LICENSE BUYBACK PROGRAMS IN COMMERCIAL FISHERIES: AN APPLICATION TO THE SHRIMP FISHERY IN THE GULF OF MEXICO

A Dissertation

by

AARON T. MAMULA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2009

Major Subject: Agricultural Economics

LICENSE BUYBACK PROGRAMS IN COMMERCIAL FISHERIES: AN APPLICATION TO THE SHRIMP FISHERY IN THE GULF OF MEXICO

A Dissertation

by

AARON T. MAMULA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Co-Chairs of Committee,	Richard T. Woodward
	Wade L. Griffin
Committee Members,	H. Alan Love
	W. Douglass Shaw
Head of Department,	John P. Nichols

May 2009

Major Subject: Agricultural Economics

ABSTRACT

License Buyback Programs in Commercial Fisheries: An Application to the Shrimp Fishery in the Gulf of Mexico. (May 2009)

Aaron T. Mamula, B.A., Oregon State University;

M.A, Southern Methodist University

Co-Chairs of Advisory Committee: Dr. Richard T. Woodward
Dr. Wade L. Griffin

This dissertation provides a thorough analysis of the costs associated with, and efficacy of, sequential license buyback auctions. I use data from the Texas Shrimp License Buyback Program – a sequential license buyback auction – to estimate the effects of a repeated game set-up on bidding behavior. I develop a dynamic econometric model to estimate parameters of the fisherman's optimal bidding function in this auction. The model incorporates the learning that occurs when an agent is able to submit bids for the same asset in multiple rounds and is capable of distinguishing between the fisherman's underlying valuation of the license and the *speculative premium* induced by the sequential auction. I show that bidders in the sequential auction do in fact inflate bids above their true license valuation in response to the sequential auction format.

The results from our econometric model are used to simulate a hypothetical buyback program for capacity reduction in the offshore shrimp fishery in the Gulf of Mexico using two competing auction formats: the sequential auction and the one-time auction. I use this simulation analysis to compare the cost and effectiveness of sequential license buyback program relative to one-time license buyback programs. I find that one-time auctions, although they impose a greater up-front cost on the management agency – are capable of retiring more fishing effort per dollar spent then sequential license buyback programs. In particular, I find one-time license buyback auctions to be more cost effective than sequential ones because they remove the possibility for fishermen to learn about the agency's willingness to pay function and use this information to extract sale prices in excess of the true license value.

ACKNOWLEDGEMENTS

This research was funded by a grant from the National Marine Fisheries Service and would not have been possible without their support. I would like to thank Thomas Osang and Kevin Marshall who encouraged me to pursue economic research beyond my master's thesis. I would also like to thank my committee members, Douglass Shaw and Alan Love, for their helpful comments on this dissertation. My major advisors, Rich Woodward and Wade Griffin deserve special acknowledgement, for their guidance and patience.

In addition to academic support, I received social support from an excellent group of friends who made my time at Texas A&M memorable – Heather, Brandon, Levan, Dave, Alex, Chris, Erin, Jamie, Lindsey, and all of the girls, past and present, of the Texas A&M Women's Club Soccer Team. You all made my time in College Station memorable.

I would like to thank my brothers, Phil and Rob, for their support and friendship. Finally, I dedicate this dissertation to my parents, Patty and Greg, who have always supported me, unconditionally, in all things.

TABLE OF CONTENTS

		Page
ABSTRACT		iii
ACKNOWLEDGEMENTS		v
TABLE OF CONTENTS		vi
LIST OF FIGURES		viii
LIST OF TABLES		x
CHAPTER		
I	INTRODUCTION	1
II	A BRIEF SURVEY OF THE THEORETICAL ANALYSIS OF AUCTIONS	6
	Introduction	6
	Benchmark Auction	7
	Sequential Auctions	12
	Summary	19
III	LESSONS FROM THE TEXAS INSHORE SHRIMP FISHERY	21
	Introduction	21
	Literature	22
	A Background on the Texas Shrimp License Buyback	25
	Data	30
	Buyback Outcomes	33
	Auction Behavior	41
	Summary of Lessons from the Texas Shrimp License Buyback	57
IV	AN EMPIRICAL MODEL OF BIDDING IN SEQUENTIAL AUCTIONS	60
	Introduction	60
	Literature Relevant to the Estimation of Dynamic Decision Processes	61

CHAPTER Page

Model 63
Estimation.......... 74
Results 81
Model Validation.......... 84
Discussion 104
Summary of Empirical Work 106

V A COST-BENEFIT ANALYSIS OF SEQUENTIAL VERSUS ONE-TIME BUYBACK AUCTIONS.......... 109

Introduction 109
Important Terms and Concepts 111
Methodology 113
A GBFSM Introduction.......... 114
Important Assumptions of the Simulation Model 125
Scenario Analysis.......... 129
Results 131
Summary of Simulation Work 169

VI SUMMARY AND CONCLUSIONS.......... 170

NOMENCLATURE.......... 175

REFERENCES.......... 176

APPENDIX A 180

VITA 181

LIST OF FIGURES

FIGURE Page

3.1 Single License Decision Tree.. 29

3.2 Catch per Unit Effort for the TX Inshore Shrimp Fishery 1995 - 2004..... 38

3.3 Vessel Length Distribution by Age of Owner in 1996.............................. 45

3.4 TX License Buyback Auction Round 1 Bids 51

3.5 TX License Buyback Auction Round 6 Bids 52

3.6 TX License Buyback Auction Round 14 Bids 52

3.7 Returns to Rejecting an Offer After It Was Granted................................. 56

4.1 Prior and Posterior Expected Probabilities
in the Sequential Bidding Problem When a Bid Is Granted...................... 69

4.2 Prior Subjective Distribution for *RPLo* = $4,000 and *RPHi* = $10,000..... 70

4.3 Flow of the Econometric Model.. 77

4.4 Average Bid and Price by Round in the
TX Shrimp License Buyback Auction 82

4.5 Actual and Predicted 1st Bids 87

4.6 Actual and Predicted 2nd Bids 88

4.7 Objective Function Values in the *RPLo* Dimension 89

4.8 Objective Function Values in the *RPSpread* Dimension 89

4.9 Numerical Derivatives of the Implied Likelihood Function
Around the Optimum 95

4.10 Objective Function Values in the *y1* Dimension....................................... 99

4.11 Objective Function Values in the *y2* Dimension....................................... 99

FIGURE Page

4.12 Prediction Error by Vessel Length 101

4.13 Prediction Error by Shrimp Price 102

4.14 Sample Observations and Price.. 102

4.15 Implied *R* Values for Average Vessel 104

4.16 Average Speculative Premium by Round for All Vessels 105

4.17 Average Speculative Premium by Round and Length Class...................... 106

5.1 An Illustration of the General Bioeconomic Fisheries
Simulation Model... 119

A.1 License Holder Age by Round of the TX Shrimp License Buyback......... 180

A.2 Average Vessel Length of TX Inshore Shrimp Fleet by Auction Round .. 180

LIST OF TABLES

TABLE Page

3.1 Selected US Fisheries Buyback Programs 34

3.2 License Purchases by Round for the TX Program 36

3.3 Key Indicators of the Health of the TX Inshore Shrimp Fishery 39

3.4 Probit Regression to Explain Auction Participation 47

3.5 OLS Estimation of the Fisherman's Bidding Function 48

4.1 Final Parameter Grids and Estimates 83

4.2 Mean Absolute Error by Bid Number 86

4.3 Standard Errors of the Parameter Estimates 98

5.1 Four Gulf Regions of Shrimp Landings in the General
Bioeconomic Fisheries Simulation Model 115

5.2 Sample of a Simulated Distribution of Bids.. 123

5.3 Baseline Scenario Results for Large Vessels 133

5.4 Baseline Scenario Results for Small Vessels 134

5.5 Baseline Landings and Catch per Unit Effort Summary
for Large Gulf Vessels 135

5.6 Gulfwide Sequential Buyback Snapshot (Large Gulf Vessels).................. 136

5.7 Gulfwide Sequential Buyback Annual Rents (7% Discount Rate)............ 137

5.8 Gulfwide One-time Buyback Snapshot (Large Gulf Vessels) 138

5.9 Gulfwide One-time Buyback Rents 139

5.10 Gulfwide Sequential Buyback and One-time Buyback Auction
Comparison 140

TABLE Page

5.11 Gulfwide Sequential Buyback Auction Average Price by Round 141

5.12 Aggregate Effects – Regional Sequential Buyback vs. Gulfwide Sequential Buyback Programs 144

5.13 Rents Under Sequential Buyback Programs 145

5.14 Aggregate Effects – Regional One-time Buyback vs. Gulfwide One-Time Buyback 147

5.15 Rent Comparison – Gulfwide One-time Buyback vs. Regional One-Time Buyback 149

5.16 Expenditures by Region ($1,000s) 151

5.17 Change in Catch per Unit Effort by Region (% Change).......................... 153

5.18 Total Rents Above Baseline (Present Value, $1,000)............................... 154

5.19 Regional Sequential Buyback Program's Change in Landings with Respect to Change in Effort (Change in lbs/Change in Days-Fished)....... 158

