An Iterative Auction for Spatially Contiguous Land Management: An Experimental Analysis

Simanti Banerjee
University of Stirling, UK

Anthony M Kwasnica, James S Shortle
Penn State University, US

This version: June 2011

Abstract

Tackling the problem of ecosystem services degradation is an important policy challenge. Different types of economic instruments have been employed by conservation agencies to meet this challenge. Notable among them are Payment for Ecosystem Services (PES) schemes that pay private landowners to change land uses to pro-environmental ones on their properties. This paper focuses on a PES scheme – an auction for the cost-efficient disbursal of government funds for selection of spatially contiguous land management projects. The auction is structured as an iterative descending price auction where every bid is evaluated on the basis of a scoring metric – a benefit cost ratio. The ecological effectiveness and economic efficiency of the auction is tested with data generated from lab experiments. These experiments use the information available to the subjects about the spatial goal as the treatment variable. Analysis indicates that the information reduces the cost-efficiency of the auction. Experience with bidding also has a negative impact on auction efficiency. The study also provides an analysis of the behavior of winners and losers at the final auction outcome. Winners and losers are found to have significantly different behavior with winners bidding much higher than their costs than losers.

Section 1: Introduction

Conservation friendly land uses for delivery of ecosystem services such as biodiversity protection (Willis 1979, Bartelt et al. 2010) often have greater effectiveness if the land uses are located on spatially adjacent properties with connections between them (Margules and Pressey 2000).Since most vulnerable ecosystems are located on private land [1], such spatially coordinated land management will require that payments be made to landowners incentivizing them to change their land uses in a spatially coordinated manner. One approach to this spatial problem is the Agglomeration Bonus (AB) proposed by Parkhurst and Shogren (2002, 2007) .The AB is a uniform rate payment scheme in a broad class of Payment for Ecosystem Schemes (PES) measures that can incentivize spatial coordination by private landowners.

PES schemes such as the AB would typically operate under a budget cap indicating a need for cost efficient fund disbursal. This efficiency objective has lead to the implementation of auction based PES schemes. The Conservation Reserve Program (CRP) in the US (Kirwan et al. 2005) and the Australian Land Recovery Program are PES policies which use auction based incentives. In the US, since 1985, the auction-like CRP mechanism has disbursed nearly $26 billion (Kirwan et al. 2005) to preserve nearly 1.8 million acres of wetlands and retire 36.8 million acres of farmland to reduce soil erosion. Most of the CRP land is found in the Northern Great Plains, Prairie Gateway and the Heartland (USDA). Under the CRP, landowners submit bids indicating what compensation they would accept to enroll lands into the program. These bids are then evaluated on the basis of a benefit-cost scoring metric termed the Environmental Benefit Index (EBI). The structure of the CRP has been adopted by conservation agencies in Australia under the Bush Tender pilot trials (Stoneham et al. 2003) and the Auction for Landscape Recovery pilot (Gole et al. 2005).

[1] The US Fish and Wildlife Services reported in 1997 that 80% of all species listed as endangered in the United States were located on private lands (GAO 1994). Similarly, in Australia 99% of all endangered ecosystems and 97% of all concerned ecosystems are located on private lands (Rolfe et al. 2009).

These auctions trials used a similar index – the Biodiversity Benefit Index (BBI) and the EBI respectively to evaluate and select bids.

The extant CRP auction however does not incorporate a spatial objective. Research on auctions for spatially contiguous land management is limited to the experimental studies by Rolfe et al. (2005) and Reeson et al. (2008). These studies evaluate the performance of auctions for the creation of landscape corridors and linkages between core areas of habitat using various scoring metrics. Rolfe et al. consider Artefactual field experiments with actual landowners using both iterative and sealed bid auctions. The iterative format incorporates limited information feedback about auction results across the iterations and a bid revision rule. Under the sealed bid format subjects are permitted to communicate and then submit bids for their management projects individually. The chief result from their experiments is that the iterative format produces spatial patterns more cost efficiently than the sealed bid format where communication prior to bid submission exacerbates rent seeking. In the domain of actual policy, the iterative format has proved useful as evinced by cost savings of nearly $820,000 in Fiscal Year 2006 (USDA) from the implementation of an iterative two-round pilot auction under the Wetland Reserve Program. Reeson et al consider an iterative auction for creation of spatial patterns with limited information feedback about auction results in a lab setting. They analyze rent seeking in the presence and absence of a bid revision rule and when the information about the maximum number of iterations is known and not known. The experiments suggest that absence of bid revision possibilities and the presence of information about the maximum number of rounds have a negative impact on rent seeking. These studies highlight the possibility of a variety of auction performance scenarios contingent on auction format and information features of the strategic environment. Thus there is a need for expanding the study of conservation auction and their design and performance analysis prior to field testing and actual policy implementation.

In this paper we present an iterative auction with a modified scoring metric representing the spatial objective. As a departure from past formats, our conservation auction considers a full information feedback about auction results at the end of iteration. Then using the theoretical notion of stability of a Nash Equilibrium of an auction, we provide some features of an allocation that can be supported as a stable configuration in the auction. We next test the economic and ecological performance of this new mechanism in the lab with subjects arranged around a circle with every player having two neighbors. All experiments have twenty periods with a maximum of ten rounds or iterations each with a between and within treatment. The information about the format of the scoring metric that indicates the spatial criterion represents the between treatment and variation of cost-benefit parameters across multiple auction periods for all subjects the within treatment. In addition to the performance analysis, we also present an analysis of individual offer behavior. Our analysis indicates that information has a negative impact on the economic performance of the conservation auction. Moreover as has been seen during the CRP auctions, experience with bidding reduces economic performance. We also obtain evidence of 1) significant behavioral differences between winning and losing bidders at the actual auction solution and 2) instances of jump bidding which is manifested as voluntary bid reductions by winners between successive iterations in order to maintain their competitiveness during the lifetime of the auction.

Section 2:The Conservation Auction Model

Let $I = \{1,2, \dots N\}$ be the set of N participants in the auction. Each participant has one project. They submit bids which represent the amount of money they are willing to accept for conservation land uses. For simplicity we assume that every bidder submits a single bid so that the total number of bids is equal to the number of participants. Let $b = (b_1, \dots . b_N)$

represent a vector of bids. Every winning bidder receives the value of their bid. Let $x \in \{0,1\}^N$ be the vector defining an allocation of winning and losing bidders. Every element $x_i = 1$ in x represents a winning bidder i and an element $x_i = 0$ represents a losing bidder.

