Does It Pay to Increase Competition in Combinatorial Conservation Auctions?

M. S. Iftekhar,[1] A. Hailu[2] and R. K. Lindner[3]

[1]*Research Associate Professor, Centre for Environmental Economics and Policy (CEEP), School of Agricultural and Resource Economics (M089), University of Western Australia, 35 Stirling Highway, Crawley, Perth WA 6009, Australia (corresponding author: phone: 61+ 08 6488 4634; fax: 61+ 08 6488 1098; e-mail: mdsayediftekhar@yahoo.com; e-mail: mdsayed.iftekhar@uwa.edu.au).*

[2]*A./Professor, School of Agricultural and Resource Economics (M089), University of Western Australia, 35 Stirling Highway, Crawley, Perth, WA 6009, Australia (phone: 61+ 08 6488 2538; fax: 61+ 08 6488 1098; e-mail: ahailu9@gmail.com).*

[3]*E./Professor, School of Agricultural and Resource Economics (M089), University of Western Australia, 35 Stirling Highway, Crawley, Perth, WA 6009, Australia (phone: 61+ 08 6488 2563; fax: 61+ 08 6488 1098; e-mail: bob.lindner@uwa.edu.au).*

Conservation auctions allow landholders to propose conservation projects and associated payments (bids) for consideration by a conservation agency. Recently, the application of iterative combinatorial auction designs has been proposed to improve outcomes of conservation auctions. In combinatorial auctions, landholders are allowed to offer projects each of which involves activities aimed at providing one or multiple services. An iterative format allows bidders the opportunity to gradually explore the type of projects they want to offer, with this process being facilitated through price feedback provided based on intermediate auction round results. Auction designs vary with the type of feedback and respond differently to market conditions. At present there is a lack of information about their performance in markets with varying degrees of competition (in terms of number of bidders and level of target). Therefore, using an agent-based simulation model, we evaluate a number of iterative auction designs. We observe that a higher degree of competition leads to a higher auction efficiency. In a high competition environment, efficiency outcomes tend to be less sensitive to auction design choices. Therefore, an auctioneer could enjoy freedom in design choice if adequate competition could be ensured. In weak competition environments, however, some auction designs perform better than others.

Les enchères de conservation permettent à des propriétaires fonciers de proposer des projets de conservation et des paiements connexes (offres) qui sont soumis à l'examen d'un organisme de conservation. Dernièrement, il a été proposé d'utiliser des mécanismes d'enchères combinatoires itératifs afin d'améliorer les résultats des enchères de conservation. Les enchères combinatoires permettent aux propriétaires fonciers de proposer des projets qui comprennent des activités destinées à fournir un ou plusieurs services. Le mécanisme itératif permet aux enchérisseurs d'examiner graduellement le type de projets qu'ils souhaitent offrir; dans ce cas, les enchérisseurs obtiennent de la rétroaction sur les prix fondée sur les résultats de tours d'enchères intermédiaires. Les mécanismes d'enchères varient en fonction de la rétroaction sur les prix et réagissent différemment aux conditions du marché. À l'heure actuelle, nous manquons d'information quant à leur performance sur les marchés lorsque les niveaux de concurrence varient (nombre d'enchérisseurs et niveau cible). À l'aide d'un modèle

Canadian Journal of Agricultural Economics 00 (2013) 1–23
DOI: 10.1111/cjag.12028

multi-agent, nous avons évalué certains mécanismes d'enchères itératifs. Les résultats de notre étude indiquent qu'un degré de concurrence élevé accroît l'efficacité des enchères. Dans un contexte où la concurrence est élevée, les résultats quant à l'efficacité sont moins sensibles au choix des mécanismes d'enchères. Ainsi, un commissaire-priseur (encanteur) pourrait jouir d'une certaine liberté quant au choix du mécanisme d'enchères s'il était possible de garantir un niveau de concurrence adéquat. Par contre, dans les contextes où la concurrence est faible, certains mécanismes d'enchères donnent de meilleurs résultats.

INTRODUCTION

Auctions are often used by government agencies to allocate contracts for environmental projects on private land. The Conservation Reserve Program of the U.S. Department of Agriculture (USDA) is one of the early applications of an auction-based mechanism to pay landholders for environmental services like wildlife enhancement, water quality improvement, erosion control, and air quality improvement (USDA 2004). In Australia, BushTender was one of the early auction-based programs with the objective of enhancing biodiversity value of remnants (Stoneham et al 2003). Since then conservation auctions have been used to procure diverse agri-environmental services, such as native vegetation conservation, wildlife protection, and salinity control (Grafton 2005). In Canada, auction-based mechanisms have been used or tested for wetland restoration (Hill et al 2011; Boxall et al 2012) and conservation easement procurement (Brown et al 2011). There have been some trials in Europe as well (Latacz-Lohmann and Schilizzi 2005).

Through conservation auctions, agencies are likely to aim either to minimize the cost of procuring a set of target services or to maximize the total environmental benefits within a given budget (Ulber et al 2011). To achieve these objectives, the auctions need to have an adequate level of competition. If an agency succeeds in maintaining an adequate level of competition, then this may significantly reduce the procurement cost by encouraging individual landholders to offer bids that are closer to their opportunity costs (Latacz-Lohmann and Hamsvoort 1997).

While the relationship between auction performance and competition structure has been the subject of many studies,[1] only few of these have focused on conservation auctions. Previously, Rolfe et al (2011) studied the impact of auction scale (in terms of funding/budget) and scope (in terms of geographical coverage and industry types) on the potential participation and bid prices in a water quality auction in North-Eastern Australia. They observed that potential bidders are likely to reduce their bid prices if

[1] In the auction literature, the relationship between price and the number of bidders has been the subject of many studies. For example, Brannman et al (1987) observed that in auctions on offshore oil rights, municipal bond markets, and timber auctions, the winning bid price falls as the number of bidders increases. Li and Perrigne (2003) observed that in first price sealed bid auctions of standing timber in France, information rents decrease with the increase in the number of bidders. They estimated that everything being equal, one additional bidder decreases the winner's information rent or profit by 19% on average. Similar trends were observed in the highway construction industry in Florida (Gupta 2002), passenger railway markets in Germany (Lalive and Schmutzler 2008), simulated multi-unit auctions (Hailu and Thoyer 2007), and simulated food grain supply chains (Goel et al 2005).

the auction targets more industries from the same region. On the other hand, widening geographical coverage and/or increasing funding scale of the auction would attract additional bidders, but bid prices are likely to increase as well, offsetting the efficiency benefits from a wider scope and scale.

In conservation auctions, the proportion of winning bids is one indicator of the degree of competition—higher percentages of winning bids indicate lower degrees of competition. For instance, the proportion of successful bids in the BushTender trial in Australia was 75%. Estimates for other conservation auctions in Australia also indicate high proportions of successful bids, with winning proportions ranging from 35% to 88% (Whitten et al 2008). Connor et al (2008) observed that the relative cost-effectiveness of these auctions is primarily due to the selection effect, as an environmental benefits index is applied to prioritize projects, rather than due to competitive-pressure effects. Most conservation auctions conducted in Australia cannot be considered to have had high rates of participation. This suggests that there is a potential for improving auction efficiency outcomes by ensuring adequate levels of competition. Relatively less is known about the competitive consequence of changes in the number and distribution of bidders in a conservation auction.

Therefore, in this paper, we have studied the effect of changes in the degree of competition on the performance of conservation auctions. We focus on combinatorial auction designs, which allow bidding on single as well as packages of environmental projects. Such auctions have recently been tested through laboratory experiments in conservation situations in France (Said and Thoyer 2007), Australia (Nemes et al 2008), and the United States (Porter et al 2009). It has been observed that combinatorial auctions could perform better than noncombinatorial auctions when bidder costs reflect synergy benefits, that is, when it is less costly for a bidder to supply multiple services simultaneously.[2]

Combinatorial auctions would allow bidders to submit bids for packages of services that enable them to exploit such synergies. However, this flexibility in bidding options could increase the bid strategy selection problem exponentially. To facilitate bidding, these auctions are therefore often run iteratively where bidders get multiple opportunities to submit and revise their bids during the course of the auction. Bids are submitted in a sequence of distinct rounds. After each round, a set of provisional winners or allocations are selected and results communicated to bidders. The auction ends when a termination rule is satisfied (Aparicio et al 2008).

