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Stirling Economics Discussion Paper 2011-19

December 2011

Online at

http://www.management.stir.ac.uk/research/economics/working-papers

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

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This version: October 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 as well as during the entire lifetime of the auction. Winners and losers are found to have significantly different behavior in this analysis. Behavior is also found to be significantly affected by the treatments as well.

Key Words: Conservation Auctions, experiments Ecosystem Services, Spatial Contiguity

JEL: C72, C73, C91, C92, L14, Q57,

Section 1: Introduction

Conservation friendly land uses on agricultural landscapes can deliver a variety of ecosystem services such as habitat and biodiversity protection benefits. However as most agricultural land is privately owned,[1]farmers will require financial compensation to implement the land use changes. Payment for Ecosystem Services (PES) schemes has come to be routinely implemented by government agencies to disburse funds to enable these changes. Besides this ecological objective, cost-effectiveness of PES schemes is also an important objective as well since conservation budgets are capped. Additionally the regulator does not possess complete information about the magnitude of the costs farmers have to incur and for which they will require payments. Thus auctions have become prevalent in the market for pro-conservation land uses between farmers and the regulator for ecosystem services delivery. Notable of these auction based PES schemes is the Conservation Reserve Program (CRP) in the US (Kirwan et al. 2005). Since 1985, the CRP has disbursed nearly $26 billion (Kirwan et al. 2005) to preserve approximately 1.8 million acres of wetlands and retire 36.8 million acres of farmland to reduce soil erosion. Bids in the CRP auction represent the compensation farmers are willing to accept to change existing land uses to pro-ecosystem services ones. These bids are evaluated and ranked in descending order on the basis of a benefit-cost scoring metric termed the Environmental Benefit Index (EBI). Then starting from the top, bids with the highest scores are selected and funds are disbursed till the program budget is exhausted. Given the structure of the scoring metric, every participant landowners finds it in their best interest to submit bids closer to their costs to improve their chances of winning. Thus in theory, the auction is cost revealing and improves the costs efficiency of the PES scheme. The structure of the CRP has been adopted by conservation

[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).

agencies in Australia under the Bush Tender pilot (Stoneham et al. 2003) and the Auction for Landscape Recovery pilot (Gole et al. 2005).

A key aspect of conservation procurement that has received limited attention is that conservation friendly land uses often deliver greater biodiversity and habitat protection benefits (Willis 1979, Bartelt et al. 2010) if they are located on spatially adjacent properties with connections between them (Margules and Pressey 2000). One approach to spatially aligning land uses across multiple private properties is the Agglomeration Bonus (AB) subsidy proposed by Parkhurst and Shogren (2002, 2007). By rewarding similar land uses on adjacent parcels, the AB provides economic incentives for the creation of non-fragmented land use patterns on the landscape. However being a uniform payment scheme, AB based policies will not be cost effective. The extant CRP auction has not given attention to the spatial objective as well. This policy gap has initiated research on auctions which target the spatial goal (Rolfe et al. 2005 and Reeson et al. 2010). These studies involve experimental analyses of various auction formats which are explicitly designed to cost-efficiently select spatially adjacent bids. Rolfe et al. consider artefactual field experiments with Australian landowners using iterative and sealed bid auctions. The iterative format incorporates limited information feedback about auction results between iterations and a bid revision rule. Under the sealed bid format subjects bid after communicating with each other. Their experimental data suggests that the iterative format is more cost efficient than the sealed bid one as communication prior to bid submission exacerbates rent seeking. This result lines up with anecdotal evidence on cost savings to the tone of nearly $820,000 in Fiscal Year 2006 through a two-round auction pilot under the Wetland Reserve Program (USDA 2009). Reeson et al. (2010) consider a lab study on an iterative auction with limited information feedback about auction results as well. They analyze the impact of a bid revision rule and presence of the information about the maximum number of iterations on rent seeking. Their experiments suggest that absence of bid revision possibilities and the presence of information about the maximum number of rounds have a positive impact on auction efficiency.

