Implementing Reverse Auctions with Screening Criteria to Provide Ecosystem Services

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Abstract

We introduce a novel auction, a uniform price auction with screening criteria, for acquiring private land to provide ecosystem services. The screening criteria is designed to classify ecosystem service suppliers (bidders) into two groups and is determined so that a bidder can not influence which group she is assigned to. The results of the screening auction are compared with more familiar discriminatory auction and uniform price auction. Results from a laboratory experiment show that the offers generated under a screening auction and a uniform price auction are significantly lower than the offers generated under a discriminatory auction under a low and a high budget scenario. However, the discriminatory auction was still able to acquire the maximum number of units compared to the other two auctions.

1. Introduction

When designing market mechanisms to implement the payment for ecosystem services (PES), conservation agents often face asymmetric information (adverse selection and moral hazard) problem. This problem can weaken the effectiveness of the proposed PES scheme. When landowners have better information than the conservation agent about their opportunity cost of providing ecosystem services (ES), landowners may exploit this advantage to gain information-rent through a conservation auction that fails to create incentives for landowners to reveal their reservation price truthfully. To mitigate the asymmetric information problem and reduce the associated information rent, conservation agents can gather more information on the landowners, offer screening contracts based on landowner characteristics, or use procurement auctions that provide incentives to landowners to reveal their opportunity costs that are close to their true reservation prices (Ferraro, 2008). In this paper, we design a new reverse auction mechanism that potentially incorporates landowners' observable characteristics to encourage the provision of ES more cost-effectively.

This paper builds on an existing, market-based conservation program called the Bobolink Project (Swallow et al. 2018). The Bobolink Project created an experimental market through which the researchers negotiated contracts with the local landowners who agreed to postpone their hay harvesting during the nesting season of grassland birds. These landowner contracts were funded through crowd-sourced donations. The project used a uniform-price reverse procurement auction to obtain landowners' bids to enroll 10-acre fields in bird-friendly hayfield management. Winning bidders were all paid the same price, and the winning price was determined by the lowest rejected offer price. In 2013, which was the first year of the experimental market, the project received bids from eight interested landowners offering a total of 200 acres, and their bids ranged from $30/acre to $150/acre. The experimental market raised enough in consumer donations to enroll all 200 acres of hayfield that was offered and paid $160/acre to all the participating landowners in 2013. In subsequent years, as the project gained more visibility, we received offers from more landowners leading to more competition among participants. In 2014 the project enrolled 340 acres of hayfields in total and paid $96.16/acre to the winning bidders, and in 2015 it enrolled 549 acres and paid $90.63/acre. For these two years, landowners' offers ranged from $25 to $200[1]. In 2014 and 2015 we were unable to enroll additional 549 acres and 251 acres, respectively, that was offered by landowners due to lack of available donations from the consumer side. Informal feedback from the public, and from conservation practitioners, has raised the question of whether paying a uniform price in the procurement auction wastes funds by paying a substantial premium to landowners who are willing to accept a low amount per acre relative to the Willingness to Accept (WTA) of the marginal farm owner. Paying a uniform price provides landowners the incentive to reveal their opportunity costs truthfully in theory, but it potentially decreases the acres enrolled by paying a substantial premium to landowners who are willing to accept a low amount per acre. Moreover, other than confirming habitat suitability, the project did not use any specific screening criteria to select the landowners to participate in the program.

In this paper, we propose to implement screening criteria that are entirely, or mainly, out of the control of landowner-bidders in an auction, to select landowners under a modified reverse procurement auction to identify the minimum price a landowner would accept and still

[1] Each year, after we announced the cut-off price for the landowners we received requests from some rejected landowners claiming that that could have managed their fields for a lower price per acre than what they offered. Since the landowners were not familiar with the auction process and their decisions involved monetary costs and benefits, we allowed some of the participants to revise their bids after submission.

participate in the program to improve the cost-effectiveness of the program. These screening criteria can be used to put landowners in categories with similar opportunity costs for their acres and then we will have landowners in each category bid in a modified uniform price reverse auction to identify who will be accepted, by category. We will not elaborate on the design of the screening criteria per se but focus on the design of the reverse auction with the screening criteria and compare the results of the screening auction with more familiar discriminatory auction and uniform price auction. We will only present the results of a screening auction from a laboratory experiment in this paper.