5.20 Landings and Effort Comparison for Regions 2 and 4.............................. 159

5.21 Landings and Effort for Inshore Fisheries Under Regional Sequential Buyback.. 160

5.22 Four Program Ranking – Rank in Parentheses... 162

5.23 Marginal Benefit and Cost to Purchase One Additional Vessel for Gulfwide Sequential Buyback Program 166

5.24 Change in Rents per Dollar Spent for Sequential Buyback Programs....... 168

CHAPTER I

INTRODUCTION

Overfishing is currently a serious concern for fisheries managers in the US and around the globe. In the March 2008 publication of the Fish Stock Sustainability Index (FSSI), the National Marine Fisheries Service reported that overfishing was occurring in 22% of US stocks. The FSSI also reports that 27% of domestic stocks are overfished. In their 2006 report, "State of the World Fisheries and Aquaculture (SOFIA)," the Food and Agriculture Organization of the United Nations reported that 25% of the world's fish stocks were overexploited.

The damage done to fish stocks through overfishing has a profound impact on marine ecosystems as well as human welfare. Many coastal communities rely on commercial fishing to provide jobs and income. When stocks become overfished the result is often economic hardship for these communities. In addition to supporting the commercial fishing industry, healthy marine ecosystems also provide benefits to recreational fishermen and ecotourists.

In recognition of the importance of marine resources and the failure of open access policies to provide healthy marine environments, fisheries management has emerged as an important topic among resource economists. The literature in resource and environmental economics now contains extensive discussions on the relative strengths of the various policies used to manage marine resources. In this dissertation I

This dissertation follows the style of *Marine Resource Economics*.

focus on one particular class of fisheries management policies: buyback programs.

Domestically, buyback programs have been used in the Northeast ground fish fishery, the Columbia River salmon fishery in Oregon and Washington and the Bearing Sea/Aleutian Islands (BSAI) crab fishery in Alaska among others. Internationally, buyback programs have been used in the Australian Northern Prawn fishery, British Columbia salmon fishery, and Norwegian purse seine fishery (case studies of these and other buyback programs can be found in Holland, Gudmundsson, and Gates 1999 and Curtis and Squires 2007).

In addition to being significant in number, many buyback programs come with a significant price tag. In 2004 the vessel buyback program carried out in the BSAI crab fishery spent over $97 million. The Texas Inshore Shrimp License Buyback Program, which will be discussed in detail in this dissertation, spent over $8 million in its first 7 years.

Buyback programs have traditionally found favor with fisheries managers because of their ability to address a range of management goals. In addition to providing capacity reduction for the purpose of reducing overfishing, buyback programs may be designed to address the problem of by catch within a fishery or used as a way to distribute disaster relief funds. Holland et al. (1999) identify three general policy aims important to fisheries managers which buyback programs may be designed to address: 1) conservation of fish stocks, 2) improvement of economic efficiency through fleet rationalization, and 3) providing transfer payments to the fishing industry. Because of their ability to address biological, economic, and social goals, buyback programs will likely continue to find a place in the manager's toolkit.

Although the economic literature on buyback programs is well developed and contains a wealth of case studies, there seems to be a shortage of empirical work addressing the question of how important design issues impact the efficacy of the program. In this dissertation I will analyze the influence that auction format has on the effectiveness of buyback programs. Given their popularity with fisheries managers and the financial commitment required to run one successfully, it is crucial to have a thorough understanding of how agents respond to the incentives created by buyback programs and the bearing this behavior has on program success.

The principal objectives of this dissertation are to develop an empirical model of bidding in a sequential buyback auction and, using results from this model, simulate sequential and one-time buyback programs for capacity reduction in the Gulf of Mexico Shrimp Fishery. The overriding goal of our study is to analyze the cost and effectiveness of sequential buyback auctions relative to one-time buyback auctions. I approach this goal in the following manner:

I first develop an econometric model of bidding under a sequential auction. The parameters of this model allow us to distinguish the license holder's true reservation price and, by comparing this underlying value with actual bids, estimate the amount by which the bidder inflates his or her bid in order to take advantage of the sequential auction structure. I term this bid inflation the *speculative premium.* I then use data from the Texas Inshore Shrimp License Buyback Program – a long running sequential auction

– to estimate the parameters of the license holder’s bidding function and the implied *speculative premium.*

I use our econometric findings to help solve a particular resource management problem – that of optimal design of a buyback auction. By simulating 2 hypothetical buyback policies for capacity reduction of the commercial shrimp fishing fleet in the Gulf of Mexico, I provide a thorough evaluation of the costs and effectiveness of sequential buyback programs (SBs) relative to one-time buyback programs (OTBs).

The remainder of this dissertation is organized as follows. Chapter II will provide a thorough literature review on auctions. In this chapter, I discuss the current economic literature on auction theory and estimation of models using auction data. One of the contributions of this dissertation is the development of a dynamic model capable of incorporating the learning that occurs in sequential auctions. Our auction literature review helps emphasize this contribution by presenting current approaches to modeling auctions.

Chapter IV contains the development of our formal econometric model and estimation results. I believe that an intriguing feature of the SB auction is that bidders have an incentive to bid above their true valuation. In the event that a bid is not accepted in the current period, the bidder will have another chance to participate in the auction again next period. This fact leads bidders to attach a *speculative premium* to the true value of the license. In Chapter IV I propose an econometric model capable of estimating this *speculative premium* and distinguishing it from the underlying value of the license.

In Chapter V I use our econometric results to inform a simulation model to compare SB auctions with OTB auctions. Chapter V uses parameter estimates from our econometric model to predict bidding behavior for a hypothetical SB auction for capacity reduction in the Gulf of Mexico's offshore shrimp fishery, including the Exclusive Economic Zone (EEZ). I then simulate an alternative policy path using a OTB program to buyback licenses in order to compare the results of these two auction forms.

Finally, concluding remarks will appear in Chapter VI. In this chapter I will provide a summary of important results and discuss some directions for future research in the area of license buyback programs.

CHAPTER II

A BRIEF SURVEY OF THE THEORETICAL ANALYSIS OF AUCTIONS

Introduction

The Texas Inshore Shrimp License Buyback Program is structured as a first-price, sealed-bid auction, which has been conducted at least once a year since its inception in 1996. In order to appreciate the contributions of the particular econometric model developed in Chapter IV it is important to understand how economists have traditionally approached auction data.

The subject of auctions has a rich history in the economics literature. In particular, because they can serve as a price discovery mechanism for goods which lack other well-defined markets, auctions are especially important in resource and environmental economics, where non-market valuation plays a critical role. Though there are many auction issues relevant to the field of resource economics in general, I focus this literature review on a particular topic germane to our principal objectives: the theoretical foundations of optimal bidding.

I begin by presenting some standard results for simple auction forms then expand our review to include results from more complicated auction forms. The remainder of this chapter will be organized as follows: first I present the derivation of optimal bidding functions for a benchmark auction. Next, I review some generalizations of those results which apply more closely to our license buyback auction. Then I move away from game theory-based models and discuss learning in sequential auctions. Finally, I discuss some literature on dynamic specifications for sequential competitive bidding and relate this literature to our model.