Thus, iterative auctions allow bidders to obtain feedback. In the course of the auction, these feedbacks are based on provisional allocations and reflect the prices implied by these allocations. These prices are designed to provide enough information to separate winning from losing bids. Beyond that, auction designs vary with the type of feedback price used. For example, the feedback prices could be either on individual items or on bundles/packages. Similarly, the prices could be the same for all bidders or different for different bidders. In this study, we focus on price feedbacks given as item prices that are the

[2] It should be noted that there has not been any field-level implementation of combinatorial auction design for conservation services. The only implementation of a full-fledged combinatorial design in agriculture was to lease marine aquaculture sites by the Department of Primary Industries in Australia (DPI 2007). Readers are referred to Iftekhar et al (2012a, 2012b) and references therein for relevant discussions on implementation of combinatorial auction designs for conservation.

same for all bidders. Item pricing is parsimonious in that one could use a limited number of prices to calculate the value of any possible package. They are easier to interpret and have been tested in a wide variety of conditions.

Parkes (2006) provides a review of alternative item price designs that have been proposed for combinatorial auctions. In this paper, we focus on three closely related item price feedback designs that approximate market clearing prices. These include the smoothed anchoring algorithm (SmAnch) of Hoffman (2006), the nucleolus-based algorithm of Dunford et al (2007), and the data envelopment analysis (DEA)-based pricing algorithm of Aparicio et al (2008). Price information produced by these algorithms reflects the aggregate outcome of the bidding strategies adopted by bidders in the previous round. As a consequence, bidders have the potential to learn from the market and adjust their bids. All of these algorithms have shown promise in previous studies on conservation auctions (Iftekhar et al 2011, 2012c). However, they have not yet been compared for cases where the degree of competition is systematically varied.

A combinatorial auction exhibits *bidder monotonicity* if adding another bidder always (weakly) reduces existing bidders' equilibrium profits and (weakly) reduces the auctioneer's cost of purchase (Ausubel and Milgrom 2006). However, defining competition is not always an easy task for combinatorial auctions, since demand and supply both relate to heterogeneous items. Under such circumstances, one might need to develop a competition index. In such auctions, bidders with interests in different items participate in the same auction. Adding an extra bidder does not necessarily increase competition for all items. In fact, it can reduce the number of standing offers on some items or bundles of items. On the other hand, changes in the composition of the auctioneer's demand target can alter the competition structure altogether.

The contribution of the paper is twofold. First, we study the effect of the degree of competition on auction performance in a conservation auction. The variation in competition is done by systematically increasing the size of the procurement targets for different bidder numbers. Second, we evaluate the performance of a selected set of competing auction designs for potential implementation in real-world conservation auctions. We assess the extent to which auction performance depends on auction design. A better understanding of both of these factors is important since conservation groups or agencies can have some degree of control on auction participation levels. An assessment of associated efficiency benefits is key to choice of auction design and the value of investments in participation enhancing activities.

SIMULATION FRAMEWORK

There are three established methodologies for designing auction markets—theoretical analysis, laboratory experiments, and computer simulations. Despite significant developments in auction theory, there is a lack of clear theoretical predictions for combinatorial auctions (Krishna 2002). Therefore, the use of laboratory experiments has become popular (Smith 1962). Some of the notable laboratory experiments on combinatorial auctions are reported in Rassenti et al (1982), Brewer (1999), Lunander and Nilsson (2004), Kwasnica et al (2005), and Chen and Takeuchi (2010). Laboratory experiments can take into account the cognitive limitations of humans and provide indications of real life behaviors of bidders (Smith 2008).

However, in our case, laboratory experiments were deemed unsuitable due to the large number of scenarios that would need to be tested. Lab experiments would have been prohibitively expensive in terms of time and money. In the presence of budget and time constraints, inadequate replications from laboratory experiments would make inferences difficult.

Therefore, we have conducted computational experiments using an agent-based model (ABM). An ABM or a multi-agent system is a system composed of multiple interacting (artificial) intelligent agents (Roth 2002), representing a system (in this case an auction market) being studied. An ABM makes it possible to easily simulate the performance of an auction design under different scenarios. Outcomes from different auction designs are submitted and results numerically compared. It is assumed that if a design is inefficient in a simple environment, then there is a limited possibility that it will be effective in a complex field setting (Hailu and Thoyer 2010). Results from the agent-based simulations modeling would then be used as a filtering mechanism for selecting suitable designs for further testing in labs and in field trials (Arsenault et al 2012).

There are few reported computational studies focusing on iterative combinatorial auction problems. Previously, Iftekhar et al (2012c) studied three price feedback designs along with three other similar designs using ABM to test the effect of bidder cost heterogeneity. They observed that DEA-based designs performed the best, followed by SmAnch- and constrained nucleolus algorithm (ConsNuc)-based auctions. Although it employs a similar computational design and is motivated by a common policy issue, Iftekhar et al's (2012c) paper differs from the current paper in the following key aspects. Iftekhar et al (2012c) studied the effect of cost heterogeneity using a limited strategy ABM. Bidding agents could bid only on four distinct projects, which were uniform (except for cost) across all scenarios. Moreover, the parameter values of the Experience-Weighted Attraction (EWA) learning were uniform for all bidders in all scenarios. In contrast, the current paper focuses on the effect of changes in competition (either in terms of number of bidders and demand ratio). We have used a heterogeneous set of bidding agents in terms of capacity and learning. For example, the projects are randomly assigned to different bidders in each replication, which ensured that the bidding population has different supply capacities depending on random draws for individual agents. Further, the parameter values of the EWA learning algorithm are randomly generated at the beginning of the auction, which means that agents would use different forms of EWA learning algorithm throughout the auction and behave differently. In summary, in this paper, we tackle a problem that has not been addressed previously: the impact of competition on combinatorial conservation auction performances when bidders are heterogeneous.

Among other studies, Parkes (2001) studied his iterative combinatorial auction design, iBundle, using computational experiments. An et al (2005) studied the impact of bidding strategies on several sealed bid and iterative combinatorial auction designs based on linear ask prices. Dunford et al (2007) compared their nucleolus-based feedback price computation algorithms with a version of the Resource Allocation Design (RAD)-based algorithm of Kwasnica et al (2005) and with an Ascending Proxy Auction. They focused on a spectrum license allocation problem in the context of the U.S. Federal Communications Commission (FCC) setting. Pikovsky (2008) compared three selected linear price auction designs and the Vickrey–Clark–Groove auction using computer simulations and laboratory experiments. The selected auction designs are Clock Combinatorial auctions

(Porter et al 2003), the RAD, and the author's own design, called ALPS. He observed that the auction designs performed very well for different value models even in the case of valuations that exhibit high synergy levels, although there are significant differences in the efficiency and revenue distributions of the evaluated designs. Aparicio et al (2008) studied the performance of their DEA-based algorithm for different value models using simulation experiments.

With the exception of Aparicio et al (2008) and Iftekhar et al (2012c), none of the previous studies have focused on multiple-item combinatorial auctions or on the impact of competition on the performance. In this paper, we focus on two dimensions or measures of competition: the size of procurement target relative to bidder capacity (i.e., the degree of rationing in an auction) and the number of bidders participating in an auction. These competition measures are varied in our simulations and the performance of different auction designs compared. Below, we provide further details on our simulations following the overview, design concepts, and details protocol of Grimm et al (2006).

Purpose

The ABM[3] simulates a multiple-unit combinatorial procurement auction. The objective of the model is to investigate how auction performance is affected by the degree of competition.

Entities, State Variables, and Scales

There are two types of agents:

1) An auctioneer representing a conservation agency. The auctioneer has a target demand for conservation and is willing to pay landholders to undertake projects to conserve a certain set of target species (malleefowl, phascogale, and python); and
2) A population of bidding agents representing landholders with different conservation projects.

