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Comparison of simultaneous and combinatorial auction designs in fisheries quota market

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ABSTRACT

Individual transferable quota (ITQ) markets are being used successfully to distribute quotas in single region and single species fisheries. In many parts of the world, the development of well crafted markets for multispecies or multiregional fisheries is still evolving. As a result, there exists an opportunity to inform policy by providing research insights into the relative merits of alternative market designs for such fisheries.

This study explored the relative merits of a simultaneous ascending auction design and an iterative combinatorial auction design for a hypothetical multiple region quota market. In a simultaneous auction, separate auctions are run in parallel for individual species or regions. During intermediate rounds, fishers can adjust their bids in auction depending on their position in the other auction. In a combinatorial auction, a fisher can purchase a combination of quotas (or a package quota) for different fish species or regions in the same auction. Being able to acquire bundles of species or regions allows fishers to take advantage of complementarities. To date, the potentials of such auctions have not been thoroughly tested in fisheries quota markets. This study found that while a simultaneous auction design was more efficient than combinatorial auction design overall, combinatorial market design took fewer rounds to make final allocations and performed better in high synergy environments.

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1. Introduction

Fishery management has evolved from open access to quota management systems; where a governmental fishing authority decides the total allowable catch (TAC) for a certain species and then sell or distribute quotas; to individual transferable quota (ITQ) systems [1,2]. The aim of an ITQ mechanism is to promote a socially optimal allocation of quota [3]. An auction allocates targeted number of quotas based on the bids submitted by fishers on their preferred number of quotas. It is expected that fishers with lower overall fishing costs per unit of catch would be able to maximize their profit within ITQ constraints [4]. In an auction, bidders face two forces; selection effect and competitive pressure. Selection effect allows an auctioneer to select suitable bids from the submitted bids. On the other hand, competitive pressure forces the bidders to submit bids close to their actual valuation. A socially optimal allocation is made when quotas are allocated to the fishers with highest valuations for them. Some of the other benefits of an auction is to generate rents for the society and impart greater transparency in quota allocation mechanism [5]. However, realization of the full benefits of an auction based mechanism depends on how well designed the mechanism is for a particular situation.

There are few studies focusing on the effectiveness of different auction based instruments to allocate ITQs. For example, Moxnes [6] compared an ITQ system and an auctioned seasonal quotas (ASQs). He used a laboratory experiment of a market with seven fishing firms. Anderson and Holland [7] used a laboratory experiment, calibrated to a representative New Zealand fishery, to assess three sealed-bid, multi-unit demand auction mechanisms under consideration for allocating quota for species being introduced into the Quota Management System. These auctions allocated the K units to the K highest bids, but prices were determined according to discriminative, Kth price, and K+1th price rules. They observed that the auctions were equally efficient, but revenue was highest in the discriminative auction, and lowest in the K+1st price auction. In another laboratory study, Anderson [8] observed that in a double auction for permanent quotas it is difficult to achieve equilibrium and markets were characterized by high volatility compared to a market when annual leases were traded. In a separate laboratory study, Anderson and Sutinen [9] evaluated impacts of two market design features on volatility during price discovery: a uniform price auction and an initial lease period, which prohibits permanent allowance transfers at the beginning of the program.

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They observed that initial lease periods effectively reduced volatility once permanent trading was introduced.

There are also a few studies observing performances of auctions in real world setting. For example, Anferova et al. [5] discussed use of an auction based mechanism to allocate fishing quotas in the Russian far east (REE). The auctions were held in the form of open outcry with ascending prices. On every auction, a certain part of the TAC was exposed. The unsold lots were offered once again on the next auction. The quota bought through auctions was valid for the current year only, with the right to catch in a certain region and in a certain time period. The reselling of quotas bought in an auction was forbidden. In New Zealand an online platform, FishStock (http://www.fishstock.co.nz/aboutauctions/), is often used for auctioning fishing quotas. Individual auctions could be conducted for a single stock or multiple stocks from the same fishing year. However, bidders are not allowed to place bids on individual stocks within an auction. Rather they enter a pool. Individual quotas are tradable only within the same fish stock, and not across regions, species or years. Winning bidders pay their winning bid amounts. Such ITQ systems are also common in other parts of the world, including Estonia and Chile [10].