2. Literature review

An auction is a common method, which involves competitive bidding to obtain goods and services for which there is no established market, to reduce strategic behavior by the participating landowners. In conservation auctions, participating landowners make bids which reflect a trade-off between their expected payoff and the probability of getting accepted. A higher bid increases the expected payoff but might reduce the probability of acceptance. Therefore, use of competitive bidding helps reveal true opportunity cost of the landowners and in the process, reduces the information rent. Auctions are increasingly being used for environmental conservation to purchase ES (Stoneham et al. 2003, Cummings et al. 2004, Horowitz et al. 2009).

Prior research has shown that auctions are an efficient way of revealing (imperfectly) a landowner's real opportunity cost of participation. In their seminal work, Latacz-Lohmann and Van der Hamsvoort (1997) show that auctions can achieve broader program goals for a given budget compared to a flat-rate offer system by reducing the "windfalls" that a landowner receives by enrolling land with a lower-than-average opportunity cost. Horowitz et al. (2009)

also report, for the Maryland Agricultural Land Preservation Foundation (MALPF) program, that a reverse auction can enroll 5% to 12% more acres than a take-it-or-leave-it offer would have enrolled under the same budget conditions. Stoneham (2003) compared a discriminative price auction with a hypothetical fixed-price scheme for Australia's Bush Tender trial and concluded that the fixed-price scheme would have cost seven times more than the actual budget to achieve the same biodiversity quality as the discriminative price auction.

Cason and Gagadharan (2004) find that, in a laboratory set-up, a discriminatory price auction performs better compared to a uniform price auction. Even if the uniform price auction creates incentives to reveal the true opportunity cost of a landowner compared to a discriminatory price auction, the heterogeneity of landowners' costs leads to a significant "over-payment" for some of the landowners, thereby reducing the efficiency of the uniform price auction. This result is similar to the inefficiency resulting from a fixed-price scheme as discussed in Stoneham (2003). Cason and Gangadharon (2004) also show that revealing the environmental benefits associated with management options reduces auction performance, in terms of fewer projects being funded given a fixed conservation budget. The researchers find similar experimental evidence in Cason and Gangadharan (2005), where they show that a discriminatory price auction tends to deliver reductions in non-point source pollution more efficiently than a uniform price auction. Schilizzi and Latacz-Lohmann (2007) compared the performance of a discriminatory auction and an equivalent fixed-rate payment mechanism in a lab experiment and found that overall the discriminatory price auction performs better in a static market setting. However, as the bidders learn from their decisions and update their bids in a dynamic market setting, the fixed-rate payment can perform as well as the discriminatory price auction.

The auctioneer's goal is to set the payment rule to maximize the output (e.g., the supply of ES) given a fixed conservation budget. In this paper, we propose a new payment rule following a uniform price reverse auction to improve the cost-effectiveness of a conservation program. Latacz-Lohmann and Schilizzi (2005) proposed the use of bidding-pools to increase the cost-effectiveness of conservation management, and to the best of our knowledge, this is the first application of the proposed idea. The idea of the bid-pool is that the auctioneer knows that there are two distinct types of auction participants: one type with higher opportunity cost and another with the relatively lower opportunity cost of conservation management. And the conservation agent would accept bids up to a higher level from the higher cost pool compared to the lower cost pool. Implementing a bid-pool is effective when the participating landowners are heterogeneous (regarding farm types, production systems, soil types, regions, etc.). Use of a bid-pool ensures that the conservation agency gets a mix of land and farm types, rather than just enrolling the "least profitable land." On the downside, the bid-pool might reduce overall competition by putting participants in separate pools (Latacz-Lohmann and Schilizzi, 2005).

3. Auction rules

A goal of this paper is to compare the effectiveness of three auction rules that could potentially be used in real life to acquire land for a conservation project. Each auction rule present different incentive for the program participants. We aim to compare several aspects of each auction format which include; i) the total number of units (or number of acres) acquired, ii) the offer prices from the participants, iii) the rent (deviation of offer prices from the induced value) generated. In this section, we describe the auction rules formally that we used in the laboratory and the field experiment.