We have used a bioeconomic model developed by Iftekhar et al (2009) to generate cost functions for a risk-neutral landholder. The model traces the population dynamics of three native endangered species (red-tailed phascogale, carpet python, and malleefowl) found in the wheatbelt of Western Australia. This model estimates optimal costs for conserving different population sizes of target species in response to landholder's conservation interventions. We assume that landholders can submit bids presenting conservation

[3] This is implemented in the General Algebraic Modeling System (GAMS©; GAMS Development Corporation, Washington, DC) program. There were several reasons for choosing this software. First, we have modeled a private value auction and assumed that the landholders do not interact with each other outside of the market (i.e., no collusion). Even in an auction market, landholder agents only engage with each other in "indirect" interactions through the auctioneer in terms of price feedback and bid revisions. Therefore, we did not need any interactive model to allow direct communication between agents. We appreciate that some other specialized agent-based modeling software would have been more suitable than GAMS in the latter case. Second, GAMS has robust nonlinear and integer optimization capabilities, which are essential to solve the winner determination problem and implement the item feedback price calculation procedures.

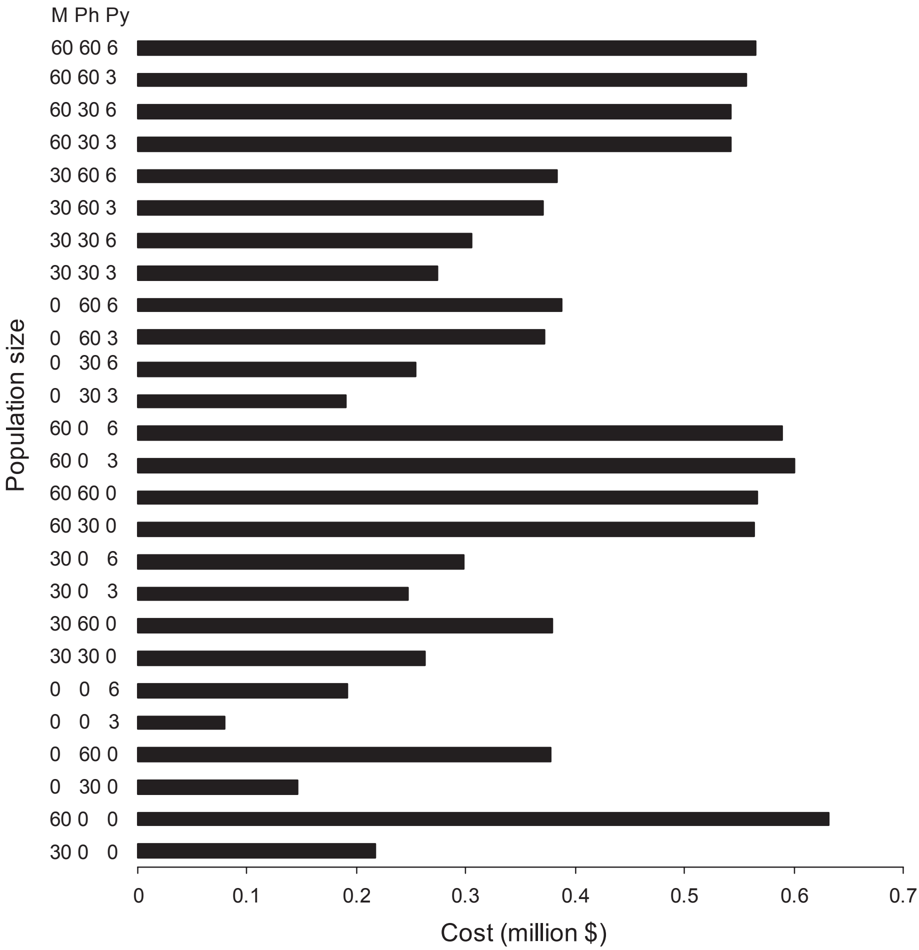

Figure 1. Conservation costs for 26 different combination of population sizes of the target species. Here, M is malleefowl, Ph phascogale, and P python. The numbers on y-axis indicate the population sizes of respective species

projects benefiting single species as well as combination of species. For individual species, a bidder can potentially offer three levels of population sizes, including an option for not offering a particular species. Therefore, a bidder has a complete set of 26 potential packages (i.e., 3^3-1), with each package representing a project benefiting one or more species and also the level of benefits expected for the species included in the package. The costs of each of these packages, as well as the levels of species benefits, are shown in Figure 1. The costs shown as well as the benefits represent outcomes over a 10-year planning horizon.[4]

[4] All bidders have same conservation cost for an identical package. However, due to random package choice and learning parameterizations, bidders will have different supply and bidding capacity in

It is unrealistic to assume that they will offer all packages in an auction round. It is possible that they might prefer some packages over others or they might be lacking adequate resources to prepare bids for all possible combination of items. Therefore, for simplicity, we assume that bidders pick a smaller subset of packages (10) to offer. Further, these packages are assumed to be randomly chosen before the beginning of an auction. Bidders are not allowed to change or replace those packages during intermediate rounds although, based on market conditions, they can revise their bids on those packages. This has been done to reduce the strategy space for the bidders.

Process Overview and Scheduling

In our ABM model, the simulated auctions involve these steps (see Figure 2).

- In the first step, bidders place bids (projects) indicating their willingness to generate conservation outcomes (i.e., species and level of conservation) and associated payments they would like to receive (i.e., their ask prices). Conservation outcomes or benefits for a bid project are measured as the expected population sizes of target species at the end of a specified planning horizon. The ask prices of the bidding landholders should reflect their cost complementarities (if any) of maintaining a certain set of species.
- In the second step, based on the submitted bids, the auctioneer provisionally selects winning bids with the objective of minimizing the procurement cost. The selection is "provisional" in that this is an iterative auction with current bids to be replaced by revised ones in a subsequent round. As part of the provisional selection processes, the auctioneer generates implied item prices to provide as feedback to bidders. Bidders use these prices to revise their bids. The details of the feedback price calculation algorithms are presented in Appendix S1.
- In the third step, bidders revise their bids based on provisional market information. The EWA learning algorithm of Camerer (2003) is used to model bidders' learning and bid revision.

The process continues until the termination rule is satisfied (e.g., a maximum number of rounds is reached) and a final allocation is made. The results from the final allocation determine auction outcomes in the form of winning bids and associated payments.

Design Concepts

Emergence: Emergent phenomena include auction outcomes (winnings, profits, and conservation expenditure) and convergence (or stability) in auction performance as a result of the agents' learning and bid revisions.

Adaptation: In each round, bidders revise their bids based on previous round auction outcomes and their individual learning.

Objective: Bidder agents aim to maximize their individual profits from winning contracts. Auctioneer agent aims to minimize the cost of procuring the target conservation demand.

---

any given round. Readers are referred to Iftekhar et al (2012c) for a distribution of the impact of unit cost variation (cost heterogeneity) on multiple unit combinatorial auction performance.

```
while replication <= R do
    Enviromnent:
    Initialize bidder population with random packages and learning model parameter values

    if round = 1 then
        Agent:
        Randomly select bid prices
        Submit bids

        Auctioneer:
        Get bids (B)
        Solve winner determination problem (WDP) to select bids
        Compute information feedback
    end
    if round > 1 and <= Ro then
        Agent:
        Retrieve information feedback from the Auctioneer
        Use EWA algorithm to calculate bid prices
        Submit bids

        Auctioneer:
        Get bids (B)
        Solve winner detemination problem (WDP) to select bids
        Compute information feedback
    end

    Store auction outcomes
end
```

Figure 2. Pseudocode for the auction model. Here, “R” refers to the maximum replication number for individual competition scenarios and “Ro” refers to maximum number of rounds an auction iterated

Interaction: The interaction between agents is indirect, through bid revision in response to auction outcomes and associated price feedback received from the auctioneer. There is no direct interaction among the agents.

Learning: Agents learn and incorporate into bidding strategies market information using the EWA learning algorithm.

Sensing: Agents know their own status (in terms of their supply capacity and costs) and receive auction outcome and implied item price information from the auctioneer.