In this paper, we adopt a similar research agenda. We examine the economic performance of an iterative auction in purchasing pro-conservation land use on spatially adjacent projects in a laboratory environment. Our conservation auction considers a full information feedback about auction results at the end of every iteration to all agents who are arranged in a circle with two neighbors each. We also modify the scoring metric to incorporate the spatial objective into the bid selection process. Given the experimental environment we are able to evaluate the impact of changing the information available to an agent during the experiment on auction performance and bidding. We introduce this information treatment by notifying subjects in few sessions about the format of the scoring metric which reflects an improved likelihood of selection if one or both of a subject's neighbors are selected. Besides evaluating auction performance, we present an analysis of bidding behavior during the entire lifetime of the auction as well as at the final allocation where the auction terminates. Our analysis indicates that information and sustained experience with bidding has a negative impact on the economic performance of the conservation auction. We also find significant behavioral differences between winning and losing bidders both during the auction and at the end of the same. We elaborate on these results below.

Section 2:The Conservation Auction

Let $I = \{1,2, \ldots N\}$ 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 the conservation projects. 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 $b = (b_1, \ldots. b_N)$ 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 winner 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 from the projects and the benefits generated when any two spatially adjacent properties are placed in the conservation program. Let vector $v = (v_1 \ldots v_N)$ represent the intrinsic benefits and constant ω represent the benefits from selecting projects adjacent to each other. Then depending upon the type of spatial arrangement of projects we obtain different formulations for the environmental value function. For this study we consider projects arranged around a circle so that the value function can be represented as

$$V(x) = \sum_{i=1}^{N} x_i v_i + \omega\left(\sum_{i=1}^{N-1} x_i x_{i+1} + x_N x_1\right) \qquad (1)$$

We consider an iterative auction model where $t = 1,2, \ldots \ldots T$ represents the rounds and T the maximum possible rounds or iterations. In each round t, bidders submit a single bid. The auctioneer then selects the provisionally winning allocation x_t^* on the basis of a scoring metric that has a benefit cost format similar to the EBI. This metric evaluates combinations of projects where the benefit of every individual project is the sum of intrinsic and spatial benefit if neighboring projects are selected. Any project has a higher score and greater likelihood of selection if its neighbors have been selected. The format of the metric for the i^{th} bidder is given by expression (2) as

$$Score = \frac{v_i x_i + \omega x_i (x_{i+1} + x_{i-1})}{b_i} \qquad (2)$$

The optimization problem to select a value of x_t given the fixed budget M for players arranged around a circular landscape is then the following

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

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

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 bids until x_t^* is obtained. In this optimization exercise, bids for spatially adjacent projects receive a higher score and hence have a greater likelihood of selection. Once x_t^* is determined it is announced to the bidders and the auction proceeds to round $(t+1)$ where the optimization exercise is repeated and $x_{(t+1)}^*$is determined. This process continues till one or both of the following stopping rules are satisfied.

1. $\bar{t} \leq t \leq T$ where $\bar{t}$ represents the minimum number of rounds.
2. Value of the objective function is same between consecutive rounds.

Condition 1 implies that the auction has to go through a minimum of $\bar{t}$ iterations before ending in order to ensure that bidders understand how to bid. Condition II signifies that for a round t to be final, the winning score between rounds t and $(t-1)$ should be equal. If this is not the case, then the auction proceeds to the next round. The second condition ensures that subjects don't try to prematurely end the auction by submitting a high bid that increases the score. If this were to happen, then losing bidders would lower their bids in the next round to and increase the score associated with the winning allocation so that the auction would be extended by another round. If for any round $\bar{t} \leq t < T$ the above conditions hold then the auction ends. Else the auction repeats through all the T rounds. In our auction, the activity rule[2] 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.

