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Investigating the performance of market-based instruments for resource conservation: the contribution of agent-based modelling

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Abstract

Auctions are increasingly being considered as a mechanism for allocating conservation contracts to private landowners. This interest is based on the widely held belief that competitive bidding helps minimize information rents. This study constructs an agent-based model to evaluate the long term performance of conservation auctions under settings where bidders are allowed to learn from previous outcomes. The results clearly indicate that the efficiency benefits of one-shot auctions are quickly eroded under dynamic settings. Furthermore, the auction mechanism is found to be inferior to fixed payment schemes except when the latter involve the use of high reserve prices.

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1. Introduction: the problem

Biodiversity conservation on private land is an example of the supply by private agents of a public good, for which there is no market to reward a landowner's efforts (Stoneham & Chaudri, 2000). Reduced land degradation, deforestation, and water quality of lakes and rivers are other such environmental public goods (or services) for which there are no readily available markets.

The traditional policy approach to these conservation issues has been regulation or negotiated contracts with fixed payment schemes. The public authority would typically forbid, constrain, or impose certain activities or outcomes, and try to enforce the regulations with fines and other legal sanctions. On-farm bush clearing in Australia is subject to such a policy. Where regulatory approaches are not used, the policy approach to conservation by private agents is through negotiated contracts, with fixed payment schemes. This has been the dominant approach in the European Union.

Both the regulatory and fixed price approaches have their limits. Regulations can be costly to enforce and lead to economically inefficient resource allocation. The fixed payment approach suffers from the information asymmetries that exist between landowners and government. Landowners usually know their supply costs far better than government does. This allows the former to extract information rents. Recognition of such limitations has in recent years increased governments' interest in economic or market-based instruments such as auctions (Murtough et al., 2002).

The idea of introducing competitive bidding among landowners has motivated interest in conservation auctions (Latacz-Lohmann & van der Hamsvoort, 1997, 1998). The risk of the bid being rejected was thought to mitigate the temptation to overbid above one's true costs. Latacz-Lohmann and van der Hamsvoort show that auctioning such contracts provide the government and society at large with two important benefits: the revelation of otherwise private information on the costs of conservation, and increased efficiency of public spending, due to the reduced extraction of information rents by landowners. Even more importantly, the auction mechanism is shown to be economically more efficient than the traditional fixed price scheme.[2] Cason, Gangadharan and Duke (forthcoming) go on to show that efficiency is further increased if some information is withheld from landowners in the auctioning process, namely the ecological scoring of their environmental services.

However, these expectations are primarily based on outcomes relating to one-shot auctions. In practice, conservation auctions would be repeated auctions where bidders have the opportunity to learn from previous outcomes. Whether a repeated auction would continue to be efficient or not is an open question. Given the complexity of the repeated auction, the theory provides insufficient guidance for predicting its outcomes and for its design.

A number of issues need to be clarified in the context of auctioning conservation contracts. Will the auction mechanism perform better over time than a (possibly negotiated) fixed price scheme? Do results previously obtained for a single auction carry forward to repeated auctions? Does increased competition among bidders really reduce private information rents?

Regarding the behaviour of landowners, the key question is what they can learn over time from previous auctions that might defeat the purpose of the auction. Landowners are assumed to maximise profits, and are therefore caught between the temptation to bid higher and the risk of not being selected by the auctioneer. It can be safely assumed that they use available information to their best advantage. As Klemperer (2002) reminds us, the opportunity for learning and strategizing can easily invalidate the predictions of one-shot auction theory.

This study conducts a simple agent-based computational experiment to assess the performance of repeated auctions under circumstances where the bidders learn from previous experience. Some of the key questions that this study attempts to answer are:

[2] This result holds subject to the higher transaction costs of an auction mechanism.

a) Does the competitive bidding process succeed in keeping informational rents to a minimum in spite of bidder learning? In other words, is competitive bidding efficient when learning is present?
b) How efficient is the repeated auction mechanism relative to the much simpler fixed price scheme? [3]

Our results indicate that the expected efficiency advantages of the auction might not survive as bidders learn to extract information rents over time, making the outcomes of the auction inferior to simpler mechanisms like fixed price schemes.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical and experimental study of auctions, identifying a role for agent-based modelling. Section 3 describes the agent-based model of auctioning conservation contracts and specifies the learning algorithm employed. The results of the study are presented and interpreted in section 4. Section 5 summarizes and concludes the paper.

2. The study of auctions: a role for ABM

To date, a complete study of auctions in their natural settings cannot be said to exist. Rather, we have a theory of highly stylised and simplified auction settings. The theory comes only at the cost of a number of simplifications, making its predictions of little practical importance or relevance to practitioners (Aschenfelter 1989; Rothkopf and Harstad 1994). As indicated in Box 1, real auctions can be quite complex and difficult to model analytically.

[3] We do not consider here the weight of an auction's higher transaction costs.