3.1. Discriminatory Auction (DA)

In a discriminatory auction, participants submit sealed bids to the auction moderator to enroll a parcel of land in a conservation program[2]. The moderator accepts bids, starting with the lowest bid first and continues to accept bids until the budget is exhausted. The winning bidders are accepted into the program and receive the payment stated in their bids. Losing bidders receive no payment. Let v_i represent the true opportunity cost of the participant and she makes an offer b_i to enroll her land. In this case, a participant's payoff from participating in the conservation program is given by the following:

$$\pi_i = \begin{cases} (b_i - v_i), \text{if the offer is accepted} \\ 0, \text{if the offer is rejected} \end{cases} \tag{1.1}$$

3.2 Uniform Price Reverse Auction (UPRA)

In a Uniform Price Reverse Auction, participants submit sealed bids to the auction moderator to enroll a parcel of land in a conservation program. The moderator accepts bids, starting with the lowest bid first and keeps accepting bids until the budget is exhausted. The winning bidders all receive the same cut-off payment. The cut-off price is determined by the lowest bid that the moderator could not accept within the available budget (this is the bid of the first rejected participant). Let v_i represent the true opportunity cost of the participant and she makes an offer b_i to enroll her land. Following the rules of the auction, the cut-off price for the winning bidder is determined to be P. Then the bidder's payoff from participating in the

[2] In the laboratory experiment with student subjects, participants were told that they own a fictitious asset which they would be selling to the auction moderator to earn a profit and their offers will be assessed based on different auction rules. This was done to keep the laboratory experiment context-free. However, in the laboratory experiment with landowner participants, farmers were told that they own a 10-acre piece of land which they would be offering to enroll in a conservation program.

conservation program is given by the following:

$$\pi_i = \begin{cases} (P - v_i), \text{if the offer is accepted} \\ 0, \text{if the offer is rejected} \end{cases} \quad (1.2)$$

3.3. Screening Auction (SA)

This auction rule recognizes that some participants may have higher opportunity costs for their land while others may have lower costs. Therefore, participants in these two groups might require different cut-off prices to enroll their land with the conservation project. For this auction, the participants are classified into two groups: a participant with a higher opportunity cost for her land is more likely to be assigned to group 1 (high-cost group), and a participant with a lower cost is more likely to be assigned to group 2 (low-cost group). The auctioneer's goal is to enroll as many acres from both the groups as possible by paying two different uniform prices to the winning bidders of the two groups. The auctioneer's optimization problem is given by the following:

$$Max \ \ (Q_1 + Q_2) \quad (1.3)$$

$$s.t \quad P_1Q_1 + P_2Q_2 \leq B \quad (1.4)$$

$$P_1 = mc_1(Q_1) \quad (1.5)$$

$$P_2 = mc_2(Q_2) \quad (1.6)$$

where Q_j is the number of acres enrolled from group $j, j = 1, 2$. P_j is the uniform price paid to the successful participants of group $j, j = 1,2. B$ is the available conservation budget. Solving the auctioneer's optimization problem provides the following equilibrium condition:

$$\frac{\partial mc(Q_1)}{\partial Q_1} + mc(Q_1) = \frac{\partial mc(Q_2)}{\partial Q_2} + mc(Q_2) \quad (1.7)$$

From (3.7), it follows that $\frac{P_1}{P_2} = \frac{1+\frac{1}{\eta(P_2)}}{1+\frac{1}{\eta(P_1)}}$, where η is the supply elasticity. The condition implies that the group with a higher elasticity of supply will receive a higher cut-off price.

