Marine Policy 38 (2013) 228–234

Contents lists available at SciVerse ScienceDirect

Marine Policy

journal homepage: www.elsevier.com/locate/marpol

Fisheries quota allocation: Laboratory experiments on simultaneous and combinatorial auctions

J.G. Tisdell *, Md Sayed Iftekhar

School of Economics and Finance, University of Tasmania, Private Bag 85, Hobart 7001, Australia

ARTICLE INFO

Article history:
Received 31 January 2012
Received in revised form
24 May 2012
Accepted 31 May 2012
Available online 7 July 2012

Keywords:
Combinatorial auction
ITQs
Simultaneous auction

ABSTRACT

Markets for individual tradeable fishing quota are evolving and maturing in many countries throughout the world. Synergies in spatial and temporal packages of fishing quotas have yet to be explored and exploited. The relative performance of simultaneous multi-round and combinatorial auctions has been well documented and explored in a number of environments including the allocation of spectrum rights by the US Federal Communications Commission, aircraft take-off and landing slots, as well as pollution emissions allowances. It is therefore timely and policy relevant to explore the relative performance of simultaneous and combinatorial fishery quota markets in controlled experimental environments. This paper reports the results of a series of economic experiments exploring the relative merits of these alternative fishing quota markets. The results provide important insights into the future development of individual tradeable fishing quotas.

1. Introduction

The distance between fishing grounds and spatial congregation of commercial fish species leads to economies of scale and scope[1] for fishers to hold packages of fishing quota. This can be achieved through formal individual tradeable quota (ITQ) systems. To date, most fishery ITQ systems have involved trade in simultaneous individual quota markets which do not lend themselves to capturing the benefits of packages. In traditional single quota markets fishers face financial exposure by having to bid in multiple auctions in order to hold appropriate packages of quota. In simultaneous multi-round auctions (SMAs) a fisher needs to buy different types of quota from different markets whereas in combinatorial markets fishers can buy packages of quota and thus avoid financial exposure.

Allocation inefficiencies and problems of financial exposure due to trade in simultaneous markets have been frequently demonstrated in other markets and experimental settings. Studies by Porter [1], Banks et al. [2], Ledyard et al. [3] and Kwasnika et al. [4] have shown that simultaneous multi-round auctions (SMAs) can result in financial exposure and are less efficient than combinatorial markets. This is particularly the case when rights are super-additive (for example, where the value of holding fishing quota units to adjoining fishing grounds is greater than their individual value). Their finding has been based on research that has focused primarily on procurement auctions for assigning telecommunication spectrum from a central authority, such as the U.S Federal Communications Commission. They found that while combinatorial auctions outperform the SMA when license values are super-additive, they often involve significant transaction cost in time to complete [5].

There are many situations where natural resource goods have interdependent values. Markets or tenders to establishing wildlife corridors, restoring environmental flow regimes or encouraging remnant bushland preservation through government tenders is becoming more common [6–8] and the value of individual offers is dependent on the offers of others. Nevertheless, work on combinatorial markets has in the large focused on procurement auction structures (see [9,10,1]). This study adds to the body of literature by exploring the relative merits of combinatorial markets for fishing quota.

An important dimension of fishery management lies in understanding short-run decision-making of fishers in their allocation of fishing intensity, site choice and target species. In the short-term, fishers make spatial decisions on whether and where to fish, and target species [11–15]. What can be caught depends on the quota holdings and with the introduction of ITQs, cap and trade markets are evolving for individual species [16,17]. Significant economies of scale can be achieved from holding packages of quota to fish at sites in close proximity. Similarly there are significant benefits from holding packages of species quotas where different species congregate in the same region and may

---

* Corresponding author. Tel.: +61 3 6226 1783.
E-mail address: john.tisdell@utas.edu.au (J.G. Tisdell).

[1] Economies of scale come about from the reduction in the average cost of holding more individual site quota units. Economies of scope arise from holding quota to multiple sites in the same region.

0308-597X/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.marpol.2012.05.039

be caught in the same netting or long lines, thus avoiding by-catch wastage and associated efficiency loss. Such packages are traded in either simultaneous or combinatorial markets and resemble a multiple unit heterogeneous goods allocation problem.

While there is an extensive body of literature on the relative merits of simultaneous and combinatorial markets, ITQs in fishery management experimental studies have focused on questions concerning the initial quota rights [18], more traditional single quota markets design questions, such as the relative merits of uniform price auctions [19] and seasonal quota auctions [20]. To date, there has been limited analysis of simultaneous and combinatorial market designs in fishery management.