Most studies have evaluated auction designs in simplified settings by focusing on a single fishery or region. However, fishers' bidding behavior in a quota market is likely to be influenced by many factors. This study is particularly interested in performance of auction designs when fishers have complementarities or interdependence in their valuations for quotas. There are two sources of synergy or complementarities in valuations of quotas: economies of scale and economies of scope. Economies of scale refer to the situation when a fisher is willing to pay more for multiple quotas for the same region. On the other hand, economies of scope refer to the situation when a fisher is willing to pay more for quotas covering different regions together. As such, the quota allocation problem resembles a multiple unit heterogeneous goods allocation problem.

In presence of complementarities, potential bidders face three problems: the exposure problem (the risks a bidder faces in trying to win a combination of quotas with complementary valuations), the coordination problem (the difficulties smaller fishers with interests on a single region face in beating bigger fishers who bid for multiple regions), and the computational complexity problem (which arises from the fact that the number of possible combinations of quotas is much larger than the number of quotas available). To ameliorate these problems, a flexible mechanism is required which would allow bidders to express an elaborate and relevant set of evaluations on different combinations of quotas. Simultaneous and combinatorial auction designs are two relevant alternatives. Both of these formats have been widely used in trading of complementary items in non-agricultural sectors [11].

In a simultaneous auction, separate auctions are run in parallel for individual species or regions. During intermediate rounds fishers can adjust their bids in auction depending on their position in the other auction. In a combinatorial auction, a fisher can purchase a combination of quotas (or a package quota) for different fisheries or regions in the same auction. Economic theory suggests that different auction systems may lead to different price equilibria under specific conditions which would ultimately affect auction outcomes. However, in absence of prior studies and clear theoretical predictions, it is not clear how these auction designs would perform in fisheries quota markets where bidders have complementary valuations for quotas [8]. Therefore, this study compared two specific designs of simultaneous (simultaneous multiple round auction of Cramton [11]) and combinatorial (iterative combinatorial auction design of Aparicio et al. [12]) auctions. To the best of our knowledge, this is for the first time these designs have been compared for fisheries quota market. As markets for fishing quotas mature, policy makers and fishers alike will be demanding greater flexibility and ability to bundle quota into rational bundles. This study provides important policy insights to the development of future ITQ market designs.

An agent-based model was constructed to numerically compare the auction designs. The model resembles a fisheries quota auction for two regions. In a simultaneous auction, separate auctions are run for both regions and fishers can submit price – quantity bids for a region. In a combinatorial auction fishers can submit price-quantity bids for both regions. The objective of the auctioneer is to maximize revenue while allocating a fixed number of quotas. The auction designs were tested using different levels of heterogeneity in terms of level of complementarities in bidder valuations. Variations in the auction environment allowed assessment of the robustness of the performance of the auction designs.

After this brief introduction, Section 2 reviews the relevant literature on simultaneous and combinatorial auction designs, Section 3 describes the experimental framework, and Section 4 presents and discusses the main results. Finally, Section 5 concludes the paper.

2. Simultaneous and combinatorial auction designs

This section describes the basic features of the studied simultaneous and combinatorial auction designs. There are some common features among the auction designs: (1) the use of multiple rounds, where bidders get multiple chances to revise their bids, (2) provision of feedbacks on standing bids and current prices, (3) winning bidders pay what they bid (discriminative pricing), (4) provisionally winning bids are determined by maximizing potential revenue subject to feasibility, and (5) provisionally winning bids remain as a standing commitment until replaced by another provisional winner. They differ in terms of how bids are constructed and how the winning bids are determined.

In simultaneous multiple round auctions, separate auctions are conducted for individual regions. In each market, bids for quota are accepted for that particular region. Winners are selected separately for each region based on their standing bids [11]. In a combinatorial auction, bidders can submit bids on a combination of quotas from multiple regions. With combinatorial auctions the clearing quota price is not necessarily the highest bid on that quota; indeed there may not even be a stand alone bid on a particular region. There are several alternative price feedback mechanisms to calculate standing prices from the provisional revenue-maximizing allocation. This study used the multiple unit forward combinatorial auction design proposed by Aparicio et al. [12] . This design provides price feedback in the form of unit quota prices that rationalizes the results of the winner determination problem. The ideal set of feedback prices would be compatible with the given allocation and the given bids, i.e., computed value for packages (i.e., sum of the quota prices multiplied by units of quota) in winning (losing) bids are not higher (lower) than the respective bids. Compatible prices provide indications to the winners, why they have won, and to the losers, why they have lost [13].

