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Sequential License Buyback Auctions: An Experimental Analysis

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Abstract *Fisheries managers use licenses as a method of capping the size of a fishing industry, but as management goals change and the size of fishery stocks fluctuate, managers may be faced with the decision to buy back licenses. The vast majority of economic literature on license buyback programs focuses on the changes to economic efficiency of the fleet, often citing changes to the composition of fleet size. However, managers have little guidance in deciding how to structure a buyback auction, despite the fact that the auction structure plays a key role in determining which licenses are retired and in the composition of the remaining fleet. With the Texas Park and Wildlife Department's Inshore Shrimp License Buyback Program as a basis for auction design, this research uses three experimental treatments to analyze how individuals respond to various reverse auction structures. In terms of the quickest license expiration, our experiments suggest that fisheries managers should select a binding auction with no sequential quality. However, we find that managers would see higher average bids from fishers in comparison to the two sequential auctions. The results are also relevant to other environmental programs in which environmental services are purchased over time in a sequential reverse auction.*

Key words Fisheries management, license buyback, reverse auction.

JEL Classification Codes Q22, Q28, C9.

Introduction

Fisheries managers use licenses as a method of capping the size of a fishing industry. But as management goals change and fishery stocks fluctuate, managers may be faced with the decision to buy back licenses. The vast majority of economic literature on license buyback programs focuses on the changes to economic efficiency of the fleet, often citing changes to the composition of fleet size. However, managers have little guidance in deciding how to structure a buyback auction. Using experimental methods, this article looks at one important part of a buyback program's design, the dynamic structure of bidding when multiple rounds are considered.

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As Holland, Gudmundsson, and Gates (1999) note, managers typically have one or more of the following goals in mind when considering vessel and license buyback programs: conservation of fish stocks, improvement of economic efficiency through fleet rationalization, and transfer payments to the fishing industry. The auction structure can play a key role in determining which licenses are retired, influencing the composition of the remaining fleet. Regardless of the managers' goal, the dynamic structure of the program will affect the extent to which those goals can be achieved.

Latacz-Lohmann and Van der Hamsvoort (1997) showed that reverse auctions can be a cost-effective way to achieve conservation goals. Along the same lines, Merrifield (1999) argues that government buyback programs should focus on the purchase of cheaper licenses, which should reflect less active fishers, before the purchase of expensive licenses, which should reflect more active and likely more efficient fishers. In practice, however, if a reverse auction occurs over several rounds, distortionary incentives are created that can induce bids that are above the reservation prices of the fishermen. Hence, by allowing fishermen to participate in successive rounds of bidding, the program may not achieve cost efficiency.

The motivating example for this article is the inshore shrimp license buyback program, administered by the Texas Parks and Wildlife Department (TPWD). The TPWD program has purchased "bay" and "bait" licenses from shrimp fishermen at least once each year since 1996. TPWD issues a request for bids, and interested fishermen submit the price that they would be willing to accept for their licenses to fish. Bids are scored by the agency based primarily on the price requested and the length of the vessel, and those bids that are relatively low are *granted*.[1] After being informed of the agency's decision, bidders are given the opportunity to *accept* the bid, meaning that their licenses could no longer be used for fishing in the inshore fisheries, or they can *reject* the bid, which means they can continue fishing and, possibly, submit a different bid in later years. In the first 14 rounds of the program, 1,207 licenses were retired at a cost of over $7.4 million (Woodward and Griffin 2008). The TPWD program has been studied in Funk *et al.* (2003), which used a simulation model to examine the effectiveness of the program. That work did not address the issue of "optimal" market design in terms of issues such as distribution impacts and relocation of retired inputs, especially taking into account strategic behavior of fishers.

The experiments presented here analyze two aspects of the bidding design used in the TPWD program: the sequential nature of the bidding process and the ability of participants to reject a bid that the agency has granted. As such, the treatments include a reverse auction with binding bids (where subjects do not have the option to accept or reject a bid); a sequential reverse auction with binding bids; and a sequential reverse auction with non-binding bids (where subjects have the option to accept or reject a bid). The experiments are used to test three hypotheses related to the design of reverse auction programs: (A) We hypothesize that in the sequential non-binding auction, we will observe low bids from individuals initially, as they learn about the values of accepted bids, and that those bids will increase over time as individuals attempt to earn greater gains in later auctions. (B) We also hypothesize that average initial bids will be highest in the two binding auctions, but that (C) Buyback of licenses will still take the longest in the non-binding auction, as individuals reject purchase offers in hopes of greater gains in a later auction. Hypothesis B can be satisfied in two ways: *i)* if there is a higher average initial bid in the binding auction than in the two sequential auctions as a result of the anticipated learning process and *ii)* if there is a higher average initial bid in the sequential binding auction than in the sequential non-binding auction, since a strategy for binding bids would be to decrease if denied by the experimenter. These questions are relevant not only to the TPWD program, but in many other reverse-auction programs that are designed to reduce pressure on the

[1] Although TPWD does not disclose the exact formula used for scoring, it is known that bids are scored such that if two vessels submit the same bid, the longer vessel's bid is more likely to be accepted.

environment or natural resources through multiple rounds of bidding, sometimes with no set terminal date. Some of the areas in which reverse-auction programs have been utilized and studied include land conservation (*e.g.*, Connor, Ward, and Bryan 2008; Schilizzi and Latacz-Lohmann 2007); irrigation reduction (*e.g.*, Cummings, Holt, and Laury 2004); and dairy termination (*e.g.*, Dixon, Susanto, and Berry 1991).

