social experiment' study, a researcher needs to be concerned with selection bias due to endogeneity of assignment. But, in a controlled experiment, since a researcher can exogenously assign a treatment level to an experimental unit, we can directly compare the responses of the experimental units to different treatments. On the other hand, since we do not adopt a structural approach, we do not have much information about the functional form of f. Consequently, the experimentalist approach focuses on establishing the causal relationship between factors and performances.

We first discuss the pairwise comparison among treatment groups. First, clock-proxy auctions did better than generalized Vickrey auctions with the full sample. We find two reasons. The first issue is coordination of bids among agents. In package auctions, the market clears not object-by-object, but as a whole. Therefore, a bid needs to find 'partner packages' with which they cover all the objects to win. But in package auctions, the number of possible packages is quite large. Given bid submission costs, each agent submits only a limited number of bids. Thus, avoiding conflicts and forming winning combinations are not trivial tasks for agents. In generalized Vickrey auctions, since it is sealed-bid simultaneous, each agent does not have any information about the behavior of other agents. On the other hand, in clock-proxy auctions, agents can observe the bids by other agents in the first stage of clock auctions. Thus this information can help the coordination among agents. Naturally, this problem is most severe in additive value cases where there are no 'focal bids'. The second issue is a low revenue equilibrium in generalized Vickrey auctions, where agents can engage in a low revenue equilibrium strategy by engaging in a demand reduction. In contrast, in clock-proxy auctions, agents have an opportunity to bid for objects, which makes a low revenue equilibrium harder to realize.

Second, clock-proxy auctions did significantly better than simultaneous ascending auctions with exposure problems, and rankings with additive values and coordination problems are ambiguous. Simultaneous ascending auctions yielded higher revenues than clock-proxy auctions. An explanation for the first result is incentive problems pointed out in previous research. The second explanation is that exposure problems in simultaneous ascending auctions sometimes lead agents to bid too aggressively, causing a loss ex post. This 'naive' bidding behavior contributed to a high revenue in simultaneous ascending auctions.

Third, complexities of trading procedures affect the performance. Large scale package auctions are difficult to grasp, and they involve various dimensions of complexities such as communication complexities and cognitive complexities. We compare the performance of two cases: with and without time limits. Removing time limits improved efficiencies, but still the outcome did not reach full efficiency because of cognitive costs and package coordination problems.

Fourth, subject characteristics affect the performance of trading procedures. We found that with professional traders, agents' payoffs were significantly higher. The differences were the biggest with generalized Vickrey auctions. One reason is that professional traders frequently engage in 'package demand reduction.' This is equivalent to demand reduction in multi-unit auctions as discussed in Ausubel and Cramton (2000). In multi-unit auctions, agents reduce bids for later units in order to reduce the market clearing price. In auctions of heterogeneous objects with package bidding procedures, reducing the bids for some packages can still affect the market clearing price. We found that professional traders engaged in demand reduction more often than students did. In these package demand reduction equilibria, the allocation is close to efficient, but the payment is very small.

After conducting pairwise comparison among a comparison group, we generalize the model to include multiple factors. Also, we are interested in a preliminary estimation of the performance functions. As a first step, we conducted a 3-way ANOVA with the dependent variables of efficiency and revenue.

An ANOVA analysis showed that auction designs have significant impact on efficiencies and seller revenue. The subject characteristics were not significant for the determination of efficiencies, but were significant for the determination of the auctioneer revenue. This result is consistent with the above explanation of strategic package demand reduction by professional traders. Furthermore, we found that the interaction terms among factors were often significant. This result suggests that the magnitude change as a result of change in trading procedures can depend on factors levels.

As a result of ANOVA, we find that the performance function f is nonlinear in parameters x, t_1 and t_2. As a preliminary step to estimating the functional form of the performance function, we estimate the quadratic response surfaces. From these parameters, we estimate the impact of auction designs on efficiencies in each valuation structure after controlling the subject characteristics. We took the additive value environment and the generalized Vickrey auction as a benchmark. That is, in this formulation, the performance of an auction mechanism in a given value structure is determined by (1) the baseline performance of generalized Vickrey auctions with additive values, (2) a differences in the auction mechanism in an additive value environment, and (3) the interaction terms depending on the value structures. In an additive value environment, we found that simultaneous ascending auctions led to higher efficiency improvements. But in the exposure value environment, due to interaction terms, clock-proxy auctions achieved higher efficiency improvements. These results are consistent with theoretical conjectures.

Let us briefly summarize the contributions of this paper.

First, the clock-proxy auction has not been previously studied; this is the first experimental evaluation of clock-proxy auctions. Furthermore, this experiments adopts a large scale setting. Previous studies such as Ledyard, Porter, and Rangel (1997) and Banks, Olson, Porter, Rassenti, and Smith (2002) involved only a small number of objects or one dimensional superadditivity. On the other hand, our setting introduces a two-dimensional superadditivity, which will allow the evaluation of complexity issues.

Second, we provide experimental evidence of various theoretical hypotheses concerning package auctions and simultaneous ascending auctions. We found that generalized Vickrey auctions suffered from low revenue equilibria, as suggested by Ausubel and Milgrom (2004). Additionally, we found that exposure problems deterred the performance of simultaneous ascending auctions, and coordination problems made the comparison between package auctions and simultaneous ascending auctions inconclusive.

Third, it is one of the first studies which documents the effect of complexities on the performance of trading procedure. Because of these bid submission costs and complexities, agents chose to focus on some limited number of objects and packages rather than spreading their efforts among many objects and packages. Furthermore, we found that removing the time limit of the round - thus decreasing the cost of bid submission - increased efficiency and revenue, but not sufficiently to realize full efficiency.

Fourth, this is one of the first studies that documents the effect of subject characteristics on the outcome of the experiments. The result that subject characteristics significantly affects the performance, especially regarding seller revenue, suggests that previously proposed estimates based on university student experiments can be potentially biased.

The rest of the paper is organized as follows. Section 2 defines the economic environments and auction mechanisms used in this experiment. Section 3 describes the experimental design. Section 4 explains our findings for pairwise comparison among treatment groups. Section 5 considers ANOVA and estimation of auction design. Section 6 concludes.

1.1 Previous Studies

Our research builds on previous experimental contributions.

Banks, Ledyard, and Porter (1989) compared object-wise double auctions, administrative process, iterative VCG mechanisms and combinatorial ascending bid mechanisms (Adaptive User Selection Mechanisms). Our results are consistent with their results: combinatorial mechanism can be effective in the presence of superadditivity.

Ledyard, Porter, and Rangel (1997) compared the performances of sequential ascending auctions, simultaneous ascending auctions, and the AUSM mechanisms. There were unit demand restrictions, three objects, or restriction to the number of packages the agents have interests in. When objects were substitutes, package bidding did not have a significant effect on performance. When there were exposure problems, AUSM led to a significantly higher efficiency but the coordination problems did not have significant impacts. Our results on the comparison between clock-proxy auctions and simultaneous ascending auctions are consistent with their results. A difference is that our setting is of much larger scale. Thus, complexity of package bidding trading procedures has an impact on performance.

Recently, Morgan (2002) conducted experiments comparing the performance of generalized Vickrey auctions and simultaneous ascending auctions in the environment of three objects and 15 agents. Little difference was found among the performance of these mechanisms. A difference between our setting and his setting is the scale of the auctions: our setting involved 16 objects. Complexity due to a large number of objects explains the difference in results.

Banks, Olson, Porter, Rassenti, and Smith (2002) considered experiments comparing the performance of simultaneous multi-round auctions, with ascending auctions having package bidding. They found that ascending auctions with package bidding achieved higher efficiencies with complementary value functions. Their results are consistent with our results. Our experimental design introduces specific value structures and subject characteristics.

Finally, let us emphasize the issues in our research which the previous research did not deal with. First, we consider a large-scale setting with a two-dimensional formulation of superadditivity. Second, we consider factor design which specifically focuses on exposure problems and coordination problems. Third, we examine the impact of complexity of trading procedures. Finally, we conduct analysis of subject characteristics.

2 Economic Environments and Auction Mechanisms

In this section we formulate the economic environment and define the auction mechanisms.

2.1 Economic Environments

We consider a complete information private value environment.

We begin with the definition of objects and packages. Suppose there are $N \in \boldsymbol{N}_{++}$(heterogeneous) objects. A package is $z = (z_1, ..., z_N)$with $z_n \in \{0, 1\}$for each n. Let Zbe the set of all packages.

There are $L \in N_{++}$agents. Let agent l's value function be $v_l : Z \to \mathbf{R}_+$.

Agent $l's$ payoff from acquiring a package z and paying $b_l(z)$is $v_l(z) - b_l(z)$.

The value function of agent $l$is additive if for any z,

$$v_l(z) = \sum_{z_m: \sum z_m = z} v_l(z_m)$$

where $z_m = \underbrace{(0, ..., 1, ..., 0)}_{m \text{ th element}}$. That is, the value of a package is equal to the sum of the values of objects comprising the package. The value function of agent $l$is superadditive if for any z,$v_l(z) \geq \sum_{z_m: \sum z_m = z} v_l(z_m)$and there is some $z$such that a strict inequality holds.

2.2 Auction Mechanisms

We now introduce auction mechanisms.

2.2.1 Generalized Vickrey Auctions

A generalized Vickrey auction (Vickrey (1961), Clarke (1971), and Groves (1973)) consists of three procedures. First, agents $l = 1, ..., L$ simultaneously place bids. Package bidding is allowed. Let $v_l' : Z \to \mathbf{R}_+$ be a bid by agent l. Given incentive constraints, v_l'may well be different from v_l. Second, the auctioneer chooses the value-maximizing allocation according to the reported valuation. Let $\{z_l^*\} = \arg\max_{\{z_l\}} \sum_l v_l'(z_l)$subject to $0 \leq \sum_l z_l \leq 1, 0 \leq z_l \leq 1, \forall l$. Third, each agent pays the externality imposed upon other agents. In order to compute the payment, the auctioneer first computes the values other agents get when the agent is absent from the auction. Let $\alpha_l = \max \sum_{m \neq l} v_m'(z_m)$subject to $0 \leq \sum_{m \neq l} z_m \leq 1, 0 \leq z_m \leq 1, \forall m$. Then, using this amount a_l, the payment is defined by $p_l = \alpha_l - \sum_{m \neq l} v_m'(z_m^*)$.

2.2.2 Simultaneous Ascending Auctions

The second auction mechanism is the simultaneous ascending auction, which proceeds in rounds. At the beginning of each round, the auctioneer sets, for each object, the provisional winner and the price $p(z_n), n = 1, ..., N$. For each object, any agent can submit a bid that is at least equal to the provisional price plus the minimum price increment. Package bidding is not allowed. At the end of the round, the auctioneer determines the provisional winner and price of each object. The provisional winner is the agent with the highest bid for that object. The auction ends at the round when no auction has any new bids. During the auction, each agent is fully informed of all bids and bidder identities.

In order to isolate the effect of package bidding, our implementation of simultaneous ascending auctions is simpler than the actual FCC auctions. For example, we do not impose eligibility rules, activity rules, or bid withdrawal; agents are not subject to any quantity cap; minimum bid increments are fixed throughout the auction.

2.2.3 Clock-Proxy Auctions

The third mechanism is clock-proxy auctions proposed by Ausubel, Cramton, and Milgrom (2004). The clock-proxy auction consists of two stages: clock auctions followed by proxy auctions. The clock proxy auctions are 'demand-query'mechanisms, and they implement the Walrasian auctioneer. First, at the beginning of each round, the auctioneer sets the price $p(z_n), n = 1, ..., N$. The prices are usually those from the previous round plus some increments (for more details, see Ausubel, Cramton, and Milgrom (2004)). Second, each agent decides whether to stay in or drop out from the auction (i.e., demand query). Third, the whole auction closes when there are no active auctions remaining. Bids at the clock auction will be used as a package bid in a proxy auction.

The proxy auctions are a version of ascending proxy auctions defined in Ausubel and Milgrom (2002). First, each agent chooses and sends their values to a proxy agent. Second, proxy agents participate in an ascending auction by bidding straightforwardly. At each round of the ascending auction, provisionally winning bidders don't do anything in this round.Third, each provisionally losing bidder (proxy) computes the current surplus for each package (valuation - standing highest bid) and chooses one package with the highest surplus. If the surplus is higher than the bid increment, he places a bid for this package: standing highest bid plus a bid increment.

If more than one proxy choose to bid for the same package, only one of them will be awarded this bid. Fourth, at the end of each round, after all agents have made their bids, the auctioneer selects the combination of non-conflicting bids that maximizes their values and chooses the start values for the next round. Fifth, the auction ends when there are no new bids from proxy agents.

The first stage of clock auctions is similar to simultaneous ascending auctions in that they allow only object-by-object bidding. However, clock auctions are distinct in that the price increases are driven by the clock set by the auctioneer. The decision problem of each agent is whether or not to drop out. The second stage of the ascending proxy auction is similar to the Vickrey auction in that it includes the package bidding procedure. However, the ascending package auction is distinct in that each agent provides a value profile to their proxy agent, and the proxy agent bids straightforwardly according to the reported value profile.

2.3 Review of Theory and Hypothesis

In this subsection, we summarize the hypothesis to be experimentally tested.

2.3.1 Substitute Case

We first consider the case where objects are substitutes. Recall that objects are substitutes if for each object m, the demand for object $m$is nondecreasing in the price $p_j, j \neq m$. That is, the demand for each good is nondecreasing in the prices of other goods. Equivalently, we can define substitutes in terms of isonotinicity of the rejected set in the set of available contracts. An example is the case where the value functions are additive. When the packages have superadditive values, this substitute relationship does not necessarily hold since the demand for object $m$may come from the package value that includes object j. It is intuitive that an increase in the set of available contracts corresponds to price decreases. A key result in case of substitutes (Gul and Stacchetti (1999) and Milgrom (2000), for example) is that a competitive equilibrium exists in this case. An intuitive argument: Consider prices and allocations obtained at the end of the process of straightforward bidding according to the true value function. At the end when there are no new bids, each bidder's allocation maximizes the payoff, given prices by the straightforward bidding. That is, it suffices for the mechanism to discover the market clearing price for each object.

Since it is sufficient to discover the prices for each object, and prices for the packages need not be discovered, it is conjectured that package bidding procedures will have little impact. Indeed, when goods are substitutes, there exists a dominant strategy equilibrium in ascending proxy auctions which will lead to Vickrey payoffs (Ausubel and Milgrom (2002)). An intuitive argument: With sincere bidding, if the payoff is less than Vickrey payoffs, then there is a blocking coalition adding that bidder because of bidder submodularity. Thus the payoff is that of Vickrey payoffs, thus a dominant strategy. These observations can be summarized in the following hypothesis:

Hypothesis 1. When the objects are substitutes, there will be little performance differences among generalized Vickrey auctions, simultaneous ascending auctions, and clock-proxy auctions.

2.3.2 Superadditive Values: Exposure problem

But when objects are complements, the equivalence no longer holds. Competitive equilibrium may fail to exist. The mechanism may need to discover both object and package prices. Generalized Vickrey auctions are still truthful. But an agent needs to report the value for all possible $2^N - 1$packages. Ascending auctions will suffer from two strategic incentive problems: exposure problems and coordination problems. Recall that exposure problems are defined as follows: when an agent has superadditive values, the value of a package is higher than the values of the objects consisting a package. If package bidding is not allowed, then the exposure problem can lead to inefficiencies. Thus, the hypothesis about exposure problems:

Hypothesis 2. When exposure problems are present, introducing package bidding procedures will improve efficiency.

2.3.3 Coordination Problem

On the other hand, package bidding procedures will introduce a coordination problem among agents against a package bidder. Recall a coordination problems applies to agents who are interested in individual objects but need to beat a package bidder. If package bidding is allowed, then coordination failure can lead to inefficiencies. This leads to the following hypothesis:

Hypothesis 3. When there are coordination problems, introducing package bidding procedures may not improve efficiency.

