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Provision Point Reverse Auction: A New Auction Mechanism with Applications for Conservation Contracts

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Rent-seeking behavior in payment for environmental services auctions reduces the number of affordable contracts and decreases environmental protection. We propose a new auction mechanism, the provision point reverse auction (PPRA), to mitigate this behavior. The PPRA includes a public component in which the probability of contract acceptance for one individual is affected by the sum of the other accepted offers. We provide theoretical support for the new mechanism and follow with laboratory experiments. The experiments yield average offers that are 12.57%–58.17% smaller than in alternate reverse discriminative auctions, with the exact difference dependent on the compared mechanism and auction parameters.

Key words: laboratory experiments, payment for environmental services

Introduction

Payment for environmental services (PES) programs have become an increasingly important component of conservation and environmental protection. Economists have taken a keen interest in programs that use reverse (or procurement) discriminative auctions to allocate contracts to individuals who provide the environmental service. Reverse discriminative auctions involve one buyer and many sellers, where the winners of the auctions receive their offer (or bid) as payment. In many reverse discriminative auctions, the buyer has a fixed budget and accepts offers in ascending order until the budget has been exhausted. In such an auction, sellers must balance potential gains in expected profit from a higher offer against corresponding decreases in the probability the offer will be given a contract by the buyer. If these auctions are conducted for multiple rounds, sellers gain information about the costs of their peers each round and use that information to increase their profits at the expense of the buyer. We call submitting an offer above one's value "rent-seeking offers" or, simply, rent-seeking behavior. Over time, as rent-seeking behavior becomes more pronounced, the buyer can afford fewer contracts and incurs a welfare loss. This can be a particularly significant problem for PES or conservation programs, as the amount of environmental benefit gained by the program may increase nonlinearly in the total number of contracts acquired. Given the large number of PES or conservation programs that use reverse discriminative auctions, rent-seeking behavior is likely decreasing social welfare substantially.

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With an eye toward mitigating rent-seeking behavior, the authors designed the "provision point reverse auction" (PPRA). The PPRA functions as a discriminative reverse auction in that there is one buyer with many sellers and each individual with an accepted offer receives their offer as payment. However, unlike other discriminative procurement auctions, in a PPRA the buyer declares a requirement that a prespecified number of offers must be affordable for any offers to be accepted. That is, if the buyer cannot afford to purchase that prespecified number of offers, given their budget constraint, then no contracts will be made with any individual.

Similar to a reverse discriminative auction, an individual participating in a PPRA must weigh increases in potential profit from a higher offer against corresponding decreases in the probability of realizing that profit. As an individual's offer becomes larger, it is also larger relative to the offers of their peers which decreases the probability the offer will be given a contract by the buyer. In a PPRA, however, a higher offer not only increases the offer relative to its peers, it also reduces the chance that the buyer can afford the prespecified number of units, which further lowers the probability of contract acceptance. We prove that this additional requirement incentivizes participants in a PPRA to submit offers closer to their costs relative to offers in a multiunit reverse discriminative auction.

The PPRA also includes a public component that serves as additional motivation for the mechanism. When an individual increases their offer, they negatively affect the expected profit of the other individuals in the auction by reducing the chance that any contracts are provided by the buyer. Thus, if individuals in a PPRA place positive utility on higher profits for their peers, they will be further incentivized to keep their offers close to their true costs.

The PPRA would also make an attractive choice to governments or nongovernment organizations (NGOs) when the organizations are faced with thresholds for environmental value. For example, suppose a government agency is interested in restoring a polluted lake and reintroducing several species of fish. The agency estimates that a pollution reduction of $X\%$ would be required for the water to be habitable for the fish. If the agency were to use a budget-constrained auction to pay neighboring individuals to abate emissions, the agency would have no guarantee that the contracts necessary for the reintroduction of the fish would be affordable. If the agency instead used a PPRA to pay individuals to reduce their emissions, the agency would either achieve the pollution reduction necessary for the reintroduction of the fish or keep their budget and attempt some other PES program. This hypothetical situation is similar to a voluntary agreement between local New York farmers and New York City over the Catskill–Delaware water system (Appleton, 2002). Instead of paying farmers to implement environmentally friendly practices, the city threatened that if 15% of the farmers did not participate in pollution abatement programs, costly regulation would take effect to achieve the desired water quality improvement.

This paper provides theoretical evidence showing that, under various assumptions, optimal offers under a PPRA are less than the optimal offers under a multiunit reverse discriminative auction, given an opportunity cost. These theoretical predictions are supported by evidence from laboratory experiments. The experimental work presented here abstracts away from the public component of the mechanism to focus on proof of concept. Ten experimental sessions were conducted with 240 student participants in total. The experimental results suggest that the PPRA reduces accepted offers by 21.55%–58.17% or 12.57%–21.59% compared to a multiunit reverse discriminative auction or a budget-constrained multiunit reverse discriminative auction, respectively, with the exact value dependent upon the target number of contracts. The effect on offering behavior is particularly pronounced for the lowest offers, which are also the offers of greatest interest to the buyer.

Literature Review

Environmental goods or services are generally not exchanged on open markets and so do not have easily observable prices. Auctions are a convenient method for exchange in settings with such uncertainty and thus present an attractive choice to policy makers interested in purchasing environmental services. Auctions for environmental services are generally multiunit procurement auctions (i.e., conservation or PES auctions generally involve one buyer purchasing multiple units of a good from multiple sellers). Unfortunately, the literature is less developed on the topic of multiunit procurement auctions than on other mechanisms, particularly for auctions where the buyer is restricted by a budget (Nautz, 1995; Latacz-Lohmann and Schilizzi, 2005; Arnold, Duke, and Messer, 2013). Harris and Raviv (1981) and Cox, Smith, and Walker (1984) provided optimal offer functions for multiunit discriminative auctions with symmetric, risk-neutral sellers whose costs are drawn from a uniform distribution. Hailu, Schilizzi, and Thoyer (2005) extended this research and provided the optimal offer function for the reverse (or procurement) multiunit discriminative auction, which they call a "target-constrained" (as opposed to budget-constrained) auction. To the best of our knowledge, no one has specified an optimal offer function for a multiunit procurement auction where the buyer is constrained by a budget. Without more robust theoretical guidance from the literature, researchers and policy makers are forced to rely on experience and experimental evidence when making their decisions about how to purchase environmental services.

When using auctions in payment for environmental services (PES) programs, buyers can opt for either a uniform second-price auction or a discriminative auction, although in practice they most often choose a discriminative format. (Latacz-Lohmann and Schilizzi, 2005). In a uniform second-price procurement auction, all individuals who submit winning offers are paid the first rejected offer. In settings where each seller has only one unit of the good to sell, individuals have the incentive to offer their true cost to the seller because increasing one's offer cannot increase their own payoff. In a discriminative procurement auction, individuals who submit winning offers receive their offers as payment, analogous to a first-price auction. Unlike the uniform second-price procurement auction, in the discriminative procurement auction the optimal offering strategy is to submit an offer higher than one's true cost. Because only individual sellers have full information on their true costs, this offering behavior leads to information rents for the sellers. There is disagreement in the literature about the relative cost effectiveness of the uniform second-price and discriminative auctions from the perspective of the buyer, which is as yet unresolved. (Goswami, Noe, and Rebello, 1996; Cason and Gangadharan, 2004; Boxall et al., 2009).

To increase the efficiency of PES or conservation programs that use discriminative auction formats, we propose the PPRA, which functions as a discriminative procurement auction with the added requirement that a certain number of units are purchased by the buyer, given a constant, exogenous budget. For example, if the provision point requirement is 80% participation, but the buyer can only afford contracts for 75% of the sellers, then no contracts will be offered and the buyer will keep their money.

The PPRA is connected to the research conducted on the provision point mechanism (PPM) for voluntary contributions to public goods (Marks and Croson, 1998; Rondeau, Poe, and Schulze, 2005). In a PPM, a public good is provided only if the total contributions exceed some predetermined threshold. If the total contributions do not exceed this "provision point," then all contributions are refunded to the participants and no amount of the public good is provided. The PPRA is essentially the reverse auction form of the PPM: Instead of a total contribution requirement, the sum of the lowest cost offers must be less than the budget for any contracts to be made.

The closest paper to the PPRA, as formulated here, is Bush et al. (2013), who attempted to reduce the upward bias in willingness-to-accept estimates in a contingent valuation study using a provision point. Their mechanism is called a PPM, after the previous literature on contributions to public goods. This paper expands upon Bush et al. by generalizing their mechanism to an auction with many possible provision point requirements and tests the auction mechanism with real money in an experimental setting. This paper additionally provides theoretical support to substantiate the experimental evidence.

The PPRA also shares attributes with the "voluntary-threat" approach, where polluters are given the option to reduce their emissions or face a penalty that grows with the quantity of pollution emitted by all individuals (Segerson and Miceli, 1999; Poe et al., 2004; Suter et al., 2010). In a PPRA, rather than choosing a pollution abatement level, the participants must decide how much profit to extract from the buyer, knowing that the possibility of higher profits decreases the probability of realizing any profit at all. Additionally, the PPRA includes an "all or nothing" threshold, while the penalty in the voluntary-threat approach is continuous.

Much of the recent literature has focused on special features of the conservation and PES settings that create complications when deciding which auction mechanism is most appropriate. Examples include environmental benefits as a function of the spatial location of the conserved land (Parkhurst et al., 2002; Lewis and Polasky, 2018; Liu et al., 2019), the availability of public information on historical auction results (Messer et al., 2017), and contract compliance as a function of mechanism choice (Jack, 2013). This paper abstracts away from these issues to focus on proof of concept for the mechanism. Future research will examine how the PPRA interacts with some of these factors.

Theory and Model

We first derive the symmetric Bayesian Nash Equilibrium optimal offer function for a multiunit reverse discriminative auction (previously derived in Hailu, Schilizzi, and Thoyer, 2005) and demonstrate several properties of that optimal offer function. Then we introduce the PPRA, characterize its expected profit function, and derive predictions for optimal behavior in a PPRA compared to a multiunit reverse discriminative auction.

Multiunit Reverse Discriminative Optimal Offer Function

Let $n \in \mathbb{N}$ denote the number of participants in an auction. In a multiunit reverse discriminative auction, the buyer is interested in purchasing $p \in \mathbb{N}$ units of a good from the n sellers. This paper refers to p as the "target" of the auction. Further, let $B \in (0,\infty)$ denote the budget if the auction is a budget-constrained multiunit auction, $v_i \in [0,1]$ denote individual i's opportunity cost or value, $o_i \in [0,\infty)$ denote their offer, $O_j(v_j)$ denote the assumed offering behavior of the other participants as a function of their values, and $O_j^{-1}(o_j)$ denote its inverse. To simplify the theory and computations, this paper makes the common assumption that all values are drawn from a standard uniform distribution. All of the auctions considered have the following properties:

i. More than one unit is being exchanged in each round;
ii. The auctions have one buyer with multiple sellers. These auctions are known as reverse (or procurement) auctions;
iii. Values (opportunity costs) are independently drawn, so an individual's value provides no information about the values of the other participants;
iv. Each bidder knows their own value, but they do not know the value of any other participant;
v. All participants, as well as the units they are trying to sell, are symmetrical and indistinguishable, so each unit provides identical benefits to the buyer;
vi. Each participant can only offer and sell one unit of the good in each round.

In addition, this paper also assumes all participants are risk neutral.

Much of the following theory relies upon order statistics, so a brief set of definitions is in order. Out of a set of n draws from a distribution with probability density function $f(x)$ and cumulative distribution function $F(x)$, the random variable $V_{(r)}$, which represents the rth-lowest draw, is called the rth-order statistic. The probability density function of $V_{(r)}$ is given by

$$f_{V_{(r)}}(x) = \frac{n!}{(r-1)!(n-1)!} F(x)^{r-1}(1-F(x))^{n-r} f(x). \tag{1}$$

For a standard uniform distribution, $f(x) = 1$ and $F(x) = x$, so that equation (1) simplifies to

$$f_{V_{(r)}}(x) = \frac{n!}{(r-1)!(n-1)!} x^{r-1}(1-x)^{n-r}. \tag{2}$$

Notice that this is a beta distribution, $B(r, n+1-r)$.