The presence of a budget constraint and absence of set number of projects to be procured makes the strategic environment and Nash equilibria of a conservation auction different from standard procurement auctions. Outlining the features of the Nash equilibrium are important. We however abstract from this traditional approach and employ the concept of stability of an equilibrium outcome to identify some theoretical features of winning and losing bidders at allocation that can be supported by the budget when the auction terminates. These features identify the scenario where bidders don't have incentive to change their behavior. Using them we select auction parameters for our experiments. A stable allocation x^* has the following properties.

i) $\forall i = 1,2, \dots N$ such that $x_i^*(b^*, M) = 0, b_i^* = c$. This condition implies that for all participants who are not part of the winning group, bids are equal to costs. As a result they are unable to reduce their bids to improve their likelihood of winning any further.

[2] In iterative auctions, often participants may only observe the outcome for the first few rounds without bidding 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 gaming situation by forcing all bidders to bid in a round to preserve their eligibility to bid in future rounds 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).

ii) $\forall i = 1,2, \ldots N$ such that $x_i^*(b^*, M) = 1,\ b_i^* \geq c_i$ and $\forall\ b_i' > b_i^*, x_i^*(b', M) = 0$ where $b' = (b_i', b_{-i}^*)$. This condition signifies 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 may cause them to be not selected in the next round.

Section 3: Experimental Design

We devote this section to the description of different aspects of our experimental design. This includes a discussion on our information treatment, the metrics to evaluate auction performance and choice of auction parameters. We conclude this section with a description of the experimental procedures.

Section 3.1: The Information Treatment

In this article, we are interested in identifying key features of the strategic environment which can influence auction efficiency. One such feature is the information content of the auction. The experimental method provides us the opportunity to pursue this goal. We implement the information treatment by notifying subjects in some sessions about the spatial objective of the auctioneer while suppressing this information in other sessions. Our rational for this treatment choice is that conservation auctions are typically large government run auctions with many participants where transparency of auction goals may be a key political requirement. Moreover inclusion of a spatial objective may contribute to cognitive complexity of farmers who are the major participants in these auctions. Hence making more information available to the participants may be an effective way of achieving the ecological objective. Yet the study on an iterative conservation auction by Cason et al.

(2003) finds that higher information content of the strategic environment reduces both economic and ecological performance. They find that when subjects know the value of the environmental benefits associated with their projects, rent seeking is intensified and both the economic and ecological performance of the auction relative to the baseline no-information scenario is reduced. Thus there is a trade-off between information revelation and auction performance. In this paper we investigate whether the negative impact of information is a phenomenon endemic to iterative conservation auctions. We implement our information treatment differently from Cason et al. In our treatment sessions termed SCORE subjects receive information about the format of the scoring metric given in expression (2) which declares the spatial target.[3] This information is suppressed in the baseline sessions termed NO-SCORE. The bits of information common to subjects in all sessions include knowledge about their own costs, the total budget and total number of participants in the session. . In keeping with the transparency objective, we include full information feedback about auction results at the end of every round of the auction. The feedback information includes the identity of winners, the value of the projects' scores and submitted bids.

Section 3.2: Auction Performance Metrics

Our auction performance metrics are similar to those developed in Cason et al. (2003) and measures both the economic efficiency and ecological effectiveness of the iterative spatial auction. These metrics are constructed on the basis of the allocation that would be chosen in the absence of asymmetric information when bids equal cost. Let this allocation be denoted by x^{max}. Given this reference point, the ecological effectiveness (EE) of the auction

[3]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.

at a stable allocation x^* is measured as the ratio of environmental benefits from x^* and x^{max}. Using expression (1) we can define EE as

$$EE(x^*; x^{max}) = \frac{V(x^*)}{V(x^{max})} \qquad (4)$$

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 achieve the ecological objective in the presence of asymmetric information 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 the ecologically effective outcome is possible even if bids are greater than costs. In this case however conservation procurement is costlier implying lower economic efficiency. Since the EE metric does not capture this economic scenario we use the economic cost efficiency metric (CE) to measure economic performance. The CE metric measures the outlay corresponding to x^* relative to that for x^{max} . This 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

$$CE(x^*; x^{max}) = \frac{\dfrac{\sum_{i=1}^{N-1}\left(v_i x_i^* + \omega x_i^* x_{(i+1)}^*\right) + v_N x_N^* + \omega x_N^* x_1^*}{\sum_{i=1}^{N} b_i^* x_i^*}}{\dfrac{\sum_{i=1}^{N-1}(v_i x_i^{max} + \omega x_i^{max} x_{i+1}^{max}) + v_N x_N^{max} + \omega x_N^{max} x_1^{max}}{\sum_{i=1}^{N} \theta_i x_i^{max}}} \qquad (5)$$