3 The Experimental Design

In the previous section, we defined three auction mechanisms and reviewed the main hypothesis of this paper. In this section, we define the experimental design and remaining two factors.

We begin with the formulation of objects and values used in the experiment. There are 16 objects and 5 agents. Each agent has a value $v^l(z_n)$for each of 16 objects. This value is fixed in all three treatments. (The values of the packages are how these treatments will differ.) We show an example of the object values by agent 1. The detailed values for other agents are in Appendix B.

800	600	200	500
500	400	400	100
700	500	400	200
200	200	200	600

Figure 2: An Example of Base Values of an Agent

3.1 The Valuation Structure

After auction design, valuation structure of agents is the second factor in this experiment. Specifically, we will consider three cases: the additive value case, the exposure problem case, and the coordination problem case. The first case is where the value of the package is given by the sum of values of the individual object composing the package. That is, for each package B, $v_l(B) = \sum_{z_n:\text{the nth element of } B_n \text{ is } 1} v_i(z_n)$. Evidently, the additive value function satisfies the substitute condition. The figure below explains the value-maximizing allocation.

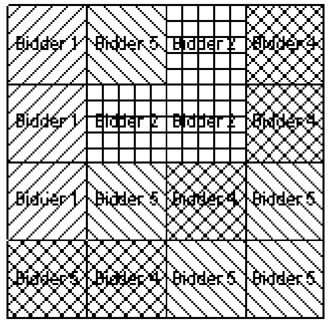


Figure 3: Efficient Allocation for The Additive Value CaSE

In the following two cases, we will consider superadditive values. Before going into the details, we first define the functional form of value functions common to these two cases. Specifically, the value of a package $z$for agent i, $v_i(z)$is given by

$$\begin{aligned} v_i(z) &= \sum_{z_k\text{:kth element of } z \text{ is } 1} v_i(z_k) \\ &+0.01 \sum_{z_{l,m}\text{:l,mth element of } z \text{ is 1 and } l,m \text{ are in the area of special interest}} \\ &\mu_i(l)\mu_i(m)v_i(z_l)v_i(z_m). \end{aligned}$$

The first term adds up the values of the individual objects contained in the package. The second term describes the superadditive values. These parameters μ^ldenote intensities of superadditive values.

In this paper, we consider a following distribution of $\mu$for each agent.Let $A_i = \{k : \mu_i(k) > 0\}$be the set of objects that agent $i$is especially interested in. We assume $A_1 = \{1, 2, 5, 6\}, A_2 = \{3, 4, 7, 8\}, A_3 = \{6, 7, 10.11\}$,$A_4 = \{9, 10, 13, 14\}$,and $A_5 = \{11, 12, 15, 16\}$. An economic interpretation is that each agent is interested in the objects close to its location. The following table explains the distribution of A_is' for agent 1-5. These distributions of A_i are common in all treatments. The only difference in two cases comes from the different values of μ. There are conflicts on objects 6, 7, 10, 11, since there are two agents who have special interest in these objects. This conflict causes coordination problems or exposure problems depending on the parameter values of μ.

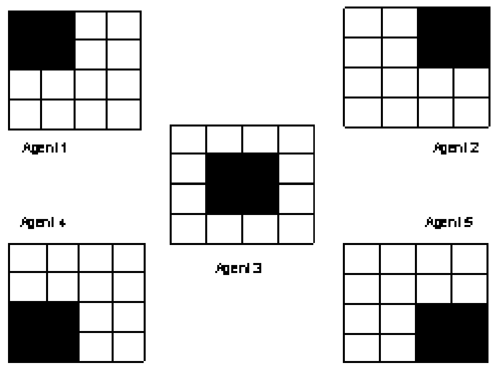


Figure 4: Areas of Interest

Let us compare this formulation with that of Banks. Olson, Porter, and Rassenti (2002). Their formulation is

$$V_i(z) = \sum_{k \in B(z)} v_i(z_k) + \lambda_i(\sum_j q)^{\beta_{ii}} + \triangle^i(\sum_{j \in X} \sum_{k \in \cup A} \delta^j(k))^{\alpha_i}$$

with the parameter values of $\lambda \in \{78, 150, 175\}$, $\beta \in \{1, 1, .65\}$, $\triangle \in \{120, 229, 230\}$,and $\alpha \in \{1.65, 1.65.2.05\}$. Their interpretation is that the second term refers to superadditivity coming from the scale economy ($q$is the population) and the third term concerns superadditivity coming from being adjacent to each other. First, they arrange the objects in a circle so that $\delta^j = 1$if and only if objects are adjacent to each other. Furthermore, the set of objects on which the agents have superadditivity is limited to the five identical objects out of the 10 (the sets $\Phi$and Ψ). Given their value of β, the superadditivity comes mostly from geographically adjacent licenses. This point is similar to ours, where superadditivity comes from the adjacency to the agent location. A first difference is that their formulation of superadditivity is based on the objects' topology forming a one dimensional structure (circle), while our formulation has a richer two dimensional structure. Second, in their formulation, the set on which superadditiviy is defined is common to all the agents, while in our case, different agents have different areas of interest which vary by location. Two implications of this difference are that package coordination among agents is more important in our model, and that our formulation allows a distinct formulation of exposure problems and coordination problems.

3.1.1 The Exposure Problem

In the second case, we consider a parameterization which focuses on the exposure problem. Specifically, we assume

$$
\begin{aligned}
\mu_1^R(1) &= \mu_1^R(2) = \mu_1^R(5) = 0.3, \mu_1^R(6) = 0.1 \\
\mu_2^R(4) &= \mu_2^R(3) = \mu_2^R(8) = 0.3, \mu_2^R(7) = 0.1 \\
\mu_3^R(6) &= \mu_3^R(7) = \mu_3^R(10) = \mu_3^R(11) = 0.3, \\
\mu_4^R(13) &= \mu_4^R(9) = \mu_4^R(14) = 0.3, \ \mu_4^R(10) = 0.1, \\
\mu_5^R(16) &= \mu_5^R(12) = \mu_5^R(15) = 0.3, \ \mu_5^R(11) = 0.1.
\end{aligned}
$$

That is, the weight of an object for an agent decreases as the distance between the agent and the center of the object increases. In this setting, we focus on the exposure problem of agent 3. In this setup, the efficient allocation is that agent 3 aggregates the objects $\{6, 7, 10, 11\}$, as shown in Figure 5.

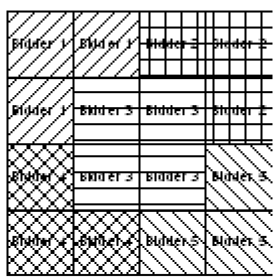


Figure 5: Efficient Allocation for Exposure Values Case

But agent 3 faces the exposure problem of having to beat other agents in auctions for objects 6, 7, 10, and 11. For each object, agent 3 is not the one with the highest valuation. If agent 3 ends up winning only one object, then agent 3 will face the risk of losing money.

Object	6	7	10	11
agent 1	400	400	500	400
agent 2	700	600	300	300
agent 3	300	500	600	600
agent 4	200	400	500	700
agent 5	200	300	700	500

Table 1: Exposure Problem

Furthermore, a competitive equilibrium does not exist here. To show this, suppose there exists a competitive equilibrium price $\{p_l\}_{l=1,\ldots,16}$. Now consider agent 1. In an equilibrium, agent 1 wins objects 1, 2, and 5 but not each of 1, 2, 5, 6. This implies that the competitive prices must be such that agent 1 finds it profitable to buy objects 1, 2, and 5 while passing on object 6. This implies the following inequalities: $p_1+p_2+p_5 \leq 2400, p_1+p_2+p_5+p_6 \geq 3591 \rightarrow p_6 \geq 1191$. Using a similar calculation, we obtain the following lower bounds for the prices for the package $\{6,7,10,11\}$: $p_6+p_7+p_{10}+p_{11} \geq 1191+942+770+799 = 3632$. But agent 3's valuation for the package, which is 3324, is less than the price. Thus competitive equilibrium prices do not exist.

3.1.2 The Coordination Problem

The next case focuses on the coordination problem, which tests the ability of trading procedures to coordinate agents to achieve an efficient allocation against package bids. First, we consider the following weights:

$$\begin{aligned}
\mu_1^R(1) &= \mu_1^R(2) = \mu_1^R(5) = \mu_1^R(6) = 0.2 \\
\mu_2^R(4) &= \mu_2^R(3) = \mu_2^R(8) = \mu_2^R(7) = 0.2 \\
\mu_3^R(6) &= \mu_3^R(7) = \mu_3^R(10) = \mu_3^R(11) = 0.2 \\
\mu_4^R(13) &= \mu_4^R(9) = \mu_4^R(14) = \mu_4^R(10) = 0.2 \\
\mu_5^R(16) &= \mu_5^R(12) = \mu_5^R(15) = \mu_5^R(11) = 0.2.
\end{aligned}$$

A graphical representation of the weights for agent 1 is given in the following table.

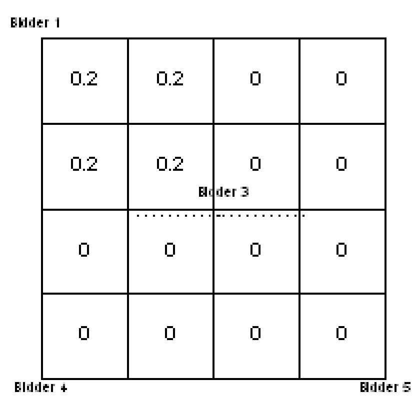


Figure 6: Weights for Agents

This case exhibits a coordination problem for agent 3 as follows. Efficient allocation would imply that agent 1 wins object 6, agent 2 wins 7, agent 4 wins 10, and agent 5 wins 11. In this case, agents 1, 2, 4, and 5 have to coordinate their bids against agent 3 who is interested in the package.

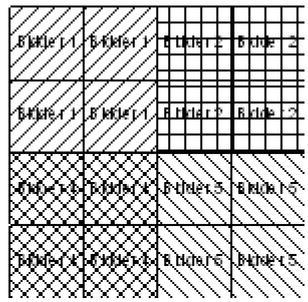


Figure 7: Efficient Allocation for Coordination Problems Case

Let us take a closer look at the valuations. Agent 3 has the valuation of 2588 for the package of 6, 7, 10, and 11. In the table below, we computed the value of the package $\{6, 7, 10, 11\}$ for agents 1, 2, 4, and 5. It becomes evident that none of these agents can act alone and still beat agent 3.

Agent 1: 1800	Agent 2: 1900
Agent 4: 1500	Agent 5: 1700

Table 2: Coordination Problem.

3.2 Subject Characteristics

The last factor we consider is subject characteristics. In order to test the effect of subject characteristics on performance, we conducted experiments with university students as well as financial or ecommerce industry professionals.

3.3 The Treatment Structure

In summary, this experiment has the following 18 possible treatment combinations, as seen in Table 2. They have fixed effects since the same levels were used for repeated experiments.

Treatment No.	Auction Factor	Value Factor	Subject Factor
1	VCG	Additive	Students
2	VCG	Additive	Traders
3	VCG	Exposure	Students
4	VCG	Exposure	Traders
5	VCG	Coordination	Students
6	VCG	Coordination	Traders
7	SAA	Additive	Students
8	SAA	Additive	Traders
9	SAA	Exposure	Students
10	SAA	Exposure	Traders
11	SAA	Coordination	Students
12	SAA	Coordination	Traders
13	Clock-Proxy	Additive	Students
14	Clock-Proxy	Additive	Traders
15	Clock-Proxy	Exposure	Students
16	Clock-Proxy	Exposure	Traders
17	Clock-Proxy	Coordination	Students
18	Clock-Proxy	Coordination	Traders

Table 3: Experimental Design

3.4 Experimental Procedures

In this section, we report the experimental procedures.

The subject pools of the experiment are Caltech students, students from other schools, and professional traders in ecommerce and financial markets. The subjects were recruited using email and postings at [recruiting web site URL]. Professional traders are defined to be ones who make or made their living through trading in securities markets or eBay markets. We asked subjects to submit their resumes to verify these qualifications. Copies of these resumes are available upon request, provided that subjects consent.

We have implemented the auction algorithms on a server at [the auction web site URL] and conducted experiments on computer networks at Caltech and Stanford University. Prior to the experiments, we distributed the instructions that are posted at the above website. We went through simple examples and asked questions before experiments started. No deceptions are involved in this experiment.

In this experiment, an experimental unit is an individual auction with each agent having a specific value structure. We had multiple observation units for each cell. Specifically, we implemented the following experimental unit structure. The order of experiment is randomized among treatments to average out the effect of drift and learning. Each subject is randomly assigned a role of one of agents 1-5 at the beginning of the session. The subjects then played three auctions, after which the agent assignments were changed. For example, if a subject starts as agent 1 and plays these three auctions, the subject would then play the role of agent 2, followed by agent 3, agent 4, and agent 5. Five subjects participated in a session. The length of session varied from three to three and one-half hours. This experimental unit design implies that we took repeated measurements to improve the power to detect effect of factors.

In total, we ran 100 auctions. The breakdown is 30 experiments each for generalized Vickrey and simultaneous ascending auctions, and 40 for clock-proxy auctions. We ran 30 clock-proxy auctions with the same round limit as the generalized Vickrey auctions and the simultaneous ascending auctions. The remaining 10 clock-proxy auctions were run without time limit. The last are excluded from the pairwise comparison of mechanisms, because they are intended only for comparison with the clock-proxy auctions that use a time limit. For a list of all experiments, see Appendix A.

4 Pairwise Comparisons

Now that we have the data from the experiments, we analyze this data to empirically study the market design problem (1). The empirical problem is simpler than the standard 'natural experiment' types of models in economics (see Angrist and Krueger (1995) for a survey), since a researcher can control the variation in the explanatory variables and the interaction among selection and treatment.

We start with a pairwise comparison of performances among treatment groups. Pairwise comparison is attractive because it entails fewer assumptions about the data generating process than would ANOVA or other linear models have.

Since we have implemented balanced design, there are same number of observations for each treatment. (The ratio of students/traders is constant - conditional on values - and each auction design has the same number of treatments for each value structure.) Thus we can compare the performance of the mechanisms, conditional on the choice of designs. We first conduct a standard t-test on the null hypothesis that performance is the same for the two treatments. To test the robustness, we consider a difference-in-difference estimator (with pretest values equal to zero) with the other factors (values, subject characteristics, a sequence in a session, and a session) fixed. This estimator will remove biases associated with common learning effects and session-level heterogeneity which might be correlated with performance. We then conduct a t-test to test the null hypothesis of zero difference. Furthermore, we consider a nonparametric Wilcoxon test to remove underlying distributional assumptions.

4.1 Dependent Variables

We measure the performance of the mechanism in terms of its efficiency and revenue. The first metric is allocation efficiency. Let $z = (z_1, ..., z_L)$ be an allocation. In this case, a relative efficiency is defined in terms of the efficient allocation. Let z^* be that efficient allocation. Then

$$\text{Efficiency (Relative)} = \sum_l v_l(z_l) / \sum_l v_l(z_l^*).$$

Let $b_l(z_l)$ be the payment by agent l for a package z_l. In this case, the auctioneer revenue is

$$\text{Revenue} = \sum_l b_l(z_l).$$

A relative revenue is defined to be

$$\text{Revenue (Relative)} = \sum_l b_l(z_l) / \sum_l v_l(z_l^*).$$

Given allocation $\{z_i\}$ and payment $\{b_i(z_i)\}$, agent i's payoff is $u_i(z_i, b_i) = v_i(z_i) - b_i(z_i)$. Then, the aggregate payoff is defined by

$$\text{Aggregate Payoff} = \sum_l u_l(z_l, b_i).$$

A relative aggregate payoff is defined by

$$\text{Aggregate Payoff (Relative)} = \sum_l u_l(z_l, b_i) / \sum_l v_l(z_l^*).$$

4.2 Vickrey Auctions Versus Clock-Proxy Auctions

We first present the results for the pairwise comparison between clock-proxy auctions and generalized Vickrey auctions.

