Coalitions, Competition, and Conservation: Spatial Procurement Auction Design and Performance

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Abstract: One objective of payment-for-ecosystem services programs that utilize procurement auctions to allocate payments is to motivate bids from producers who implement similar conservation practices and are located spatially adjacent to each other. This spatial coordination of winners is beneficial for enhanced production of many ecosystem services and biodiversity conservation. In this paper, we introduce a model of bidder behavior in a spatial procurement auction, which offers a bonus payment and quality premium to bids that are part of a coalition of adjacent bidders, to motivate a laboratory experiment in which participants submit bids in auctions under different information, communication, and landscape treatments. We find that auction design leads to different impacts on auction performance and bidder behavior based on the landscape type in which the auction is conducted. Whether due to excessive rent-seeking or the challenges of coordination among large coalitions, auction performance in a landscape with a single large coalition is shown to lag behind that of landscapes in which there are multiple, smaller coalitions.

Preliminary Draft, Please Do Not Distribute

Section 1: Introduction

Agricultural landscapes can deliver a wide variety of ecosystem services through adoption of pro-conservation land use practices on the properties of agricultural producers. Conservation auctions have been implemented by government agencies in different countries as part of various Payment for Ecosystem Services Schemes (PES) to select producers who would implement these practices and to elicit the payments required for doing so. Given the challenge of valuing the benefits of non-market ecosystem services by resource- and time-constrained government agencies, the main objective of auction implementation is to ensure selection of PES participants who can deliver the environmental benefits in a cost-effective fashion. This cost-effectiveness is achieved with auction implementation by introducing competition into the bid-submission process to restrict the bidders' requests for the total compensation they are willing to accept to implement a conservation practice. Examples of such auction based policies include the Conservation Reserve Program (CRP) in the US, the Higher Level Stewardship Scheme in the UK and numerous field programs such as the Bush Tender Trial in Australia, to name a few.

In addition to the cost-effectiveness goal, researchers have explored the extent to which these incentive mechanisms can be used to achieve various ecological objectives which would significantly enhance the benefits of from conservation practice adoption. One such objective is how to select bids from producers who implement similar practices and who are located spatially adjacent to each other i.e. are neighbors and/or are within a given distance from each other on the landscape. This spatial coordination of winners is beneficial for enhanced production of many ecosystem services such as water quality improvements, conservation of target species and wetland and in general habitat restoration. Work by Banerjee et al, (2015) and Crawczyk et al.,

(2016) to mention a few have focused on conservation auctions that explicit consider spatial coordinated project selection as a goal of the action.

Given this context, in the current paper we present the structure of a spatial conservation auction and evaluate the performance of the auction and individual behavior using results obtained from controlled laboratory experiments. Our auction incorporates an agglomeration bonus component (Parkhurst and Shogren 2007, Banerjee 2017), whereby bids for the same practices from neighboring producers have a higher chance of being selected in the auction, because coordinated, aggregated adoption of the same conservation practices generates additional benefits that accrue non-linearly. Past research by Banerjee and Conte (2018) has indicated the overall complexities associated with the bid-submission process in aspatial conservation procurement auctions. These complexities are expected to be further magnified in spatial conservation auctions. Some of this complexity is due to the fact that bidders face a choice of several available conservation practices (e.g., riparian buffer, cover crops, pollinator and other animal foraging patches etc.) before submitting an offered price for the conservation practice (Conte and Griffin 2017). In keeping with the findings of Conte and Griffin (2017) and Banerjee at Conte (2018), we evaluate auction performance and bidder behavior by varying to key auction design features in ways meant to explore the tradeoffs between efforts to alleviate bidding complexity in the auction and concerns of facilitating additional rent-seeking and collusive bidding. These alternative design features are implemented as between-subject treatments in the laboratory experiments.

The first design feature is the manner in which information about environmental benefits of different land use practices is provided to program participants. We consider three alternatives with regard to environmental benefit information: a baseline setting in which no environmental benefit information is provided to bidders; a second treatment in which absolute benefit information is provided for the different practices; and, finally, a third scenario in which benefit information about a bidder's available conservation practices is provided as a ranking of the quality of their available practices. The second design feature is the extent to which communication between bidders is allowed during the bidding process. With this feature, we consider bidder behavior and auction performance in the presence or absence of communication opportunities between bidders and their geographical neighbors. Understanding the response to communication opportunities is critical in the spatial context, because, auctions are adopted in the context of asymmetric information to induce competition in a way to reduce the advantages of this information asymmetry. But in the case of a spatial conservation procurement auction there is an advantage to society of fostering coordination in order to achieve spatially-aggregated coalitions of bidders offering to adopt the same conservation practice if selected in the auction. Additionally, communication may alleviate bidding complexity, leading to the submission of more cost-effective bids. Managing the tradeoffs between possibly increased collusive bidding by allowing bidders to communicate and the increase in coordinated, and therefore, beneficial bidding, is a key objective of government agencies aiming to increase the cost-effectiveness of auction-based PES programs around the world. In the absence of prior information about whether the positive or negative effects of information provision and communication will dominate, the results of our inquiry should be a meaningful contribution to the conservation auction design literature.

In addition to the above mentioned aspects of our auction, we pay attention to the nature of the spatial configurations targeted by the auction. Spatial targeting and creation of specific configurations of land use practices on geographical landscapes has long been a subject matter of conservation biology, reserve design for species conservation (Diamond 1975; May 1975) and ecosystem services provision research. The SLOSS debate in conservation biology considers the relative merits of aggregating conserved habitat in a Single Large contiguous area, which minimizes edge effects, versus Several Small reserves, which allows for greater resilience of the targeted habitat in relation to climate change, disaster, and disease (Abele and Connor, 1979; Etienne and Heesterbeek, 2000). In fact, this spatial configuration issue relates to modern portfolio theory in finance, and a focus on the spatial distribution of conservation across the landscape is the focus of the emerging field of conservation finance.

In our experiments, we consider bidding behavior under three different spatial-configuration scenarios, each representing the spatial setting favored by the auctioneer with perfect information about the costs of conservation practice implementation. Specifically, we consider bidder behavior and auction performance in three different experimental landscapes: Single-Large, Several-Small and Asymmetric configurations that involve the creation of a single large coalition of bidders offering the same conservation practice; two smaller, but equal-sized, coalitions of bidders with the same conservation practice ; and two smaller, but unequal-sized, coalitions of bidders with the same conservation practice, respectively.

A focus on the spatial configuration of land use practices affords us the opportunity to link our findings to the conservation biology, conservation finance, ecosystem services, and natural reserve design literatures. Additionally, this focus presents the opportunity to systematically evaluate the bidding behavior of participants depending upon whether or not they are part of the coalition of winners that would be selected by the auctioneer in the absence of asymmetric conservation practice cost information. This analysis allows exploration of the manner in which bidders' location within the winning coalition and on the landscape has bearing on their bidding behavior and the implications of this behavior on auction performance. We believe this to be, a seemingly critical aspect of spatial PES program design that has been relatively neglected in the existing literature, to the best of our knowledge.

To guide our empirical analysis, we present a model of optimal bidding behavior in a conservation procurement auction that provides both a bonus payment and attached a quality premium for spatially-agglomerated conservation-practice coalitions. Modeling optimal bidding behavior in procurement auctions under conditions that reflect the realities of conditions on the ground is extremely challenging, especially when allowing for asymmetric bidders. To gain some insight into the expected outcomes of our various treatments, we proceed with the assumption that bidders make choices about the offered price to submit in their bid, conditional on conservation-practice choice, with an exogenously-determined bid cap. With this assumption in place, and a further functional form assumption about the distribution from which this bid cap is drawn, we utilize comparative statics to explore how changes in key parameters of interest (e.g., the bid cap, the coalition size, etc.) affect bidder behavior. These theoretical findings are tested using our observed behavior from the laboratory experiment sessions.

The empirical results in this paper stem from an initial comparison of the main treatments implemented in the experimental design with regard to both overall auction performance, as measured by the cost-effectiveness of auction conditional on the optimal provision with perfect information, and bidder behavior, as measured by the cost-effectiveness of the individual bid relative to the optimal bid available based on each bidder’s endowed conservation practices. Preliminary results indicate that the impact of the two information treatments on auction cost-effectiveness relative to when benefit information is unavailable depends on coalition type and communication opportunities. In the absence of communication opportunities, provision of ranked benefit information enhances auction performance in both the Single-Large and Asymmetric landscapes compared to the baseline of no information about environmental quality. However, when bidders have the opportunity to communicate with neighbors, provision of absolute benefit information enhances cost-effectiveness for the Several-Small and Asymmetric landscapes, while the ranked information treatment only improves auction cost-effectiveness in the Several-Small landscape. Generally, across all treatments and coalition types, repeated auction interaction is shown to increase cost-effectiveness, a finding that contrasts with existing results in the spatial conservation procurement auction literature. One explanation for this result is that item-selection is endogenous to the bid-formation process in our auctions, which is a realistic condition that has been abstracted from in many other studies on this issue. Finally, in the absence of benefit information, auction cost-effectiveness is significantly lower in the Single-Large landscape relative to the Several-Small and Asymmetric landscapes. This result is not unexpected, because the Single-Large landscape requires substantial coordination between bidders, which, if realized, results in more confidence in the desirability of bids from coalition members, allowing increased rent-seeking behavior by these bidders.

Focusing on individual bidder behavior, we find that the efficacy of the information and communication treatments is predicated on the nature of the landscape coalition and is different depending upon whether we consider the behavior of players who are part of the winning coalition in the absence of asymmetric information and those who are not.

Our paper proceeds as follows. In Section 2, we present a theoretical model of bidding behavior in the spatial auction. This is followed by a description of the experimental design and procedures, and econometric methods in Section 3. The results are presented in Section 4 followed by the conclusion in Section 5.