Literature Review

Fisheries Buyback Programs

License and vessel buyback programs have been used in many fisheries throughout the world with varying degrees of success (Curtis and Squires 2007). While such programs can be used to achieve a range of management objectives, from increasing economic efficiency to providing disaster relief, such programs also face a number of challenges as enumerated by Groves and Squires (2007). First, such programs often face problems that arise due to informational asymmetry. The consequence is that the retired vessels tend to be those that are already harvesting the fewest fish (adverse selection). Problems of moral hazard can also arise if vessel owners choose to remain in an otherwise unprofitable fishery in order to reap the benefits of a buyback, or even enter into a fishery in the hopes that they will eventually be paid to exit (Clark, Munro, and Sumaila 2005). Buybacks can also be less efficient than desired if the remaining license holders increase their effort, offsetting the gains that were achieved by the reduction in effort. An additional problem arises when it is the license that is retired rather than the vessel itself, since the vessel can then be used to exploit other related fisheries, causing a shift in effort rather than a reduction.

All of the above challenges are well known in the literature, and programs have taken steps to mitigate the problems that can arise. For example, licenses in the TPWD program are tied to a specific length, and when an owner replaces his or her vessel, there are limits on the extent to which the length can increase. Other characteristics of the vessel, such as hull type and horsepower, however, are not restricted, so those inputs can expand leading to effort creep in the fishery (Wilen 1979). In some programs, fishers who sell their licenses are allowed to re-enter the fishery through purchase of an existing license. While this prevents the total number of fishers from increasing, it may not achieve the desired affect of reducing capacity in the fishery (Holland, Gudmundsson, and Gates 1999). For example, in the New England groundfish fishery, an operator may sell his license and then buy an inactive license in order to reenter the fishery (Groves and Squires 2007, p. 23). This becomes an important factor to consider, as the goal of several NOAA Fisheries buyback programs has been to reduce industry capacity as much as possible with the provided budget (Kirkley, Walden, and Waters 2004). Even with use of weighting criteria, the incentive to the industry of post-buyback investments can undo some of the program's achievements (Weninger and McConnell 2000).

Groves and Squires provide a careful review of the numerous design issues that must be addressed when a reverse auction is used in a buyback program, including the type of auction used (first or second price, open call, or sealed bid), the information available to bidders, and the question of how bids should be scored. They also discuss the advantages and disadvantages of carrying out the program in multiple rounds, which is our primary focus here.

Although there has been a dramatic expansion in the theoretical and empirical analyses of auctions in the last decade, that literature provides little guidance with regard to the multiple-rounds question that we consider here. The basic theoretical models of auctions (*e.g.*, McAfee and McMillan 1987) are for single-unit auctions and, almost always, single-round auctions. In these cases, theory provides strong results, providing the foundation for econometric analysis (*e.g.*, Guerre, Perrigne, and Vuong 2000), and the lessons have been applied for use in numerous auctions (*e.g.*, Whitford 2007; Klemperer 2004).

In contrast, the theoretical foundation for sequential auctions is not as robust. Krishna (2002, ch. 15), for example, develops a theoretical model for sequential auctions, but under the assumptions necessary to obtain his analytical results, he finds that bids in any round of the auction should be independent of prices in previous rounds, a result that is inconsistent with earlier work (Oren and Rothkopf 1975) and with the available evidence in the TPWD auction (Mamula *et al.* 2007). The use of experimental methods in this case, therefore, is particularly valuable.

Analytical Framework

Our hypotheses build upon the optimization problems that a bidder in these auctions faces. Utilizing the format of McAfee and McMillan (1987), the objective of a bidder is to develop a bidding strategy that maximizes expected payoffs. In the case of a non-sequential auction, such a bidder solves the problem:

$$V = \max_b \pi(b)\, b + \left(1 - \pi(b)\right) R, \tag{1}$$

where R is the return associated with retaining the asset for a single period, π (b) is the subjective probability that the bid is accepted, and V is the value function. In the sequential auction[2] with binding bids, a bidder must solve:

$$\begin{aligned} V_t &= \max_b \pi_t(b) b + \left(1 - \pi_t(b)\right)\left[\left(1 - p_t\right)\left(R + V_{t+1}\right) + p_t R\left(T - t\right)\right] \\ V_T &= \max_b \pi_T(b) b + \left(1 - \pi_T(b)\right) R, \end{aligned} \tag{2}$$

where p_t is the probability that the auction is discontinued in round t. There is now a subscript on π since the setup can change from one period to the next as bidders update their beliefs and the number of licenses still held by other bidders changes. In the last term in the V_t equation, R is multiplied by (T−t) since it is assumed that even if the program ends, a bidder whose license has not expired will be able to earn R per period until the end of the planning horizon. The potential for updating probabilities builds upon Jeitschko's (1998) model of a sequential auction wherein bidders may update their beliefs about the valuation type of their opponents. In the sequential binding auction, the terminal problem would be identical to that in the non-sequential auction but for the opportunity of participants to update their beliefs.

In the sequential auction with non-binding bids, a bidder must solve:

$$\begin{aligned} V_t = \max_{b \in \mathbb{R}, A \in \{0,1\}} & \pi_t(b)\left\{A \cdot b + (1 - A)\left[\left(1 - p_t\right)\left(R + V_{t+1}\right) + p_t R\left(T - t\right)\right]\right\} \\ & + \left(1 - \pi_t(b)\right)\left[\left(1 - p_t\right)\left(R + V_{t+1}\right) + p_t R\left(T - t\right)\right], \end{aligned} \tag{3}$$

where a participant accepts (A=1) or rejects (A=0) a bid after it has been granted by the experimenter. By not being bound by a bid, a participant may choose to initially bid lower than he or she would in the binding sequential auction and in, by extension, the non-sequential auction. Equation (3) can be rewritten:

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[2] As discounting is not explicitly introduced into the sequential experimental treatments, it is not included in these equations; yet we acknowledge the role it would play in field settings.

$$V_t = \max_{b \in \mathbb{R}^+, A \in \{0,1\}} \pi_t(b) A \cdot b + (1 - \pi_t(b) A)\left[(1-p)(R + V_{t+1}) + pR\right],$$

with terminal period problem ($p_T = 1$):

$$V_T = \max_{b,\, A \in \{0,1\}} \pi_T(b) Ab + \left[(1 - \pi_T(b) A)\right] R.$$

Since we do not have information on an individual's subjective probability that a bid is accepted, especially with the assumption that it is changing over time, nor on an individual's attitude towards risk, a clean solution for optimal bidding strategy is unlikely. Still, the results of these experiments may provide support for intuitive assumptions about a bidder's behavior under various buyback mechanisms, and the results of this study will have implications for auction design, particularly in cases where managers would like to purchase licenses as quickly as possible at the lowest possible price.

