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Balancing Complexity and Rent-Seeking in Multi-Attribute Conservation Procurement Auctions: Evidence from a Laboratory Experiment*

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Abstract

Conservation procurement auctions are implemented under conditions that deviate from those assumed to derive predictions of bidder behavior. Existing research has emphasized the sensitivity of auction performance and bidder behavior to auction design choices. In the conservation context, procuring agencies must decide how to provide bidders with information about the environmental quality of different conservation practices to manage the trade-off between an increased probability of selecting the optimal practice and increased rent-seeking behavior associated with this information. We utilize an induced-value laboratory experiment to explore how access to quality information and variation in the bid-submission protocol can best be combined to improve auction performance. We find that the auction performs best when a bid-menu format, in which subjects submit bids for all their practices, is combined with information about the environmental quality rank of available conservation practices.

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1 Introduction

Payment-for-ecosystem-services (PES) schemes financially compensate private producers for implementing various conservation practices on their properties that generate ecosystem-service benefits for society. Conservation procurement auctions have been adopted in several PES programs due to the theoretical potential of an auction to overcome the challenges of information asymmetry under specific conditions (McAfee and McMillan, 1987; Vickrey, 1961). Examples include the Conservation Reserve Program (CRP) in the U.S. (Hellerstein et al., 2015), Bush Tender Pilots in Australia (Stoneham et al., 2003), and Higher Level Stewardship Schemes in the UK (Short et al., 2000). However, conditions of conservation procurement auctions deviate from those under which auctions theoretically achieve their optimal performance, necessitating studies that explore alternative auction designs. This need is magnified due to evidence of extensive rent seeking in CRP contracts (Kirwan et al., 2005; Ulber et al., 2011) and recent reductions in conservation budgets, including the budget for the CRP (Claassen et al., 2016).

Procurement auctions can mitigate the information advantage held by sellers regarding the cost of producing the goods and services available for sale. In the context of conservation procurement auctions, agricultural producers have more detailed understanding than procuring agencies about the opportunity and management costs of foregoing intensive land uses to pursue conservation practices. This advantage is magnified by bidders' ability to select a conservation practice from among several available conservation practices for consideration in the auction (Claassen et al., 2008). On the other hand, understanding the landscape-level processes that generate ecosystem services and the techniques used to value these services requires resources that producers are unlikely to possess, but may be available to conservation-procuring agencies (Glebe, 2013; Stoneham et al., 2003). So, conservation auctions also feature a potential information advantage for the procuring agency, related to the environmental quality stemming from different conservation practices.

Both the general and conservation auction design and implementation literature has focused on how the auctioneer can generate improved auction performance by modifying various features of the auction. One such feature is adopting different information revelation strategies about various aspects of the auction so as to improve auction performance and limit rent seeking. Procurement auctions in general, and conservation procurement auctions in particular, can be quite complex for bidders, as the goods and services being procured are often evaluated based on multiple characteristics in addition to their price, including quality, quantity, delivery time, etc., meaning these are multi-attribute auctions. In these settings, providing additional information can facilitate bid construction and improve auction performance (Gwebu et al., 2012) by reducing the difficulty of generating a successful bid (Messer et al., 2016a). The improved auction performance resulting from information access that reduces the difficulty of bid formation must be evaluated against the possibility of increased rent premiums due to this information (Strecker, 2010).[1]

In multi-attribute conservation auctions, bids for submitted conservation practices are evaluated on the basis of offered price and the resultant environmental quality. A notable feature of these auctions is that the relationship between a conservation practice's cost and quality may not be clear to bidders. As both of these attributes vary spatially and correlation between them can vary (Babcock et al., 1996; Heimlich, 1989), lack of information about environmental quality could contribute to auction complexity and limit a bidder's ability to identify her optimal practice for submission. This possibility suggests that the impacts of access to quality information may vary depending on the bid-submission protocol. One common protocol, the bid-menu format, involves bidders submitting bids for all of their available practices, with the best bid for each bidder chosen by the auctioneer. Another common protocol, the single-item format, requires the bidder to select one of her available practices for submission, meaning that the conservation practice and quality is endogenously

[1] Furthermore, information feedback about auction outcomes can lead sellers to learn about their competitors' costs and can lead to strategic bidding that negatively impacts the total procurement costs of the auctioneer, if the level of auction competition is low (Cason et al., 2011).

determined during the bid-formation process.

A recent strain of the literature has explored how access to information about the environmental quality of conservation practices affects auction performance and bidder behavior. In the setting of an induced-value laboratory experiment, Conte and Griffin (2017a) find that access to quality information increases auction performance and decreases rent-seeking when bidders select one of three conservation practices for submission and the price they are willing to accept to implement it. This experiment uses a single-round procurement auction, the format employed by the CRP. In a related laboratory study, Messer et al. (2016a) find that revelation of prior auction results increases the rent premiums obtained by sellers in subsequent auctions in a single-round auction with multiple enrollment periods. Such learning and magnified rent-seeking is characteristic of multi-round procurement auctions, in which bidders can conditionally update their beliefs about the probability of acceptance (Banerjee et al., 2015; Cason et al., 2003).

To the best of our knowledge, there is no study that provides a comparative analysis of the effects of information revelation and bid-submission protocol on auction performance while also considering auction complexity in a multi-round auction. We use an induced-value laboratory experiment to address this gap in the literature. The iterative format of the auction design in our experiment additionally affords us the opportunity to explore the mechanisms behind the alternative findings in Cason et al. (2003), which uses the bid-menu submission format in an iterative auction, and those in Conte and Griffin (2017a), which considers a single-round auction with a single-item submission format. Finally, our comparison of the alternative bid-submission protocols explores how this aspect of auction design can best be paired with access to environmental quality information to achieve improved auction performance, while reducing auction complexity.

In our experiment, the bid-submission protocol treatment is implemented in a within-subject design and the information treatment follows a between-subject design, in which participants receive information about the absolute values of the environmental quality of their available conservation practices in some sessions and the relative ranking of the benefits from their available conservation practices in others. The ranked-benefit information treatment simulates conditions faced by information-constrained producers in reality - these producers might have a good idea about which practice generates the highest or lowest benefits on their property but are not aware of the actual magnitudes of these benefits. The design of our information-revelation choices follows the results in Conte and Griffin (2017a), which finds that providing information either in ranked or absolute value format is better than not providing any environmental quality information to bidders at all, prompting the question about which information format yields better performance outcomes in an iterative setting, independent of the transparency consideration.

Our results indicate that, in the multi-round auction setting, the bid-menu format, which places the responsibility of conservation-practice selection on the procuring agency, improves auction performance relative to the single-item format, suggesting that bid-formation may be a complex task for auction participants. This result holds regardless of the form in which quality information is provided to the bidders. Moreover, auctions in which quality rankings rather than values are provided perform better across both bid-submission formats, as the ranked quality information increases the challenge of identifying the optimal conservation practice, keeping rent-seeking in check. This outcome may be expected given the increased rent-seeking made possible by access to absolute benefit information in a multi-round format (Cason et al., 2003). However, our results are obtained in an multi-round auction with offers constrained to be of equal or lesser value for a given item across rounds, a design feature intended to mitigate the rent-seeking opportunities afforded by such a format.

Our experimental design illustrates a clear tension associated with the impact of how quality information is provided in the single-item bid-submission protocol. While having only quality-rank information reduces rent-seeking, bidders have greater difficulty identifying their optimal conservation practice when the magnitudes of environmental quality are unknown. This difficulty challenges auction cost-effectiveness through the submission of bids that do not include the optimal conservation practice. While the auction mechanism is able to increase the percentages of winning bids that include the optimal item across both forms of quality information in this bid-submission format, these percentages are lower than those for the same quality information level in the bid-menu format. The challenge of identifying the optimal item for submission partially explains the improved auction performance observed in the bid-menu format.

These findings emphasize the importance of both the form of quality information provided to bidders as well as the choice of bid-submission protocol in determining procurement auction performance. The interaction between these two elements of auction design that we explore in this paper is useful in identifying the determinants of conflicting results in the literature regarding the role of quality information access in determining auction performance. Furthermore, these results emphasize the challenge of forming a successful bid in these multi-attribute auctions and the trade-offs that should be considered during conservation auction design regarding the interaction between these different elements of auction design and resulting auction performance.