Section 2: Theoretical Model of Bidder Behavior

We generate predictions of bidder behavior in the presence of a payment-for-ecosystem-services (PES) program with an auction-based payment-allocation mechanism and a preferred spatial allocation of conservation practices by the procuring agency under the assumption that producers are utility-maximizing agents. We assume that producers will select for implementation, from the available conservation practices, the practice that maximizes expected utility from auction participation. With consideration of the spatial agglomeration of conservation, there is a tension between private and socially optimal item selection and the benefits of auction participation depend on the size of the conservation coalition generated by the bidders. The challenge for regulators is to design the auction in such a way as to facilitate submission of socially-preferable conservation practices without heightening rent-seeking behavior.

We further assume that, conditional on submitting a bid in the auction, producers choose the offer for conservation practice j , θ_j, to maximize the increase in expected utility relative to their *status quo* utility. Then, the bid-submission process for the producers includes a conservation practice selection phase followed by an offer formation phase. The producer's item-selection problem is given by

$$\arg\max_{j^*} E[u(j)] - u(0)$$

where $u(j)$ represents the utility associated with the bid for conservation practice j, chosen to maximize the expected utility of auction participation, and $u(0)$ represents *status quo* utility. The producer's offer-formation problem is given by

$$\max_{\theta_j} E\left[u\left(j, \theta_j\right)\right]$$

We define expected utility from a bid for conservation practice *j* in the following way

$$E\left[u\left(j,\theta_j\right)\right] = \sigma\left[m\left(\pi(j) - \pi(0) + E\left[B_j\right] + \theta_j\right) - \psi_2\left(\rho_j\right)\right] + [1-\sigma]m\pi(0) \quad (1)$$

Here, m is the marginal utility of income, j is the bidder's chosen conservation practice, ρ_j is a vector of non-price attributes of the PES program, and σ is the probability of offer acceptance. Conservation practice j will affect agricultural income π and conservation payments received by the producer conditional on acceptance in the auction, which include the expected payments for spatially-coordinated conservation ($E\left[B_j\right]$) and the offered price (θ_j). If there were no difference between the privately- and socially-optimal conservation practice, there would be no need for any such additional payments. Given the information asymmetry about the cost of conservation due to auctioneer uncertainty about producer behavior in the absence of the PES program, these additional payments will be made to all producers in the accepted coalition, whether or not there is a difference between the privately- and socially-optimal practice. The expected payments for spatially-coordinated conservation depend on the number of adjacent landowners engaging in the same conservation practice. So, $E\left[B_j\right]$ will be a function of the size of the spatial conservation coalition created by the producers. Disutility from PES program participation, $\psi_2\left(\rho_j\right)$, comprises the utility loss associated with program compliance once accepted into the program.

Bids in conservation procurement auctions have two attributes: environmental quality and offered price. To mitigate the challenge of evaluating bids on multiple attributes, conservation procurement auctions rely on scoring systems to evaluate bids. Here, we adapt the approach in Forster (2016), which is an expanded version of the model proposed in Glebe (2013). Allowing for bids of heterogeneous quality requires the use of a scoring metric that allows evaluation of both the requested price and the environmental benefits of the conservation practice. To evaluate these two-dimensional bids, we assume that the auctioneer ranks bids based on their score, which is defined as the offered price divided by the environmental benefit of the chosen conservation practice.

When the spatial pattern of conservation practices affects the benefits of conservation, the score is equal to the offered price, θ_j, divided by the aggregate environmental benefit, which comprises the benefits of practice j on the parcel, e_j, as well as the expected benefits of aggregated adoption of conservation practice j, $E[q_j]$[1]. Let β_j represent the bid-benefit score of a bid for conservation practice j, where $\beta_j = \frac{\theta_j}{e_j + E[q_j]}$.

Let $n = 1, \ldots, N$ index the number of bids submitted in the auction. The probability of the *nth* bid being accepted depends on how that bid, θ_j, compares to the other submitted bids. Expectations about bid acceptance depend on the producer's selected conservation practice and offered price, as well as her beliefs about the conservation practices and offered prices submitted by other auction participants.

In our base model, as in Forster (2016), we assume that bidders are certain of the environmental benefits that will be provided by a conservation practice implemented on their land, though we allow for the possibility that their beliefs of e_j are not equal to the true e_j associated with their selected conservation practice.

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[1] Previous research has commented on the reduced performance of conservation procurement auctions that fail to calculate the value of ecological benefits of conservation, meaning that outcomes are evaluated based on their cost-effectiveness, rather than their efficiency (e.g., Conte and Griffin 2019; Duke et al. 2013).

Bidders develop a perception of the probability of acceptance for bids associated with different available conservation practices based on an expectation of the maximum bid-benefit score, $\tilde{\beta}$ that will be accepted in the auction. We assume that this expectation is given exogenously.

Let $\bar{\beta}$ and $\underline{\beta}$ represent the expected upper and lower bounds of the maximum bid-benefit score. Let $f(\tilde{\beta})$ be the expected density function of $\tilde{\beta}$. We allow the perceived probability of acceptance for each available conservation practice, $\tilde{\sigma}$, to differ from the actual probability of acceptance, σ.

For a given β, determined by the aggregate environmental benefits and offered price of a given conservation practice, the expected probability that the bid will be accepted is given by

$$\tilde{\sigma} = P\left(\beta \le \tilde{\beta}\right) = 1 - F(\beta) \qquad (2)$$

Differential-price auctions with multiple accepted items are not incentive compatible, and bidders will attempt to use their information advantage to extract rent from the procuring agency in the form of offered prices that exceed the net cost of their submitted conservation practice $(\pi_0 - \pi_j)$. Bidders face a tradeoff in the choice of submitted bid for a given conservation practice, with higher prices increasing the profit earned conditional on offer acceptance, while simultaneously reducing the probability that the offer is accepted. Here, we see that $\frac{\partial \tilde{\sigma}}{\partial \theta} = \frac{\partial F(\beta)}{\partial \beta} \frac{\partial \beta}{\partial \theta} = -f(\beta) < 0$.

Producers will select the conservation practice that offers the greatest expected profit, which must be at least as great as their utility when no conservation practices are adopted, if the individual rationality condition holds

$$u_j[1 - F(\beta)] + (u_0)F(\beta) \geq u_0 \tag{3}$$

where u_j is the utility associated with the bidder's optimal available conservation practice. So, producers will choose a bid, θ_j, for their optimal conservation practice that maximizes the expected net payoff from PES-program participation, which is given by

$$\left[m\left(\pi(j) - \pi(0) + E\left[B_j\right] + \theta_j\right) - \psi_2\left(\rho_j\right)\right][1 - F(\beta)] \tag{4}$$

The above expression represents the net benefits of bid-submission, namely the difference between the expected utility of auction participation and *status quo* utility. The optimal bid for a given conservation practice is found by maximizing equation 4 with respect to θ_j. Before proceeding with the derivation of the optimal bid, let c_j represent the full cost of implementing conservation practice j, where $c_j = \pi(0) - \pi(j)$.

The derivative of equation 4 with respect to θ_j is given by

$$m[1 - F(\beta)] + \left[m\left(\theta_j^* + E\left[B_j\right] - c\right) - \psi_2\left(\rho_j\right)\right]\frac{\partial 1 - F(\beta)}{\partial \theta_j^*} = 0 \tag{5}$$

Recalling the definition of β, we see that

$$\frac{\partial 1 - F(\beta)}{\partial \theta_j^*} = \frac{\partial F(\beta)}{\partial \beta}\frac{\partial \beta}{\partial \theta_j^*} = \frac{-f(\beta)}{e_j + E[q_j]} \tag{6}$$

Substituting equation 6 into equation 5 yields

$$m[1- F(\beta)] = \left[m\left(\theta_j^* + E\left[B_j\right] - c\right) - \psi_2\left(\rho_j\right)\right] \frac{f(\beta)}{e_j+E[q_j]} \tag{7}$$

which can be rearranged to yield

$$\theta_j^* = c - E\left[B_j\right] + \frac{\psi_2\left(\rho_j\right)}{m} + \frac{[1- F(\beta)](e_j+E[q_j])}{f(\beta)} \tag{8}$$

For a closed-form solution, we must make a functional-form assumption for the cumulative distribution of β. We will assume a uniform distribution, so that

$$F(\beta) = (\beta - \underline{\beta})\,(\bar{\beta} - \underline{\beta})^{-1} \tag{9}$$

where $\bar{\beta}$ and $\underline{\beta}$ are the producer's beliefs about the upper and lower limits of the bid-benefit scoring index, β. Taking the derivative of $F(\beta)$ with respect to β yields $f(\beta) = (\bar{\beta} - \underline{\beta})^{-1}$. Then, $\frac{[1- F(\beta)]e}{f(\beta)} = \bar{\beta}(e_j + E\left[q_j\right]) - \theta_j^*$. As a result, conditional on submitting a bid for conservation practice j, the optimal bid, θ_j^*, is given by

$$\theta_j^* = \frac{m\left(c-E[B_j]+\bar{\beta}(e_j+E[q_j])\right)+ \psi_2(\rho_j)}{m(2+\frac{E[q_j]}{e_j})} \tag{10}$$

Comparative statics can be used to develop predictions about bidder behavior in spatial conservation procurement auctions. If we begin with the case of the optimal bid in the absence of spatially-varying benefits from conservation (e.g., $E\left[B_j\right], E\left[q_j\right] = 0$), we see that the optimal bid should be increasing in the cost of conservation, c, the environmental quality of the conservation practice, e_j, and the upper limit of the bid-benefit scoring index $\bar{\beta}$.[2] Re-evaluating these relationships when there are positive expected payments and expected benefit premiums for spatially-coordinated conservation, we see that the optimal bid is less responsive to changes in the cost of conservation practices, while it is more responsive to changes in the quality of the conservation practice and the upper limit of the bid-benefit scoring index, relative to the case when there are no spatially-varying benefits from conservation (e.g., $E\left[B_j\right], E\left[q_j\right] = 0$)[3].