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 submitted bids equal costs and the auction is cost efficient.[4] Finally we also measure seller profits or the total Information Rents. This metric captures the degree of competition since inter-bidder competition reduces the value of bids submitted and final rents. The metric is represented as

$$Rents = \sum_{i=1}^{N}(b_i^* - c_i)x_i^* \qquad (6)$$

Section 3.3: Choice of Experimental Parameters in the Auction

We used four sets of cost-benefit parameters for the twelve periods in the auction. We assigned parameters to the periods on an ad-hoc basis to prevent ordering effects and to ensure that subjects had the chance of winning at least three times if the actual winning allocations coincided with the stable allocations considered while choosing the parameters. We chose the parameters such that under each group candidate stable allocations x^* corresponded to different performance values and spatial configurations and that the full information allocation x^{max} pertained to a variable number of projects. Let G1 represent parameter set 1 and G2 the set 2 so on and so forth. Then for G1, G3 and G4, the full information allocation comprised of four projects and for G2, the number was three. Considering the candidate stable allocations, under G1 and G4, four adjacent projects could form the stable solution; for G2, the number is three with two adjacent and one isolated project and finally under G3 three of the four selected projects could be adjacent to each other. We used 350 experimental dollars as the auction budget in all the periods. The value of ω was fixed at 50. Table 1 represents the parameters used for the experiment.

[44] We note that the value of CE can be greater than 1. This may happen when the bids not selected are very high and the budget is insufficient to procure more projects. If the auction ends then a lot of money remains with too little conservation procured. This scenario represents a highly inefficient outcome.

INSERT TABLE 1&2 HERE

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 $7. The exchange rate to convert experimental dollars earned during the session to actual dollars was 1 US$ for 15 experimental dollars. Neutral terminology was used in the instructions. The term QUALITY was used to refer to the environmental value and the term ITEM was used to denote a land management project. Twelve experimental sessions were conducted with the 6 subjects across the computerized interface programmed in Z-Tree (Fischbacher 2007). All the twelve paying periods had a minimum of 5 and a maximum of 10 rounds. 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. Table 2 represents our experimental design.

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[5]. In addition as mentioned, 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

[5] Screenshots of the computerized experiment and instructions are provided in the Appendix.

(Fischbacher 2007). Subjects could decrease bids by at least 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 bidding behavior at the individual level. The auction performance analysis indicates the negative impact of increased information on the economic performance of the auction. 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 we also present an analysis of bidding behavior during the lifetime of the auction.

Section 4.1: Analysis of Market Performance

We analyze the auction performance with data from the final round (the binding round) of every period.[6] Figures 1-3 represent the average inter-temporal values of metrics across all sessions by treatment. The figures indicate that the value of CE is greater for the 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 as well. However we see no significant difference in EE across the treatment. Additionally we observe a

[6]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.

negative impact of bidder experience on economic performance (both in terms of CE and rents).

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 payments made in different periods are different, we use the log of total rents in a session as the dependent variable in the analysis. Both the log of total rents and CE metric can have values greater than one. Thus we consider a random effects model to analyze the two economic efficiency metrics. However, EE cannot have a value greater than 1 by construction so that the ecological effectiveness of the auction is analyzed by a random effects tobit model specification. 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 explain part of the variation in auction performance. We conjecture that when subjects know that neighbors' selections influence their own likelihood of selection in x_t, they will be able to use this location based information and the knowledge of provisional auction outcome (available to them via full information feedback) to submit bids which improve both their chances of being included in x^* and earn higher rents. 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 inter-temporal rent seeking. 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 to capture the impact of the iterative format on performance. Since we are considering a descending price auction the estimate for Round will be negative. Finally, since we chose the cost-benefit parameters to obtain different metric values at the candidate stable solutions, we expect the dummy variable estimates for the different parameter groups to be significantly different relative to the omitted category.