The Screening Auction establishes competition that lets participants compete primarily within their group. For this auction, participants of each group submit sealed bids to the auction moderator to enroll their land with the conservation project. After the moderator receives the bids from the participants, the moderator ranks the bids from members of each group based on the bids offered within that group. The moderator accepts bids, starting with the lowest bid first and keeps accepting bids from both the groups to enroll as many acres as possible within the budget. The moderator does so while balancing the cost of enrolling from each of the two groups. The winning bidders within each group are paid the cut-off price of their group. The cut-off price will equal the lowest bid for each group that the moderator could not accept within the available budget. Let v_i represent the true opportunity cost of the participant and she makes an offer b_i to enroll her land. Following the rules of the screening auction, the cut-off price is determined to be P_j for group j. Then a winning bidder's payoff in group j from participating in the conservation program is given by the following:

$$\pi_{ij} = \begin{cases} (P_j - v_i), \text{if the offer is accepted} \\ o, \text{if the offer is rejected} \end{cases} \tag{1.8}$$

4. Treatments and Experimental Design:

We conducted 12 experiment sessions in the department of Agricultural and Resource Economics at the University of Connecticut during November 2017 and April 2018. Most of the subjects were recruited through UCONN daily digest, a university mailing list consisting of undergraduate students from various academic majors. We conducted experiments through networked computer terminals using z-tree (Fischbacher, 2007).

Each session consisted of 10 participants. Each participant received a $5 show-up fee. Each experimental session lasted between 90 to 120 minutes with an average individual payoff around $26. Participants were not allowed to talk to each other during the sessions and could not observe each other's choices. Experiment instructions were read out aloud.

The participants of the laboratory experiment were told that they own a fictitious asset that they needed to sell to the auction moderator to earn profits. The value of the asset was predetermined and given to the participants at the beginning of each period. The range of induced (asset) values was generated from the actual offers that we collected from landowners during a field experiment testing the same hypothesis conducted in Spring 2017. We used a within-subject experimental design where each participant made decisions under three different treatment plans: i. a discriminatory auction (DA), ii. a uniform price reverse auction (UPRA) and iii. a screening auction (SA). Within each treatment, we used two different budget scenarios: a low budget scenario and a high budget scenario. We used two different variations of the screening auction: the first variation is used as the baseline, where the auction moderator has perfect information regarding the opportunity cost of the asset of each participant and therefore, can screen the participants from lowest to highest asset values. The lowest five participants were assigned to the "low cost" group, and the highest five participants were assigned to the "high cost" group. In the second variation, which mimics the real world, the auction moderator has imperfect information regarding the opportunity cost of the asset and therefore, uses imperfect screening criteria to assign groups. Here the participants with the lower induced values are more likely to be assigned to the "low cost" group, and the participants with higher induced values are more likely to be assigned to the “high cost” group. Under the imperfect screening scenario, a low-cost participant can still be assigned to a high-cost group and *vice-versa*. The order of the treatments was randomized. Each treatment consisted of 30 decision-making rounds under two different budget scenarios, and each session consisted of 180 rounds. The order of the treatments is presented in table 1. This sequence of experiments yielded a total of 21,600 bid level observations.

5. Results

We tested the performance of the three auction rules based on the following outcome variables of interest: the offers made by the participants, the rent (absolute difference between offer and induced value) earned by the participants and the total number of units acquired.

Table 2 provides the summary statistics for each treatment. As we expected, the offers made by the participants under the DA treatment are higher compared to the offers made under the UPRA and SA treatments under both the low budget and high budget scenario, while the offers under the UPRA and SA treatments are almost similar in magnitude[3]. The deviation between the induced values and the offer prices by the participants is maximum for the DA treatment compared to the other two treatments. The rent is higher under SA compared o URA in the low budget scenario however, the rent is higher under UPRA compared to SA in the high budget scenario. However, we also see that the DA treatment acquired the maximum number of units under both the budget scenario compared to the UPRA and SA treatments. The UPRA treatment acquired more units under the low budget scenario compared to the SA treatment while the SA treatment acquired more under the high budget scenario.

[3] A paired t-test shows that the offers made under UPRA and SA are not statistically different under both the high and the low budget scenario.