4.2.1 The Full Sample

We first compare the performance taking the whole sample. Because of balanced design, this comparison is valid.

Result 1. *Clock-proxy auctions produced significantly higher efficiency levels than generalized Vickrey auctions did.*

	Obs	REfficiency	RRevenue	RProfit
Clock-Proxy	28	0.8564	0.4277	0.3372
Generalized Vickrey	30	0.7439	0.3772	0.2521
Difference		0.113	0.051	0.082

Table 4: Summary Statistics of Clock-Proxy Auctions and Generalized Vickrey Auctions: the Full Sample

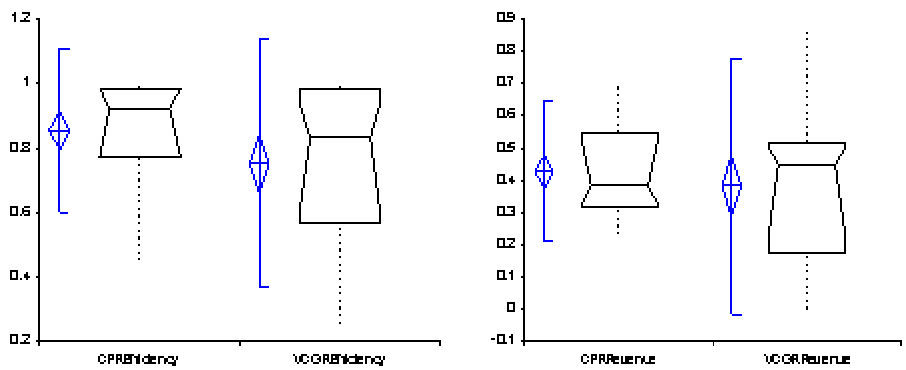


Figure 8: Box Plots of Efficiencies and Revenues

	Efficiency	Revenue	Profit
T Test with Unequal Variance	2.20 (0.0323)	1.01 (0.3183)	0.87 (0.3903)
T Test for a Difference	2.44 (0.0177)	1.01 (0.3154)	0.88 (0.3837)
Wilcoxon for a Difference	2.53 (0.0057)	1.95 (0.0254)	0.48 (0.3150)

Table 5: Statitical Tests of the Hypothesis of Equal Performances between Clock-Proxy Auctions and Generalized Vickrey Auctions: the Full Sample

These results imply that clock-proxy auctions outperformed generalized Vickrey auctions in our experiments. In terms of relative efficiency, the null hypothesis is rejected at the 5% level. Clock-proxy auctions have a higher seller relative revenue according to a nonparametric Wilcoxon test. An implication of this result is that hypothesis 1 - performances are the same with substitutes - does not hold for generalized Vickrey auctions and clock-proxy auctions.

A reason for this efficiency difference is the package coordination problem. In package auctions, the market clears as a whole, not individually. A bid needs 'partner bids' to cover the whole allocation. For example, in order for a bid {1,2,5,6} to win, it is necessary to have package bids which cover *exactly* {3,4,7,8,9,10,11,12,13,14,15,16}. In an idealized world where bid submission costs are all zero, agents could feasibly submit bids for all possible packages, thus coordination would not be an issue. But in a realistic situation where there are bid submission costs and agents submit bids only for a subset of all possible packages, coordination becomes an issue. For example, in generalized Vickrey auctions, which are sealed and simultaneous, agents are in the dark about bids made by other agents. By contrast, in clock-proxy auctions, agents can observe the first stage clock bids and use that information to ease these coordination problems. This coordination is hardest when there are no obvious packages to bid, that is, in a case without superadditivity.

Another reason for revenue difference is a low-revenue equilibrium in generalized Vickrey auctions. In addition to a truth-telling equilibrium, there are additional equilibria that imply low revenue for the auctioneer. As we will see, although student subjects were unlikely to achieve a low revenue equilibrium, professional traders often played a low revenue equilibrium. (Of course, the number of auctions participated in by students and traders is identical between two treatments.) One form of a bidding pattern is that each agent bids exactly for the package that is a part of an efficient allocation, and does not bid at all for any other package. In this setting, removing an agent does not cause externalities on other agents. Therefore, the payment by each agent is equal to zero. This results in zero revenue for the auctioneer. For example, in auction ADD-VCG-09, agents achieved an efficiency level of 8400 but the auctioneer revenue was 0. In this auction, agent 1 placed only one bid, agent 2 placed only five bids, agent 3 placed only one bid, agent 4 placed only four bids, and agent 5 placed only one bid. As a result, the allocation with the second highest value is zero for every agent. An equilibrium of that extreme level was not observed in clock-proxy auctions where there was a clock stage. In the first stage of clock-proxy auctions, agents have an opportunity to bid for a single object, which can upset the low-revenue equilibrium.

4.2.2 Additive Values

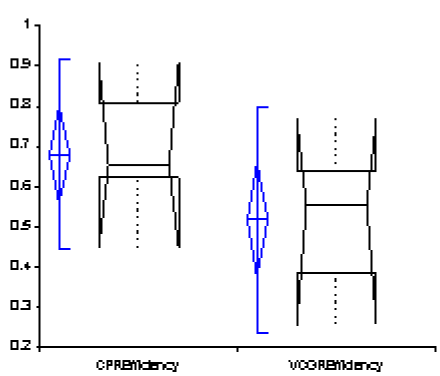
We then compare the performance in additive value cases. The null hypothesis of equal relative efficiency is rejected.

Result 2. In the additive value case, clock-proxy auctions achieved higher efficiencies. In both auctions, full efficiency was not achieved.

	Obs	Efficiency	Revenue	Profit
Clock-Proxy	8	0.6789	0.4797	0.1992
Generalized Vickrey	10	0.5368	0.3713	0.1654
Difference		0.142	0.108	0.034

Table 6: Summary Statisticsn of Clock-Proxy Auctions and Generalized Vickrey Auctions: Additive Values

Even with additive values, clock-proxy auctions and generalized Vickrey auctions did not achieve full efficiency. A standard result suggests that each agent may engage in straightforward bidding to achieve full efficiency in these auctions. Nevertheless, in the experiments, agents with bid submission costs engage in strategic bidding or do not enter a sufficient number of bids to realize full efficiency. For example, in ADD-VCG-02, user 4 submitted a bid for the whole package 1-16. Other agents, submitting only several bids, could not form a coalition to upset this bid.



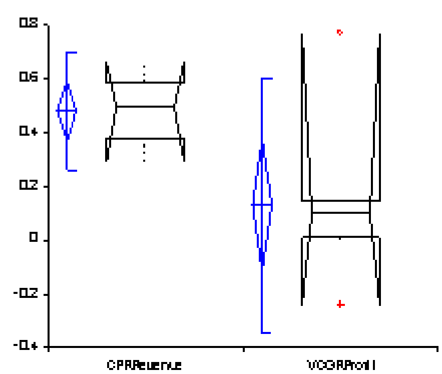


Figure 9: Box Plots of Efficiencies and Revenues

	Efficiency	Revenue	Profit
T Test (Unequal Variance)	2.01 (0.0619)	1.23 (0.2383)	0.28 (0.7838)
T Test for a Difference	1.50 (0.1546)	1.09 (0.2934)	0.51 (0.6144)
Wilcoxon for a Difference	1.74 (0.0409)	1.73 (0.0410)	0.84 (0.2021)

Table 7: Test Statistics of the Hypothesis of Equal Performances between Clock-Proxy Auctions and Genearlized Vickrey Auctions: Additive Values

4.2.3 The Exposure Problem

Next we consider the exposure problem case. In this case, clock-proxy auctions have higher efficiency levels, but the differences are not statistically significant.

	Obs	Efficiency	Revenue	Profit
Clock-Proxy	10	0.9828	0.4061	0.5767
Generalized Vickrey	10	0.8968	0.4566	0.4402
Difference		0.086	-0.505	0.136

Table 8: Summary Statistics of Clock-Proxy Auctions and Genearlized Vickrey Auctions: the Exposure Problem

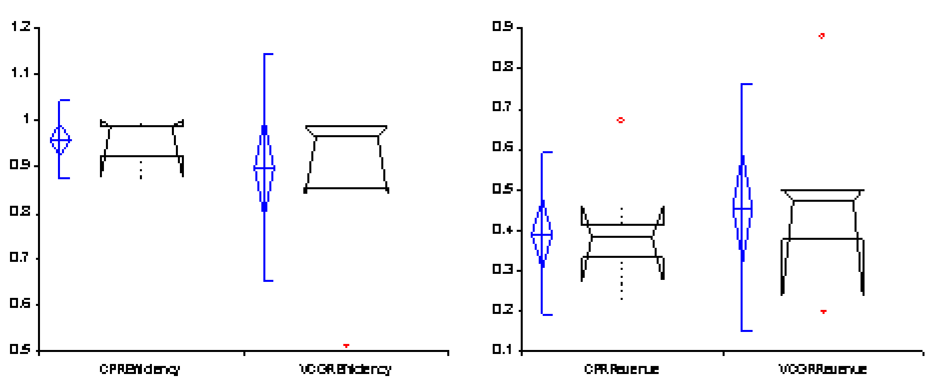


Figure 10: Efficiencies and Revenues

	Efficiency	Revenue	Profit
T Tests	1.81 (0.1023)	-0.75 (0.4682)	1.26 (0.4682)
T Tests for a Difference	1.68 (0.1092)	-0.64 (0.5298)	1.10 (0.2852)
Wilcoxon for a Difference	1.29 (0.0992)		

Table 9: Test Statistics of Clock-Proxy Auctions and Generalized Vickrey Auctions: the Exposure Problem

Result 3. In the Exposure problems case, clock-proxy auctions achieved higher efficiency levels, but the difference was not statistically significant.

Thus, in an environment with exposure problems, clock-proxy auctions achieved similar results in terms of efficiency. A difference from the additive case is that with superadditive values, each agent tends to bid with packages with higher values. This eased coordination among agents. Thus, both auctions achieved a very high level of efficiency, compared with other cases.

4.2.4 The Coordination Problem

Finally, we move to the case of coordination problems. The results are similar to the coordination problem case.

	Obs	Efficiency	Revenue	Profit
Clock-Proxy	10	0.872	0.4079	0.4642
Generalized Vickrey	10	0.7981	0.3038	0.4943
Difference		0.074	0.104	0.0301

Table 10: Summary Statistics of Clock-Proxy Auctions and Generalized Vickrey Auctions: the Coordination Problem

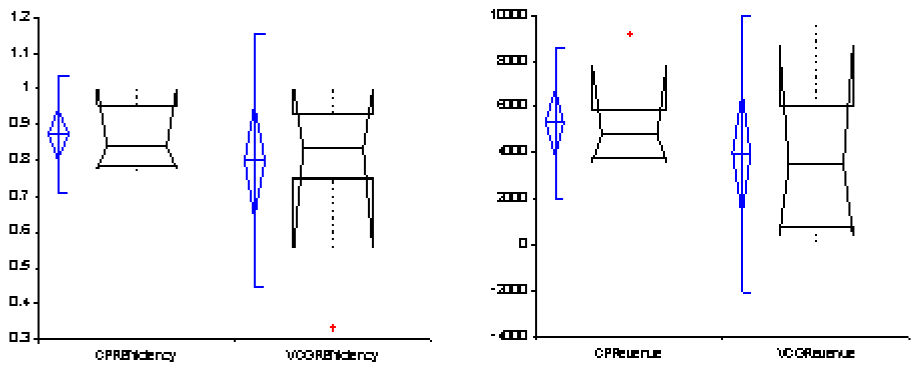


Figure 11: Box Plots of Efficiencies and Revenues

	Efficiency	Revenue	Profit
T Tests	0.99 (0.3428)	1.03 (0.3184)	-0.32 (0.7548)
T Tests for a Difference	1.12 (0.2759)	1.50 (0.1498)	-0.35 (0.7320)
Wilcoxon for a Difference	1.19 (0.1151)	1.57 (0.0575)	

Table 11: Hypothesis Testing of Equal Performances between Clock-Proxy Auctions and Generalized Vickrey Auctions: the Coordination Problem

Result 4. In the coordination problems treatment, clock-proxy auctions achieved higher efficiency levels than generalized Vickrey auctions did, but the differences were not statistically significant.

4.3 Clock-Proxy Auctions vs. Simultaneous Ascending Auctions

The previous subsection compared clock-proxy auctions with generalized Vickrey auctions. This subsection compares clock-proxy auctions with simultaneous ascending auctions.

4.3.1 The Full Sample

We start with a comparison between two auctions at the aggregate level. Clock-Proxy auctions outperformed SAA in the Wilcoxson test, while the two other tests are inconclusive. On the other hand, auction revenues are unambiguously higher for simultaneous ascending auctions.

	Obs	Efficiency	Revenue	Profit
Clock-Proxy	28	0.8564	0.4277	0.4287
SAA	30	0.8284	0.6725	0.1559
Difference		0.028	-0.2447	0.173

Table 12: Summary Statistics for Clock-Proxy Auctions and Simultaneous Ascending Auctions: the Full Sample

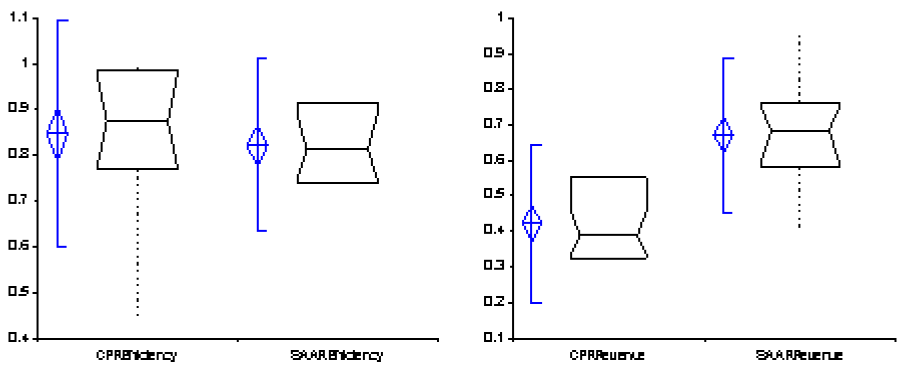


Figure 12: Box Plots of Efficiencys and Revenues

	Efficiency	Revenue	Profit
T Tests	0.78 (0.4381)	-7.12 (<.0001)	5.39 (<.0001)
T Tests for a Difference	1.17 (0.2479)	-4.89 (<.0001)	4.41 (<.0001)
Wilcoxon for a Difference	2.21 (0.0133)	-4.41 (<.0001)	4.41 (<.0001)

Table 13: Hypothesis Testing of the Equal Performances Between Clock-Proxy Auctions and Simultaneous Ascending Auctions: the Full Sample

Result 5. In all treatments, clock-proxy auctions achieved higher efficiency levels than simultaneous ascending auctions did, but the differences were not statistically significant. The simultaneous ascending auctions achieved significantly higher revenues.

Efficiency comparison between clock-proxy auctions and simultaneous ascending auctions depends on the setup. Indeed, clock-proxy auctions outperformed in the case of exposure problems, but simultaneous ascending auctions outperformed in the case of additive values and coordination problems. A difference from Ledyard, Porter, and Rangel (1997) is that we consider a large-scale 16-object setting in contrast to their 3-object setting. The number of possible package combinations is far larger in our setting, which makes complexity issues significant. These complexities make agent coordination harder in package auctions.