Simultaneous markets, as the name suggests, involve markets for individual species or fishing sites operating in parallel. Fishers enter each market as a buyer or seller reflecting on their current quota holdings. Their choice of purchase or sale depends not just on the market price in that market, but the prices and expected outcomes of the other markets. During trade fishers adjust their offerings according to the interactions, outcomes and updated expectations arising from the markets. In a combinatorial auction, a fisher trade combinations of quotas (a package of quota) for different fish species or fishing sites in the same market.

Iftekhar and Tisdell [21] explored the relative merits of a simultaneous ascending auction design and an iterative combinatorial auction design for a hypothetical multiple region fishery quota market. This study extends their work in an experimental economics environment in which individuals act as traders competing with robots for fishing quota. This work provides an important extension to the work by Iftekhar and Tisdell [21] by providing insights into the actions of individuals as well as agent in such market designs. In the optimization work of Iftekhar and Tisdell [21] the traders were computer agents with pre-determined learning algorithms. In this environment traders are actual people, albeit in a laboratory environment, doing and learning as people do. The experimental laboratory, like that of a glass house experiment in agriculture, provides important insights that should be avoided in the real world. The laboratory allows us to test policy options under controlled conditions. It is important to be able to apply the same level of rigour to ITQ policy options as is done in medical and agricultural trials under controlled laboratory conditions, especially when the alternative is to simply trial policy options in the field where the consequences of poorly crafted policy could be significant. If market designs do not perform well under the controlled conditions of a laboratory they are unlikely to perform well in the complexity of the real world. Those options that show merit under controlled conditions are worthy of further consideration and potentially trialled in the field. In a formal experimental setting, this paper questions whether combinatorial ITQ markets are superior to simultaneous markets in terms of aggregate revenue, aggregate efficiency and degree of rent extraction.

2. Experimental design and methods

To explore the impact of individual inclusion a 2×3 design was used in this study. The main treatment difference between the two market designs (simultaneous and combinatorial) were blocked by three combinations of robot agents and human participants, as shown in Table 1. The experiment design used in this study is consistent with that used in Iftekhar and Tisdell [21] in that in each auction eight bidders (four humans and four robots) competed for eight quotas to fish in region A and eight quotas to fish in region B. Each participant (be they human or robot) could purchase maximum of four quotas for a single region.

Table 1
Distribution of player type in different bidder set.

Player ID	Player type	Bidder set		
		I	II	III
1	Human	AB	AB	A
2	Human	AB	AB	A
3	Human	AB	A	B
4	Human	AB	B	B
5	Robot	A	AB	AB
6	Robot	A	AB	AB
7	Robot	B	A	AB
8	Robot	B	B	AB

Table 2
Maximum willingness to pay for different combinations of items for different bidder types.

Combinations	A	B	Bidder type AB	Bidder type A	Bidder type B
1	1	1	11	10	10
2	1	2	20	13	22
3	1	3	32	17	37
4	1	4	44	22	55
5	1	0	4	8	2
6	2	1	20	22	13
7	2	2	33	25	25
8	2	3	47	29	41
9	2	4	63	34	58
10	2	0	11	20	5
11	3	1	32	37	17
12	3	2	47	41	29
13	3	3	65	45	45
14	3	4	84	49	62
15	3	0	19	35	9
16	4	1	44	55	22
17	4	2	63	58	34
18	4	3	84	62	49
19	4	4	106	67	67
20	4	0	28	53	14
21	0	1	4	2	8
22	0	2	11	5	20
23	0	3	19	9	35
24	0	4	28	14	53
25	0	0	0	0	0

This study uses Iftekhar and Tisdell's [21] specifications to generate individual bidders valuation. In their model, the individual bidder's valuations for different combinations are expressed in terms of value for a quota for region a and b (ν_i^a, ν_i^b), and potential quota values superadditivities (α_i and β_i). In this study three types of bidders are envisaged: bidders with higher valuation or preferences for region A (hereafter bidder type A), bidders with higher valuation for region B (hereafter bidder type B) and bidders with equal valuation for both regions (hereafter bidder type AB). The distribution of maximum values (willingness to pay) for the different combinations of quotas is presented in Table 2. These values represent the additional value a fisher would have for holding sets of quota for different species or regions.