5.1. Offer prices

We next present a more detailed analysis of individual offers using a random effects regression model. Our within-subjects experiment design resulted in a nested data structure, where the participants are nested within periods and periods are nested within sessions. Following the linear hierarchical model language, we have a three-level model with participants being level 1, periods being level 2 and sessions being level 3. Under this set-up, responses of participants within the same session could be more alike than responses of participants from different sessions. Also, responses of one participant within multiple periods of the same treatment are likely to be correlated. By incorrectly modeling the dependency in the data structure will produce biased standard errors (citation). To analyze individual bidding behavior, we employ the following regression model:

$$C_{ijk} = X_{ijk}\beta + v_k + u_{jk} + e_{ijk} \tag{1.9}$$

where C_{ijk} is the offer made by participant i in period j in session k. X_{ijk} includes the induced values assigned to the participants (*cost*), the treatment dummies for different auctions (*UPRA* and *SA*), order of the treatments, and the interactions of treatment dummies with the order. We include two random effects; v_k is session specific effect and u_{jk} is period specific effect. And finally, e_{ijk} is the residual error term. A log-likelihood ratio test between the random effects model and the linear regression result provides justification for the use of a random effects model (χ^2= 77.82, p<0.0001).

Results from the random effects model are presented in table 3. Columns 1 and 2 presents results from the low budget scenario while columns 3 and 4 present the high budget scenario using the data from the last 15 experimental periods. Results show that the offers are significantly lower for the *SA* and the *UPRA* treatment compared to the baseline treatment *DA* *under* both the budget scenarios. This finding is consistent with the incentive properties of the auctions. Since the winning participants receive their offers stated in their bids under *DA*, they have the incentive to inflate their offers to maximize profit, whereas in *UPRA* and *SA* the participants' offers do not determine their payments, so they have no incentive to inflate their offers. The reduction in offer is higher for *UPRA* in the low budget scenario (column 2) while the reduction is higher for *SA* in the high budget scenario (column 4). The coefficient for the induced value (*cost*) is positive under both the budget scenario which implies that a participant offers a higher bid if she gets a higher induced value. The interaction terms between the induced value (*cost*) and treatment dummies (*UPRA* and *SA*) are positive and significant which indicates that individuals with higher induced value offers a higher bid under *SA* and *UPRA*. Interestingly the increment is higher in magnitude for *UPRA* ($0.124 for *UPRA* and $0.118 for *SA*) under the low budget scenario and higher in magnitude for *SA* ($0.427 under *SA* and $0.384 under *UPRA*) under the high budget scenario.

5.2. Number of units acquired

Next, we analyze the number of units that could be acquired for a given conservation budget under the three auction rules discussed above using a random effects regression model, controlling for period and session effects (Table 4) using equation 1.9 (replace the dependent variable). We use *DA* treatment as the baseline. Results indicate that under the low budget scenario the *DA* treatment generates the maximum number of projects, followed by *UPRA* and *SA*. Under the high budget scenario, the *DA* treatment still generates the maximum number of projects, followed by *SA* and then *UPRA*. This observation is surprising, as we just saw in the previous section that the *DA* treatment also generated higher offers, on average, from the participants compared to the *SA* and *UPRA* treatments. However, our findings are in line with Cason and Gangadharan (2004, 2005) who reported similar observations.

5.3. Rent (deviation of offer prices from induced values)

Finally, we analyze the distribution of the rent, the deviation of participants' offers from their assigned induced values, using a random effects model (equation 1.9). The results are reported in table 5. Again, we use *DA* as the baseline treatment. Our results indicate that the offer deviation from cost is significantly lower for the *UPRA* and *SA* treatments compared to the *DA* treatment.

3.6. Conclusion

Our results indicate that the screening auction and the uniform price auction are generating the expected offers compared to a discriminatory auction as the offers are significantly lower under SA and UPRA. However, the DA is still generating the maximum number of units. Our conjecture is that the group size plays an important role in retaining the gains from the lower offers generated under a screening auction. In our experimental setting the group sizes are relatively low (up to 5 participants per group) in a screening contract. Our next steps would be to analyze the impact of the group sizes on the number of units acquired.