The regression equation for this analysis is

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

$$(i = 1,2, \ldots \ldots .12; t = 1,2, \ldots \ldots 12) \tag{7}$$

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. Group 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 relative to those which can be obtained under the other categories. 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 3 HERE

Table 3 presents the regression results for the three metrics. As conjectured, the estimate for the information treatment dummy is negative and significant in the CE (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). Thus we conclude that increased transparency in the current conservation auction only serves to reduce the economic performance of the mechanism without any significant impact on ecological effectiveness. This result provides support for careful consideration of the nature of information to be revealed to participants in large public conservation auctions which function under budget caps.

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 analysis represents the reduction in economic performance over time. This adverse impact of experience has policy significance since conservation agencies repeat these auctions over multiple years. For example the 41st signup (repetition) of the CRP was implemented in months of March and April of 2011 (USDA 2011). Given this repetition induced familiarity in the auction, participants can learn to submit higher bids and potentially earn greater rents in future signups. Such experience induced rent seeking has in fact been observed under the CRP where in later signups landholders were found to be submitting bids near the bid cap – the maximum reserve price for a project in an area (Kirwan et al. 2005). Thus conservation value procurement gets costly over time. The positive and significant (at 1%) estimate for Log of Period in the rents regression has a similar interpretation. The effect is however inelastic given the iterative descending price nature of the auction whereby rents fall across rounds. Experience is also found to have a negative and significant (at 10%) impact on EE i.e. the auctions capacity to procure ecosystem services. The negative impact of learning is by no means specific to conservation auctions. However the pervasiveness of this impact in the current domain regardless of auction features underscores the need for innovative auction design to reduce this experience induced rent seeking and reduction in efficiency.

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 as is to be expected given the decreasing price format. Similar results have been obtained by Rolfe et al. (2009) in a multi-round iterative auction for rangeland management in Australia. 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 4 HERE

We obtain positive and significant estimates for G2 and G3 for the EE model implying that environmental performance under these groups is significantly better than under G4. However we find no significant difference in EE between G4 and G1 Table 4 summarizes the actual values of the metrics from the experiment along with the values at the candidate stable allocation used to choose the parameters. We see that there is no significant different in the actual mean EE values between G1 and G4 (nearly 0.75). Mean values of the EE metric are however greater under both G2 and G3 relative to G4 all else constant. The differences in the mean of actual rents in Table 4 suggest significantly different degrees of rent seeking between parameter groups. The negative and significant dummy estimates in the rents regression substantiate this result with rents earned under all parameter categories lower relative to that under G4. Finally no significant differences emerge in CE between groups relative to G4. This result implies that there is no significant difference in the costs of a unit of conservation values under different parameter groups relative to the omitted category. This result is also supported by the mean values of CE between 0.81 and 0.84 for all groups in the sessions.

Section 4.2: Analysis of Bidding at Final Auction Allocation

In Section 2 we have identified the theoretical features of the winning and losing bidders at a stable allocation where the auction ends. The main differentiating feature between winners and losers is the deviation of their bids from costs. Table 4 also indicates that there is not a very big gap between the means of the actual EE and CE values and those at the candidate stable allocation the candidate ones used to choose the auction parameters. Thus we can conjecture that subject behavior at the final allocations in the experiments is consistent with the properties of the stable allocation. In order to formalize this conjecture, we analyze bid data from the final round of each auction period in a random effects instrumental variable model. Our main thesis here is to examine whether the theoretical difference between winning and losing bidders has a counterpart in the experimental data. 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 control for whether a subject was part of the winning allocation or not in the period (we term this variable Winner), agent learning (captured by the reciprocal of the Period variable), variation in information content and cost-benefit parameters, and Round values for every period to explain the variation in the markup data.[7] The regression equation is represented as