The auctioneer has information about both the intrinsic ecological benefits from conservation land uses on the N properties and the benefits generated when any two spatially adjacent properties are placed in the conservation program. Let vector $v = (v_1 \dots v_N)$ represent the intrinsic benefits. Let matrix **B** be a $N \times N$ matrix where each element (i, j) represents the agglomeration benefit from selecting bids for the i^{th} and j^{th} projects. All diagonal elements of the matrix are zero since a project is not its own neighbor. Also if any off-diagonal element (i, j) is zero, it indicates that the projects i and j are not contiguous to each other or there is no environmental benefit from accepting these projects into the program. In order to count the benefits from contiguous project selection once, we assume **B** to be a triangular matrix. The value of the elements in **B** depends upon the spatial configuration of the projects on the landscape. Let the general form of the auctioneer's value function when spatial patterns matter be

$$V(x) = x'v + x'Bx \qquad (1)$$

The first term in (1) is the total intrinsic benefits of all selected projects and the second term represents the benefits from selecting adjacent projects. We assume that the agglomeration benefit from parcels is identical and represented by a factor d. The general form of the environmental value function (1) for a candidate circular landscape[2] is

[2] The circular configuration is a simplistic representation of landscapes where the identity of neighbors for every property is different. This is a general type of a landscape where connected land uses can improve nesting and foraging habitat for birds, natural pollinators like bees etc

$$V(x) = \sum_{i=1}^{N} x_i v_i + d(\sum_{i=1}^{N-1} x_i x_{i+1} + x_N x_1) \tag{2}$$

Section 2.1: The Auctioneer's Problem

Let $t = 1,2, \dots \dots T$ index the rounds in the auction where T is the maximum possible rounds or iterations. In each round, bidders submit a single bid. The auctioneer selects the provisionally winning allocation x_t^* for round t on the basis of a scoring metric that has a benefit cost format. The optimization problem to select a value of x_t given the fixed budget M is the following

$$\max_{x_t^*} \sum_{i=2}^{N-1} \frac{v_i x_i + d x_{it}(x_{(i+1)t} + x_{(i-1)t})}{b_{it}} + \frac{v_N x_N + d x_{Nt}(x_{1t} + x_{(N-1)t})}{b_{Nt}} + \frac{v_1 x_1 + d x_{1t}(x_{2t} + x_{Nt})}{b_{1t}}$$

$$\text{Subject to } \sum_{i=1}^{N} x_{it} b_{it} \leq M \tag{3}$$

Expression (3) represents a knapsack problem (Kellerer et al. 2004) and we use a greedy algorithm to obtain the value of x_t^* . This algorithm is a local optima generating algorithm. It starts with an initial set of winning bidders and replaces them with other non-selected objects until x_t^* is obtained. In this optimization exercise, given the nature of the scoring metric, for any allocation of projects, bids for spatially adjacent projects receive a higher score owing to the factor d and hence have a higher chance of being selected. Once x_t^* is determined it is announced to the bidders and the auction proceeds to round $(t + 1)$ where the process is repeated and $x_{(t+1)}^*$is determined. This process continues till one or both of the following stopping rules are satisfied.

I. $\bar{t} \leq t \leq T$ where $\bar{t}$ represents the minimum number of rounds.

II. $V(x_t^*) = V(x_{t-1}^*)\ \forall t < T$

Condition 1 implies that the auction has to go through a minimum of $\bar{t}$ iterations prior to ending. The minimum rounds ensure that bidders gain familiarity with bidding in the auction environment. Condition II implies that for a round t to be final, the winning score across consecutive rounds should be equal. If for any round $\bar{t} \leq t < T$ both conditions I and II hold then the auction ends. Else the auction repeats through T rounds and ends automatically.

In our auction the activity rule[3] is implicit within the auction procedure. Bids in any round are restricted to be positive and less than or equal to the past round's bids. Thus if a bidder does not place a bid, then the value of their bid for that round becomes zero. Since bids are decreasing between rounds, a zero bid implies that bidders essentially lose the opportunity to participate since they can't lower their bids anymore. Thus waiting is dis-incentivized.

Section 2.2: Features of a stable auction allocation

Given the budget constraint, the total number of selected projects is endogenously determined in the auction on the basis of the bids submitted. In the absence of a set number of projects that the auctioneer seeks to purchase from the participants, the nature of strategic interactions between bidders and expression for a Nash Equilibrium outcome(s) is hard to determine. As a second-best option we outline some conditions on the basis of stability features of a Nash Equilibrium outcome of an auction which should hold for winning and losing bidders in the final round of the auction. Thus an allocation x^* is a stable allocation if

[3] In iterative auctions, often participants may only observe the outcome for the first few rounds to obtain information about winners and their bids (if revealed) on the basis of which they bid in future rounds. Such waiting prolongs the auction and provides the bidders an opportunity to game it. An activity rule avoids this situation by forcing all bidders to bid in a round to be able to bid in subsequent rounds. Activity rules have been used in the FCC auctions (Plott 1997), and airwaves auctions (McAfee and McMillan 1996).

Condition 1:

$$\forall i = 1,2, \dots N \text{ such that } x_i^*(b^*, M) = 0, b_i^* = c$$

Condition 2:

$$\forall i = 1,2, \dots N \text{ such that } x_i^*(b^*, M) = 1,$$

- $b_i^* \geq c_i$
- $\forall\, b_i' > b_i^*, x_i^*(b', M) = 0$ where $b' = (b_i', b_{-i}^*)$

Condition 1 implies that for all losing participants, , bids are equal to costs so that they are unable to reduce their bids to improve their likelihood of winning. Condition 2 indicates that winners' bids are very near their costs and they don't have any incentive to submit higher bids to earn more rents as that will remove them from the stable winning allocation.