A set of experimental sessions were established for the two market designs. The first set of experimental sessions involved submitting offers to simultaneous markets. Market A was a quota market to fish in location A and market B a fish quota market to fish in location B (hereafter item A and item B). The second set of experimental sessions involved participants submitting offers to a combinatorial market. In each round bidders had options to submit maximum of three bids; two on the individual locations (A and B) and one on the package (hereafter package AB). In other words, they could demand quotas for individual regions as well as for both regions up to their maximum capacity. For each market design three different combinations (bidder sets) of robot and human players were used. As shown in Table 1, bidder set I consisted of human package bidders and robot item bidders; bidder set II consisted of a combination of robot and human package and unit bidders; and bidder set III consisted of human individual item bidders and robot package bidders. Four experimental sessions for each bidder set was conducted as shown in Table 3. Each experimental session consisted of 20 rounds with four human and four robot participants.

The experiments were carried out at the University of Tasmania Experimental Economics Laboratory, Australia, using specially developed computer software. Participants were students at the University. At the beginning of each experiment, participants were asked to read a set of instructions on a computer. They then went through a series of questions on the computer to test their understanding of the instructions (copies of the instruction files and associated quizzes are available from authors). Once participants correctly answered all the questions they could access the experimental interface. Researchers were on hand to address any queries. In accordance with standard experimental protocols, participants were not permitted to talk or interact during the experiment other than through the experimental software.

In each period of the experiment, participants lodged their offers for A, B and AB (in the case of the combinatorial experiments) through the web interface. In both market designs robots used a best response strategy to select a suitable package in each round. The best response strategy is based on the expected surplus which is calculated as the difference between the maximum valuation and the current computed value of the package. The experimental software generated the robot offers using the Expected Weighted Attraction (EWA) learning algorithm outlined in [21]. Given the complete set of offers, successful offers were selected using the GAMS© CONOPT solver algorithm. Participants were then provided with a table summarizing their offers made; the status of those offers and the experimental income earned each round. Overall, 24 independent computerized sessions were conducted in the experimental economics lab at the University of Tasmania from July to August 2011. Each session lasted approximately one and half hours. In addition to their auction earnings, subjects earned a show-up fee of A$10. The average earning (including the show up fee) was A$38 (A$1 ~ US$1.02).

Table 3
Experimental design.

Market design	Bidder set		
	I	II	III
Simultaneous	4 sessions	4 sessions	4 sessions
Combinatorial	4 sessions	4 sessions	4 sessions

3. Performance measures and analysis

Following three main indicators have been used to measure aggregated outcomes of the auction designs:

- Total Rev (REV): As the objective of the auction was to maximize profit from the sale of a fixed number of quotas, total revenue raised from the market is a good standard indicator of the performance of the auctions.
- Allocative efficiency (AE): Allocative efficiency shows the degree to which the total value to the winners of the items being auctioned is maximized. AE is maximized when contracts are allocated among bidders with the highest aggregate demand [22]. It is measured as the ratio of the total valuations of the auction allocation and the optimal allocation [4]. A value of 1.0 indicates optimal allocation.
- Degree of rent extraction (RE): Degree of rent extraction estimates the profit made by the winning bidders. The degree of rent extraction was measured as the ratio of the auctioneer's revenue to optimal valuation deducted from one. Values higher than zero indicate the presence of rent extraction. The higher the RE, the higher are the winners' profits.

An autoregressive panel regression was estimated to explore the overall impact of auction designs (Design) and bidder types on three main outcomes an auction: revenue (REV), allocative efficiency (AE) and degree of rent extraction (RE). Finally, in order to understand the performance of different types of bidders the bid value ratio (BVR) and profits earned by individual bidders in different auction environments were calculated and compared.

4. Results and discussion

The data analysis began with estimates of a series of panel data models to explore the impact of alternative markets designs and bidder types on total revenue, allocative efficiency and rent extraction (Table 4). To explore the impact of auction design in

Table 4
Panel regression models of auction outcomes (Rev, AE and RE) with auction designs and bidder sets.

Equation	1	2	3	4	5	6	7	8	9
Dependent variable	Rev	AE	RE	Rev	AE	RE	Rev	AE	RE
Constant	132.97	0.86	0.37	153.87	0.89	0.27	150.17	0.91	0.29
	(7.63)**	(0.02)**	(0.04)**	(7.63)**	(0.02)**	(0.04)**	(7.63)**	(0.02)**	(0.04)**
Design	20.78	0.05	−0.10	20.78	0.05	−0.10	20.78	0.05	−0.10
	(4.40)**	(0.01)**	(0.02)**	(4.40)**	(0.01)**	(0.02)**	(4.40)**	(0.01)**	(0.02)**
Bidder set I	17.20	0.04	−0.08	−3.70	0.01	0.02			
	(5.39)**	(0.01)**	(0.03)**	(5.39)	(0.01)	(0.03)			
Bidder set II	20.89	0.03	−0.10				3.70	−0.01	−0.02
	(5.39)**	(0.01)**	(0.03)**				(5.39)	(0.01)	(0.03)
Bidder set III				−20.89	−0.03	0.10	−17.20	−0.04	0.08
				(5.39)**	(0.01)**	(0.03)**	(5.39)**	(0.01)**	(0.03)**
Wald statistics	39.38**	39.51**	37.95**	39.38**	39.51**	37.95**	39.38**	39.51**	37.95**

Standard error in parentheses.