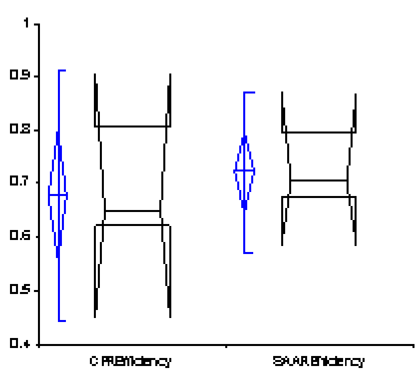
Simultaneous ascending auctions achieved a significantly higher auctioneer revenue. This result is consistent with previous results in Banks, Olson, Porter, Rassenti, and Smith (2002). One explanation is overbidding in exposure problem structure. Another observation is that in simultaneous ascending auctions, the structure of competitions was clear to the agents and led to more aggressive bidding behavior.

4.3.2 Additive Values

We begin with the case of additive value functions.

	Obs	Efficiency	Revenue	Profit
Clock-Proxy	8	0.6789	0.4797	0.1992
SAA	10	0.7624	0.6505	0.1119
Difference		-0.0835	-0.1708	0.087

Table 14: Summary Statistics of Clock-Proxy and Simultaneous Ascending Auctions: Additive Values



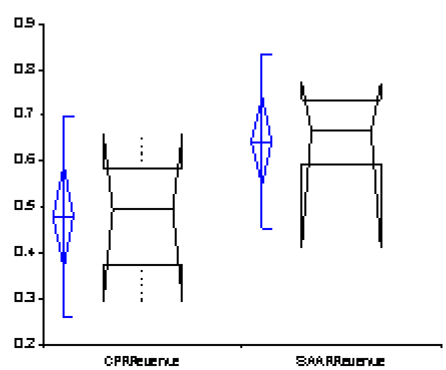


Figure 13: Box Plots

	Efficiency	Revenue	Profit
T Tests	-1.36 (0.2060)	-2.99 (0.0114)	0.98 (0.3525)
T Tests for a Difference	-0.59 (0.5653)	-2.09 (0.0545)	1.20 (0.2481)
Wilcoxon for a Difference	-1.73 (0.0410)		

Table 15: Hypothesis Testing of Equal Performances between Clock-Proxy Auctions and Simultaneous Ascending Auctions: Additive Values

Result 6. Simultaneous ascending auctions fared better than clock-proxy auctions in the additive case, but the difference was statistically insignificant.

Ledyard, Porter, and Rangel (1997) found that efficiency of simultaneous ascending auctions with additive values is close to full efficiency. The difference between our results and their results is due to the larger scale of our auctions. Agents often chose to concentrate on a subset of the objects, and this leads to a lower efficiency.

4.3.3 The Exposure Problem

We now compare the performance in the case of exposure problems. Clock-proxy auctions outperformed simultaneous ascending auctions: the null hypothesis of equal level of relative efficiency was rejected.

	Obs	Efficiency	Revenue	Profit
Clock-Proxy	10	0.9828	0.4061	0.5767
SAA	10	0.8925	0.6862	0.2063
Difference		0.09	-0.2801	0.37

Table 16: Summary Statistics of Clock-Proxy Auctions and SImultaneous Ascending Auctions: the Exposure Problem

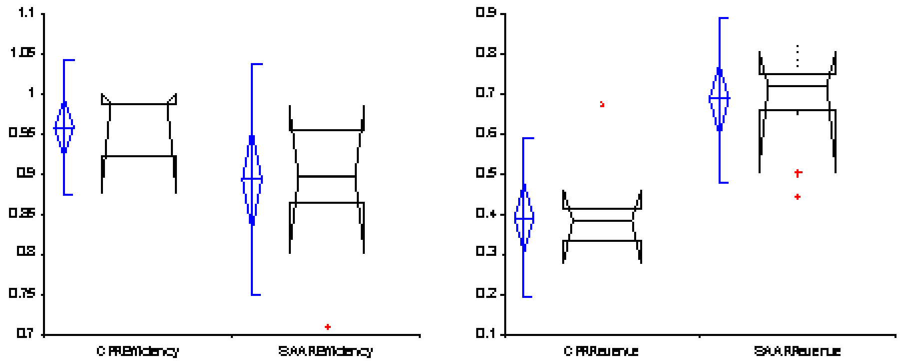


Figure 14: Box Plots of Efficiencies and Revenues

	Efficiency	Revenue	Profit
T Tests	3.20 (0.0099)	-5.37 (<.0001)	6.87 (<.0001)
T Tests for a Difference	2.88 (0.0096)	-3.04 (0.0067)	3.59 (0.0020)
Wilcoxon for a Difference	3.68 (0.0001)	-2.38 (0.0086)	3.99 (<.0001)

Table 17: Hypothesis Testing of Equal Performances between Clock-Proxy Auctions and Simultaneous Ascending Auctions: the Exposure Problem

Result 7. Clock-proxy auctions did better than simultaneous ascending auctions in the Exposure problems case.

This result is consistent with hypothesis 2 (concerning standard exposure problems). It is harder to aggregate objects without package bidding, since an agent would incur the possibility of loss. On the other hand, clock-proxy auctions can aggregate packages through package bidding.

4.3.4 The Coordination Problem

Finally we consider coordination problem value structures. Clock-proxy auctions did slightly better than simultaneous ascending auctions, but the difference is statistically insignificant.

	Obs	Efficiency	Revenue	Profit
Clock-Proxy	10	0.872	0.4079	0.4642
SAA	10	0.8301	0.2729	0.1494
Difference		0.042	-0.1494	0.315

Table 18: Summary Statistics of Clock-Proxy Auctions and Simultaneous Ascending Auctions: the Coordination Problem

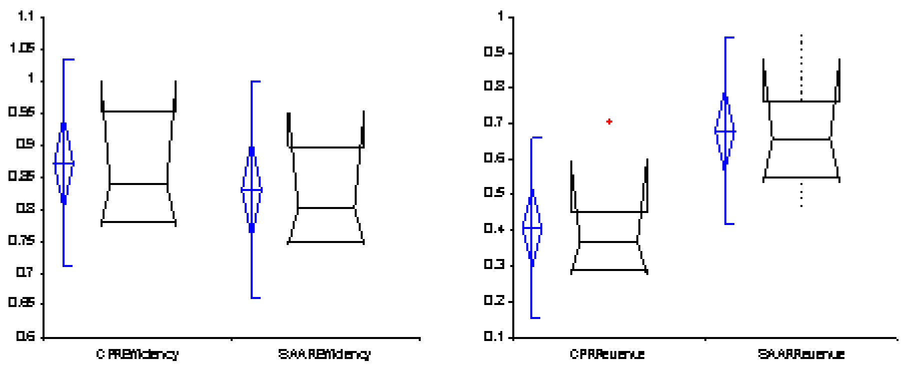


Figure 15: Box Plots.

	Efficiency	Revenue	Profit
T Tests	0.92 (0.3675)	-3.90 (0.0011)	4.04 (0.0009)
T Tests for a Difference	0.87 (0.3954)	-3.15 (0.0052)	2.57 (0.0151)
Wilcoxon for a Difference	1.57 (0.00576)	-3.19 (0.0007)	

Table 19: Hypothesis Testing of Equal Performances between Clock-Proxy Auctions and Simultaneous Ascending Auctions: the Coordination Problem

Result 8. In Coordination Problems, Clock-proxy auctions and simultaneous ascending auctions did statistically equally well

The results are consistent with hypothesis 3 (which predicts that because of coordination problems, package bidding procedures will not improve efficiency that much).

4.4 Subject Characteristics

We now compare the performance between professional traders and students in regard to coordination. The table below shows that professional traders achieved much higher payoffs. Interestingly, efficiencies were unaffected. This was due to the package demand reduction problem: professional traders reduced demand for packages, thus reducing the market clearing price. This demand reduction does not affect efficiencies in a single unit auction.

	Obs	Efficiency	Revenue	Profit
Traders	25	0.7445	0.3566	0.3879
Students	25	0.8006	0.5887	0.2118
Difference		-0.056	-0.2321	0.176

Table 20: Summary Staistics of Auctions with Professional Traders and Students

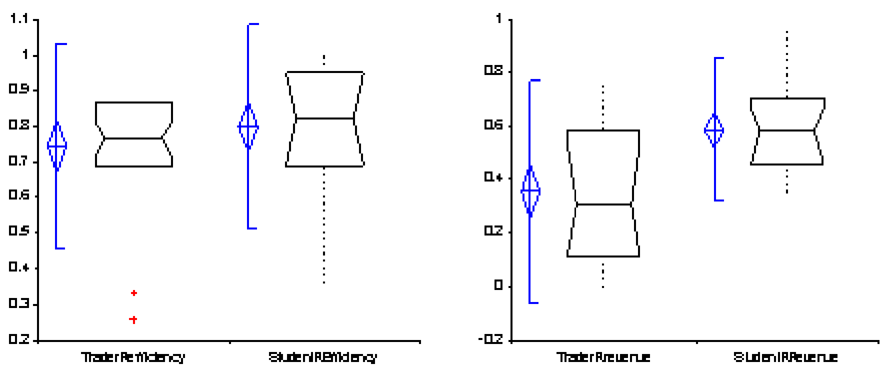


Figure 16: Box Plots.

	Efficiency	Revenue	Profit
T tests	-1.13 (0.2626)	-3.86 (0.0003)	2.57 (0.0135)
T Tests for a Difference	-1.22 (0.2330)	-4.61 (0.0001)	3.11 (0.0049)
Wilcoxon for a Difference	-0.80 (0.2112)	-3.74 (<.0001)	3.21 (0.0013)

Table 21: Hypothesis Testing of Equal Performances between Professional Traders and Students

Result 9. Subject characteristics significantly affected seller revenues, but not efficiencies.

We now focus on the case of Vickrey auctions. Here, traders obtained significantly higher profits. This result confirms conjectures in Ausubel and Milgrom (2004) that a low revenue equilibrium is a serious problem in generalized Vickrey auctions.

	Obs	Efficiency	Revenue	Profit
Traders	9	0.6188	0.1098	0.509
Students	9	0.7563	0.5548	0.2016
Difference		-0.056	-0.4449	0.307

Table 22: Summary Statistics of Auctions with Professional Traders and Students: Generalized Vickrey Auctions

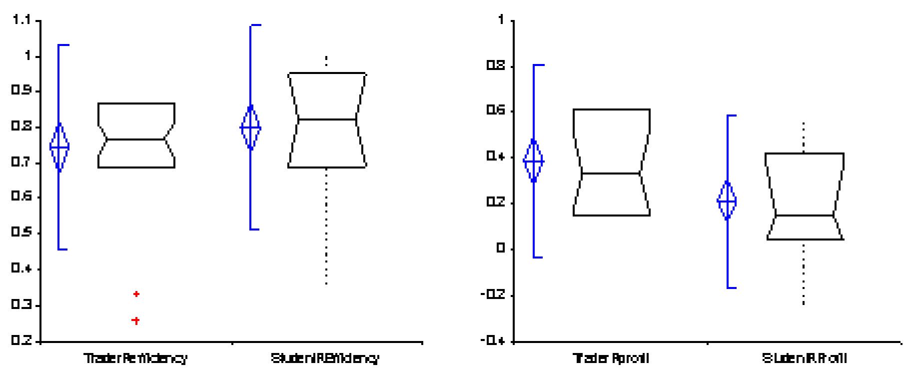


Figure 17: Box Plots.

	Efficiency	Revenue	Profit
T test	-1.30 (0.2109)	-6.87 (<.0001)	2.42 (0.0281)
T Test for a Difference	-1.35 (0.2187)	-8.82 (<.0001)	2.18 (0.0066)
Wilcoxon for a Difference	-1.82 (0.0341)	-3.69 (.0001)	1.82(0.0341)

Table 23: Hypothesis Testing of Equal Performances between Professional Traders and Students: Generalized Vickrey Auctions

4.5 Time Limit

One of the hypotheses we advance in this paper is that complexity of package bidding rules can cause package coordination problems. In order to test the hypothesis, we compare the performance of clock-proxy auctions with two treatments: with and without a time limit to input the bid.

This sub-experiment might also address whether removing the time limit leads to full efficiency. Specifically, in the exposure value treatment, the optimal allocation is that agent 3 wins a package {6,7,10,11}. But in order for this allocation to take place, agents 1-4 need to submit supporting packages of {1,2,5}, {3,4,8}, etc., which are not 'intuitive' to submit. On the other hand, the second best allocation has agents 1-4 submitting packages of {1,2,5,6}, {3,4,7,8}, and others, and these packages are 'intuitive' given the areas of influence. So we hypothesize that when there is no time limit to submit bids and the only problem is communication complexity, agents might be able to coordinate on efficient allocation, but when there are time limits, agents might not be able to coordinate on efficient allocation. Moreover, if there are cognitive complexity and package coordination problems involved (with or without a time limit), agents might not be able to coordinate on efficient allocation.

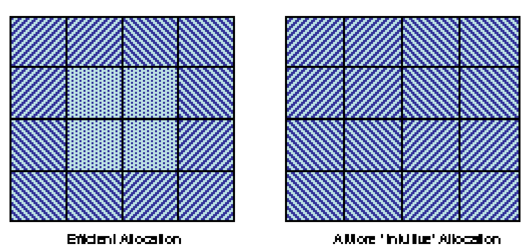


Figure 18: Efficient Allocation and A More 'Intuitive' Allocation

Removing the time limit improved efficiency and the auctioneer revenue, but the effects are not statistically significant. Even removing the time limit did not lead to full efficiency. Only 2 out of 10 cases without time limit led to full efficiency. A preliminary conclusion:

Result 10. Communication complexity and cognitive complexity affect auction performance.

5 Characterizing the Properties of the Performance Function

5.1 ANOVA Analysis

5.1.1 Efficiency

In the previous section, we have studied a pairwise comparison among treatment groups. In this section, we will conduct analysis of variance to understand interaction among multiple factors. Since an equilibrium analysis of these package auctions is not yet fully developed, we will not conduct structural analysis. Instead, we will conduct an ANOVA analysis to test the main effect of these factors and the magnitude of interaction effects. The standard ANOVA statistical model is given by

$$\begin{aligned}
& \text{REfficiency}_{ijk} \\
= \; & \text{Auction}_i + \text{Value}_j + \text{Subject}_k \\
& + \text{Auction}_i \times \text{Value}_j + \text{Auction}_j \times \text{Subject}_k + \text{Value}_j \times \text{Subject}_k \\
& + \text{Auction}_i \times \text{Value}_j \times \text{Subject}_k + \varepsilon_{ijk}
\end{aligned}$$

In this model, the differences in outcome are explained by (1) the main effect of auction design, value structure, and subject characteristics, and (2) the interaction effect between factors. Notably, the interaction term does not imply multiplication among factors. First we estimate with dependent variables to be efficiencies. The estimation results are given below.

Relative Efficiency	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	1.59206	0.1137	7.57	<.0001
Error	73	1.0969	0.015		
Correlated Total	92	2.690			

Table 24: ANOVA Full Tests for Efficiency

These results support the null hypothesis that auction design has significant impact on efficiencies. Interestingly, for type I and III tests, subject characteristics did not have a significant effect. This result is consistent with a pairwise comparison in the previous section and the package demand reduction hypothesis explained in previous subsections.