BOX 1: Characterisation of conservation contracts (ü)

CRITERIA	AUCTION CATEGORY DESCRIPTORS	
Timing	One-shot	Repeated ü
	Simultaneous ü	Sequential
Items	Single	Multiple ü
	Indivisible Divisible	Identical Different ü
Auction type	One-sided ü	Two-sided
	Open	Sealed-bid ü
	1st price 2nd price Dutch English	1st price ü 2nd price Standardü Vickrey
Reserve price	With reserve price	Without reserve price ü
CRITERIA	**BIDDER DESCRIPTORS**	
Value type	Private value ü	Common value
	IPVü – Affiliated	Pure – Almost
Bidder numbers	Fixed ü	Variable
		Exogenous Endogenous
	Known ü	Uncertain
Bidder info	Symmetric	Asymmetric ü
	Risk neutralü	Risk averse
		for sequential & repeated auctions: No learning Learningü (what, how)
Bidder strategy	No collusionü	Collusion
	No gamingü	Gaming of auction
CRITERIA	**AUCTION INFORMATION DISCLOSURE BY AUCTIONEER**	
Announce	Winning bid or bids	or notü
	Reserve price	or notü
	Best estimate price forecasts	or notü

2.1 The theoretical and analytical study of auctions

Since Vickrey's seminal contribution in 1961, the game theoretic approach has become the predominant tool for the study of auctions in the economics literature.[4] Vickrey's work laid the foundations for the theoretical analysis of auctions, which, over the four decades since, has developed into a large body of literature. A number of reviews of this literature have been written, providing an overview of its achievements and of its shortcomings. Major reviews include Cassady's book (1967) and survey papers by Engelbrecht-Wiggans (1980), McAfee and McMillan (1987), Milgrom (1985, 1989), Wilson (1992), Rothkopf and Harstad (1994), and Klemperer (1999, 2002).

Given our focus on the practical problems of auction design and implementation, and on the prediction of outcomes, Rothkopf and Harstad's (1994) and Klemperer's (2002) critical reviews provide a good vantage point from which to view the achievements and shortcomings of this literature. Most of the theory on auctions has focused on the one-shot auction of a single indivisible good, when real settings most often involve repeated auctions with multiple units (Klemperer 1999, 2002). Theory has also targeted issues like independence of bidder values, revenue equivalence among auction types, bidder risk aversion and informational symmetry, to the detriment of issues closer to real world settings, like bidder learning, variable number of bidders, collusive behaviour and opportunistic 'auction gaming' (Bower & Dunn 2001), all of which can in practice have drastic consequences (Klemperer 2002). It has been clearly demonstrated that relaxing assumptions leads to striking changes in model predictions (Rothkopf and Harstad 1994); in particular, auction outcomes are very sensitive to their informational structure. This observation is particularly important for the new and emerging field of study, auctions for biodiversity conservation on private land (Stoneham et. al., 2000).

[4] Before 1961, the strategic interactions between bidders were not directly considered and each bidder was viewed as playing a game against nature; that is, without considering the other players' strategies. Friedman (1956) exemplifies this early approach.

In the case of conservation auctions, the gap between theory and reality becomes pronounced due to the dynamic nature of repeated auctions. In other words, these auctions are repeated games (Hausch, 1986, 1993; Engelbrecht-Wiggans, 1994; Bikhchandani, 1988). However, the literature on repeated games is not very useful for studying these auctions (Rothkopf and Harstad 1994). First, the number of action choices (strategies) available to bidders is not finite. Second, the context for the auction (or the game) changes as participants gain information from past auctions. Third, the number and the identity of bidders do not necessarily stay the same over time.

A major obstacle to improved problem representation under standard approaches is the resulting loss of analytical tractability. Relaxing simplifying assumptions quickly leads to intractable models or confusing results. To a large extent, these limitations can be attributed to the tools available to economists. More recently economists have turned to both human-subject and computational experiments to incorporate increased realism and complexity in modelling auctions.

2.2 Experimental Studies of Auctions

2.2.1 Real Experiments

Experiments using human-subjects are relatively recent and have allowed economists to test theoretical predictions[5]. The experimental study of auctions consists of running artificial auctions in laboratory settings, often (but not always) with university students. These auctions are in a sense 'real', involving real people, real goods and real money, while at the same time allowing for the control of most or all factors affecting the outcomes.

Experiments do, however, suffer from the somewhat artificial setting they thus set up. Although real goods and real money are involved, the stakes are usually small and the participants typically inexperienced by comparison with auctions occurring in natural

[5] One of the first to do so, since the early 1960's, was Vernon L. Smith (see Smith, 1990).

settings. This leads to the problem of “parallelism” (Friedman and Sunder, 1994: 15-16). Parallelism does not affect the validity of the experiments themselves relative to the theoretical proposition that needs to be tested, but rather the extrapolation of experimental results to the real world. Thus care must be taken when interpreting experimental results obtained in the context of the assumptions usually made in the theoretical literature.

Furthermore, in parallel to the analytical literature, the experimental literature on auctions, as reviewed by Kagel (1995), has focused on simpler auction types. Issues explored include: the effects of varying the number of bidders in the auction; the impact of uncertainty of the number of bidders; the effect of bidder values ‘affiliation’; the effects of reporting price information back to bidders; bidders’ attitude to risk; and the potential and consequences of collusion. Little work has been done in comparison on repeated auctions and on the impact of bidder learning and ‘gaming’ of the auction (when bidders try to change the rules over time).

Laboratory experiments have allowed the testing of some major predictions made by auction theory, by showing, for example, that with more competitors, bidders bid higher (more aggressively) in first price auctions, lower in third price auctions, and do not change their bids in second price (Vickrey) auctions. As for the impact of concealing information about the number of rivals, experiments have shown that doing so raises the average market price of the item being auctioned. This is predicted by theory, provided that bidders are assumed to have constant or decreasing absolute risk aversion, a variable that is unobservable.

This last result is illustrative of the problems that can arise when comparing theoretical predictions with observations using human subjects in the study of auctions. In order to interpret experimental findings, one may need to rely on unobservable variables such as agents’ degree of risk aversion. This reliance leads to circular reasoning, since knowing whether agents exhibit risk aversion or not has to be inferred from their bidding behaviour. Resorting to computational experiments, where the attributes and behaviour rules of agents are perfectly known or explicitly modelled, can break this logical circle.