As expected, we see that the optimal bid is increasing in the producer's belief about the upper limit of the bid-benefit scoring index, $\bar{\beta}$. Specifically, $\frac{\partial \theta_j^*}{\partial \bar{\beta}} = \frac{(e_j + E[q_j])}{2 + \frac{E[q_j]}{e_j}}$, which is positive given the positive numerator and denominator. We also see that the optimal bid is decreasing in the expected payments for spatially-coordinated conservation, $E\left[B_j\right]$. Specifically, $\frac{\partial \theta_j^*}{\partial E[B_j]} = \frac{-1}{2 + \frac{E[q_j]}{e_j}}$, which is negative given the negative numerator and the positive denominator. This result is intuitive, as the existence of additional payments for spatially- coordinated conservation helps relax the link between bid amount and the expected profit conditional on offer acceptance. This link is what prevents discriminatory-price conservation procurement auctions from being incentive compatible, as the bid amount impacts both the probability of acceptance and the bidder's profit if her bid is accepted.

Finally, we explore the impact of the expected benefit premium for the aggregated adoption of the same conservation practice on the optimal bid. We see that the relationship is

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[2] The partial derivatives that lead to these conclusions are as follows: $\frac{\partial \theta_j^*}{\partial E[B_j]} = \frac{-1}{2}, \frac{\partial \theta_j^*}{\partial c} = \frac{1}{2}, \frac{\partial \theta_j^*}{\partial e_j} = \frac{\bar{\beta}}{2}, \frac{\partial \theta_j^*}{\partial \beta} = \frac{e_j}{2}$.

[3] Specifically, $\frac{\partial \theta_j^*}{\partial c} = \frac{e_j}{2e_j + E[q_j]} < \frac{1}{2}, \frac{\partial \theta_j^*}{\partial e_j} = \bar{\beta}\left(1 - \frac{2e_j(e_j + E[q_j])}{(2e_j + E[q_j])^2}\right) > \frac{\bar{\beta}}{2}$, and $\frac{\partial \theta_j^*}{\partial \bar{\beta}} = \frac{e_j(e_j + E[q_j])}{2e_j + E[q_j]} > \frac{e_j}{2}$.

indeterminate. Specifically, $\frac{\partial \theta_j^*}{\partial E[q_j]} = m(\frac{e_j\overline{\beta}}{2+\frac{E\left[q_j\right]}{e_j}} - \frac{1}{e_j})$. Whether the optimal bid is increasing in the benefit premium for spatially-coordinated conservation depends on the relative magnitudes of the two terms in parentheses in the above equation.

In most theoretical and experimental work in this area, the additional payment, $E\left[B_j\right]$, and the benefit premium, $E\left[q_j\right]$, for spatially-coordinated conservation is based on an agglomeration bonus (Parkhurst and Shogren 2007). In the typical design, the agglomeration bonus is an increasing function of the number of a bidder's neighbors who submit bids for the same conservation practice as her. So, the additional payment to any one bidder will depend on both the size of the coalition of coordinated bidders and her location in the coalition, with interior bidders receiving a greater additional payment than the edge bidders. This accounting method is also used to determine the benefit premium. Expectations of these values will be increasing in the number of neighbors who submit bids for the same conservation practice.

The expected bonus associated with spatially-coordinated conservation and the expected benefit premium for this same aggregated adoption of the same conservation practice could be independent determinants of bidder behavior in conservation procurement auctions with spatially-targeted conservation goals. However, in practice, each of these terms typically depends on the number of producers participating in the coalition of coordinated conservationists. So, from the perspective of each producer, we might re-write $E\left[B_j\right]$ and $E\left[q_j\right]$ as $E\left[B_j(n)\right]$ and $E\left[q_j(n)\right]$, respectively. With this done, we can now explore how the optimal bid varies in response to the size of the coalition that the producer anticipates for her chosen conservation practice. We see that $\frac{\partial \theta_j^*}{\partial n} = \frac{\left(-\frac{E\left[B_j\right]}{\partial n} + \beta\frac{-\partial E\left[q_j\right]}{\partial n}\right)\left(2+\frac{E\left[q_j\right]}{e_j}\right) - \frac{-1\partial E\left[q_j\right]}{e_j\ \partial n}(c - E\left[B_j\right] + \overline{\beta}(e_j + E[q_j]))}{(2+\frac{E\left[q_j\right]}{e_j})^2} - \frac{m\psi_2(\rho_j)}{e_j(2+\frac{E\left[q_j\right]}{e_j})^2}$. The sign of the relationship is indeterminate and depends on the parameterization of the landscape in which the conservation procurement auction is being conducted.

Achieving a coalition of bidders offering the same conservation practice requires coordination, which will depend on the ability to communicate among bidders and the ability of each bidder to identify the practice that will be most popular with her neighbors. Choices in auction design will impact this ability, as will the landscape in which the bids are made.

The appeal of an auction mechanism to allocate funds in PES programs stems from its ability to induce competition among bidders to mitigate rent-seeking opportunities. In part, this is achieved by limiting communication between bidders and controlling the information available in the bid-formation process. However, when the benefits of conservation vary spatially and depend on landscape-level outcomes, coordination becomes potentially beneficial from the perspective of the auctioneer: by signaling commitments to adoption of certain conservation practices, bidders can increase the size of the conservation coalition. Previous research on conservation procurement auctions has demonstrated that the bid-formation process is challenging (Banerjee and Conte 2018) and that access to information about the environmental quality of available conservation practices can lead to identification of more cost-effective practices for submission while also affecting rent-seeking behavior, with the direction seemingly based on whether or not item selection is an aspect of the bid-formation process (Conte and Griffin 2017; Cason et al. 2003).

The configuration of the landscape is of critical importance in determining the cost-effectiveness of conservation procurement auctions with a spatial focus. Variation in watershed location, soil type, slope, and other parcel characteristics that vary spatially can, along with the impacts of the limited budget, impact the potential size of the coalition of producers who submit bids for a spatially-coordinated conservation practice. As the above model demonstrates, bidding behavior depends on the bidder’s expectation of the payments available for coordinated conservation and the quality premium awarded to such bids. These expectations will vary with the size of the coalition predicted for each conservation practice as well as the bidder’s confidence that she has selected the practice that best takes advantage of the potential coalition. For these reasons, we explore auction performance and bidder behavior across different landscape types, varying levels of information about practice quality, and alternate communication treatments, as described below.

Section 3: Experimental Design, Procedures, and Econometric Methods

Section 3.1: Experimental Design and Procedures

We report data for 30 groups, with 12 participants per group, as presented in Table 1, yielding a data set with 360 participants. The two treatments of interest include (*i*) the presence of communication opportunities with right and left neighbors (denoted by COMM and NO-COMM) and (*ii*) the information treatment represent the manner in which environmental benefits information of the conservation practices is presented to the participating bidders (denoted by NO-INFO, VALUE and RANK). The role of these variables in influencing behavior is studied through a full factorial balanced between-subject treatment implementation giving rise to six different types of experimental treatments as presented in Table 1.

Finally, owing to our interest in spatial coordination, in addition to the information and communication treatments, we consider three different types of spatial configurations of winning bidders that could be selected by the auctioneer in the absence of asymmetric information. Figure 1 presents the spatial targets considered, each corresponding to a particular land us practice/project referred to by the colors Blue, Green and Red in the auction. The first pattern is the Single-Large configuration, the second termed Several-Small and the last one the Asymmetric configuration. These three configurations in a simple but realistic fashion mimic different coalitions of players adopting similar land use practices that on real geographical landscapes play a significant role in the provision of different ecosystem services such as biodiversity conservation benefits, overall ecosystem resilience etc.

Table 1: Experimental Design

Communication Treatment	Information Treatment		
	Without Benefit Information	With Absolute Value Benefit Information	With Rank Value Benefit Information
Without Communication	NO-COMM-NO-INFO (5 sessions)	NO-COMM-VALUE (5 sessions)	NO-COMM-RANK (5 sessions)
With Communication	COMM-NO-INFO (5 sessions)	COMM-VALUE (5 sessions)	COMM-RANK (5 sessions)

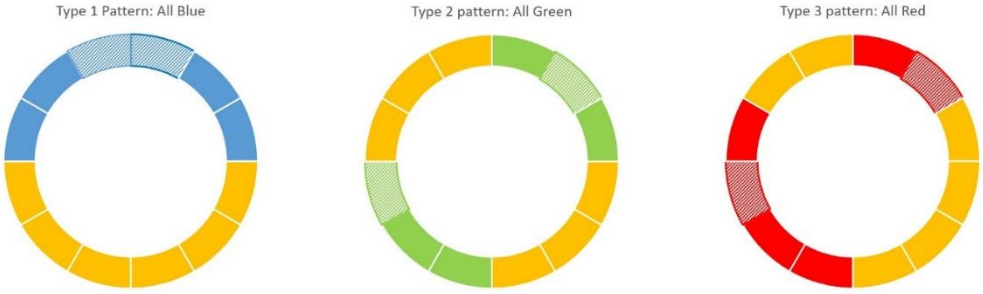

Figure 1: First-Best Spatial Configurations in 9 Auction Periods (3 periods per type)

The experiment was implemented in Ztree (Fischbacher 2007) and consisted of three stages. Stage 1 involved risk attitudes elicitation through an incentivized Holt-Laury lottery presented in the Appendix (Holt and Laury 2002). Stage 2 was composed of the conservation auction and Stage 3 involved a demographic survey. All lottery amounts were presented in real USD and payoffs from the auction were recorded in experimental currency units (ECU), which were converted into real USD at an exchange rate of 27 ECU per 1 USD. Lottery selection and payment were determined at the end of Stage 2 in order to prevent any possible wealth effects arising from participants having knowledge about the money they had made in Stage 1, which could impact their auction bidding behavior. Participants also received a $9 show-up fee. Average earnings were about $27.37 for an experiment last for two hours.