The auction formats considered have expected profit functions given by

(3) $$E[\Pi] = (o_i - v_i) \times \Pr(o_i \in \mathbb{O}),$$

where $\mathbb{O}$ is the set of accepted contracts. The form of $Pr(o_i \in \mathbb{O})$ depends on the auction used as well as the parameter values chosen. As an individual increases their offer, potential profit, given by $(o_i - v_i)$, increases, but $Pr(o_i \in \mathbb{O})$, the probability of realizing the potential profit, decreases. Thus, picking the optimal offer for a given value requires balancing these two effects.

For the multiunit reverse discriminative auction auction, expected profit is given by

(4) $$E[\Pi] = (o_i - v_i) \times \Pr(o_i < O_{(p)}),$$

where $O_{(p)}$ is the pth-lowest offer submitted by the other participants. From equation (2) and assuming that all values are drawn from a standard uniform distribution, the probability that an individual's offer is one of the p smallest offers is given by the function

(5) $$g\left(n, p, O_j^{-1}(o_i)\right) = \frac{(n-1)!}{(p-1)!(n-p-1)!} \int_{O_j^{-1}(o_i)}^{1} u^{p-1}(1-u)^{n-p-1} du.$$

Intuitively, the g function takes in an individual's offer, o_i, and transforms it into an opportunity cost through $O_j^{-1}(\cdot)$. $O_j^{-1}(o_i)$ denotes the opportunity cost draw that would result in the offer o_i from the other participants in the auction, assuming the common offering behavior $O_j(\cdot)$. This opportunity cost can then be used to calculate the probability the offer is one of the p smallest offers using the properties of order statistics and the given distribution for opportunity costs. From this point on, $g(n, p, O_j^{-1}(o_i))$ will be simplified as $g(O_j^{-1}(o_i))$.

Given an expected profit function, we are interested in the offer that, for each possible value, maximizes expected profit. That is, we are interested in a function which takes in an individual's opportunity cost and returns their expected profit maximizing offer. Even more, we are interested in the offer function that is also a symmetric Bayesian Nash equilibrium. A symmetric Bayesian Nash equilibrium is an optimal offer function in which—if an individual is participating in an auction in which they assume the other individuals submit offers according to an offer function $O_j(v_j)$—the optimal response is to also submit offers according to $O_j(v_j)$.

Hailu, Schilizzi, and Thoyer (2005) derive the symmetric Bayesian Nash equilibrium for a multiunit reverse auction. A proof and confirmation of their results is included in the Online Supplement (www.jareonline.org). In a multiunit reverse auction (also known as a target-constrained auction), a participant in the auction is interested in the probability that their offer will be one of the p lowest offers out of the n offers submitted by the n participants. The symmetric Bayesian Nash equilibrium for a multiunit procurement auction is

(6) $$O_{i,TC}^{*}(v_i) = \frac{\int_{v_i}^{1} u^{p}(1-u)^{n-p-1} du}{\int_{v_i}^{1} u^{p-1}(1-u)^{n-p-1} du}.$$

The optimal offer function, $O_{i,TC}^{*}(v_i)$, takes in an individual's value and returns the optimal offer (i.e., the offer that maximizes expected profit) for that value. Given this optimal offer function, low-value individuals can extract substantial rents (equivalent to many times their opportunity costs) from the buyer. Intuitively, for lower opportunity costs, an individual can increase their offer above their opportunity cost to increase potential profits while only slightly decreasing the probability that their offer will receive a contract. On the other hand, when an individual with high opportunity cost submits an offer higher than their opportunity cost, they have a small chance that their offer will be accepted. As a result, the optimal offer function converges to cost revealing offers as an individual's opportunity cost approaches 1. Note that $O_{i,TC}^{*}(v_i)$ is not defined when $v_i = 1$. Propositions 1 and 2 are expansions upon Hailu, Schilizzi and Thoyer's results. Their proofs are given in the Online Supplement.

PROPOSITION 1. *As v_i approaches 1, the symmetric Bayesian Nash equilibrium offer for the target-constrained auction, $O^*_{i,TC}(v_i)$, converges to 1.*

PROPOSITION 2. *$O^*_{i,TC}(v_i)$ is a strictly increasing function of v_i for $v_i \in [0,1)$.*

Proposition 2 will prove critical when comparing optimal offering behavior between the multiunit reverse discriminative auction and the PPRA.

Set-Up for the PPRA

The PPRA is a discriminative reverse auction with the added requirement that p of the n total offers must be affordable for any contracts to be made, given the exogenous budget B. We call this additional requirement the "provision point requirement." In a PPRA, an individual has to consider several factors when choosing their offer. Like most discriminative auctions, the individual must weigh the increase in potential profit from a higher offer against the decreased probability that a given offer will be accepted. In a PPRA, a higher offer decreases the probability of contract acceptance through two avenues. First, a higher offer makes it less likely that the offer will be one of the p lowest offers and thus less likely that the offer will receive one of the p possible contracts. Second, a higher offer decreases the probability that the provision point requirement will be met and thus reduces the probability that any contracts will be provided.

The provision point requirement can be viewed as an "average" reservation price. In reverse auctions, a reservation price is the highest acceptable offer a seller can make to the buyer. By setting the budget and the provision point, the buyer implies that they will not spend more than B/p, on average, for the p units. The average reservation price allows individuals with opportunity costs higher than the average reservation price to receive a contract by incentivizing lower opportunity cost individuals to submit lower offers. For example, in a PPRA, an individual can submit a bid higher than B/p and still receive a contract if at least one of the other p lowest offers is less than B/p, while this is not possible in an auction with a reservation price of B/p.

Looking back to equation (3), in a PPRA, the probability that an offer, o_i, receives a contract is the probability that o_i is one of the p lowest offers times the probability that the provision point requirement is met given that o_i is one of the p lowest offers. If either the provision point requirement is not met or o_i is not one of the p lowest offers, then o_i will not receive a contract. Thus, the expected profit function for an individual participating in a PPRA is given by

$$E[\Pi] = (o_i - v_i) \times \Pr\left(o_i < O_{(p)}\right) \times \Pr\left(\sum_{j=1}^{p-1} O_{(j)} + o_i \leq B | o_i < O_{(p)}\right), \quad (7)$$

where the third term on the right side is the probability that the provision point requirement is met, given that o_i is one of the p lowest offers.

When considering the probability that the provision point requirement will be met, an individual is interested in the expected value of the excess budget, given the sum of the expected offers of the other low-cost individuals. That is, the individual is interested in the difference between the budget and what they expect the sum of the other $p-1$ lowest bids to be. If their offer is one of the p lowest and is greater than the excess budget, the provision point requirement will not be met because the sum of the p lowest offers will exceed the budget. On the other hand, if their offer is one of the p lowest and is less than the excess budget, the provision point requirement will be met as the sum of the p lowest offers will be less than the budget. If we assume that the other individuals submit offers according to a common offer function, $O_j(\cdot)$—and we assume the budget, B, is given exogenously—then the expected value of the excess budget given that o_i is one of the p lowest offers, denoted by Θ, is

$$E[\Theta] = B - \sum_{j=1}^{p-1} E\left[O_j(v_{(j)}) | o_i < o_{(p)}\right], \quad (8)$$

where $v_{(j)}$ is the jth lowest opportunity cost. Intuitively, the expected value of the excess budget tells an individual the expected offer that, on average, would just meet the provision point requirement. The variance in the distribution of the excess budget suggests the degree to which the probability the provision point requirement will be met changes with small changes in an individual's offer. Given that the offer function for other individuals will generally not have a closed form, it seems unlikely that a closed-form representation of equation (8) exists.

To summarize, an individual's probability of submitting one of the p lowest offers, given their offer and assumed offering behavior of other individuals, is described by equation (5). Given the individual submits one of the p lowest offers, the probability that the provision point requirement is met is given by the probability that o_i is less than the excess budget, with the expected value of the excess budget given in equation (8).

Before we proceed further, we require the following axiom, which is suggested by Proposition 1:

AXIOM 1. *If the probability that an individual receives a contract is 0 in any auction, then their optimal offering behavior is to submit an offer at their opportunity cost.*

This axiom is important because it defines optimal offering behavior for values for which the optimal offer function might not be defined. For example, the optimal offer function for the multiunit reverse discriminative auction (see equation 6) is not defined when $v_i = 1$. A natural conclusion from this fact is that the optimal offer for individuals with $v_i = 1$ is 1 in both the multiunit reverse discriminative auction and the PPRA. With this background, we provide the following proposition:

PROPOSITION 3. *Suppose $O^*_{i,TC}(v_i|n,p)$ is the symmetric Bayesian Nash equilibrium optimal offer function for the multiunit reverse discriminative auction with a target of $p < n$ and $O^*_{i,PP}(v_i|n,p,B)$ is a symmetric Bayesian Nash equilibrium optimal offer function for the PPRA with a provision point requirement of $p < n$ and a budget of B. (From this point on, $O^*_{i,TC}(v_i|n,p)$ and $O^*_{i,PP}(v_i|n,p,B)$ will be simplified as $O^*_{i,TC}(v_i)$ and $O^*_{i,PP}(v_i)$, respectively.) Additionally, assume that Axiom 1 holds. Then, $O^*_{i,TC}(v_i) = O^*_{i,PP}(v_i)$ if and only if either (i) any single participant in the auction cannot affect the probability that the provision point requirement is met by increasing or decreasing their offer or (ii) $v_i = 1$.*

See the Online Supplement for the proof for Proposition 3. This proposition provides our first theoretical prediction: When the parameters of a PPRA are such that no single participant can affect the probability that the provision point requirement is met, the optimal offer function for all participants in the auction is the optimal offer function for a multiunit reverse discriminative auction. Proposition 4 expands upon Proposition 3.

PROPOSITION 4. *Suppose $O^*_{i,TC}(v_i)$ is the symmetric Bayesian Nash equilibrium optimal offer function for the multiunit reverse discriminative auction with a target of $p < n$ and $O^*_{i,PP}(v_i)$ is a symmetric Bayesian Nash equilibrium optimal offer function for the PPRA with a provision point requirement of $p < n$ and a budget of B. Further suppose that $O^*_{i,TC}(v_i)$ is convex in v_i.*[1] *If a participant in the auction can impact the probability that the provision point requirement is met, then $O^*_{i,TC}(v_i) > O^*_{i,PP}(v_i)$ for all v_i.*

See the Online Supplement for the proof for Proposition 4. Propositions 3 and 4 tell us that we expect the optimal offer curve for the PPRA to be weakly below the optimal offer curve for a multiunit reverse discriminative auction with the same parameter values. The degree to which the optimal offer curve for the PPRA lies below the optimal offer curve for the multiunit reverse discriminative auction depends on the parameter values chosen. Note that these propositions do not make assumptions about the uniqueness of the symmetric Bayesian Nash equilibrium for the PPRA, but they do state that any symmetric Bayesian Nash equilibria for the PPRA must be less than the symmetric Bayesian Nash equilibrium for the target-constrained auction.

[1] The convexity assumption holds for every set of parameter values we have tested.

Experimental Design and Protocol

To test the theoretical predictions, ten experimental sessions were conducted with a total of 240 undergraduate student participants in Cornell University's Lab for Experimental Economics and Decision Research.[2] Informed consent was obtained from all participants, in accordance with IRB regulations. The ten sessions were divided into five treatments of two sessions each. The five treatments consisted of one "budget-constrained" (BC) multiunit reverse discriminative treatment with a budget of $4.42, two "target-constrained" (TC) multiunit reverse discriminative treatments with targets of five and three, and two provision point treatments with a budget of $4.42, one with a provision point requirement of five and the other with a provision point requirement of three. For clarity and to ease comparisons between treatments, this paper will, from this point on, refer to multiunit reverse discriminative auctions as "target-constrained" auctions and multiunit reverse discriminative auctions with budgets as "budget-constrained" auctions. Each session lasted at most 40 minutes.[3]

Table 1 summarizes the number of sessions, participants, total offers, and other pertinent data. Note that two sessions were conducted for each treatment, so that each treatment had 48 participants in total. The following analysis is between subjects rather than within subjects: Students were not allowed to participate in more than one session, and each session conducted auctions for only one treatment. Average earnings were approximately $24 for each participant, with a range of $12–$35. In each session, the 24 students were split evenly into three groups. Before the start of each session, the participants were given written instructions, which are included in the Online Supplement. These written instructions include the following information:

i. the number of participants in a group (eight);
ii. the target or provision point requirement (five or three), if relevant;
iii. the budget ($4.42), if relevant; and
iv. the common distribution from which all opportunity costs were drawn, U(0,2).