Experimental Procedure

In order to test our hypotheses, a controlled laboratory experiment is used in which subjects play the role of fishers in a license buyback auction. In this role, subjects may submit bids to the experimenter in order to sell a license. Individual profit is determined by the sale of a license plus the earnings from utilizing an unsold license. The experiment is designed so that subjects have the incentive to maximize their returns, either from holding their licenses or selling them in the auction. Since these experiments are not attempting to capture differences stemming from risk-averse behavior, subjects are not provided a personal budget or any form of income other than the licenses.[3]

Three treatments are used in this experiment. The first treatment, referred to in this article as the *individual binding treatment*, has five rounds of a reverse auction. In these rounds, subjects have only one license on which to submit a bid to the experimenter. A distinctive feature of this treatment is that, at the beginning of the next round, the subjects' license inventory is reset, so sales in one round do not have any implications for the availability of licenses to sell in the next round. In this and all other treatments, the marginal value of each license is drawn from a distribution so that the value of each participant's license may be different. Once all bids are collected, the experimenter ranks the bids from lowest to highest and buys as many licenses as his[4] budget allows. In doing so, the experimenter conducts a discriminatory price auction. In the case of a tied bid, the experimenter randomly chooses one bid to grant. Subjects are then notified whether their bids were granted or denied, and the next round begins; no other information on accepted bid prices is available to the subjects. Each subject's profit from utilizing a license changes randomly from round to round to reduce the ability to gather expectation on a particular license's value. While the participants are told that all bidders are drawn from the same distribution, they do not know the values of the other bidders' vessels. In this treatment the experimenter's budget remains the same from round to round, but subjects are simply notified that the experimenter's budget will fall within a range of \$400 to \$600. This reflects a situation in which fishers in a buyback auction would not know the agency's budget exactly, but would have an expectation of the range for the budget.

[3] This obviously suppresses factors that may be important in "real world" auctions. However, it allows the experiments to focus more directly on the sequential auction issues, which are the focus of this research.
[4] A masculine pronoun will indicate the experimenter; a feminine pronoun will indicate the subject.

In such a case, a fisher may try to estimate the auction budget through knowledge of one's own license value and the number of licenses to be bought back. A subject is also not informed of the other subjects' license values, reflecting that fishers do not know with absolute certainty the value that another fisher places on her license. As has been shown experimentally, the information available to bidders can have important consequences for the efficiency of an auction (*e.g.*, Kagel and Levin 1986). In this case, the information provided to participants is comparable to that available to participants in the TPWD program.

The second treatment, referred to in this article as the *sequential binding treatment*, has from four to ten rounds of a reverse sequential auction. In these rounds, each subject has three licenses on which to submit a bid to the experimenter. Subjects may only submit a bid for their lowest-valued license in each round; this corresponds to the idea that fishers would use their lowest-valued license to learn about the auction process and gather information on a price that the agency is willing to pay before they submit bids on their higher valued licenses.[5] Unlike the individual binding treatment, subjects' license inventory in the next round is dependent on the experimenter's decision to grant or deny a bid in the current round. If a subject sells all three of her licenses before the end of the experiment, she submits a blank bid sheet to the experimenter, so that other subjects do not gain information on the number of licenses remaining in the auction. After notifying subjects whether their bids were granted or denied at the end of the fourth round, the experimenter rolls a die. If an odd number is rolled, another auction round is held, and a die is rolled again at the end of that auction. If an even number is rolled or it is the end of the tenth round, no more auctions are held. This design is used to reflect that, if a buyback auction is not a one-time instance, fishers can expect a certain number of auctions, after which there is a risk that a subsequent auction will not occur. In the buyback program used by the TPWD, the use of sequential auctions implies at least two auctions for fishers, but the exact number of auctions, or even licenses to be bought back, is not specified in the program.

As in the individual binding treatment, subjects are informed of a range in which the budget falls, although the initial budget is, in fact, the same across all experiments of this treatment. In this case, subjects are informed that the budget falls within a range of $4,000 to $6,000 in round 1. However, in the sequential treatment a license's intrinsic value is equal to a constant amount that can be earned in the current period and all future periods.[6] Hence, as the number of periods proceeds, the value of each license declines over time. If the treatment ends before round 10 with the roll of the die, a subject still earns monies from utilizing the license through round 10, capturing the ability of a fisherman to still utilize an unsold license even if no more government auctions occur. Tables 1 and 2 show how changes occur over rounds in the budget and in the minimum potential value of one license; subjects are provided with a form of table 2, individualized to their own licenses, to use in the experiment. For example, at the start of round 1 a license generating $70 per period would have an intrinsic value of $700, while by the start of round 6 this falls by 50% to $350. Since the value of licenses falls over time, the budget available to the experimenter to purchase licenses in each period is also reduced linearly over time so that a similar number of licenses is purchased in each round (table 1).

[5] Although fishers in the Texas inshore shrimp fishery may submit a bid for each license held during an auction, this simplification for the experimental design allows observation of a potential learning process. In the case of such a process, fishers would likely submit bids on their least-valued license, as that bid has the greatest likelihood of being granted.

[6] The assumption that the return is constant is a reasonable abstraction as long as the buyback program does not affect market prices. This is certainly a reasonable assumption for the TPWD program, since the Texas shrimp market is very small relative to the national and international markets that drive prices.