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Table 1 Treatment Arrangement of Experimental Sessions with students

	1st (30 pds)	2nd (30 pds)	3rd (30 pds)	4th (30 pds)	5th (30 pds)	6th (30 pds)
Session 1	DA-L	UPRA-L	SA-L	DA-H	UPRA-H	SA-H
Session 2	DA-L	SA(PI)-L	UPRA-L	DA-H	SA(PI)-H	UPRA-H
Session 3	UPRA-L	DA-L	SA-L	UPRA-H	DA-H	SA-H
Session 4	UPRA-L	SA(PI)-L	DA-L	UPRA-H	SA(PI)-H	DA-H
Session 5	SA-L	UPRA-L	DA-L	SA-H	UPRA-H	DA-H
Session 6	SA(PI)-L	DA-L	UPRA-L	SA(PI)-H	DA-H	UPRA-H
Session 7	DA-H	UPRA-H	SA-H	DA-L	UPRA-L	SA-L
Session 8	DA-H	SA(PI)-H	UPRA-H	DA-L	SA(PI)-L	UPRA-L
Session 9	UPRA-H	DA-H	SA-H	UPRA-L	DA-L	SA-L
Session 10	UPRA-H	SA(PI)-H	DA-H	UPRA-L	SA(PI)-L	DA-L
Session 11	SA-H	UPRA-H	DA-H	SA-L	UPRA-L	DA-L
Session 12	SA(PI)-H	DA-H	UPRA-H	SA(PI)-L	DA-L	UPRA-L

DA= Discriminatory Auction, UPRA = Uniform Price Reverse Auction, SA = Screening Auction, L = Low Budget, H = High Budget, PI = Perfect Information

Table 2: Summary of performance indicators by treatment

Budget Scenario	Performance Indicator	Auction rule	Mean	Median	Std. Dev	Min	Max	No. of observation
Low budget	Contribution	DA	3464.10	3456.18	132.22	3269.67	3736.00	30
		UPRA	3166.86	3199.97	161.40	2721.59	3422.959	30
		SA	3174.46	3151.31	136.13	2910.25	3634.54	30
	project funded	DA	3.26	3.25	.22	2.83	3.75	30
		UPRA	2.86	2.83	.19	2.5	3.33	30
		SA	2.62	2.67	.18	2.25	2.83	30
	Information rent	DA	309.70	312.47	48.67	223.94	436.96	30
		UPRA	256.20	241.52	59.24	161.50	428.24	30
		SA	301.87	305.11	48.40	216.34	434.05	30
High Budget	Contribution	DA	4088.49	4086.07	114.55	3824.83	4248.42	30
		UPRA	3330.71	3339.06	142.27	3047.76	3547.37	30
		SA	3319.59	3335.41	188.56	2974.61	3626.83	30
	project funded	DA	6.54	6.5	.24	6.17	7.25	30
		UPRA	5.71	5.67	.22	5.33	6.17	30
		SA	5.94	5.92	.25	5.5	6.5	30
	Information rent	DA	833.42	829.67	97.15	675.90	1064.32	30
		UPRA	352.99	346.65	59.34	241.67	465.92	30
		SA	277.78	271.54	58.14	187.59	400.41	30

Table 3: Random-effects regression results of participant offers

	Low Budget	low budget	High Budget	High budget
Cost (induced value)	0.852***	0.854***	0.519***	0.517***
	(0.01)	(0.01)	(0.01)	(0.01)
SA	-717.020***	-284.166***	-2215.123***	-2480.877***
	(50.85)	(83.96)	(55.34)	(92.64)
UPRA	-706.468***	-463.042***	-2002.272***	-2186.451***
	(46.32)	(76.11)	(51.74)	(84.68)
cost x SA	0.119***	0.118***	0.425***	0.427***
	(0.01)	(0.01)	(0.01)	(0.01)
cost x UPRA	0.126***	0.124***	0.381***	0.384***
	(0.01)	(0.01)	(0.01)	(0.01)
SA * PSreening	-68.551*	-82.351	-1.049	5.043
	(34.62)	(70.69)	(39.10)	(78.59)
constant	740.371***	518.355***	2436.729***	2616.515***
	(42.26)	(72.58)	(53.32)	(77.10)
order effects	no	yes	no	yes
order-treatment interaction	no	yes	no	yes
log likelihood	-45344.30	-45292.69	-45998.79	-45953.03
N	5,760	5,760	5,760	5,760

Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 4: Random-effects regression results of total number of projects funded