2 Performance and Complexity of Bid Submission in Multi-Attribute Procurement Auctions

Procurement auctions are employed in many contexts to overcome information advantages held by sellers, such as electronic commerce (Haruvy and Katok, 2013), open-market operations by central banks (Armantier et al., 2013), and PES programs like the CRP (Hellerstein et al., 2015). A key aspect of many of these auctions is that the goods being purchased possess multiple attributes, in addition to the price, that must be evaluated in the winner-determination process. The presence of multiple attributes for submitted items increases the complexity of bid submission. In the case of conservation auctions, bidders must evaluate the potential conservation practices based on cost as well as the levels of environmental quality associated with each practice (Claassen et al., 2008; Hellerstein et al., 2015), which might be computationally challenging and cognitively complex. Providing information about auction features increases the transparency of the auction process, making it easier for bidders to identify the auctioneer's preferred items (Teich et al., 2006). This issue is of particular relevance in a conservation context, given the information advantage held by procuring agencies regarding the environmental quality of different conservation practices as well as producers' preferences for having this information in order to assess whether they want to participate in PES programs or not (Nebel et al., 2017).

Koppius and van Heck (2003) and Strecker and Seifert (2003) use laboratory experiments to evaluate the performance of a single-round, multi-attribute auction in which bidders are able to infer the auctioneer's preference for a particular attribute and hence her utility function. Both of these studies indicate that information revelation improves auction performance. In the conservation context, Conte and Griffin (2017a) find that information about environmental benefits provided in different formats (in absolute terms or in ranked form) in a single-round auction is performance enhancing compared to outcomes in the absence of quality information.

The complexity of bid-formation with multi-attribute items (such as those encountered while selling spectrum licenses in telecommunication (Kwasnica et al., 2005)) suggests that multi-round auctions, which provide information feedback that facilitates learning and simplifies the bid-formation process while mitigating bidding errors, might improve auction performance (Parkes and Kalagnanam, 2005). Depending upon the nature of information feedback, multi-round auctions can also promote transparency and bidder validation of auction outcomes (Parkes, 2006), which would be essential to the success of large public auctions such as conservation auctions (Messer et al., 2016a).[2]

The trade-off associated with bid revisions and information feedback in multi-round auctions is that they allow bidders to update their beliefs about the probability of acceptance, which might magnify rent-seeking. Furthermore, this auction format provides bidders with the opportunity to signal information and collude with each other, which would further reduce performance (Fabra, 2003; Parkes, 2006).[3] Given the increased ability of bidders to seek rents, results from studies on multi-round conservation auctions are less ambiguously in favor of increased information provision and auction transparency. For example, Banerjee et al. (2015) find that auction performance measured in terms of cost-effectiveness, falls significantly when the auctioneer announces a preference for spatially adjacent projects for which they are willing to make bonus payments to auction winners. Similarly, Cason et al. (2003) obtain evidence of collusive bidding, higher rent premiums and lower cost effectiveness when subjects have information about environmental benefits of their practices, despite this information leading to greater benefit procurement. While information about the auctioneer's preferences and the iterative structure of multi-round auctions can reduce auction complexity, the combination of these two design choices results in a tradeoff between the ability to select conservation practices with a high probability of acceptance and the rent premium associated with submitted bids.

[2] Palm-Forster et al. (2016) indicate that program complexity reduces participation in USDA conservation programs and an iterative structure might as well be perceived as too complex although it allows producers opportunities to revise bids and improve their chances of being selected in subsequent iterations.

[3] The potential for such performance reductions is even more critical for procurement auctions that are run repeatedly through time with the same bidding pool, such as those for highway construction contracts (Porter and Zona, 1993), procurement of milk supplies for schools (Pesendorfer, 2000) and in the conservation auction domain both in the lab (Banerjee et al., 2015; Cason et al., 2003) and under actual policy implementation (Kirwan et al., 2005; Ulber et al., 2011).

The studies by Cason et al. (2003) and Conte and Griffin (2017a) utilize different bid-submission formats, which may contribute to their conclusions about the impacts of access to environmental quality information. In the auctions studied in Conte and Griffin (2017a), bidders must select one of their available items for submission, making the bidder fully responsible for evaluating their three endowed practices in search of the optimal item for submission. This step affords bidders greater control over their choices, which is a desirable feature.

However, such control can come at the expense of substantial complexity, causing bidders to incur high private transaction costs (Mettepenningen et al., 2009). Such cognitive complexity has been raised as a concern in the general procurement auction context as well, leading to mechanism design research in search of simple, but high-performing, auction designs Chen-Ritzo et al. (2005). In the experiments presented in Cason et al. (2003), bidders submit a menu of bids for all their items, meaning that the act of item-selection is the responsibility of the procuring agency.

The bid-menu format simplifies the offer-formation process by removing item-selection from the process, implying that it might be able to overcome some of the reduction in auction performance observed by Conte and Griffin (2017a) when information is provided in a ranked format and not in absolute value terms, in a single-round auction. However, the bid-menu format does not generate the performance improvements in an iterative setting when subjects have information about the auctioneer's preferences (Cason et al., 2003). The existing literature has not resolved the preferred auction and bid submission formats. We study behavior and performance of an iterative auction under two quality information conditions and two bid-submission formats in a controlled laboratory setting to improve understanding of how these aspects of auction design impact conservation procurement auction outcomes.

3 Experimental Design and Econometric Methods

3.1 Experimental Design

Our induced-value lab experiment used a combined between-subject and within-subject design to explore how variation in access to quality information and the bid-submission process respectively impact auction complexity and hence performance and participant behavior.[4] Participants earned cash payouts based on their experimental choices, which asked participants to respond to the incentive structure faced by producers in a conservation procurement auction. No conservation framing was used in the experiment because an environmental context can influence behaviors and confound treatment effects (Cason and Raymond, 2011). There were two information treatments: *Quality Value*, in which participants were shown the magnitude of the environmental quality value of the three available items, and *Quality Rank*, in which only the relative ranking of the three items was revealed. In addition to the complexity issue, this treatment explores the tradeoff associated with information disclosure, namely the attempt to strike a balance between providing enough information to facilitate successful bid formation but not so much as to magnify rent-seeking behavior (**?**).

The bid-submission treatment compared outcomes in the *Item* and *Menu* treatments. The *Item* treatment included an item-selection stage in the bid-formation process, in which participants first chose one of their three available items and then submitted an offer (price) for it. Thus, item selection was endogenous to offer formation in this treatment. In the Menu treatment, participants submitted offers for all items, with item selection being undertaken by the auctioneer. Given this experimental design, there were four treatments overall: *Value-Item*, *Value-Menu*, *Rank-Item*, and *Rank-Menu*.

[4] The within-subject design increases the sample size and minimizes the error variance associated with participant heterogeneity. It does raise the possibility of carryover (Charness et al., 2012) and experimenter demand effects (Zizzo, 2010) between treatments, which we control for by balancing the within-subject treatment.

We conducted eight experimental sessions, each with twelve student participants recruited from undergraduate economics classes and previous laboratory experiments, at a private university in the fall of 2016 and the spring of 2017.[5] Sessions lasted approximately 120 minutes and participants earned a mean payment of $33.25 for their time, including a $10 show-up payment. Participants engaged in the auction through a graphical user interface implemented using Z-tree, allowing for automated offer/bid submission and calculation of auction outcomes (Fischbacher, 2007). Each session included a *Menu* treatment and an *Item* treatment, with sessions 1 through 4 involving *Value* treatments and sessions 5 through 8 the *Rank* treatments. Four sessions were run for each of the quality treatments (*Value* and *Rank*). Within a session, each bid submission treatment included eight multi-round periods, with a minimum of three rounds and a maximum of five rounds per period.

To facilitate ready comparison to the broader literature, the process of generating values for the cost and quality parameters in our experiment was based on approaches used in Cason et al. (2003), Hellerstein and Higgins (2010), and Conte and Griffin (2017a). Due to evidence from the field that the environmental benefits of retiring land from production and the costs of doing so may be negatively correlated, positively correlated, or uncorrelated (Babcock et al. (1996); Heimlich (1989)), these values were independently drawn from separate cost and quality distributions. Each participant was given three items to choose from that differed only in their realized cost and quality draws. Each cost draw, c_{ij}, for player i and item j, was drawn from a uniform distribution on support {500, 1000} and each quality draw, q_{ij}, came from a uniform distribution on support {50, 100}. Participants were unaware of the underlying distributions from which cost and quality parameters were drawn, though they were informed that these draws were independent. Random cost and quality draws introduce variation that might confound hypothesis testing, so we generated triplets of cost and quality endowments for all participants, which were then reallocated in the other treatment by first reassigning them to new participants within a period, and then reordering periods.