Another result is that interaction terms are often significant. This implies that the impact of auction design depends significantly on the underlying value structure (Value × Mechanism) and subject characteristics

Relative Efficiency	DF	Type I SS	Mean Square	F Value	Pr > F
Value	2	1.9902	0.9951	26.12	<.0001
Mechanism	2	3.1873	0.4553	11.95	<.0001
Subject	1	0.0335	0.0335	0.88	0.3515
Value*Mechanism	4	0.4097	0.1024	2.69	0.0377
Value*Subject	1	0.1886	0.3484	9.14	0.0034
Mechanism*Subject	2	0.1436	0.0717	1.88	0.1593
Value*Mechanism*Subject	2	0.0256	0.0128	0.34	0.7155

Table 25: ANOVA Effect Tests for Efficiency

Relative Efficiency	DF	Type I SS	Mean Square	F Value	Pr > F
Mechanism	7	1.0868	0.1552	10.53	<.0001
Value	2	1.0277	0.5139	34.86	<.0001
Subject	1	0.0142	0.0142	0.96	0.3295
Value*Mechanism	4	0.1634	0.0408	2.77	0.0334
Value*Subject	1	0.2012	0.2012	13.66	0.0004
Mechanism*Subject	2	0.0534	0.0267	1.81	0.1703
Value*Mechanism*Subject	2	0.0132	0.0066	0.45	0.6416

Table 26: Robustness Check: ANOVA Effect Tests for LR Efficiency

(Mechanism $\times$ Subject). The first term represents that the performance of package auction rules depends on the underlying value structure, as predicted in previous theoretical results. The second interaction term represents that subject sophistication affects the performance of the auctions, which is interpreted as a measure of complexities. The result is robust to reformulation of the model that takes the logarithm of relative efficiency.

5.1.2 Seller Revenue

Then we conduct an ANOVA analysis of seller revenue.

Relative Revenue	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	2.7984	0.1999	10.92	<.0001
Error	73	1.3367	0.0183		
Correlated Total	92	4.1340			

Table 27: Main Tests for Revenue

Relative Efficiency	DF	Type I SS	Mean Square	F Value	Pr > F
Mechanism	7	1.5067	0.7533	41.14	<.0001
Value	2	0.0354	0.0177	0.97	0.3181
Mechanism *Value	2	0.1268	0.0317	1.73	0.1901
Subject	1	0.6932	0.6932	37.86	<.0001
Mechanism*Subject	4	0.3159	0.1579	8.80	0.0004
Value*Subject	1	0.1026	0.1026	5.72	0.0194
Mechanism*Value*Subject	2	0.0177	0.0088	0.50	0.6114

Table 28: Effect Tests for Revenue

We find that auction design has significant impact on seller revenues. Interestingly, the value structures are insignificant and subject characteristics have a very high F Value. This result is consistent with the previous pairwise comparison.

5.2 Estimating the Effect of Alternative Auction Designs

We now move to the estimation of impact of auction design on performance, specifically efficiency and seller revenue.

5.2.1 Efficiency

We start our analysis with efficiency. The previous results show that the relationship between these factors and efficiencies are nonlinear. Given the previous ANOVA results, we estimate the following model of performance functions $f(x;t)$ to estimate the effect of auction design with the baseline the generalized Vickrey auctions with additive valuation structure. This model is obtained from dropping StudentDummy and Student*Value*Mechanism which were not significant, and approximating the interaction term by using multiplied terms. We compare the result of estimation from the linear models with that of nonlinear models. The estimation results are given below.

This linear model shows that both simultaneous ascending auctions and clock-proxy auctions have similar effects, which contradicts the results from pairwise comparisons.

The quadratic model shows that both simultaneous ascending auctions and clock-proxy auctions provide significant efficiency improvements over generalized Vickrey auctions. Moreover, the estimation result shows that comparisons of efficiency improvement between simultaneous ascending auc-

Dependent Variables	REfficiency	REfficiency
Intercept	0.5819 (14.63)	0.5367 (2.43)
ExposureDummy	0.2444 (6.41)	0.3600 (6.02)
CoordinationDummy	0.1774 (4.90)	0.2613 (4.37)
SAADummy	0.0844 (2.40)	0.2332 (3.33)
CPDummy	0.0919 (2.56)	0.1541 (1.91)
SAADummy*ExposureDummy		-.2248 (-2.56)
CPDummy*ExposureDummy		-.0773 (0.39)
SAADummy*CoordinationDummy		-.1948 (-2.30)
CPDummy*CoordinationDummy		-.0722 (-0.81)
StudentDummy	0.0305 (0.83)	
SAADummy*StudentDummy		-.3328 (-4.35)
CPDummy*StudentDummy		-.2345 (-2.93)

Table 29: Regression Results for Efficiency

tions and clock-proxy auctions depend on the underlying valuation structure. In the additive value case, simultaneous ascending auctions provided 7% efficiency improvements. However, in the case of exposure problems, clock-proxy auctions will have 7% better efficiency over simultaneous ascending auctions, due to interaction terms. In coordination problems, the level is 4%. These quantitative levels are consistent with the theory. Moreover, these negative interaction terms are significant only for simultaneous ascending auctions, not for clock-proxy auctions. The result suggests that an efficiency impact of auction design depends on underlying valuation structure.

5.2.2 Revenue

We now consider similar estimation for revenues.

Estimation results are consistent with the previous pairwise comparisons. Subject characteristics - rather than value structures - play a significant role in the determination of revenue. In addition, simultaneous ascending auctions have significant positive impact on revenue.

6 Conclusion

In this paper we have studied the design of auction mechanisms to allocate heterogeneous objects using experimental comparison among Generalized

Dependent Variables	RRevenue	RRevenue
Intercept	0.2404 (5.44)	0.1098 (2.43)
ExposureDummy	-.0661 (-1.56)	
CoordinationDummy	-.0001 (-0.00)	
SAADummy	0.2952 (7.56)	0.5281 (8.26)
CPDummy	0.0357 (0.90)	0.2023 (2.96)
StudentDummy	0.2270 (5.59)	0.3824 (6.33)
SAADummy*StudentDummy		-.3328 (-4.35)
CPDummy*StudentDummy		-.2345 (-2.93)
ExposureDummy*StudentDummy		-.03508 (-0.87)
CoordinationDummy*StudentDummy		0.0682 (1.44)

Table 30: Regression Results for Revenue

Vickrey auctions, simultaneous ascending auctions, and clock-proxy auctions. We found that clock-proxy auctions are unambiguously more efficient than generalized Vickrey auctions; but its comparison with simultaneous ascending auctions is ambiguous. We found that a large scale setting leads to higher complexity, which in package auctions tends to frustrate agent-coordinating behavior. There were multiple dimensions of complexity, such as communication complexity and cognitive complexity. The results suggest the importance of dealing with these complexities in the design of the trading rules. Finally agent characteristics have a significant impact on the performance of the experiments. We found the experimental approach to gain insight over the standard structural approach, the latter being limited by lack of data and/or its rationality assumptions. Our further agenda along this line of problems includes the application of bootstrap and nonparametric methods to estimate the performance function.

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7 Appendix A: Experimental Design

Additive Environment Treatment

Name	Value	Treatment	Date	Location	Subjects
ADD-VCG-1	ADD	VCG	01/22/05	Stanford	Students
ADD-VCG-2	ADD	VCG	01/22/05	Stanford	Students
ADD-VCG-3	ADD	VCG	01/22/05	Stanford	Students
ADD-VCG-4	ADD	VCG	01/22/05	Stanford	Students
ADD-VCG-5	ADD	VCG	01/22/05	Stanford	Students
ADD-VCG-6	ADD	VCG	01/22/05	Stanford	Students
ADD-VCG-7	ADD	VCG	01/22/05	Stanford	Traders
ADD-VCG-8	ADD	VCG	01/22/05	Stanford	Traders
ADD-VCG-9	ADD	VCG	01/22/05	Stanford	Traders
ADD-VCG-10	ADD	VCG	01/22/05	Stanford	Traders
ADD-SAA-1	ADD	SAA	01/22/05	Stanford	Students
ADD-SAA-2	ADD	SAA	01/22/05	Stanford	Students
ADD-SAA-3	ADD	SAA	01/22/05	Stanford	Students
ADD-SAA-4	ADD	SAA	01/22/05	Stanford	Students
ADD-SAA-5	ADD	SAA	01/22/05	Stanford	Students
ADD-SAA-6	ADD	SAA	01/22/05	Stanford	Students
ADD-SAA-7	ADD	SAA	01/22/05	Stanford	Traders
ADD-SAA-8	ADD	SAA	01/22/05	Stanford	Traders
ADD-SAA-9	ADD	SAA	01/22/05	Stanford	Traders
ADD-SAA-10	ADD	SAA	01/22/05	Stanford	Traders
ADD-CP-1	ADD	CP	01/22/05	Stanford	Students
ADD-CP-2	ADD	CP	01/22/05	Stanford	Students
ADD-CP-3	ADD	CP	01/22/05	Stanford	Students
ADD-CP-4	ADD	CP	01/22/05	Stanford	Students
ADD-CP-5	ADD	CP	01/22/05	Stanford	Students
ADD-CP-6	ADD	CP	01/22/05	Stanford	Students
ADD-CP-8	ADD	CP	01/22/05	Stanford	Traders
ADD-CP-9	ADD	CP	01/22/05	Stanford	Traders

Exposure Problem Treatment

CUN-VCG-1	CUN	VCG	01/22/05	Stanford	Traders
CUN-VCG-2	CUN	VCG	01/22/05	Stanford	Traders
CUN-VCG-3	CUN	VCG	01/22/05	Stanford	Traders
CUN-VCG-4	CUN	VCG	01/22/05	Stanford	Traders
CUN-VCG-5	CUN	VCG	01/22/05	Stanford	Traders
CUN-VCG-6	CUN	VCG	01/23/05	Caltech	Students
CUN-VCG-7	CUN	VCG	01/23/05	Caltech	Students
CUN-VCG-8	CUN	VCG	01/23/05	Caltech	Students
CUN-VCG-9	CUN	VCG	01/23/05	Caltech	Students
CUN-VCG-10	CUN	VCG	01/23/05	Caltech	Students
CUN-SAA-1	CUN	SAA	01/22/05	Stanford	Traders
CUN-SAA-2	CUN	SAA	01/22/05	Stanford	Traders
CUN-SAA-3	CUN	SAA	01/22/05	Stanford	Traders
CUN-SAA-4	CUN	SAA	01/22/05	Stanford	Traders
CUN-SAA-5	CUN	SAA	01/22/05	Stanford	Traders
CUN–SAA-6	CUN	SAA	01/23/05	Caltech	Students
CUN-SAA-7	CUN	SAA	01/23/05	Caltech	Students
CUN-SAA-8	CUN	SAA	01/23/05	Caltech	Students
CUN-SAA-9	CUN	SAA	01/23/05	Caltech	Students
CUN-SAA-10	CUN	SAA	01/23/05	Caltech	Students
CUN-CP-1	CUN	CP	01/22/05	Stanford	Traders
CUN-CP-2	CUN	CP	01/22/05	Stanford	Traders
CUN-CP-3	CUN	CP	01/22/05	Stanford	Traders
CUN-CP-4	CUN	CP	01/22/05	Stanford	Traders
CUN-CP-5	CUN	CP	01/22/05	Stanford	Traders
CUN-CP-6	CUN	CP	01/23/05	Caltech	Students
CUN-CP-7	CUN	CP	01/23/05	Caltech	Students
CUN-CP-8	CUN	CP	01/23/05	Caltech	Students
CUN-CP-9	CUN	CP	01/23/05	Caltech	Students
CUN-CP-10	CUN	CP	01/23/05	Caltech	Students

Coordination Problem Treatment

CRN-VCG-1	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-2	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-3	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-4	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-5	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-6	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-7	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-8	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-9	CRN	VCG	01/09/05	Caltech	Students
CRN-VCG-10	CRN	VCG	01/09/05	Caltech	Students
CRN-SAA-1	CRN	SAA	01/09/05	Caltech	Students
CRN-SAA-2	CRN	SAA	01/09/05	Caltech	Students
CRN-SAA-3	CRN	SAA	01/09/05	Caltech	Students
CRN-SAA-4	CRN	SAA	01/09/05	Caltech	Students
CRN-SAA-5	CRN	SAA	01/09/05	Caltech	Students
CRN–SAA-6	CRN	SAA	01/09/05	Caltech	Students
CRN-SAA-7	CRN	SAA	01/09/05	Caltech	Students
CRN-SAA-8	CRN	SAA	01/09/05	Caltech	Students
CRN-SAA-9	CRN	SAA	01/09/05	Caltech	Students
CRN-SAA-10	CRN	SAA	01/09/05	Caltech	Students
CRN-CP-1	CRN	CP	01/09/05	Caltech	Students
CRN-CP-2	CRN	CP	01/09/05	Caltech	Students
CRN-CP-3	CRN	CP	01/09/05	Caltech	Students
CRN-CP-4	CRN	CP	01/09/05	Caltech	Students
CRN-CP-5	CRN	CP	01/09/05	Caltech	Students
CRN-CP-6	CRN	CP	01/09/05	Caltech	Students
CRN-CP-7	CRN	CP	01/09/05	Caltech	Students
CRN-CP-8	CRN	CP	01/09/05	Caltech	Students
CRN-CP-9	CRN	CP	01/09/05	Caltech	Students
CRN-CP-10	CRN	CP	01/09/05	Caltech	Students

Treatment Without Time Limit

CRN-CP-1*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-2*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-3*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-4*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-5*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-6*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-7*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-8*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-9*	CRN	CP	01/23/05	Caltech	Students
CRN-CP-10*	CRN	CP	01/23/05	Caltech	Students

8 Appendix B: Object Values for Each Agent

800	600	200	500
500	400	400	100
700	500	400	200
200	200	200	600

Bidder 1

300	200	500	700
700	700	600	700
200	300	300	200
300	200	200	400

Bidder 2

400	200	200	400
200	300	500	600
300	600	600	200
200	300	400	400

Bidder 3

300	200	200	800
300	200	400	800
600	500	700	200
500	700	500	200

Bidder 4

400	600	300	300
200	200	300	300
400	700	500	600
600	400	700	700

Bidder 5

9 Appendix C: Instructions

9.1 The Goals of the Project

The goal of this project is to experimentally study the individual decision behavior in a strategic environment with the purpose of applying the insights to the design of allocation mechanisms to improve social efficiency. Specifically we study the allocation mechanisms of multiple, heterogeneous, and indivisible objects when the value structure exhibits superadditivity.

Some motivations for this study are following: (1) the design of an allocation mechanism when the objects are indivisible and when the preferences involve superadditivity has been an interesting question in theory and practice (e.g. FCC spectrum auctions), (2) understanding of the actual behavior of agents in a situation where the standard assumption of unbounded computation and communication complexity is nontrivial, is helpful to improving the understanding of rationality assumptions in economics.

In order to achieve these goals, we run a series of experiments on auctions to collect data on individual choices, efficiency, and revenue.

9.2 The Procedure of the Experiments

We present a series of auctions where you decide the bids. We will record the bidding data on the computer for future analysis.

Specifically, the proceedings of the session are as follows:

1. We explain the goal of this project, the structure of the decision problems, and the specific definitions of the auction environments where these decisions take place.

2. We then introduce the auction software and explain how to interact with the software and how to express the decisions that you make. We will then run some practice auctions.

3. We will distribute the materials, which will characterize the decision problems. More specifically, the value sheet is what the decision problems are based on.

4. We present a series of auctions and ask you to place bids on the objects.

9.3 The Decision Problems

Here we explain the decision problems you are going to solve.

1. Your goal is to maximize the payoff from the auctions. In each auction, you decide the bids, and these bids decide the allocation and the payment of the auction. You obtain values from the allocation. The payoff from

the auction is the difference between the values of the allocation and the payment. For example, if you obtain object 3, the value of the object is 100, and the payment needed to obtain object 3 is 50, then the payoff is 50. Given this structure, your objective is to choose bids which maximize the payoffs from the auctions.
2. Given the structure of this decision problem, we need to understand three issues. The first issue is how the allocation relates to values, the second issue is how to decide bids, and the third issue is how the bids lead to allocations and payments. Then, we explain how to choose bids when we discuss the auction program interface.