Several studies have compared efficiency of combinatorial auctions with other types of auctions [14]. For example, Ledyard et al. [15] reviewed 130 auction experiments conducted for allocating personal communications licenses by the Federal Communications Commission of USA. They observed that over a very wide range of complementarities, combinatorial auction (weakly) dominates simultaneous auction, which in turn (weakly) dominates sequential auction. Lunander and Nilsson [16] conducted a series of laboratory experiments comparing the bidding behavior for multiple contracts in three different sealed bid auction mechanisms; first-price simultaneous, first-price sequential and first-price combinatorial bidding. The experiments were based on experiences from a public procurement auction of road markings in Sweden. They found the combinatorial bidding mechanism was the most efficient. Cramton et al. [17] noted that where complementarities are both strong and varied across bidders, package bids could improve the efficiency. Goeree et al. [18] made similar observations. But in case of un-related goods, sequential and simultaneous auctions generate similar revenue [19].

While these studies suggest the use of combinatorial markets over other forms, their research and subsequent findings and recommendations did not consider fisheries quota auctions, where the level of synergy between species/regions could vary. To explore the relative merits of simultaneous and combinatorial ITQ markets this study used a simulation agent based framework.

3. Simulation framework

An agent based model (ABM) incorporates two types of agents representing the actual players in an ITQ market. In this study these are:

- Fishers bidding for ITQs. Each fisher has a budget (or maximum willingness to pay) associated with different combinations of ITQs from different regions.
- Auctioneer (agency), which selects winning bids and awards contracts based on the pre-determined criteria. The auctioneer has a fixed number of quotas to sell based on and estimated a maximum sustainable yield (MSY) or maximum economic yield (MEY).

In the ABM model used in this study the simulated auctions involved four steps.

- In the first step, bidders placed price-quantity bids indicating their willingness to purchase a number of quotas.
- In the second step, based on submitted bids, the auctioneer provisionally selected winning bids with the objective of maximizing revenue from selling the targeted number of quotas. The selection was 'provisional' in that this is an iterative auction with current bids replaced by revised bids in the following round.
- In the third step, as part of the provisional selection processes, the auctioneer generated implied quota prices to provide as feedback to bidders, who used these prices to revise their bids.
- In the fourth step, bidders revised their bids based on provisional market information. The Experience Weighted Attractions learning (EWA) algorithm of Camerer [20] was used to model bidders' learning and bid revision.

The process continued until a termination rule was satisfied (i.e., a maximum number of rounds was reached) and a final allocation, in the form of winning bids and associated payments was made. The key features of the simulation study: market demand, bidding strategies adopted by individual bidders, and the Experience Weighted Attraction (EWA) learning algorithm used to model bidder learning are described below. This is followed by a description of the auction scenarios that have been used to compare the auction designs. The last sub-section outlines the performance indicators used to analyze the results.

3.1. Market demand

Market demand was estimated from the sum of individual fisher's demand. The individual fisher's valuation for a quota was parameterized by the following expression:

$$v_i^m = \pi_i^m \cdot \left(\sum I_i^m\right)^{\alpha_i} \cdot \left(1 + \sum I_i^n\right)^{\beta_i}$$

Where

v_i^m	maximum value bidder i is willing to pay for a quota to fish in region m
I_i^m	number of quotas under consideration by bidder i to fish in region m
π_i^m	stand alone value for a quota to bidder i to fish in region m
α_i	economies of scale parameter for bidder i
I_i^n	number of quotas won by bidder i to fish in region n
β_i	economies of scope parameter for i

The first term represents the stand alone value (v_i^m) for a quota to fish at region m. The next two terms are added to model two potential quota values superadditivities. The second term captures a scale economy a fisher achieves when she wins multiple quotas for a region, m. The parameter α_i determines individual bidder's degree of cost complementarities from acquiring multiple quotas for a given region. The third term attempts to capture quota value superadditivity that results from a fisher winning quotas for both regions. Parameter β_i determines the sensitivity of bidder's valuation for winning quotas for different regions together. In combination the values of two parameters determine the level of complementarity a fisher would enjoy in his or her valuations for multiple regions and multiple quotas.