[5]See the supplement for example experiment instructions from the *Value-Item* treatment.

Participants were not informed of the fixed budget of 4,500 experimental currency units (ECUs), in each auction period, a figure that was constant across treatments. This hidden budget information setting was employed to maintain consistency with related research (e.g., Cason et al., 2003; Conte and Griffin, 2017a).[6] As explained below, the selected measure of auction performance was designed to accommodate variation in total expenditures across periods, which is possible with a constant available budget due to the purchase of a discrete set of items.

Each session included the following four components that proceeded in order: a paid exercise to determine each participant's risk preferences based on Holt and Laury (2002); an unpaid practice auction sharing the design of the first treatment in the session to familiarize participants with the user interface; and two experimental treatments on the basis of which participants were paid. Immediately prior to data collection, instructions were read aloud to participants to maintain an environment of common knowledge in the experiment. Instructions clearly indicated that the buyer preferred high-score (low-cost and high-quality) items, meaning that the offered price and item quality were counteracting acceptance criteria. As such, maximizing their net returns required a seller to carefully balance their asking price against the uncertain probability of offer acceptance.

After bid submission in a round was complete, offers were given a score equal to the quality of the submitted item divided by the offer price.[7] These scores were then ranked in descending order and bids were provisionally accepted based on their score until the budget was exhausted. Participants were informed whether or not their offer had been provisionally accepted at the end of the round. In the *Menu* treatments, the notification of provisional

[6]Messer et al. (2014) suggests that seller rents are sensitive to access to information about the budget level in an experimental discriminatory land procurement auction; however, the treatments considered in that study do not lead to a clear directional conclusion about the optimal information-revelation strategy for our study.

[7]Babcock et al. (1997) shows that this format produces cost-effective outcomes under various degrees of correlation between cost and quality.

acceptance specified which of the three items, if any, had been accepted. Participants then had the opportunity to adjust their offers in response to the information about the provisional status of their offer from the previous round, although the submitted price for a given item could only be reduced across rounds within a period.[8]

Auctions proceeded through the bid submission and winner determination routine to a subsequent round until a minimum of three rounds had been played. At this point, a stopping rule was evaluated to determine if the auction would end or if another round of bidding would be conducted.[9] If the stopping rule was never satisfied, the auction repeated through the maximum of five rounds.[10] At the conclusion of each period, participants were informed about whether or not their offer had been accepted and winners' earnings were updated on the basis of the difference between their winning item's offer and its corresponding cost. We adopted this discriminatory-price design as it has been shown to perform better than alternative fixed-price payment mechanism or uniform price auction (Cason and Gangadharan, 2004; Horowitz et al., 2009; Messer and Allen, 2010), although this advantage has been shown to diminish with bidder experience (Schilizzi and Latacz-Lohmann, 2007). Participant earnings were announced and added to their updated personal cumulative earnings total recorded in ECUs.

3.2 Econometric methods

Non-parametric tests and econometric models are employed to explore the impacts of our selected treatments on auction performance through an understanding of how bidder behavior varies in response to the alternative treatments. We first introduce our definition of auction performance and our approach to estimating the treatment effects on this outcome

[8] Restricting price changes on submitted bids for a given item to reductions only was a design decision motivated by results in the literature illustrating the increased rent-seeking opportunities in multi-round auctions (Parkes, 2006).

[9] In this study, the auction ended after a round if the cost of all procured items and the sum of the scores of these items between consecutive iterations was the same and a minimum of three rounds had been played.

[10] Of the 128 periods conducted in the experiment, 111, or 86.72%, ran for the full five rounds.

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), $\frac{\sum q_i^a / \sum p_i}{\sum q_i^o / \sum c_i^o}$, 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 (i.e. the one with the highest endowed score), and c_i^o represents the cost of bidder i's optimal item. POCER has been employed to measure cost-effectiveness in related studies (see e.g., Cason et al., 2003; Conte and Griffin, 2017a,b). The measure of optimal cost-effectiveness is created by ranking the endowed scores (q_{ij}/c_{ij}) of all conservation choices and selecting those with the highest scores (with a maximum of one choice per participant) iteratively until the next selection would exceed the budget. The acceptance algorithm in the auction ranks offers by score, defined as $\frac{q_i}{p_i}$, where p_i refers to the price of the submitted item and q_i its quality. In these auctions, bids are accepted in rank order, highest score first, until the offered price of the marginal bid exceeds the conservation budget ($4,500$ ECUs). This approach maximizes the score of all accepted items and is consistent with the approach used to generate the POCER metric.

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:

$$POCER_{tg} = \alpha + X_{tg}\beta + Z_{tg}\gamma + \nu_{tg} \tag{1}$$

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 (the indicator for the *Rank-Menu* treatment is excluded from the regressions as a reference). Z_{tg} denotes the period number within a given treatment, which measures treatment experience, and interactions between this term and the *Item* treatment indicator.[11]

3.2.2 Bidder behavior

Auction complexity can have substantial impacts on bidder behavior and overall auction performance. As noted, the *Item* treatments might be considered to be more complex from the bidders' perspective, as they require bidders to select one of the three available items for submission prior to the offer-formation process. We use a logistic regression to evaluate the factors that influence item choice in the *Item* treatment, with item characteristics used as predictors for the binary dependent variable y_{ijt} (1 for the item selected, zero otherwise). The model is:

$$y_{ijt} = 1[\alpha + X_{ijt}\beta + u_{ijt}] \geq 0 \tag{2}$$

where u_{ijt} is distributed extreme value conditional on X_{ijt}, i indexes experiment participants, j indexes items, and t indexes auction periods. X_{ijt} comprises item characteristics that vary based on the treatment being studied. For the *Value-Item* treatment, X_{ijt} comprises indicator variables that take on a value of 1 if the item chosen has the minimum cost, has the maximum quality, or has the maximum score of those available. X_{ijt} also includes the

[11] Each treatment has the same number of auction periods across sessions, and our 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).

endowed score variable, which refers to an item's endowed quality divided by its cost. For the *Rank-Item* treatment, indicator variables related to score are replaced by a variable that records the quality rank of the chosen action in X_{ijt}. This regression model was run independently for each treatment and for the pooled observations from the *Value-Item* and *Rank-Item* treatments. We cluster standard errors at the session level to allow for unobserved heteroskedasticity and serial correlation within each session.

Finally, 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 two-dimensional procurement 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 (2017b) and use the percentage of the optimal score ($POScore$) as our measure of bid competitiveness. $POScore$ for seller i is defined as $\frac{q_i^s/p_i}{q_i^o/c_i^o}$, where p_i represents the offered price of the item, q_i^s represents the submitted item's quality, and q_i^o and c_i^o represent the quality and cost of seller i's optimal item, respectively.[12] We see that for seller i's optimal conservation item, meaning that it has the maximum score $(\frac{q_i}{c_i})$ of the three available items, $POScore = \frac{c_i^o}{p_i}$. This feature is important, because it indicates that the determinants of $POScore$ will vary depending on whether or not the submitted bid is for the optimal item. Moreover, $POScore$ should be independent of item quality for the optimal item in each endowed item triplet. This feature suggests that the exploration of bidder behavior and how it impacts auction performance will benefit from doing so across all bidders, but also for those who were able to identify and submit their optimal item in the *Item* treatment or place bids strategically to maximize optimal item selection in the *Menu* treatment.

[12]In the *Menu* treatments, bids are submitted for all items, meaning that there will be three submitted items for each seller in each auction round rather than the single item submitted in each round in the *Item* treatment. We explore the determinants of $POScore$ across all items in all treatments as well as for subsets of items, to reflect the possibility that bidding behavior by bidders in the *Menu* treatment might vary across their three endowed items, when they know that at most one of their items will be accepted in a given auction period.