Benchmark Auction

As with many empirical studies using auction data, our challenge is to use observed data on bids to get some information on license holder's private values. Traditional empirical work has relied heavily on auction theory to provide a closed form expression for optimal bidding strategies. These bidding functions relate observed bids to unobserved values and, it is through these functions, that researchers have typically derived information about private valuations. Although there are a number of thorough surveys on optimal bidding in the literature (Milgrom and Weber 1982; Milgrom 1985; Wilson 1987; Milgrom 1989), in the following section I will focus on the presentation of McAfee and McMillian (1987).

McAfee and McMillan show that a Nash Equilibrium for a first-price, sealed-bid auction can be found by maximizing the expected payoffs of an arbitrary bidder. In this section I present the technical details of this approach as they are important for understanding theoretically consistent bidding functions in general. I will also show that this approach generalizes to the bidding functions for auctions which may violate one or more of the four assumptions presented below. The simplest case is what the authors refer to as the benchmark model. The benchmark model imposes the following four assumptions:

1. The bidders are risk neutral.
2. The independent-private-values assumption applies. This means that each bidder has his own value for the object and that this value is independent of other bidders' values.
3. The bidders are symmetric. This assumption requires that all private values come from a single distribution.
4. Payment is a function of bids alone. A common violation of this assumption is the case where royalties are required of the winning bidder.

Given these assumptions one can consider bidder i, who has valuation v_i and believes all other bidders will bid according to a function β. He must choose his bid b_i in order to maximize his expected payoff. Bidder $i's$ expected payoff is the product of the probability that he wins the auction with bid b_i and his payoff if he wins. This is expressed compactly as:

$$\pi_i = (v_i - b_i)F(v_i) \qquad (2.1)$$

Here F(v) denotes the distribution of private values and $\beta(v_i) = b_i$, which implies that $\beta^{-1}(b_i) = v_i$. Using this notation, (2.1) can be rewritten as:

$$\pi_i = (v_i - b_i)[F(\beta^{-1}(b_i)]^{n-1} \qquad (2.2)$$

In the equation above, n represent the number of bidders. Each bidder chooses his bid to maximize expected payoff, so he chooses b_i to satisfy the first order condition that $\frac{\partial \pi_i}{\partial b_i} = 0$. Next one takes the total differential of π_i with respect to v_i:

$$\frac{d\pi_i}{dv_i} = \frac{\partial \pi_i}{\partial v_i} + \frac{\partial \pi_i}{\partial b_i}\frac{db_i}{dv_i} = \frac{\partial \pi_i}{\partial v_i}$$

By differentiating (2.1) one can see that the condition for an optimally chosen bid is:

$$\frac{d\pi_i}{dv_i} = \frac{\partial \pi_i}{\partial v_i} = [F(\beta^{-1}(b_i))]^{n-1} \tag{2.3}$$

Since only bidder i has been considered up to this point, (2.2) is a best response function for any decision rule B that i's rivals may use. In equilibrium all bidders should be playing their best response strategy. If the Nash condition that the rivals' use of B must be consistent with rationality is imposed and the assumption of symmetry is invoked, then bidder $i's$ optimal bid must be the bid implied by the decision rule B. This means that Nash Equilibrium implies that $b_i = \beta(v_i)$. One can substitute this condition into equation (2.2) to get an expression for bidder $i's$ expected payoff in equilibrium:

$$\frac{d\pi_i}{dv_i} = [F(v_i)]^{n-1} \tag{2.4}$$

McAfee and McMillan show that 2.3 can be solved by integration, imposing the endpoint condition that $\beta(v_l) = v_l$. This condition states that the bidder with the lowest possible valuation earns no profits. The authors show that the solution to the differential equation in (2.3) is given by:

$$\beta(v_i) = v_i - \frac{\int_{v_l}^{v_i} [F(\xi)]^{n-1} d\xi}{[F(v_i)]^{n-1}} \quad i = 1,2,\ldots,n \tag{2.5}$$

This function gives each individual's bidding rule in equilibrium. The equilibrium is symmetric in that all bidders have the same optimal bidding rule, only the private value changes. As an example,[1] consider a special case where F is uniformly distributed and the lowest possible valuation is 0. The optimal bidding strategy noted in (2.4) implies that bidder with valuation v submits a bid of $B(v) = \frac{(n-1)v}{n}$. In this special case, each bidder shades his bid by the constant $\frac{(n-1)}{n}$.

Empirical studies using auction data have relied on bidding functions derived from game theory-based models, like the model of McAfee and McMillan presented above. This model has several restrictive assumptions which probably cannot realistically be thought to hold for many auctions in practice. In the next section I review the presentation by Krishna (2002) for a model in which one of these assumptions, namely that of bidder symmetry, is violated.

Bidder Symmetry

In the shrimp license buyback auction, which I model in this dissertation, the assumption of a single distribution for private values seems quite unrealistic. According to experts on this particular fishery there is substantial incidence of latent effort. Having a number of license holders who do not fish but who are eligible to participate in the

---

[1] It should be reiterated that this example is given in McAfee and McMillan (1987).

auction, it would seem more plausible to model the private values as coming from two separate distributions. At least it makes intuitive sense that one should think about license holders active in the fishery as having private values which differ systematically from those license holders who are not active. Allowing for asymmetric bidders presents problems for the derivation of equilibrium strategies. Krishna (2002) shows that an analytical solution to the system of differential equations characterizing the equilibrium bidding strategies in the case of asymmetric bidders can be found only in a few special cases. In general, the solution must be found using numerical methods for specific distributions. This certainly complicates the recovery of the distribution of private values, but does not make it impossible. In fact, Perrigne and Vuong (1996) discuss a method for structural estimation of an asymmetric, first-price auction within the independent private-values assumption, which does not rely on explicit calculation of the optimal bidding function.

In this section I have discussed some important results regarding bidder asymmetries in an attempt to understand how relaxing the assumptions of McAfee and McMillan's benchmark model affect the derivation of the optimal bidding function. An important lesson from this discussion is that as we begin to relax the assumptions of the baseline model, clean closed-form solutions for optimal bidding rules become extremely difficult and often times impossible to derive. In the next section I take another step toward the true auction model for our process and begin our discussion of sequential auctions.

Sequential Auctions

So far I have discussed bidding strategies only in the context of single-shot auctions. However, one of the most interesting features of the shrimp license buyback auction is its repeated nature. The auction takes place at least once, and in some cases, multiple times per year. One might conjecture that this sequential auction format would encourage speculation as license holders know, if they bid too high, they will get another chance to sell next period. We have seen that, in single-shot auctions, bidders chose a bidding strategy which is a best response to the strategy of rival bidders. Here the strategic element is bidder against bidder. When auctions are sequential in nature one must consider an additional strategic element of bidders against time. In this section I review literature on sequential auction theory and learning in auctions and the dynamics of competitive bidding in order to help us deal with these additional complications.

Although there are a number of important empirical studies on sequential auctions in the literature (Ashenfelter 1989; Neugebauer and Pezanis-Christou 2007; Ginsberg and van Ours 2007), this review will be confined to the theory of optimal bidding. An excellent overview of bidding functions for sequential auctions can be found in Krishna (2002). An approach similar to that used by McAfee and McMillan to derive equilibrium bidding strategies for a single round auction is applied by Krishna to sequential auctions. I present Krishna's derivation here in detail primarily because it will help illustrate some of the limitations of traditional game theory-based models. For our analysis it is important to understand why these models fail to explain observed bidding behavior.