Table 1
Budget in Sequential Treatments

Round	1	2	3	4	5	6	7	8	9	10
Budget ($)	4,800	4,320	3,840	3,360	2,880	2,400	1,920	1,440	960	480

Table 2
Minimum Potential License Value in Sequential Binding Treatment

Round	1	2	3	4	5	6	7	8	9	10
License 1 ($)	70	70	70	70	70	70	70	70	70	70
Total Value ($)	700	630	560	490	420	350	280	210	140	70

The third treatment, referred to in this article as the *sequential non-binding treatment*, is identical to the sequential binding treatment, except that subjects may reject the experimenter's offer to buy a license. That is, once the experimenter notifies the subjects if their bids were granted or denied, any subject with a granted bid must then decide whether to go through with the sale by accepting or rejecting the experimenter's purchase offer.[7] All subjects return the offer sheet to the experimenter, even if their bid was denied by the experimenter, so subjects do not gain information on the number of licenses sold. Such non-binding rules are used in TPWD's buyback program.

Each experimental session is comprised of the individual binding treatment and either the sequential binding treatment or the sequential non-binding treatment. This results in each session having in the range of nine to fifteen auction rounds, depending on what round the sequential treatments end. For an experimental session, student subjects[8] were recruited—by email and through in-class signups—to appear at an appointed time at the Policy Simulation Laboratory, located at the University of Rhode Island. They were told they would receive a five-dollar participation fee and would have the "opportunity to earn considerably more" during the experiment. If there were more than the needed 10 subjects, then extra subjects were randomly selected, paid their participation fee, and dismissed. After reading consent forms, subjects were shown into the laboratory and seated at individual terminals, with barriers to discourage talking and impair visibility of others' materials. The experimenter then read aloud the instructions (available from authors) as subjects followed along on their instruction handout, explained how to use the bid forms and read the license value forms, and led subjects through a practice round. In the practice round, subjects were provided a license and were able to submit a bid to the experimenter. After answering any questions, the experimenter began the individual binding treatment.

[7] To avoid confusion, the words "grant" and "deny" are used to refer to the experimenter's decisions. The words "accept" or "reject" refer to the decisions by the subjects.

[8] In principle, use of students in experiments over individuals with 'specialized knowledge' should not vary in certain types of experiments, given proper training and sufficient monetary incentives to perform well in an experimental market. In this case, we are testing the fundamentals of auction types. We included some comparison to field results from the Texas buyback program to highlight similarities, despite the experiment not being parameterized to parallel that particular program. In several instances, experimental data using college students has been compared to data using 'professionals.' Generally, very small differences are found. Because the structure of the experiment is relatively simple and the financial calculations are not very complex, we are comfortable with using our results to infer something about the design of license buyback auctions.

Next, the experimenter read instructions explaining the sequential treatment (either binding or non-binding) as subjects followed along on their own instruction handout, and subjects participated in another practice round before beginning the sequential treatment of the experiment. The two practice rounds were identical to the subsequent rounds, but without financial implications. Following the experiment, subjects' earnings, *i.e.*, profit from license sales and from utilizing unsold licenses, were converted to US dollars, and they were paid as they left the lab. For the sessions containing the sequential binding treatment, earnings averaged $19.00 with a standard deviation of $5.82 (range of $5.00 to $35.00). For sessions containing the sequential non-binding treatment, earnings averaged $17.87 with a standard deviation of $5.66 (range of $5.00 to $32.00). Sessions lasted approximately one hour and 45 minutes each. Six sessions containing the sequential binding treatment were run, and five sessions containing the sequential non-binding treatment were run. A total of 110 participants were used.

Results

The findings of this experiment are separated into three sections. In the first section, the bid-to-license value percentage is examined. The data indicate that individuals in the binding treatment make the highest bids with regards to the license value. Relative to the licenses' intrinsic value, individuals in the two sequential treatments make similar bids, on average. In the second section, the sequential non-binding treatment is examined in more detail. Less than 25% of purchase offers from the experimenter are rejected, and almost 50% of those licenses are eventually sold for prices equal to or greater than 120% of the license value. The third section examines the number of licenses purchased. The data indicate that individuals are constrained only by the experimenter's budget in selling licenses in both the binding and sequential binding treatment. Individuals in the sequential non-binding treatment are not affected by that budget constraint until later rounds, as they choose to reject purchase offers from the experimenter in initial rounds.

Bid-to-License Value Percentage

Figure 1 displays as a percentage the bids relative to the licenses' value in the three treatments. All bids are used in the analysis, not just accepted offers. The trend of all bids over time can play an important role in auction design for fisheries managers. The most noticeable change across rounds occurs in the binding treatment, where the percentage shows a significant decline. This trend, however, is probably due to experience the subjects gain in submitting competitive bids, since the average value of the licenses does not change over time and there is no strategic reason for the bids to fall. For the sequential treatments, the starting values are quite similar, between 112 and 115% of the licenses' values, almost equal to the final average value in the binding treatment. For the first four rounds of the sequential treatments, the binding and non-binding treatments followed the same path almost exactly. After that, the sequential binding treatment declined slightly to 105% of the licenses' values, while the average ratio for the nonbinding treatment increased to over 115% by the end of the seventh round. However, the statistical significance of this divergence is quite weak due to the fact that the number of observations in the later rounds declines substantially as the buyback program was brought to a close with the roll of a die.

In figure 2, the standard deviation of the observations from figure 1 is shown.[9] The standard deviation is calculated by calculating the bid-to-value ratio, expressed as a per-

[9] Figure 2 does not present rounds 6 and 7, as only one session exists for each of the two sequential treatments and no sessions exist for the binding treatment.

centage, for each subject, and then calculating the standard deviation of these ratios for each round. Each of the three treatments shows slight variability in the standard deviation, but none consistently has the lowest or highest standard deviation. There is no strong trend in the variability over time.