3.2. Defining the mark up and bidding strategies

A bidder's set of strategies is specified as the set of mark-up choices that can be applied to budget. It was assumed that a bidder has access to a set of twenty strategies ($s^1 - s^{20}$). Each strategy was assigned a mark-up value. The mark up value for strategy s^1 was 0.05. Thereafter, the mark-up value gradually increased with an increment of 0.05 to a final mark-up value for the last strategy of 1. For example, selection of the first strategy (s^1) in any round would mean that bidder was bidding one-twentieth of the maximum value for quota (s) (i.e., $v(s_{ij}^1) = v_i^m \times I_i^m \times 0.05$). On the other hand, selection of s^{20} means that the bidder would bid at his or her actual budget constraint (i.e., $v(s_{ij}^{20}) = v_i^m \times I_i^m \times 1$). In the first round, bidders do not have any prior experience. Therefore, it was assumed that bidders randomly selected a quantity of quota and related strategy. In the following round, bidders used price feedback information to identify the most profitable quantity of quotas to submit. They then used the Experience Weighted Attraction (EWA) learning algorithm to determine suitable pricing strategy. In order to speed up the auction and quickly make final allocation, provisionally winning bids were considered in the following round. The model allowed bidders to learn.

3.3. EWA learning algorithm

Bidders relied on EWA algorithm to process feedback information in both types of auctions. Bidders could evaluate pay-offs related to alternative strategies. Each strategy had a pre-defined attraction value, which was updated after each round. Updating was done by multiplying the lagged attractions $q_{ij}^g(t-1)$ and a lagged experience weight $N(t-1)$ depreciated in terms of a memory retention parameter, ϕ and adding the expected payoff $R_{ij}(s_{ij}^g, s_{-ij}(t))$ from a strategy. Attractions were then divided by an updated experience weight, $N(t)$ to get final values for $q_{ij}^g(t)$. Updated attractions were used to determine the probability of choosing a strategy, $p_{ij}^g(t+1)$ [20]. The set of equations used in the model is as follows:

$$q_{ij}^{g}(t)=\frac{\phi\cdot N(t-1)\cdot q_{ij}^{g}(t-1)+[\delta+(1-\delta)\cdot I(s_{ij}^{g},s_i(t-1))]\cdot R_{ij}(s_{ij}^{g},s_{-ij}(t))}{N(t)}$$

where

$$R_{ij}^{g}=\begin{cases} v(s_{ij}^{20})-v(s_{ij}^{g}) & \text{if } CV_{ij}(t)\le v(s_{ij}^{g}) \\ 0 & \text{otherwise}\end{cases}$$

$$N(t)=\phi\cdot(1-k)\cdot N(t-1)+1 \quad t\ge 1$$

$$p_{ij}^{g}(t+1)=\frac{e^{\lambda.q_{ij}^{g}(t)}}{\sum_G e^{\lambda.q_{ij}^{s}(t)}} \tag{1}$$

It should be noted that expected pay-off was calculated as the difference between the maximum WTP for the quota $v(s_{ij}^{20})$ and the valuation for the strategy, $v(s_{ij}^{g})$. In a combinatorial auction, bidders can incorporate synergy values directly in their calculations of expected profit. However, in the simultaneous auction, bidders could realize synergy values if and only if they win quotas for both regions. Therefore, when bidders won quotas only for a single region, the valuation for a strategy ($v(s_{ij}^{g})$) was calculated by ignoring the superadditivity resulting from economies of scope. To be competitive a bidder only considered those strategies for which the valuation for the quota was higher than the computed value of the item, $CV_{ij}(t)$. Another parameter δ depicts the weight each bidder attaches to foregone payoffs relative to realized payoffs. The pay-off from a non-selected strategy was multiplied by δ. The values of ϕ and k, and δ and λ were set at 0.5 and 0.8 respectively. Selection of these values allowed bidders to explore different strategies in response to market information before selecting the final strategy.

3.4. Computational experiments

Given the market demand, strategies and learning algorithms, auction designs for different levels of complementarities and diversity in the bidder population were tested. It was assumed that the level of synergy between bidders in ITQ fishery markets has a significant impact on the relative performance of simultaneous and combinatorial auctions. Two sets of test cases were used to analyze performance:

3.4.1. Test 1

The first test explored the performance of the auction designs under different levels of synergy. The model consisted of a homogenous population of eight fishers, each having a demand for four quotas for each region. All fishers used the same set of bidding strategies. Level of synergy was defined in two dimensions: economies of scale and economies of scope. Each dimension was modeled at three levels (0, 0.5 and 1). Therefore, in total nine synergy scenarios were considered as shown in Table 1. In order to maintain a similar level of competition across the different scenarios, the target was set in such a way that two bidders could fulfill it in optimal allocation.