Section 3: Experimental Design

Section 3.1: The Information Content of Conservation Auctions

Information about different features of the auction environment often has a significant impact on auction performance. Cason et al. (2003) have considered experiments with knowledge of the environmental value from a project as the treatment variable. Their analysis suggests that extra information exacerbates rent seeking and reduces both the economic and ecological performance of the auction relative to the baseline scenario. In our study we build on this result by considering the impact of revealing a different piece of information about the strategic environment to the bidder. The chief motivation for this treatment specification is to stress test the iterative format in an increasingly transparent setting which is policy relevant. Under a between-treatment scenario, subjects in the treatment sessions receive information about the format of the scoring metric.[4] The scoring metric is a benefit-cost ratio where the benefit from a project is a sum of its intrinsic environmental benefit and the benefit from

[4]Rolfe et al. have conducted artefactual field experiments where farmers receive information about the format of the metric. They however don't evaluate the impact of providing this information on auction performance.

spatial contiguity. The benefit from spatial contiguity in turn depends upon the number of winning neighbors. The format of the metric is given by expression (4). Thus a project has a higher score and greater likelihood of selection if its neighbors have been selected by the greedy algorithm than if the neighbors are not chosen.

$$Score = \frac{v_i x_i + d(x_{i+1} + x_{i-1})}{b_i} \tag{4}$$

In addition to providing the above information in the treatment sessions, all subjects receive information about their costs, the total budget and total number of participants. In addition, as part of the full information feedback at the end of a round, the identity of winners, the value of the subjects' scores, and the value of all submitted bids in every round is provided to all subjects. The information treatment sessions are termed the SCORE sessions and the baseline sessions are termed NO-SCORE sessions. We consider six sessions for each treatment.

Section 3.2: Auction Performance Metrics

Experimental data from the SCORE and NO-SCORE sessions can be used to evaluate both economic efficiency and ecological effectiveness in our study. In defining these metrics we consider the allocation chosen in the absence of asymmetric information when bids equal cost as the reference point. Let this allocation be denoted by x^{max}. We then construct metrics to evaluate the economic and ecological performance of the auction at any stable final allocation x^* relative to x^{max}. The ecological effectiveness (EE) of the auction at the stable allocation x^* is measured as the ratio of environmental benefits from x^* and x^{max}. Using expression (1) we can define EE as

$$EE(x^*; x^{max}) = \frac{V(x^*)}{V(x^{max})}$$

The value of EE indicates the impact of asymmetric information on ecological performance. Closer the value of EE to 1, better is the capacity of the auction to deliver ES relative to the full information outcome. A value of 1 (when $x^* = x^{max}$) indicates that the auction is successful in selecting the allocation that would be achieved in the absence of asymmetric information. Yet this outcome is possible even if bids are greater than costs. However although ecologically effective the allocation under the latter scenario requires a greater financial outlay indicating dearer conservation procurement and lower economic efficiency. We compute the economic cost efficiency metric (CE) to represent the economic performance of the conservation auction. Under CE we measure the actual outlay in the auction relative to the outlays to support x^{max} . The CE metric is a ratio of two ratios. The numerator ratio represents environmental benefit from the stable allocation x^* relative to the total outlay associated with it. The denominator is the corresponding benefit-cost ratio for x^{max}. Thus with θ_i being the cost of project i, CE can be represented as

$$CE(x^*; x^{max}) = \frac{\dfrac{\sum_{i=1}^{N-1} v_i x_i^* + dx_i^* x_{(i+1)}^* + v_N x_N^* + dx_N^* x_1^*}{\sum_{i=1}^{N} b_i^* x_i^*}}{\dfrac{\sum_{i=1}^{N-1} v_i x_i^{max} + dx_i^{max} x_{i+1}^{max} + v_N x_N^{max} + dx_N^{max} x_1^{max}}{\sum_{i=1}^{N} \theta_i x_i^{max}}}$$

For any set of cost and benefit parameters which determines x^{max}, higher rent seeking is associated with lower CE values. A value of CE equal to 1 indicates that bids submitted equal costs and the auction is most efficient.[5] The CE metric picks up the effect of

[55] We note that the value of CE can be greater than 1. This may happen when the unselected bids are very high and the budget is insufficient to procure more projects. Here a lot of money is left over and very little conservation is purchased. This scenario represents a highly inefficient outcome.

the unspent budgets left over after winners are paid in the auction. This is important as the money left over can have alternative uses.

Finally for the bidders, the total Information Rents or seller profits within a session are calculated as the sum of the difference between winning bids and costs for all winners. This metric also captures the degree of competition in the auction since competition between bidders reduces the value of submitted bids and final rents. The metric is represented as

$$Rents = \sum_{i=1}^{N} (b_i^* - c_i) x_i^*$$

Section 3.3: Choice of Experimental Parameters in the Auction

We consider four sets of parameters for twelve auction periods for the six participants arranged around a circle. We assigned parameters to periods on an ad-hoc basis to prevent ordering effects and to subjects such that every subject could potentially win at least three times. . Let G1 represent parameter set 1 and G2 the set 2 so on and so forth. We choose the parameters on the basis of the following features of the stable allocation x^* relative to x^{max} First, we make choices such that candidate stable allocations can produce different metric values. Second, we select the parameters such that x_{max} for each regime corresponds to a different number of projects. Thus for G1, G3 and G4, x^{max} has four projects and for G2, the number is three. Finally, under every regime, different spatial configurations can be obtained. Under G1 and G4, four adjacent projects can make up the stable solution. With G2, three projects can form a stable allocation with two adjacent to each other and under G3 three of the four selected projects can be adjacent to each other. These parameter sets serve as the secondary within treatment in the analysis. We use 350 experimental dollars as the auction budget in all the 12 periods. The value of environmental benefit from selecting any two adjacent projects on the spatial grid is 50. Table 1 represents the parameters used for the experiment.

INSERT TABLE 1 HERE

Section 3.3.1: Project pivotalness

The scoring metric indicates that the likelihood of project selection is a function of one's own and neighbors' cost-benefit values and is increasing in the number of neighbors selected. Thus if projects have low cost and high benefit neighbors, they have a greater likelihood of being selected than when they are surrounded by one or both high-cost low-benefit) neighbors and vice versa. The same effect holds for the neighbors as well. Thus a project and its neighbors generate an externality for each other by influencing each other's chances of selection. We will refer to this externality feature as the *pivotalness* of the project. This project pivotalness sets the current auction apart from the ones considered by (Cason et al. 2003 2004, 2005) where the metric and hence likelihood of selection is a function of only one's own cost-benefit profile.