9.4 The Allocation and the Value

We first discuss the allocation and the value.
1. Let us explain the objects to be auctioned. In this auction, there are 16 objects arranged in a rectangle. Intuitively, these objects have an analogy to the distribution of spectrum licenses in the United States. For example, agent 1 might be located at Seattle, the object 1 is a license for the state of Washington, agent 2 is located at Massachusetts, agent 3 is located at Chicago, and so on.
2. An allocation for you means how many of these 16 objects you win. Mathematically, the allocation is defined as a subset of these 16 objects. An example is a collection of objects 1, 2, and 5, represented by {1,2,5},

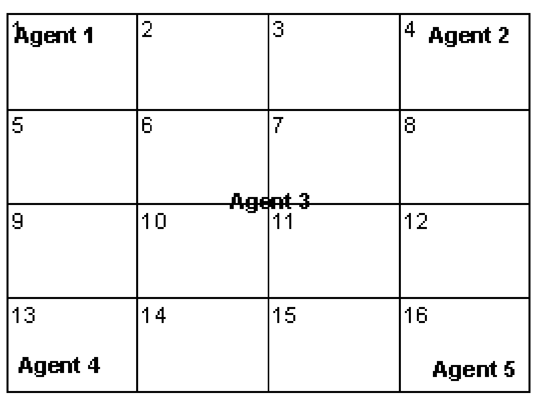


Figure C1. Objects and Agents.

3. You obtain economic values from an allocation. For example, in spectrum auctions, a company obtains profits from running a business using these licenses. Each of you can have different values even for the same object. For example, if a company is located in Seattle, it might attach a higher value for the license in the state of Washington than a company located in Florida since it will have a lower operating cost. These values are defined in the value sheet, which will be distributed before the auction.

Package	Value	Price
1	800	
2	600	
3	200	
4	500	
5	500	
6	400	
7	400	
8	100	
9	700	
10	500	
11	400	
12	200	
13	200	
14	200	
15	200	
16	600	
1 2	1832	
1 2 5	2962	
1 2 5 6	3591	
1 2 6	2400	
1 5	1661	
1 5 6	2217	
1 6	1296	
2 5	1370	
2 5 6	1902	
2 6	1072	
5 6	960	

Table 31: A Value Sheet

4. Let us explain how to read this sample value sheet. The upper parts define

the value of each object. For example, it says that the value of object 1 is 800. The second part of the value sheet defines the values of the packages. For example, the value of the package {1,2} is 1832.

5. Let us explain superadditivity of values. Superadditivity implies that the value of a package is larger than the sum of the values of the objects which comprise the package. For example, consider the package {1,2}. The value of this package is 1832. But object 1 and 2 have values of 800 and 600. This is an example of superadditivity, since the value of the package is larger than the sum of the values of the individual objects. An economic reason for superadditivity is that there are cost savings from acquiring geographically adjacent objects. For example, suppose a company has licenses which are geographically closely located. The company may be able to save on sales or operating costs since it can share labor or equipment in two areas. But there are limitations on superadditivity. That is, you have superadditive values only for a subset of the objects. It is not that agent 1 has superadditive values for every package. Agent 1 has values only for a package which is a subset of {1,2,5,6}.

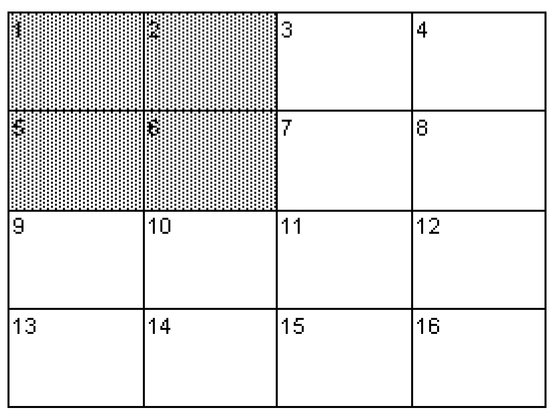


Figure C3. Area of Interest.

If agent 1 gets objects from the set {1,2,5,6} and objects outside of this set, then the total value is the sum of the package contained within the set {1,2,5,6} and the values of the objects outside this set. For example, if agent 1 gets the objects {1,2,5,9}, then its value is the sum of the package {1,2,5}, which is 2962, and the value of object 9, which is 700, so the total value is 2962+700=3662. An interpretation is that agent 1 has ‘an area of interest’ of objects close to its ’headquarters.’

9.5 Generalized Vickrey Auctions

The first mechanism we consider in this experiment is the generalized Vickrey auction.

1. Let us begin with a special case. It is a second price auction. In the second price auction, each agent competes for a single object. In a second price auction, an agent with the highest bid will win the object. The price the winner pays is *the second highest bid*. Let us consider an example. Suppose there are three agents, 1, 2, and 3. Suppose agent 1's bid is 10, agent 2's bid is 9, and agent 3's bid is 12.

	Bids
Agent 1	10
Agent 2	9
Agent 3	12

Table 32: An Example of a Second Price Auction

The winner is agent 3 with the highest bid, and the price that agent 3 is going to pay is the second highest bid of 10 by agent 1.

2. One way to understand the pricing rule in a second price auction, which will generalize to the payment rule in the generalized Vickrey auction, is that the price in the second price auction is determined by the externality imposed upon other agents. The price that agent 3 is going to pay is the externality imposed upon agents 1 and 2. If agent 3 is absent, then agent 1 is going to win the object with the bid of 10. But since agent 3 is present, agent 1 is not going to win the object. In a sense, agent 1 loses 10 because of agent 3. In other words, agent 3 imposes an externality of 10 on agent 1. According to this pricing rule, agent 3 is going to pay the price of 10. Please note that agent 3 pays to the seller, and not to agent 1.

3. A generalized Vickrey auction can be best understood as a generalization of second price auctions. In generalized Vickrey auctions, first, you submit bids not only for each object, but also for packages. It is a sealed-bid, so that you do not observe bidding behavior by others when you submit a bid. Also you submit bids only once. The seller chooses the allocation which maximizes the value for the seller expressed in the bids. The prices are determined as the externality imposed upon the others.

4. Let us explain an example for 3 objects. Suppose agents 1, 2, and 3 bid as follows.

The value-maximzing allocation: agent 1 wins object 1 and agent 2 wins package $\{2, 3\}$. The total value is 25. The price paid by agent 2 is defined

	Agent 1	Agent 2	Agent 3
Object 1	5	1	3
Object 2	4	1	3
Object 3	3	3	1
Package {1,2}	9	12	6
Package {1,3}	8	14	4
Package {2,3}	7	20	4
Package {1,2,3}	12	21	7

Table 33: An Example of Bids

as (the value of the allocation to other agents when agent 2 is absent from the auction) - (the value of the allocation to other agents when agent 2 is present in the auction). Let us compute the first term. Consider the auction without agent 2. The value-maximizing allocation is agent 1 wins package {1,2,3}. The total value for agents 1 and 3 in the current allocation is 5. The price paid by agent 2 is 12-5=7. An alternative interpretation is that an agent pays the minimum price which will be needed to win the package. These two interpretations are equivalent, as is most clearly seen in the case of a second price auction.

If there are ties among the bids, a tie will be broken randomly.

9.5.1 The Computer Program Interfaces of Generalized Vickrey Auctions

In the previous subsection, we explained generalized Vickrey auctions. In this experiment, we ask you to bid in the computer programs. We will explain how it works here.

1. Please read the instructions before the actual auctions since these auction mechanisms may look quite complicated for the first time. Also please let us know any questions at any time.

2. Please log in to your computers and open Internet Explorer. Then go to [the auction web site URL] and click Participate. Please type in user name and password as explained in the material.

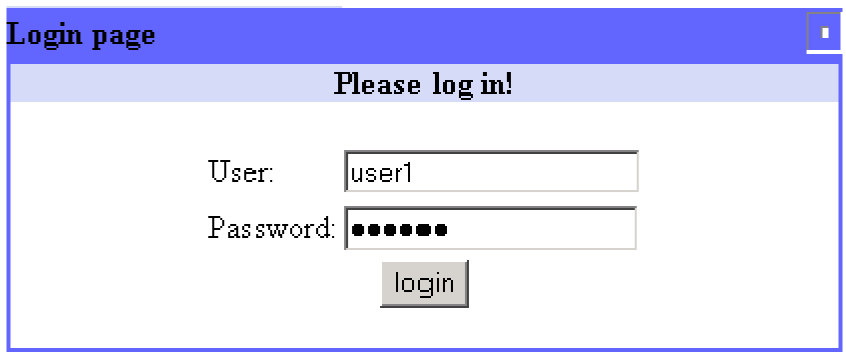


Figure C1. The Login Screen.

3. Then please go to the Auction list screen.

Figure C2. A List of Auctions.

4. Choose auctions and obtain informations from the configuration screen.

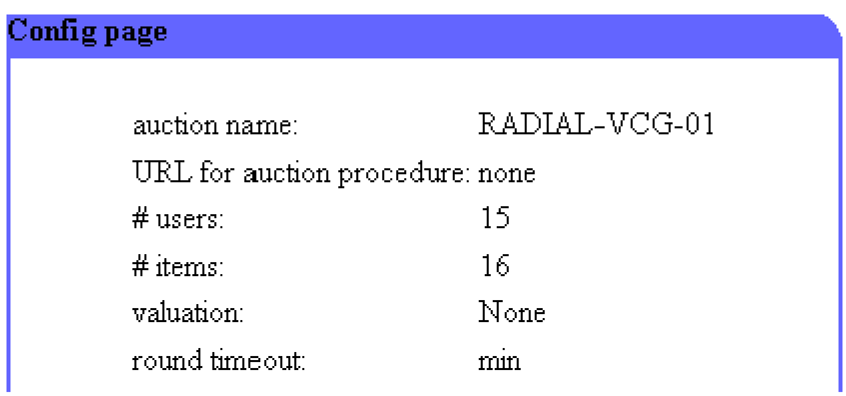


Figure C3. A Configuration Screen.

5. Click Vickrey. It will lead to a bidding screen. The bids must be entered by the end of the round time.

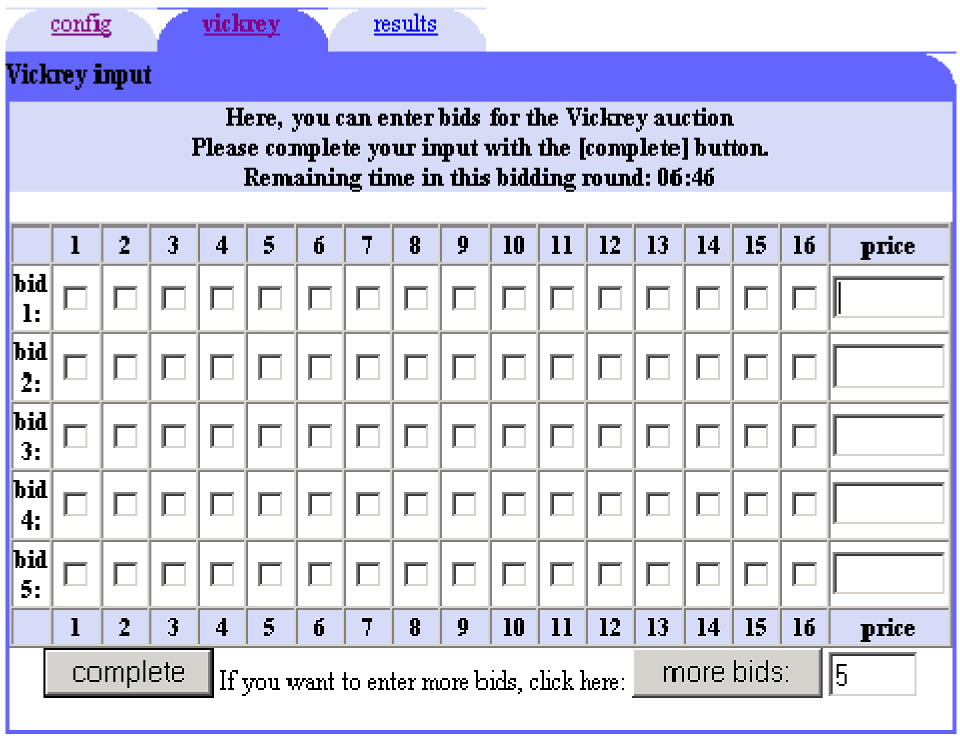


Figure C4. A Bidding Screen.

6. Create bids. To create a bid, check the objects and input the bid in the right space. Here is an example of a bid for a package $\{1, 2\}$ with the price of 200.

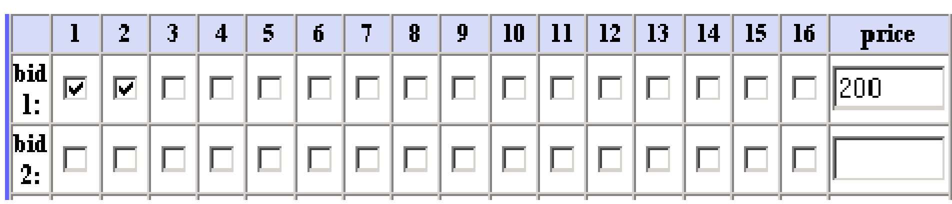
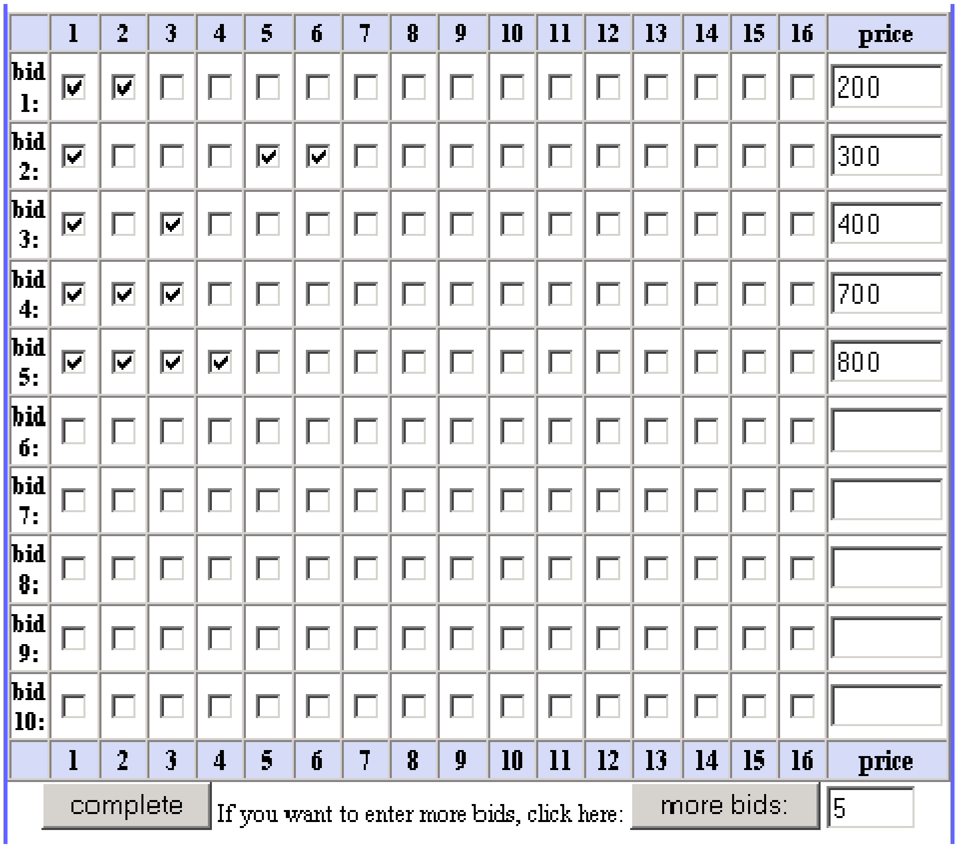


Figure C5. A Bid.