For simplicity, consider first a sequential auction with two objects. Assume that each bidder has single unit demand and that bidders' private values are random draws from a single distribution, F. This symmetry among bidders leads to a symmetric equilibrium. In the second period, the payoff to an arbitrary bidder (call him bidder 1) from bidding an amount z is:

$$\pi(z, x; y) = F_2(z|Y_1 = y_1)[x - \beta_2(z, y_1)] \qquad (2.6)$$

In this case Y_1 defines the highest of the n-1 values, Y_2 the second highest, and so on. F_2 is the distribution of Y_2 and y_1 is the winning bid of the first period. β_2 is the bid function for the second period and x is a private value. The first order condition for optimal bidding requires that the derivative of (2.6), with respect to z, equal 0 for all x.

$$f_2(x|Y_1 = y_1)[x - \beta_2(x, y_1)] - F_2(x|Y_1 = y_1)\beta'_2(x, y_1) = 0 \qquad (2.7)$$

$$\Rightarrow \beta'_2(x, y_1) = \frac{f_2(x|Y_1 = y_1)}{F_2(x|Y_1 = y_1)}[x - \beta_2(x, y_1)] \qquad (2.8)$$

We also have the endpoint condition that $\beta_2(0, y_1) = 0$. This condition says that a bidder with a private value of 0 for the object will bid 0. The probability that bidder 1 wins the second auction is the probability that the second highest order statistic, Y_2 is less than bidder 1's bid (z) conditional on the fact that $Y_1 = y_1$. This last equality says that the first order statistic (Y_1, the highest of the N-1 values) is no longer bidding in the second period because it won the auction in the first period. Since the values are drawn independently, this probability is equal to the probability that Y_1^{N-2} (the highest of the remaining N-2 values) is less than z, given that Y_1^{N-2} is less than the winning bid from the first round. These properties will help us simplify the differential equation in 2.8. Given the information above one can express the probability that bidder 1 wins the auction in the second round as:

$$\begin{aligned} F_2(z \mid Y_1 = y_1) &= F_1^{N-2}(z \mid Y_1^{N-2} < y_1) \\ &= \frac{F(z)^{N-2}}{F(y_1)^{N-2}} \end{aligned} \tag{2.9}$$

Using (2.9) in (2.8), Krishna expresses the differential equation in (2.8) as:

$$\beta_2'(x, y_1) = \frac{(N-2) f(x)}{F(x)}[x - \beta_2(x, y_1)] \tag{2.10}$$

This can be equivalently expressed as:

$$\frac{\partial}{\partial x}(F(x)^{N-2} \beta_2(x, y_1)) = (N-2)F(x)^{N-3} f(x)x \tag{2.11}$$

The solution to this differential equation is also provided by Krishna and characterizes equilibrium bidding in the second round:

$$\begin{aligned} \beta_2(x) &= \frac{1}{F(x)^{N-2}} \int_0^x F(y)^{N-2} dy \\ &= E[Y_2 \mid Y_2 < x < Y_1] \end{aligned} \tag{2.12}$$

Working backwards, the first period analysis begins by considering what happens if bidder 1 does not bid according the equilibrium strategy, $\beta_1(x)$ but instead bids $\beta_1(z)$. In the case that $z \geq x$, bidders 1's payoff is:

$$\pi(z, x) = F_1(z)[x - \beta_1(x)] + (N-1)(1 - F(x))F(x)^{N-2}[x - \beta_2(x)] \tag{2.13}$$

In the case that z < x, then the payoff is:

$$\pi(z, x) = F_1(z)[x - \beta_1(z)] + [F_2(x) - F_1(x)][x - \beta_2(x)] + \int_z^x [x - \beta_2(y_1)] f_1(y_1) dy_1 \tag{2.14}$$

For (2.7) we have the following first order condition:

$$0 = f_1(z)[x - \beta_1(z)] - F_1(z)\beta'_1(z) - (N-1)f(z)F(x)^{N-2}[x - \beta_2(x)] \quad (2.15)$$

The first order condition for equation 2.7 is:

$$0 = f_1(z)[x - \beta_1(z)] - F_1(z)\beta'_1(z) - f_1(z)[x - \beta_2(z)] \quad (2.16)$$

In equilibrium it is optimal to bid $\beta_1(x)$, so setting z = x in either first order condition gives:

$$\beta'_1(x) = \frac{f_1(x)}{F_1(x)}[\beta_2(x) - \beta_1(x)] \quad (2.17)$$

Krishna shows that, by invoking the boundary condition that $\beta_1(0) = 0$, one can

rearrange (2.11), expressing it as:

$$\frac{d}{dx}[F_1(x)\beta_1(x)] = f_1(x)\beta_2(x) \quad (2.18)$$

which has the following solution:

$$\begin{aligned} \beta_1(x) &= \frac{1}{F(x)}\int_0^x \beta_2(y)\, f_1(y_1)dy \\ &= E[Y_2 | Y_1 < x] \end{aligned} \quad (2.19)$$

These results are summarized as Krishna's Proposition 15.1[2]:

> Suppose bidders have single-unit demand and two units are sold by means of sequential first-price auctions. Symmetric equilibrium strategies are
>
> $$\beta_1^I(x) = E[Y_2 | Y_1 < x]$$
> $$\beta_2^I(x) = E[Y_2 | Y_2 < x < Y_1]$$

The two-unit sequential auction case can be generalized to a case where K units

[2] Krishna (2002, pg. 214).

are sold in sequential, first-price auctions. By following essentially the same procedure of maximizing expected payoffs, Krishna shows that the equilibrium bidding rule in any period, k, is given by:

$$\beta_k(x) = \frac{1}{F(x)^{N-k}} \int_0^x \beta_{k+1}(y)\, d(F(y)^{N-k}) \tag{2.20}$$

An explicit solution to (2.17) can be derived by working backwards and is expressed in a generalization of proposition 15.1. Proposition 15.2[3] states**:**

> Suppose bidders have single-unit demand and K units are sold by means of sequential first-price auctions. Symmetric equilibrium strategies are given by
>
> $$\beta_k{}^I(x) = E[Y_k < x < Y_{k-1}]$$
>
> where $\beta_k{}^I(x)$ denotes the bidding strategy in the kth auction and $Y_k \equiv Y_k{}^{(N-1)}$ is the kth highest of N-1 independently drawn values.

Krishna shows that the same approach used earlier to derive an expression for the equilibrium bidding strategy for a simple auction (what was referred to as the benchmark model by McAfee and McMillan) can also be used to derive closed form representations for optimal bidding strategies in a much more complicated auction.

These results concerning bidding strategies presented here are significant because the game theoretic foundations of auction theory rely on attributing characteristics of auctions, such as observed prices, to strategic behavior. Once we

[3] From Krishna (2002, p.215)

derive a bidder’s best response function to an arbitrary strategy that he supposes his rival(s) to be using, the Nash condition is exploited to yield each bidder’s equilibrium bidding function. This traditional approach would suggest that our problem of modeling the shrimp license buyback program is simply a problem of choosing the correct auction model, obtaining an expression either analytically or numerically for optimal bidding strategies, then applying one of the empirical techniques survey by Perrigne and Vuong (1999) to back out a set of private valuations.

Learning in Sequential Auctions

The game theory-based models presented earlier largely ignore the component of information transmission over time. We see this quite clearly in Krishna’s proposition 15.2 which states that equilibrium strategies for a given round of a sequential auction are independent of realizations of price in previous bidding rounds. Although it seems quite intuitive that bidder’s should use information from prior rounds when submitting bids in a sequential auction, I could find very little in the auction literature attempting to incorporate learning.

Jeitschko (1998) presents a model where bidders update a subjective probability regarding the valuation type of their opponents in a sequential auction. His model is a sealed bid, first-price auction with three players and two rounds. Each player can be one of two types: a high type or a low type. A high type bidder has high value for the object being auctioned and a low type bidder has a low value for the object. He also assumes that players have unit demand. Learning is introduced in his model because each bidder has a belief about the type of the other bidders. After observing the outcome of the first auction, the remaining players revise their beliefs about their opponent's type. Jeitschko shows that the information generated by the sequential auction format has a positive value to bidders. He contrasts the equilibrium strategies resulting from a model allowing learning with the equilibrium implied by a myopic model and finds that bidders who are allowed to react to information place lower bids, on average, and have higher payoffs. This result is important for our study in that it suggests, quite strongly, that the true model for sequential auction data should include information transmission over time.