** Significant at 0.01.

Table 5
Panel regression models of auction outcomes (Rev, AE and RE) within bidder sets.

Bidder set	Constant	Design	Wald statistics
I			
Rev	157.46 (10.63)**	16.19 (6.72)*	5.79***
AE	0.94 (0.02)**	0.03 (0.01)*	4.27
RE	0.26 (0.05)**	−0.08 (0.03)*	5.15***
II			
Rev	173.53 (9.95)**	7.63 (6.29)	1.47
AE	0.92 (0.02)**	0.03 (0.01)*	5.18***
RE	0.18 (0.05)**	−0.04 (0.03)	1.69
III			
Rev	106.62 (9.33)**	37.78 (5.90)**	41.02**
AE	0.81 (0.03)**	0.09 (0.02)**	23.11**
RE	0.49 (0.04)**	−0.18 (0.03)**	40.55**

Standard error in parentheses.

* Significant at 0.05.

** Significant at 0.01.

*** Significant at 1.

more detail individual models for each bidder type were estimated (Table 5). This was followed by a graphical analysis of auction outcomes through rounds. The analysis concludes with a discussion of mean bid value ratio and profit earned by different types and natures of bidders in individual rounds in different bidder type combinations. Overall, the combinatorial auction design performed better than the simultaneous auction design.

Table 4 summarizes the panel regression models of auction outcomes with auction designs and bidder types. The combinatorial auction design produced significantly higher revenue, allocative efficiency and less rent extraction than simultaneous auction design. In terms of revenue through rounds the superiority of the combinatorial auction design was most evident in bidder set III (see Fig. 1) with average revenue higher in combinatorial auctions in all rounds. For bidder sets I and II the average revenue in combinatorial auction was high in the majority of rounds. In the case of bidder set I average revenue was consistently higher from round 11 onwards. Within the combinatorial design similar amount of revenue was generated across all bidder sets ($p > 0.05$). The average revenue in the combinatorial auction experiments for bidder sets I, II and III were \$191 (±\$23), \$191 (±\$18) and \$186 (±\$23), respectively.

On the other hand, average revenue in the simultaneous auction design is significantly different across bidder sets ($p = 0.006$). The average revenues in the simultaneous auction experiments for bidder sets I, II and III were \$175 (±\$24), \$183 (±\$21) and \$146 (±\$13), respectively. This trend is similar for allocative efficiency and degree of rent extraction indicators.

One of the primary objectives of quota allocation by government agencies is to make a socially optimal allocation. Overall, combinatorial auction design has achieved higher allocative efficiency than simultaneous auction design. Individually, combinatorial auction design achieved 2.73, 3.19 and 8.65 percentage points significantly higher allocative efficiency than simultaneous auction for bidder sets I, II and III, respectively. Moreover, combinatorial auction design achieved optimal allocative efficiency (i.e., AE = 1) in 90%, 88% and 93% of the auction rounds with bidder sets I, II and III, respectively. On the other hand, similar figures for simultaneous auction are 73%, 64% and 34%, respectively.

In terms of rent extraction the combinatorial auction design has allowed less degree of rent extraction (10% points) than simultaneous auction design. Combinatorial auction design has achieved similar level of degree of rent extraction with all bidder types. On the other hand, RE estimate was the lowest for simultaneous auction for bidder set II (0.136 ± 0.986) followed by bidder set I (0.1717 ± 0.1137) and bidder set III (0.3082 ± 0.063).