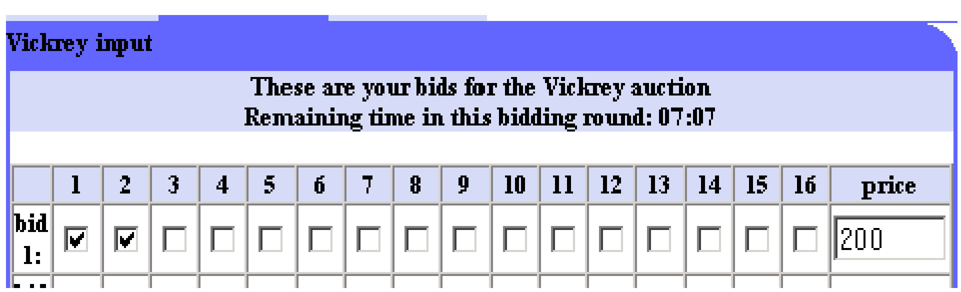
7. To increase the number of bids, click the ‘more bids’ box.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	price
bid 1:	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	200
bid 2:	☑	☐	☐	☐	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	300
bid 3:	☑	☐	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	400
bid 4:	☑	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	700
bid 5:	☑	☑	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	800
bid 6:	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	
bid 7:	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	
bid 8:	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	
bid 9:	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	
bid 10:	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	price

Figure C6. More Bids.

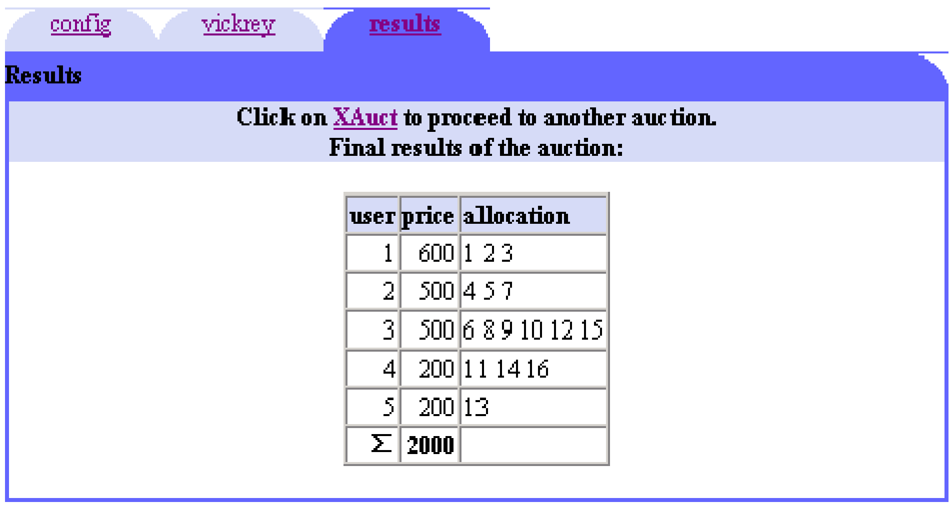
8. Click 'complete' when you are done.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	price
bid 1:	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	200

Figure C7. Waiting for an End of the Auction.

9. The result of the auction will be displayed at the result section. This example shows that agent 1 won the allocation 1,2,3 with the price of 600.



user	price	allocation
1	600	1 2 3
2	500	4 5 7
3	500	6 8 9 10 12 15
4	200	11 14 16
5	200	13
Σ	**2000**	

Figure C8. A Result.

9.6 Simultaneous Ascending Auctions

We next consider simultaneous ascending auctions.
1. Let us consider the simplest case: ascending auctions for a single object. In this interpretation, each agent submits a bid in each round of bidding. A bid must be higher than the highest bid submitted in the previous round. The auction ends when no agent submits a bid for a round. The agent with the highest bid wins at the price of the bid when the auction ended. Suppose, in the first round, agent 1 bids 10 and agent 2 bids 15. At the end of the first round, a provisional winner is agent 2 with a bid of 15. In the second round, suppose agent 1 makes a counter bid of 20 and agent 2 keeps the bid of 15. Then at the end of the second round, agent 1 is the provisional winner with the bid of 20. Suppose, in the third round, neither agent 1 nor agent 2 make their bid. Then the auction closes. The winner is agent 1 with the payment of 20.
2. Simultaneous ascending auctions run an ascending auction for each object. The auction ends when there are no bids for any of the auctions in a bidding round. That is, the market clears for each object. The (provisional) winner and the minimum price of a round are determined object-wise. A price can be different for each object. On the other hand, the auctions close simultaneously. That is, an auction closes only when there are no new bids for any auction.

9.6.1 The Computer Program Interfaces of the Simultaneous Ascending Auctions

1. Log in to the program as before.
2. Go to the auction list screen and click on 'simultaneous ascending auction'.
3. It will direct you to a configuration screen which displays information about the auction name, the number of users and items, the round time out, and the minimum increments.

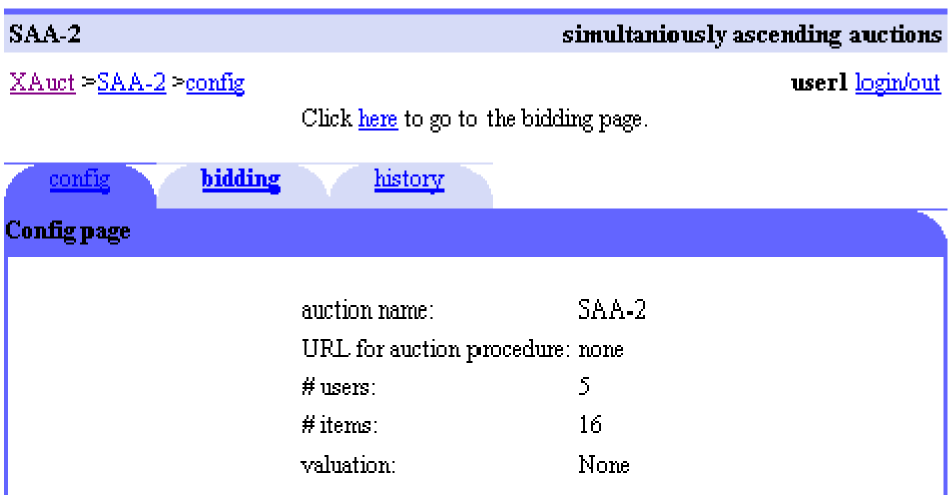
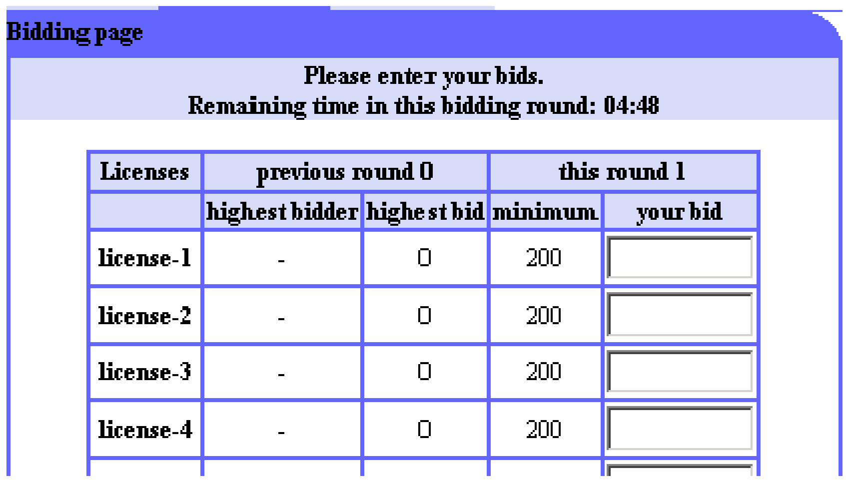


Figure C9. A Configuration Screen for SAA.

4. Click 'bidding'. It will lead to a bidding screen. Here you can input your bid for each object. There are time limits for each round and you need to finish bidding within the time limit. For example, the next screen shows the situation when you inputted a bid of 100 for object 1.
5. Confirm your bid at the bottom of the screen. It will ask you to wait until a round is over.



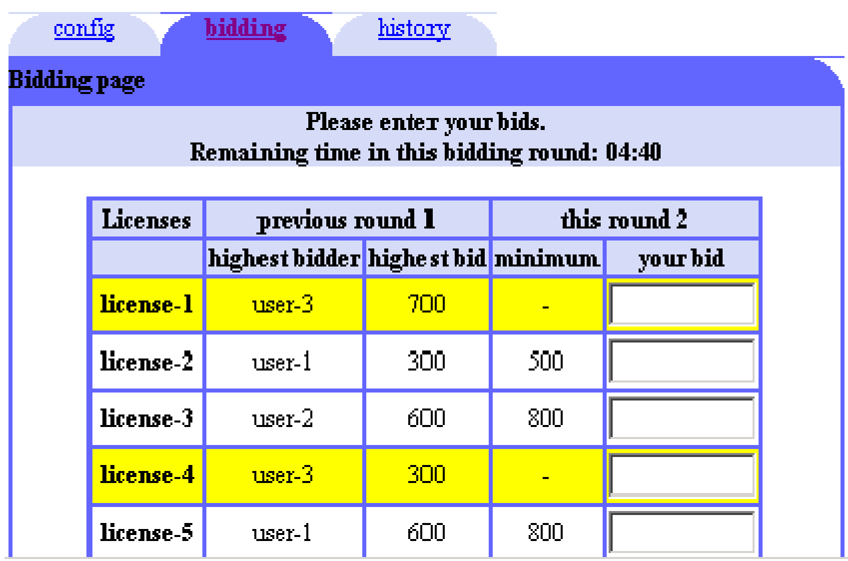
Bidding page

Please enter your bids.
Remaining time in this bidding round: 04:48

Licenses	previous round 0		this round 1	
	highest bidder	highest bid	minimum	your bid
license-1	-	0	200	
license-2	-	0	200	
license-3	-	0	200	
license-4	-	0	200	

Table C10. A Bidding Screen.

6. When a round is over, it will lead to a new round. The next screen shows that agent 3 is the provisional winner of object 1 at the price of 700.



config bidding history

Bidding page

Please enter your bids.
Remaining time in this bidding round: 04:40

Licenses	previous round 1		this round 2	
	highest bidder	highest bid	minimum	your bid
license-1	user-3	700	-	
license-2	user-1	300	500	
license-3	user-2	600	800	
license-4	user-3	300	-	
license-5	user-1	600	800	

Table C11. Round 2.

7. Input a new bid in this round in the same way as in round 1.
8. When the auction ends, the result is displayed under the 'result' tab. Under the 'history' tab, the whole bidding history of the auction is available.

Results page

Click on XAuct to proceed to another auction.
Final results of the auction:

user	price	allocation
1	900	2 5
2	1800	3 6 7
3	1000	1 4

Licenses	final round 2	
	highest bidder	highest bid
license-1	user-3	700
license-2	user-1	300
license-3	user-2	600
license-4	user-3	300
license-5	user-1	600
license-6	user-2	700
license-7	user-2	500

Figure C12. An Auction Result.

config results history

History page

Round 2 go to: round 2

		Bids of all bidders					Results of round 2	
Licenses	minimum	1	2	3	4	5	highest bidder	highest bid
license-1	900	-	-	=700=	-	-	user-3	700
license-2	500	=300=	-	-	-	-	user-1	300
license-3	800	-	=600=	-	-	-	user-2	600
license-4	500	-	-	=300=	-	-	user-3	300
license-5	800	=600=	-	-	-	-	user-1	600
license-6	900	-	=700=	-	-	-	user-2	700
license-7	700	-	=500=	-	-	-	user-2	500

Table C13. An Auction History.

9.7 Clock-Proxy Auctions

The last mechanism we consider is clock-proxy auctions.
1. Clock-proxy auctions consist of two stages: clock auctions in the first stage and proxy auctions in the second stage.
2. The first stage clock auction is similar to ascending auctions in that there are no package bids. The difference is that the price goes up automatically at each round of the clock auction. In ascending auctions, the price goes up as a result of bidding. That is, in clock auctions, the price is raised automatically by the auctioneer, and the agents choose whether to drop out or to stay in the auction. An example is a flower auction in The Netherlands. For example, consider an auction of a flower with three agents. The price starts from zero. The price goes up from zero to 10, 20, 30... Suppose agent 3 drops out at the price of 20. Then there are only two agents, agent 1 and agent 2, in the auction. Then the auction ends when one of the remaining two agents drops out. Suppose agent 2 drops out at the price of 30. Then agent 1 is the winner with the price of 30.

3. After the clock auction, the auction moves to the second stage of the proxy auction. In this proxy auction. each agent can submit, as in the generalized Vickrey auction. a package bid. A difference is that the allocation and the price are determined by an ascending proxy auction.
4. In order to understand how an ascending proxy auction works, let us explain how this auction works in the case of a single object. The proxy bidding is similar to the one used in eBay. In these auctions, an agent tells the maximum amount that the agent is willing to pay for the object. Then the computer program, known as the proxy agent, bids on behalf of the agent by increasing the price little by little. Essentially, in a proxy auction, the agent provides a maximum amount that it is willing to pay, to the proxy agents, and the proxy agents will try to win the object at the lowest price.
5. Let us extend our understanding to the heterogeneous objects case by moving to ascending proxy auctions. A similarity with the single object case is that each agent send the bids to the proxy agent. The only difference is that the agent can place bids on packages in addition to bids for a single object, as in Vickrey auctions. The proxy agents try to win one package for the agent, with the lowest price. Let us explain this point using a numerical example. Suppose there are two objects A and B and that the bids must be integers. Also suppose that the values that an agent gave to the proxy agent are $v(A) = 10, v(B) = 5, v(A, B) = 20$ and the current prices of the objects and package are $b(A) = 4, b(B) = 3, b(A, B) = 15$. The principle that the proxy agent follows is to bid on the package with the minimum price needed

to win the package so as to maximize the gain from winning the auction. Let us consider what happens if an agent bid on A. The minimum price needed to win A is 5. At this price of 5, the payoff is 10-5=5. Now consider B, in which case, the gain is 5-4=1. For package A,B, the gain is 20-16=4. Since the payoff is highest for bidding on A, the proxy agent will bid on A for the agent.
6. Let us explain the relation between clock auctions and proxy auctions. The outcome of the clock auctions does not determine the final allocation. But, the bids at the clock auction will be used at the proxy auctions: the proxy agent will consider bids at the clock auctions in addition to bids at the proxy auctions.