A group size of eight was chosen because relatively small group sizes (i) increased the sample and (ii) made each participant have a greater individual impact on the probability the provision point requirement would be met. For the first PPRA treatment, a provision point requirement of $p = 5$ was chosen so that a relatively large number of participants could contribute to the provision point requirement, while a target of six or seven individuals might have led to larger offers in the target-constrained auction, as a higher target increases the optimal offer from equation (6). In addition, initial parameters were chosen so that the participants in the auction could not divide the budget equally among themselves. That is, the budget was selected so that the fifth-highest opportunity cost in each group was larger than the budget divided by 5. To test the robustness of the mechanism, these sessions were followed with an additional PPRA treatment but with a provision point requirement of three rather than five. In this second PPRA treatment, the budget divided by 3 was larger than the third-highest opportunity cost in all groups, loosening the budget constraint.

For the purpose of common knowledge, a researcher read from a series of Microsoft PowerPoint slides which included an overview of the experimental instructions. After the presentation, all subjects participated in five practice rounds in which parameter values varied. The practice rounds allowed participants to test offering strategies without having to worry about affecting their earnings.

[2] For the auction to function, 24 undergraduates were required for each session. To increase the probability of 24 students attending the experiment, 32 students were recruited each session. Overbooked students were given $10 and allowed to sign up for the experiment during a different time. On two occasions, fewer than 24 students showed up for the experiment. These sessions were cancelled, and the students who showed up were given $10 and allowed to sign up for a different future session.

[3] We also conducted a pilot session with 24 participants and slightly different parameters. The pilot session was for the PPRA, with opportunity costs U(0,1) and 32 rounds. The pilots allowed us to determine appropriate number of rounds and payments as well as power analyses. To find a difference in average offers of 20% with desired power of 0.90 and a significance level of 0.05, given the standard deviations observed in the pilot, we determined that we would need a total sample of at least 37 participants in each round. Thus, we decided upon samples of 48 (two sessions of 24 participants each) for each treatment.

Table 1. Summary Experimental Design

Treatment	Sessions	Participants per Session	Rounds	Groups	Total Offers	Provision Points
PPRA - 5	2	24	16	3	768	96
PPRA - 3	2	24	16	3	768	96
Budget	2	24	16	3	768	n/a
Target - 5	2	24	16	3	768	n/a
Target - 3	2	24	16	3	768	n/a

Notes: The table details the number of sessions, participants, rounds, groups per round, total offers made within each treatment, and total opportunities to meet the provision point requirement (if applicable) for each treatment. The first two rows provide data for the PPRA treatments with provision point requirements of 5 and 3, respectively; the third row provides data for the budget-constrained treatment with a budget of $4.42; and the final two rows provide data for the target-constrained treatment with targets of 5 and 3, respectively.

The practice rounds also increased the participants familiarity with their mechanism by altering the parameter values between rounds. The auctions were programmed using Microsoft Excel. In each round, the participants selected an offer between $0 and $7, where $7 was set as the maximum allowable offer.[4] After each round, the participants were informed whether their offer was accepted and how much they were paid. Participants were not allowed to revise their offers within a round. If they were in the PPRA treatment, they were also informed if the provision point requirement was met. After the five practice rounds, opportunity costs were rerandomized and a series of eight rounds began where the budget, target, provision point requirement and opportunity costs for each individual were fixed. Before the ninth round, the groups and opportunity costs were randomized once more and another eight rounds were conducted to end the experiment. Participants were randomly reassigned to new groups so that the knowledge of their peers' offering behavior could be limited as much as possible. Participants were not paid for the practice rounds but were paid based on the results of all 16 rounds that followed. While opportunity costs varied between individuals in each session, they did not vary across sessions. That is, the same sets of opportunity costs were used in each session for each treatment.[5]

Results

This section first presents differences in means between auction formats and follows with efficiency and environmental benefit analyses.

Difference in Means

The first comparison between auction formats is a simple unconditional difference in means test between treatments and within rounds. The experimental format provides two sets of eight rounds, which are pooled to increase statistical power. That is, the offers from rounds 1 and 9 are considered jointly, the offers from rounds 2 and 10 are considered jointly, and so on. Given the varying parameter values, average offers were compared between formats with comparable restrictions; that is, the target-constrained auction with a target of five, the budget-constrained auction with a budget of $4.42, and the PPRA with a provision point requirement of five and a budget of $4.42 were

[4] A maximum offer was required to prevent individuals from offering infinity. To maintain uniformity, the same maximum offer was applied to all formats, even the budget constrained auction, where an offer of $7 could never be accepted. The $7 cap was chosen so that participants wouldn't feel that their offers were censored. Of the 3,840 total offers, only five were submitted at the $7 maximum.

[5] These opportunity costs for rounds 1–8 were 1.35, 0.19, 1.07, 0.46, 0.97, 1.62, 0.68, 1.77, 1.28, 0.11, 1.52, 0.75, 0.75, 0.56, 1.76, 1.36, 0.70, 1.27, 0.34, 0.22, 1.05, 0.14, 1.55, and 1.11, respectively. For rounds 9–16, the opportunity costs were 1.78, 1.03, 1.63, 0.49, 0.6, 1.24, 0.04, 0.74, 1.59, 1.06, 1.95, 1.25, 0, 0.42, 0.10, 1.08, 1.57, 0.5, 0.75, 1.60, 0.50, 1.66, 1.32, and 0.27, respectively.

Table 2. Mean Offers: Target = 5, Budget = $4.42, PPR = 5

	Mean Offers			Difference: PPRA &	
	PPRA	TC	BC	TC	BC
Rounds	1	2	3	4	5
1 & 9	1.124	2.716	1.383	1.593***	0.259***
	(0.450)	(1.105)	(0.687)	(0.123)	(0.086)
2 & 10	1.115	2.440	1.401	1.324***	0.285***
	(0.487)	(0.740)	(0.670)	(0.090)	(0.085)
3 & 11	1.143	2.389	1.372	1.246***	0.228***
	(0.498)	(0.644)	(0.620)	(0.083)	(0.081)
4 & 12	1.145	2.257	1.420	1.111***	0.274***
	(0.490)	(0.501)	(0.859)	(0.071)	(0.101)
5 & 13	1.137	2.223	1.347	1.086***	0.209***
	(0.464)	(0.430)	(0.529)	(0.065)	(0.072)
6 & 14	1.200	2.161	1.335	0.961***	0.135*
	(0.577)	(0.371)	(0.508)	(0.070)	(0.078)
7 & 15	1.167	2.090	1.360	0.923***	0.193**
	(0.475)	(0.328)	(0.550)	(0.059)	(0.074)
8 & 16	1.186	2.101	1.364	0.915***	0.178**
	(0.576)	(0.604)	(0.587)	(0.085)	(0.084)
All	1.152	2.297	1.373	1.115***	0.220***
	(0.507)	(0.662)	(0.633)	(0.030)	(0.029)

Notes: Single, double, and triple asterisks (*,**,***) indicate significance at the 10%, 5%, and 1% level, respectively. The table contains the mean for each of the three auction treatments and difference in means between the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each *t*-test is conducted with a sample of 96 for each treatment: 24 observations for each round, with a total of 48 after the rounds are pooled, and two sessions for each treatment.

compared, and then the target-constrained auction with a target of three, the budget-constrained auction with a budget of $4.42, and the PPRA with a provision point requirement of three and a budget of $4.42 were compared. Tables 2 and 3 report the results. For each set of pooled rounds, every treatment has 96 observations. Differences in means across the individual (not pooled) rounds are provided by Tables S1–S8 in the Online Supplement. The decreased power results in the loss of some significance, but the direction of the differences is largely the same.

In Tables 2 and 3, columns 1, 2, and 3 provide the mean offers for each treatment in each set of rounds, while columns 4 and 5 provide the difference in means between the treatments and the PPRA. There are several important results in Table 2. First, the target-constrained treatment has higher average offers than either of the other two treatments. Indeed, the difference in means between the the PPRA and the target-constrained treatment is above $1 in most rounds. Second, the budget-constrained treatment has higher average offers than the PPRA as well, albeit to a lesser extent. In most rounds, the budget-constrained treatment has offers more than $0.20 higher than its provision point counterpart. Third, notice that while the average offers are relatively stable across rounds for the PPRA and budget-constrained auction, the target-constrained auction saw its average offers decrease over time, which is suggestive of learning over time. Table S9 in the Online Supplement reports regressions of offers on opportunity costs and round number. The table shows that the target-constrained auctions experienced substantial, statistically significant learning over time, while learning in the PPRA and budget-constrained auction was more limited.

Table 3 provides the results from additional experiments with different parameter values, where both the target constraint and the provision point requirement were set to three. First, note that the

Table 3. Mean Offers: Target = 3, Budget = $4.42, PPR = 3

	Mean Offers			Difference: PPRA &	
	PPRA	TC	BC	TC	BC
Rounds	1	2	3	4	5
1 & 9	1.249	1.631	1.383	0.382***	0.134
	(0.628)	(0.556)	(0.687)	(0.086)	(0.095)
2 & 10	1.197	1.454	1.401	0.257***	0.203**
	(0.561)	(0.407)	(0.670)	(0.071)	(0.089)
3 & 11	1.252	1.409	1.372	0.157**	0.120
	(0.639)	(0.381)	(0.620)	(0.076)	(0.091)
4 & 12	1.269	1.400	1.420	0.131	0.151
	(0.672)	(0.457)	(0.859)	(0.083)	(0.111)
5 & 13	1.239	1.362	1.347	0.123	0.108
	(0.636)	(0.481)	(0.529)	(0.081)	(0.084)
6 & 14	1.225	1.361	1.335	0.137	0.111
	(0.601)	(0.695)	(0.508)	(0.094)	(0.080)
7 & 15	1.319	1.339	1.360	0.021	0.041
	(0.766)	(0.584)	(0.550)	(0.098)	(0.096)
8 & 16	1.323	1.412	1.364	0.089	0.041
	(0.922)	(0.785)	(0.587)	(0.124)	(0.112)
All	1.259	1.421	1.373	0.162***	0.114***
	(0.685)	(0.563)	(0.633)	(0.032)	(0.034)

Notes: Single, double, and triple asterisks (*,**,***) indicate significance at the 10%, 5%, and 1% level, respectively. The table contains the mean for each of the three auction treatments and difference in means between the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each *t*-test is conducted with a sample of 96 for each treatment: 24 observations for each round, with a total of 48 after the rounds are pooled, and two sessions for each treatment.

pooled average offers are always less in the PPRA than in either the target- or budget-constrained auctions but that the differences are not statistically significant in most rounds. This agrees with our intuitive expectations, where a smaller target with a constant budget is less restrictive than a larger target with the same budget. Indeed, these results are generally consistent with the contention that, even when the provision point requirement is not more restrictive than the target or budget constraint, the provision point auction provides lower average offers. Also note that, with these parameter values, the target- and budget-constrained auctions provide more comparable average offers than those seen in Table 2, where the target-constrained auction resulted in substantially higher offers.

Tables 2 and 3 provide differences in means across all offers. The buyer, however, is primarily interested in the lowest p offers because those offers actually receive contracts and result in payments from the buyer. Table 4 reports the difference in means for the lowest five offers between the target-constrained treatment with a target of five, the budget-constrained treatment with a budget of $4.42, and the PPRA with a budget of $4.42 and provision point requirement of five. Table 4 shows comparable differences to Table 2 and provides additional support that the PPRA may be an attractive alternative to the target- and budget-constrained auctions from the perspective of the buyer. Indeed, the mean of the five lowest offers in a PPRA was 19.4%–25.6% smaller in the tested PPRAs than the comparable budget-constrained auction, depending on the rounds being compared. One advantage of comparing the lower offers is that large outliers are removed from the comparison. The results in Table 4 are also shown in Figure S1 in the Online Supplement.