Stochasticity: Before the start of an auction, the parameter values for individual agents' learning algorithm and supply capacities are randomly generated. Bid selection strategy is driven by expected profits and is probabilistic.

Collectives: There is no collective decision making in the model.

Observation: Based on the auction literature, we have used three indicators to measure auction outcomes: allocative efficiency (AE), degree of rent extraction (RE), and speed of auction (Round). AE shows the degree to which contracts have been allocated among bidders in such a way that the target demand is met at the lowest possible social cost. AE is maximized when the auction selects the least cost sources to meet the demand (Pekeč and Rothkopf 2003). On the other hand, the degree of RE relates to profits made by winning bidders. It is calculated as the profit earned by individual bidder agent in proportion to its supply (actual) cost. When RE is minimized, bidders' aggregate net income is minimized (Kwasnica et al 2005). As an additional criterion, we have also estimated the speed of the auction as a measure of the pace at which auction achieves its final allocation. This is represented by the number of rounds it takes for an auction to achieve its maximum AE (i.e., peak performance).

Initialization

Depending on the competition scenario at the beginning of an auction, the target demand for the auctioneer and a certain number of landholder agents are randomly generated. Individual agent's bidding profile (in terms of their supply capacity and learning algorithm) is also randomly generated.

Input Data

The model does not use any external input data.

Submodel

Our model consists of three submodels:

- Auctioneer's bid selection model
- Individual landholder's bidding model
- Feedback price calculation model

The submodels are described below.

Auctioneer's bid selection model

The auctioneer is interested in selecting packages to achieve a certain population size of target species, where $u_h \in \Re^+$ refers to the auctioneer's target sizes for species h. Individual landholders submit a set of bids $\langle \lambda^1_{ij}, p_{ij} \rangle$, where $\lambda^h_{ij} \geq 0$ is the population size of species h and p_{ij} is the bid price offered in j from bidder i. The winner determination problem (WDP) is a problem that the auctioneer solves to find the least expensive set of bids, under the constraint that the agency satisfies its target (Iftekhar et al 2011). Formally, the WDP is

$$
\begin{aligned}
Z = \min \sum_{i=1}^{N} \sum_{j=1}^{m} p_{ij} x_{ij} \\
s.t. \sum_{i,j} \lambda_{ij}^{h} x_{ij} \geq u_h \\
\sum_{i} x_{ij} \leq 1 \\
x_{ij} \in \{0, 1\}
\end{aligned}
\tag{1}
$$

where Z is the minimized cost and x_{ij} is the indicator variable for winning condition. The first constraint ensures satisfaction of purchase target. The second and third constraints prevent selection of multiple projects from a single bidder and partial project selection, respectively.

Individual landholder's bidding model

In each round, agents make a decision on how much to bid on individual packages. For simplicity, the indexation for individual packages has been suppressed in the following discussion. We assume that bidders have access to a set of 10 bidding strategies (s1–s10). These strategies are markup factors that are used to multiply or scale up the package costs in the construction of bids. The value of each strategy is incremented by a factor of 0.1 starting from s1 (0% markup) to s10 (90% markup). At the beginning of the auction, a bidder does not have any experience about the market and picks up a markup strategy randomly. In subsequent rounds, bidding behavior depends on item price feedback received and the status of their own bid. As indicated above, bidders use the EWA learning scheme of Camerer (2003) to revise their bids.

The EWA learning algorithm is a hybrid model combining both reinforcement and belief learning model. The reinforcement and belief learning is connected through different weighting attached to realized payoffs and expected payoffs. Therefore, it is suitable for modeling bidding behaviors in games where bidders have information about foregone payoffs associated with strategies they did not utilize. This model has been highly successful in explaining behavior across a wide range of games (Valluri and Croson 2005; Ho et al 2008; Zhu et al 2012). Following Camerer (2003), we describe the details of the EWA model below.

Let s_i^g denote the strategy g of bidder i and $v(s_i^g)$ the value or bid amount associated with that strategy. The set of strategies adopted by bidder i in round t is denoted by $s_i(t)$. The bidder's payoff from adopting s_i^g in round t depends on strategies adopted by other bidders, $s_{-i}^g(t)$ and is denoted by $R_i(s_i^g, s_{-i}^g(t))$. Each strategy has a numerical attraction or propensity $q_i^g(t)$ attached to it, which shapes the probability $p_i^g(t+1)$ of adopting a particular strategy in the following round.

The attraction, $q_i^g(t)$, attached to each strategy is initially set to a prior value and is then revised or adjusted through the auction rounds. The rate of adjustment depends on the amount of experience a bidder accumulates about the market over a period of time. This is captured through an experience weight variable, $N_i(t)$, which depends on the forgetting parameter, φ_i, and the experience weight growth parameter, k_i

$$N_i(t) = \varphi_i \cdot (1 - k_i) \cdot N_i(t-1) + 1 \tag{2}$$

Here, $N_i(t)$ measures the marginal contribution of new information. The decay parameter, φ_i, measures the responsiveness to new information of bidder i. When φ_i is lower, a bidder is responsive to the most recent observations and discounts old observations more quickly. The parameter k_i controls the growth of experience weight. The larger the value of k_i is, the more quickly bidders converge and lock into one strategy (Ho et al 2008). Once the experience weight ($N_i(t)$) is updated, the attraction $q_i^g(t)$ is revised as the sum of a discounted and experience-weighted previous attraction $q_i^g(t-1)$ and a weighted expected payoff from round t, normalized by the updated experience weight

$$\begin{aligned} q_i^g(t) &= \frac{\varphi_i \cdot N_i(t-1) \cdot q_i^g(t-1) + \left[\delta_i + (1-\delta_i) \cdot I\left(s_i^g, s_i(t-1)\right)\right] \cdot R_i^g}{N(t)} \\ &\text{where} \\ R_i^g &= \begin{cases} v\left(s_i^g\right) - c\,(package) & \text{if } pr\,(package) \geq v\left(s_i^g\right) \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{3}$$

Here, *c (package)* and *pr (package)* are the actual cost and current market price of the package, respectively. The bidder will consider the expected payoff of the strategies, which will allow the bidder to bid below or equal to the market price of the package. The indicator variable $I\left(s_i^g, s_i(t-1)\right)$ is 1 if the strategy was played in the previous round (i.e., $s_i^g = s_i(t-1)$) and 0 otherwise. In other words, if the strategy was played in the previous round the expected payoff is added in full, while if it was not played the expected payoff is discounted by a payoff discount factor, δ_i. In iterative combinatorial auctions, how strongly the bidder is motivated by the market information regarding unused strategies is determined by δ_i. Higher δ_i means bidders, using price information, treat selected and other strategies similarly. The use of a low δ_i is plausible if the bidder does not have full confidence about the market information with regard to unused strategies that are conveyed through the price signal. Finally, the probability of selecting a strategy depends on the updated attraction weight and a payoff sensitivity parameter, λ_i

$$p_i^g(t+1) = \frac{q_i^g(t)^{\lambda_i}}{\sum_G q_i^g(t)^{\lambda_i}} \tag{4}$$

Following the work of Camerer and Ho (1999) and Camerer (2003), parameter values for individual bidder's learning algorithm were randomly generated in the range of 0–1. Bidders would act differently depending on parameter value choices. For example, a player with $\varphi_i = 0$ would have zero memory and only rely on information from immediately preceding round. Similarly, a value $\delta_i = 0$ would restrict a player to consider payoffs from the strategy played before and ignore any information related to unplayed strategies.

Table 1. Number of bidders in the optimal allocation for different competition scenarios

	Degree of rationing (DR)		
Size of bidder population	DR20	DR40	DR60
10 (BN10)	2	4	6
20 (BN20)	4	8	12
30 (BN30)	6	12	18

Feedback price calculation model

The auctioneer uses a price feedback algorithm to generate item prices that are communicated back to bidders as guidance for further bidding. Combinatorial auction designs differ in their determination of item prices. In this study, we evaluate three alternative approaches. The ConsNuc of Dunford et al (2007) uses a key concept in coalitional game theory that is generally used to distribute payoffs among different groups of players. The SmAnch was tested by the FCC out of a practical concern regarding large observed fluctuations in license prices between auction rounds; large fluctuations can significantly reduce the guidance function of item prices and thus affect auction efficiency (Kwerel and Rosston 2000). The third algorithm is based on DEA, which is a mathematical tool generally used to compare efficiencies of production units. Aparicio et al (2008) have proposed the algorithm for use in multiple-unit forward combinatorial auctions. The mathematical details of these algorithms are provided in Appendix S1.