At the beginning of Stage 2, participants were provided with a randomly determined ID ranging between 1 and 12 to establish right and left neighbor identity as well as location on the circular networked landscape on which the iterative conservation auction would be implemented. We chose this circular networked structure for multiple reasons. First, neighbor number is the same for every subject on the circle, providing us the opportunity to establish behavioral benchmarks about bidding behavior without having to worry about people bidding differently owing to having different number of neighbors and hence a different spatial bonus earning potential (which can confer locational advantages to some and disadvantages to others). Second, a different spatial setup, such as a lattice, star or a line, would vary in both neighbor identity and number and would cause different participants at different locations to have different communication profiles. While this feature is realistic and interesting, we choose to sacrifice some realism to establish behavioral benchmarks for a symmetric neighborhood setup to which results of future experiments (which consider asymmetric neighborhood structures) can be compared. Moreover, the goal of the auction is to allow participants to coordinate their item/bid submissions so that they can earn the bonus payment. Yet, Chwe (2000) indicates that different communication profiles can hinder coordination between players in a strategic setting and provides additional motivation for adopting our symmetric neighborhood setup.

We also adopted a fixed-matching scheme, whereby neighbor identity remained unchanged during the experiment. We made this choice to facilitate subject learning in the complex auction environment and also to allow for the build-up of reputational incentives. Furthermore, the fixed-matching scheme reflects the reality that, on agricultural landscapes, land is owned and/or managed by the same individual or entity for long periods of time, although we acknowledge that a random-matching protocol would allow for communication to have a more prominent role in influencing bidding and auction outcomes because neighbor identity is changing every period.

Participants received detailed instructions about participation in the auction in the form of a handout and slide presentation (see Appendix for handout provided to subjects for the Comm-Value treatment). As noted already, in the auction, each participant was endowed with three projects (denoted by items in the instructions), named Red, Green, and Blue. Each project had an associated cost and quality value, which was revealed to participants in the two INFO treatments. Participants always had information about their cost values to reflect the fact that, in reality, producers generally have a good idea about the costs of implementing specific pro-conservation projects on their lands. Each auction treatment comprised nine periods, with each period composed of multiple rounds. During each auction round, participants first chose the item they wanted to sell and then the price at which they would sell this item (so bids are two-dimensional). After all participants had made their item selections and submitted their offered prices in each round, the winning combination of projects was calculated by the computer, the auctioneer. This winner determination involved evaluating the ratio of the sum of environmental benefits of all possible combinations of submitted items and the sum of offer prices submitted for these items to select the combination of projects which maximized the value of this ratio and could be supported by the budget. Once this winning allocation was determined, it was announced to every participant. The auction then proceeded to the next round. In this round, if participants submitted the same item from the previous round, their price from the previous round was available as the default price. Participants had the option to reduce the value of the price. The computer flashed an error message if the price submitted was less than the item's cost or greater than the price submitted in the previous round.[4] Depending upon auction outcome in the previous round, participants could also select and submit a bid for a different one.

Each auction period comprised a minimum of four rounds and a maximum of seven rounds, during which participants submitted their bids. These bounds on the total number of rounds each period were not announced to the participants, to prevent any possible end-game effects, which have been found in public goods games (Andreoni 1988) and conservation auctions (Reeson et al. 2011). For the same reason, Participants did not know about the maximum number of periods in each auction treatment. We chose these experimental parameters to ensure that each session did not last for more than two hours (especially for the COMM treatments) which could have comprised data quality owing to participant fatigue. Additionally, we implemented a minimum number of rounds to provide participants with the opportunity to learn and settle on a bidding strategy in a period without having to worry that the auction might end before an equilibrium had been reached. After the completion of three rounds, a stopping rule was applied at the end of every subsequent round to assess whether the period should end or continue for another round. This rule was satisfied if

1. The score of the selected items was the same between the current and previous round

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[4] We did not permit participants to increase prices for the same item between consecutive rounds due to concern about rent-seeking opportunities in multi-round auctions (references??) and because we wanted to avoid the possibility of participants failing to find an optimum bidding strategy, preventing the auction from finding an optimum solution. Moreover, this feature conforms to actual conservation auctions which have a descending price format.

2. The total money needed to purchase the provisionally selected items in the current and previous round was the same

At the end of each round in a period and at the end of each period, participants received feedback about auction outcomes on a Results Screen . This screen included information about (*i*) whether their bid had been accepted, (*ii*) whether their neighbors' bids had been accepted and, if yes, which colored item had been included in the accepted bid, (*iii*) their provisional earnings for the round or their actual earnings if they were winners in the period and (*iv*) the total bonus earned. For easy reference, the quality value in VALUE-NO-COMM and VALUE-COMM sessions, the quality ranking in the RANK-NO-COMM and RANK-COMM sessions and the cost values of the submitted item was also provided. Finally, this screen included a History Table that recorded the above values for all rounds of a period and all auction periods. Because the information presented in these tables is similar, the round-level and period-level History tables were clearly highlighted on the Results screen to prevent any potential confusion among participants.

In the COMM treatments, at the beginning of each auction round, participants had the opportunity to message their neighbors for a duration of 30 seconds through two chat boxes displayed on their screen. Once this time had elapsed, the chat content was displayed for an additional 10 seconds, after which participants proceeded to the item-selection phase of the auction period. Instructions barred participants from revealing their identity to neighbors and asked them to be civil to one another. All features of the auction could be discussed through the communication channels.

We used three different sets of cost and quality values to determine the cost and quality endowments for each subject in a period. Each set corresponded to one of the three targeted spatial coalition patterns and was used in three auction periods thus minimizing the influence of any possible scale effects. The values were drawn from two uniform distributions - $cost \sim (0, 1000]$ and $quality \sim (0, 100]$. Given the cost and quality draws, the budget of 4500 ECU was set so that, in the absence of asymmetric information, the first-best allocation of items would maximize enrollment, comprise six projects in all periods, have the highest total score, involve the selection of multiple items of the same color, and represent different spatial configurations.[5] Table 2 includes the parameter values and the different features of the first-best allocation for each set. The highlighted green cells represent the items that are part of the targeted coalitions and which would be selected in the absence of asymmetric information. Additionally, of the coalition items, the ones highlighted in red represent players for whom the item that is privately optimal to submit is different from those which are socially optimal and hence part of the first best coalition.

Finally, these endowments were assigned to participants such that (*i*) even if neighbors exchanged cost and quality endowment information through chat windows, participants did not know that the endowments from the past periods were being repeated, (*ii*) never faced the same endowment in multiple periods, and (*iii*) if everyone bid at cost, then across all nine periods, six participants in each session would win four times and the other six would win five times. In order to facilitate understanding of auction features, participants answered a quiz and participated in a practice period before bidding in the actual auction. They were also provided with a handout (see Appendix) containing information about salient features of the auction for

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[5] We chose the budget to achieve a 50% acceptance rate of bids, on average, to introduce enough competition in the auction to balance against the possible efficiency reduction arising from the incentives for collusive bidding behavior, a particular concern in the COMM sessions.

reference during the course of the experiment. A flow-chart was also provided to clearly represent auction progression.

The experiments were conducted at the University of Nebraska-Lincoln between February 2017 and April 2018. Participants were recruited from the university student population. Experiments did not include contextual terminology relevant to farmland conservation policies, conservation auctions and PES since context loaded terminology can influence subject behaviors and confound the treatment effect (Cason and Raymond 2011).

Table 2: Cost and Quality Values for Items

Item Quality								
Single-Large			Several-Small			Asymmetric		
Red	**Green**	**Blue**	**Red**	**Green**	**Blue**	**Red**	**Green**	**Blue**
50	78	63	72	100	86	**93**	97	54
71	67	51	100	65	84	**98**	93	86
86	60	62	83	63	69	88	75	50
88	87	**95**	54	**89**	97	91	78	100
77	94	**86**	88	**98**	93	63	61	52
51	78	**98**	87	**75**	50	81	83	94
95	77	**82**	91	78	100	**88**	50	67
57	59	**99**	63	61	52	**95**	93	89
54	60	**74**	81	83	94	**87**	80	85
89	75	86	50	**87**	75	**100**	72	86
92	56	51	93	**94**	89	100	65	74
80	84	68	85	**87**	89	83	63	69
Item Cost								
872	586	780	696	828	690	**679**	933	905
768	775	916	882	871	801	**600**	862	501
832	654	754	938	714	916	818	653	938
876	968	**572**	905	**679**	921	748	914	994
938	809	**550**	501	**600**	862	653	893	872
616	669	**925**	818	**653**	938	675	891	796
590	843	**513**	748	914	994	**752**	712	640
837	775	**895**	653	893	861	**510**	813	721
930	875	**520**	646	889	795	**701**	605	801
620	726	929	712	**750**	640	**765**	696	690
987	876	688	813	**513**	721	882	873	801
957	844	831	605	**700**	801	942	714	916

Section 3.2: Econometric methods

The impacts of our selected treatments on auction performance are explored using nonparametric tests and econometric models. The above theoretical model provides an understanding of how bidder behavior varies in response to the alternative treatments presented in the experiment, and this informs our empirical analysis. We first introduce our definition of auction performance and our approach to estimating the treatment effects on this outcome variable before moving on to discuss bidder behavior across treatments.

3.2.1 Auction performance

The metric used to evaluate auction performance across treatments must be designed to reflect the realities of conservation procurement auctions. These auctions lead to the purchase of discrete conservation practices, meaning that the budget is rarely fully exhausted. Variation across auction periods in total expenditures, even with a constant available budget, requires a metric for the cost-effectiveness of the auction that accounts for such variability in auction expenditures.