Table 4. Mean Lowest Five Offers, Pooled Rounds

	Mean Offers			Difference: PPRA &	
	PPRA	**TC**	**BC**	**TC**	**BC**
Rounds	**1**	**2**	**3**	**4**	**5**
1 & 9	0.822	2.160	1.042	1.339***	0.220***
	(0.316)	(0.765)	(0.394)	(0.107)	(0.065)
2 & 10	0.814	2.069	1.093	1.255***	0.280***
	(0.292)	(0.608)	(0.320)	(0.087)	(0.056)
3 & 11	0.838	2.104	1.095	1.266***	0.256***
	(0.323)	(0.495)	(0.307)	(0.076)	(0.058)
4 & 12	0.848	2.027	1.070	1.179***	0.222***
	(0.323)	(0.397)	(0.306)	(0.066)	(0.057)
5 & 13	0.854	2.025	1.089	1.171***	0.235***
	(0.299)	(0.352)	(0.246)	(0.060)	(0.050)
6 & 14	0.885	2.016	1.103	1.131***	0.218***
	(0.307)	(0.333)	(0.223)	(0.058)	(0.049)
7 & 15	0.886	1.962	1.099	1.076***	0.213***
	(0.325)	(0.281)	(0.223)	(0.055)	(0.051)
8 & 16	0.870	1.934	1.094	1.064***	0.225***
	(0.310)	(0.298)	(0.224)	(0.056)	(0.049)
All	0.852	2.037	1.086	1.185***	0.234***
	(0.311)	(0.471)	(0.285)	(0.026)	(0.019)

Notes: Single, double, and triple asterisks (*,**,***) indicate significance at the 10%, 5%, and 1% level, respectively. The table contains the mean of the lowest five offers for each of the three auction treatments and difference in means between the five lowest offers for the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 60 for each treatment: 15 observations for each round, with a total of 30 after the rounds are pooled, and two sessions for each treatment.

Table 5 reports the difference in means for the lowest three offers between the target-constrained treatment with a target of three, the budget-constrained treatment with a budget of $4.42, and the PPRA with a budget of $4.42 and provision point requirement of three. Table 5 shows statistically significant differences in means between the three auction formats in most rounds and thus suggests that the PPRA can yield improvements in the buyer's welfare for an additional set of parameter values. More specifically, the mean of the three lowest offers in tested provision point auctions was 8.9%–15.7% smaller than the comparable mean in the budget-constrained auctions, depending on the rounds. Indeed, Table 5 provides more compelling evidence than Table 3 that the PPRA can lower offers, even when the provision point requirement is less strict. Despite fewer observations and less power, significant differences in offers between the PPRA and target-constrained auction remain in all pooled rounds. Significant differences in offers between the PPRA and budget-constrained auctions remain in most of the pooled rounds as well. The results shown in Table 5 are also presented in Figure S2 in the Online Supplement.

Efficiency Analysis

This paper is interested not only in comparing the three auction treatments with each other but also against the theoretical predictions for the uniform reverse auction. In a uniform reverse auction, the buyer sets a target and the winning individuals receive the first rejected offer as payment, similar to a Vickrey second-price auction. Theoretically, we expect individuals in a uniform procurement auction will submit their opportunity costs as their offers. To compare the auction formats, this paper

Table 5. Mean Lowest Three Offers, Pooled Rounds

	Mean Offers			Difference: PPRA &	
	PPRA	TC	BC	TC	BC
Rounds	1	2	3	4	5
1 & 9	0.750	1.142	0.823	0.392***	0.073
	(0.279)	(0.346)	(0.284)	(0.074)	(0.066)
2 & 10	0.777	1.094	0.922	0.317***	0.145**
	(0.268)	(0.257)	(0.253)	(0.062)	(0.061)
3 & 12	0.845	1.100	0.937	0.255***	0.092
	(0.237)	(0.248)	(0.266)	(0.057)	(0.059)
4 & 12	0.827	1.081	0.918	0.254***	0.091
	(0.241)	(0.224)	(0.269)	(0.055)	(0.060)
5 & 13	0.836	1.033	0.979	0.197***	0.143**
	(0.238)	(0.204)	(0.231)	(0.052)	(0.055)
6 & 14	0.864	1.010	0.995	0.176***	0.131***
	(0.211)	(0.219)	(0.190)	(0.051)	(0.047)
7 & 15	0.872	0.993	1.002	0.121**	0.130***
	(0.193)	(0.223)	(0.200)	(0.049)	(0.046)
8 & 16	0.849	0.992	0.998	0.143***	0.149***
	(0.206)	(0.200)	(0.207)	(0.048)	(0.049)
All	0.828	1.056	0.947	0.228***	0.119***
	(0.236)	(0.247)	(0.244)	(0.020)	(0.020)

Notes: Single, double, and triple asterisks (*,**,***) indicate significance at the 10%, 5%, and 1% level, respectively. The table contains the mean of the lowest three offers for each of the three auction treatments and difference in means between the three lowest offers for the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each *t*-test is conducted with a sample of 36 for each treatment: 9 observations for each round, with a total of 18 after the rounds are pooled, and two sessions for each treatment.

uses three criteria to measure their efficacy. The first measure is social efficiency, which is defined as follows:

$$\text{(9)} \qquad \text{Social Efficiency} = \frac{\sum_{i=1}^{p} v_{(i)}}{\sum_{i=1}^{p} v_i} \times 100,$$

where $v_{(i)}$ is the ith-smallest opportunity cost in the auction. In other words, social efficiency is the minimum opportunity cost required to supply five contracts divided by the sum of the opportunity costs of the individuals who actually received contracts. From society's perspective, welfare is maximized when the individuals with the lowest opportunity cost receive the available contracts.

The second measure is simply the total cost to the buyer of purchasing p contracts. This allows us to compare cost savings for the buyer across the different auction mechanisms and thus the amount of money the buyer must spend, on average, for the p units.

Finally, this paper uses a "cost effectiveness" measure to further compare how costly the auctions are for the buyer. While a socially efficient auction will procure goods only from the lowest-cost sellers, the buyer is only interested in minimizing their total cost for procuring the goods. That is, the buyer doesn't care if the goods they purchase come from individuals with the lowest costs so long as they pay as little as possible. The "cost effectiveness" measure is defined as follows:

$$\text{(10)} \qquad \text{Cost Effectiveness} = \frac{\text{Uniform Auction Cost} - \text{Other Auction Cost}}{\text{Uniform Auction Cost} - \text{Total Opportunity Cost}} \times 100\%,$$

Table 6. Efficiency Measures

	OC 1	Uniform 2	TC-5 3	TC-3 4	PPRA-5 5	PPRA-3 6
Social efficiency	100.00%	100.00%	71.46% (14.89%)	64.61% (24.65%)	95.98% (9.40%)	76.80% (22.85%)
Avgerage per unit cost of providing five units	$0.60	$1.33	$2.04	–	$0.81	–
Avgerage per unit cost of providing three units	$0.35	$0.88	–	$1.06	–	$0.83
Cost effectiveness	100.00%	0.00%	−97.96% (29.65%)	−33.82% (34.21%)	71.12% (12.03%)	9.66% (35.92%)

Notes: The table contains efficiency measures for several different auction formats. Numbers in parentheses are standard errors. Column 1 contains the results from a theoretical discriminative auction where all individuals submit their opportunity costs as offers. Column 2 contains the predicted results from a uniform-price auction. Columns 3–4 contain the results for the target-constrained auction. Columns 5–6 contain the results for the PPRA in rounds where the provision point requirement was met.

where “Other Auction Cost” is the total cost of the compared auction and “Total Opportunity Cost” is the sum of the opportunity cost for all individuals who receive a contract. By definition, if the participants submitted offers equal to their opportunity costs, the cost efficiency measure would be 100%, while the cost efficiency measure is 0% for the uniform auction.[6]

Table 6 provides the efficiency and cost effectiveness measures for the various auctions by their parameter values. Column 1 provides the measures for a hypothetical discriminative auction where individuals submit their opportunity costs as offers. In such an auction, all of the welfare gains would be given to the buyer and the auction would be 100% socially efficient. As such, it serves as the ideal auction from the perspective of the buyer. While such an auction is likely not implementable, it serves as a useful comparison for the PPRA: The closer the PPRA is in cost to the hypothetical OC auction, the more cost efficient the PPRA is at procuring the purchased goods. The uniform auction (column 2) provides a meaningful comparison because it has attractive efficiency attributes and is implementable. There are two important problems to discuss before continuing to the efficiency measures. First, we cannot compare the budget-constrained auction to the other formats directly with these measures because the buyer, in the experiments, was almost never able to afford five contracts in the budget-constrained treatment. Second, the provision point auctions didn’t always result in contracts in the treatment with PPR = 5, as the provision point requirement wasn’t met in approximately 33% of the rounds. (The PPR was met in every round for the treatment with PPR = 3.) As a result, it isn’t always sensible to compare the PPRA to the target-constrained and uniform-price auctions. Instead, this paper presents only the efficiency measure for the PPRA when the provision point requirement was met. This alters the efficiency estimates slightly when the PPR = 5 but does not alter the analysis when the PPR = 3.

Unsurprisingly, given the theoretical predictions, the target-constrained auction performs the worst by all three measures, regardless of the parameter values. Indeed, the target-constrained auction costs over twice as much, on average, as the PPRA and costs nearly 80% more than the predictions for the uniform auction as well, when $p = 5$. On the other hand, the PPRA was only slightly less socially efficient than the predictions for the uniform auction when $p = 5$, although the PPRA achieved lower social efficiency than the predictions for the uniform-price auction when $p = 3$. In summary, the PPRA performs better than the uniform-price auction from the perspective of the buyer and slightly worse than the uniform-price auction from the perspective of social efficiency. However, the difference in the social efficiency measure is not statistically significant for the session where the provision point requirement was equal to five.

[6] One can think of the “cost effectiveness” measure as a “private” efficiency measure for the buyer.

Table 7. Average Environmental Benefits

	OC	BC	PPRA - 3	PPRA - 5
No threshold	5.50	3.74	3.00	3.18
	(0.51)	(0.65)	(0.00)	(2.42)
Threshold: five contracts	5.00	0.57	0.00	3.18
	(0.00)	(1.60)	(0.00)	(2.42)
Threshold: three contracts	3.00	3.00	3.00	1.91
	(0.00)	(0.00)	(0.00)	(1.45)

Notes: The table contains the average environmental benefit provided by different auction formats. The first row is average environmental benefit when the total environmental benefit is the number of accepted contracts. The second row displays the average environmental benefit when there is no benefit if less than five contracts are accepted but five units of environmental benefit when five or more contracts are accepted. The third row displays the same results as the second except the discontinuity in the benefits function occurs at three rather than five contracts.

Environmental Benefits

The efficiency analysis demonstrates the relative costs of the different auction formats, but we are also interested in the total benefit that the contracts provide. By assuming different environmental benefit functions, we can see how the PPRA performs (i) when the environmental benefits function is linear in the number of contracts and (ii) when there is a discontinuity in the benefits function. Table 7 displays the mean environmental benefits associated with budget-constrained auction and PPRA. Each plot of land is assumed to provide one unit of environmental benefit, so that with the "no threshold" environmental benefit function the total environmental benefits provided by a group in a round is simply the sum of the accepted contracts. With the "threshold" environmental benefit functions, however, there is a discontinuity in the benefit function so that a group provides X units of environmental benefit when at least X contracts are made but no environmental benefits otherwise. For example, row 2 of Table 7 provides the average environmental benefits when there is a discontinuity in the environmental benefits function such that no benefits are provided unless at least five contracts are secured.[7]

While this analysis is hardly reflective of all possible benefit functions and the differences between the PPRA treatments and the budget-constrained treatment are insignificant due to limited observations, the results provide an indication that the success of the PPRA will be dependent on whether it is appropriate for a given setting. Indeed, while the PPRA provides slightly less average benefits than a budget-constrained auction with a linear benefits function, the PPRA with the provision point requirement set at the threshold provides more than 5 times the average environmental benefit.

Finally, an important conclusion from Table 7 is that setting the provision point requirement at the threshold is critical: If the provision point requirement is set too high, average environmental benefits will suffer when contracts which would meet the threshold are rejected, while if the provision point requirement is set too low, insufficient contracts will be made to achieve environmental benefits.

Discussion

Given the structure of the PPRA, we believe it will be particularly effective when three criteria hold true. First, if there is a threshold of interest, the PPRA can ensure the government either some level of environmental service or the welfare they obtain from retaining their budget and expending it on an alternative PES program. Additionally, as seen in Table 7, setting the provision point to the

[7] Because the target-constrained auctions always procure the same quantity of environmental benefits regardless of the cost, they are not included in this analysis.

threshold can dramatically increase the environmental benefit provided by the program compared to a budget-constrained auction.