Simulation Experiments

The study evaluates auction performance for different scenarios where the number of bidders, the degrees of rationing ratios, and the price feedback algorithms are varied. The structure of the computational experiment, in terms of population size of bidders in an auction (BN) and degree of rationing (DR), is presented in Table 1. We considered three bidder population sizes: 10, 20, and 30 bidders. We will refer to these cases as BN10, BN20, and BN30. These numbers were chosen roughly based on participation numbers observed in recent auctions in Australia. Whitten et al (2008), for example, observed that the number of participants in the pilot conservation auctions under the second phase of the market-based instruments pilot program of the Australian government varied from 10 to 40, with most of the pilot auctions having less than 30 participants.

We considered three levels in the degree of rationing, with these levels defined in terms of the proportion of bidders that could satisfy the auctioneer's target demand (DR20, DR40, and DR60). In this context, DR20, for example, denotes the case where the target is set in such a way that it could be met by 20% of the bidders in a cost optimal allocation. The higher the percentage of bidders in the optimal allocation, the weaker is the competition. Since the population sizes also vary in our simulations, we vary the procurement target so that we have auctions that have the same number of bidders but different degrees of rationing. As a result, the number of bidders in the optimal allocation changes when either the population size or the degree of rationing changes as shown in Table 1.

Table 2. AE, RE, and auction speed (Round) results

	AE			RE			Round		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Design									
ConsNuc	97.36	2.02	97.30	0.48	1.18	0.00	37	44	18
DEA	99.04	1.25	99.50	0.02	0.22	0.00	22	26	13
SmAnch	97.50	1.92	97.30	0.37	0.99	0.00	38	45	45
BN									
10	97.68	2.01	97.70	0.52	1.35	0.00	17	26	8
20	98.06	1.86	98.40	0.21	0.66	0.00	35	40	18
30	98.15	1.85	98.40	0.13	0.44	0.00	45	46	46
DR									
20	99.39	1.20	100.00	0.03	0.39	0.00	15	22	8
40	97.96	1.49	97.80	0.20	0.76	0.00	37	40	22
60	96.55	1.83	96.70	0.63	1.27	0.00	45	47	25
Total	97.97	1.92	98.35	0.29	0.92	0.00	32	40	16

Notes: Here, SD refers to standard deviation. The median value of RE is zero in all cases.

In all our simulations, individual auctions run for 200 rounds. This large number of rounds was necessary to give ample times to the agents to explore and settle down on a selected strategy. However, to smooth out the effect of stochastic elements and eliminate starting point bias, we replicate each competition scenario 1,000 times. The results we report are averages over these replications.

RESULTS

We start by comparing differences in the performance across auction designs (Design) and the two measures of competition just described—degree of rationing (DR) and number of bidders (BN). Results for the three measures of auction performance (AE, RE, and Round) are summarized in Tables 2–4. A nonparameteric Manning–Whitney U-test statistic is used to compare differences across auction features.

Auction Outcomes: Efficiency and RE

Mean and median AE and RE values are presented in Table 2. It can be observed that all designs have achieved very high AE (>96%). However, the Mann–Whitney U-test results show that the level of competition (both BN and DR) in an auction has a statistically significant effect on AE and the degree of RE in an auction (Table 3). AE significantly increases with the increase in bidder number and declines with increases in target demand relative to aggregate bidder capacity (Table 2). The degree of RE is higher when competition is weaker, that is, for auctions with lower number of bidders and/or larger target demand levels. These results suggest that it is difficult for an auction to make optimal allocation if the target size is relatively large, and the likelihood of contracts being allocated to suppliers who do not have cost advantages are larger.

Table 3. Pairwise comparison between auction design features for a two-sided Mann–Whitney U-tests: z-statistics

Comparison	AE	RE	Round
Design			
ConsNuc versus DEA	– 59.27**	– 47.43**	– 17.66**
ConsNuc versus SmAnch	– 3.77**	– 6.13**	– 0.26
SmAnch versus DEA	– 57.31**	– 42.88**	– 17.78**
BN			
BN10 versus BN20	– 13.10**	– 8.33**	– 47.52**
BN10 versus BN30	– 17.00**	– 9.15**	– 63.52**
BN20 versus BN30	– 4.12**	– 2.46*	– 18.87**
DR			
DR20 versus DR40	– 69.83**	– 27.50**	– 53.32**
DR20 versus DR60	– 98.71**	– 61.14**	– 64.55**
DR40 versus DR60	– 51.00**	– 40.63**	– 11.03**

Note: ** and * refer to significance at 1% and 5% levels, respectively.

Table 4. Pairwise comparison between auction designs in individual competition scenarios for two-sided Mann–Whitney U-tests: z-statistics

		AE			RE			Round		
BN	DR	ConsNuc versus DEA	ConsNuc versus SmAnch	DEA versus SmAnch	ConsNuc versus DEA	ConsNuc versus SmAnch	DEA versus SmAnch	ConsNuc versus DEA	ConsNuc versus SmAnch	DEA versus SmAnch
10	20	– 7.61**	– 0.85	– 6.77**	– 3.29**	– 0.64	– 3.82**	– 2.47**	– 0.90	– 1.45
	40	– 21.45**	– 0.89	– 22.31**	– 13.76**	– 2.28*	– 11.91**	– 3.34**	– 0.17	– 3.60**
	60	– 26.62**	– 0.88	– 27.06**	– 25.87**	– 3.90**	– 23.81**	– 5.87**	– 2.02*	– 3.03**
20	20	– 15.55**	– 0.88	– 14.80**	0.00	– 1.42	– 1.42	– 16.07**	– 0.65	– 16.37**
	40	– 33.58**	– 3.14**	– 32.21**	– 12.19**	– 3.98**	– 9.38**	– 14.33**	– 0.06	– 14.66**
	60	– 36.50**	– 5.19**	– 36.05**	– 27.00**	– 4.20**	– 24.40**	– 5.58**	– 1.94*	– 7.62**
30	20	– 15.87**	– 3.04**	– 13.41**	– 1.00	– 1.00	0.00	– 22.92**	– 1.92*	– 22.22**
	40	– 35.08**	– 0.48	– 35.35**	– 11.14**	– 2.21*	– 9.59**	– 21.01**	– 1.96*	– 20.13**
	60	– 37.97**	– 7.94**	– 37.48**	– 27.17**	– 2.63**	– 24.64**	– 4.51**	– 3.70**	– 1.01

Note: ** and * refer to significance at 1% and 5% levels, respectively.

Among the studied auction designs, DEA-based auctions generate the best allocative and RE outcomes. For example, a DEA-based auction would achieve 99.04% AE compared to a ConsNuc based auction with 97.36% efficiency (Table 2). Similarly, DEA-based design leads to significantly lower RE rates than the other two auction designs (Table 3).

The individual auction designs responded differently to changes in the degree of competition. DEA-based ones achieved higher AE ($p < 0.01$) for all competition scenarios (Table 4). There is little difference between the AE outcomes from the SmAnch and ConsNuc algorithms except for the BN20DR40, BN20DR60, BN30DR20, and BN30DR60 comparison cases. In terms of RE rates as well, the DEA-based design generates significantly lower rent than other two designs for all competition scenarios except for BN20DR20 and BN30DR20, and the SmAnch-based design generates significantly less rent than ConsNuc-based design (except for BN10DR20, BN20DR20, and BN30DR20) (Table 4).