$$y_{it} = \propto + D + G1 + G2 + G3 + \beta(\frac{1}{t}) + \delta R_t + W_{it} + u_i + \varepsilon_{it}$$

$$(i = 1,2, \ldots \ldots .72; t = 1,2, \ldots \ldots 12; N = 846) \quad (8)$$

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%). Of interest to us is the positive and significant estimate (at 1%) for the Winner variable indicating that winners' markups are significantly higher than the losing bidders' markups. Thus winners' bids are further away from their costs than those of the losing bidders. This indicates significant behavioral differences between winning and losing bidders at an actual auction outcome in adherence with the theoretical features of the stable allocation. This result is informative for a discussion on the properties of the Nash equilibria of the conservation auction. Characterizing the features of an auction outcome on the basis of stability feature of Nash equilibrium outcomes is second best and does not guarantee that the actual outcome is a Nash equilibrium. However the close correspondence

[7] 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 introduces endogeneity into the regression analysis. Thus we use the value of the winner variable from the preceding 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 for all periods is approximately 0.82 justifying the use of this instrument.

between the theoretical and actual behavior of agents at the final allocation indicates that this final allocation and a Nash equilibrium allocation are rightfully aligned.

We also obtain a positive and significant (at 5%) estimate for the treatment dummy implying 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 in periods under these groups are 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 as represented in Table 4.

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. With greater experience bidders place higher bids and retain more 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 as well. 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: Bidding Behavior across Multiple Iterations

In this section we present an analysis of bidding behavior during the lifetime of the experimental auction. An interesting feature of iterative auctions is jump bidding. Jump bidding entails winning bidders in a round submitting bids in excess of the minimum bid decrement in subsequent rounds. Such jump bidding prolongs auctions and reduces the rents earned by jump bidders if they win. According to Isaac et al. (2007) bidders despite winning practice such jump bidding early on in the auction and/or persistently from beginning till the end, to maintain their competitiveness in the auction even though this might cause them to lose some rent. Their theoretical model predicts that the small jumps allow bidders to move up to a winning bidding trajectory and stay there such that they can finally win the auction by defeating competitors. We use the experimental data from the conservation auction sessions to examine the bid decrements across consecutive time periods to identify the prevalence of jump bidding.

For this analysis we compute a composite period-round variable termed date. Table 6 presents a summary of the bid decrement data for the 72 subjects for all auction dates. We classify this data by the information treatment and the winning or losing status of the bidder from the previous date. We term the absolute value of the decrement at a date as the jump from the previous date. Table 6 presents the jump data. For $N = 5454$, there are a total of 3113 instances of bid reductions. Of these observations there are 334 instances (for SCORE and NO-SCORE sessions) where subjects reduced their bids even if they won in the previous date. These 334 instances of bid reductions correspond to jump bidding behavior in our auction.

INSERT TABLE 6 HERE

In order to examine whether the jumps are endemic to our budget constrained conservation auction, we consider a random effects tobit analysis with jump variable as the dependent variable[8]. We conjecture that the number of neighbors selected in the previous

[8] For the analysis we drop the jump observation for the date corresponding to the first round of a new period. This is because a new period corresponds to different parameters and hence a different set of bids which are unrelated to the bids submitted at the previous date which corresponds to the final round of the previous period. In addition we drop 3 observations which recorded positive jump values owing to software error. These observations corresponded to the penultimate round in Period 9 for subjects 61, 62, and 63.To maintain consistency and avoid holes in the data set we removed the observations for the next date as well.

date, winning status of the player from the previous date, whether the subject had information about the format of the scoring metric and the experience with bidding explains the variation in the value of the jumps. We also include the parameter dummies to incorporate possible impacts of our secondary within treatment. The regression expression is represented as

$$y_{id} = \propto + W_{i(d-1)} + \delta N_{d-1} + \beta d + D + G2 + G3 + G4 + P[dummies] + u_i + \varepsilon_{id}$$

$$(i = 1,2, \ldots \ldots .72; d = 1,2, \ldots \ldots 100; N = 5448) \tag{9}$$

Here d is used to represent the date variable which is also the time variable for our unbalanced panel with a maximum size of 100. We include the date variable to pick up the impact of experience on jump values and the Period dummies to capture any effect at the overall Period level[9].