The possibility of collusion amongst bidders has been little studied in the theoretical literature, partly because auction theory is primarily based on non-cooperative game theory. Introducing cooperative behaviour in a non-cooperative context introduces complexities that can make the problem analytically intractable, unless some drastic simplifications are made. This poses a problem to experimentalists if they need a clear theoretical benchmark for interpreting laboratory outcomes. Few instances of collusion, and in particular, of long lived and successful collusions, have been observed in laboratory settings (Kagel, 1995). This is in stark contrast to what happens in the real world, where collusion is a constant worry for auctioning agents (Cassady, 1967; Rothkopf and Harstad, 1994, Klemperer, 2002). Where conspiracies among bidders were allowed, if not facilitated, in the lab, interpreting the results proved to be difficult and subject to alternative explanations (Isaac and Walker, 1985; Kagel, 1995: 652-4). These studies showed however the existence and durability of collusion should be linked, at least in common value auctions, to the announcement of a reserve price. Unfortunately for practitioners, the theory predicts that reserve prices in this case will be announced, when in practice they nearly never are. Thus again, theory and empirical observations cannot be put together because of the existence of some unobserved variable linking the two. Computational experiments can be useful here to bridge the gap.

2.2.2 Computational Experiments

Computational economics has at least two functions with respect to theory. Its complementary function is to carry a problem beyond the analytical capabilities of theoretical analysis. The supplementary function is to fill in a void when theory is not available, or when it provides insufficient guidance. This is the case with repeated auctions, where bidders interact over time and have opportunities for learning and strategizing.

The 1990s have witnessed the rapid growth of interest in agent-based computational economics (ACE). ACE is the application to economic problems of agent-based modelling (ABM) which is the study of artificial societies of interacting autonomous agents that directly emulate the behaviours of individuals, institutions and environmental components that make up the system being studied (Epstein and Axtell, 1996; Parunak et al 1998; Tesfatsion, 2002). Unlike conventional or equation-based approaches, the starting point in ACE is the specification of agent attributes and behaviours rather than equations relating system level variables to describe the dynamics of the system. Therefore, ABM is better suited to the study of systems where modelling outcomes can be gainfully enriched through the explicit incorporation of phenomena like agent heterogeneity, local interactions and networking, inductive learning, as well as through the relaxation of restrictive assumptions that are required to derive results under conventional analysis (Tesfatsion 2002).

The last few years have seen a dramatic increase in the application of ACE to fields as diverse as evolution of behavioural norms (Axlerod, 1997; Axtell et al., 1999); financial markets and evolution of trade networks (Kirman, 1997; Tesfatsion, 1997); labour markets (Pingle & Tesfatsion, 2001), electricity auction markets (Nicolaisen et al., 2001; Dunn & Oliveira, 2001; Bower & Dunn, 2001), and structural changes in agriculture (Balmann et al., 2001; Berger, 2001).

While pioneering agent-based modelling work in economics began at least with Thomas Schelling's elegant studies from the 1960's and 1970's (Schelling 1978), interest in ABM has grown rapidly as a result of increasing computer power and the emergence of object-oriented programming (OOP) languages such as SmallTalk, C++, Objective-C, and the increasingly popular Java. OOP languages provide a natural means for representing agents as software objects encapsulating attributes and behaviours (rules). Interest in ABM has also been aided by the growing interest in complex systems analysis following work at the Santa Fe Institute and IIASA Laxenburg; the contributions of experimental economics (Kagel and Roth, 1995); and, most importantly perhaps, the recent realisation that computational and experimental methods can usefully complement theoretical and analytical approaches as is the case in other sciences (Pingle and Tesfatsion, 2001).

2.2.3 Comparing real and ABM-computational experiments

Computational and real experiments can be compared on a number of factors. In terms of the approach to inference, the experimental methods are “bottom-up” rather than “top-down” approaches to science, allowing for the emergence of aggregate or macro-level phenomena from the interaction of individual agents. For this reason, both methods can be used to analyse problems that are more complex or richer problems that would be difficult to handle analytically. The two experimental approaches differ on a number of criteria as indicated in table 1. Some of the major differences between the two relate to:

- model construction or experimental setup,
- the degree of control the researcher has over the experiment, and
- the temporal length of the problems addressed in the experiment.

The temporal length of the analysis is especially relevant for the study of conservation auctions. The two experimental approaches can be employed in a complementary manner. For example, real experiments can be useful in generating data needed to characterize the behaviour of computational agents while computational experiments can be used to thoroughly explore the longer term outcomes.

Table 1. Comparison of real (human-subject) and computational experiments

Criteria	Computational Experiments	Human Experiments
Approach to inference, or micro-macro relationship	Individual based or "bottom up" approach allowing for the emergence of aggregate or macro phenomena from the interaction of software agents	Individual based or "bottom up" approach allowing for the emergence of aggregate or macro phenomena from the interaction of participants
Specification of behavioural rules	Allows for the specification of behavioural rules underlying choices. Rules of game and behaviours of agents can be evolved	Need to clarify rules of the game and incentives but not rules for making choices. Rules and incentives usually held constant for a given session.
Informational problems	Adequacy of agents' behavioural rules (Are they correctly specified?)	Observability of variables from theoretical models (e.g. risk aversion, beliefs)
Degree of control	Investigator has complete control over attributes and behaviours of computational agents	Incomplete, as participating individuals might have different perceptions than those intended by the researcher
Explanation of agents' choices	Known, or can be traced back	Need to be inferred from subject's choices
Temporal length of analysis	Flexible. Long term analysis causes no difficulties	Short, due to cost and time considerations, except (sometimes) over Internet
Representativeness / realism	Subject to the accuracy of investigator's specification of details and scope of analysis	Problems of "Parallelism", especially magnitude of stakes (much smaller in lab than in real world) and subjects' experience.
Data	Need to calibrate model and create initial population representing subject population	Generated by participants' choices and strategies; can provide the foundation for calibrating computational agents
Cost	Inexpensive, except for analyst's time and salary	Higher costs of conducting experiments as well as any incentives provided to participants