Along with the final efficiency outcomes, it is also useful to examine the frequency with which the auction was able to make an optimal allocation (i.e., AE = 1) to get an understanding of their overall performance. Overall, in only 28.20% of simulated rounds do the iterative auction designs tested in this paper generate a fully optimal allocation, and the degree of competition is observed to have a significant effect on this frequency. For example, optimal allocation is most frequently made with the smallest target demand (i.e., DR20: 69.30%), which is significantly higher than auctions with medium demand (DR40: 14.36%, Mann–Whitney U-test; $z = -48.605, p = 0.000$, two-sided) or with larger demand (DR60: 1.14%, Mann–Whitney U-test; $z = -41.338, p = 0.000$, two-sided). The difference between two high demand cases (DR40 and DR60) is also significant. On the other hand, the effect of bidder population size is found to be moderate, with no statistically significant difference ($p > 0.10$) in the frequency of fully optimal allocation outcomes between BN30 (30.11%) and BN20 (28.16%) cases. However, for the smallest bidder population cases (BN10), the frequency of optimal allocation outcomes is significantly lower (26.52%) than is the case for the other population scenarios.

Examining the impact of auction design, the performance differences are more prominent when the frequency of optimal allocation is considered. Overall, in 41.82% of the simulated rounds, the DEA-based design generates an optimal allocation. This is significantly higher than the corresponding figures for the SmAnch (22.15%)- and ConsNuc (20.83%)-based designs. The difference between the SmAnch and the ConsNuc designs is also found to be statistically significant in this case. It is important to note that in scenarios with larger demand levels and larger bidder populations, the ConsNuc (BN30DR60) and SmAnch (BN20DR60 and BN30DR60) designs failed to achieve optimal allocation (i.e., AE = 1) for any simulated round.

Speed of Convergence

In order to measure the speed of convergence, we look at how quickly the auction arrives at the best possible AE under different competition scenarios. Overall, the auction designs were able to achieve the best AE within 47 simulation rounds. Both bidder population size and the degree of rationing have a significant effect on the number of rounds it takes for an auction to reach its peak performance (Round in Table 2). In particular, it takes a significantly higher number of rounds for the auction to make a final allocation for a larger population size (BN30) and larger target demand (DR60). For example, on average, an auction with a small bidder population (BN10) takes 28 fewer rounds to make best allocation compared to an auction with a large bidder population (BN30). Similarly, an auction with a small target (DR20) takes 30 fewer rounds compared to an auction with a large target (DR60). This suggests that it would require higher administration costs to allocate larger targets during actual implementations of the auction.

In Figure 3, the trends in median AE achieved by different designs are presented for different competition scenarios. Looking across auction designs, on average, auctions based on DEA algorithms have taken significantly fewer rounds to reach peak

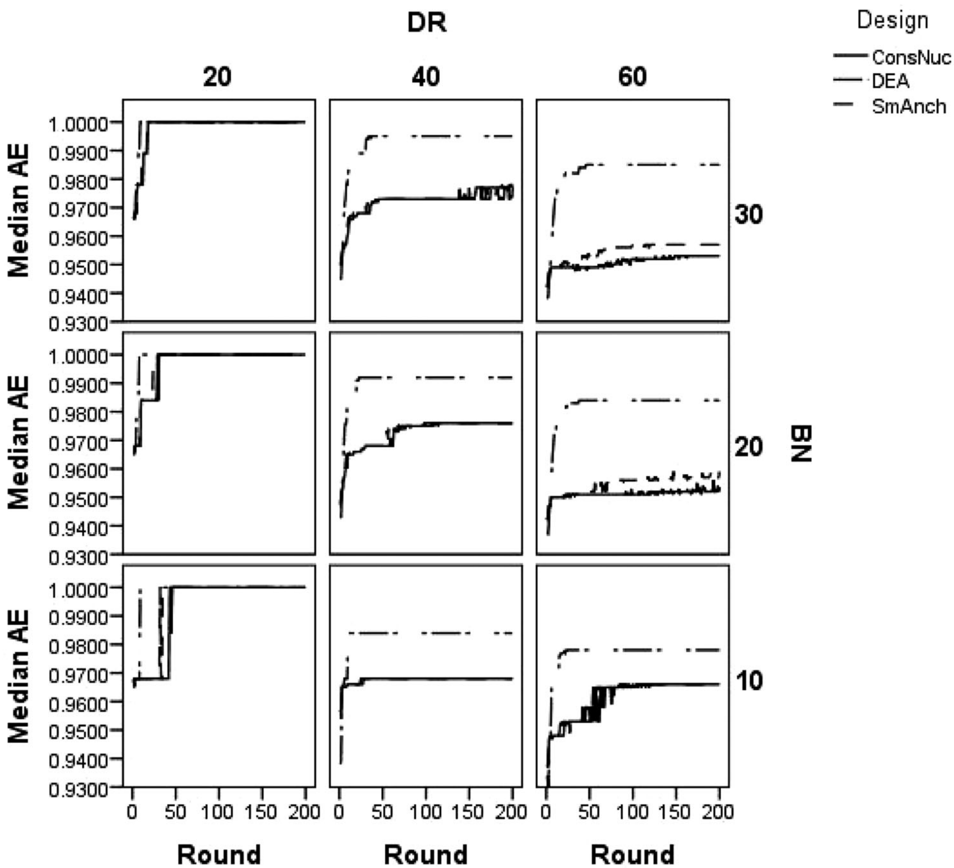

Figure 3. Median AE estimate achieved by the auction designs for individual competition scenarios varying in bidders' number (BN) and degree of rationing (DR)

performance compared to auctions based on SmAnch and ConsNuc designs. The results again show no statistically significant difference in speed estimates for the SmAnch and the ConsNuc designs (Table 3). However, pairwise comparison for individual competition scenarios (in Table 4) indicate that the SmAnch-based auction design has taken statistically significantly (5% level) fewer rounds than the ConsNuc-based design in scenarios with larger bidder populations and/or larger demand levels (such as BN10DR60, BN20DR60, BN30DR20, BN30DR40, and BN30DR60). DEA-based algorithms take significantly fewer rounds than the other two designs in all competition scenarios (except for BN10DR20 and BN30DR60 with SmAnch design) (Table 4).

DISCUSSION

In this paper, we studied the impact of the degree of competition (in terms of the number of bidders and the level of demand target) on auction performance for selected iterative combinatorial auction price feedback designs. A total of nine simulations were undertaken for each design, considering three different bidder population sizes and three different degrees of rationing.

Results from the analyses show that both bidder numbers and levels of the target demand have significant influences on auction performance. AE improves (declines) with increases (declines) in bidder numbers and with declines (increases) in the level of target demand relative to bidder capacity. Similarly, the degree of RE is higher (lower) in auctions with lower (higher) bidder population sizes and in auctions with higher (lower) levels of procurement targets. The observed trends on efficiency outcomes are probably due to the fact that with intense competition, only a small subset of bidders can be winners; whereas with a reduced competition level, a larger subset of bidders is selected, allowing winners to extract higher profits. With the increase in bidder numbers and reductions in target demand, the auctioneer has more options to procure items and bidders are in competition with a wider range of competitors. In fact, in noncombinatorial auction settings, subject to some restrictions on the seller's choice of mechanism, an auction with $N + 1$ bidders beats any standard mechanism for selling to N bidders (Bulow and Klemperer 1996).

Auction speeds are affected differently by changes in the level of target for different population sizes. In general, auctions with a small target (DR20) take fewer rounds to find best final allocation than auctions with a larger target (DR60). On the other hand, convergence takes longer when the bidder population is large.

There are not many studies estimating structural effect of competition on iterative combinatorial auction designs. Goel et al (2005) studied the effect of competition on the performance of an iterative combinatorial auction framework-based food grain supply chain. They defined the level of competition as the relative number of bidders that are competing to supply a given variety of food grain. The results indicate a significant reduction (ranging from 5% to 27%) in grain prices with an increase in competition. However, they did not report changes in allocative and RE efficiencies and their findings are not directly comparable to ours.