After presenting the results for auction design the performances of individual bidder sets was explored. Among the individual bidder sets, overall, bidder set III has performed significantly worse than other two bidder sets (see Table 4). In bidder set III, all human bidders are item bidders and all robot bidders are package bidders. With this bidder set, players operating in the simultaneous auction design achieved significantly less revenue compared to combinatorial auction design. It is the scenario when human item bidders enjoyed most flexibility as indicated by their bid value ratio.[2] For example, for item bidder A the bid value ratio for their preferred item (A) was 0.76 (se = 0.01), which is substantially lower than their respective bid value ratio in combinatorial auction (0.87, se = 0.02). Similarly, for item bidder B, the bid value ratio was significantly lower in simultaneous auction (0.60, se = 0.01) compared to that observed in the combinatorial auctions (0.83, se = 0.21). Subsequently, their average profits earned in individual rounds was substantially higher in the simultaneous auctions compared to combinatorial auctions. For example, the average profit for bidder type A was \$9.37 (se = 0.52) in simultaneous auctions, whereas, in combinatorial auctions average profit was \$1.58 (se = 0.33). Similar estimates for bidder type B were \$13.69 (se = 0.83) and \$1.72 (se = 0.29) in simultaneous and combinatorial auctions, respectively. Moreover, robot bidders (which are all package bidders in this scenario) bid very conservatively to avoid exposure problem (average loss −\$0.88, se = 0.14). As a consequence they did not provide enough competition to the human bidders. Furthermore, the simultaneous auction mechanism suffered from efficiency and revenue loss with bidder set III. On the other hand, in combinatorial auctions, robot package bidders achieved higher average profit (\$3.62, se = \$0.40) than their counterparts in bidder set II (\$2.38, se = \$0.47). Human item bidders suffered from coordination problems and could not provide adequate competition. As a consequence, combinatorial auctions also suffered from revenue loss with bidder set III.

Overall, the performances of bidder sets II and III were not significantly different (Table 4). However, as mentioned above, auction designs performed differently with different bidder sets (Table 5). For example, with bidder set I simultaneous auction has achieved less aggregate revenue than combinatorial auction. Here, all human participants are package bidders and robot bidders are item bidders. In simultaneous auction human package bidders suffer from exposure problem as indicated by their bid value ratio (Fig. 2). The average bid value ratio for individual quota was 0.88 (se = 0.01) for quota A and 0.90 (se = 0.01) for quota B. However, when their bids for both markets were combined the ratio was 0.55 (se = 0.02). Similar estimate for combinatorial auction was 0.84 (se = 0.01). This result is supported by the findings of Kwasnica et al. [4] that in the presence of strong complementarity, package bidders are reluctant to bid above their valuations for individual regions, reduce their chance of winning and fail to benefit from their synergy values. As a consequence, package bidders won only 27% of the times. On the other hand, when they bid above their value for an individual region they ran the risk of losing money—as indicated by their profit earnings (loss −\$0.63, se = 0.66). In the absence of strong competition from human package bidders robot bidders (item bidders) won 73% times. They also enjoyed flexibility in setting their bid prices and enjoyed positive profits (for bidder type A, \$8.41, se = 0.51 and for bidder type B, \$5.79, se = 0.52).

---

[2] In fact potentially all four human bidders could win given optimal allocation in this bidder set.