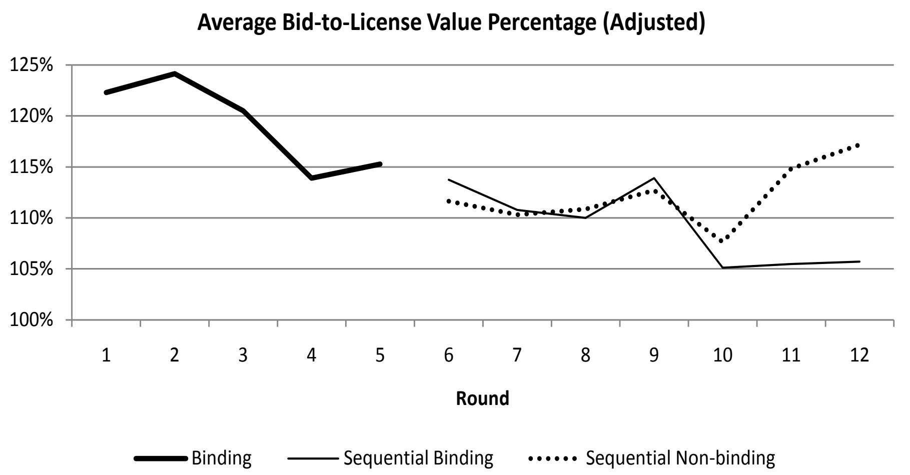

Figure 1. Average Bid-to-License Value as a Percentage

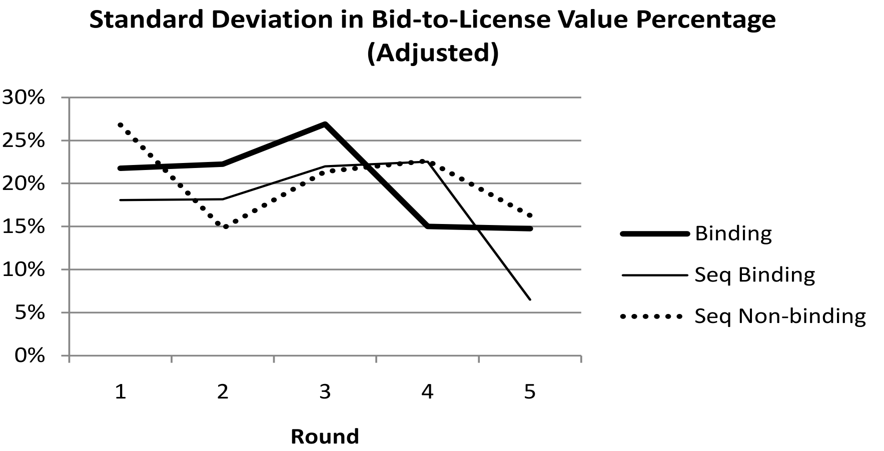

Figure 2. Standard Deviation in Bid-to-License Value Percentage

The graphical evidence provides little support for hypothesis B, that bids in early rounds will be higher in the binding auctions. To evaluate this hypothesis more rigorously, we run two regressions using round as the independent variable and the bid-to-license ratio (expressed as a percentage) as the dependent variable for the three auction treatments. We use a censored Tobit model with a lower bound of zero. The first results are presented in table 3, in which the simplest model is presented, with one regression for each of the three treatments. Notably, in terms of highest to lowest bid-to-license value, the constant term ranks the auctions in the following order: binding treatment, sequential binding treatment, and sequential non-binding treatment. This provides support to the first part of hypothesis A: In the sequential non-binding treatment, low bids are observed initially, as individuals learn about the values of accepted bids. Also of note is that the coefficient on round is significantly negative for binding treatment, less than zero (but only significant at the 16% level) for the sequential binding treatment, and positive but not significantly different from zero for the sequential non-binding treatment. As noted above, the results from the binding round may be biased by the learning that has occurred and are not strictly comparable with the sequential treatments. However, the results definitely suggest constant bids for the sequential non-binding treatment and are not consistent with the last part of hypothesis A: that in the sequential non-binding treatment, bids will increase over time as individuals attempt to earn greater gains in later auctions.

Table 3
Model of Bids-to-License Values

	Treatment 1 Binding N=542	Treatment 2 Sequential Binding N=266	Treatment 3 Sequential Non-binding N=226
Constant	125.70 [0.0000]*	114.25 [0.0000]	109.95 [0.0000]
Round	–2.27 [0.0003]	–1.02 [0.1625]	0.26 [0.7833]

* *p* values are in brackets.

In our second set of regressions, shown in table 4, we incorporate dummy variables so that two treatments could be compared. The bid-to-license value percentage is still used as the dependent variable. In addition to the constant term, three independent variables are used: round, a dummy variable representing one of the two auctions in the regression, and round multiplied by the dummy variable. As expected, given the learning that appears to have taken place in the binding treatment in the two regressions with the binding treatment as the base case (A and B), the dummy variables are negative and statistically significant, indicating the binding treatment has a higher initial bid than both the sequential binding and the sequential non-binding treatments. In the regression with the sequential binding treatment as the base (C), the dummy variable is negative, though not significant at the 10% level, which may suggest that the sequential binding treatment has a higher initial bid than the sequential non-binding treatment.

The only interaction term that is statistically significant in table 4 is in regression A, where the binding and sequential non-binding treatments are compared. Bids in the sequential non-binding treatment do not tend to decline over time, while those in the individual binding treatment do. Regression C provides some evidence, though not statistically significant, that the bids in the sequential binding treatment decline on a path that differs from the non-binding treatment, which is weak support for hypothesis B. While the addition of a sequential component alone does not alter the bid path with statistical significance, the addition of both a sequential component and the incentive to reject a purchase offer alters the path with statistical significance.

Table 4
Regressions Comparing Treatments using Dummy Variables and Interaction Terms*

	A	B	C
Base treatment	Binding	Binding	Sequential Binding
Alternate treatment	Sequential Non-binding N=768	Sequential Binding N=808	Sequential Non-binding N=492
Constant	125.70 (2.15) [0.0000]	125.70 (2.03) [0.0000]	114.25 (2.71) [0.0000]
Dummy (for alternate treatment)	–15.75 (3.71) [0.0000]	–11.45 (3.30) [0.0006]	–4.30 (4.01) [0.28]
Round	–2.27 (0.65) [0.0005]	–2.27 (0.61) [0.0002]	–1.02 (0.81) [0.2065]
Interaction term on round (for alternate treatment)	2.53 (1.11) [0.0222]	1.25 (0.99) [0.2082]	1.29 (1.19) [0.2814]

* Standard errors are in parentheses; *p* values are in brackets.