We utilize the percentage of optimal cost-effectiveness ratio (POCER), $\frac{\Sigma q_i^a / \Sigma p_i}{\Sigma q_i^o / \Sigma c_i^o}$, to measure auction performance, where q_i^a represents the quality of the accepted bid from winning bidder i, p_i represents the offer price of the accepted bid, q_i^o represents the quality of bidder i's optimal item, and c_i^a represents the cost of bidder i's optimal item. In a spatial auction, the score of a producer's bid depends on the bids of her neighbors. We define the optimal item as the one that provides the greatest social benefit, given the parcel's location, under the assumed condition that the procurer has full information about the cost and quality of all conservation practices available to bidders. POCER has been employed to measure cost-effectiveness in related studies (see e.g., Conte and Griffin 2019; Banerjee and Conte 2018; Cason et al. 2003).

The estimated regressions used to explore the treatment effects on POCER assume a random-effects, session-level error structure, with confidence intervals generated via bootstrap. The regressions are of the form:

$$POCER_{tg} = \alpha + X_{tg}\beta + Z_{tg}\gamma + \left(X_{tg} \times Z_{tg}\right)\delta + \nu_{tg} \qquad (11)$$

where *t* indexes auction periods within a session and g indexes sessions. $POCER_{tg}$ represents the value of the cost-effectiveness metric for period *t* in session g. X_{tg} is a vector of treatment indicator variables related to environmental quality information (the indicator for the *No Information* treatment is excluded from the regressions as a reference). Z_{tg} is a variable measuring the period number within a given treatment. The interaction term between X_{tg} and Z_{tg} allows experience to impact auction performance differently across information treatments[6]. Models of the above specification are run separately across each landscape type (e.g., *Single Large*, *Several Small*, and *Asymmetric*) for *Communication* and *No Communication* treatments.

3.2.2 Bidder Behavior

Exploration of how bidder behavior varies across treatments, potentially leading to differential auction performance, focuses primarily on the determinants of cost effectiveness at the participant level. As the conservation auctions being studied are multi-attribute procurement

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[6] Each treatment has the same number of auction periods across sessions, and out focal research question does not concern session-level effects. So, standard errors are clustered at the session level as opposed to the use of a multilevel model (Gelman 2006).

auctions, the offered price seems to be an inadequate measure of bid competitiveness, or rent-seeking. Instead, we follow the approach of Conte and Griffin (2019) and use the percentage of the optimal score (POScore) as our measure of bid competitiveness. POScore for seller *i* is defined as $\frac{q_i^s + E[q_i^s]/p_i}{q_i^o + E[q_i^o]/c_i}$, where p_i represents the offered price of the submitted item, q_i^s represents the submitted item's quality, $E[q_i^s]$ represents the expected benefit premium associated with bidder i's submitted conservation practice, and q_i^o, $E[q_i^o]$, and c_i^o represent the quality, expected benefit premium, and cost of seller i's optimal item, respectively. We see that for seller i's optimal item, meaning that it has the maximum score $(\frac{q_i + E[q_i^o]}{c_i})$ of the three available items, $POScore = \frac{c_i^o}{p_i}$. Thus, the determinants of POScore will vary depending on whether or not the submitted bid is for the bidder's optimal item. We also see the importance of the expected benefit quality premium in determining POScore, meaning that the expected coalition size will be an important determinant of POScore, so we will conduct our analyses of bidder behavior for each of the three experimental landscape types separately.

We explore the determinants of these POScore values across item choices and participants through random-effects models with bootstrapped standard errors clustered at the session level. The estimated models are specified as follows:

$$POScore_{it} = \alpha + X_{it}\beta + Z_{it}\gamma + \nu_{it} \qquad (13)$$

where i indexes experiment participants and t indexes auction periods. X_{it} comprises characteristics of submitted conservation actions including cost, quality, and the minimum cost and maximum quality indicators. The components of the vector Z_{it} relate to bidder characteristics, including indicators related to whether or not the bidder’s privately-optimal and socially-optimal bid is the same, whether the bidder’s bid was provisionally accepted in the previous round of the auction and a variable counting the number of the bidder’s neighbors whose bids were provisionally accepted in the previous auction round.

Section 4: Results

We initially consider the treatment impacts on overall auction performance. We begin with summary statistics to support the predictions from the theoretical model and then move on to regression analyses. Having considered the treatment effects on overall auction performance, we turn to determinants of individual bidder behavior.

Section 4.1: Auction Performance

Table 3 presents the average session-level values for key auction performance variables across our information and communication treatments for the three spatial configurations considered with corresponding standard errors in parentheses. The three performance measures are POCER, as described above, the average total quality provided in each auction period, and the average rents in each auction period, where rent describes payments made above the reservation wage of the bidder. While there are a limited number of replications across our communication and quality-information treatments, a comparison of the provided summary statistics provides motivation for our more comprehensive regression analysis of results and offers suggestive evidence of behavior that is consistent with the predictions from the theoretical model.

We begin by looking for trends across information and communication treatments within each landscape type. In the Single-Large landscape, we see that the No-Info treatment is associated with the lowest POCER levels, regardless of the communication treatment. We also see the impacts of communication on auction performance differing based on the quality information treatment. For example, communication increases average total quality procured in the auction in the No-Info and Value treatments, while this measure of auction performance drops in the Rank treatment when bidders are able to communicate. We see a similar divergence of communication effects when considering average rents, with communication increasing rents in the No-Info and Rank treatments, while decreasing rents in the Value treatment.

For a systematic analysis of auction level cost efficiency measured by POCER, we present the results of two sets of clustered regressions for each communication treatment. For each of these two treatments, we present three models each corresponding to a particular spatial configuration. The dependent variable in the analysis is session level POCER value for a particular period. The independent variables include dummy variables for the Information Value and Information Rank treatments with the No-Information treatment being the omitted category, the Period variable and finally interaction terms between Period and the two information treatment dummy variables. The standard errors are clustered by individual session level. Table 4 presents the results from experimental sessions without communication.

Table 3: Session Level Averages with Standard Errors in parenthesis

	Single-Large			Several-Small			Asymmetric		
Treatments	POCER	Average Quality	Average Rents	POCER	Average Quality	Average Rents	POCER	Average Quality	Average Rents
NoComm-	0.80	585.53	216.60	0.88	627.40	238.07	0.86	621.67	174.93

NoInfo									
	(0.01)	(10.25)	(41.56)	(0.01)	(13.84)	(41.49)	(0.02)	(14.66)	(28.22)
NoComm-Rank	0.86	634.00	209.33	0.89	621.07	216.93	0.91	661.00	220.87
	(0.01)	(11.40)	(33.85)	(0.01)	(10.07)	(29.93)	(0.01)	(10.29)	(34.76)
NoComm-Value	0.83	599.33	305.27	0.87	621.60	300.53	0.88	626.20	255.83
	(0.01)	(9.72)	(45.78)	(0.01)	(10.78)	(27.77)	(0.01)	(10.85)	(36.35)
Comm-NoInfo	0.81	599.93	246.99	0.88	632.47	190.96	0.90	650.93	213.13
	(0.02)	(12.68)	(41.85)	(0.01)	(12.78)	(27.48)	(0.01)	(13.98)	(40.17)
Comm-Rank	0.83	610.80	223.57	0.90	628.27	218.44	0.92	658.73	233.75
	(0.02)	(13.68)	(43.80)	(0.01)	(13.02)	(28.40)	(0.01)	(13.48)	(34.00)
Comm-Value	0.85	624.93	218.04	0.90	635.53	195.19	0.93	670.80	199.17
	(0.02)	(11.00)	(40.67)	(0.01)	(15.26)	(21.96)	(0.01)	(13.21)	(34.15)

Table 4: POCER Analysis for No-Communication Treatment Sessions

	(1)	(2)	(3)
Independent variables	Single Large	Several Small	Asymmetric
Value Treatment	0.0354	0.0218	0.00315
	(0.0253)	(0.0250)	(0.0424)
Rank Treatment	0.0696**	0.0154	0.102***
	(0.0315)	(0.0363)	(0.0338)
Period	0.00367	0.00364***	0.00709***
	(0.00631)	(0.000976)	(0.00119)
Value Treatment X Period	-0.00159	-0.00594*	0.00248
	(0.00774)	(0.00298)	(0.00366)
Rank Treatment X Period	-0.00104	-0.00208	-0.00979**
	(0.00699)	(0.00436)	(0.00432)
Constant	0.783***	0.863***	0.822***
	(0.0214)	(0.0208)	(0.0261)
Number of Observations	45	45	45
R-squared	0.279	0.042	0.237
Number of sessions	15	15	15

*Note: The dependent variable is the session level POCER for a particular period with the No-Information treatment being the omitted base category. Standard errors are clustered by experimental session. * represents significance at the 10% level, ** at the 5% level and *** at the 1% level.*

We observe that in the Single Large and Asymmetric landscapes, access to ranked environmental quality information significantly improves auction cost-effectiveness relative to auctions without information about these benefits. Auction experience seems to have a differential impact on performance depending upon the spatial configuration. In the Single-Large landscape, there is no significant impact of experience on auction performance across information treatments.

In the Several-Small landscape, auction performance improves with bidder experience in the absence of quality information and with ranked quality information, though this positive effect is mitigated in the auctions with quality value information. This result highlights the tension of information access in auction performance, with quality information helping bidders to identify the most cost-effective items that provide reward for spatial coordination, while also helping the bidders realize that they have an advantage based on the characteristics of their item and their location in the landscape, which can increase rent-seeking.

The estimate for the interaction term between Period and the Rank treatment for the Asymmetric configuration is negative, suggesting that the benefits of auction experience for auction performance in the no information and value information treatments in this landscape are significantly mitigated with ranked environmental benefit information.