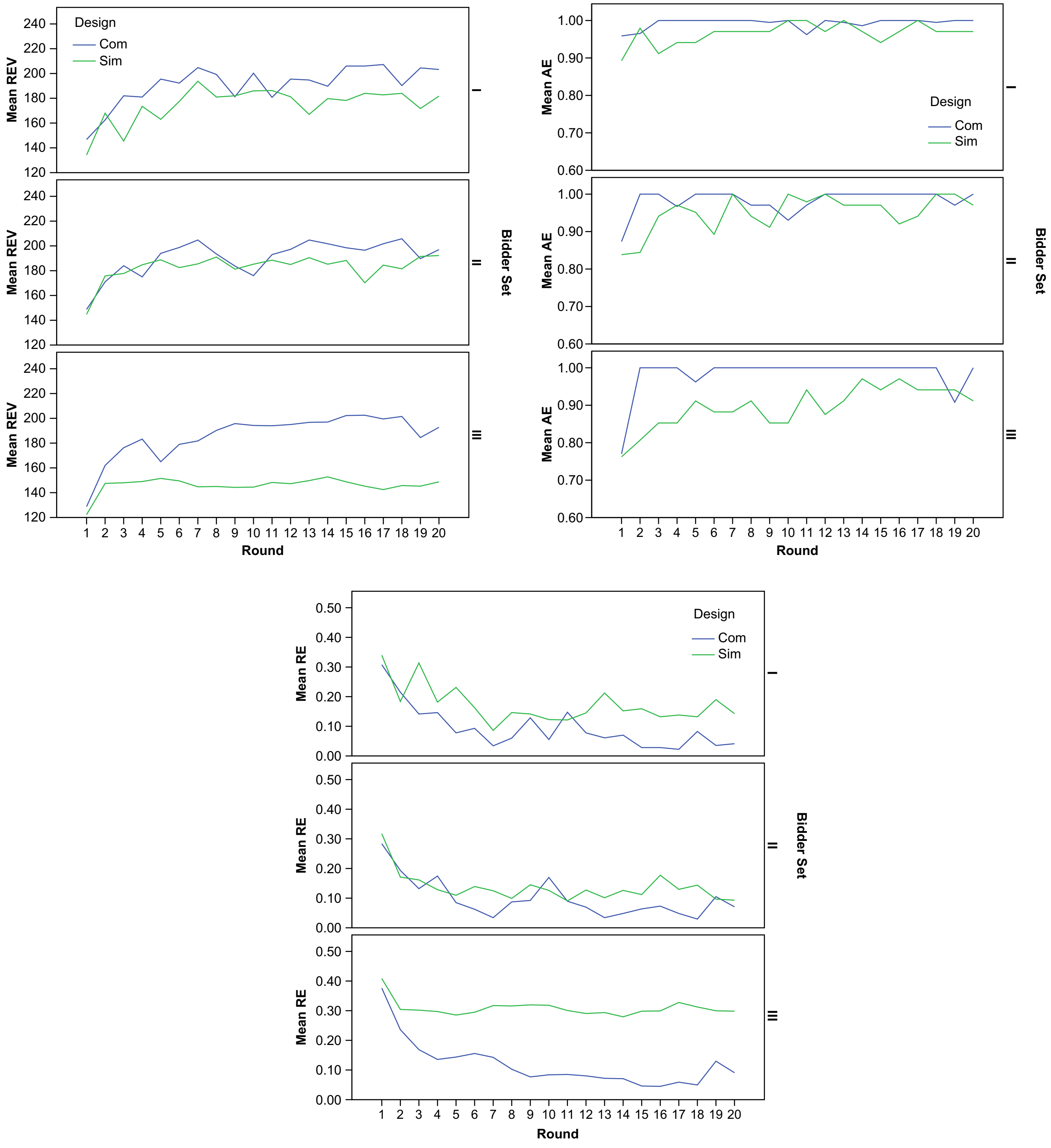

Fig. 1. Trends in average auction outcomes (Rev, AE and RE) by design and bidder set.

With bidder set II, where human bidders have both types of valuations (item bidders and package bidders) there was no significant difference in the performance of simultaneous and combinatorial auction designs in terms of total revenue earning and degree of rent extraction (Table 5). This result is driven by the competitive behavior of the human item bidders. In this scenario, human item bidders bid more competitively in simultaneous auctions than in combinatorial auctions as indicated by their bid value ratio. For item bidder A, for example, the bid value ratio for their preferred item (A) was 0.87 (se=0.02), which was higher than their respective bid value ratio in combinatorial auction (0.81, se=0.03). Similarly, for item bidder B the bid value ratio was substantially higher in simultaneous auctions (0.79, se=0.02) compared to in combinatorial auctions (0.58, se=0.04). On the other hand, human item bidders earned less profit than they have achieved in bidder set III (for bidder type A \$4.48 (se=0.41) and for bidder type B \$5.79 (se=0.93)). Similar trends were observed for robot item bidders. Robot package bidders incurred less loss (−\$0.13, se=0.25) than they have suffered in bidder set III. All these factors have contributed in bringing the performance of the