3. The agent-based auction model

3.1 Overview

Two types of agents representing the actual players in a real auction are incorporated in the model. These are:

a) Farmer agents bidding for environmental conservation contracts. Each farmer has an environmental quality value and an opportunity cost associated with putting the land being offered under conservation. The environmental quality value on the land responds to and increases under conservation. The growth in this value is specified to be logistic.

b) A government agent which selects winning farmers and awards contracts based on the criteria applying under the particular auction format being used. The government agent has a fixed budget.

Each auction round incorporates the following three major steps or activities.

Step 1: Farmers construct their bids. The bids farmers make depend on their respective opportunity costs, their previous bid prices as well as their success or failure in the previous auction. For example, if a farmer agent was successful in the previous bid, then it tends to bid the same or a higher price. In the very first period, farmers have no prior experience and start by bidding their true opportunity costs. The details of the learning algorithm used to select the mark-ups are described in more detail below.

Step 2: The government agent ranks the bids submitted by farmers based on the auction criteria, selects winners accordingly and informs each bidder whether it has been successful or not.

Step 3: Farmer agents update their contract status based on the message from the government agent. Environmental quality values on land owned by farmers which have been awarded contracts increase according to the growth rules applying for the particular simulation. (In this particular study, it is assumed that environmental quality on land that is not covered by a contract does not deteriorate.)

3.2 Auction Implementation

A discriminatory sealed-bid auction format targeting program objectives rather than enrolment is used by the government agent. Under this format each winning bidder is paid only its bid amount, and thus different bidders may be receiving different payments for the same service. The selection process under this auction type involves two steps:

Step 1: Ranking all bids received from farmers based on the ratio of environmental quality per bid dollar.

Step 2: Awarding conservation contracts to bidders starting from the one offering the highest environmental quality per dollar until the budget is fully allocated.

The discriminatory auction format is expected to extract some of the information rents from bidders enabling the bidder to award more contracts than is possible under a fixed price scheme or a uniform price auction in which each bidder would be paid the same price per environmental quality (i.e. the bid to environmental quality ratio of the marginal or last ranked winner). The discriminatory auction format has been used in the US CRP program and in the BushTender trials in Victoria.

3.3 Learning algorithm

The repeated auction constitutes an environment where the bidders can acquire and utilize information from previous auction outcomes. Roth and Erev (1995) and Erev and Roth (1998) have developed learning algorithms for strategically interacting economic agents based on the reinforcement principle that is widely accepted in the psychology literature. Under this learning algorithm, an agent's tendency to implement an action is strengthened (*reinforced*) or weakened depending upon whether the action produces favourable results or not. The algorithm also allows for exploration or *experimentation* with new alternatives. The Roth-Erev algorithm or modified versions of it have been used in several agent-based studies of electricity markets (e.g. Nicolaisen *et al* 2001; Bunn and Oliveira 2001). The learning algorithm employed in our study has a structure similar to that used by Bunn and Oliveira (2001) but the computation of expected profits and expected probabilities has been adapted to the problem at hand.

The learning that a farmer agent undertakes focuses on the mark-up that it can apply to its previous period bid price (i.e. bid to environmental quality ratio). Agents can choose to maintain the same price by choosing a mark-up of 1.0. But they can also raise (lower) their bid price from its previous level by choosing mark-up levels that are above (below) 1.0. The mark-ups are partitioned into 11 discrete intervals, namely, 0.5 to 1.5. Therefore, as in Bunn and Oliveira, there is no artificial upper limit on the price that bidders put on their benefits. However, bidders do not bid below their opportunity costs.

Each agent goes through the following four steps in its selection of the mark-up for the upcoming auction.

Step 1: *Computation of expected profits for all the mark-up choices*. This involves the computation of a profit margin for each mark-up and the multiplication of the profit margin by a probability of acceptance to obtain the expected profit from the mark-up. While the computation of the profit margin is a straightforward exercise, the computation of the acceptance probability requires the use of the feedback from the previous auction together with an assumption regarding the possible values for the cut-off price (i.e. maximum accepted price) in the upcoming auction. If the farmer agent was successful (unsuccessful) in the previous auction, then it ignores mark-ups that are lower than one (higher than one) but formulates a subjective probability of acceptance over the remaining mark-ups. The distribution of the probability of acceptance over the mark-ups is assumed to take a binomial distribution. That is, the probability of acceptance of a mark-up m_x that is x intervals or steps below or above 1.0 is given by:

$$\Pr obability\ that\ m_x\ will\ be\ accepted = \binom{n}{x} p^x (1-p)^{(n-x)} \tag{1}$$

Where: n is the total number of mark-ups feasible for the current period, excluding the mark-up of 1.0 ($x = 0$) that corresponds to maintaining the same price. The value of p refers to the probability of marking one step up (down) as opposed to maintaining the same price. A value of 0.5 for p is used in our simulations.

Step 2: *Ranking of the mark-up choices based on their expected profits*.