We measure project pivotalness on the basis of the degree to which the value of the objective function in expression (3) drops if that project is removed from x^{max}. Greater the fall in the value of (3), greater is the pivotalness of the project. For example, for set G4, the value of (4) when $x^{max} = \{2,3,4,5\}$ is 17.91. Now if project 4 with a benefit-cost profile of $\{277,69\}$ is removed from the auction, then $x^{max} = \{1,2,3\}$ is obtained with value of expression (4) reducing by 6.64. This value drop is higher than the drop of 6.55 obtained if project 3 with benefit-cost profile of {235, 51} is excluded from x^{max}. Thus project 4 is more pivotal than project 3 in x^{max}. We note that project 4 is more pivotal than project 3 despite having a higher cost. This is because it has a higher benefit and is flanked by two low cost neighbors (project 5 with a cost of 87 and project 3) which improves its chances of selection. Project 3 on the other hand is adjacent project 2 which has a benefit-cost profile of {280,137} with the cost being nearly 40% of the total budget and project 4. Again project 3 is ranked second in pivotalness owing to its low cost and because it enhances both projects 2 and 4's chances of selection of. Projects 2 and 5 have low pivotal ranks by virtue of their benefit-cost profiles and their location which is at the edge of x^{max} .

Table 2 presents the degree of pivotalness of projects comprising x^{max} and project pivotal rank on the basis of change in value of expression (3) from project displacement for all regimes. For both G1 and G2, the lowest cost project is most pivotal and is at the centre of other selected projects such as in G1 or has at least one neighbor like in G2. For G3 and G4, while the highly pivotal projects don't have the lowest cost they have high benefit values. Projects by virtue of their pivotalness have a greater chance of selection and earning higher rents. An analysis the data collected indicates that in most sessions the actual x^* corresponds to the candidate stable allocation used to select the parameters. Also the average value of the metrics in the sessions across parameter regimes is not significantly different from those in the candidate solutions. This is represented in Table 3.

Section 3.4: Description of Experimental Procedure

Experiments were conducted at the Laboratory of Economics, Management and Auctions (LEMA) at Penn State University between March and April 2010 using participants randomly selected from the Penn State student population. The sessions lasted between an hour and an hour and half. Subjects were paid a show-up fee of $7. The exchange rate to convert experimental dollars earned during the session to actual dollars was 15 experimental dollars per real dollar. Neutral terminology was used in the experimental instructions. The term QUALITY was used to refer to the environmental value and the term ITEM was used to denote a land management project. At the beginning of every session a non-paying training period with two rounds was conducted in order to demonstrate to the participants how the auction would work. Arbitrary cost-benefit values were used for this purpose. Twelve experimental sessions were conducted with the 6 subjects across the computerized interface programmed in Z-Tree (Fischbacher 2007).[6] All paying periods had a minimum of 5 and a maximum of 10 rounds. This is presented in Table 4.

During the experiment after subjects submitted bids in a round, the computer displayed a results screen showing the submitted bids and the identity of provisional winners. In addition, all players saw their own score for the current round, their bids from the current and past rounds, their costs and the number of neighbors selected in the current round. Their cost and previous round's bid were visible to the subjects whenever they submitted a bid. Bids were always restricted to be greater than costs and the bid from the previous round was automatically submitted in the next round by Z-Tree (Fischbacher 2007). Subjects could decrease bids by a minimum decrement of 50 experimental cents between iterations. The provisional winners in any round became final winners of a period if the stopping rules were satisfied. During a session, the identity and location of players on the circle remained unchanged.

Section 4: Results

We use the experimental data to evaluate mechanism performance at the group level and behavior at the individual level. The group level analysis of auction performance indicates the impacts of introducing greater governmental transparency in the implementation of conservation auction policies. The within parameter treatment allows us to evaluate how performance varies under different parameter values and the extent to which group behavior

[6] The instructions for the experiments are available on request.

is consistent with the features of the stable allocation. Next using individual level data we are able to postulate whether behavior of subjects at an actual auction outcome is consistent with the theoretical properties of a stable allocation. Finally using data from all rounds and periods we present an analysis of jump bidding behavior of bidders.

Section 4.1: Analysis of Market Performance

We analyze the performance of the auction on the basis of the three performance metrics with data from the final round (the binding round) of every period.[7] Figures 1-3 represent the average inter-temporal values of metrics across all sessions by treatment. Comparing between treatments, the value of CE is greater for all SCORE sessions relative to NO-SCORE ones except in periods 5 and 12. The rent values are found to be higher in all SCORE sessions relative to NO-SCORE sessions. However we see no significant difference in the percentage ecological benefits across treatments. Additionally we observe a negative impact of bidder experience on economic performance.

INSERT FIGURES 1-3 HERE

We use random effects panel regressions to test the significance of the above results with the session representing the random effect. Since the total outlays made under different regimes are different, we use the log of total rents in a session as the dependent variable in the regression rather than the rents metric. Since the value of log of rents and CE can be greater than 1, we use simple random effects models for these metrics. For the ecological

[7] We could record data for all the 12 periods of the NO-SCORE sessions and 3 SCORE sessions. For the remaining 3 SCORE sessions, the last period was lost owing to software error. Also in some periods, the stopping rule was violated owing to a glitch in program and the auction continued for more rounds than it should have. Here we applied the stopping rule forcefully to end the auction and did not include the data from subsequent rounds in the analysis.

effectiveness metric we employ a random effects Tobit model since its value cannot exceed one by construction. We expect the information treatment, experience with bidding (which is captured by the Period variable), the number of rounds within any period and the value of benefit-cost parameters to have an impact on performance. We conjecture that when subjects know that neighbors influence their selection in x_t, they will be able to use this information and knowledge of provisional auction outcomes (available to them via full information feedback) to submit bids which improve both their chances of being finally included in x^* and increase their rents by virtue of their locational advantage. Thus the information dummy should have a negative sign in the analysis of CE and EE and a positive sign for the analysis of rent seeking. We include the Period variable in our analysis since familiarity with the auction environment (especially in the PES domain where auctions are repeated multiple times) can have a significantly negative impact on economic performance by intensifying rent seeking. Rent seeking makes every unit of conservation procured dearer and reduces the ecological performance of the auction. Thus based on our conjecture the estimate for Period should have a negative sign for the CE and EE models and a positive sign for the rents regression. We include the Round variable in the analysis is to capture the impact of the iterative format on performance. Since we are considering a descending price auction, the estimate for Round should be negative. Finally, since we chose parameter values on the basis of varying metric values at the candidate stable solutions, we expect the actual values of performance metrics to be consistent with these candidate values and reflect the differences between them. The regression equation for this analysis is