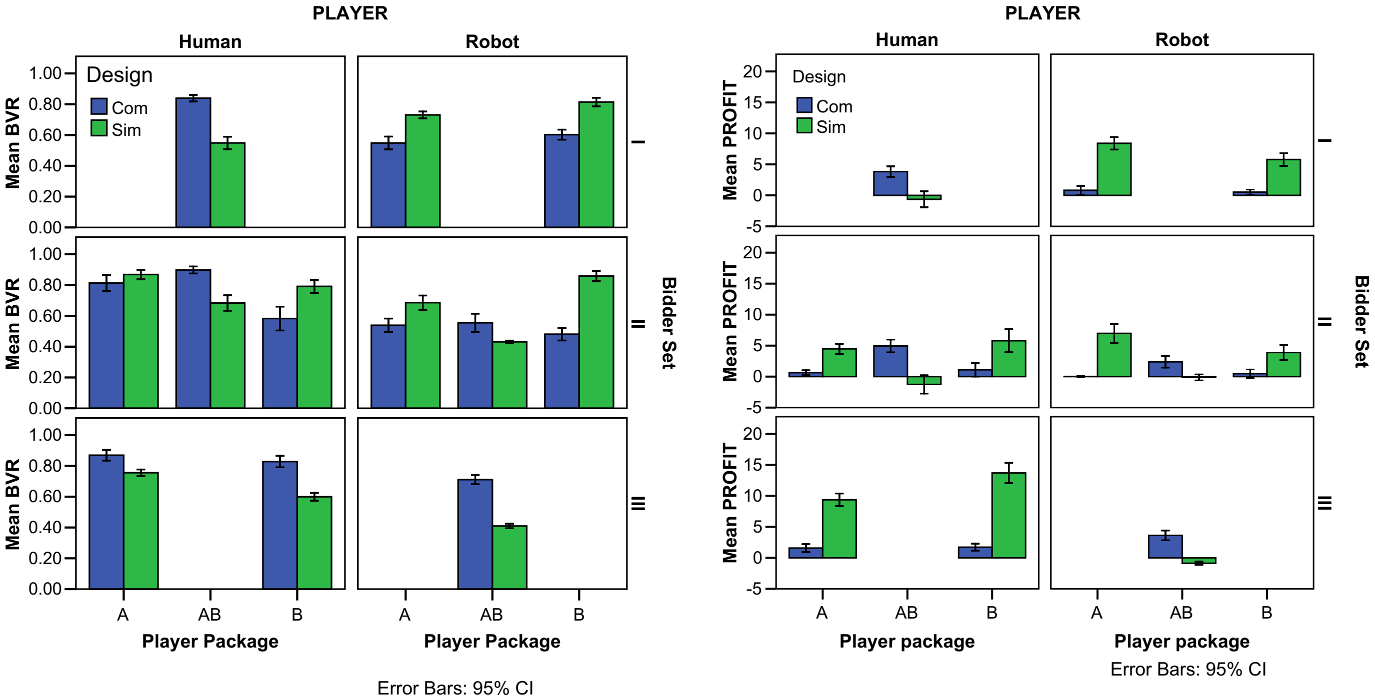

Fig. 2. Mean bid value ratio (BVR) and profit earned by different type and nature of bidders in individual rounds in different bidder set combinations.

simultaneous auction closer to combinatorial auction for bidder set II.

The results indicate that in simultaneous auctions, package bidders could suffer from losses. On an individual level, 44% and 50% of the human package bidders lost money (i.e., the cumulative profit at the end of a session was negative, but not sufficient to fall into house money in terms of participant payments) with bidder sets I and II, respectively, under the simultaneous auction. Similarly, 50% of the robot package bidders lost money in bidder sets II and III, respectively in simultaneous auction. This suggests that some portion of the revenue in simultaneous auction comes from the package bidders who are making a loss. Similar observations have been found by many authors in laboratory experiments [23]. For example, Kwasnica et al. [4] found in their simultaneous multi-round auction experiments that 35% of the bidders lost money. Lunander and Nilsson [24] observed at least one bidder suffering from losses in 38% of their sealed bid first price auction experiments.

In summary, the aggregate performance of combinatorial auction is best when all human bidders are package bidders. On the other hand, simultaneous auction performed best when half of the human bidders are package bidders and half item bidders. In general, both designs allowed higher degree of rent extraction when all human bidders were item bidders. However, the auctioneer should be careful about the winner's curse problem in simultaneous auctions. It is plausible that in real world application bidders with loss can withdraw their bids at the end of an auction. Therefore, as a post hoc analysis auction outcomes were recalculated by considering allocations made to only bidders with non-negative profit. However, the relative ranking of the auction designs do not change in for different bidder type combinations.

5. Conclusions

The laboratory provides a formalized, replicable approach to rapidly assess alternate policy directives. It allows policy makers the opportunity to explore policy options while holding various extraneous factors constant. Well-designed experiments allow policy makers to evaluate the efficacy of policy directives and provide sufficiently robust information to circumvent or mitigate the consequences of inappropriate policy options prior to trialing in the real world. The laboratory environment does not reflect the real world, rather a world in which key policy drivers can be explored under controlled conditions. Those options which show merit in the laboratory could be considered for trial in small scale real world case studies.

This study explored the performance of selected simultaneous and iterative combinatorial auction designs in a fishery given different bidder types. In individual session four humans competed against four robots using a learning algorithm. The results showed that overall efficiency outcomes of combinatorial auction design were better than simultaneous auction design. However, the auctioneer needs to be aware of the possible distribution of valuations of potential bidders. Performance of the human bidders indicate that when heterogeneous bidders participate in the same auction, it is likely that both designs would perform equally well in terms of aggregate revenue. However, in real world setting the two auction designs may attract different types of bidders. It has been shown in this paper and in other studies in non-fisheries market that in simultaneous auction global bidders with significant synergies in their valuations may suffer from significant losses. Therefore, they would be reluctant to participate in a simultaneous auction. On the other hand, for local or regional (item) bidders, it is beneficial to participate in simultaneous auction as they can earn higher profit then attending in combinatorial auctions.