3.4.2. Test 2

The second test examined the impact of synergy in a different way. The proportion of the high synergy bidders in an otherwise bidder population (eight bidders) with no synergy values was increased through five levels as shown in Table 2. HS0 means all bidders had no complementarities in the valuation of their quotas ($\alpha_i=0$ and $\beta_i=0$). HS25 means that two bidders (2/8=25%) were high synergy bidders ($\alpha_i=0.50$ and $\beta_i=0.50$) and the remainder had no complementarities in their valuation of quotas. In order to get multiple data points the designs were tested for two different degrees of competition, DR25 and DR50. In the first competition scenario (DR25) two bidders could fulfill the target in optimal allocation. In the second scenario the target was expanded to require four bidders to fulfill it in optimal allocation.

In both tests, the auctions were run for 100 rounds, which was sufficient for the designs to reach convergence. To smooth out the effect of stochastic elements the simulations were run 100 times for each scenario.

Table 1
Synergy scenarios and optimal revenue from selling target number of quotas for individual scenarios.

Economies of scope	Economies of scale		
	0	0.5	1
0	0.0064	0.0128	0.0256
0.5	0.014310835	0.02862167	0.05724334
1	0.032	0.064	0.128

Table 2
Synergy scenarios and optimal revenue from selling target number of quotas for individual scenarios.

	DR25	DR50
HS0	0.0064	0.0128
HS25	0.02862167	0.03502167
HS50	0.02862167	0.05724334
HS75	0.02862167	0.05724334
HS100	0.02862167	0.05724334

3.5. Performance measures and analysis

Three indicators have been used to measure auction outcomes: allocative efficiency (AE), degree of rent extraction (RE) and speed of convergence (Round) [13,21–23]. Allocative efficiency shows the degree to which contracts are allocated among bidders with the highest aggregate demand. AE is maximized when the total value to the winners of the items being auctioned is maximized [24]. It is measured as the ratio of the total valuation of an allocation X to the maximum total valuation X^* [25]. Higher values are more desirable, with a value of 1.0 being the best possible. On the other hand, degree of rent extraction estimates the profit made by the winning bidders. Given the resulting allocation X, the degree of rent extraction was measured as the ratio of the auctioneer's revenue to maximum total valuation deducted from one. Values higher than zero indicate the presence of rent extraction. When RE is minimized, bidders' aggregate net income is minimized. The higher the RE, the higher are the winners' profits. Finally, the speed of convergence, measured by the number of iteration rounds before the RE value stabilized was estimated.

4. Results and discussion

A univariate ANOVA was carried out to test the overall impact of auction features: auction designs (Design), economies of scale (scale), economies of scope (scope), proportion of high synergy bidders and degree of competition on three outcomes of an auction: AE, RE and Round. Where the overall impact of an auction feature on an outcome was significant, a least significant difference (LSD) t-test was carried out to find out the source(s) of differences. This allowed comparison of the results at various levels of data aggregation. Results are discussed in the following subsections starting with the results for test 1.

4.1. Results for test 1

Analysis of the main affects show that the level of complementarity (both scale and scope) in an auction has significant effects on the degree of rent extractions and number of rounds taken to make a final allocation (Table 3). On average, degree of rent extraction significantly increases with the increase in both economies of scale and economies of scope. On the other hand, auction speed significantly increases (declines) with increase (decline) in economies of scale (scope). The significant effect of the interaction term for auction design and level of complementarity (Design*Scale and Design*Scope) indicates that the effect of changes in level of complementary is different for different auction design. Therefore, the results were separated for individual auction designs.

For combinatorial auction, AE tended to increase with increase in economies of scale, although the trend is not significant (Table 4). On the other hand, there was no clear trend in the degree of rent extraction with the changes in economies of scale. It took fewer rounds to make final allocation for bidders with higher degree of economies of scale. For example, the number of rounds required to make a final allocation is reduced by 73% when the level of economies of scale changes from 0 to 0.5. In other words, performances of combinatorial auction in terms of auction speed improved with the increase in economies of scale.

For simultaneous auction, AE did not show any clear trend with the increase in economies of scale. However, the degree of rent extraction gradually increased with the increase in economies of scale. For example, RE estimate increased by 85% as the level of economies of scale changed from 0 to 1. This suggests that it is difficult for a simultaneous auction to make optimal allocation if bidders have larger economies of scale in their valuations of quotas. Similar to the combinatorial auction, the simultaneous auction also took less number of rounds to make a final allocation with the increase of economies of scale.