Second, we believe that the PPRA will be particularly effective for auctions with small numbers of participants who all operate in a given region. As the number of participants in a PPRA becomes smaller, the ability of any individual to affect the probability the provision point requirement is met increases, which increases the impact of the provision point requirement on offering behavior (see Propositions 3 and 4).

Third, the PPRA will be most effective at reducing offers when the cost of running an auction is low and when the buyer can move the program to a new location when the provision point requirement isn't met. As seen in Table 7, the buyer may forgo substantial welfare opportunities if they cannot eventually provide contracts to some individuals, and thus the ability to move the auction to a new location at relatively little cost will decrease the chance the buyer will not able to purchase some environmental service.

As an example of a setting that satisfies these three criteria, consider the BirdReturn© program in California, in which conservationists and aviphiles pay rice farmers in the Central Valley of California to flood their paddies to create small habitats for migratory birds. The number of rice farmers in a given area is relatively small (only 60 farmers have enrolled in the program at any point since 2014), and if a certain number of these "pop-up habitats" are not created, then the birds will not be able to use the regions as stepping stones along their journey. Several potential areas in the Central Valley could serve as pop-up habitats, so the conservationists and aviphiles could move to a new location if they cannot afford a certain number of contracts.

While the PPRA has the potential to function well in some settings, it certainly would not be appropriate for all procurement auctions. For example, electricity markets use reverse auctions to allocate contracts to energy producers. A PPRA in this context would mean that no electricity would be produced when the provision point requirement is not met, which would be an unacceptable outcome given that demand for electricity is inelastic.

Conclusion

This paper introduces a new auction mechanism designed for conservation and PES settings. The PPRA uses codependent expected profit functions for individuals seeking to provide environmental services to decrease rent-seeking behavior. This decrease in strategic behavior has the potential to increase the efficiency and cost effectiveness of conservation and PES programs while simultaneously decreasing uncertainty for the purchasers of the environmental goods. The experimental and theoretical results support this claim, showing that the PPRA can save the procurer 21.55%–58.17% or 12.57%–21.59% of their costs on average, compared to a multiunit reverse discriminative auction or budget-constrained multiunit reverse discriminative auction, respectively, with the exact value dependent upon the target number of contracts. Given that environmental benefit functions are often nonlinear in the number of contracts accepted, lower offers can lead to more environmental protection and thus welfare increases for society. Further, the PPRA also improves social efficiency over the multiunit reverse discriminative auction, reducing the total cost of the environmental service to society. Future research will expand the empirical support for the PPRA to field settings or continue theoretical examination to consider optimal offering behavior in repeated rounds or in settings with public communication between the participants. Settings in which environmental benefits are a function of spatial proximity of conserved land also provide a particularly fruitful area of research.

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Online Supplement: Provision Point Reverse Auction: A New Auction Mechanism with Applications for Conservation Contracts

Stephen Otto, Gregory Poe, and David Just

Multiunit Reverse Discriminative Auction Symmetric Optimal Offer Function

We confirm the symmetric Bayseian Nash equilibrium found by Hailu, Schilizzi, and Thoyer (2005). In a multiunit reverse auction (also known as a target-constrained auction), a participant in the auction is interested in the probability that their offer will be one of the p lowest offers out of the n offers submitted by the n participants. This probability is represented by $g(O_j^{-1}(o_i))$ in equation (5). The expected profit for an individual in this auction is then represented by

$$E[\Pi] = (o_i - v_i) \times g(O_j^{-1}(o_i)), \tag{S1}$$

which is a more specific representation of equation (4). The first-order conditions to maximize equation (S1) are

$$g(O_j^{-1}(o_i)) + (o_i - v_i)\frac{\partial g(O_j^{-1}(o_i)}{\partial o_i}\frac{\partial O_j^{-1}(o_i)}{\partial o_i} = 0. \tag{S2}$$

Recalling that

$$\frac{\partial f^{-1}(x)}{\partial x} = \frac{1}{f'(f^{-1}(x)}, \tag{S3}$$

equation (S2) simplifies to

$$g(O_j^{-1}(o_i)) + (o_i - v_i)\frac{\frac{\partial g(O_j^{-1}(o_i)}{\partial o_i}}{\frac{\partial O_j(O_j^{-1}(o_i))}{\partial o_i}} = 0. \tag{S4}$$

In equilibrium, $o_i = O_j(v_i) = O^*_{i,TC}(v_i)$. Equation (S4) becomes

$$v_i\frac{\partial g(v_i)}{\partial o_i} = g(v_i)\frac{\partial O^*_{i,TC}(v_i)}{\partial o_i} + O^*_{i,TC}(v_i)\frac{\partial g(v_i)}{\partial o_i}. \tag{S5}$$

Integrating both sides of equation (S5) with respect to o_i yields

$$-\int_{v_i}^{1} u\frac{\partial g(u)}{\partial o_i}du = O^*_{i,TC}(v_i)g(v_i). \tag{S6}$$

Dividing both sides by $g(v_i)$ and noting that $g(1) = 0$, we have

$$O^*_{i,TC}(v_i) = \frac{-\int_{v_i}^{1} u\frac{\partial g(u)}{\partial o_i}du}{-\int_{v_i}^{1}\frac{\partial g(u)}{\partial o_i}du}. \tag{S7}$$

Given that, according to equation (5),

$$\text{(S8)} \qquad \frac{\partial g(u)}{\partial o_i} = \frac{(n-1)!}{(p-1)!(n-p-1)!} u^{p-1}(1-u)^{n-p-1},$$

the symmetric Bayesian Nash equilibrium for the multiunit reverse discriminative auction is given by

$$\text{(S9)} \qquad O^*_{i,TC}(v_i) = \frac{\int_{v_i}^{1} u^p (1-u)^{n-p-1} du}{\int_{v_i}^{1} u^{p-1}(1-u)^{n-p-1} du}.$$

Proposition 1 Proof

PROPOSITION 1. *As v_i approaches 1, $O^*_{i,TC}(v_i)$ converges to 1.*

Proof. For all $v_i \in (0,1)$, the numerator of $O^*_{i,TC}(v_i)$ is less than the denominator, so $O^*_{i,TC}(v_i)$ is bounded above by 1 for $v_i \in (0,1)$. Further, given that a nonnegative expected profit requires $O^*_{i,TC}(v_i) \geq v_i$, $O^*_{i,TC}(v_i)$ is bounded below by v_i. Both $y = v_i$ and $y = 1$ converge to 1 as v_i approaches 1, so $O^*_{i,TC}(v_i)$ converges to 1 as v_i approaches 1 by the sandwich theorem. ■

Proposition 2 Proof

PROPOSITION 2. *$O^*_{i,TC}(v_i)$ is a strictly increasing function of v_i for $v_i \in [0,1)$.*

Proof. The following proposition and proof are made simpler by rewriting $O^*_{i,TC}(v_i)$ with the regularized beta function, given by

$$I_x(a,b) = \frac{\int_0^x t^{a-1}(1-t)^{b-1} dt}{B(a,b)}.$$

To rewrite $O^*_{i,TC}(v_i)$ in terms of the regularized beta function, we multiply the numerator and denominator of $O^*_{i,TC}(v_i)$ by $\frac{B(p+1,n-p)}{B(p+1,n-p)}$, where $B(p+1,n-p)$ represents the beta function with parameters $p+1$ and $n-p$. This yields

$$\text{(S10)} \qquad \begin{aligned} O^*_{i,TC}(v_i) &= \frac{\int_{v_i}^{1} u^p (1-u)^{n-p-1} du \times \frac{B(p+1,n-p)}{B(p+1,n-p)}}{\int_{v_i}^{1} u^{p-1}(1-u)^{n-p-1} du \times \frac{B(p,n-p)}{B(p,n-p)}} \\ &= \frac{1 - I_{v_i}(p+1,n-p)}{1 - I_{v_i}(p,n-p)} \times \frac{B(p+1,n-p)}{B(p,n-p)}. \end{aligned}$$

Given that $B(x,y) = \frac{\Gamma(x)\Gamma(y)}{\Gamma(x+y)}$, equation (S10) simplifies to

$$\text{(S11)} \qquad O^*_{i,TC}(v_i) = \frac{1 - I_{v_i}(p+1,n-p)}{1 - I_{v_i}(p,n-p)} \times \frac{p}{n}.$$

One convenient property of the regularized beta is that

$$\text{(S12)} \qquad I_{v_i}(p+1,n-p) = I_{v_i}(p,n-p) - \frac{v_i^p (1-v_i)^{n-p-1}}{pB(p,n-p)},$$

and thus equation (S11) can be rewritten as

$$\text{(S13)}\quad \begin{aligned} O^*_{i,TC}(v_i) &= \frac{1 - I_{v_i}(p, n-p) + \frac{v_i^p (1-v_i)^{n-p-1}}{pB(p,n-p)}}{1 - I_{v_i}(p, n-p)} \times \frac{p}{n} \\ &= \frac{p}{n} + \frac{v_i^p (1-v_i)^{n-p-1}}{nB(p,n-p)(1 - I_{v_i}(p,n-p))}. \end{aligned}$$

Applying the quotient rule, the derivative of $O^*_{i,TC}(v_i)$ with respect to v_i is

$$\text{(S14)}\quad \begin{aligned} \frac{\partial O^*_{i,TC}(v_i)}{\partial v_i} = &\Big[\Big(\Big(pv_i^{p-1}(1-v_i)^{n-p-1} + (n-p-1)(1-v_i)^{n-p-2}v_i^p\Big) \\ &\times (nB(p,n-p)(1 - I_{v_i}(p,n-p))) \\ &+ nv_i^p(1-v_i)^{n-p-1}v_i^{p-1}(1-v_i)^{n-p-1}\Big)\Big] \\ &\div n^2 B(p,n-p)^2 (1 - I_{v_i}(p,n-p))^2 \end{aligned}$$

Factoring out v_i^{p-1} and $(1-v_i)^{n-2p-2}$ and dividing the numerator and denominator by n yields

$$\text{(S15)}\quad \frac{\partial O^*_{i,TC}(v_i)}{\partial v_i} = \frac{v_i^{p-1}(1-v_i)^{n-2p-2}((1-v_i)^p(p - nv_i + v_i)B(p,n-p)(1 - I_{v_i}(p,n-p)) + (1-v_i)^n v_i^p)}{nB(p,n-p)^2(1 - I_{v_i}(p,n-p))^2}.$$

We want to show that

$$\text{(S16)}\quad 0 < \frac{v_i^{p-1}(1-v_i)^{n-2p-2}((1-v_i)^p(p - nv_i + v_i)B(p,n-p)(1 - I_{v_i}(p,n-p)) + (1-v_i)^n v_i^p)}{nB(p,n-p)^2(1 - I_{v_i}(p,n-p))^2}$$

for all $v_i \in (0,1)$. Note that $v_i^{p-1}(1-v_i)^{n-2p-2}$ and $pB(p,n-p)^2(1 - I_{v_i}(p,n-p))^2$ are both positive, and thus both can be cancelled out without affecting the direction of the inequality. Inequality (S16) thus holds when

$$\text{(S17)}\quad -(1-v_i)^p(p - nv_i + v_i)B(p,n-p)(1 - I_{v_i}(p,n-p)) < (1-v_i)^n v_i^p.$$

Dividing both sides by $n(1-v_i)^p B(p,n-p)(1 - I_{v_i}(p,n-p))$ yields

$$\text{(S18)}\quad -\Big(\frac{p}{n} - v_i + \frac{v_i}{n}\Big) < \frac{(1-v_i)^{n-p} v_i^p}{nB(p,n-p)(1 - I_{v_i}(p,n-p))}.$$

A slight rearrangement of terms yields

$$\text{(S19)}\quad v_i\Big(1 - \frac{1}{n}\Big) < \frac{p}{n} + \frac{(1-v_i)^{n-p} v_i^p}{nB(p,n-p)(1 - I_{v_i}(p,n-p))}$$