We next compare constant terms, representing auction cost-effectiveness in the absence of quality information, across the three landscapes. We see that cost-effectiveness is highest for the Several-Small landscape and lowest for the Single-Large landscape. This result could be explained by one of two mechanisms. First, it might be due to increased rent-seeking by bidders in the Single-Large landscape, where players feel more certainty about the size of their coalition. Alternatively, this result could be due to the fact that coordination is more difficult in larger groups than in smaller groups (Van Huyck et al. 1991, Banerjee et al. 2012). We will turn to analyses of bidder behavior to identify what behavior is responsible for this result. Chi-square tests comparing the equivalence of these constants indicate a significant difference between the Single-Large and Several-Small landscapes at the 5% level of significance. Additionally, Chi-square tests comparing the results of the full model across landscapes indicate an overall significant difference, indicating that auction performance is significantly different under different information conditions for the three landscapes considered in the absence of communication between participants.

We now turn to a similar analysis of auction performance for sessions that permitted communication between participants. Table 5 presents the results of the regression analyses and indicates that, similar to the no-communication treatments, the effect of the quality information treatment depends upon the spatial configuration of the landscape.

In the Single-Large landscape, there is no significant information treatment effect. However, in both the Several-Small and Asymmetric landscapes, the presence of absolute environmental quality information improves auction performance, albeit marginally, although for the Several-Small case, auction experience erodes the beneficial effect. This positive impact of access to quality value information can be linked to the overall challenge of completing the bid-formation process successfully in spatial conservation procurement auctions. In the Single-Large landscape, communication opportunities do not improve auction performance, which again could be a result of increased rent-seeking facilitated by this information or the challenge of organizing a single large coalition of bidders. However, for the two other landscapes, the presence of communication opportunities allows subjects to use the quality information to bid in a way to improve auction outcomes. This outcome is obtained for the Rank information treatment for the Several-Small landscape as well.

Focusing on auction experience, it is clear that at least for the Single-Large and Several Small settings, auction experience improves outcomes in the no-qaulity information treatments. However, for the Asymmetric configuration, auction experience does not play any significant role for any information treatment condition. This finding is contrary to what we obtain when evaluating the no-communication sessions and might suggest that, at least for the Asymmetric landscape, the presence of communication opportunities ensures that enhanced auction cost-effectiveness is not predicated on subjects having to interact.

Table 5: POCER Analysis for Communication Treatment Sessions

	(1)	(2)	(3)
Independent Variables	Single Large	Several Small	Asymmetric
Value Treatment	0.0287	0.0641*	0.0851*
	(0.0366)	(0.0321)	(0.0445)
Rank Treatment	0.0335	0.0312**	0.0358
	(0.0453)	(0.0137)	(0.0435)
Period	0.0161*	0.0105***	0.00620
	(0.00867)	(0.00149)	(0.00616)
Value Treatment X Period	0.000645	-0.00881**	-0.00808
	(0.00935)	(0.00382)	(0.00650)
Rank Treatment X Period	-0.00369	-0.00378	-0.00295
	(0.0106)	(0.00251)	(0.00700)
Constant	0.750***	0.831***	0.861***
	(0.0345)	(0.0102)	(0.0410)
Observations	45		
R-squared	0.365	0.240	0.217
Number of clusters	15		

*Note: The dependent variable is the session level POCER for a particular period with the No-Information treatment being the omitted base category. Standard errors are clustered by experimental session. * represents significance at the 10% level, ** at the 5% level and *** at the 1% level.*

Finally focusing on the constant terms, we again see the magnitude is the smallest for the Single-Large landscape, while it is highest for the Asymmetric landscape. Comparing auction performance within landscapes across communication treatments, the magnitude of the constant term, representing auction performance in the absence of environmental quality information, is smaller in the presence of communication. However, per Chi-square tests comparing estimates across models, these differences are not significant. However, Chi-square tests comparing whether these constants are different from each other for the Communication treatment indicate a significant difference at the 1% level of significance when comparing the Single-Large and Several-Small landscapes and at the 10% level of significance for the Single-Large and the Asymmetric landscapes. Similar results are obtained when comparing the full model across landscapes in the no-Communication treatment.

Section 4.2: Bidding Behavior

In this section, we present separate analyses of bidding behavior, captured by the POSCORE metric, across our three landscape types for the NO-COMM and COMM treatments. In presenting our results, we organize findings by participants who are part of the first-best winning coalition (as represented in Table 2) and those who are not. The focus on coalition and non-coalition bidders is predicated on the fact that, given the spatial nature of the auction mechanism, bidders at specific landscape locations may have strategic advantages. In particular, we expected these advantages to be greatest for coalition members, who have a higher likelihood of being selected than non-coalition members, absent excessive rent-seeking due to their preferred location.

In Tables 6-9, we present the results of POSCORE regressions, with standard errors clustered at the session level. Per the theoretical model introduced in Section 2, and as explained in the econometric methods section, the independent variables in the analysis include the Cost and Quality of the submitted item, two indicator variables taking a value of one if the selected item corresponds to the item with the lowest cost or the highest quality, two indicator variables to control for the Value and Rank information treatments, the Period variable to control for auction experience, and an interaction term between Period and the Information treatments, and two variables recording whether the bidder was a winner in the penultimate round of the current auction period and the number of the bidder's neighbors whose bids were also selected in that auction round. Finally, we include an indicator variable (Conflict) that takes on a value of 1 for bidders who are part of the first best winning coalition and whose item cost and benefit parameters were such that there was a conflict between the item that was privately optimal for them to submit (the item with the highest benefit cost score without inclusion of the spatial bonus and premium) and the item that was socially optimal and would ensure that this bidder would be selected as part of the winning coalition. Figure 1 presents the positions of bidders under each landscape type who faced this conflict. We discuss the salient results of Tables 6 and 7 together, followed by the same for Tables 8 and 9.

4.2.1 Behavior of Non-coalition members:

For participants who are not included in the first-best winning coalitions, Item Cost has a negative (although a weakly statistically significant) impact on POSCORE for the Several-Small landscape for the NO-COMM sessions only. Recalling the formula for POSCORE, this outcome is possible if higher the cost of the selected item, higher is the offer submitted for it. Next, focusing on item quality, the estimates for each landscape condition across both NO-COMM and COMM treatments are positive and significant. This outcome is largely a function of the calibration of the auction environment on the basis of the cost and benefit values for individual items and the uniform distributions that these are drawn from. Intuitively this result suggests that higher the quality associated with an item, higher the POSCORE value and lower the rent seeking associated with it. The significant and positive estimate for the dummy variable recording whether the submitted item corresponds to that with the maximum quality magnitude, aligns with this result as well. Also, the estimate for the minimum cost dummy variable is positive and significant for all landscape conditions.

Next, we see that relative to the baseline NO-INFO treatment, the bidding behavior in RANK information treatments is associated with significantly higher POSCORE values for both Single-Large and Several-Small coalitions in the NO-COMM sessions only. On the other hand when considering the VALUE treatment, the estimate is marginally significant for the Asymmetric coalition only for the COMM sessions. These results signify that the role of information on bidding and rent seeking is different under different landscape configurations and is moderated by the presence of communication opportunities.

Additionally, the estimates for the information treatments signify that in this complex spatial auction, having environmental benefit information (in which ever format this information is provided) facilitates the bid submission process, and reduces the intensity of rent seeking. Also, winning status of the bidder in the last but final round of the auction significantly impacts POSCORE values in the case of the Several-Small configuration only for sessions where communication is permitted with neighbors. The estimate for the Winning Neighbor variable from the previous round is positive and significant for the Single-Large configuration only for both the NO-COMM treatments and for all configurations under the COMM treatment. Given the spatial nature of the auction and reputation and experience that builds up during repeated interactions owing to the fixed matching scheme, if more neighbors were selected in the previous round of a period, a bidder might temper their rent seeking tendencies leading to higher POSCORE values in the final round of a period to maximize the likelihood of winning in that period. That this effect is significant and positive (at least at the 10% level of significance) for all landscapes for the COMM sessions is indicative of the important role that communication serves in facilitating coordination in this auction.

Table 6: POSCORE results for NO-COMM treatments for Non-Coalition Members

	(1)	(2)	(3)
VARIABLES	Single-Large	Several Small	Asymmetric
Item Cost	-0.000102	-0.000375*	-0.000237
	(8.57e-05)	(0.000202)	(0.000151)
Item Quality	0.00263***	0.00347***	0.00506***
	(0.000702)	(0.000362)	(0.000469)
Minimum Cost Dummy	0.0473***	0.141***	0.109***
	(0.0155)	(0.0377)	(0.0314)
Maximum Quality Dummy	0.153***	0.0826***	0.0954***
	(0.0241)	(0.0282)	(0.0274)
Winner in Previous Round	-0.00216	0.00486	0.0201
	(0.0173)	(0.0139)	(0.0156)
Winning Neighbors from Previous Round	0.0320***	-0.0223	0.00563
	(0.0122)	(0.0172)	(0.0139)
Value Treatment	0.0502	0.00943	0.0123
	(0.0436)	(0.0289)	(0.0245)
Rank Treatment	0.102***	0.0431**	-0.00973
	(0.0389)	(0.0215)	(0.0279)
Value Treatment X Period	-0.00607	-0.00206	-0.00140
	(0.00873)	(0.00488)	(0.00403)
Rank Treatment X Period	-0.0182**	-0.00905**	0.000861
	(0.00736)	(0.00437)	(0.00220)
Period	0.00908	0.00711**	0.000355
	(0.00695)	(0.00320)	(0.00205)
Constant	0.546***	0.757***	0.555***
	(0.0855)	(0.192)	(0.120)
Observations	270	270	270
R-squared	0.499	0.468	0.458