$$y_{it} = \propto + D + G1 + G2 + G3 + \beta lnt + \delta lnR_t + u_i + \varepsilon_{it}$$

$$(i = 1,2, \dots \dots .12; t = 1,2, \dots \dots 12) \tag{5}$$

Here y_{it} is the dependent variable representing the value of the metric for each period expressed as a function of the information treatment dummy D, the log of Period t and final Round variable R_t for every period t and the parameter dummies G1 through G3. The log specifications for Period and Round provide estimates for growth rates and elasticities. Regime G4 and the NO-SCORE treatments represent the omitted categories. . We consider G4 as the omitted category as the total rents at a candidate stable allocation is the highest under G4 and the expected EE is the lowest. Since we consider a random effects structure the error term comprises of the component u_i which is the time invariant unobserved heterogeneity associated with every session *i* uncorrelated with the independent variables in the model and the random component ε_{it}.

INSERT TABLE 4 HERE

Table 4 presents the regression results for the three metrics. As conjectured, the estimate for the information treatment is significant in the economic efficiency CE (negative and significant at 5%) and log of total rents (positive and significant at 5%) models. There is however no significant effect of enhanced information on EE. The negative sign for CE suggests that given the budget all purchased conservation units are more expensive in the presence of information about the spatial goal relative to when this information is absent. The positive estimate in the rents regression implies that when subjects know the format of the scoring metric, they successfully exploit their locational and cost advantages to retain higher rents (on winning).

The estimate for the log of Period is significant at 5% for the CE and at 1% in the rents and at 10% in the EE regression. The negative sign of the estimate in the CE and EE models represents the reduction in auction performance with increase in inter-temporal learning. This adverse impact of experience has significance for policy implementation since conservation agencies run multiple conservation auctions. Here with greater familiarity, stakeholders can submit higher bids and earn higher rents. Such experience induced rent seeking has been observed under the CRP where over time landholders kept bidding near the bid cap – the maximum possible bid for a project in an area (Kirwan et al. 2005). The positive and significant (at 1%) estimate for Log of Period in the rents regression has similar interpretation. The effect is however inelastic owing to the iterative descending price nature of the auction. Focusing on EE, the effect is found to be negative and significant at 10% implying an increase in the price of conservation units owing to rent seeking which reduces the total units of conservation purchased over time.

The log of Round is significant at 10% level in the CE model and at 1% for the rents and EE models. The sign of the estimate is negative for the rents regression and positive for the other two. The signs of the estimate in the three regressions represent the iterative descending price format. In addition, the elasticity estimate in the rents regression is less than one indicating that within a period, bidders always try to retain as much rent as possible as they reduce the bids submitted between rounds. This result is true regardless of the information content of the auction.

INSERT TABLE 5 HERE

We obtain positive and significant values for the estimates for G2 and G3 for the EE model implying that environmental performance under these regimes is significantly better than under G4. However we find no significant difference in ecological effectiveness between G4 and G1 suggesting the presence of intensified rent seeking tendencies under the G1 and G4 periods which causes the mean EE values to be the same under these regimes (nearly 0.75 according to Table 3). Rent seeking in all periods also prevents any significant differences in economic performance in the CE model under all regimes relative to G4. However we find significant differences in the degree of rent seeking under the three regimes relative to G4. The signs are negative indicating that relative to G4 rents earned under all other parameter profiles is significantly lower. This result is consistent with the features of the candidate stable allocations used to choose the experimental parameters.

Section 4.2: Analysis of Bidding Behavior

The theoretical features of the stable allocation indicate a behavioral difference between the winning and the losing bidders. We statistically analyze bid data from the final round of each auction period in a random effects instrumental variable model to assess whether subject behavior at the final allocations in the experiments is consistent with the properties of the stable allocation. For this analysis the dependent variable is the markup of bid over costs for every bidder in the final round of all the periods. We then evaluate how presence of agent learning (captured by the reciprocal of the Period variable), the information and the parameter treatments, Round values for every period, and whether a subject was part of the winning allocation or not in the period (we term this variable Winner) explain the variation in the markup data.[8] The regression equation is represented as

$$y_{it} = \propto + D + G1 + G2 + G3 + \beta\left(\frac{1}{t}\right) + \delta R_t + W_{it} + u_i + \varepsilon_{it}$$
$$(i = 1,2, \ldots \ldots .72; t = 1,2, \ldots \ldots 12; N = 846) \quad (6)$$

[8]The probability of winning in any round is a function of the bids relative to cost represented by the markup value. Again markup earned is a function of whether a subject wins or not. Thus inclusion of the Winner variable for the current round introduces endogeneity into the analysis. Thus we use the value of the winner variable from the past round as the instrument for the Winner variable for the final round. The correlation coefficient between the Winner variable for the final round and the penultimate round in a period is approximately 0.82 justifying the use of this instrument.

Here y_{it} is the dependent variable representing the markup. It is expressed as a function of the treatment dummy D, the learning variable $(\frac{1}{t})$, the Round variable R_t, the Parameter dummies and the Winner variable W_{it}. The error term comprises of the component u_i which is the time invariant unobserved heterogeneity associated with every subject i and the random component ε_{it}.

Table 5 represents the set of estimated coefficients for this model. The constant term is positive and significant (at 1%). We also obtain a positive and significant estimate (at 1%) for the Winner variable indicating that winners' markups are significantly higher than the losing bidders' markups. Thus behavior of winning and losing bidders at an actual auction outcome is consistent with the theoretical features of the stable allocation.

The positive and significant (at 5%) estimate for the treatment dummy implies that bid markups in the SCORE sessions are higher than in the NO-SCORE sessions. Since markups represent individual rents, this result is consistent with our previous result on intensified rent seeking in the SCORE sessions. Also the estimates for G1 through G3 are negative and significant indicating that on an average markups submitted under these regimes is lower than those submitted under regime G4. This result is consistent with highest value of group level rents under G4 relative to G1 through G3 at the candidate stable solution.