The effect of changes in economies of scope was more prominent on the performances of the auction designs. For combinatorial auctions, allocative efficiency (degree of rent extraction) increased (declined) with the increase in economies of scope. For example, AE (RE) estimates increased (declined) by 0.33% (15.38%) when the level of economies of scope increased from 0 to 1. Combinatorial auction design also took less number of rounds to make final allocation with the increase in economies of scope. On the contrary, the efficiency outcomes of simultaneous auction gradually declined with the increase in economies of scope. For example, AE (RE) estimates declined (increased) by 0.08% (95.78%) when the level of economies of scope increased from 0 to 1. Moreover, for simultaneous auction it took more rounds to make final allocation for bidders with higher level of economies of scope.

Overall, based on average estimates simultaneous auction achieved higher efficiency outcomes compared to combinatorial auctions across all complementarity scenarios. For example, average AE (RE) was 0.23% (60.19%) higher (lower) for simultaneous auction than combinatorial auction. However, simultaneous auction required more number of rounds to make final allocation. This might have some practical implications in real world auction. Moreover, RE estimates for individual high complementarity scenarios (such as, $\alpha_i = 1$ and $\beta_i = 1$) indicated that simultaneous auction allowed higher degree of profit to winning bidders (Fig. 1). Therefore, the auctioneer should be careful about level of complementarities or synergies in individual bidder's valuations.

4.2. Results for test 2

The second test studied the effect of increase in proportion of high synergy bidders for auctions with different degrees of competition.

Table 3
Univariate ANOVA statistics of different performance measures for test 1.

	AE		RE		Round	
	Type III Sum of Squares	Sig.	Type III Sum of Squares	Sig.	Type III Sum of Squares	Sig.
Corrected Model	0.013	***	1.430	***	334215	***
Intercept	1843.129	***	3.424	***	284395	***
Scale	0.001		0.139	***	132225	***
Scope	0.001		0.249	***	3039	**
Design	0.002	***	0.528	***	49178	***
Scale*Scope	0.002	*	0.034	***	1547	
Scale*Design	0.001		0.060	***	29975	***
Scope*Design	0.004	**	0.185	***	76440	***
Scale * Scope * Design	0.002	**	0.145	***	63102	***
Error	0.448		2.896		440828	
Total	1892.391		7.508		1072520	
Corrected Total	0.461		4.326		775044	
Adjusted R Squared	0.018		0.325		0.095	

Table 4
Means comparison of AE, RE and Round for auction designs and different levels of economies of scale and economies of scope for test 1.

Design		AE		RE		Round	
		Com	Sim	Com	Sim	Com	Sim
Scale	0.00	0.9953a	0.9991a	0.0556a	0.0056a	13.42a	29.84a
	0.50	0.9969a	0.9996a	0.0625a	0.0336b	4.11b	7.97b
	1.00	0.9977a	0.9982b	0.0616a	0.0384c	4.19b	9.77b
	Total	0.9966	0.9990	0.0599	0.0238	7.24	17.26
Scope	0.00	0.9940a	1.0000a	0.0559a	0.0017a	14.44a	8.80a
	0.50	0.9986b	0.9974b	0.0765b	0.0369b	2.98b	22.88b
	1.00	0.9973b	0.9992a	0.0473c	0.0403b	4.30b	22.91b
	Total	0.9966	0.9990	0.0599	0.0238	7.24	17.26

*Means in each column, followed by at least one letter in common are not significantly different at 5% probability level using LSD t test for individual auction feature.