	Low Budget	low budget	High Budget	High budget
Cost (induced value)	-0.00005***	-0.00005***	-0.00005***	-0.00004***
	(0.00)	(0.00)	(0.00)	(0.00)
SA	-0.713***	-0.893***	-0.803***	-1.130***
	(0.04)	(0.07)	(0.05)	(0.08)
UPRA	-0.166***	-0.208**	-0.597***	-0.626***
	(0.04)	(0.06)	(0.05)	(0.07)
cost x SA	0.000006	0.000003	-0.00002	-0.00002*
	(0.00)	(0.00)	(0.00)	(0.00)
cost x UPRA	-0.00002	-0.00002*	-0.00001	-0.00002
	(0.00)	(0.00)	(0.00)	(0.00)
SA x PSreening	0.326***	0.254***	0.793***	0.712***
	(0.03)	(0.06)	(0.04)	(0.07)
constant	3.305***	3.294***	6.575***	6.517***
	(0.04)	(0.06)	(0.07)	(0.07)
order effects	no	yes	no	yes
order-treatment interaction	no	yes	no	yes
log likelihood	-4855.321	-4770.225	-5893.858	-5643.363
N	5,760	5,760	5,760	5,760

Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

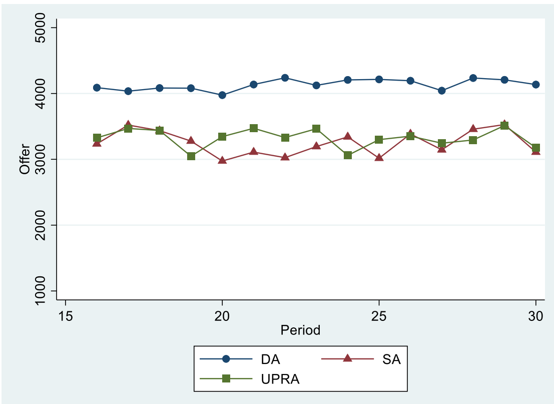
Table 5: Random-effects regression results of rent earned by participants

	Low Budget	low budget	High Budget	High budget
Cost (induced value)	-0.123***	-0.123***	-0.478***	-0.479***
	(0.01)	(0.01)	(0.01)	(0.01)
SA	-623.292***	-760.147***	-1977.896***	-1991.544***
	(47.81)	(74.94)	(50.83)	(85.39)
UPRA	-510.803***	-733.896***	-1683.728***	-1600.412***
	(43.55)	(68.72)	(47.54)	(77.96)
cost x SA	0.164***	0.161***	0.422***	0.422***
	(0.01)	(0.01)	(0.01)	(0.01)
cost x UPRA	0.130***	0.130***	0.353***	0.353***
	(0.01)	(0.01)	(0.01)	(0.01)
SA x PScreening	136.519***	48.148	-63.780	-175.514*
	(32.57)	(58.74)	(35.88)	(72.82)
constant	714.309***	855.226***	2455.837***	2406.998***
	(39.95)	(51.58)	(47.73)	(74.25)
order effects	no	yes	no	yes
order-treatment interaction	no	yes	no	yes
log likelihood	-44989.718	-44924.311	-45509.886	-45462.5
N	5,760	5,760	5,760	5,760

Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Figure 1: Average offer prices by participants under DA, SA and UPRA treatments between periods 15 and 30

High budget scenario



Low budget scenario

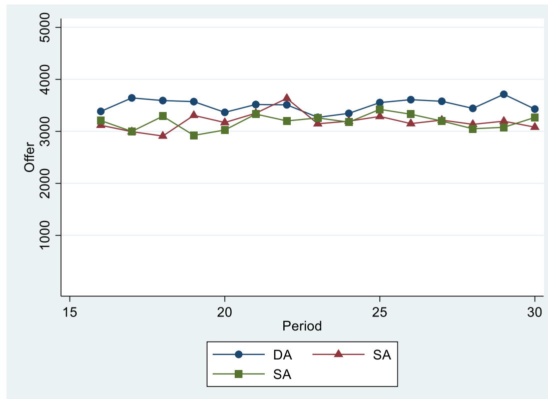
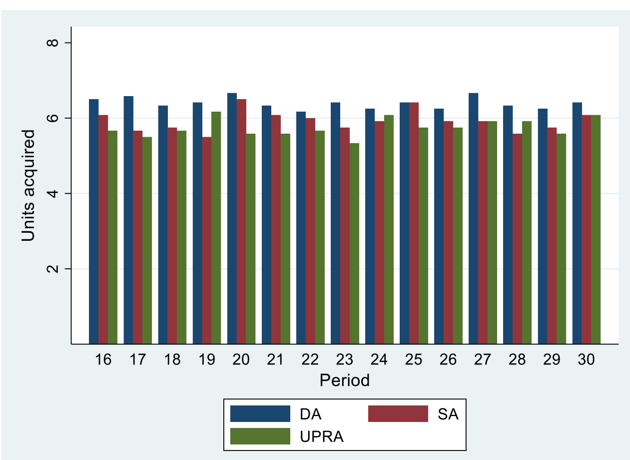