Recently, the heavy reliance on strategic behavior to explain bidding has been challenged in the experimental literature, most notably by Ginsberg (1998) and Deltas and Kosmopoulou (2004). Among the most troubling results is Krishna's derivation of optimal bidding functions in sequential auctions, which show that the bids in any round of the auction should be independent of prices in previous rounds. The trends in our data clearly indicate the presence of a speculative component which seems to be due to the dynamic nature of the problem. In the early rounds of the auction we observe very high bids which seem to be distributed quite randomly. As the auction progresses we see bids tending to cluster very tightly around the average buyback price. In the second round of the auction there are a large number of very high bids but by the twelfth round bids are clustered very tightly around what these license holders think the agency will accept. These data suggest that there is a pronounced learning component in this auction and some type of probability updating may help explain bidding behavior. Our challenge then is to find a model flexible enough to allow us to analyze the speculative premium induced by the sequential nature of the auction while retaining some consistency with theory.

In Chapter IV I will contend that the problem of an individual license holder in this auction can be visualized as a dynamic optimization problem where the fisherman balances current expected payoff (which is reflected by the bid amount) and the discounted future payoff from keeping the license for another period. This approach is not entirely new. Oren and Rothkopf (1975) showed that dynamic programming can be used to derive optimal bidding strategies when a bidder's strategy in one auction affects his rivals' strategies in subsequent auctions.

The authors use the bidder's strategy as the control in their model and use the collective behavior of the bidder's rivals as the state variable. The state equation in their model represents the rival's reaction to the bidder's strategy. My model is similar in that I am modeling the bidding problem as a dynamic, multistage process where the bid in a given period is the control. However, I consider the state variables to be parameters of a distribution reflecting the bidder's subjective probability that a bid will be accepted. As he places bids and observes the outcome (either agency accepts his bid or rejects it) he revises this subjective probability. Our state equation is one which describes how the parameters of the distribution change as the bidder receives information over time.

Summary

The economic literature has a long history of using a game-theory based approach to derive the functions defining optimal bidding in an auction. While this approach has been effective in addressing certain questions of traditional interest (for example, many of the works cited in this chapter have as a principal objective the comparison of revenue properties across different types of auctions), it seems to lack the flexibility to shed light on our principal question of interest: does the sequential auction induce a *speculative premium*.

Although the model I present in Chapter IV represents a departure from the main approaches surveyed in this literature review, the importance of this chapter should not be underestimated. In fact our departure from more traditional modeling methods illustrates one important contribution of our work: namely, the estimation of a dynamic optimization based model for optimal bidding in a sequential auction which does not rely on the assumption of truthful revelation.

CHAPTER III

LESSONS FROM THE TEXAS INSHORE SHRIMP FISHERY

Introduction

The ability of buyback programs to successfully promote efficiency has been questioned extensively in the economic literature (Larkin, Keithly, Adams, and Kazmierczak 2004; Mullin 2001; Weninger and McConnell 2000). However, despite economists' concerns, buyback programs continue to find favor with fisheries managers who often must balance biological, economic, and social goals.

In Chapter I I refer to 3 criteria which fishery managers must frequently consider when making policy: biological conservation, economic efficiency, and welfare. Because buyback programs may be designed to address all three of these goals, they have traditionally found favor with fisheries managers. If buyback programs are able to address biological, economic, and social goals within a single policy, then they will likely continue to be implemented as budgets permit.

Given the past popularity and likely continued implementation of buybacks in fisheries management, it is important to understand how these programs affect fisheries and how individuals respond to the incentive structures created by them. In this chapter I use the Texas Inshore Shrimp License Buyback Program as a backdrop for understanding the effects of buybacks on demographics and fleet characteristics of the fishery, as well as understanding how individuals behave under a buyback management regime.

I present data on fleet size and composition, bidder characteristics, and bidding behavior in order to completely describe this program. Fleet statistics speak to the effect that the program has had on the shrimp fleet in the Texas bays. Individual characteristics shed light on the state of the bidders in the fishery and, finally, individual behaviors illustrate how agents respond to the sequential auction format.

The goals for this chapter are two-fold. First, I aim to provide an understanding of how buyback programs affect the nature of the fisheries they govern by presenting trends in Texas Inshore Shrimp Fishery data. I also hope to provide a clear picture of how individual agents respond to the incentive structure provided by sequential buyback auctions in order to help fisheries managers understand the implications of this type of program.

Literature

Our data analysis makes an important contribution to two existing bodies of literature. The first is a general discussion on the role of buyback programs in fisheries management and the second is a well-know sequential auction phenomenon, the declining price anomaly. Here I discuss briefly how our study contributes to these two areas of research.

The recent popularity of buyback schemes as a fisheries management tool has produced a large and growing body of literature on the effects of buyback programs on overcapitalized fisheries. Holland et al. (1999) provide an extensive review buyback programs throughout the world. They present evidence from a number of programs in order to make some general conclusions regarding the ability of buyback programs to conserve stocks, rationalize the fleet and provide income redistribution. Grooves and Squires (2007) follow up on this work and present a thorough overview of general reasons for and consequences of buyback programs. Our study fits within this body of literature by providing an in-depth account of the impact of a particular buyback type (the sequential license buyback program) on the Texas inshore shrimp fishery.

The Declining Price Anomaly

The general subject of auctions is a well explored topic in the economic literature with a variety of sub-topics. One of these subtopics is the declining price anomaly, a phenomenon observed in many sequential auctions. Since the Texas Shrimp License Buyback Program provides a set of data generated by a sequential auction, these observations provide some empirical evidence relevant to the discussion of the declining price anomaly.

This auction mechanism provides many opportunities for fishermen to behave strategically. Each round of bidding gives participants new information about the probability that a particular bid will be granted. The sequential nature of the auction allows bidders to use information from previous rounds in forming bids for the next round. The focus of the next chapter in this dissertation will be modeling how bidders use this information.

It has been noted that, in sequential auctions, identical items tend to sell for less in later rounds than in earlier ones. This phenomenon has been termed the “declining price anomaly” and several empirical studies in the economic literature have confirmed its existence (Ashenfelter 1989; McAfee and Vincent 1993; van den Berg, van Ours, and Pradhan 2001). A clear and concise summary of relevant auction theory is provided by van den Berg et. al (2001):

> Somewhat loosely, one may state than an English auction is truth-revealing whereas a Dutch auction requires strategic behavior. The simple structure of the one-unit English auction vanishes if two identical objects are auctioned sequentially. Now, in the first round it is optimal for bidders to shade their bids to account for the option value of participating in the subsequent second round (Robert J. Weber, 1983). Bidders with a higher valuation also have a higher option value. Therefore, they shade their bids in the first round by a greater amount than do bidders with a lower valuation. As the auction proceeds, the number of bidders decreases. Over the sequence of auctions, the number of objects decreases as well. The first fact has a negative effect on the competition for an object and second has a positive effect. Both effects cancel out and prices follow a martingale. As a result, all gains to waiting are arbitraged away and the expected prices in both rounds are the same. The latter result also holds for sequential auctions of more than two objects and does not depend on whether the auction is English or Dutch. This neat theoretical result is not supported by empirical research, which usually finds price declines.

While our data includes bidders who are sellers not buyers, their behavior can still be interpreted in the context of the declining bid anomaly. Bidders who are buyers decrease their probability of success as they adjust their bids downwards and for bidders who are selling it is the opposite. In examining the data from the buyback program, I will show that participants tend to bid high (decreasing their probability of success early on) in early rounds and, as the auction progresses and they learn about the agency's values, bids decline (increasing their probability of success later). This pattern runs contrary to empirical evidence from traditional auctions which finds that buyers' bids tend to be high early on and decline as the auction progresses.

A Background on the Texas Shrimp License Buyback

Biology[4]

The lifecycle of the Gulf of Mexico panaeid (brown, pink, and white shrimp) is approximately one year. Mature shrimp spawn in the gulf and their eggs are carried into freshwater estuaries by the tides. Juvenile shrimp migrate from the estuaries into the bays the, eventually, the offshore gulf where the cycle continues.