Acknowledgments

The authors are grateful to the work of Angus Scheibner and Joal Fishwich for the work in the laboratory to make this work possible. Financial support was received from UTAS Business Faculty Research Grant. The authors would also like to thank the anonymous referee and editor for their constructive comments and suggestions. All errors and omissions remain with the authors.

References

[1] Porter D, Rassenti S, Roopnarine A, Smith V. Combinatorial auction design. Proc Natl Acad Sci USA 2003;100:11153–11157.

[2] Banks JS, Ledyard JO, Porter DP. Allocating uncertain and unresponsive resources: an experimental approach. Rand J Econ 1989;20:1–25.

[3] Ledyard JO, Porter D, Rangel A. Experiments testing multiobject allocation mechanisms. J Econ Manage 1997;6:639–675.

[4] Kwasnica AM, Ledyard JO, Porter D, DeMartini CA. new and improved design for multiobject iterative auctions. Manage Sci 2005;51:419–434.

[5] Bykowsky MM, Cull RJ, Ledyard JO. Mutually destructive bidding: the FCC auction design problem. J Regul Econ 2000;17:205–228.

[6] Stoneham G, Chaudhri V, Ha A, Strappazzon L. Auctions for conservation contracts: an empirical examination of Victoria's BushTender trial. Aust J Agric Resour Econ 2003;47:477–500.

[7] Latacz-Lohmann U, Hamsvoort CVD. Auctioning conservation contracts: a theoretical analysis and an application. Am J Agric Econ 1997;79:407–418.

[8] Latacz-Lohmann U, Hamsvoort CVD. Auctions as a means of creating a market for public goods from agriculture. J Agric Econ 1998;49:334–345.

[9] Rassenti SJ, Smith VL, Bulfin RL. A combinatorial auction mechanism for airport time slot allocation. Bell J Econ 1982;13:402–417.

[10] Cramton P, Shoham Y, Steinberg R. Combinatorial auctions. Cambridge MA: The MIT Press; 2006 p. 649 + xv.

[11] Hilborn R, Ledbetter M. Analysis of the British Columbia salmon purse-seine fleet: dynamics of movement. J Fish Board Can 1979;36:384–391.

[12] Bockstael NE, Opaluch JJ. Discrete modeling of supply response under uncertainty: the case of the fishery. J Environ Econ Manage 1983;10: 125–137.

[13] Daw TM. Spatial distribution of effort by artisanal fishers: exploring economic factors affecting the lobster fisheries of the Corn Islands, Nicaragua. Fish Res 2008;90:17–25.

[14] Sanchirico JN, Wilen JE. A bioeconomic model of marine reserve creation. J Environ Econ Manage 2001;42:257–276.

[15] Eales J, Wilen JE. An examination of fishing location choice in the pink shrimp fishery. Mar Resour Econ 1986;2:331–351.

[16] Hamon K, Thébaud O, Frusher S, Little L. A retrospective analysis of the effects of adopting individual transferable quotas in the Tasmanian red rock lobster, Jasus Edwardsii, fishery. Aquat Living Resour 2009;22:549–558.

[17] Christy T. Fisherman quotas: a tentative suggestion for domestic management. Occasional paper series. Occasional paper no 19, (NOAA-76022508), Rockville: National Oceanic and Atmospheric Administration (NOAA), November; 1973.

[18] Anferova E, Vetemaa M, Hannesson R. Fish quota auctions in the Russian far East: a failed experiment. Mar Policy 2005;29:47–56.

[19] Anderson CM, Sutinen JG. The effect of initial lease periods on price discovery in laboratory tradable fishing allowance markets. J Econ Behav Org 2006;61:164–180.

[20] Moxnes E. Individual transferable quotas versus auctioned seasonal quotas, an experimental investigation. System Dynamics Group, University of Bergen; 2010. p. 29.

[21] Iftekhar MS, Tisdell JG. Comparison of simultaneous and combinatorial auction designs in fisheries quota market. Mar Policy 2012;36:446–453.

[22] Pekeč A, Rothkopf MH. Combinatorial auction design. Manage Sci 2003;49:1485–1503.

[23] Kagel JH, Lien YC, Milgrom P. Ascending prices and package bidding: a theoretical and experimental analysis. Am Econ J Microecon 2010 160–185.

[24] Lunander A, Nilsson JE. Taking the lab to the field: experimental tests of alternative mechanisms to procure multiple contracts. J Regul Econ 2004;25:39–58.