Using DEA-based price feedback algorithms, Aparicio et al (2008) found AE to be higher than 90% and bidders profit less than 15%. Pikovsky (2008) compared RAD and some other item-price-based iterative combinatorial auction designs for different bundling strategies and value environments. His simulation experiments showed that the mean AE ranged between 93.60% and 98.63%. Similarly, in another set of simulation experiments, Dunford et al (2007) observed very high AE (above 95%) for Nucleolus-based auction designs. In another set of laboratory experiments on an iterative combinatorial auction, Scheffel et al (2012) found high AE (above 90%) and low-profit extraction rates (less than 20%). For single-shot combinatorial auctions, Goeree et al (2007) observed AE levels higher than 90% in their laboratory experiments.

Results from these studies indicate that it is typical to have small differences in the performance of iterative auctions. Therefore, as an alternative measure, we have examined the frequency of optimal allocation, which also points to changes in auction performance as a result of changes in the degree of competition. It can be observed that a change in the procurement target level has the most significant effect on auction performance. For example, the frequency of optimal allocation declined by 68 percentage points when the procurement target is tripled. On the other hand, the effect of bidder population size is found to be moderate; the frequency of optimal allocation increased by only four percentage points when the bidder population size was tripled (i.e., increased from 10 to 30).

A comparison of individual designs indicate that, overall, the DEA-based design was superior to the other two designs in terms of AE, degree of RE, and auction speed. These results are supported by the findings of Iftekhar et al (2012c). It should be noted that the DEA prices are generated in such a way that the computed value for any package (both winning and losing) will not exceed its submitted bid price. As a consequence, bidders reacting to such price feedbacks are more likely to revise down their bids for subsequent rounds in order to stay competitive. On the other hand, SmAnch- and ConsNuc-based algorithms are more constrained by the individual winning bids since these algorithms calculate the item prices so that the computed values for individual winning packages are equal or greater than the respective bids. This might encourage bidders to revise up their bids on winning packages. This has two effects. First, if some bidders adopt such strategic bidding, it reduces competitive pressure on other bidders; and, second, when the majority of (or all) bidders adopt such strategic bidding, it leads to a deterioration in auction performance. Therefore, an auctioneer should carefully select a design for their particular context especially when they expect the degree of competition to be weak.

CONCLUSION

Combinatorial auctions have the potential to improve incentive programs aimed at conserving nature. Although these auctions have been used to allocate significant economic assets, there are not many examples of real-world implementation in relation to environmental services (Iftekhar et al 2012b). Well-designed auctions would improve the flexibility of current auctions and performance. Results from our analysis indicate the importance of market structure on auction outcomes. Our simulation results show that with the increase in the level of target demand (i.e., weakening competition), both allocative and RE efficiencies decline. With regard to the size of the target, smaller targets tend to generate more optimal contract allocation. Increased competition in the form of higher bidder numbers also increases efficiency, albeit at moderate scale. Moreover, it takes a higher number of rounds to make a final allocation when the bidder population is bigger, which suggests the presence of a trade-off between maximizing efficiency and minimizing number of rounds to reduce transaction costs. In real-world auctions, the exact nature of the trade-off between the two would depend on the structure and scale of costs.

From an organizational perspective, these results indicate that the auctioneer would benefit from arranging auctions with a high degree of competition. That is, budgetary and AE outcomes can be improved through effort focused on improved auction participation. There are different ways by which this can be promoted, including setting a limit on the fraction of the contracts allocated to selected bidders. Such a limit can encourage small bidders to participate in the auction, although its effect (and those of other approaches) on efficiency outcomes should be investigated carefully.

An alternative avenue for agencies is to make bidder participation worthwhile by providing participation payments (Flambard and Perrigne 2006). Participating in a competitive tender comes at a cost to landholders in terms of time and money, which may include a nonrefundable entry fee as well as the costs of valuing resources and preparing bids. Landholders will be less likely to take part if they perceive their chances of success as being low compared to the opportunity cost of participation. Therefore, payments for participation may cover the opportunity costs of participation to the bidder and can be efficiency enhancing: bidders are compensated for their contribution to auction efficiency.

Finally, auctioneers can reduce the cost of participation in auctions. First, they could educate potential bidders on combinatorial bidding. Second, the auctioneer could standardize auctions by selecting a fixed set of rules that would improve transparency and allow bidders work their strategies more easily. For example, our results indicate that DEA-based price feedback schemes generally work better than alternatives. Third, auctioneers could develop online resources that would allow bidders to trial auctions and improve their bid preparation skills. Such investments would improve participation and reduce transaction costs that are generally high in the case of conservation auctions.

ACKNOWLEDGMENTS

This study originates from the Ph.D. thesis work of M. S. Iftekhar, which was submitted to the University of Western Australia. The study of M. S. Iftekhar was supported by the International Postgraduate Student Research Scholarship and UWA Postgraduate Award Schemes. Prof. John Tisdell of UTAS has made some valuable suggestions on the draft. The authors wish to acknowledge the contributions of two anonymous reviewers and the Editor through comments that significantly improved the paper.

REFERENCES

An, N., W. Elmaghraby and P. Keskinocak. 2005. Bidding strategies and their impact on revenues in combinatorial auctions. *Journal of Revenue and Pricing Management* 3 (4): 337–57.

Aparicio, J., M. Landete, J. Monge and I. Sirvent. 2008. A new pricing scheme based on DEA for iterative multi-unit combinatorial auctions. *Top* 16 (2): 319–44.

Arsenault, A., J. Nolan, R. Schoney and D. Gilchrist. 2012. Outstanding in the field: Evaluating auction markets for farmland using multi-agent simulation. *Journal of Artificial Societies and Social Simulation* 15 (1): 11.

Ausubel, L. M. and P. Milgrom. 2006. The lovely but lonely Vickrey auction. In *Combinatorial Auctions*, edited by P. Cramton, Y. Shoham and R. Steinberg, pp. 17–40. London: The MIT Press.

Boxall, P. C., O. Perger and K. Packman. 2012. An experimental examination of target based conservation auctions. Paper presented at the Australian Agricultural and Resource Economics Society 56th Annual Conference, Fremantle, February 7–10.

Brannman, L., J. D. Klein and L. W. Weiss. 1987. The price effects of increased competition in auction markets. *The Review of Economics and Statistics* 69 (1): 24–32.

Brewer, P. J. 1999. Decentralized computation procurement and computational robustness in a smart market. *Economic Theory* 13 (1): 41–92.

Brown, L. K., E. Troutt, C. Edwards, B. Gray and W. Hu. 2011. A uniform price auction for conservation easements in the Canadian prairies. *Environmental and Resource Economics* 50 (1): 49–60.

Bulow, J. and P. Klemperer. 1996. Auctions versus negotiations. *The American Economic Review* 86 (1): 180–94.

Camerer, C. 2003. *Behavioral Game Theory: Experiments in Strategic Interaction*. Princeton, NJ: Princeton University Press.

Camerer, C. and T. H. Ho. 1999. Experience-weighted attraction learning in normal form games. *Econometrica* 67 (4): 827–74.

Chen, Y. and K. Takeuchi. 2010. Multi-object auctions with package bidding: An experimental comparison of Vickrey and *i*BEA. *Games and Economic Behavior* 68 (2): 557–79.

Connor, J. D., J. R. Ward and B. Bryan. 2008. Exploring the cost effectiveness of land conservation auctions and payment policies. *Australian Journal of Agricultural and Resource Economics* 52 (3): 303–19.

Department of Primary Industries [DPI] 2007. Auction of marine aquaculture sites in Victoria: A review of concepts and practice. Evaluation Report Number 10. Melbourne: Department of Primary Industries.

Dunford, M., K. Hoffman, D. Menon, R. Sultana and T. Wilson. 2007. Testing linear pricing algorithms for use in ascending combinatorial auctions. Technical Report, George Mason University.

Flambard, V. and I. Perrigne. 2006. Asymmetry in procurement auctions: Evidence from snow removal contracts. *Economic Journal* 116 (514): 1014–36.

Goel, A., C. W. Zobel and E. C. Jones. 2005. A multi-agent system for supporting the electronic contracting of food grains. *Computers and Electronics in Agriculture* 48 (2): 123–37.

Goeree, J., C. A. Holt and J. Ledyard. 2007. An experimental comparison of flexible and tiered package bidding. Report to the FCC Wireless Telecommunications Bureau. California: Federal Communications Commission.