History

The shrimp fishery has traditionally been the largest and most valuable fishery in the state. Prior to the license buyback program Texas had historically managed its shrimp fishery through closures. This allowed shrimp to reach a larger size before harvest and larger shrimp fetch high prices. However, between 1970 and the start of the buyback program in 1995 there was a severe increase in effort in the Texas bays. This effort increase led to a shortage of large shrimp for inshore as well as offshore gulf shrimpers (Robinson, Cambell, and Butler 1994). To counteract the income effects of harvesting smaller shrimp, fishermen resorted in increasing effort in an attempt to land more total pounds.

The shrimp license buyback program, administered by the Texas Parks and Wildlife Department (TPWD), was adopted in 1995 to address the sharp decline in

[4] Biological information is taken from Texas Parks and Wildlife Department (2002). Readers interested in a more detailed discussion of the lifecycle for Gulf of Mexico shrimp should consult this report.

profitability of the shrimp fishing industry[5]. TPWD began retiring licenses in 1996. Partial funding for the license buybacks was created through a $3 increase in the cost of the saltwater fishing stamp. The overriding goal of this program was to reduce overcapitalization without imposing severe economic damages on coastal communities (TPWD 2002).

Licenses

In Texas, each shrimp boat can hold up to three licenses; a bay license, bait license and gulf license. Only bay and bait licenses are eligible for buyback; gulf licenses are not. Each of these three licenses confers on its owner a different set of rights.

Bay and bait licenses allow the holder to shrimp only in the bays and estuaries whereas a gulf license permits the holder to fish in the offshore areas. Additionally, a federal permit is required to shrimp beyond 9 nautical miles out to 200 nautical miles. A bait license allows its holder to fish major bays and bait bays year round but imposes a 200 pound bag limit. Additionally, from November 15th to August 15th at least half the catch must be kept in live condition. A bay license allows its holder to fish major bays during the spring open season, from May 15th to July 15th, and the fall open season, from August 15th to November 30th. Bay license holders may also fish major bays south of the Colorado River during the winter open season from February 1st to April 15th. There are

[5] Funk, Griffin, Mjelde and Ward (2003) provide a good discussion of the legislation enacting the program and the funding structure.

no bag limits imposed during the winter or fall open seasons while the spring open season has a 600 pound bag limit[6].

Auction Rules

In order to understand the trends observed in this auction, it is important to understand the basic rule structure of the program. The auction itself is a reverse sequential auction with nonbinding bids. In the following discussion, I provide an explanation of the auction mechanism.

The Texas Inshore Shrimp License Buyback Program purchases bay and bait shrimp licenses via a sequential auction. At the start of each bidding round, license holders may state a price at which they are willing to sell their license. TPWD then scores these bids based primarily on the length of the vessel being bid on[7]. After scoring the bids, TPWD makes formal offers to buy as many of the top scored bids as their budget for that round allows. At that point, the license holder has an opportunity to withdraw his or her bid and keep the licenses or sell the licenses for the bid price. For this reason, we must distinguish between a bid that is accepted by TPWD and a bid that is accepted by the fisherman. In the language of this program a bid is "granted" if it is accepted by TPWD and a bid is said to be "accepted" if the offer from TPWD is accepted by the fisherman. In order for a license to be bought back it must be granted and accepted. Once a license is bought back, it is retired from the fishery.

[6] For a complete description of the rights associated with each type of shrimp license see TPWD 2005.
[7] We do not have the exact format that TPWD uses to score bids. Through personal communication with Robin Reichers we know that vessel length is the most important component of the bid score.

The Decision Making Environment

The introduction of the sequential buyback program created a rich decision environment for shrimp license holders. In order to understand the many interesting effects of this program on the fishery and fishermen's interaction with it, it is important to understand the choices available to bidders in the auction.

Beginning in 1996 license holders could decide to use or sell either of two licenses. Licenses were also made transferable so, in addition to deciding whether to sell a boat's license back to TPWD or use it to fish, each owner had a third option: sell the license to another fisherman. We can view each owner as managing a portfolio of assets consisting of vessels and licenses, which define the rights of those vessels. In each round of the auction the owner has the option of altering his or her portfolio by selling assets.

From Figure 3.1 one can see the options available to a single license holder in the fishery. In each period a license holder must decide whether to try and sell the license in that period. There are two possible markets for sales: the transfer market and the buyback market. In the decision tree above, both of these decisions end in the owner exiting the fishery. However, since the program retires only the licenses, sale of one license does not preclude the fisherman from participating in other fisheries for which he or she still owns a license or using the vessel in some other way. If a fisherman decides not to attempt a sale, he or she can lease the license in that period or use it. These actions end with the designation *B*. This is meant to convey that if the fisherman follows the *Not Sell* portion of the decision tree he or she will end up in a state next period where all the original options are available.

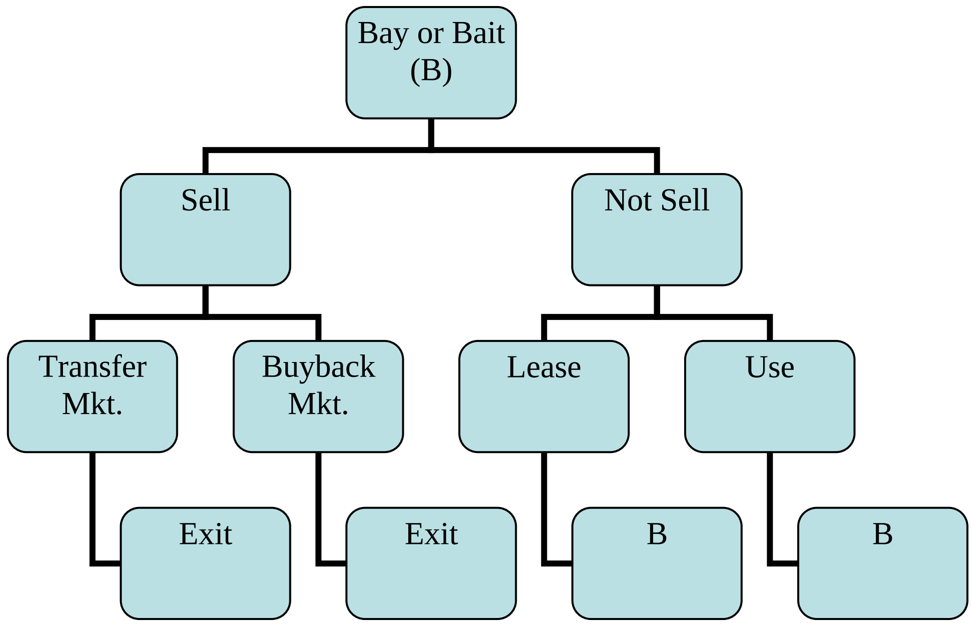

Figure 3.1. Single License Decision Tree

The decisions involved in holding a single license are complex, but few fishermen in this fishery owned a single license at the start of this program. Most license holders in our data set held both a bay and bait license. For shrimpers holding bay and bait licenses on their boats the options available in each period expand greatly. Those license holders owning both bay and bait licenses for a single boat can decide, not only whether to sell a license, but also how many and which license(s) to sell..

To avoid over complication I don't develop the possibility of adding a gulf license to the asset mix, which adds further important complications. However, the reader should realize that, in addition to a bay and bait license for a vessel, an owner may hold a gulf license for that same vessel. In addition to the complexity added by the gulf license, some owners posses multiple vessels. This expands the number of possible actions in the license holder’s portfolio management problem even further.

Re-entry

Once a license is purchased it is retired but, because licenses are transferable, it is possible for a license holder to re-enter the fishery after selling a license. However, this would require buying a license from a current license holder. So, while re-entry is possible, the moratorium placed on new shrimp licenses in 1995 guarantees that in order for someone to enter, or re-enter, the fishery someone else must exit.

This auction mechanism allows for a wide range of choices among bidders and leaves open much potential for strategizing. In the sections that follow, one will explore the bidding patterns observed under this sequential auction. First, one briefly discuss the data relevant for this analysis.

Data

For this study I use data provided by TPWD. The data come from multiple different files and, because there are some slight differences, it is important to explain each.

First, the bidding rounds file contains a round-by-round record of every bid submitted in the auction. This source reports the vessel and license being bid on, the amount of the bid, whether TPWD granted the bid and, if the bid was granted, whether the individual accepted that bid.