9.7.1 The Computer Program Interfaces of the Clock-Proxy Auctions.

1. Choose a CP auction. It will lead to a 'config' screen.

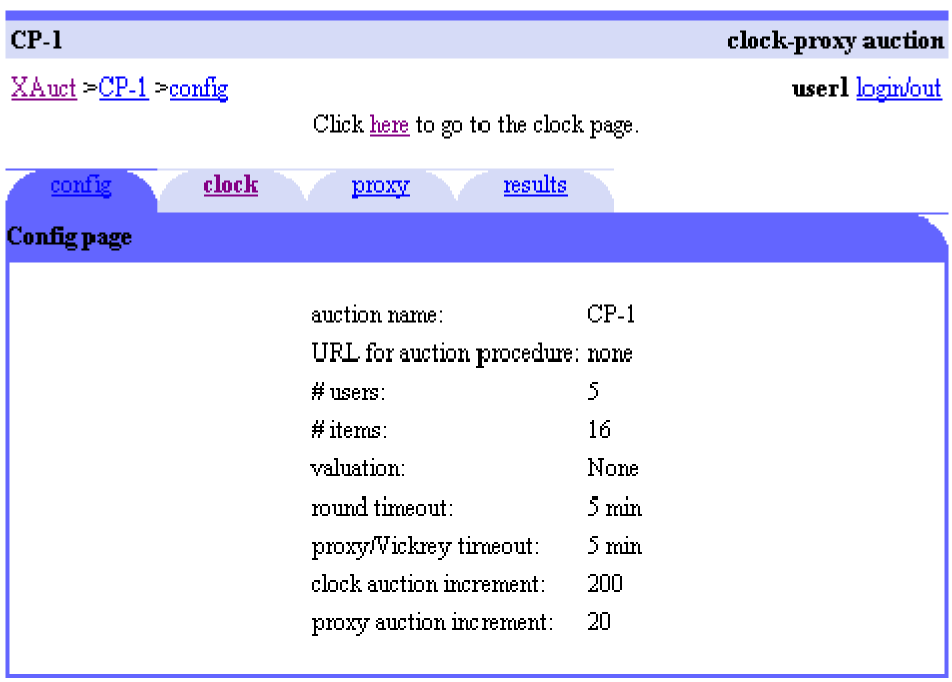
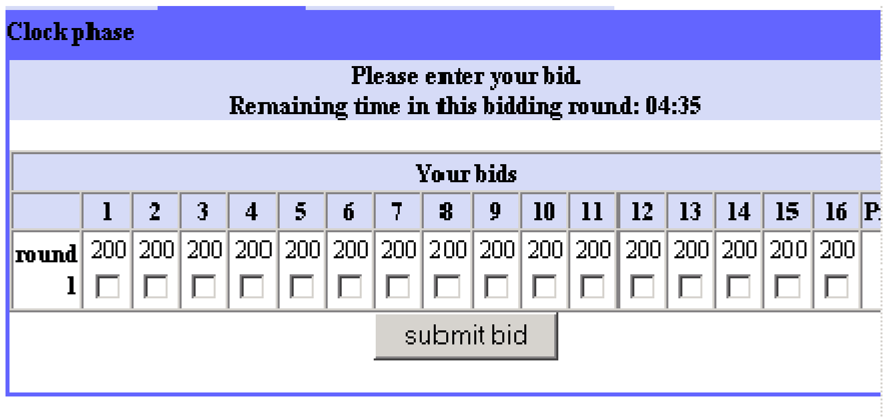


Figure C14. A Configuration Screen for a Clock-Proxy Auction.

2. Click the clock tab. It will lead to the first stage of the clock auction.



Clock phase

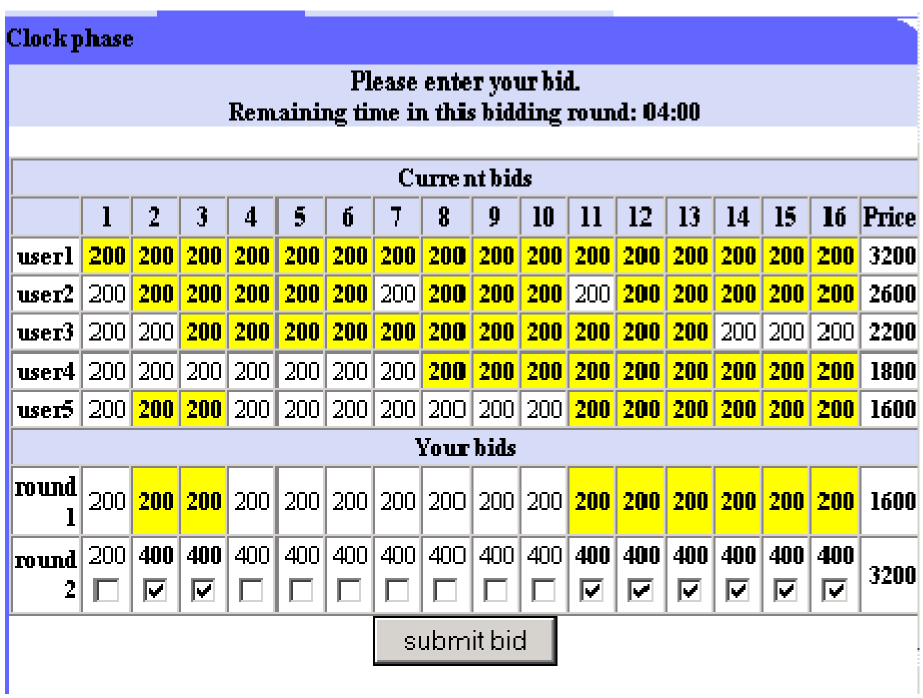
Please enter your bid.
Remaining time in this bidding round: 04:35

Your bids																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	P
round 1	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	

submit bid

Figure C15. A First Stage of a Clock Auction.

Clicking the box below the price will imply staying in the auction. Otherwise, it will imply dropping out of the auction.
3. After the first round is over, the price will go up, and it will lead to the second stage.



Clock phase

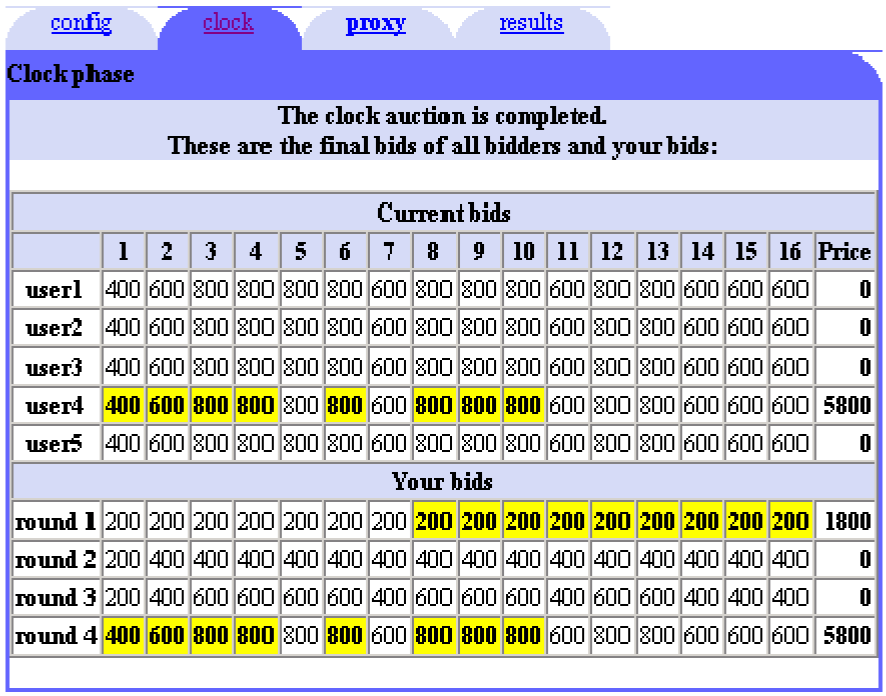
Please enter your bid.
Remaining time in this bidding round: 04:00

Current bids																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Price
user1	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**3200**
user2	200	**200**	**200**	**200**	**200**	**200**	200	**200**	**200**	**200**	200	**200**	**200**	**200**	**200**	**200**	**2600**
user3	200	200	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	200	200	200	**2200**
user4	200	200	200	200	200	200	200	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**200**	**1800**
user5	200	**200**	**200**	200	200	200	200	200	200	200	**200**	**200**	**200**	**200**	**200**	**200**	**1600**
Your bids																	
round 1	200	**200**	**200**	200	200	200	200	200	200	200	**200**	**200**	**200**	**200**	**200**	**200**	**1600**
round 2	200	**400**	**400**	400	400	400	400	400	400	400	**400**	**400**	**400**	**400**	**400**	**400**	**3200**

submit bid

Figure C16. The Second Stage of a Clock Auction.

4. Continue bidding. At the end, it will display the results of the clock auction.



config | clock | proxy | results

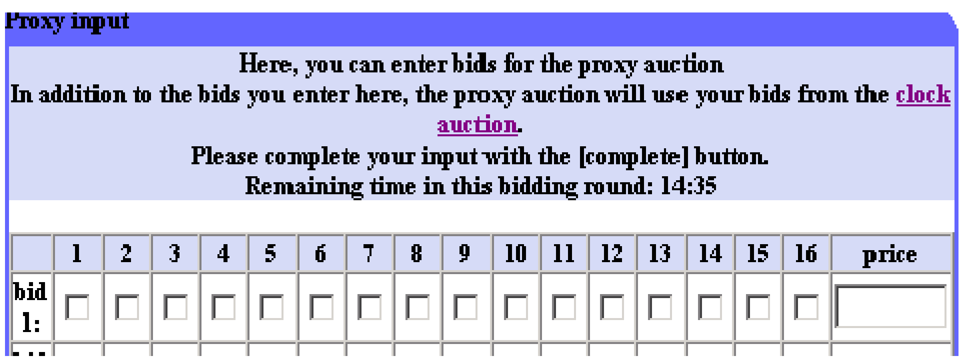
Clock phase

The clock auction is completed.
These are the final bids of all bidders and your bids:

Current bids																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Price
user1	400	600	800	800	800	800	600	800	800	800	600	800	800	600	600	600	0
user2	400	600	800	800	800	800	600	800	800	800	600	800	800	600	600	600	0
user3	400	600	800	800	800	800	600	800	800	800	600	800	800	600	600	600	0
user4	400	600	800	800	800	800	600	800	800	800	600	800	800	600	600	600	5800
user5	400	600	800	800	800	800	600	800	800	800	600	800	800	600	600	600	0
Your bids																	
round 1	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	1800
round 2	200	400	400	400	400	400	400	400	400	400	400	400	400	400	400	400	0
round 3	200	400	600	600	600	600	400	600	600	600	400	600	600	400	400	400	0
round 4	400	600	800	800	800	800	600	800	800	800	600	800	800	600	600	600	5800

Figure C17. A Result of a Clock Auction.

5. Move to the proxy auctions by clicking the tabs in the screen.



Proxy input

Here, you can enter bids for the proxy auction
In addition to the bids you enter here, the proxy auction will use your bids from the clock auction.
Please complete your input with the [complete] button.
Remaining time in this bidding round: 14:35

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	price
bid 1:																	

Figure C18. Inputting a Proxy Bid.

6. Place proxy bids and click complete.

config | clock | proxy | results

Proxy input

These are your bids for the proxy auction
In addition to these bids, the proxy auction will use your bids from the clock auction.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	price
bid 1:	☑	☑	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	800
bid 2:	☑	☑	☐	☐	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	2000
bid 3:	☐	☑	☑	☐	☑	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	600
bid 4:	☑	☐	☐	☐	☑	☑	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	1200
bid 5:	☐	☑	☑	☐	☐	☑	☑	☑	☐	☐	☐	☐	☐	☐	☐	☐	1000
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	price

Figure C19. Proxy Bids.

7, At the end of the auction, the results will be displayed.

Results

Click on XAuct to proceed to another auction.
Final results of the auction:

user	price	allocation
1	1400	1 2 5 6
2	400	10
4	400	11 12
5	800	13 14 15 16 3
Σ	**3000**	

Figure C20. A Result of a Clock-Proxy Auction.

10 Appendix D: Software Used to Conduct Auctions

The auction experiments discussed in this paper were conducted using software implemented by Eiichiro Kazumori and Yaakov Belch. This software presents a comprehensive suite of package auction mechanism implementations, including the standard single unit auction.

Single Unit Auctions	First Price Auctions Second Price Auctions Ascending Price Auctions Descending Price Auctions Clock Auctions
Auctions for Heterogeneous Objects	Simultaneous Ascending Auctions Simultaneous Descending Auctions Simultaneous Clock Auctions Bernheim-Whinston Menu Auctions (exclusive/nonexclusive bids) Vickrey Auctions (exclusive/nonexclusive bids) Ausubel-Milgrom-Cramton Clock-Proxy (exclusive/nonexclusive bids) Clock-Vickrey (exclusive/nonexclusive bids)

Figure D1: The List of Implemented Auctions.

The software uses the algorithm of Zhong, Cai, and Wurman (2003) for clock-proxy auctions.

10.1 Configuration of Simultaneous Ascending Auctions

1. Choose ascending auctions.

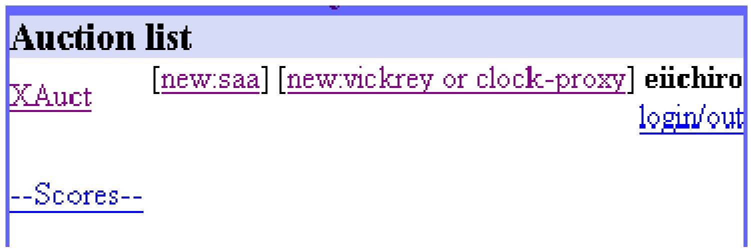


Figure D2: A Choice of Auctions.

2. Choose parameter values.

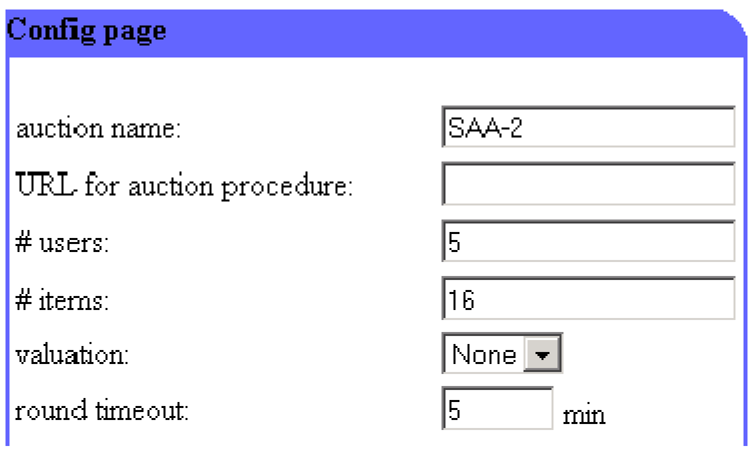


Figure D3: A Choice of Parameters.

10.2 Configuration of Generalized Vickrey and Clock-Proxy Auctions.

1. Choose package auctions in a previous screen.
2. Set up parameters.

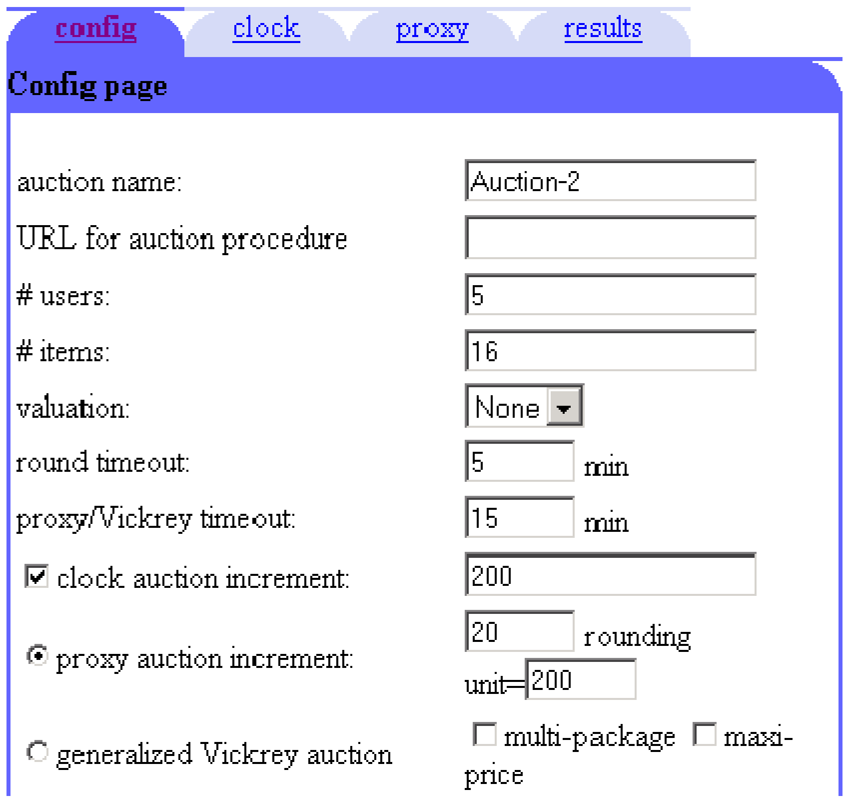


Figure D4: Parameters for Package Auctions.