Figure 2: Average number of units acquired under DA, SA and UPRA treatments between periods 15 and 30

High budget scenario



Low budget scenario

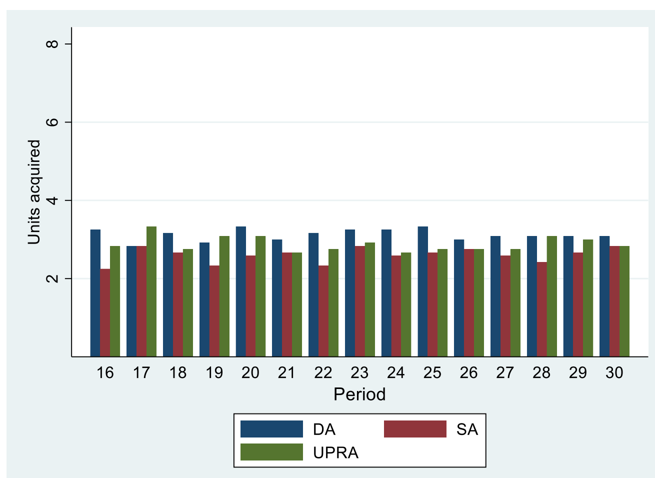


Figure 3: Average rent (deviation from induced values) earned by participants under DA, SA and UPRA treatments between periods 15 and 30

High budget scenario

Low budget scenario

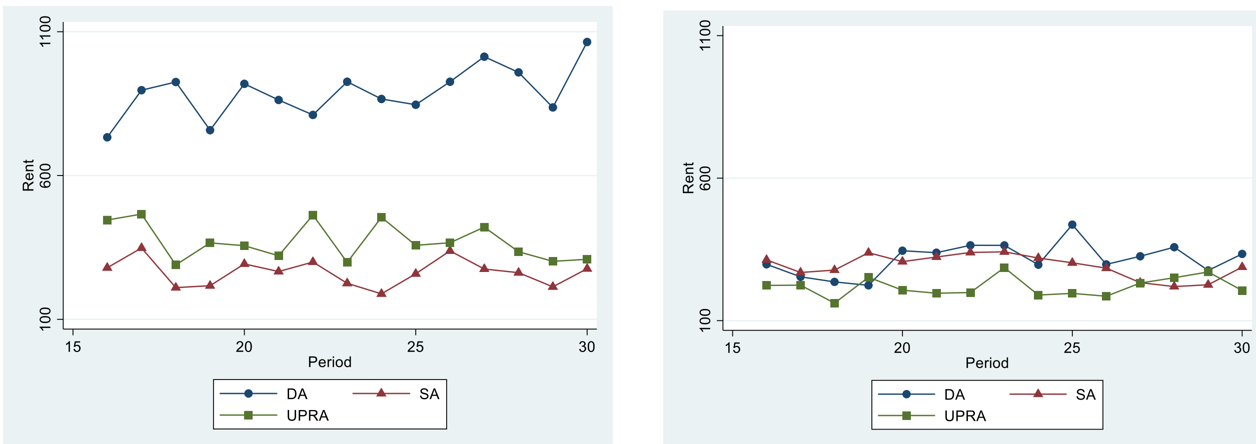


Figure 4: Group level participants offers under Perfect and Imperfect Screening between periods 15 and 30

Group 1 (low cost group)

Group 2 (high cost group)