To further evaluate hypothesis B that average initial bids will be highest in the two binding auctions, we employ a Bayesian Markov Chain Monte Carlo (MCMC) approach. A Bayesian linear model is developed using: *i)* the likelihood function from the linear regression (table 3) with normally distributed errors and *ii)* a diffuse normal prior probability density function with mean centered at zero. The Bayesian approach allows a great deal of flexibility in relating complex relationship of parameters. In this case, the marginal posterior probability distributions are generated from the difference of the treatment effect parameters in order to assess the probability that these differences are different from zero. This Bayesian linear model was run in WinBUGS, drawing 100,000 posterior samples with a burn-in of 5,000 samples[10] to allow for the MCMC process to converge to the true posterior distribution. Figure 3 shows the marginal posterior probability distributions for the three differences of the treatment parameters that were compared.[11] Three βs are sampled, corresponding to the constant terms for the regression for each treatment, and each β is the added effect a particular treatment has on the average initial bid, such that β_b, β_{sb}, and β_{snb} denote the effects of binding, sequential binding, and non-binding treatments. Table 5 shows the numerical results of the posterior probability density function. Although the two sequential treatments have the smallest difference in average initial bids, hypothesis B is supported in that the 95% confidence interval does not include zero, supporting the hypothesis that the binding treatments result in a higher initial bid than the non-binding treatment.

[10] A burn-in of 5,000 iterations is used "to eliminate the influence of the starting value" of draws from the population (Greene 2003, p. 446). The draws are made by MCMC sampling.
[11] In figure 3, β_b is the effect of the individual binding treatment on the bid, β_{sb} is the effect of the sequential biding treatment, and β_{snb} is the effect of the sequential non-binding treatment.

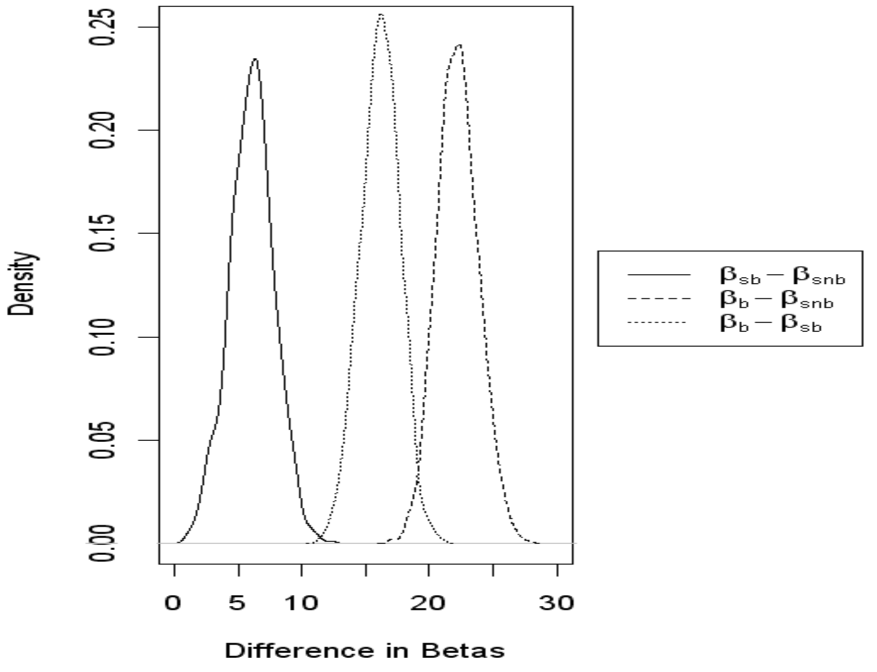

Figure 3. Probability Density Function for the Difference in Treatment Betas

Table 5
Statistical Summary for the Difference in Treatment Betas*

	$\beta_b - \beta_{snb}$	$\beta_b - \beta_{sb}$	$\beta_{sb} - \beta_{snb}$
Mean	22.6	16.2	6.1
Standard deviation	1.6	1.5	1.8
95% central credible interval	(19.2, 25.5)	(13.1, 19.0)	(2.6, 9.5)

* β_b is the effect of the individual binding treatment on the bid, β_{sb} is the effect of the sequential biding treatment, and β_{snb} is the effect of the sequential non-binding treatment.

Support of hypothesis B has important policy implications. Since lower average initial bids occur in the non-binding treatment, if those bids are accepted by the fishermen, fisheries managers would expect a higher license return per dollar spent in the auction. Figure 4[12] is essentially the inverse of figure 1, but now represents the return per dollar spent in each of the three experimental treatments. The sequential binding treatment has the highest return in most rounds, whereas the binding treatment has the lowest return. Both treatments exhibit a trend for higher license returns over time, which corresponds with table 3 that the average bid-to-license ratio decreases over time. In the sequential non-binding treatment, a notable amount of fluctuation occurs in the license returns; this is likely the result of subjects exploring the range of prices for granted bids before proceeding with a sale.

[12] Rounds 6 and 7 are not displayed, as only one session exists for each of the two sequential treatments, and no sessions exist for the binding treatment.