Step 3: *Computation of perceived utilities for each mark- up a la* Bunn and Oliveira (2001). Note that the 'utility' here has a different interpretation than holds in the standard use of the term. It is a rescaled ranking score for the mark-ups that incorporates the effects of a search propensity parameter that encapsulates the *experimentation* learning principle (see Bunn and Oliveira 2001 and

Nicolaisen *et al* 2001). The perceived utility of the mark-up is computed as follows (Bunn and Oliveira 2001):

$$Utility\,of\;m_x = U.\left(\frac{search\;propensity - n}{search\;propensity}\right)^{(rank\;of\;m_x - 1)} \qquad (2)$$

Where the parameter values of 1000, 4, and 3 are used for *U*, *search propensity* and *n*. These choices for the parameter values concentrate the probability of mark-up selection (i.e., next step) among the three top ranked ones (Bunn and Oliveira 2001).

Step 4: *Computation of policies or probability of choice among the different mark-ups*. This involves normalizing the utilities from Step 3 as follows to obtain probability values that add up to 1.0:

$$\Pr obability\,of\;\;picking\,m_x = \frac{Utility\,of\;m_x}{\sum_k Utility\,of\;m_k} \qquad (3)$$

These probability values are used to randomly select among the feasible mark-ups. The selected mark-up forms the basis for the agent's next bid. The learning algorithm allows for both the *exploitation* (of proven price choices) and *exploration* (of new prices) aspects of the price or bid choice.

4. Results and discussion

The experimental setup used to generate the results for the discriminatory auction mechanism is based on a simulation of 30 successive auctions. There is a fixed population of 100 agents bidding for conservation contracts in each of these auction rounds. The opportunity cost and initial environmental quality values for these agents were both randomly drawn from uniform distributions between 0.5 and 1.5. These values should be considered as normalized values of the actual values. The opportunity cost of each agent remains fixed throughout the 30 periods, as is the government budget of $30. The level of the budget was chosen to be roughly equal to 30% of total opportunity cost. The environmental quality value, however, responds to conservation effort and follows a logistic growth curve with a growth rate of 1.0% per time period and a maximum limit of

20 units. One thousand runs of these successive auctions (using different random seeds) were used to generate the average results discussed below. (Reference to results from one particular run refer to the run with a random seed of 1972.)

For comparison purposes, fixed price schemes were also simulated with identical parameter specifications as for the auction. Three reserve prices, namely, 0.85, 1.00 and 1.15, were used. The reserve price of 1.00 refers to the average opportunity cost of the population of bidding agents. The other two reserve prices were included to assess the sensitivity of the performance of the scheme to variations in the reserve price used.

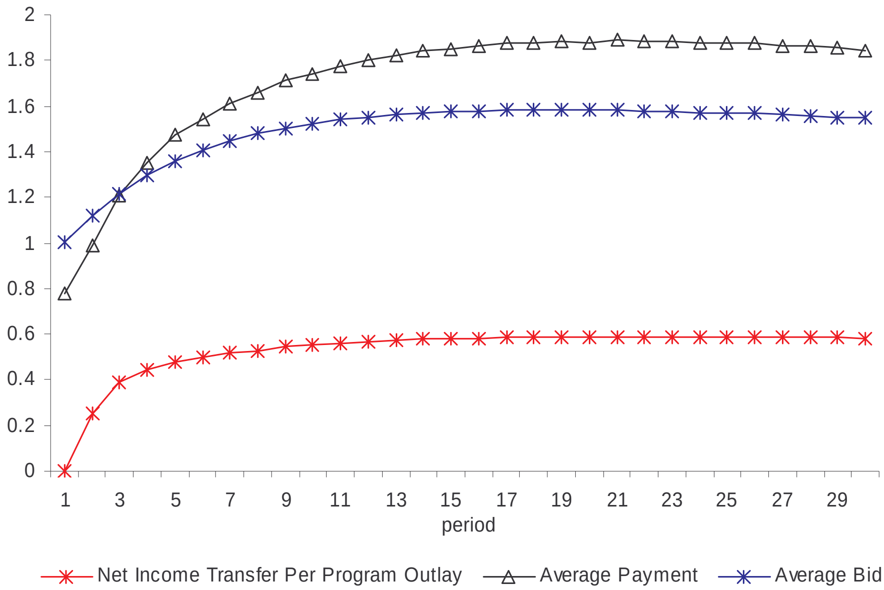
The results on the efficiency of the auction and its distributional outcomes are presented below. Its performance is then compared to that of the fixed price scheme on a range of efficiency and equity criteria.

Efficiency of auction

An attractive theoretical feature of the discriminatory auction is its potential for reducing information rents that would accrue to bidders. The auctioneer ranks the bids according to their environmental benefit-to-cost ratios and assigns contracts in such a way that the total environmental services purchased with the budget are maximized. This maximization of benefits relies on two things. The first is the ranking by the auctioneer of the bids submitted to enable the selection of the least cost providers of environmental values. The second is the payment of discriminatory prices (i.e., payment that are just equal to declared opportunity costs) to the winning bidders. As the discussion below clearly shows, the presence of learning and experimentation on the part of the bidders may lead to outcomes where both these sources of efficiency are not realized.

Total environmental benefits as well as benefits per program outlay improve over time with the auction. This trend is accompanied by two other trends with equity and efficiency implications. First, there is a crowding out of program participants as the number of bidders hired by the auctioneer falls down. In about seven periods, the number of winning bidders is reduced to less than half of what it was in the beginning of the program. Second, the proportion of payments over and above true opportunity costs increases equally rapidly. The proportion of net income transfers in program payments rises to more than 50% within eight periods; in other words, *more than half of the payments constitute informational rents*. See Figure 1. This shows that the efficiency performance of the auction is much lower than one would expect based on the literature on single shot auctions.