INSERT TABLE 7 HERE

Table 7 presents the results of this analysis. The constant term is positive and significant (at 1%). We obtain a negative and significant estimate (at 1%) for the winning status of the individual, $W_{i(d-1)}$ from the previous date. Thus holding other variables fixed the subject who won in the preceding date implements a smaller decrement than those who lost in the preceding date. Thus in our auction, in the majority of cases, bid reducing tendencies correspond to losing bidders reducing their bids to win in the next date rather than winning bidders reducing bids to maintain their winning positions till the auction terminates. This estimate for the date variable is negative and significant (at 1%). One of the reasons for jump bidding as the auction proceeds is to maintain competitiveness. However over time

[9] In the analysis owing to inclusion of the parameter dummies, three period dummies are dropped due to multi-colinearity.

familiarity with bidding enables bidders to assess their competitive positions in the auction. Given this familiarity, bidders don't have to implement jumps or they can reduce the value of the jumps in the future and still maintain their likelihood of winning. The estimate for the information dummy is positive and significant (at 1%) suggesting that relative to those in the NO-SCORE sessions, subjects lower their bids by a greater amount in the SCORE sessions. In the SCORE sessions, subjects are aware of the importance of neighbors' selections on their own likelihood of winning. Thus relative to NO-SCORE bidders who don't have this information, they implement greater bid reductions to enhance or maintain their competitive positions and likelihood of selection. The estimate for the number of winning neighbors from the previous date is negative and significant (at 10%). Since neighbors' selection improves a subject's likelihood of selection, greater the number of selected neighbors lower would be the bid decrement a subject would implement in the next date. This result seems contradictory to our previous explanation regarding the positive information dummy estimate. However we note that the observation of the number of winning neighbors from the past date establishes the *actual* competitiveness of a bidder in being selected in the next date. This actual competitiveness is different from the competitiveness a bidder *perceives* to have from knowing that their neighbors' selections play a positive role on their own likelihood of selection. Finally the positive and significant (at 1%) estimates for G2 through G4 implies that there are differences in bid reductions relative to the omitted group – G1. The positive signs indicate that relative to G1, greater bid decrements are affected at dates corresponding to the remaining parameter categories.

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.

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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 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 to be played	5	5
Payment structure	$7 show up fee Exchange rate – 15 experimental dollars for every US $	

Table 3 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 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: 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 6: 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 7: Estimates (Standard Error) for Bid Reductions for all Dates

	Dependent Variable : Bid reduction at a Date
Winning Status from Previous Date	-31.96* (0.82)
Winning Neighbors from Previous Date	-1.05** (0.58)
Dummy	6.66* (2.18)
Experience	-0.51* (0.08)
G2	38.25* (6.01)
G3	19.05* (3.01)
G4	32.26* (4.78)
Time2	-32.39* (5.32)
Time3	10.28* (2.00)
Time4	-23.55* (4.19)
Time6	-8.58* (2.04)
Time7	8.62* (1.97)
Time9	37.31* (5.32)
Time11	26.08* (4.12)
Time12	13.55* (2.93)
Constant	4.91 (1.94)
Number of Observation	5448
Number of Groups	72
Unit of Observation	Individual Subject