The estimate for Learning is negative and significant (at 5%) indicating that in the initial periods where levels of learning are high, markups demanded and earned are lower. Over time with experience induced learning, bidders place higher bids and retain higher rents in the event of winning. The positive trend in the average markup graphs for both SCORE and NO-SCORE in Figure 4 substantiates this claim. This result corresponds to significantly higher rent seeking in the latter periods as established in the previous auction performance analysis. Finally, the sign of the estimate for the Round variable is negative and significant (at 1%) indicating that a greater number of iterations within a period reduces markups.

Section 4.3: Analysis of Jump Bidding

In this section we present an analysis of jump bidding observed during the course of the experiment. Jump bidding involves the scenario where winning bidders in a round submit bids in excess of the minimum bid decrement amount (in an iterative descending auction) in subsequent rounds. Such bidding behavior prolongs auctions as well as reduces the rents earned by jump bidders if they win. According to Isaac et al. (2007) bidders practice such jump bidding – bid at the decrement/increment or some other level early on in the auction and/or persistently from beginning till the end, to maintain one's competitiveness in the auction even though this might cause them to lose some rent. Their theoretical model indicates that the small jumps allow bidders to move up to a bidding trajectory and stay there such that they can finally win the auction by defeating competitors.

We present a summary of the bid decrement data for the 72 subjects for all rounds in the auction in Table 7. We classify this data by the information treatment and the winning or losing status of the bidder in the previous round in a period. The value of the decrement can be zero or negative. For $N = 5454$ there are a total of 3113 observations corresponding to instances where bidders exclusively reduce their bids in any round relative to the previous round. Of these 3113 observations there are 334 instances where subjects reduced their bids even if they won in the previous round of a period and 2679 cases where they did not win in the previous round. These 334 instances of bid reductions correspond to jump bidding behavior in the present scenario.

INSERT TABLE 7 HERE

For a detailed exposition of the jump bidding issue, we consider a random effects tobit analysis where the value of the bid decrement from one round to the other is the dependent variable. We conjecture the number of neighbors selected in the previous round, whether the player themselves were selected in the previous round, if the subject had information about the format of the scoring metric and the level of inter-temporal learning will have an impact on bid reduction behavior. The regression expression is represented as

$$y_{id} = \propto + W_{i(d-1)} + \delta N_{d-1} + \beta\left(\frac{1}{d}\right) + D + G1 + G2 + G3 + P[2-12] + + u_i + \varepsilon_{id}$$

$$(i = 1,2, \ldots \ldots .72; d = 1,2, \ldots \ldots 100; N = 5454) \tag{7}$$

For this analysis, we compute a composite period-round variable to record the bid decrements for subjects across all rounds of all periods. We term this as the date variable represented by d in the regression equation (3). Using date as the time variable gives rise to an unbalanced panel with a maximum size of 100. We represent learning in this model by the reciprocal of the date variable - $\left(\frac{1}{d}\right)$. In addition we also include the parameter dummies to account for differences in bid decrements under different cost-benefit regimes as well as Period dummies to capture any effect at the overall Period level.

INSERT TABLE 8 HERE

Table 8 presents the results of this analysis.[9] The constant term is positive and significant (at 1%). We obtain a positive and significant estimate (at 1%) for the winning status of the individual, $W_{i(d-1)}$ from the previous date. This indicates that the average value of bid decrements is significantly higher for winners than for the losing bidders. This result captures the jump-bidding tendencies observed in the data (Table 7). The estimate for the

[9] Time period dummies for periods 5,8 and 10 are dropped owing to multi-colinearity that arises from the inclusion of the parameter dummies.

number of winning neighbors from the previous date is positive and significant (at 5%). Since neighbors' selection improves a subject's likelihood of selection, greater the number of selected neighbors higher would be the bid decrement a subject would place in the next date to retain their chances of winning in this date as well. The estimate for the information dummy is negative and significant (at 5%) suggesting that relative to those in the NO-SCORE sessions, subjects lower their bids by a smaller amount in the SCORE sessions. We explain this result by arguing that in the SCORE sessions, subjects have incorporated the impact of neighbors on their own levels of competitiveness. In a scenario of full information feedback about auction results at each date, their submitted bid decrements are lower relative to subjects in the NO-SCORE sessions who don't have this information and hence cannot assess their competitiveness vis-à-vis their neighbors. The estimate for the inter-temporal learning is negative and significant (at 1%) as is to be expected. Over time as subjects learn about bidding and gather more experience, they form an idea about their degree of competitiveness in the auction which permits them to reduce the level of decrements and try to earn higher rents. Finally the negative and significant (at 1%) estimates for G2 through G4 indicate the difference in average bid reductions relative to the omitted group – G1. The negative signs indicate that relative to regime G1, levels of rent seeking are higher in the other regimes manifested by lower bid decrements.

Section 5: Conclusion

The dual objective of ecological and economic efficiency that needs to be pursued in the delivery of ecosystem services given fixed budgets provides motivation for the development of the conservation auctions literature. . This paper considers the structure of an iterative auction for the selection of bids for projects adjacent to each other. Besides providing a characterization of an actual conservation auction solution we analyze the impact of information about the spatial objective on auction performance. Our main result is that greater transparency and inter-temporal learning reduces the economic cost-efficiency of the mechanism. Thus this paper sets up the need for more research on conservation auction design to formulate a mechanism which will be robust to greater transparency of the conservation agency and inter-temporal learning. it is also necessary to explore the nature of the Nash Equilibrium that can be obtained in the iterative auction where the number of projects are endogenously selected. We also need to consider more complex spatial configurations and interactions between adjacent bidders in them since actual landscapes can rarely be approximated by circular grids where every landowner has the same number of neighbors. As threats for ES increase, incentive based mechanisms to promote voluntary conservation of natural resources is necessary. Additionally, with limited budgets, economic efficiency of the incentive mechanisms is a central objective. Thus, policy making needs to focus on mechanisms that target various ecological criteria. The current interest in both research and policy circles are to explicitly incorporate the spatial criterion into the auctions so that it can be attained in an economically efficient manner. This paper contributes to this policy making exercise.

References

Cason, T. N., L. Gangadharan, and C. Duke. 2003. A laboratory study of auctions for reducing non-point source pollution. *Journal of Environmental Economics and Management* 46 (3): 446-71.

Claassen, R., L. Hansen, M. Peters, V. Brenneman, M. Weinberg and others. Agri-Environmental Policy at the Crossroads: Guideposts on a Changing Landscape. AER 794, January 2001.