*Note: The dependent variable is the POSCORE for the i^{th} non-coalition participant for a particular period with the NO-INFO-NO-COMM treatment being the omitted base category. Standard errors are clustered by experimental session. Number of clusters 15. * represents significance at 10% level, ** at 5% level and *** at 1% level.*

Table 7: POSCORE results for COMM treatments for Non-Coalition Members

	(1)	(2)	(3)
VARIABLES	Single-Large	Several-Small	Asymmetric
Item Cost	-0.000131	-0.000198	-0.000198
	(9.37e-05)	(0.000132)	(0.000121)
Item Quality	0.00355***	0.00232***	0.00427***
	(0.000808)	(0.000465)	(0.000341)
Minimum Cost Dummy	0.0364	0.125***	0.142***
	(0.0265)	(0.0307)	(0.0255)
Maximum Quality Dummy	0.151***	0.104***	0.128***
	(0.0167)	(0.0182)	(0.0135)
Winner in Previous Round	0.00431	0.0252**	-0.00840
	(0.0257)	(0.0108)	(0.0155)
Winning Neighbors from Previous Round	0.0390***	0.0238**	0.0143*
	(0.0130)	(0.00956)	(0.00829)
Value Treatment	0.0360	0.0340	0.0383*
	(0.0240)	(0.0485)	(0.0228)
Rank Treatment	-0.00512	-0.0465	0.0271
	(0.0392)	(0.0642)	(0.0304)
Value Treatment X Period	-0.00455	-0.00329	-0.00183
	(0.00396)	(0.00658)	(0.00339)
Rank Treatment X Period	0.00148	0.00657	-0.00206
	(0.00749)	(0.00850)	(0.00419)
Period	0.00640	0.00470	0.00217
	(0.00417)	(0.00626)	(0.00283)
Constant	0.535***	0.684***	0.548***
	(0.117)	(0.0979)	(0.126)
Observations	270	270	270
R-squared	0.560	0.460	0.674

*Note: The dependent variable is the POSCORE for the i^{th} non-coalition participant for a particular period with the NO-INFO-COMM treatment being the omitted base category. Standard errors are clustered by experimental session. Number of clusters 15. * represents significance at 10% level, ** at 5% level and *** at 1% level.*

Finally, auction experience plays a significant role when benefit information is unavailable for the Several-Small configuration only under the COMM treatment. The estimate for the interaction term between the Period variable and the Rank treatment is negative and significant for both the Single-Large and Several-Small settings. For the first configuration type, this finding suggests that effectiveness of Ranked information in facilitating bid submission and tempering rent seeking goes down with increases experience although the effect is weak enough for the positive effects of ranked benefits information to remain. For the second configuration, the negative estimate indicates that providing more information when the auction is run on a landscape where the target configuration is of the Several-Small type, over time might intensify rent seeking, and lower POSCORE values.

4.2.2 Behavior of Coalition members:

Focusing on coalition members, we see that effect of different auction variables is different across configuration types. Interestingly, while the effect of offer cost on POSCORE is significant for all configurations under NO-COMM and COMM (except the Asymmetric condition in COMM sessions), both Tables 8 and 9 indicate that the nature of the relationship differs by landscape coalition type. For participants who are part of the Single-Large coalition, the estimate for Item Cost is negative and significant but for the other two configurations (whenever significant), the estimate is positive. These results are consistent with the fact that being part of the Single-Large coalition confers substantial strategic locational advantage to these players allowing them to submit higher offers for high-cost submitted items. Such locational strategic advantage is however not conferred to the members of the two smaller size sub-coalitions under the Several-Small and Asymmetric landscapes. As a result, even if their submitted items have higher costs, the offer is lower (leading to a higher POSCORE value).

Additionally, we note that the sign of the estimate for Item Cost for the Several-Small and Asymmetric coalition targets different between coalition and non-coalition members suggesting differences in behavior between these two groups of people at least in the NO-COMM sessions.

Similar to the findings for the non-coalition members, the estimates for the Item Quality variable, the Maximum Quality dummy and Minimum Cost Dummy variable are positive and significant for most coalition types both in the presence and absence of communication (whenever the estimates are significant). Next, under all other coalition types, the POSCORE value corresponding to coalition members is significantly and positively influenced by whether the member was selected as a winning bidder in the previous auction round.

This outcome suggests that a winning coalition member is expected to try to retain their winning advantage and submit lower offers (which would increase their POSCORE value) in the current round. This finding is true regardless of whether bidders can communicate with their neighbors. Next, the effect of neighbors' past round winning status is a significant predicator of POSCORE (although only marginally) only for the Asymmetric coalition for the NO-COMM sessions. In the COMM sessions no such effect is observed which is not surprising given the information exchanged through communication channels between coalition members and their neighbors.

Again the effect of the information treatments while positive is obtained for the Several-Small coalition type only. In the NO-COMM sessions, relative to the NO-INFO condition Value information leads to higher POSCORE values and less intensive rent seeking for coalition members. On the other hand, for the COMM sessions, behavior varies significantly relative to the baseline NO-INFO condition for the Rank treatment only. Auction experience has a positive impact in POSCORE magnitudes but this is true under the NO-INFO condition only for the

Several-Small case for the NO-COMM treatments and for both the Several-Small and Single-Large cases for the COMM treatments.

Table 8: POSCORE results for NO-COMM treatments for Coalition Members

	(1)	(2)	(3)
VARIABLES	Single-Large	Several Small	Asymmetric
Item Cost	-0.000523***	0.000394**	0.000216**
	(9.76e-05)	(0.000171)	(0.000107)
Item Quality	0.00414***	0.00398**	0.00153
	(0.000906)	(0.00163)	(0.00118)
Minimum Cost Dummy	-0.0173	0.218***	0.135***
	(0.0230)	(0.0373)	(0.0355)
Maximum Quality Dummy	0.0765***	0.0114	0.114***
	(0.0177)	(0.0208)	(0.0242)
Winner in Previous Round	0.0610**	0.0585*	0.0922***
	(0.0283)	(0.0314)	(0.0157)
Winning Neighbors from Previous Round	0.0294	0.00564	-0.0183*
	(0.0208)	(0.0160)	(0.0101)
Conflict	0.0782***	0.147***	0.0773***
	(0.0206)	(0.0209)	(0.0177)
Value Treatment	-0.000798	0.0863***	-0.00872
	(0.0276)	(0.0331)	(0.0497)
Rank Treatment	0.0239	0.0482	0.0902
	(0.0296)	(0.0359)	(0.0587)
Value Treatment X Period	-0.00654	-0.0160**	0.00142
	(0.00449)	(0.00639)	(0.00563)
Rank Treatment X Period	-0.00400	-0.0114*	-0.00948
	(0.00552)	(0.00601)	(0.00778)
Period	0.00468	0.00710*	0.00487
	(0.00367)	(0.00408)	(0.00467)
Constant	0.701***	0.00423	0.354***
	(0.118)	(0.255)	(0.127)
Observations	270	270	270
R-squared	0.463	0.281	0.329

*Note: The dependent variable is the POSCORE for the i^{th} coalition participant for a particular period with the NO-INFO-NO-COMM treatment being the omitted base category. Standard errors are clustered by experimental session. Number of clusters 15. * represents significance at 10% level, ** at 5% level and *** at 1% level.*

Table 9: POSCORE results for COMM treatments for Coalition Members

	(1)	(2)	(3)
VARIABLES	Single-Large	Several-Small	Asymmetric
Item Cost	-0.000466***	0.000505***	0.000159
	(9.97e-05)	(9.93e-05)	(0.000141)
Item Quality	0.00475***	0.00553***	0.00296**
	(0.000734)	(0.000646)	(0.00125)
Minimum Cost Dummy	-0.0245	0.260***	0.0855**
	(0.0269)	(0.0163)	(0.0366)
Maximum Quality Dummy	0.112***	0.0297	0.0745***
	(0.0209)	(0.0187)	(0.0274)
Winner in Previous Round	0.0538**	0.0345*	0.0864***
	(0.0233)	(0.0178)	(0.0236)
Winning Neighbors from Previous Round	0.0189	0.00560	-0.00553
	(0.0159)	(0.0119)	(0.0174)
Conflict	0.0681***	0.168***	0.0507**
	(0.0161)	(0.0176)	(0.0211)
Value Treatment	0.0677***	0.0766	-0.000854
	(0.0213)	(0.0493)	(0.0546)
Rank Treatment	0.0539	0.104***	-0.0481
	(0.0329)	(0.0273)	(0.0542)
Value Treatment X Period	-0.0124**	-0.00951	-0.00108
	(0.00550)	(0.00674)	(0.00712)
Rank Treatment X Period	-0.0102*	-0.0156***	0.00588
	(0.00578)	(0.00377)	(0.00823)
Period	0.0153***	0.0168***	-0.00172
	(0.00289)	(0.00204)	(0.00555)
Constant	0.542***	-0.288***	0.384***
	(0.0938)	(0.111)	(0.144)
Observations	270	270	270
R-squared	0.564	0.530	0.283

*Note: The dependent variable is the POSCORE for the i^{th} coalition participant for a particular period with the NO-INFO-COMM treatment being the omitted base category. Standard errors are clustered by experimental session. Number of clusters 15. * represents significance at 10% level, ** at 5% level and *** at 1% level.*

However, when environmental benefit information is available, coalition members demonstrate some degree of rent seeking with increasing auction experience. This outcome is observed under the Rank treatment for the Single-Large and Several-Small coalitions when communication is presented and for the Several-Small case for the NO-COMM sessions. It is also observed for the Value treatment for the Several-Small coalition when communication is not allowed and for the Single-Large coalition when it is.

Finally, our experimental parameterization allows us to evaluate behavior of coalition members for whom there is a conflict in item selection. We observe that the Conflict dummy variable is positive and significant under both NO-COMM and COMM treatments and for all three coalitions. These bidders although part of the winning coalition are unsure about which item would be the best to submit – their individually optimal item or the socially optimal item. This unsureness contributes to their lower rent seeking levels and hence higher realized POSCORE values.