Notice that the right side of inequality (S19) is the optimal offer function for $O^*_{i,TC}(v_i)$ from equation (S13). Also note that $(1 - \frac{1}{n}) < 1$. Equation (S19) thus implies

$$\text{(S20)}\quad v_i\Big(1 - \frac{1}{n}\Big) < v_i < O^*_{i,TC}(v_i)$$

Given that profit maximization requires $O^*_{i,TC}(v_i) > v_i$ for all $v_i \in [0,1)$, the optimal offer function is increasing for all $v_i \in [0,1)$. ■

Proposition 3 Proof

PROPOSITION 3. *Suppose $O^*_{i,TC}(v_i|n,p)$ is the symmetric Bayesian Nash equilibrium optimal offer function for the multiunit reverse discriminative auction with a target of $p<n$ and $O^*_{i,PP}(v_i|n,p,B)$ is a symmetric Bayesian Nash equilibrium optimal offer function for the PPRA with a provision point requirement of $p<n$ and a budget of B. (From this point on, $O^*_{i,TC}(v_i|n,p)$ and $O^*_{i,PP}(v_i|n,p,B)$ will be simplified as $O^*_{i,TC}(v_i)$ and $O^*_{i,PP}(v_i)$, respectively.) Additionally, assume Axiom 1 holds. Then $O^*_{i,TC}(v_i) = O^*_{i,PP}(v_i)$ if and only if either (i) any single participant in the auction cannot affect the probability that the provision point requirement is met by increasing or decreasing their offer or (ii) $v_i = 1$.*

Proof. The expected profit function for the multiunit reverse discriminative auction is given by (2). Let $g(n,p,o_i)$ represent the probability that an offer is one of the p lowest and let $o^*_{i,TC}$ represent the optimal offer, given v_i, in a multiunit reverse discriminative auction. Note that $g(n,p,o_i)$ is a decreasing function in o_i; the larger o_i, the less likely it is one of the p lowest offers. Expected profit for the multiunit reverse discriminative auction is maximized where the first order conditions are met:

$$\text{(S21)} \qquad (o^*_{i,TC} - v_i) = \frac{-g(n,p,o^*_{i,TC})}{\left(\dfrac{\partial g(n,p,o^*_{i,TC})}{\partial o^*_{i,TC}}\right)}$$

Let $w(n,p,B,o_i)$ represent the probability that the provision point requirement will be met and let $o^*_{i,PP}$ represent the optimal offer, given v_i, in a PPRA. Note that $w(n,p,B,o_i)$ is a nonincreasing function of o_i; as a given offer gets larger, the likelihood that the provision point requirement is met does not increase. Then the first order condition for profit maximization for the PPRA is:

$$\text{(S22)} \quad (o^*_{i,PP} - v_i) = \frac{-g(n,p,o^*_{i,PP}) \times w(n,p,B,o^*_{i,PP})}{\left(\dfrac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}} \times w(n,p,B,o^*_{i,PP}) + \dfrac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} \times g(n,p,o^*_{i,PP})\right)}$$

Suppose $O^*_{i,TC}(v_i) = O^*_{i,PP}(v_i)$. Then $o^*_{i,TC} = o^*_{i,PP}$ for all v_i. Multiplying the top and bottom of the right-hand side of (S22) by the reciprocal of its numerator yields

$$\text{(S23)} \quad (o^*_{i,PP} - v_i) = \frac{-1}{\left(\dfrac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \dfrac{1}{g(n,p,o^*_{i,PP})} + \dfrac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \dfrac{1}{w(n,p,B,o_{i,PP^*})}\right)}$$

From (S21), and given that $o^*_{i,TC} = o^*_{i,PP}$, we have

$$\text{(S24)} \qquad (o^*_{i,PP} - v_i) = \frac{-1}{\left(\dfrac{-1}{(o^*_{i,PP} - v_i)} + \dfrac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \dfrac{1}{w(n,p,B,o_{i,PP^*})}\right)}$$

Multiplying both sides by the denominator of the right-hand side yields

$$\text{(S25)} \qquad (o^*_{i,PP} - v_i) \times \left(\frac{-1}{(o^*_{i,PP} - v_i)} + \frac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{w(n,p,B,o_{i,PP^*})}\right) = -1$$

which simplifies to

$$\text{(S26)} \qquad 0 = (o^*_{i,PP} - v_i) \times \left(\frac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{w(n,p,B,o_{i,PP^*})}\right)$$

Equation (S26) implies that either $o^*_{i,PP} = v_i$ or $\frac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} = 0$. Given that $o^*_{i,TC} = v_i$ only when $v_i = 1$, the two optimal offer functions can be the same only when each participant cannot affect the probability the provision point requirement is met by changing their offer or $v_i = 1$.

To prove the other direction, suppose that no individual can affect the probability that the provision point requirement is met by changing their offer. Then, by definition, $\frac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} = 0$ and, using (S22)

$$\text{(S27)} \qquad (o^*_{i,PP} - v_i) = \frac{-g(n,p,o^*_{i,PP}) \times w(n,p,B,o^*_{i,PP})}{\left(\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}} \times w(n,p,B,o^*_{i,PP}) + 0^* g(n,p,o^*_{i,PP})\right)}$$

Simplifying (S27) provides

$$\text{(S28)} \qquad (o^*_{i,PP} - v_i) = \frac{-g(n,p,o^*_{i,PP})}{\left(\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}}\right)}$$

which is the first order condition for the multiunit reverse discriminative auction. If instead of assuming that no individual can affect the probability the provision point requirement is met we assume that $v_i = 1$, the result follows immediately from Axiom 1. ■

Proposition 4 Proof

PROPOSITION 4. *Suppose $O^*_{i,TC}(v_i)$ is the symmetric Bayesian Nash equilibrium optimal offer function for the multiunit reverse discriminative auction with a target of $p < n$ and $O^*_{i,PP}(v_i)$ is a symmetric Bayesian Nash equilibrium optimal offer function for the PPRA with a provision point requirement of $p < n$ and a budget of B. Further suppose that $O^*_{i,TC}(v_i)$ is convex in v_i.*[1] *If a participant in the auction can impact the probability that the provision point requirement is met, then $O^*_{i,TC}(v_i) \geq O^*_{i,PP}(v_i)$ for all v_i.*

Proof. Equations (S21) and (S22) provide the first order conditions for the optimal offer for an individual competing in a multiunit reverse discriminative auction and a PPRA, respectively. Note that $g(n,p,o^*_i)$ and $w(n,p,B,o^*_i)$ are decreasing and nonincreasing in o^*_i, respectively, so that both $\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}}$ and $\frac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}}$ are less than or equal to zero. We prove by contradiction. Suppose that $o^*_{i,TC} \leq o^*_{i,PP}$. Then, combining (S23) and (S21), we have:

$$\text{(S29)} \qquad \frac{-1}{\left(\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{g(n,p,o^*_{i,PP})} + \frac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{w(n,p,B,o_{i,PP^*})}\right)} > \frac{-g(n,p,o^*_{i,TC})}{\left(\frac{\partial g(n,p,o^*_{i,TC})}{\partial o^*_{i,TC}}\right)}$$

[1] The convexity assumption holds for every set of parameter values we have tested.

Note that both sides of the inequality are positive. Thus, multiplying both sides of the inequality by their reciprocal does not reverse the inequality. The resulting rearrangement is given by

$$\text{(S30)} \quad -\left(\frac{\partial g(n,p,o^*_{i,TC})}{\partial o^*_{i,TC}}\right) \times \frac{1}{g(n,p,o^*_{i,TC})} > \left(-\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{g(n,p,o^*_{i,PP})} - \frac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{w(n,p,B,o_{i,PP^*})}\right)$$

Given our assumptions about $w(n,p,B,o_{i,PP})$ and $g(n,p,o_{i,PP})$, we know that

$$\text{(S31)} \quad -\frac{\partial w(n,p,B,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{w(n,p,B,o_{i,PP^*})} \geq 0$$

and

$$\text{(S32)} \quad -\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{g(n,p,o^*_{i,PP})} \geq 0$$

Returning to (S30), if the sum of (S31) and (S32) is less than the left-hand side of (S30), then we know that (S32) is also less than the left-hand side of (S30).

$$\text{(S33)} \quad -\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}} \times \frac{1}{g(n,p,o^*_{i,PP})} < -\left(\frac{\partial g(n,p,o^*_{i,TC})}{\partial o^*_{i,TC}}\right) \times \frac{1}{g(n,p,o^*_{i,TC})}$$

which further implies that

$$\text{(S34)} \quad -\frac{g(n,p,o^*_{i,PP})}{\left(\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}}\right)} > -\frac{g(n,p,o^*_{i,TC})}{\left(\frac{\partial g(n,p,o^*_{i,TC})}{\partial o^*_{i,TC}}\right)}$$

The completion of this proof requires a lemma.

LEMMA 1. *Suppose $O^*_{i,TC}(v_i)$ is the symmetric Bayesian Nash equilibrium optimal offer function for the multiunit reverse discriminative auction with a target of $p < n$. Additionally, suppose that $O^*_{i,TC}(v_i)$ is a convex function. Then the difference between a given optimal offer, $o^*_{i,TC}$, and its corresponding value, v_i, is a decreasing function in v_i.*

Proof. Equation (S21) provides the first order condition for the optimal offer, given a value v_i, in a multiunit reverse discriminative auction. The left-hand side of (S21) provides the difference between an optimal offer and its corresponding value. Taking a derivative with respect to v_i on both sides yields

$$\text{(S35)} \quad \frac{\partial O^*_{i,TC}(v_i)}{\partial v_i} - 1 = \partial\left(\frac{-g(n,p,o^*_{i,TC})}{\left(\frac{\partial g(n,p,o^*_{i,TC})}{\partial o^*_{i,TC}}\right)}\right)/\partial v_i$$

Proposition 2 states that $O^*_{i,TC}(v_i)$ is an increasing function, and the convexity assumption implies that the second derivative of $O^*_{i,TC}(v_i)$ is positive over the range [0,1) as well. If $\frac{\partial O^*_{i,TC}(v_i)}{\partial v_i}$ was greater than 1 for any v_i in this range, then $\frac{\partial O^*_{i,TC}(v_j)}{\partial v_i}$ would also have to be greater than 1, for any

$v_j > v_i$, by convexity. Recall that $O^*_{i,TC}(v_i)$ is bounded below by the 45 degree line and that $O^*_{i,TC}(v_i)$ converges to 1 as v_i converges to 1, by Proposition 1. If the derivative of $O^*_{i,TC}(v_i)$ was ever greater than 1, then $O^*_{i,TC}(v_i)$ would not converge to 1 as v_i converged to 1. Thus, $\frac{\partial O^*_{i,TC}(v_i)}{\partial v_i}$ can never be greater than 1. This fact, along with Equation S35, immediately provides the desired result. ■

Lemma 1 states that

$$\text{(S36)} \qquad \partial \left(\frac{-g(n,p,o^*_{i,TC})}{\left(\frac{\partial g(n,p,o^*_{i,TC})}{\partial o^*_{i,TC}}\right)} \right) / \partial v_i < 0$$

The only avenue through which v_i affects $-\frac{g(n,p,o^*_{i,PP})}{\left(\frac{\partial g(n,p,o^*_{i,PP})}{\partial o^*_{i,PP}}\right)}$ is o_i. Further, because o_i is an increasing function of v_i, we have

$$\text{(S37)} \qquad \partial \left(\frac{-g(n,p,o^*_{i,TC})}{\left(\frac{\partial g(n,p,o^*_{i,TC})}{\partial o^*_{i,TC}}\right)} \right) / \partial o_i < 0$$

Inequality (S37), along with the assumption that $o^*_{i,PP} > o^*_{i,TC}$, implies that equation (S34) is a contradiction. ■

Instructions

(Differences across instructions are highlighted in yellow.)

This experiment is a study of individual decision-making in a group setting. If you follow these instructions carefully and make informed decisions, you will earn money. The money you earn will be paid to you, in cash, after the experiment has concluded. We ask that you do not use any electronic devices during this experiment, including cell phones, tablets, etc. We further ask that you do not communicate with your peers in any capacity. If you have any questions, please raise your hand and the researchers will come to assist you.