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

Figure 1 Average Cost Efficiency by Period

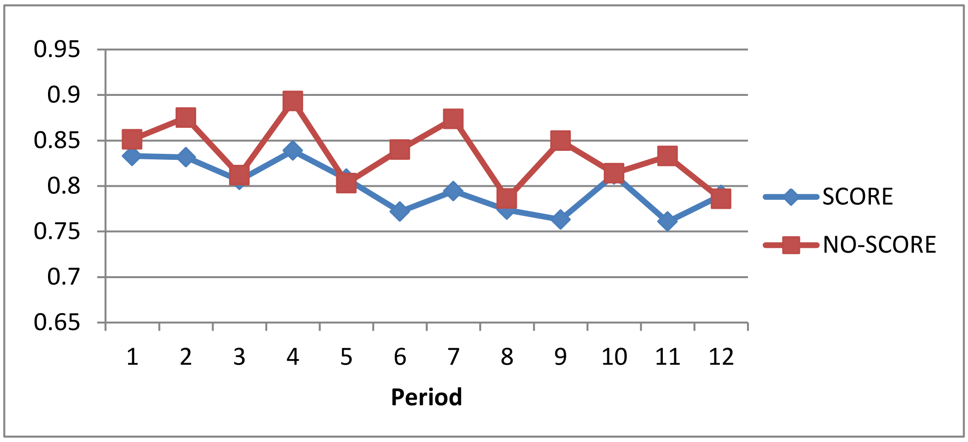

Figure 2 Average Log Rents by Period

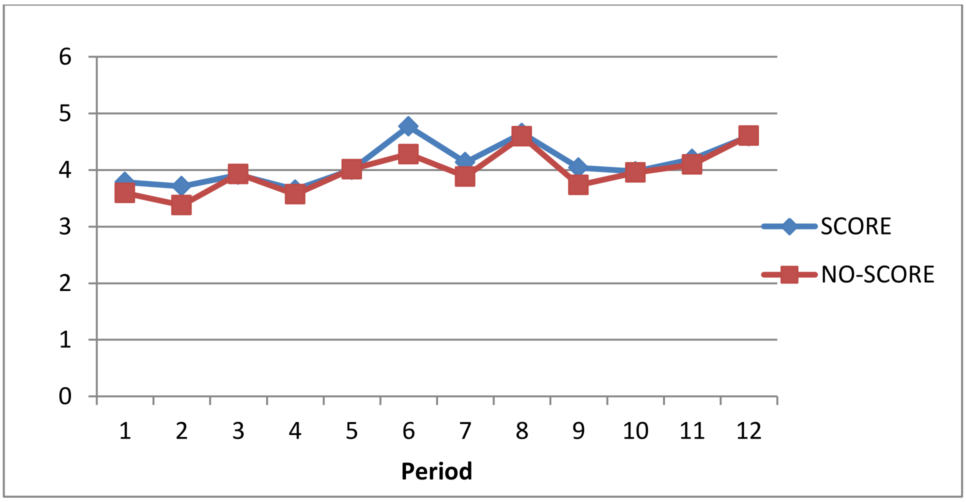

Figure 3 Average Ecological Effectiveness by Period

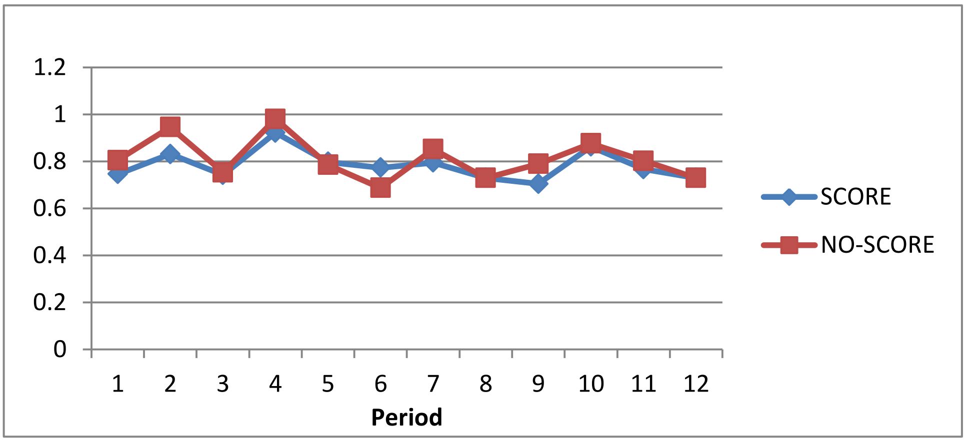

Figure 4 Markup in Final Round