Grafton, Q. 2005. Evaluation of round one of the market based instruments pilot program. Report to the National Market Based Instrument Working Group. Canberra: National MBI Working Group.

Grimm, V., U. Berger, F. Bastiansen, S. Eliassen, V. Ginot, J. Giske, J. Goss-Custard, T. Grand, S. K. Heinz and G. Huse. 2006. A standard protocol for describing individual-based and agent-based models. *Ecological Modelling* 198 (1): 115–26.

Gupta, S. 2002. Competition and collusion in a government procurement auction market. *Atlantic Economic Journal* 30 (1): 13–25.

Hailu, A. and S. Thoyer. 2007. Designing multi-unit multiple bid auctions: An agent-based computational model of uniform, discriminatory and generalised Vickrey auctions. *Economic Record* 83 (S1): S57–S72.

Hailu, A. and S. Thoyer. 2010. What format for multi-unit multiple-bid auctions? *Computational Economics* 35 (3): 189–209.

Hill, M. R. J., D. G. McMaster, T. Harrison, Hershmiller A. and T. Plews. 2011. A reverse auction for wetland restoration in the Assiniboine River Watershed, Saskatchewan. *Canadian Journal of Agricultural Economics* 59 (2): 245–58.

Ho, T. H., X. Wang and C. Camerer. 2008. Individual differences in EWA learning with partial payoff information. *Economic Journal* 118 (525): 37–59.

Hoffman, K. 2006. Choosing a combinatorial auction design: An illustrated example. In *Perspectives in Operations Research. Perspectives in Operations Research Papers in Honor of Saul Gass' 80th Birthday*, edited by B. A. Francis, C. F. Michael and L. Bruce, pp. 153–77. Golden: Springer US.

Iftekhar, M. S., A. Hailu and R. K. Lindner. 2009. Auction designs for native biodiversity conservation on private lands. In *Ecological Restoration*, edited by G. H. Pardue and T. K. Olvera, pp. 1–45. New York: Nova Science Publishers.

Iftekhar, M. S., A. Hailu and R. K. Lindner. 2011. Item price information feedback in multiple unit combinatorial auctions: Design issues. *IMA Journal of Management Mathematics* 22 (3): 271–89.

Iftekhar, M. S., A. Hailu and R. K. Lindner. 2012a. Combinatorial auction designs for biodiversity conservation. *Society & Natural Resources: An International Journal* 25 (10): 965–79.

Iftekhar, M. S., A. Hailu and R. K. Lindner. 2012b. Combinatorial auctions for procuring agri-environmental services: A review of some design issues. *Australasian Journal of Environmental Management* 19 (2): 79–90.

Iftekhar, M. S., A. Hailu and R. K. Lindner. 2012c. The effect of bidders' heterogeneity on combinatorial conservation auction designs. *Environmental and Resource Economics* 53 (1): 137–57.

Krishna, V. 2002. *Auction Theory*. Orlando: Academic Press.

Kwasnica, A. M., J. O. Ledyard, D. Porter and C. DeMartini. 2005. A new and improved design for multiobject iterative auctions. *Management Science* 51 (3): 419–34.

Kwerel, E. R. and G. L. Rosston. 2000. An insiders' view of FCC spectrum auctions. *Journal of Regulatory Economics* 17 (3): 253–89.

Lalive, R. and A. Schmutzler. 2008. Exploring the effects of competition for railway markets. *International Journal of Industrial Organization* 26 (2): 443–58.

Latacz-Lohmann, U. and C. V. D. Hamsvoort. 1997. Auctioning conservation contracts: A theoretical analysis and an application. *American Journal of Agricultural Economics* 79 (2): 407–18.

Latacz-Lohmann, U. and S. Schilizzi. 2005. Auctions for conservation contracts: A review of the theoretical & empirical literature. Report to the Scottish Executive Environment and Rural Affairs Department. Edinburgh: Scottish Executive Environment and Rural Affairs Department.

Li, T. and I. Perrigne. 2003. Timber sale auctions with random reserve prices. *Review of Economics and Statistics* 85 (1): 189–200.

Lunander, A. and J.-E. Nilsson. 2004. Taking the lab to the field: Experimental tests of alternative mechanisms to procure multiple contracts. *Journal of Regulatory Economics* 25 (1): 39–58.

Nemes, V., C. R. Plott and G. Stoneham. 2008. Electronic BushBroker exchange: Designing a combinatorial double auction for native vegetation offsets. http://expecon.gsu.edu/plott.pdf (last accessed July 20, 2011).

Parkes, D. C. 2001. Iterative combinatorial auctions: Achieving economic and computational efficiency. Ph.D. dissertation, University of Pennsylvania.

Parkes, D. C. 2006. Iterative combinatorial auctions. In *Combinatorial Auctions*, edited by P. Cramton, Y. Shoham and R. Steinberg. London: The MIT Press.

Pekeč, A. and M. H. Rothkopf. 2003. Combinatorial auction design. *Management Science* 49 (11): 1485–503.

Pikovsky, A. 2008. Pricing and bidding strategies in iterative combinatorial auctions. Ph.D. dissertation, Munchen eingereicht und durch die Fakultat fur Informatik.

Porter, D., S. Rassenti, A. Roopnarine and V. Smith. 2003. Combinatorial auction design. *Proceedings of the National Academy of Sciences of the United States of America* 100 (19): 11153–57.

Porter, D., S. Rassenti, W. Shobe, V. Smith and A. Winn. 2009. The design, testing and implementation of Virginia's NOx allowance auction. *Journal of Economic Behavior & Organization* 69 (2): 190–200.

Rassenti, S. J., V. L. Smith and R. L. Bulfin. 1982. A combinatorial auction mechanism for airport time slot allocation. *Bell Journal of Economics* 13 (2): 402–17.

Rolfe, J., R. Greiner, J. Windle and A. Hailu. 2011. Testing for allocation efficiencies in water quality tenders across catchments, industries and pollutants: A north Queensland case study. *Australian Journal of Agricultural and Resource Economics* 55: 518–36.

Roth, A. E. 2002. The economist as engineer: Game theory, experimentation and computation as tools for design economics. *Econometrica* 70 (4): 1341–78.

Said, S. and S. Thoyer. 2007. Agri-environmental auctions with synergies. Working Paper, LAMETA, Laboratoire Montpellierain d'Economie Theorique et Appliquée.

Scheffel, T., G. Ziegler and M. Bichler. 2012. On the impact of package selection in combinatorial auctions: An experimental study in the context of spectrum auction design. *Experimental Economics* 15 (4): 667–92.

Smith, V. L. 1962. An experimental study of competitive market behavior. *The Journal of Political Economy* 70 (2): 111–37.

Smith, V. L. 2008. *Rationality in Economics: Constructivist and Ecological Forms*. New York: Cambridge University Press.

Stoneham, G., V. Chaudhri, A. Ha and L. Strappazzon. 2003. Auctions for conservation contracts: An empirical examination of Victoria's BushTender trial. *The Australian Journal of Agricultural and Resource Economics* 47 (4): 477–500.

Ulber, L., S. Klimek, H. H. Steinmann, J. Isselstein and M. Groth. 2011. Implementing and evaluating the effectiveness of a payment scheme for environmental services from agricultural land. *Environmental Conservation* 1 (1): 1–9.

USDA. 2004. *FSA Handbook—Agricultural Resource Conservation Program*. Washington, DC: United States Department of Agriculture.

Valluri, A. and D. C. Croson. 2005. Agent learning in supplier selection models. *Decision Support Systems* 39 (2): 219–40.

Whitten, S., A. Reeson, J. Windle and J. Rolfe. 2008. Barriers to and Opportunities for Increasing Participation in Conservation Auctions. Paper presented at the Australian Agricultural and Resource Economics Society 52nd Annual Conference, Canberra, February 5–8.

Zhu, L., K. E. Mathewson and M. Hsu. 2012. Dissociable neural representations of reinforcement and belief prediction errors underlie strategic learning. *Proceedings of the National Academy of Sciences* 109 (5): 1419–24.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1: Iterative combinatorial auctions: feedback price calculation