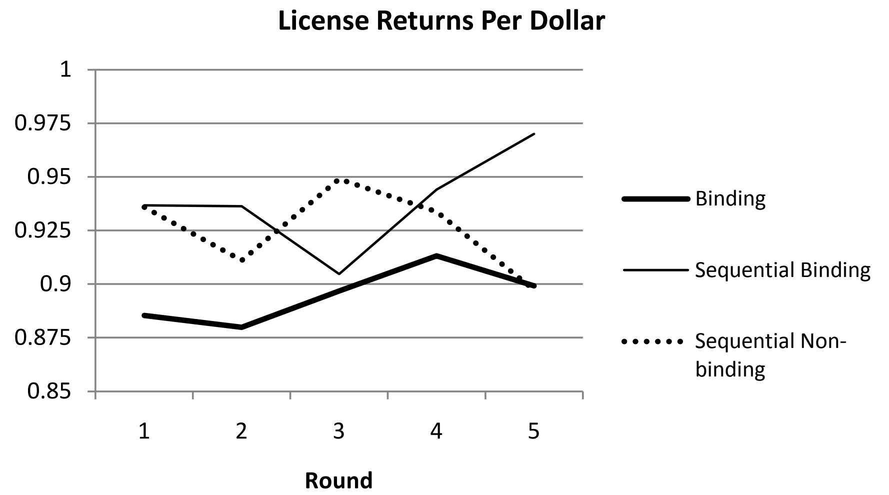

Figure 4. License Returns Per Dollar Spent in Treatment Auctions

Sequential Non-binding Treatment

In this section, data solely from the sequential non-binding treatment are examined for trends resulting from subjects' ability to reject purchase offers from the experimenter. In figure 5, the number of rejections for a specific license is displayed. Of the 64 bids that were granted by the experimenter, 49 were then accepted by the bidder, leaving slightly less than 25% of purchase offers rejected by the subjects. This experimental finding is consistent with the relatively uncommon rejection of purchase offers in the Texas Program (Mamula *et al.* 2007). An almost equal number of purchase offers were rejected by subjects once and twice. The implication of this for government license buyback programs relates to the time required to obtain a specific number of licenses from the industry. Not only are some subjects deferring buyback payments once, an equal number of subjects choose to defer payments twice for the same license.

Figure 5. Number of Offers Rejected by Bidder

Figure 6 displays the percentage increase in license price that was achieved by the 11 bidders who initially rejected a granted bid. Sessions ended before four licenses could be purchased by the experimenter, so only eleven observations are recorded. Of those eleven, a less than 20% increase from the initial rejected purchase offer, in terms of bid to license value, is observed in the sale of nine licenses. These returns are lower than those reported for the Texas Program (Mamula *et al.* 2007), where the majority were sold for more than a 20% gain. However, the experimental setting probably leads to a higher discount rate than would likely be seen in the field and may promote less aggressive bidding from subjects, since the odds of another auction are smaller. Figure 7 displays the returns from accepted purchase offers in comparison to the license value for those same 11 observations. Excluding the three cases that did not make a positive return, five of the remaining eight subjects had gains equal to or greater than 20% of the license value, closer to the results found in Texas (Mamula *et al.* 2007).

Figure 6. Returns to Bidder in Accepted Offer Over Rejected Offer

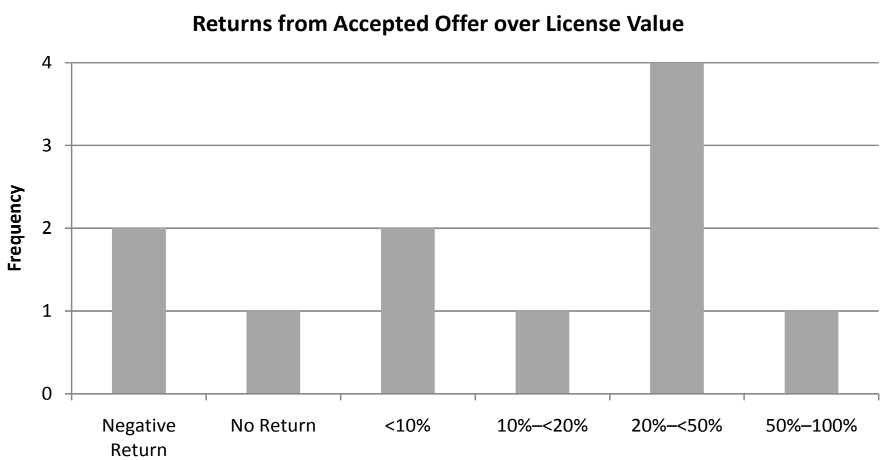

Figure 7. Returns to Bidder on Accepted Offer in Relation to License Value

Licenses Purchased

Figure 8 shows the percentage of licenses purchased in each round of the binding, sequential binding, and sequential non-binding treatments. The binding treatment has two data sets graphed: one data set with 10 licenses available to purchase and a scaled data set with 30 licenses, as this corresponds to the number in the two sequential treatments. While a perfect comparison cannot be made to the sequential treatments, general statements may still be made with regards to the binding treatment. In the first round, the experimenter purchased a similar number of licenses in the sequential binding treatment and in the binding scaled data set. It is not until the fourth round for the sequential binding treatment and the fifth round for the sequential non-binding treatment that a similar number of licenses are purchased as in the binding data set.

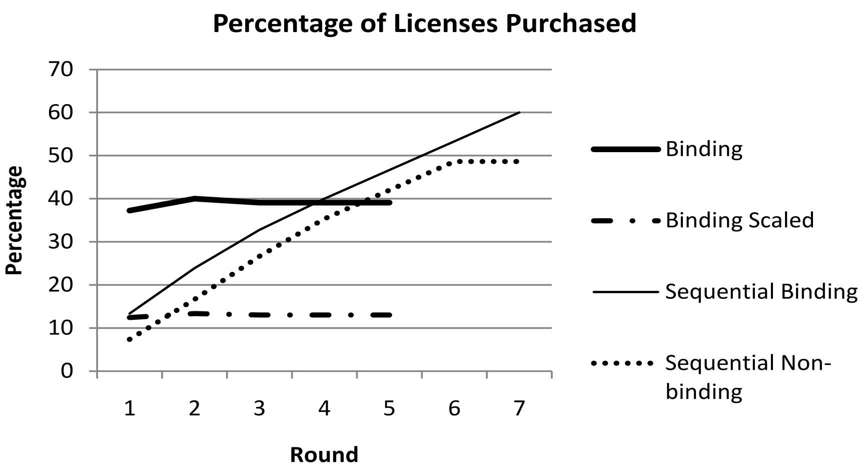

Figure 8. Percentage of Licenses Purchased in Treatments

One contrast of note is between the two sequential treatments. Although the percentages of licenses purchased increase in a parallel fashion, the sequential non-binding treatment has a roughly one round lag relative to the sequential binding treatment. This lag is a result of subjects' choice to reject the experimenter's purchase offer in the initial rounds and to accept the experimenter's purchase offer in later rounds. Depending on the time between auctions held by fisheries managers, this lag may hold a significant role in stock recovery. The sequential non-binding treatment also lags behind the scaled binding data set in the same fashion as it does with the sequential binding treatment, such that both binding treatments buy back licenses at a faster rate. As such, the data from the three treatments supports hypothesis C, that buyback of licenses will take the longest in the non-binding auction.