Figure 1: Some performance indicators for the discriminatory auction



Program participation and distribution of payments

About 55% percent of the bidders are never selected. Generally, these tend to be the high cost bidders. Most of the remaining bidders manage to procure ten or more contracts from the 30 auction rounds, with the average number of contracts acquired being about 12 and the maximum being 17. That is, the bidder that was most successful in acquiring contracts was not selected in 13 of the rounds. These numbers clearly indicate the intensity of the competition among the 'active' bidders, reminding us of a 'basket of crabs' where each individual manages to get on top but is quickly pushed back under.

This ‘active’ set of bidders mainly includes bidders with the lowest opportunity costs of conservation. The total opportunity cost of this group is also roughly within the reach of the government budget. In other words, under perfect information, this group would have been hired in its entirety to undertake the conservation works. However, after the initial seven rounds, the auction mechanism manages to hire the services of only 16 or 17 bidders (i.e. 40% compared to the perfect information setting without rent extraction).

The auction creates a re-enforcement or amplification mechanism by which those who lost in the initial bidding rounds are unlikely to be able to get in again: very few actually do. The auction also transforms the remaining group of ‘active’ bidders into a predatory subgroup that continuously extracts rents from the auction mechanism. However, in any given period, the rent is being extracted by only the winning subset of this group, while the rest are ‘learning’ to change their bid prices to improve their chances of winning next time round.

Fixed price scheme versus discriminatory auction

A widely held belief is that an auction outperforms a fixed price scheme in terms of economic efficiency. This may be true of single shot auctions, but, as will now appear clearly, is unlikely to be true of repeated auctions with learning. To test this belief, we used the agent-based model to compare the performances of the auction and fixed price mechanisms. The results highlight elements of the auction dynamics that are not fully appreciated in the context of single shot auctions. These are summarized in Table 1.

The performance of the auction relative to the fixed price scheme depends on the reserve price of the latter. With a reserve price set at the average opportunity cost of 1.0, the auction is found to be inferior in terms of efficiency, participation (about 45% less bidders), and the provision of environmental benefits. The auction provides lower rates of environmental benefits in return for the social costs incurred (by a factor of 0.89), and also per dollar of program outlay (by a factor of 0.58). The proportion of net income transfer in program payments is much higher under the auction than under the fixed price scheme. In other words, the informational rents extracted are higher, by a factor of 2.24.

The relative performance of the auction deteriorates relative to the fixed price scheme that has a reserve price lower than average opportunity cost (column 1 of Table 1). The outcomes of the auction are more similar to those of the fixed price scheme with higher reserve prices (column 3 of Table 1) and, therefore, higher built-in net income transfers. In sum, the auction is inferior to fixed payment mechanisms with a built-in check on the amount of money that can be handed out to individual bidders. The auction limits the total, but not the individual amount of payments. As a result, bidders collectively determine the cut-off price, leading to the division of the budget into a smaller number of bigger chunks. This process of concentration reflects the collective marking-up of individual bids that occurs among successful bidders. Relative to the fixed-price scheme, the auction mechanism has obvious implications in terms of distributional equity.

Table 1. Performance of environmental conservation discriminatory auction relative to fixed price schemes

	Relative to fixed price scheme with a reserve price of 85% of mean opportunity cost	Relative to fixed price scheme with a reserve price of 100% of mean opportunity cost	Relative to fixed price scheme with a reserve price of 115% of mean opportunity cost
Proportion of winners among participants	0.54	0.61	0.71
Total social or opportunity cost of conservation activities	0.60	0.60	0.64
Environmental benefits per dollar of opportunity cost	0.44	0.89	1.64
Net income transfer per program outlay	2.65	2.24	1.88
Environmental benefit value per program outlay	0.27	0.58	1.14
Average payment to winners	1.91	1.62	1.41
Gini coefficient of environmental benefit distribution among bidders	0.91	1.12	1.42

The extraction of rents: how does it happen?

The most fundamental observation in the results presented above relates to the mechanism by which a simple learning process involving the use of past information and experimentation with new bid prices enables bidders to extract rents. The particular set up here starts with an auction where all the participants bid their true opportunity costs in the very first round. Over time, bidders utilize the information they obtain from the auctions, either exploiting further their previously successful price choices or using the feedback from the previous auction to experiment with new bid mark-ups. This process of learning and adjustment leads the successful or infra-marginal[6] bidders to mark up their bids up to the point where their respective bid to environmental quality ratios are equal to that of the marginal bidder.

The following two diagrams help explain the outcomes of this learning process. The opportunity cost of involvement for the bidders is indicated on the x-axis. Contracting bidders start by bidding (and getting paid) different prices, reflecting their individual opportunity costs. The program payment rates are marked by asterisks in Figures 2(a) and 2(b). In the first period the winning bid to environmental quality rates range from about 0.4 to 0.9 and involve some bidders who had initial opportunity costs close to the maximum observed in the population of agents (see Figure 2(a)). But these differences in prices disappear over time. The spread in these prices is reduced as the infra-marginal bids catch up with the marginal winning bid eventually forming a narrow band of bid prices, as shown in Figure 2(b) (for the 15th period).[7] Just above this narrow band of winning bids is another band of 'active', but currently not selected, competitors. These two narrow bands represent the two components of the 'active' bidders some of who replace each other from one period to the next – generating the "basket of crabs" effect.