Faith, D. P. (1994). Phylogenetic pattern and the quantification of organismal biodiversity. *Phil. Trans. R.Soc. Lond. B* Vol. 345, pp. 45.

Fischbacher U. 2007. z-Tree: Zurich Toolbox for Readymade Economic Experiments. *Experimental Economics* 10: 171-178

Gilpin, M. E. in *Viable Populations for Conservation* (ed. Soulé, M. E.) pp. 126 (Cambridge Univ. Press, New York, 1987).

Gole, C., Burton, M., Williams, K.J., Clayton, F., Faith, D.P., White, B., Huggett, A. and Margules, C. (2005). *Auction for Landscape Recovery: ID 21 Final report, September 2005*. Commonwealth Market Based Instruments program, WWF Australia. Available from URL: http://www.napswq.gov.au/mbi/round1/project21.html [accessed 18 Aug 2006].

Hajkowicz, S., A. Higgins, K. Williams, D. P. Faith, and M. Burton. 2007. Optimisation and the selection of conservation contracts*. *Australian Journal of Agricultural and Resource Economics* 51 (1): 39-56.

Kirwan, B., R. N. Lubowski, and M. J. Roberts. 2005. How cost-effective are land retirement auctions? estimating the difference between payments and willingness to accept in the conservation reserve program. *American Journal of Agricultural Economics* 87 (5): 1239.

McAfee, R. P., and J. McMillan. 1996. Analyzing the airwaves auction. *Journal of Economic Perspectives* 10(1): 159-175.

Plott, C. R. 1997. Laboratory experimental testbeds: Application to the PCS auction. *Journal of Economics & Management Strategy* 6 (3): 605-38.

Reeson AF, Rodriguez L, Whitten SM, Williams KJ, Nolles K, Windle J, Rolfe J. Applying competitive tenders for the provision of ecosystem services at the landscape scale: Paper. Applying Competitive Tenders for the Provision of Ecosystem Services at the Landscape Scale. Paper accepted for BIOECON conference, Cambridge, September 2008.

Rolfe, J., and J. Windle. 2006. Using field experiments to explore the use of multiple bidding rounds in conservation auctions. *Canadian Journal of Agricultural Economics*.

Rolfe, J., J. Windle, and J. McCosker. 2009. Testing and implementing the use of multiple bidding rounds in conservation auctions: A case study application. *Canadian Journal of Agricultural Economics/Revue Canadienne d'Agroeconomie* 57 (3): 287-303.

Vane-Wright, R. I., C. J. Humphries, and P. H. Williams. 1991. What to protect?--systematics and the agony of choice. *Biological Conservation* 55 (3): 235-54.

Table 1: Parameters for Experiments

	Budget – $350 Environmental Benefit from Two Adjacent Projects – 50							Periods in which used
G1	Benefit	245	150	215	209	195	285	2, 4, 10
	Cost	100	40	90	95	85	112	
G2	Benefit	204	349	213	295	363	271	3, 5, 11
	Cost	112	105	89	146	95	110	
G3	Benefit	210	215	220	265	145	145	6, 8, 12
	Cost	140	95	103	85	130	60	
G4	Benefit	252	269	241	280	235	277	7, 9, 13
	Cost	87	124	100	137	51	69	

Table 2: Pivotalness of Winning Projects by Parameter Regime

Set	Winning Project	Change in Value of Objective Function	Pivotal Rank
G1	3	0.2	IV
	4	1	II
	5	6.36	I
	6	0.86	III
G2	3	1.12	I
	4	0.07	III
	6	0.36	II
G3	1	3.17	II
	2	3.17	II
	3	4.57	I
	5	2.41	III
G4	2	0.24	IV
	3	6.55	II
	4	6.64	I
	5	3	III

Table 3 Experimental Design

	Treatment	
	SCORE	**NO-SCORE**
Number of sessions	6	6
Number of players in a session	6	6
Number of periods per session	13 (one practice period)	13 (one practice period)
Maximum number of rounds	10	10
Minimum number of rounds played	5	5
Payment structure	$7 show up fee Exchange rate – 15 experimental dollars for every US $	

Table 4: Summary of Performance Metrics in Auction by Parameter Group

		Number of Observations	Mean	Standard Deviation	Minimum Value	Maximum Value	Stable Allocation
Ecological Effectiveness	G1	36	0.757	0.09	0.55	0.92	1
	G2	36	0.903	0.12	0.59	1	1
	G3	36	0.8	0.08	0.58	0.94	0.84
	G4	33	0.723	0.06	0.47	0.95	0.72
Economic Cost Efficiency	G1	36	0.819	0.05	0.63	0.91	0.9
	G2	36	0.844	0.07	0.68	0.94	0.78
	G3	36	0.812	0.08	0.66	0.96	0.8
	G4	33	0.812	0.07	0.7	1.02	0.8
Total Information Rents	G1	36	52.12	27.56	7	160.5	35
	G2	36	44.34	18.85	17.5	111	33
	G3	36	59.54	15.65	33	101	35
	G4	33	101.57	25.26	36	141	101

Table 5 Regression Results for Market Performance

Dependent Variable	Economic Efficiency	Log of Rents	Ecological Effectiveness
Estimate (Standard Error)	**Random Effects**	**Random Effects**	**Random Effects Tobit**
Constant	.8060* (.046)	4.8873* (.230)	.5703* (.059)
Information Dummy	-.0422* (.014)	.1981** (.079)	-.0415 (.028)
Ln(Period)	-.0227** (.009)	.1781* (.047)	-.0207*** (.011)
Ln(Final Round)	.0380*** (.022)	-.3989* (.111)	.1114* (.028)
G1	-.0179 (.019)	-.5380* (.096)	.0039 (.023)
G2	.0201 (.017)	-.7717* (.086)	.1702* (.021)
G3	-.0011 (.016)	-.5137 * (.081)	.0766* (.019)
Number of observations		141	
Number of groups		12	
Panel Variable		Session	

*** Represents estimate is significant at 10%, ** represents estimate is significant at 5%, * represents estimate is significant at 1%