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:

$$POScore_{it} = \alpha + X_{it}\beta + Z_{it}\gamma + \nu_{it} \tag{3}$$

where i indexes experiment participants and t indexes auction periods. As above, $POScore_{it}$ is defined as $\frac{q^s_{it}/p_{it}}{q^o_{it}/c^o_{it}}$. If participant i selects the highest-score action in period t, then $POScore_{it} = \frac{c^o_{it}}{p_{it}}$. X_{it} comprises characteristics of submitted conservation actions including cost, quality, minimum cost and maximum quality indicators. The components of the vector Z_{it} vary across the models and relate to bidder characteristics, including the scenario in which the participant switched between the lottery pairs in a risk-preference elicitation exercise based on Holt and Laury (2002).

4 Results

In the first sub-section, we present the results of our treatment implementations on auction performance, as measured by POCER. In the next subsection, we turn to the analyses of bidder behavior. First, we focus on item selection then we consider offer formation across all treatments and use $POScore$ as our metric of choice.

4.1 Auction performance

Summary statistics provide an introductory exploration of the impact of our information and bid-submission treatments on auction performance. Table 1 reports how access to quality information and variation in the bid-submission process impacts the auction mechanism's performance in every period pooled across all sessions. We see that the cumulative quality provided by the auction is, on average, higher in the *Rank* treatment than in the *Value* treatment and that this difference is significant at the 5% level (columns 1 through 3). Given that both treatments consist of identical endowed triplets of conservation action items, it is not surprising that total expenditures are not statistically different across treatments, though it is worth noting that the budget is, on average, not fully expended in either treatment. Also, while the ratio of the average quality purchased to the optimal quality (obtained in the absence of asymmetric information about item costs) is only marginally higher in the *Rank* treatment, the average amount of quality provided per unit of expenditure is significantly higher in this treatment. Moreover, the constant endowments across treatments leads to the same ratio of optimal quality per unit of expenditure, so that the higher and significant POCER value in the *Rank* treatment can be attributed to the aforementioned higher mean quality per unit of expenditure.

We now turn our attention to columns 4 through 6 of table 1 to consider the impact of the bid-submission process on auction performance. Here, we see that the total quality provided is significantly higher in the *Menu* treatment relative to the *Item* treatment, leading to a higher ratio of actual to optimal quality in this treatment. Given the indistinguishable total expenditures across treatments, this leads to a significantly higher mean realized quality per unit of expenditure in the *Menu* treatment. Finally, we see a significantly higher POCER value in this treatment that is significant at the 1% level.

Table 2 presents results of regression models that provide further exploration of the effects of access to quality information in different formats and bid-submission design on auction performance. The models utilize a random-effects method, meaning that the session-level effects are assumed to be uncorrelated with the independent variables, and cluster standard errors at the session level, with the confidence intervals generated through bootstrapping. The effects of the quality-information and bid-submission treatments are consistent across models and align with the unconditional means reported in table 1. Considering the results of model 1, POCER is lower in each of the *Value-Item*, *Rank-Item*, and *Value-Menu* treatments relative to the base of 0.92 in the *Rank-Menu* treatment. These results are robust, with similar magnitudes, when controlling for treatment experience (model 2).

Our findings align with the expected impact of auction complexity on performance, with the auctioneer responsible for item selection in the *Menu* treatment, which reduces complexity of bid formation and improves auction performance. The tension inherent in the *Value* treatment, with access to quality information reducing the challenge of identifying the bidder's strongest endowed action while also increasing the opportunity for increased rent-seeking, is apparent in the results depicted in table 2. The *Value-Item* treatment is the worst-performing design of the alternative designs explored. Given the magnitudes of the coefficients on the *Rank-Item* indicator, the results also suggest that the bid-menu format is better able to reduce the complexity of bid formation and mitigate the rent-seeking opportunities afforded through access to quality value information. Finally, experience in the experiment is detrimental (although marginally so) to auction performance. This finding is aligned with past results about experience-induced rent seeking in both auction experiments (Schilizzi and Latacz-Lohmann, 2007) and during actual policy implementation, such as for the CRP (Kirwan et al., 2005; Ulber et al., 2011). We now turn to an exploration of bidder behavior to illuminate the forces behind the auction performance results displayed in table 2.

4.2 Bidder behavior

We first provide a detailed analysis of the item-selection process to comment on the pathways through which auction complexity drives outcomes under the two information treatments. Then, we turn to results of our *POScore* regressions for a systematic analysis of offer formation.

4.2.1 Item selection

In our experimental context, each bidder's optimal item is the item with the maximum endowed score, which is the item's quality divided by its cost. Participants should find it easier to identify this item under the *Value* treatments than under the *Rank* treatments, given that cost and quality values are drawn independently. Table 3 presents details about the percentage of bids that involve the optimal item across various rounds in all periods for each treatment. This statistic is presented for different rounds within a period to reflect that participants' ability to identify the optimal item will change across rounds in a period as they update their beliefs and gain more experience.

Within the *Item* treatment, under the *Value-Item* condition, we observe that the optimal item was selected roughly 75% of the time, which is significantly higher than the corresponding percentages in the *Rank-Item* treatment (columns 1-3, top panel). This result is in line with our expectations, as participants are favorably disposed to identify the optimal item under the *Value-Item* treatment.[13] It is worth noting the substantial increase in this percentage from early rounds to the final round in the *Item-Rank* treatment. This outcome shows the powerful impact of updating beliefs permitted within multi-round auctions on bidder behavior. Columns 4 through 6 of the table present statistics for all bids that were accepted in the auction. This includes both the provisional non-final-round bids and the final-round winning bids that were used to make experimental payments. We see that accepted items are more likely to include the optimal item across both quality information treatments. While the *Item* treatment complicates the process of item-selection by including it in the bid-formation process, the auction mechanism is relatively robust, with more than 88% of optimal items selected as final winners under both information conditions (column 6,

[13]The rounds and combinations of rounds included in the table were chosen to ensure that the statistics included behavior from all periods and sessions in the experiment. Several periods did not reach round four, which is why results for rounds four and five are not analyzed separately. The results presented in table 3 are consistent when the analyses are conducted for each round in each period and other combinations of rounds.

top panel). Finally, there is no significant difference in the percentage of optimal items accepted by the auction across the two information conditions, despite table 2 indicating that performance is poorer under the *Value-Item* treatment relative to the *Rank-Item* treatment. Reconciling these results means that while the same items may be procured under both treatments, more is paid out for these items in the presence of quality value information.

The *Menu* treatment does not require participants to identify the optimal item for submission. Hence, the percentage of bids including the optimal item in this treatment, whether in the *Value-Menu* or *Rank-Menu* treatment is 0.333, which follows from the fact that participants submit bids for all items in this treatment (columns 1-3, bottom panel). The advantage of a bid-menu protocol in improving auction performance through acceptance of optimal items in the winning allocation (columns 4-6, bottom panel), is evident, with at least 95% of winnings bids including the optimal item across both the *Value-Menu* and *Rank-Menu* treatments during intermediate and final rounds of the auction periods. In addition, comparing across the upper and lower panels, significantly more optimal items are selected in the winning allocation under the *Menu* treatments than in the *Item* treatments, which corroborates our findings in table 1 regarding the performance improving features of the *Menu* treatment.[14]

We now turn to regression results for a more comprehensive understanding of the factors that generate the item-selection outcomes presented in the top panel of table 3 for the *Item* treatments. Table 4 contains results of our item-selection analysis. In the *Value-Item* treatments (column 1), participants are able to compute the endowed score of each of their three items, so that the probability of item selection is significantly increasing in this value. Furthermore, maximum-score and maximum-quality items are significantly more likely to be selected in this treatment, although there is no such increase in selection probability for the

[14]The differences across the *Item* and *Menu* treatments for each set of rounds are significant at the 1% level for both the *Value* and *Rank* treatments, based on Wilcoxon rank-sum tests.

minimum-cost item. In all, the results suggest that participants used the information about environmental quality to select items for submission that gave them the best chance to be accepted in the auction.

In the *Rank-Item* treatments, participants are unable to calculate the actual score of their items and only had detailed cost information. For this reason, we see that the minimum cost item is significantly more likely to be selected in this treatment. We also see that the probability of item selection decreases significantly as the quality rank value of the item increased. This is not surprising, as the instructions indicated that the item with a quality rank of 1 had the highest quality. Given that our experimental participants are informed about the format of the scoring metric and the auctioneer's preference for items with high quality per unit of cost, these two findings indicate that a higher POCER value and hence lower rent seeking in the *Rank-Item* treatment can be predominantly attributed to computational complexity rather than lack of comprehension about the strategic setting.