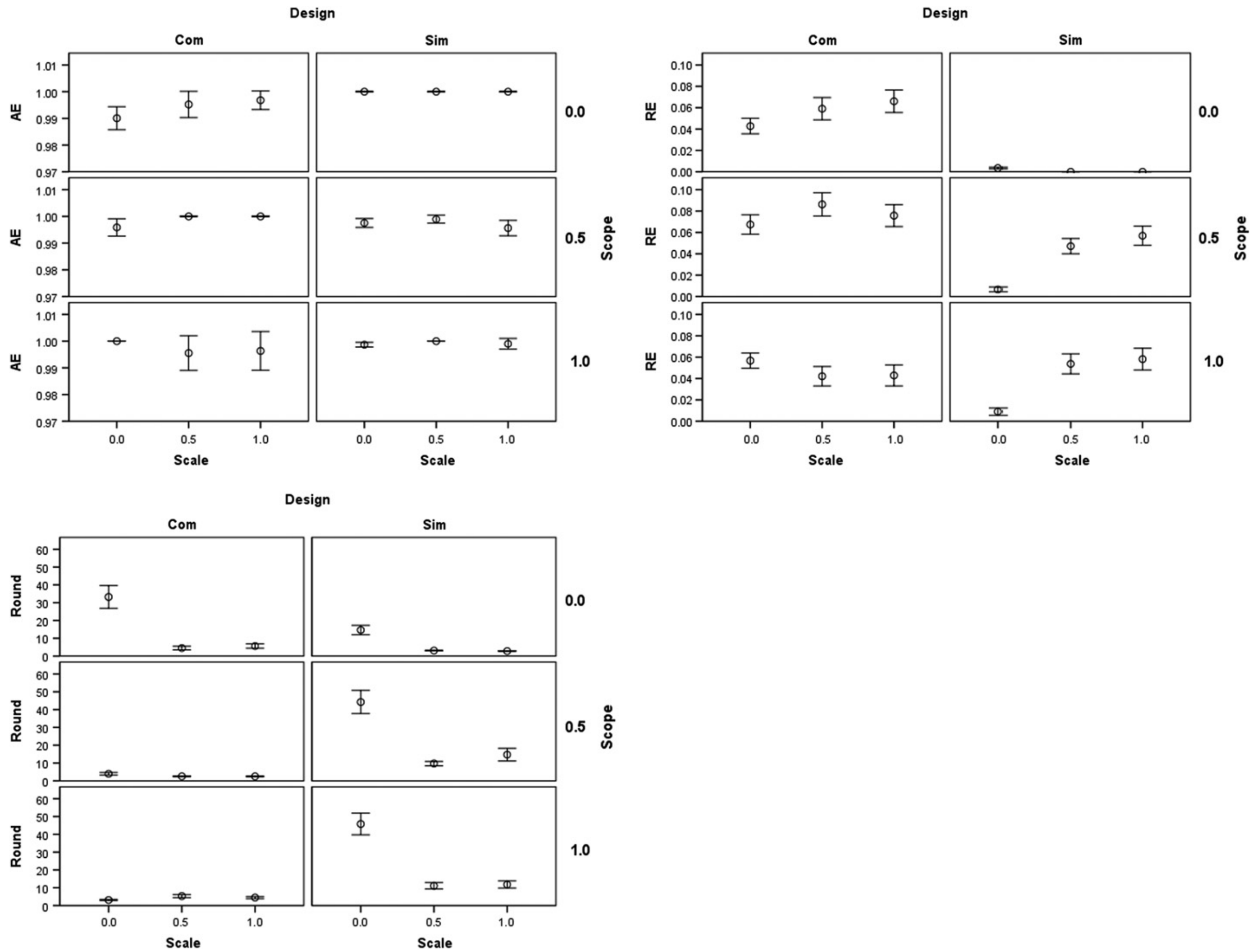

Fig. 1. Average auction outcomes (AE, RE and Round) achieved by the auction designs for individual synergy scenarios varying in economies of scale (scale) and economies of scope (scope) in test 1.

Table 5
Univariate ANOVA statistics of different performance measures for test 2.

	AE		RE		Round	
	Type III Sum of Squares	Sig.	Type III Sum of Squares	Sig.	Type III Sum of Squares	Sig.
Corrected Model	0.198	***	22.789	***	247956	***
Intercept	1972.183	***	42.195	***	418386	***
DR	0.035	***	2.162	***	22869	***
HS	0.013	***	14.100	***	88551	***
Design	0.091	***	3.239	***	305	
DR*HS	0.004		2.478	***	37277	***
DR*Design	0.038	***	0.099	***	1304	**
HS*Design	0.014	*	0.249	***	67626	***
DR*HS*Design	0.004		0.461	**	30024	***
Error	1.834		12.122		575481	
Total	1974.215		77.106		1241823	
Corrected Total	2.032		34.911		823437	
Adjusted R Squared	0.089		0.649		0.294	

Results from ANOVA analysis in Table 5 indicate that both the proportion of high synergy bidders and degree of competition in an auction have significant effects on auction performances (AE, RE and Round). However, the significant effects of the interaction terms for auction design, degree of competition and proportion of high synergy bidders (Design*DR, Design*HS and Design*HS*DR) indicate that the effect of changes in proportion of high synergy bidders are different for different auction design and for different degrees of competition. Therefore, the results for individual auction designs and level of competition are discussed separately.

For combinatorial auction, there is no clear trend in AE with the changes in proportion of high synergy bidders for auction

Table 6
Means comparison of AE, RE and Round for auction designs and different levels of economies of scale and economies of scope for test 2.