In order to incorporate demographic variables that may affect the license holder's bidding function I use the license holder database. This data set contains records for all license holders in the fishery from 1997 – 2004. This file gives us vessel lengths, dates of birth, and home ports for all license holders in the fishery. This demographic and vessel characteristic data is important in helping us determine factors influencing bidding behavior.

In many cases, auction data is only available for individuals who submitted winning bids. An advantage of this data over traditional auction generated data sets is that it contains information on all license holders, regardless of whether or not they chose to bid. Therefore, in addition to observing factors affecting the size of a participant's bid, I also observe factors affecting the decision to place a bid.

At this point it is worth emphasizing that, while the first round of bidding was carried out in 1996, the data only contain demographic information for license holders beginning in 1997. So while I can report on auction statistics (number of licenses purchased, amount spent, and average license price) for all 14 rounds, statistics such as average length for vessels in the fleet or average age for all license holders can be calculated only for rounds 2 – 14.

In addition to the auction and license holder data sets I also have data from TPWD on vessel upgrades. Anytime a license holder alters a vessel it is recorded as a vessel upgrade. The reader should understand that vessel upgrades include purchasing a new boat or altering the length and/or horsepower of the current one. TPWD currently has in place a restriction on the percentage by which fisherman can increase the length or horsepower of their vessel. This restriction is in place to prevent capital stuffing[8] or effort creep that may occur with a buyback program.

Finally, I have economic data specific to the Texas bay system provided by TPWD. This includes landings, ex-vessel values, and prices for shrimp from 1972 – 2002.

Licenses in the Fishery in 1997

The first year in which I have data for all license holders in the fishery is 1997. I use this year as a baseline, from which changes are measured. Here I offer a picture of the inshore shrimp fishery at the beginning of the buyback auction as a basis for future comparisons.

At the start of our data in 1997 there were 2,948 shrimp licenses eligible for buyback. Almost all of these licenses were held by individuals, not companies or corporations. Of the licenses eligible for sale at the start, 817 individual fishermen and 1,792 unique vessels can be identified. Of the unique vessel owners in the fishery in 1997, 33% owned multiple boats and 67% were single vessel owners.

Among all licenses eligible for buyback, bay and bait licenses were almost equally represented. There were 1,501 bay licenses and 1,447 bait licenses in the fishery in 1997. The vast majority (96%) of vessels in the fleet held both bay and bait licenses together.

---

[8] Capital stuffing or effort creep is a well know phenomenon in regulated fisheries. The reader is referred to Townsend (1985) or, for a more specific discussion of capital stuffing in the Texas Inshore Shrimp Fishery, the reader may refer to Funk, Griffin, and Mjelde (2003).

Although they cannot be sold back, gulf licenses represent a potentially important part of our data set. In 1997 about 30% of the vessel owners in the inshore fishery also held a gulf license on at least one of their vessels. Moreover, about 10% of these owners held a gulf license on the same vessel that was licensed to shrimp the bay system.

In sum, the Texas inshore shrimp fishery is comprised of a large number of small owner/operators. The average vessel length for the fleet in 1997 was about 38 feet. About one third of the fishermen owned multiple vessels and this same fraction held a gulf shrimp license. In the next section I will look in detail at the auction's effects on this fishery.

Buyback Outcomes

In the previous section I presented a picture of the Texas inshore shrimp fishery in 1997. In the discussion which follows I will examine the effect that the first 14 rounds of the buyback auction had on this fishery. In particular I will provide a summary of expenditures and key buyback results.

Scale of the Buyback Program

Perhaps one of the most distinguishing aspects of the Texas shrimp license buyback program is its size. Table 3.1 shows a comparison of buyback programs in recent U.S history[9]. Like many state run buyback programs it is small relative to federally funded vessel buyback programs, but the Texas program is small even by state

[9] The data in this table come from Muse (1999) as well as from our own data on the Texas inshore shrimp fishery provided by TPWD.

standards. From its start in 1996 to the 14th round in 2004 the Texas Inshore Shrimp License Buyback Program spent \$8.3 million, a modest sum in comparison to other programs.

Table 3.1

Selected U.S Fisheries Buyback Programs

Fishery	**Date**	**Total Cost (million \$s)**	**Type**
BSAI Crab Fishery	2004	97.4	Vessel/License
Bering Sea Pollack Fishery	1998	90.2	Vessel/License
NE Groundfish	1995-1998	24.4	Vessel/License
WA Salmon Fishery	1995-1998	13.5	License
TX Inshore Shrimp Fishery	1996-2004	8.3	License

Although the Texas program operates on a financially smaller scale than most U.S. buyback programs, the number of licenses sold through the buyback is quite large. Table 3.2 shows the licenses retired in each round of the Texas program through the 14th round. From the table below, one can see that TPWD typically buys back between 50 – 100 licenses per round. Furthermore, because the agency frequently holds more than one bidding round per year, the total number of licenses bought out exceeded 100 in most calendar years. In 1996 and 1997 the agency purchased only 30 and 37 permits respectively. TPWD purchased at least 100 permits in every year from 1998 to 2004. During that time, the fewest number of permits purchased in any year was 105 in 2000. This was the fishery's most financially successful year so it is not surprising to see relatively few owners selling back[10]. The largest number of licenses purchased in any single year was 219 in 2001. As a point of comparison, Washington State's Salmon License Buyback scheme retired 822 permits while the total number of licenses retired by the Texas program is 1,207 and counting.

Licenses Retired

Through the 14th round of the Texas buyback 1,207 license had been retired. Excluding the 30 licenses which were bought out in the first round, this leaves 1,177 licenses purchased between 1997 and 2004. This amounts to a 40% reduction in the number of licenses over the relevant time period.

[10] Personal communication with Michael Travis, Industry Economist, National Marine Fisheries Service, Southeast Regional Office.

Table 3.2

License Purchases by Round for the TX Program[11]

Round	**Year**	**Licenses Sold**	**High**	**Low**	**Avg. Purchase Price**	**Total Spent**
1	1996	30	$6,000	$220	$3,394	$101,820
2	1997	41	$6,000	$100	$3,104	$127,227
3	1998	59	$6,400	$1,500	$3,692	$217,855
4	1998	53	$6,500	$2,500	$3,553	$188,345
5	1998	75	$7,000	$2,500	$4,632	$347,400
6	1999	116	$8,000	$2,500	$5,571	$646,250
7	2000	105	$8,600	$1,500	$6,273	$658,698
8	2001	77	$8,000	$2,500	$6,038	$465,000
9	2001	144	$8,500	$3,000	$6,255	$900,685
10	2002	122	$8,950	$3,000	$6,632	$809,185
11	2002	86	$9,500	$2,500	$6,998	$601,896
12	2003	117	$9,500	$2,300	$7,322	$856,694
13	2004	77	$9,000	$5,500	$7,464	$574,740
14	2004	105	$15,000	$4,360	$8,396	$881,670
Auction Totals		**1,207**				**$7,431,465**

Given this 40% reduction in the number of shrimp permits in the fishery, a natural question to follow up with is, has this reduction led to measurable changes in the inshore shrimp fishery? In this section I will examine changes in the biologic and economic health of the fishery during limited entry.

[11] A similar table appears in Reichers, Griffin, and Woodward (2007). Our table here includes rounds 13 and 14 of the auction.

Effort

Effort, measured in days fished[12], dropped about 70% for the Texas inshore shrimp fishery from 1995 - 2004[13]. In addition, TPWD fly-over counts[14] taken in 1995 and 2004 show a 67% decline in number of vessels on the water on opening day. In 1995, 886 vessels were counted on the water on opening day. By 2004 only 293 vessels were counted on opening day. It should be noted that this decline is greater than the drop in licenses attributable to the buyback program, suggesting that some fishermen may be holding on to their license in order to sell it back, while using it less frequently.

CPUE

Catch per unit of effort (CPUE) is an important indicator of fleet efficiency. From Figure 3.2 one see that CPUE in the Texas bay system stayed approximately constant from 1995 to about 2002 and increased precipitously in 2003 and 2004. The difference from 1995 to 2004 was about 233 pounds per unit effort, which amounts to an increase of about 40% in CPUE. And during this time, total licenses in the fishery fell by 34%.