4.2.2 Offer formation

We next focus on the analyses of offer formation and rent-seeking behavior in all four treatments using the $POScore$ metric to explain the auction performance results depicted in table 2. We first consider the determinants of $POScore$ for all submitted final-round offers across all auction periods. These results are presented in table 5.[15] The results in table 5 are somewhat unexpected.[16]

For bidders who select their optimal item, $POScore$ will be independent of item quality and may be either increasing or decreasing in item cost, based on how that cost impacts the

[15]The results of these models are qualitatively similar to those obtained when bids from all rounds are considered. These results are presented in table 1 of the supplement.

[16]The results of these models are not substantively affected by the inclusion of additional bidder-level characteristics - age and gender, in the random-effects models. These results are presented in table 2 of the supplement.

offered price.[17] For bidders who do not select the optimal item, $POScore$ will be increasing in item quality and decreasing in item cost. Considering the first row of table 5, we see that the coefficient on item cost is negative and statistically significant in all treatments, save the *Value-Item* treatment. The results in table 5 are based on all bids submitted across all treatments. In the *Menu* treatments, bidders had to generate offers for all available items (recall the results from table 3 for the *Menu* offers). It is possble that bidders might have generated intentionally-high, and thus unsuccessful, offers for their lower-score items to ensure that their optimal item would be accepted by the auctioneer. This behavior, potentially beneficial in the *Menu* treatments, is sub-optimal and decreases expected payoffs in the *Item* treatments. The negative coefficient on the cost variable in the *Rank-Item* condition suggests that the lack of accurate quality information in this treatment is a real challenge to successful offer formation.

The results in the second row likewise suggest the challenge of optimal offer formation in this auction. This row shows how $POScore$ varies with item quality. Knowing that $POScore$ should be independent of item quality if the optimal item is selected, it is surprising to see that the coefficient on this variable is positive ans statistically significant across all treatments. This relationship across treatments should only occur if participants were not submitting bids for their optimal (maximum endowed score) item in the *Item* treatments. The result could possibly be explained in the *Menu* treatments if bidders in this treatment knew that they were forming offers for their non-optimal items. To ensure that participants were able to identify successful strategies despite the complexity of some of the treatments, we turn to table 6, which presents results of the same models as presented in table 5, but run only on bids that included the optimal item in each bidder's endowment.

[17] $POScore$ is defined as $\frac{q_i^s/p_i}{q_i^o/c_i^o}$ and is equal to $\frac{c_i^o}{p_i}$ for the optimal item, meaning that $\frac{\partial POScore}{\partial q_i^o} = 0$ and $\frac{\partial POScore}{\partial c_i^o} = \frac{p_i(c_i^o) - \frac{\partial p_i}{\partial c_i^o} c_i^o}{(p_i(c_i^o))^2}$ for optimal items.

Here, we see the expected relationships between our explanatory variables and the outcome variable of interest. *POScore* is increasing in cost across all four treatments, with a 100-unit increase in optimal-item cost leading to a 3 percentage-point increase in *POScore* in the *Rank* treatments and a 4 percentage-point increase in *POScore* in the *Value* treatments. This result is intuitive, as rent-seeking is less viable for high-cost items. Although we are considering bids only for optimal items, we do see negative and significant relationships between *POScore* and item quality across all treatments. This finding suggests that these bidders are engaging in increased rent-seeking behavior for high-quality, optimal items, which is supported by the negative coefficients on the maximum-quality indicator variable across all treatments, though these coefficients are only strongly statistically-significant in the *Menu* treatments. These results are a testament to strategic bidding and gaming in the auction. Finally, considering the entire data set, we see that there is a reduction in *POScore* in the *Value-Item* treatment and *Value-Menu* treatments relative to the *Rank-Menu* treatment, which confirms previous results.[18]

5 Discussion

There are a number of market failures associated with land-use decisions that result in inefficient land-cover change decisions. Payment-for-ecosystem-services (PES) programs have been adopted in a variety of situations around the globe to address the inefficiency of such land-use decisions. In these programs, multi-attribute procurement auctions have been implemented to overcome the information advantage possessed by producers regarding the costs of various conservation practices. In this context, procuring agencies have an advantage regarding their understanding of the environmental quality of the conservation practices, as they possess the resources and expertise to compute the environmental quality of these practices. These auctions are implemented based on theoretical predictions of their ability to

[18] Results for models like those presented in table 6 for only non-optimal items are presented in table 3 in the supplement.

achieve cost-effective procurement, though field conditions vary substantially from assumed conditions. So, exploration of auction design alternatives and their impacts on bidder behavior and auction performance is an active area of research (e.g., Arnold et al., 2013; Duke et al., 2013; Kawasaki et al., 2012; Messer et al., 2016a).

Yet, regulators may be slow to embrace modifications to existing auction designs owing to administrative burden arising from unfamiliarity with the auction procedures (Messer et al., 2016b). Producers might find sophisticated auction designs overly taxing as well, leading to a reduction in auction participation (Palm-Forster et al., 2016). Moreover, if they find the auction too complex, bidders might adopt strategies based on psychological considerations that are not cognitively costly to implement, but which may not necessarily lead to optimal bid formation. For example, rather than carefully considering the current costs of the practices and identifying one or a few that would maximize their likelihood of acceptance, producers might anchor current bid offers to payments they have received during past signups for similar or other practices under the procurement auction or other programs. Such behavior is not uncommon in auctions as has been presented by (Ariely and Simonson, 2003) who find that final prices of tickets auctioned for the 2000 Rose-Bowl game were significantly anchored to the starting sales prices for the tickets. Producers may also exhibit loss-aversion and experience an endowment effect (Ariely et al., 2005) with respect to their land, whereby they might bid at the announced bid-cap to reflect their emotional attachment to the land.

In addition to the issue of complexity, which prevents uptake of auctions as allocation mechanisms in PES programs, another problem is the potential for rent-seeking in discriminatory-price auctions (Arnold et al., 2013; Kirwan et al., 2005), which are not incentive compatible (Latacz-Lohmann and Van der Hamsvoort, 1997). Despite the issue of rent-seeking in discriminatory-price auctions, in which the submitted offer impacts not only the probability of acceptance, but also the payment conditional on acceptance, discriminatory price auctions have been shown to outperform uniform-price auctions in a conservation context (Cason and Gangadharan, 2005). We should note that this finding hinges on the features of the economic environment, such as the existence of perfect monitoring of environmental actions implemented. Auctions have also been found to perform better than fixed-price payment schemes in conserving more acres (Horowitz et al., 2009; Messer and Allen, 2010).Kawasaki et al. (2012) compare the performance of a uniform and discriminatory price conservation auction and find that the former is more efficient in an setting with imperfect monitoring of environmental compliance. These concerns notwithstanding, conservation auctions do present a politically viable mechanism for procurement of environmental benefits from agricultural landscapes by maintaining producer sovereignty, as participants have considerably flexibility in deciding their submitted conservation practices and offer amounts.

Our results show that providing ranked environmental quality information and removing item selection from the bid-submission process improves auction performance. While access to only ranked quality information means that participants cannot compute the exact score of their items to identify their optimal item for submission, this form of environmental quality information successfully reduces the rent premiums sought by bidders. Overall, these countervailing effects lead to improved performance under both of the bid-submission protocols explored in our experimental setting. In addition, implementation of a bid-menu format relaxes the computational cost associated with bid formation, leading to a reduction in complexity that contributes to improved performance under both quality information treatments. The results of our study underscore the tension between auction feasibility and performance, stemming from the public transaction costs of administration and participation (Mettepenningen et al., 2011), which are expected to be higher for an iterative bid-menu setup. Indeed this issue is expected to become increasingly important for PES programs as conservation budgets are lowered.