Discussion

Despite the ability of buyback programs to reduce fishing pressure, questions of how various auction structures affect payments remain unanswered. This article examines three auction designs and tests three hypotheses related to the design of reverse auction programs. As this research has found, the auction structure selected by fisheries managers has an effect not only on the payments to fishers (and therein, the amount of government budget spent) but also on the rate at which licenses are retired from the industry.

Our first hypothesis (A) is that in the sequential non-binding treatment, low bids will be observed initially and will then increase over time. As seen in the regression results in table 3, the sequential non-binding treatment has, with statistical significance, the lowest initial bids of the three treatments; so support exists that low bids are observed initially in the sequential non-binding treatment. Interestingly, we find bids declining over time in the two binding treatments and increasing in the non-binding treatment, though most of these results are not statistically significant. While 20% of the subjects take advantage of the non-binding auction to increase their returns over the previously rejected bid, their returns are not increased by a large percentage. As a result, we do not find support for the hypothesis that bids will increase over time in the sequential non-binding treatment.

Hypothesis B is that higher average initial bids will occur in the two binding treatments than in the sequential non-binding treatment. By running a series of regressions with dummy variables, we find that the highest average initial bid will occur in the individual binding treatment, the second highest average initial bid will occur in the sequential binding treatment, and the lowest initial bid will occur in the sequential non-binding treatment. These results are confirmed by the posterior probability density function, as the data in table 5 display a statistical difference in the effect of the three treatments on the average initial bids. Therefore, we do find support for hypothesis B, which has implications for the license returns per dollar spent in auctions.

Finally, hypothesis C relates to the length of time it will take to buy back licenses. As seen in figure 8, a comparable percentage of licenses may be purchased in both the binding treatment and sequential binding treatment, but a lower percentage of licenses will be purchased in the sequential non-binding treatment. The difference arises because of the ability of bidders to reject a purchase offer. The rationale for an individual choosing to reject a purchase offer is to potentially have greater returns in a later auction. As a result, hypothesis C is supported in that buyback of licenses will take the longest in the non-binding auction, as individuals reject purchase offers in hopes of greater gains in a later auction.

Together, these results suggest that the design of a buyback program will vary depending on the goals and constraints of the fisheries management agency implementing the program. If the goal of fisheries managers is to retire licenses as quickly as possible, they should select the binding auction with no sequential component. However, our results suggest that this would result in higher average bids from fishers (relative to the licenses' underlying value). This may be an ideal design choice if conservation of fish stocks is a major driver in license buyback, but the buyback program would need to be well funded to account for the high bids from fishers.

If there is less urgency in the desire to remove the licenses, then the sequential non-binding treatment holds an advantage for fisheries managers with a fixed budget. In fisheries where capacity reduction is important but the 'ideal' size of the fleet is uncertain, the retention of a sequential component could be useful, since it would allow for learning over time. The lowest bids are observed in this auction design, so managers will be able to reach the desired number of expired licenses with a smaller budget, but spread over a longer period of time than either of the two binding auctions. Also, in terms of fisheries managers working with fishers to develop a buyback scheme, this would likely prove to be a preferable choice for fishers, as they have the greatest control over the expiration of their licenses. Lastly, since a smaller portion of the budget is spent in sequential non-binding auctions than in sequential binding auctions, fishery managers may simply be able to hold the next auction sooner, as unspent monies would be held. In the Texas Program there have been several years with multiple auctions (Mamula *et al.* 2007). However, if fishers are maximizing their expected value according to equations 2 and 3, an anticipated change in the time between auctions would affect the single-period return and thus cause fishers to rethink their bidding strategy.

If the management agency's goal is a rapid reduction in the number of licenses, fisheries managers with smaller annual budgets may choose a sequential binding auction. This type of auction draws higher bids than those seen in a sequential non-binding auction but also retires licenses faster, since fishers do not have the option of rejecting a purchase offer. Fishers here have less control over the expiration of their licenses, so this may appear to them as a less ideal design than the sequential non-binding auction. Finally, if a large initial budget is possible and timely license expiration is needed, fisheries managers would likely advocate a single binding auction. The bottom line is that our analysis indicates that all three auction designs have some advantages and may hold a place in fisheries management.

As Holland, Gudmundsson, and Gates (1999) point out, economic efficiency of the fleet through rationalization is often an aim in license buyback programs, so future research could involve design of experiments where: *i)* subjects are not restricted to which license they can bid on and *ii)* bids are weighted to reflect the effect their purchase would have on economic efficiency of the fleet. In the case of weighted bids, the experimenter would not necessarily view all bids equally, but take into consideration the amount of harvesting power that would be retired from the industry with the purchase of a particular license. As quota management becomes more widely used as a management tool, this experimental research could expand to be inclusive of the ability of fishers to trade licenses among one another, as is the case with some current license programs.

With regards to the Texas Inshore Shrimp License Buyback Program, Robin Riechers (2008) of the Texas Parks and Wildlife Department commented, "The program did not have a target" level of reduction and thus no clear terminus. In replicating this in the sequential treatments, subjects face a degree of risk in that the exact number of auctions is not announced. The effect of this uncertainty is not a focus of this article, but future research could explore how individuals behave in sequential non-binding auctions without this uncertainty.

Recommendations for an auction scheme should only be made once the aim of fisheries managers is known. As discussed, each of the three auction schemes has strengths and weaknesses, and we recommend that managers exploit the strengths of a particular auction design to meet their goals.

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