Section 5: Conclusion

Location clearly impacts the environmental benefits associated with the adoption of different conservation practices across the landscape. In this paper, we consider how auction design choices relating to information access and bidder communication impact auction performance and bidder behavior across different landscape types, which impact the size of the optimal winning bidder coalition. Motivated by the findings of a model of bidder behavior in a spatial conservation procurement auction, we explore the tradeoffs that exist in spatial conservation procurement auctions regarding the amount of coordination allowed between bidders through a laboratory experiment.

We find that auction design leads to different impacts on auction performance and bidder behavior based on the landscape type in which the auction is conducted. Whether due to excessive rent-seeking or the challenges of coordination among large coalitions, auction performance in the Single-Large landscape is shown to lag behind that of landscapes in which there are multiple, smaller coalitions. Policy makers and organizations overseeing PES programs should be able to utilize technological advances in remote sensing and machine learning to put our findings about the impacts of landscape type on optimal access to information and coordination between bidders to use.

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Appendix: Experimental Instructions

General Information:

Welcome! This is an experiment in economic decision making and it has **two stages**. You will be paid in cash on the basis of your choices in this experiment. If you follow the instructions carefully, you will be well-prepared to succeed today.

Your total earnings in Stage 1 will be recorded in real US$ and earnings from Stage 2 will be recorded in experimental currency units (ECU). At the end of the experiment, ECU will be converted to U.S. dollars at the rate of 1 U.S. dollar for every 27 ECU and will be added to your earnings from Stage 1. In addition to the earnings from Stages 1 and 2, you will also be paid a show-up fee of $9.

If you have any questions during the experiment, please raise your hand and wait for the experimenter to come to you. **Please do not talk, exclaim, or look at the computer screens of other participants during the experiment**. Cell phones must be switched off or placed into airplane mode. Participants intentionally violating the rules will be asked to leave the experiment and will not be paid.

Please raise your hand if you have any questions or click "Continue" to proceed to Stage 1.

New Screen: Stage 1 Instructions

In Stage 1, you will be given 10 different **scenarios** in which you must choose between **alternatives LEFT** and **RIGHT**. In each **scenario**, the **alternative LEFT** gives a certain payment. If you choose **alternative RIGHT**, your payment depends on chance. Let us consider an example **scenario**.

Example: Here you must decide whether you prefer **alternative LEFT** in which you receive **$1.75 for certain** or **alternative RIGHT** in which there is a **50% chance that you receive $2.50 and a 50% chance that you receive $0.**

LEFT	Please indicate your choice	**RIGHT**
$1.75 for certain	**LEFT○ ○RIGHT**	50% chance of $2.50 and 50% chance of $0.

Earnings in Stage 1

Earnings for Stage 1 will be calculated at the end of the experiment. Only one of the 10 scenarios **will be used for computing your earnings in Stage 1.**

Please raise your hand if you have any questions. Otherwise, click "Continue to Stage 1 Task" to proceed.

Earnings in Stage 1

We will now determine the earnings from Stage 1. Remember that only one of the 10 decisions you made will be used for computing your earnings in Stage 1. The **scenario** will be selected at random - the experimenter will publicly draw a card from a shuffled deck of cards numbered 1 through 10 (corresponding to the 10 **scenarios**). Each **scenario** has the same probability of being picked. The **scenario** picked will be the same for *everyone* in the room.

Once the **scenario** has been picked, another card will be randomly picked from a deck of two cards that contains one face card (a Jack) and one non-face card (#2). **The card drawn will determine the earnings of everyone that picked** alternative **RIGHT for the** scenario **chosen in the first card draw:**

- If the Jack is picked, those that picked RIGHT will receive the high payoff ($2.50).
- If the #2 card is picked, those that picked RIGHT will receive $0.

Everyone that picked LEFT will receive the certain payoff for the **scenario**.

Please raise your hand if you have any questions. Otherwise, click "Continue"

Description of Stage 2 Setting

In this stage, everyone is in a 12-person group and has a randomly assigned unique Subject ID visible on your screen. Please only use this ID to identify yourself in the experiment. The **12** people are arranged around a circle. The numbers on the circle represent every person in your group. On this circle, everyone has two neighbors - **a right or anti-clockwise** neighbor and **a left or clockwise** neighbor. **Your neighbors will be the same all throughout Stage 2.**

Please note: ID assignments have been randomly determined for all participants and does not reflect anyone's computer terminal or seating location.

Description of Auction

- In Stage 2, you will participate in multiple auctions with many rounds. Each round has many steps
- In each auction, you have three types of items – **Red, Green,** & **Blue**.
- Each item has a **Cost** and **Quality.** These values will change from auction to auction.
- These values will be shown on your computer screen.
- Your items' values are not known to others and vice-versa.
- In the auction, you will select one of your items and submit a Bid at which you are willing to sell this item. This Bid is the price you will receive for that item if it is selected in the auction.

Communication between Rounds of an Auction:

During an auction round, you can discuss all aspects about the auction with your neighbors through on-screen chat windows. But please (1) **only use your ID to identify yourself** and (2) **be civil to one another and do not use profanities**.

Only you and the neighbor you are communicating with will be able to view these messages. You will be able to communicate for 30 seconds in each round before the chat windows disappear automatically. All messages exchanged in previous rounds will be visible to you when you are communicating with your neighbors in the current round.

Item and Bid Selection

During an auction round, you will select and submit a bid for one of your items. The computer is the auctioneer. In every auction, the computer has the same budget that it wants to use up to buy some of the submitted items. The computer will choose items such that the sum of item qualities is maximized for the total money spent. The value of this budget will not be known to you.

For this, the computer calculates the Total Score of all combinations of submitted items and selects the winners, given the budget. The group members that own the selected items are the **temporary winners** of that round. Then the next round begins and the process is repeated. This process continues till the **final round** is reached. The people who are selected as temporary winner in this round become the **final winners**. These individuals' items are purchased by the computer and they receive a profit that contributes to their experimental earnings.

If your item has not been selected in a round, a decrease in your item's bid or selection of a different item may improve your chances of being selected in the next round. **The computer will display an error message if you (i) submit a bid that is less than the cost of your item or (ii) submit a higher bid for an item in a round if it was selected in the previous round.**

How the Computer Determines Winners in A Round

The computer values the quality of an item but also how many of the same colored item are offered by neighbors. To decide which items to purchase, the computer calculates the Total Score for all possible combinations of submitted items that can be bought with the budget and selects the combination with the highest Total Score. The Total Score comprises of two values – Total Quality and Total Bid of the combination. For this the computer executes the following steps.

1. It selects one of the item combinations which can be bought with the budget
2. For Total Quality calculation, the computer sums up the quality of all items in this combination. It then adds a **Premium Value** for each item in this combination that has a neighboring item of the same color. The greater the number of neighboring identical items included, the greater the Premium added to the sum of quality.
    - **In the experiment the Premium Value is 25.**
3. For Total Bid calculation, the computer sums up the bids of all items. Then, for all selected neighboring items of the same color, an additional **Bonus** payment is added to the sum of bids. The greater the number of same colored neighboring items included in the selected combination, the greater is the Bonus, added to the sum of bids.

    - **In the experiment the Bonus is 50 ECU**.
4. It then calculates the Total Score = ratio of the Total Quality and Total Bid

The computer repeats these steps for all combinations and then selects the combination which has the highest Total Score.

Although the computer prefers to purchase blocks of items of the same color, winning combinations may also include items of participants who are not neighbors or are neighbors but submitted different colored items. These items are not assigned Premium Values and Bonuses when calculating the Total Score.

Also, it is possible that the computer will not buy an item from you in any round of the auction. Since item selection in a round depends on everyone's submissions, it is also possible that even if you were a temporary winner in the previous round, you will not be selected in the current round.

Information you will receive after winners are determined

The computer will display the following information at the end of a round.

1. Whether you are a temporary or final winner
2. The color, cost and submitted bid of your item
3. Whether your neighbors have been selected or not
4. The color of your neighbors' submitted items
5. Your profit and bonus earnings for that round. Note that if the current round is the final round, and if you are selected as a temporary winner in this round, you will be the final winner in the auction. The displayed profit will be your profit for this auction.

Description of Auction Earnings

Each auction has multiple rounds and which round is final is not known in advance. Different auctions can have a different number of rounds. The computer will only make a purchase in the **final round**. If you are a temporary winner in a round and this round happens to be the **final round**, you become the **final winner** of the Auction as a whole. Experimental earnings are only affected if your bid is selected in the final round of an auction. If you are a final winner of an auction, your Profit in that auction will be

$$\textbf{Profit} = (\textbf{Bid} - \textbf{Cost}) + \textbf{Bonus x Neighbor}$$

The value of the term Neighbor in the expression is given by the following table

Neighbor Status	**Both Neighbors selected & submitted same colored item as you**	**One Neighbor selected & submitted same colored Item as you**	**Both Neighbors selected but only one neighbor submitted the same colored item as you**	**Both Neighbors selected but submitted different colored Item as you**	**No Neighbor selected**
Neighbor =	2	1	1	0	0
Bonus Added to Profit	100 ECU	50 ECU	50 ECU	0 ECU	0 ECU

Thus greater the number of neighbors who are selected and submitted the same colored item as you, greater is the bonus you receive and greater is your auction profit if you are a final winner.

Important: you pay an item's cost only if you are a final winner. If you are not a final winner and do not sell an item, your earnings for that auction are zero.

Once you review this information, please click **“Proceed to Quiz”**. After the quiz which checks your understanding of Stage 2, there will be a practice auction. This auction will only have 2 rounds so that you can become familiar with the auction. Your choices in the quiz and practice auction will not influence your cash payment in any way.