We find that the bid-menu protocol can be useful in managing the trade-offs associated with the provision of quality information to bidders in conservation procurement auctions. The finding that the treatment with ranked benefit information and bid-menu format achieved the best auction performance in our multi-round auction in which offer adjustments across rounds were constrained to be reductions, highlights the importance of the choice of auction format (single-round versus multi-round) in explaining the different impacts of access to quality information on auction performance in the Cason et al. (2003) and Conte and Griffin (2017a) studies. This is outcome suggests that regulatory agencies might prefer to implement a conservation auction with a bid-menu submission protocol with ranked environmental-quality information to enhance auction performance, while lowering the computational costs and hence private transaction costs associated with offer-formation. Providing environmental quality information can also promote greater auction transparency and hence producers' trust in the government, which could be useful in encouraging their participation and subsequent enrollment of high-quality lands in the PES program. One challenge to the policy-relevance of a bid-menu protocol is the extent to which procuring agencies possess sufficiently-detailed understanding of the various conservation practices available across the landscape and the cost involved in identifying the preferred subset of these practices that should be included for eligibility in the auction. Training of officials at procuring agencies and guidance offered to potential auction participants can thus be instrumental in effective implementing conservation auctions (Messer et al., 2016b).

6 Conclusion

The conservation context poses a number of challenges to the successful implementation of multi-attribute procurement auctions to allocate payments in PES programs. Because theoretical predictions cannot be derived when assuming many real-world conditions, laboratory experiments provide a valuable setting in which to explore the implications of alternative auction designs on performance prior to implementation in actual PES programs. Future study will utilize induced-value laboratory experiments to explore how the complexity of bid-formation affects auction performance and bidder behavior when auction participation is endogenous. We fully acknowledge that our results may be dependent on the parameterization of our experiment and other features such as the iterative descending price format and the context-neutral framing. Thus, we believe that further exploration of the issues presented here would represent meaningful contributions to the literature for both interested researchers and practitioners. Results of these new studies should be combined with the present one to inform the design of field experiments with actual producers to obtain evidence of whether the results of this experiment are externally valid. The combination of lab and field results will provide the guidance needed to design actual conservation policy geared toward improved welfare outcomes from land-use decisions.

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Table 1: Period-level descriptive statistics

	Value Treatment	Rank Treatment	Difference	Item Treatment	Menu Treatment	Difference
Total quality provided	549.05	563.95	-14.91	547.36	565.64	-18.28
	(4.32)	(5.20)	0.0331	(4.56)	(4.90)	0.0123
Total expenditures	4140.52	4121.19	19.33	4140.38	4121.27	19.17
	(23.85)	(28.45)	0.500	(26.71)	(25.78)	0.6320
Average quality/optimal quality	0.8721	0.8964	-0.0243	0.8697	0.8988	-0.0292
	(0.005)	(0.006)	0.0501	(0.006)	(0.007)	0.0071
Average quality/expenditures	0.1326	0.1369	-0.004	0.1323	0.1372	-0.005
	(0.001)	(0.001)	0.0001	(0.001)	(0.001)	0.0001
Optimal quality/expenditures	0.1505	0.1505	0.0000	0.1505	0.1505	0.0000
	(0.001)	(0.001)	1.0000	(0.001)	(0.001)	1.0000
POCER	0.8814	0.9093	-0.0279	0.8789	0.9118	-0.0329
	(0.004)	(0.004)	0.0000	(0.005)	(0.004)	0.0000
Observations	64	64	128	64	64	128

Notes: All offers. Standard errors in parentheses. The third and fifth columns report the difference between column one values and column two values and column three values and column four values, respectively, with the p-value from a Wilcoxon rank-sum test of the equality of each variable across the two samples presented beneath each difference.

Table 2: Auction performance – Percentage of optimal cost-effectiveness ratio

	Model 1	Model 2
Value x Menu Treatment	-0.0248***	-0.0190**
	(0.0077)	(0.0100)
Value x Item Treatment	-0.0608***	-0.0550***
	(0.008)	(0.0117)
Rank x Item Treatment	-0.0298***	-0.0298***
	(0.0071)	(0.0070)
Period Indicator		-0.0027*
		(0.0015)
Period x Item Interaction		-0.0013
		(0.0022)
Constant	0.9242***	0.9362***
	(0.0068)	(0.0062)
Observations	128	128

Notes: The dependent variable is the percentage of the optimal cost-effectiveness ratio achieved. The unit of observation is an auction period. The *Rank-Menu* treatment is the base case. Bootstrapped standard errors clustered at the session level are reported in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance for a two-tailed hypothesis test based on a t distribution with 7 degrees of freedom, respectively.

Table 3: Optimal-item selection descriptive statistics

	All Selected Items			Winning Items		
	Round 1	Rounds 1-3	Final Round	Round 1	Rounds 1-3	Final Round
Item x Quality Value Treatment	0.7474***	0.7413***	0.7604**	0.8817	0.9004***	0.9082
	(0.022)	(0.014)	(0.022)	(0.024)	(0.013)	(0.021)
Observations	384	1,152	384	186	562	196
Item x Quality Rank Treatment	0.6484	0.6337	0.6927	0.8394	0.8397	0.8894
	(0.024)	(0.014)	(0.024)	(0.026)	(0.015)	(0.022)
Observations	384	1,152	384	193	580	199
Menu x Quality Value Treatment	0.3333	0.3333	0.3333	0.9875	0.9646	0.9701
	(0.0139)	(0.008)	(0.0139)	(0.009)	(0.008)	(0.012)
Observations	1,152	3,456	1,152	160	594	201
Menu x Quality Rank Treatment	0.3333	0.3333	0.3333	0.9598	0.9625	0.9758
	(0.0139)	(0.008)	(0.0139)	(0.015)	(0.009)	(0.011)
Observations	1,152	3,456	1,152	174	587	207

Notes: Standard errors in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance from a Wilcoxon rank-sum test of the equality of the percentage of offers including the maximum-score item between treatments.

Table 4: Bidder behavior – Item selection

	Value x Item	Rank x Item	Both Treatments
Action Endowed Score	1.8323***		2.0085***
	(0.2316)		(0.1724)
Minimum Cost	0.0729	0.4257***	0.1574***
	(0.0589)	(0.0249)	(0.0423)
Maximum Quality	0.1905***		0.1694***
	(0.0265)		(0.0363)
Maximum Score	0.4247***		0.3339***
	(0.0300)		(0.0385)
Action Quality Rank		-0.2286***	
		(0.0255)	
Constant			
Observations	1,440	1,404	2,844

Notes: The dependent variable is an indicator variable taking on the value of 1 if the conservation action was submitted for consideration in the auction. The unit of observation is an auction period. Bootstrapped standard errors clustered at the session level are reported in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance for a two-tailed hypothesis test based on a t distribution with 7 degrees of freedom, respectively.

Table 5: Bidder behavior – Percentage of optimal Score (final-round offers)

	Value x Menu	Value x Item	Rank x Menu	Rank x Item	All Observations
Cost	-0.0003***	0.0000	-0.0003***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Quality	0.0039***	0.0016*	0.0043***	0.0023***	0.0036***
	(0.0001)	(0.0009)	(0.0001)	(0.0002)	(0.0001)
MinCost	0.1182***	0.0548***	0.1251***	0.0660***	0.1079***
	(0.0014)	(0.0138)	(0.0023)	(0.0126)	(0.0030)
MaxQual	0.0763***	0.0409***	0.0772***	0.0386***	0.0726***
	(0.0028)	(0.0108)	(0.0024)	(0.0054)	(0.0033)
Quality Value x Single Item Treatment					0.0012
					(0.0051)
Quality Rank x Single Item Treatment					0.0203***
					(0.0076)
Quality Value x Bid Menu Treatment					-0.0026
					(0.0037)
Period Indicator	-0.0034***	0.0015	-0.0025***	-0.0022	-0.0027***
	(0.0003)	(0.0036)	(0.0005)	(0.0031)	(0.0005)
Torder	0.0059*	0.0149	-0.0095***	0.0275*	0.0026
	(0.0032)	(0.0102)	(0.0019)	(0.0146)	(0.0038)
H and L Switching Round	-0.0020*	0.0024	0.0037	0.0087	0.0007
	(0.0012)	(0.0017)	(0.0031)	(0.0063)	(0.0018)
Constant	0.6203***	0.5974***	0.5831***	0.5749***	0.6010***
	(0.0057)	(0.0965)	(0.0195)	(0.0377)	(0.0165)
Observations	1,152	384	1,152	384	3,072

Notes: The dependent variable is the percentage of the optimal score achieved. The unit of observation is an auction period. Bootstrapped standard errors clustered at the session level are reported in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance for a two-tailed hypothesis test based on a t distribution with 7 degrees of freedom, respectively.