However, the process of competition also implies that the government receives higher environmental quality levels per dollar of program payments over time. This results from

[6] An infra-marginal bidder is one who is ranked higher by the auctioneer than the marginal or lowest ranked winner.
[7] It should be noted, however, that the convergence occurs earlier than period 15.

improvements or increased supply of environmental quality. It also results from bidders' continuous experimentation with alternative prices, which allows previously unsuccessful bidders to outbid previous winners forcing the latter to mark down their bid rates. As a result, the convergence of the ratios of bids to environmental quality values is a moving convergence. Program payments per environmental quality converge towards the decreasing marginal cost of benefit provision. See also Figures 3 and 4.

Figure 2. Distributions of bid to environmental quality and government payment to environmental quality ratios for period 1.

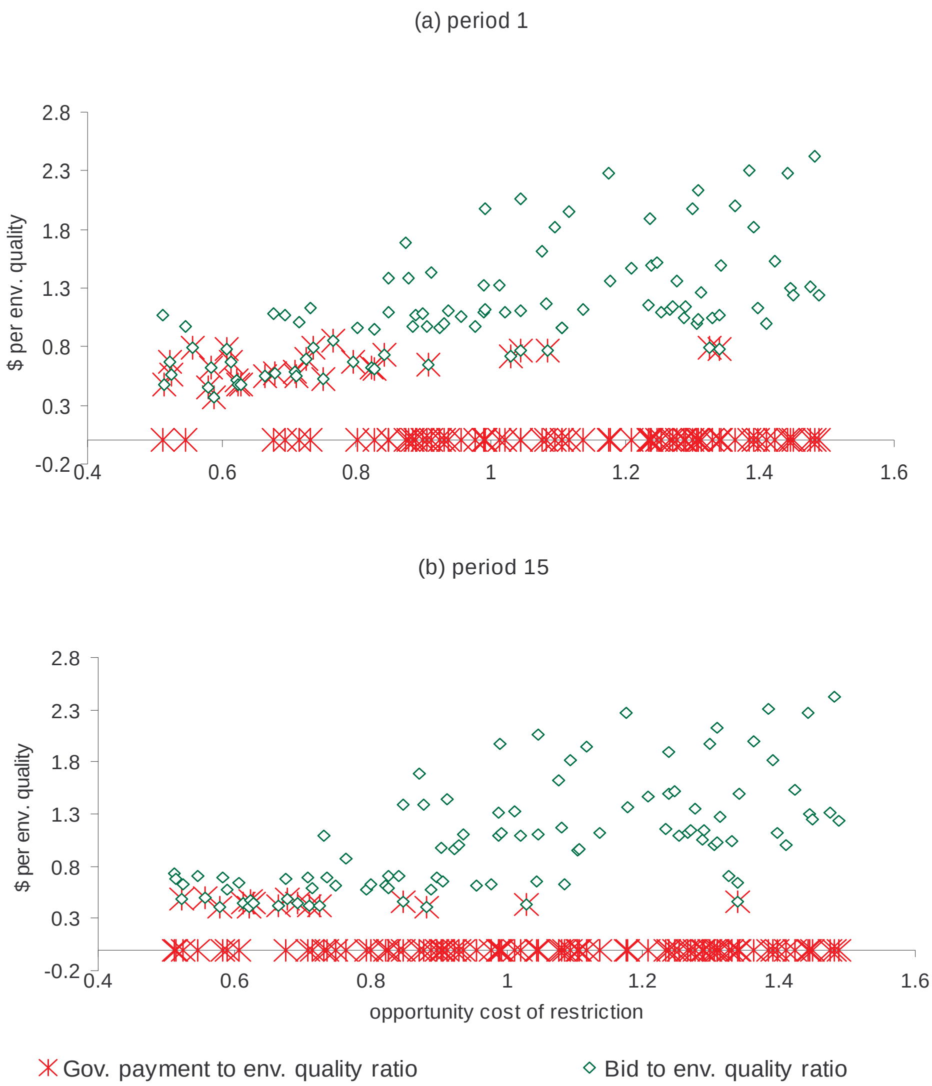


Figure 3. Bid-benefit ratio versus percentage of times that a bidder was selected: The entire history plus some selected years.