In this experiment, you are a member of a group consisting of eight individuals. You and the other seven individuals each own one unit of a good that can be rented out each round. Each unit of the good is indistinguishable from any of the other units owned by your fellow participants. Additionally, each participant in your group will be given an individual valuation for their own unit of the good, which we will call their opportunity cost (more details will follow). Individuals who do not rent out their unit will receive this opportunity cost as payment at the end of each round. (PPRA/TC) A single buyer is interested in renting five units of the good each round. (The buyer is not interested in renting more than five units) (PPRA/BC) However, the buyer has a limited budget and thus will pay individuals for their units using an **auction**. The auction will be conducted as follows:

- Each round, you will submit an offer representing the amount of money for which you would be willing to rent out your unit during that round. (Your offers will be capped at $7 each round. If you try to submit an offer higher than $7, you will be asked to enter a different offer.)
- Your peers will also submit their own offers for their units.
- (PPRA/TC) The buyer will then rank these offers in ascending order and provide contracts to the lowest offer, then the second lowest offer, and so on until the fifth lowest offer. (BC) The

buyer will then rank these offers in ascending order and provide contracts to the lowest offer, then the second lowest offer, and so on until the buyer's budget is exhausted.

- If you do receive a contract from the buyer, the buyer will take your unit (for that round) and **you will receive your offer as payment (for that round)**.
- If you do not receive a contract from the buyer, **you will keep your unit and receive your opportunity cost as payment for that round.**

(PPRA Only) However, the buyer is only interested in offering contracts to individuals in your group if they can afford at least five of the offers. From this point on, this number (five) will be referred to as the **funding threshold**. If, given the offers that your group submits, the buyer cannot afford the five lowest offers, then no individual will receive a contract, regardless of the magnitude of their offer. If the buyer can afford at least five offers then the buyer will offer contracts to the participants that submitted the five lowest offers, as described above.

An individual's opportunity cost (in experimental dollars) will be drawn from a **uniform distribution** from **0 to 2**, in increments of 0.01. In other words, you will randomly receive a number between 0 and 2, where each number is equally likely to be drawn. For example, the odds that you receive opportunity cost = 1.15 are the same as the odds that you receive opportunity cost = 0.82 are the same as the odds that you receive opportunity cost = 0.23, etc. As such, each of the eight individuals in your group will be randomly assigned an opportunity cost and will formulate offers given this information. **All individuals in your group know only their own opportunity costs and that the other individuals in their group have opportunity costs drawn from the same distribution. You will not know the opportunity costs of any of your peers.**

After eight rounds, you will be randomly assigned to a new group of eight individuals. (The random assignments were made before this session by drawing numbers from a hat. The assignment will not be based on the offers made in previous rounds.) In addition, you will receive a new opportunity cost, drawn from the same distribution as before. Each of the other 23 participants in this room will also be randomly assigned to a new group of eight individuals, and will also draw new opportunity costs. This process will occur every eight rounds. If there are any questions about this process, please raise your hand and ask one of the researchers.

The experiment will be complete after 16 rounds. All experimental dollars will be converted to real dollars using a one-to-one ratio. Before the experiment begins, the researcher will briefly discuss the experiment with you using a PowerPoint presentation. There will also be five practice rounds where all 24 participants will participate in rounds of the auction. After these rounds, new opportunity costs and groups will be assigned, and the experiment will begin.

Summary

- At the beginning of the experiment, you will receive a randomly drawn opportunity cost between 0 and 2, with each value in that range being equally likely.
- Based on that opportunity cost, each round you will submit an offer to the buyer for your unit.
- (PPRA/BC) The buyer has a budget, $4.42, with which to award contracts. The buyer accepts offers in ascending order, from smallest to largest. (TC) For each round, if out of your group of eight, your offer is one of the five lowest offers, you will receive your offer as payment.
- (PPRA Only) For each round, if out of your group of eight, the buyer cannot afford the lowest five offers, then no contracts will be awarded. If the buyer can afford the five lowest offers, then exactly five contracts will be made with the participants who submitted the five lowest offers.

- In a given round, if you receive a contract, you will rent out your unit and receive your offer as payment for that round. (You will earn your offer instead of your opportunity cost as payment.)
- If you do not receive a contract, you will keep your unit and earn your opportunity cost as payment for that round.
- (PPRA) For additional clarification: in order to receive your offer as payment instead of your opportunity cost, your offer must be accepted by the buyer. For your offer to be accepted, your offer must be one of the five lowest, and the sum of the five lowest offers must be less than the buyer's budget. If those two conditions are not met, you will receive your opportunity cost as payment. (TC) For additional clarification: in order to receive your offer as payment instead of your opportunity cost, your offer must be accepted by the buyer. For your offer to be accepted, your offer must be one of the five lowest. If your offer is not one of the five lowest offers, you will receive your opportunity cost as payment.
- After each round, you will once again have possession of your unit, and will be able to participate in the auction during the next round.
- After eight rounds, you and the other 23 participants in the experiment will be randomly assigned to new groups of eight with new, randomly assigned opportunity costs. The budget and funding threshold will remain constant across all 16 rounds.

Figures and Tables

Table S1. Mean Offers – Target = 5, Budget = $4.42, PPR = 5, Rounds 1–8

	Mean Offers			Difference: PPRA &	
	PPRA	**TC**	**BC**	**TC**	**BC**
Rounds	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
1	1.083	2.725	1.372	1.642***	0.289**
	(0.523)	(1.198)	(0.667)	(0.189)	(0.122)
2	1.104	2.523	1.436	1.419***	0.332***
	(0.460)	(0.802)	(0.690)	(0.133)	(0.120)
3	1.159	2.509	1.324	1.350***	0.165
	(0.489)	(0.780)	(0.560)	(0.133)	(0.107)
4	1.140	2.363	1.488	1.223***	0.348**
	(0.476)	(0.607)	(1.091)	(0.111)	(0.172)
5	1.115	2.329	1.332	1.214***	0.217**
	(0.447)	(0.531)	(0.535)	(0.100)	(0.101)
6	1.210	2.303	1.320	1.093***	0.110
	(0.652)	(0.439)	(0.499)	(0.113)	(0.118)
7	1.138	2.211	1.364	1.073***	0.226**
	(0.438)	(0.391)	(0.517)	(0.085)	(0.098)
8	1.129	2.183	1.384	1.054***	0.255**
	(0.434)	(0.370)	(0.676)	(0.082)	(0.116)

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The above table contains the mean for each of the three auction treatments and difference in means between the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 48 for each treatment: 24 observations for each round, with a total of 48 across both sessions for each treatment.

Table S2. Mean Offers – Target = 5, Budget = $4.42, PPR = 5, Rounds 9–16

	Mean Offers			Difference: PPRA &	
	PPRA	**TC**	**BC**	**TC**	**BC**
Rounds	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
9	1.164	2.708	1.394	1.544***	0.230*
	(0.455)	(1.015)	(0.713)	(0.161)	(0.122)
10	1.127	2.357	1.365	1.230***	0.238*
	(0.518)	(0.671)	(0.654)	(0.122)	(0.120)
11	1.128	2.270	1.42	1.142***	0.292**
	(0.512)	(0.448)	(0.677)	(0.098)	(0.123)
12	1.150	2.151	1.351	1.001***	0.201*
	(0.508)	(0.339)	(0.539)	(0.088)	(0.107)
13	1.159	2.117	1.361	0.958***	0.202*
	(0.483)	(0.264)	(0.528)	(0.079)	(0.103)
14	1.190	2.018	1.350	0.828***	0.160
	(0.498)	(0.210)	(0.522)	(0.078)	(0.104)
15	1.196	1.970	1.356	0.774***	0.160
	(0.512)	(0.187)	(0.587)	(0.079)	(0.112)
16	1.243	2.019	1.345	0.776***	0.102
	(0.689)	(0.765)	(0.487)	(0.149)	(0.122)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The above table contains the mean for each of the three auction treatments and difference in means between the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 48 for each treatment: 24 observations for each round, with a total of 48 across both sessions for each treatment.

Table S3. Mean Lowest 5 Offers – Rounds 1–8

	Mean Offers			Difference: PPRA &	
	PPRA	**TC**	**BC**	**TC**	**BC**
Rounds	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
1	0.762	2.144	1.019	1.382***	0.257**
	(0.334)	(0.880)	(0.451)	(0.172)	(0.103)
2	0.819	2.128	1.111	1.309***	0.292***
	(0.282)	(0.719)	(0.383)	(0.141)	(0.087)
3	0.866	2.128	1.073	1.262***	0.207**
	(0.321)	(0.621)	(0.366)	(0.128)	(0.089)
4	0.861	2.063	1.052	1.202***	0.191**
	(0.327)	(0.512)	(0.365)	(0.111)	(0.089)
5	0.841	2.068	1.088	1.227***	0.247***
	(0.279)	(0.446)	(0.290)	(0.096)	(0.073)
6	0.880	2.116	1.108	1.236***	0.228***
	(0.295)	(0.419)	(0.241)	(0.094)	(0.070)
7	0.890	2.034	1.125	1.144***	0.235***
	(0.324)	(0.343)	(0.260)	(0.086)	(0.076)
8	0.871	2.036	1.101	1.165***	0.230***
	(0.296)	(0.344)	(0.255)	(0.083)	(0.071)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The above table contains the mean of the lowest five offers for each of the three auction treatments and difference in means between the five lowest offers for the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 30 for each treatment: 15 observations for each round, with a total of 30 across both sessions.

Table S4. Mean Lowest 5 Offers – Rounds 9–16

	Mean Offers			Difference: PPRA &	
	PPRA	TC	BC	TC	BC
Rounds	(1)	(2)	(3)	(4)	(5)
9	0.881	2.176	1.065	1.295***	0.184**
	(0.291)	(0.645)	(0.333)	(0.129)	(0.081)
10	0.809	2.010	1.076	1.201***	0.267***
	(0.306)	(0.477)	(0.247)	(0.103)	(0.072)
11	0.811	2.080	1.116	1.269***	0.305***
	(0.328)	(0.335)	(0.239)	(0.086)	(0.074)
12	0.835	1.991	1.088	1.156***	0.253***
	(0.324)	(0.236)	(0.238)	(0.073)	(0.073)
13	0.867	1.982	1.090	1.115***	0.223***
	(0.322)	(0.223)	(0.199)	(0.071)	(0.069)
14	0.891	1.916	1.099	1.025***	0.208***
	(0.322)	(0.170)	(0.207)	(0.067)	(0.070)
15	0.882	1.890	1.073	1.008***	0.191***
	(0.331)	(0.179)	(0.178)	(0.069)	(0.069)
16	0.869	1.833	1.089	0.964***	0.220***
	(0.329)	(0.201)	(0.193)	(0.070)	(0.070)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The above table contains the mean of the lowest five offers for each of the three auction treatments and difference in means between the five lowest offers for the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 30 for each treatment: 15 observations for each round, with a total of 30 across both sessions.

Table S5. Mean Offers – Target = 3, Budget = $4.42, PPR = 3, Rounds 1–8

	Mean Offers			Difference: PPRA &	
	PPRA	TC	BC	TC	BC
Rounds	(1)	(2)	(3)	(4)	(5)
1	1.229	1.809	1.372	0.580***	0.248
	(0.525)	(0.572)	(0.667)	(0.112)	(0.123)
2	1.174	1.553	1.436	0.379***	0.262**
	(0.480)	(0.412)	(0.690)	(0.091)	(0.121)
3	1.189	1.513	1.324	0.324***	0.135
	(0.417)	(0.385)	(0.560)	(0.082)	(0.101)
4	1.233	1.507	1.488	0.274***	0.255
	(0.494)	(0.515)	(1.091)	(0.103)	(0.173)
5	1.221	1.390	1.332	0.169*	0.111
	(0.511)	(0.331)	(0.535)	(0.058)	(0.107)
6	1.264	1.328	1.320	0.064	0.056
	(0.716)	(0.319)	(0.499)	(0.113)	(0.126)
7	1.334	1.372	1.364	0.038	0.030
	(0.817)	(0.618)	(0.517)	(0.148)	(0.140)
8	1.199	1.335	1.384	0.136	0.185
	(0.623)	(0.464)	(0.676)	(0.112)	(0.113)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The above table contains the mean for each of the three auction treatments and difference in means between the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 48 for each treatment: 24 observations for each round, with a total of 48 across both sessions for each treatment.