	Degree of competition			
	DR25		DR50	
Design	Com	Sim	Com	Sim
HS	AE			
HS0	0.988830a	1.000000a	0.968850a	1.000000a
HS25	0.997740b	1.000000a	0.981870a	0.999680a
HS50	0.994540a	0.999470a	0.968060a	1.000000a
HS75	0.996140b	0.998940a	0.985110b	1.000000a
HS100	0.996700b	0.999470a	0.985030b	1.000000a
Total	0.994790	0.999576	0.977784	0.999936
	RE			
HS0	0.045790a	0.002920a	0.110990a	0.005670a
HS25	0.360980b	0.208180b	0.312900b	0.226180b
HS50	0.135550c	0.074330c	0.320680b	0.280480c
HS75	0.095820d	0.057380d	0.207110c	0.081430d
HS100	0.089800d	0.052960d	0.175340d	0.060520e
Total	0.145588	0.079154	0.225404	0.130856
	Round			
HS0	35.09a	17.46a	30.61a	22.03ad
HS25	3.78b	7.31b	42.49b	14.46b
HS50	4.91c	11.71c	7.58c	7.26c
HS75	2.98d	12.61c	5.78c	18.05ab
HS100	2.66e	12.31c	4.85c	25.34ad
Total	9.88	12.28	18.26	17.43

*Means in each column, followed by at least one letter in common are not significantly different at 5% probability level using LSD t test for individual auction feature.

with strong competition (DR25). In low competition environment (DR50), allocative efficiency is lowest for scenario HS50. This is the scenario when high synergy bidders comprise half of the bidder population and they face least amount of competition from the remaining bidders. Allocative efficiency outcomes of the simultaneous auction are comparatively less affected by the changes in proportion of high synergy bidders.

On the other hand, the degree of rent extraction estimates show similar trends for both auction designs. For example, in high competition scenario (DR25) both auction designs have allowed highest proportion of rent for scenario HS25. This is the scenario where there are only two high synergy bidders who can purchase the entire allocation of quotas at higher profit. Similarly, in low competition scenario (DR50) the RE estimate is highest for scenario HS50. In this scenario, high synergy bidders face comparatively less competition (Table 6).

General efficiency improved when the degree of competition was strengthened. The observed trends on efficiency outcomes is probably due to the fact that with intense competition only a small subset of bidders can be winners; whereas, with a reduced competition level a larger subset of bidders, who can try to manipulate the market and extract more profit, are selected. Among the individual auction designs, average estimates of the performance indicators show that in both competition environments simultaneous auction has performed better than combinatorial auction.

5. Concluding remarks

This study explored the impact of the degree of complementarity (in terms of the economies of scale and the economies of scope) in an auction on the performance of selected simultaneous and iterative combinatorial auction designs. In the first test, a total of 9 simulations were undertaken for each design, considering three different levels of economies of scale and economies of scope. The simulation results showed that efficiency outcomes of the auction designs are affected differently by changes in level of complementarity. Efficiency outcomes of combinatorial auction gradually improve with the increase in both economies of scale and economies of scope. Conversely, the efficiency outcomes of simultaneous auction gradually decline with the increase in both economies of scale and economies of scope.

In the second test, a total of 10 simulations were undertaken for each design considering five different proportions of high synergy bidders and two different levels of competition. In general, both designs allowed higher degree of rent extraction when bidder population is heterogeneous and high synergy bidders are smaller proportion and face less competition. Overall, in both tests, simultaneous auction perform better than combinatorial auction, although it is sensitive to level of complementarity. From an organizational perspective, these results indicate that the auctioneer should be careful in selecting a suitable auction design since performances of the auction designs are highly dependent on the market structure, such as degree of competition, type of bidders participate in the auction and the nature of complementarities.

The policy implications of these findings are important. The results of this study suggest that when designing markets for ITQs, policy makers need to be cognitive of the level of complementarity in quota holdings and the level of competition for such quotas. The results of this study suggest that policy makers should undertake a study into the level of competition and synergy (in terms of economies of scope and scale) in the initial data collection phase of market design. The decision to introduce simultaneous or combinatorial markets should be based on the level of competition and complementarity in bidders' valuation. It is likely that immature ITQ markets will be thin and as a result, level of competition will be low. As markets grow, greater competition will potentially evolve and with it an understanding of more complex market designs. This suggests that in the first phase of market designs, policy makers may consider the use of simultaneous ITQ markets and then as the markets mature and grow, introduce combinatorial market designs if significant complementarities exist. Introducing combinatorial markets to fisheries where there is low competition and immature markets may not be the optimal policy choice.

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