Table 6: Bidder behavior – Percentage of optimal Score (final-round offers for optimal items)

	Value x Menu	Value x Item	Rank x Menu	Rank x Item	All Observations
Cost	0.0004***	0.0004***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Quality	-0.0029***	-0.0038***	-0.0020***	-0.0021***	-0.0026***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
MinCost	-0.0157**	-0.0031	-0.0047	-0.0054	-0.0092***
	(0.0069)	(0.0053)	(0.0040)	(0.0071)	(0.0032)
MaxQual	-0.0278***	-0.0032	-0.0306***	-0.0096*	-0.0195***
	(0.0015)	(0.0048)	(0.0059)	(0.0052)	(0.0026)
Quality Value x Single Item Treatment					-0.0376***
					(0.0066)
Quality Rank x Single Item Treatment					-0.0106
					(0.0084)
Quality Value x Bid Menu Treatment					-0.0141**
					(0.0061)
Period Indicator	-0.0027**	-0.0009	0.0002	-0.0031***	-0.0015***
	(0.0011)	(0.0014)	(0.0010)	(0.0012)	(0.0006)
Torder	0.0070***	0.0051	-0.0159***	0.0225	0.0039
	(0.0013)	(0.0054)	(0.0027)	(0.0190)	(0.0047)
H and L Switching Round	-0.0005	0.0020	0.0038	0.0059	0.0018
	(0.0012)	(0.0016)	(0.0044)	(0.0048)	(0.0019)
Constant	0.9756***	0.9270***	0.9442***	0.8911***	0.9538***
	(0.0257)	(0.0280)	(0.0213)	(0.0364)	(0.0170)
Observations	384	292	384	266	1,326

Notes: The dependent variable is the percentage of the optimal score achieved. The unit of observation is an auction round. Bootstrapped standard errors clustered at the session level are reported in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance for a two-tailed hypothesis test based on a t distribution with 7 degrees of freedom, respectively.

Supplemental Material for Balancing Complexity and Rent-Seeking in Multi-Attribute Conservation Procurement Auctions: Evidence from a Laboratory Experiment

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Supplemental Material

Example Instructions

Experiment Instructions

Welcome to the experiment. This is an experiment in market decision making. If you follow the instructions carefully and make good decisions, you will be well-prepared to succeed in today's experiment. In today's session, you will participate in a lottery and a series of auctions. Your cash earnings today will consist of a $10 show-up payment and payments based on your performance in the lottery and auctions.

Lottery Period

The session will begin with the lottery experiment. We will read through the instructions for the lottery together and then proceed to the software interface.

In this part of today's session, you are asked to make a choice in 11 different paired lotteries. Each lottery has different possible combinations of payoffs. Your task will be to consider each lottery and select A or B using the scroll bar to indicate a preference for taking part in sub-lottery A or sub-lottery B. Consider the payoffs associated with selecting A or B for each of the 11 choices and pick accordingly, as your selection will affect your payoff for completing this task.

After you are finished selecting A or B for the 11 choices, please press click here to continue. When you come to collect your earnings at the end of the experiment, one of the lotteries will be selected at random to determine your payoff. These payoffs are in USD, not experimental currency units like the rest of today's session.

Only one of the 11 paired lotteries will be used for computing your earnings in this period. The paired lottery will be selected at random at the end of the experiment - the experimenter will draw a card from a shuffled deck of cards (Ace through Jack, corresponding to the paired lotteries 1-11). Each paired lottery has the same probability of being picked. The draw will take place in public at the front of the room. The paired lottery that is picked will be the same for everyone in the room.

Once the paired lottery has been picked, another card will be randomly drawn from a shuffled deck of cards (Ace through ten). The drawn card will determine everyone's earnings from the lottery period, whether they chose lottery A or B for the selected lottery pair.

The payoff from the lottery will be added to your show-up payment and your earnings from the rest of the experiment.

Auction Instructions

We will now proceed to the next phase of today's session, where you will make decisions in an auction environment. During this part of the experiment, you will earn money in Experimental Currency Units (ECUs). At the end of the experiment, these will be converted to real dollars at a rate of 35 ECUs per $1, and you will be paid as you leave. This is in addition to the $10 show-up payment and your lottery earnings.

For this experiment, you will be in a group with 11 other participants. Each group participant has been provided with a Participant ID, which has been randomly assigned. This ID will remain the same during the entire experiment.

How you make money

In today's experiment, you will participate in multiple auction periods. In each auction period, you will have three types of items available to sell: Red, Blue, and Green items. Each type of item has a cost and quality, which will vary from period to period and across participants. The cost and quality values of your items in one period are in no way linked to those in other periods, and the cost and quality values of your items within a period are not linked either. At the beginning of each period, you will be given access to information about your items for sale, but you will not be given information about the cost and quality values for other participants' items.

There will be multiple rounds within a given period in which you will try to sell your items. In each round, you must select one of the three items (Red, Green, or Blue) for sale and the price at which you would like to sell it (your offer).

Your selected item and offer will be collected via the software interface and will not be known to other participants. Do not use a dollar sign when entering your offer through the software interface.

The experimenter, who is the buyer, has a limited budget and cannot purchase all items offered by all participants in the auction. Moreover, you can sell only one item, and if you sell that item, then you must pay that item's cost. If you are able to sell an item once an auction period is complete, your earnings in that auction period will be equal to the value of your offer minus the cost of the item sold.

Period Earnings = Offer Cost

For example: suppose you choose the Blue item for sale (which has a cost of 200 ECU) and offer it at a price of 220 ECU. If this offer is accepted, then your earnings that period would be 220 200 = 20 ECU. These period earnings are recorded and added to your session earnings. If you do not sell an item, your earnings for that period are zero; you only pay an item's cost if you are able to sell that item.

Score

To rank bids for acceptance, the experimenter turns your offer and quality information into a score using the following rule

Score = Quality/Offer

The experimenter, who is the buyer, values high-score items and uses a scoring rule to help ensure the budget is spent on cost-effective items. Therefore, the likelihood that your bid (an item and its offered price) will be accepted is based on

- the offer and the quality of your item
- the quality and offers of items from the 11 other auction participants

The end of a period

If you are unable sell an item in a round, you can submit a different offer for the same item or an offer for a different item in the next round. Please note that the experimenter prefers high-score items, which help to maximize the total quality of items purchased, while spending the least amount of money. If your offer has not been accepted in the current round, a decrease in your offer, or selection of a different item, may improve your chances of selling an item in the next round. In these auctions, you are only able to maintain or reduce your offer for a given item from one round to the next (attempting to increase the offer for an item will result in an error message).

Once all offers have been submitted in a round, the experimenter determines the score for each offer and identifies the participants whose items have the highest scores and would be purchased with the available budget. These participants are the set of **provisional winners** for the current round. Provisional winners and losers are notified and the auction proceeds to the next round, where everyone submits offers again and the process is repeated. For this experiment, a period will end when a stopping rule, related to the scores of selected items and the expense of these items, is satisfied.

When the stopping rule is satisfied, the auction period ends, and the provisional winners of the current round become the final winners of the current period. The earnings of the winners are updated based on their accepted offers and costs. The experiment then moves to the next period.

Please note that the final round in each auction period will not be announced until after it is completed, and which round is final may vary across auction periods.

Changes from the basic setup

You are now familiar with the basic design of an auction period. During the course of the experiment, there will be changes to the design of the auction. After a number of periods, rather than selecting a single item for sale and entering an offered price, you will be asked to submit offered prices for each of your three available items in the three boxes on your computer screen. The experimenter will inform you when this change will be made. All other auctions features will remain the same.

The screenshot below presents the alternative auction software interface in which participants will be asked to submit offered prices for each of the three available items.

Questions

How well you understand these rules and procedures are an important determinant of how much you earn in today's session. Think back over the instructions, and if you have any questions, please raise your hand now. We will conduct a practice auction next to give you an opportunity to familiarize yourself with the auction interface. None of the earnings in the practice auction will influence your cash payment today. Once the auctions begin, no talking will be permitted among participants.