Table 6: Estimates (Standard Error) for Average Markup for Final Round

	Dependent Variable : Markup over costs in Final Round of Period
Dummy	.061** (0.163)
Winner	0.179* (0.018)
Learning (1/Period)	-0.094** (0.038)
Final Round	-0.017* (.004)
G1	-0.055*** (0.026)
G2	-0.156* (.023)
G3	-0.115* (0.022)
Constant	0.324* (0.036)
Number of Observation	846
Number of Groups	72
Unit of Observation	Individual Subject

*** Represents estimate is significant at 10%, ** represents estimate is significant at 5%, * represents estimate is significant at 1%

Table 7: Frequency table for non-zero bid reductions by previous winning status and information treatment*

	SCORE	NO-SCORE	Total
Won at past date	281(1257)	153(1213)	334(2470)
Lost at past date	1413(1587)	2166(1397)	2679(2984)
Total	1694(2844)	1419(2610)	3113(5454)

*Figures in brackets indicate total number of observations under each category

Table 8: Estimates (Standard Error) for Bid Reductions for all Dates

	Dependent Variable : Bid reduction at a Date
Winning Status from Previous Date	32.089* (0.824)
Winning Neighbors from Previous Date	1.285** (0.587)
Dummy	-3.784** (1.856)
Learning (1/Date)	-54.843* (8.552)
G2	-15.865* (2.676)
G3	-15.837* (2.557)
G4	-17.624* (2.639)
Time2	5.009* (1.725)
Time3	-14.005* (2.401)
Time4	0.772 (1.575)
Time6	0.784 (1.575)
Time7	-1.301 (1.517)
Time9	-19.126* (2.622)
Time11	-3.294** (1.566)
Time12	1.051 (1.657)
Constant	9.422* (2.92)
Number of Observation	5454
Number of Groups	72
Unit of Observation	Individual Subject

** Represents estimate is significant at 5%, * represents estimate is significant at 1%

++Some Period Dummies have been removed with the inclusion of G2, G3 and G4 owing to multi-colinearity

Figure 5-1 Average Cost Efficiency by Period

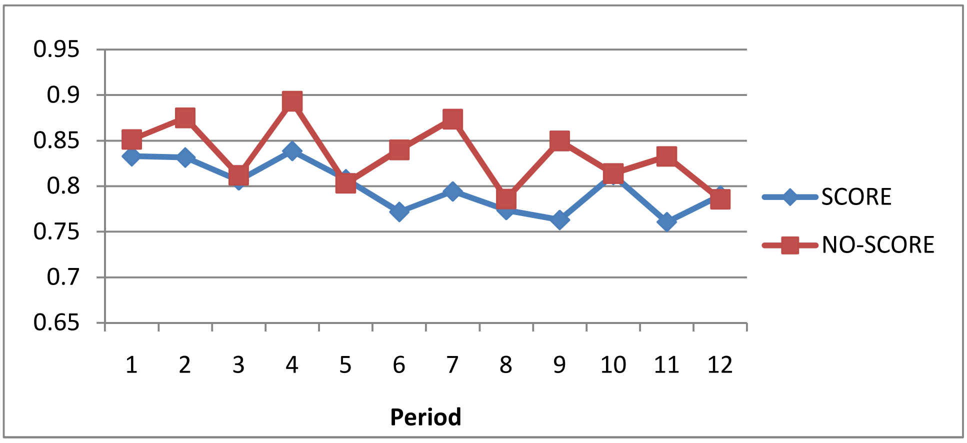

Figure 5-2 Average Markup by Periods

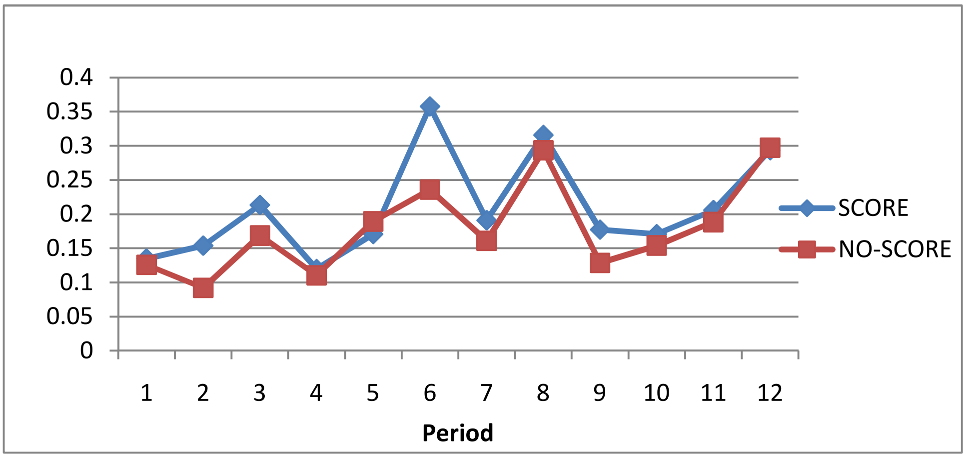

Figure 5-3 Average Ecological Effectiveness by Period

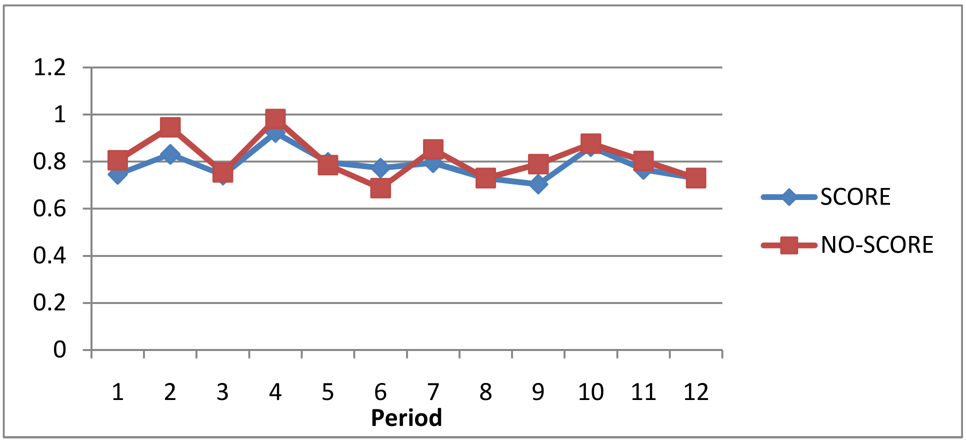

Figure 4 Markup in Final Round