Table S6. Mean Offers – Target = 3, Budget = $4.42, PPR = 3, Rounds 9–16

	Mean Offers			Difference: PPRA &	
	PPRA	TC	BC	TC	BC
Rounds	(1)	(2)	(3)	(4)	(5)
9	1.268	1.453	1.394	0.185	0.126
	(0.722)	(0.483)	(0.713)	(0.125)	(0.146)
10	1.221	1.356	1.365	0.135	0.144
	(0.636)	(0.381)	(0.654)	(0.107)	(0.132)
11	1.315	1.305	1.420	−0.01	0.105
	(0.803)	(0.351)	(0.677)	(0.126)	(0.152)
12	1.305	1.293	1.351	−0.012	0.046
	(0.816)	(0.365)	(0.539)	(0.129)	(0.141)
13	1.256	1.334	1.361	0.078	0.105
	(0.745)	(0.597)	(0.528)	(0.138)	(0.132)
14	1.185	1.394	1.350	0.209	0.165
	(0.463)	(0.934)	(0.522)	(0.150)	(0.101)
15	1.303	1.306	1.356	0.003	0.053
	(0.721)	(0.551)	(0.587)	(0.131)	(0.134)
16	1.447	1.490	1.345	0.043	−0.102
	(1.140)	(1.009)	(0.487)	(0.220)	(0.179)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The above table contains the mean for each of the three auction treatments and difference in means between the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 48 for each treatment: 24 observations for each round, with a total of 48 across both sessions for each treatment.

Table S7. Mean Lowest 3 Offers – Rounds 1–8

	Mean Offers			Difference: PPRA &	
	PPRA	TC	BC	TC	BC
Rounds	(1)	(2)	(3)	(4)	(5)
1	0.747	1.277	0.750	0.530***	0.003
	(0.298)	(0.274)	(0.306)	(0.095)	(0.101)
2	0.775	1.204	0.888	0.429***	0.113
	(0.259)	(0.231)	(0.316)	(0.082)	(0.096)
3	0.836	1.212	0.873	0.376***	0.037
	(0.255)	(0.236)	(0.322)	(0.082)	(0.097)
4	0.844	1.189	0.867	0.345***	0.023
	(0.210)	(0.185)	(0.336)	(0.066)	(0.093)
5	0.855	1.114	0.957	0.259***	0.102
	(0.209)	(0.146)	(0.282)	(0.060)	(0.083)
6	0.853	1.054	0.991	0.201***	0.138**
	(0.217)	(0.202)	(0.223)	(0.070)	(0.073)
7	0.849	1.036	1.017	0.187***	0.168***
	(0.198)	(0.185)	(0.259)	(0.064)	(0.036)
8	0.801	1.010	0.995	0.209***	0.194**
	(0.211)	(0.182)	(0.261)	(0.066)	(0.079)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The above table contains the mean of the lowest three offers for each of the three auction treatments and difference in means between the three lowest offers for the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 18 for each treatment: 9 observations for each round, with a total of 18 across both sessions.

Table S8. Mean Lowest 3 Offers – Rounds 9–16

	Mean Offers			Difference: PPRA &	
	PPRA	**TC**	**BC**	**TC**	**BC**
Rounds	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
9	0.752	1.007	0.896	0.255**	0.144
	(0.267)	(0.366)	(0.247)	(0.107)	(0.086)
10	0.779	0.985	0.957	0.206**	0.178**
	(0.284)	(0.239)	(0.172)	(0.088)	(0.078)
11	0.854	0.988	1.000	0.134*	0.146**
	(0.225)	(0.211)	(0.182)	(0.073)	(0.068)
12	0.811	0.973	0.969	0.162*	0.158**
	(0.274)	(0.211)	(0.174)	(0.081)	(0.076)
13	0.817	0.953	1.001	0.136	0.184**
	(0.269)	(0.224)	(0.173)	(0.083)	(0.075)
14	0.876	0.965	0.999	0.089	0.123*
	(0.210)	(0.231)	(0.157)	(0.074)	(0.062)
15	0.896	0.950	0.998	0.054	0.092*
	(0.190)	(0.254)	(0.123)	(0.075)	(0.053)
16	0.897	0.973	1.001	0.076	0.104*
	(0.194)	(0.220)	(0.141)	(0.069)	(0.057)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The above table contains the mean of the lowest three offers for each of the three auction treatments and difference in means between the three lowest offers for the TC and BC auction treatments and the PPRA, with the standard deviations and standard errors below for the means or differences in means, respectively. Each t-test is conducted with a sample of 18 for each treatment: 9 observations for each round, with a total of 18 across both sessions.

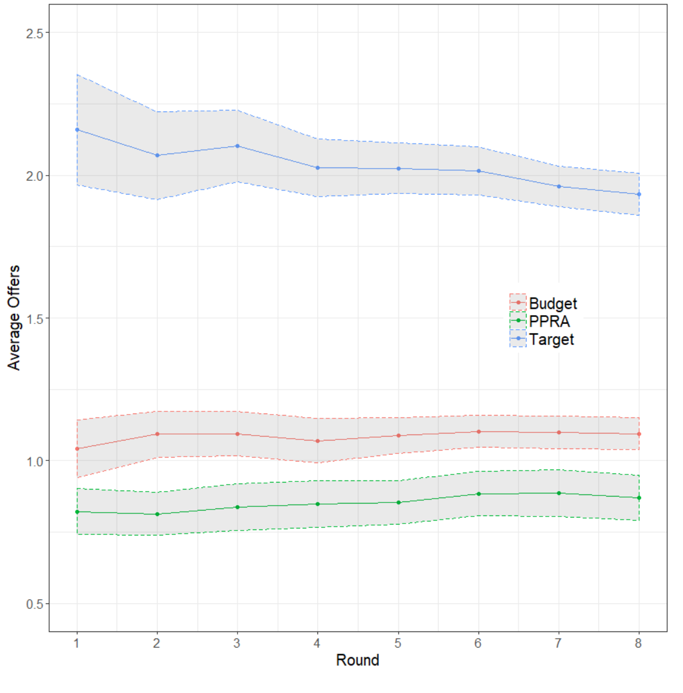

Figure S1. Average Five Lowest Offers: Target/PPR = 5

Notes: The above figure contains average lowest five offers for each auction format, with 95% confidence interval bands. The rounds are pooled, so that on the x-axis round 1 contains the offers for rounds 1 and 9, round 2 contains the offers for rounds 2 and 10, etc.

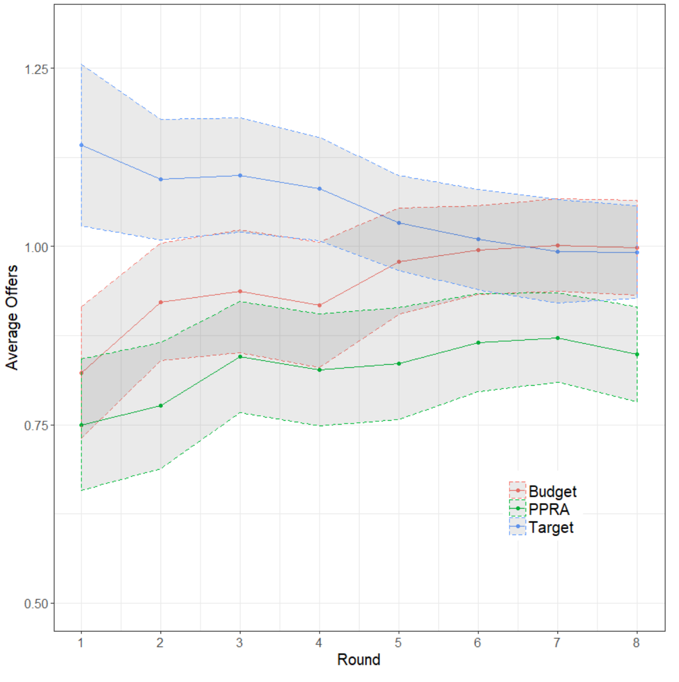

Figure S2. Average Three Lowest Offers: Target/PPR = 3

Notes: The above figure contains average lowest three offers for each auction format, with 95% confidence interval bands. The rounds are pooled, so that on the x-axis round 1 contains the offers for rounds 1 and 9, round 2 contains the offers for rounds 2 and 10, etc.

Table S9. The Effect of Learning on Average Offers

	(1)	(2)	(3)	(4)	(5)
Variables	**Offers**	**Offers**	**Offers**	**Offers**	**Offers**
Constant	0.435***	0.473***	2.372***	1.094***	1.053***
	(0.008)	(0.050)	(0.164)	(0.052)	(0.149)
Opportunity Cost	0.716***	0.765***	0.266***	0.505***	0.365***
	(0.019)	(0.041)	(0.099)	(0.040)	(0.068)
Round	0.004	0.007	−0.038***	−0.018***	−0.003
	(0.004)	(0.009)	(0.007)	(0.003)	(0.008)
Treatment	PPRA-5	PPRA-3	TC-5	TC-3	BC
Observations	768	768	768	768	768

Notes: *** p<0.01, ** p<0.05, * p<0.1. The above table contains regressions of offers on opportunity costs and rounds for the different auction formats. Columns (1) and (2) contain the regressions for the PPRA with provision points of 5 and 3, respectively, columns (3) and (4) contain the results for the target-constrained auctions with targets of 5 and 3, respectively, and column (5) contains the results for the budget-constrained auction with a budget of 4.42. Standard errors are clustered by groups.

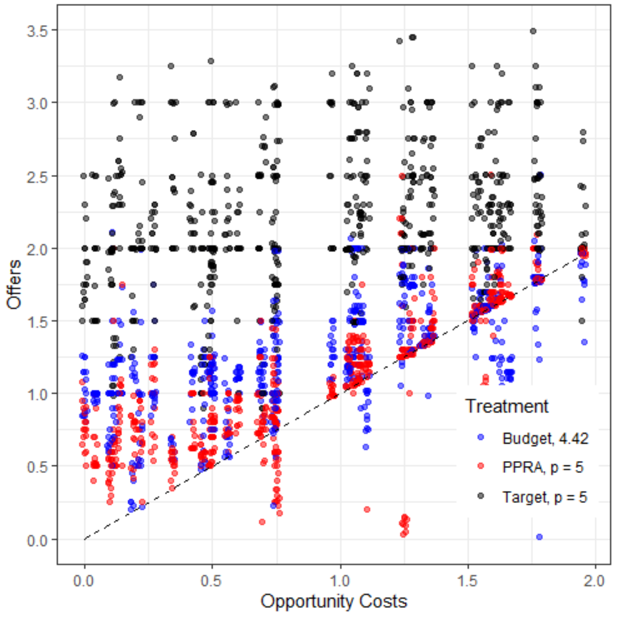

Figure S3. Comparison of Offers, PPR = 5: All Rounds

Notes: The above figure contains the individual offers for all participants in the target-constrained and PPRA where the target and provision point requirement is set to 5, and the budget-constrained auction where the budget is set to $4.42.

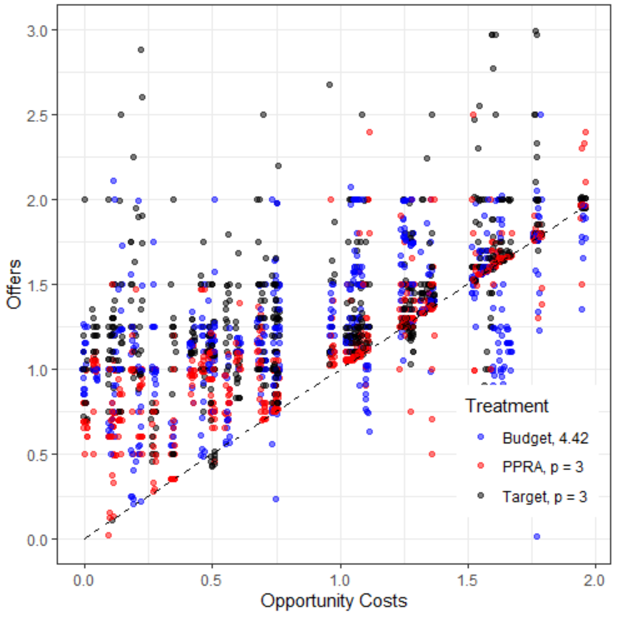

Figure S4. Comparison of Offers, PPR = 3; All Rounds

Notes: The above figure contains the individual offers for all participants in the target-constrained and PPRA where the target and provision point requirement is set to 3, and the budget-constrained auction where the budget is set to $4.42.

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