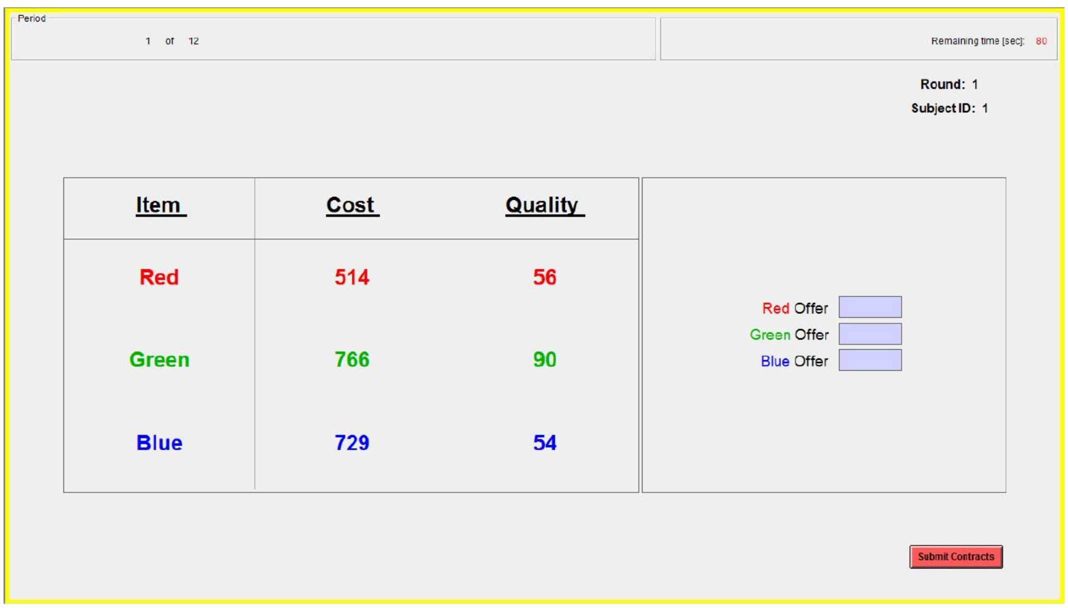
Period
1 of 12
Remaining time [sec]: 80
Round: 1
Subject ID: 1
Item
Cost
Quality
Red
514
56
Green
766
90
Blue
729
54
Red Offer
Green Offer
Blue Offer
Submit Contracts

Table 1: Bidder behavior – Percentage of optimal Score (all offers and all rounds)

	Value x Menu	Value x Item	Rank x Menu	Rank x Item	All Observations
Cost	-0.0003***	0.0001**	-0.0003***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Quality	0.0036***	0.0011	0.0046***	0.0023***	0.0036***
	(0.0002)	(0.0008)	(0.0001)	(0.0002)	(0.0002)
MinCost	0.1079***	0.0481***	0.1169***	0.0614***	0.0988***
	(0.0022)	(0.0124)	(0.0032)	(0.0067)	(0.0025)
MaxQual	0.0755***	0.0438***	0.0640***	0.0524***	0.0682***
	(0.0050)	(0.0118)	(0.0032)	(0.0074)	(0.0039)
Quality Value x Single Item Treatment					-0.0010
					(0.0077)
Quality Rank x Single Item Treatment					0.0213**
					(0.0085)
Quality Value x Bid Menu Treatment					-0.0064
					(0.0059)
Period Indicator	-0.0023***	0.0006	-0.0020**	-0.0019	-0.0022***
	(0.0005)	(0.0014)	(0.0009)	(0.0015)	(0.0006)
Torder	0.0115***	0.0046	-0.0171***	0.0397**	0.0054
	(0.0037)	(0.0035)	(0.0027)	(0.0161)	(0.0054)
H and L Switching Round	0.0003	0.0014	0.0049	0.0115*	0.0024
	(0.0017)	(0.0030)	(0.0040)	(0.0060)	(0.0025)
Constant	0.5906***	0.6293***	0.5447***	0.5664***	0.5745***
	(0.0164)	(0.0424)	(0.0233)	(0.0607)	(0.0262)
Observations	5,544	1,872	5,328	1,860	14,604

Notes: The dependent variable is the percentage of the optimal score achieved. The unit of observation is an auction round. Bootstrapped standard errors clustered at the session level are reported in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance for a two-tailed hypothesis test based on a t distribution with 7 degrees of freedom, respectively.

Table 2: Bidder behavior – Percentage of optimal Score (final-round offers)

	Value x Menu	Value x Item	Rank x Menu	Rank x Item	All Observations
Cost	-0.0003***	0.0000	-0.0003***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Quality	0.0039***	0.0016*	0.0043***	0.0023***	0.0036***
	(0.0001)	(0.0009)	(0.0001)	(0.0001)	(0.0001)
MinCost	0.1183***	0.0560***	0.1251***	0.0664***	0.1079***
	(0.0014)	(0.0140)	(0.0024)	(0.0117)	(0.0029)
MaxQual	0.0762***	0.0420***	0.0772***	0.0391***	0.0727***
	(0.0027)	(0.0111)	(0.0024)	(0.0048)	(0.0034)
Quality Value x Single Item Treatment					0.0017
					(0.0058)
Quality Rank x Single Item Treatment					0.0203***
					(0.0073)
Quality Value x Bid Menu Treatment					-0.0021
					(0.0045)
Period Indicator	-0.0034***	0.0015	-0.0025***	-0.0022	-0.0027***
	(0.0003)	(0.0035)	(0.0005)	(0.0029)	(0.0004)
Torder	0.0058***	0.0148	-0.0091***	0.0261**	0.0024
	(0.0022)	(0.0102)	(0.0028)	(0.0129)	(0.0040)
H and L Switching Round			0.0035	0.0088	0.0006
			(0.0031)	(0.0062)	(0.0017)
Female Indicator			0.0058	0.0102*	-0.0001
			(0.0121)	(0.0059)	(0.0065)
Year of Graduation			0.0050	0.0024	0.0034
			(0.0044)	(0.0029)	(0.0028)
Constant	0.6043***	0.6124***	-9.5589	-4.2780	-6.2552
	(0.0094)	(0.1029)	(8.9145)	(5.8013)	(5.7169)
Observations	1,152	384	1,152	384	3,072

Notes: The dependent variable is the percentage of the optimal score achieved. The unit of observation is an auction period. Bootstrapped standard errors clustered at the session level are reported in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance for a two-tailed hypothesis test based on a t distribution with 7 degrees of freedom, respectively.

Table 3: Bidder behavior – Percentage of optimal Score (final-round offers for non-optimal items)

	Value x Menu	Value x Item	Rank x Menu	Rank x Item	All Observations
Cost	-0.0004***	-0.0002***	-0.0004***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Quality	0.0049***	0.0054***	0.0050***	0.0050***	0.0049***
	(0.0001)	(0.0009)	(0.0001)	(0.0005)	(0.0000)
MinCost	0.1681***	0.1747***	0.1600***	0.1490***	0.1625***
	(0.0017)	(0.0407)	(0.0023)	(0.0227)	(0.0026)
MaxQual	0.0808***	0.0427	0.0870***	0.0879***	0.0822***
	(0.0051)	(0.0265)	(0.0025)	(0.0147)	(0.0032)
Quality Value x Single Item Treatment					0.0331***
					(0.0079)
Quality Rank x Single Item Treatment					0.0286***
					(0.0070)
Quality Value x Bid Menu Treatment					0.0034
					(0.0039)
Period Indicator	-0.0025***	-0.0066	-0.0028***	0.0006	-0.0027***
	(0.0005)	(0.0069)	(0.0009)	(0.0044)	(0.0005)
Torder	0.0053	0.0248	-0.0069***	0.0401***	0.0061*
	(0.0037)	(0.0158)	(0.0022)	(0.0122)	(0.0032)
H and L Switching Round	-0.0015	-0.0000	0.0050*	0.0052	0.0012
	(0.0010)	(0.0031)	(0.0029)	(0.0091)	(0.0014)
Constant	0.6002***	0.4610***	0.5590***	0.5159***	0.5684***
	(0.0085)	(0.1110)	(0.0213)	(0.1188)	(0.0190)
Observations	768	92	768	118	1,746

Notes: The dependent variable is the percentage of the optimal score achieved. The unit of observation is an auction round. The *Rank-Menu* treatment is the base case. Robust standard errors clustered at the session level are reported in parentheses. One, two, and three stars indicate 10 percent, 5 percent, and 1 percent significance for a two-tailed hypothesis test based on a t distribution with 7 degrees of freedom, respectively.