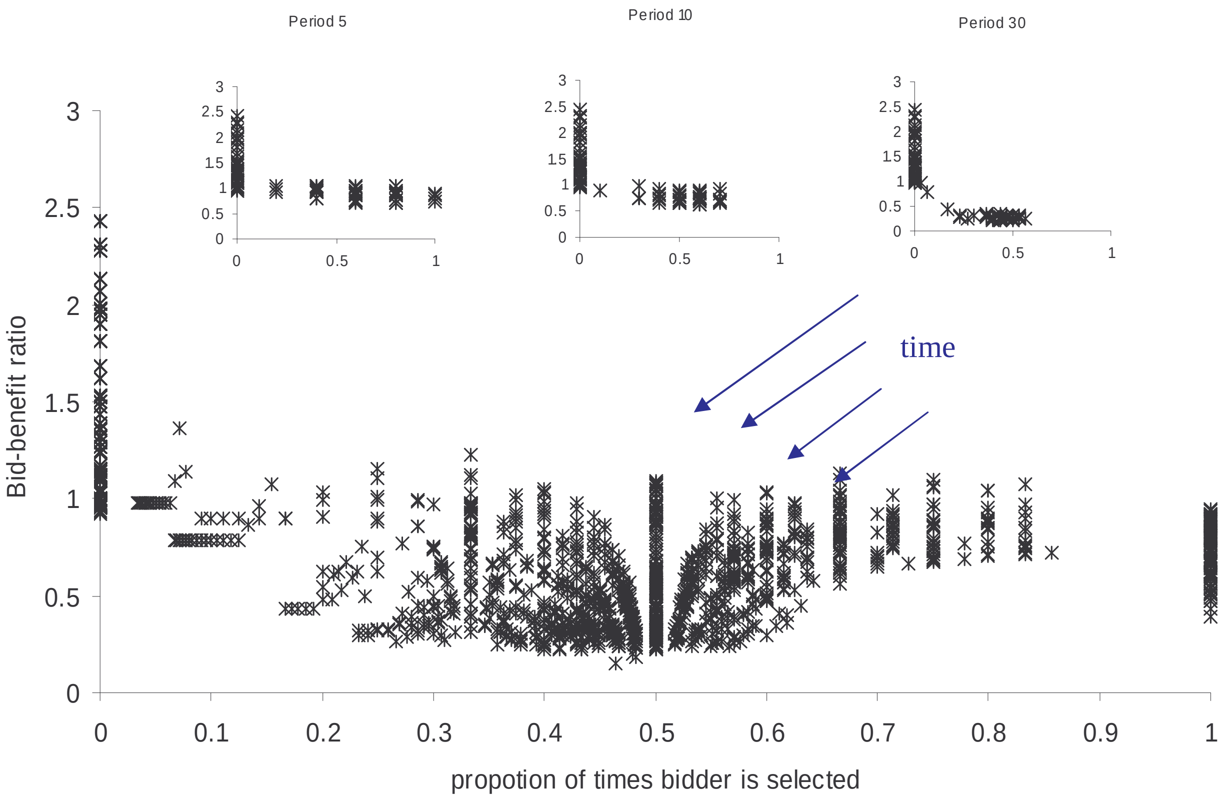
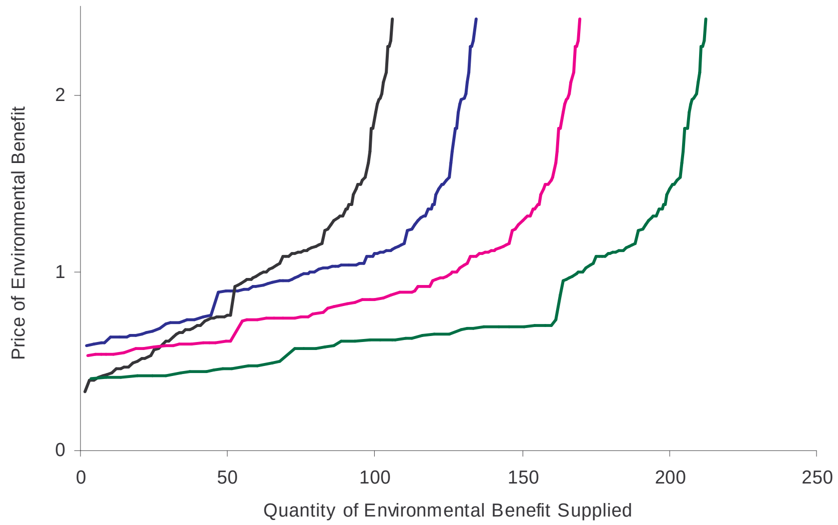


Figure 4. Environmental benefit supply curves over time



5. Conclusions

This study has attempted to evaluate the performance of conservation auctions under dynamic settings using agent-based modelling. The economic agents represented in the model are farmers bidding to offer their environmental services and a government agent with a fixed budget awarding conservation contracts through auctions. The auction mechanism evaluated is a discriminatory sealed-bid auction in which a government agent ranks submitted bids according to their respective benefit-costs ratios, where the benefits are represented by environmental quality values. Bidders are allowed to learn from previous auction results and experiment with alternative bidding strategies. The level of environmental quality managed by each winning bidder responds positively to conservation effort, so that auction outcomes have cumulative effects. A variant of the reinforcement learning algorithm is employed here. The reinforcement learning algorithm is widely accepted in the psychology literature and has recently been adopted in economics research. The auction simulation results are assessed based on a run of 30 consecutive rounds. The performance of the auction mechanism is also compared to the performance of a fixed payment scheme under three alternative reserve price scenarios.

The simulation results provide insights into the long term performance of auctions that lead us to question commonly held assumptions. First, there is a marked difference between the short term and long term efficiency of conservation auctions. In particular, repeated auctions involve the payment of substantial rents to winning bidders as the latter quickly learn to mark up their bids matching the bid to benefit ratio corresponding to the marginal winner. In the simulations conducted here, net transfer payments account for more than half of the total program payments in all the periods other than the first few. The auction mechanism also leads to a much lower program participation rate than would be possible without rent extraction. The total number of participating bidders is split into two main groups as the auction rounds proceed. The first group is mainly one of high cost bidders that are quickly rendered ‘inactive’ and do not succeed in acquiring conservation contracts. The second group constitutes the ‘active’ bidders that have learnt to price their services within a narrow margin of the marginal or most expensive winner.

Second, the fixed price scheme with reserve prices set at average opportunity cost or below outperforms the auction mechanism in terms of participation, efficiency and environmental benefit generation. The auction mechanism compares more favourably only to fixed prices schemes with higher reserve prices. This is because the higher reserve prices involve built-in net income transfers that are similar to those achieved by bidders who learn to 'game' the auction over time.

The main conclusion from this study is that the efficiency benefits of single shot auctions do not necessarily extend to repeated auctions. Even simple learning processes ensure that bidder prices adjust to extract almost all information rents despite competitive bidding conditions.

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