---

[12] One day fished is equal to 24 hours of continuous trawl time.
[13] This figure is calculated from effort estimated by Griffin. Effort estimates from NMFS show a similar pattern of decline.
[14] On August 15th (Opening day of the fall open season) TPWD performs aerial counts of actual number of vessels in each major bay. It should also be noted that the aerial counts performed on the first day of spring open season, May 15th, reveal a similar pattern.

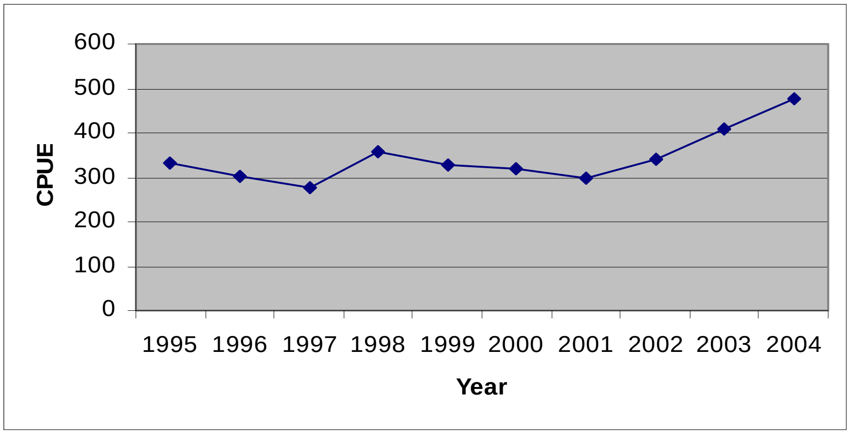

Figure 3.2. Catch per Unit Effort (CPUE) for the TX Inshore Shrimp Fishery 1995 - 2004

Landing and Ex-vessel Values

While the recent rise in CPUE suggests that the inshore shrimping fleet is harvesting with greater efficiency, the trends in shrimp landing and ex-vessel values paint a much gloomier picture. From data kept by TPWD for the Texas bay system I calculate that, in 2004, landings for pink and brown shrimp from the Texas bays were down 77% from the ten year average from 1985-1995. Additionally, ex-vessel values for pink and brown shrimp were down 86% from the average of the ten year period preceding limited entry. Table 3.3 provides an illustration of changes in key indicators during limited entry.

Table 3.3

Key Indicators of the Health of the TX Inshore Shrimp Fishery

	Ex-Vessel Value	Ex-Vessel Price	Landings	Fly-Over Vessel Count	CPUE
Baseline[15]	12,424.21	3.13	5,221.63	886	0.55
2004	5,336.20	3.03	3,307.80	293	0.80
% Change	-57	-3	-37	-67	+45

Prices

The pricing trends for Texas shrimp have been a complicating factor for analysis of the buyback program. Examining data specific to the Texas bay system, one can see the same effect. In the five year period preceding 2002 the average price for brown and pink shrimp from the Texas bays was $1.82 per pound. In the three year period from 2002-2004 the average price was $1.08 per pound, a 40% decline. The price for white shrimp from the Texas bay system experienced a 28% drop in price during this period (again comparing the average price for the five years preceding 2002 with the 2002 – 2004 average).

This price break coincided with a European Union ban on Thai shrimp which, along with several other factors[16], resulted in a significant increase in U.S shrimp imports (NMFS 2004). Exogenous factors affecting shrimp prices, such as increased imports,

[15] The baseline for comparison for Ex-Vessel Value, Landings, and Ex-Vessel Price is a ten year average for the period before limited entry (1985-1995). The baseline for Fly-Over Count and CPUE is 1995.
[16] A thorough discussion of the factors affecting returns to shrimping in Texas can be found in Haby, Miget, Falconer, and Graham (2002).

make it difficult to assess the buyback programs' effects on the economics of the inshore shrimp fishery in Texas.

Capital Stuffing

A major critique of buyback programs is that they will tend to induce capital stuffing. By removing effort from the fishery and pushing up the output price, those owners who stay in will have an incentive to expand their operations. Considering the economic state of the fishery discussed previously it is probably not surprising that there is little evidence to suggest that capital stuffing has been a problem.

In addition to license holder demographics and bidding behavior, I have data on the number of vessel upgrades. Through 2004, TPWD processed 250 vessel upgrades. Among these, 149 were upgrades to a larger vessel and, while boat length is not a perfect indicator for capacity, this is the best proxy currently available. The 149 vessel upgrades that involved a size increase account for roughly 8% of the vessels in the fleet in 1997. The average size increase of these upgrades was 3.6 feet. So, while we do see a small percentage of owners expanding operations, the overall incidence of capital stuffing appears small, which comes as no great surprise considering the economic conditions prevailing in the fishery.

Outcome summary

The statistics presented in this section are meant to illustrate the state of the Texas inshore shrimp fishery. I have provided statistics on key economic and biological indicators in order to try and measure the program's impact on the fishery. Among the many trends presented here one stands out as particularly salient: real effort[17] *has* declined substantially since the imposition of limited entry.

However, because of the price shock realized in 2002, it is very difficult to attribute effort reductions solely to the buyback program. At most it can be concluded that the program is adding another incentive to what was *already* a very strong case for exiting this fishery. However, since intervention in fisheries typically arises in order to address an already bleak situation, the same can easily be said for fleet rationalization in general. In the sections that follow I will move away from the macro discussion and focus on several interesting micro issues. I will analyze the buyback program's effects on age composition in the fishery, vessel characteristics, and explore individual behavior in the auction itself.

Auction Behavior

In this section I will take an informal look at some important factors influencing bidding behavior in the sequential auction. Unfortunately, practical considerations prevent us from incorporating all of these into the formal econometric structure of Chapter IV. Hence, these observations provide strong motivation for extensions to our econometric model.

Because much of the money used to finance the Texas program is generated by the state in the form of fees on recreational and commercial fishermen, the funds

[17] As noted in Griffin, Shah, and Nance (1997), "A unit of nominal effort is defined as net(s) being pulled in the water for a period of 24 hours (known in the industry as a day fished). Standardized effort is defined as adjusted nominal effort based on the relative fishing power (RFP) of each vessel in the Gulf of Mexico shrimp fleet relative to a standard vessel."

available in any given year are small. Due to these financial constraints the program is run as a sequential auction. In each round the agency uses its budget to buy back as much capacity as they can afford and, when more money becomes available, they hold another round. This sequential format leads to behavioral complexities and interesting dynamic pricing patterns. In the sections that follow I will explore some of the factors influencing observed behavior in the auction and outcomes associated with the repeated game set-up.

Age/Length Effects

In this section I examine the interaction between two key proxy variables and the buyback program. I use vessel length as a proxy for effort and license-holder age serves as a proxy for experience. Here I present the effects of the buyback on average age and vessel length in the inshore shrimping fleet as well as patterns in auction bidding across different age and vessel size classes.

Although it is difficult to determine what effect the buyback program has had on productivity in this fishery, its impact on the characteristics of the fishery are clear. Two effects on fleet composition which stand out are the program's effect on average age of the license holders in the fishery and average vessel size in the inshore shrimp fleet. This buyback auction has demonstrated a propensity to buyout older license holders and smaller vessels.

First I look at the age of those shrimpers choosing to exit the fishery by selling back licenses. These figures show that older license holders are tending to sell out of this fishery faster than young ones. At the start of this buyback program, the average age of all license holders in the fishery was 47. By round 14 this average had increased by only 2 years to 49. Calculating the average age for fishermen who sold their licenses in each round, we find that the mean age of sellers exceeds the mean age of all license holders in every round. Apparently older fishermen are more likely to get out of the fishery—not surprising—but they also find the buyback program to be more attractive than the transfer market. Given the tendency of the buyback to remove older license holder from the fishery, it is very possible that many participants are using the buyback to generate some savings for retirement. These results are illustrated in Figure A.1 in Appendix A.

Next, I examine changes in vessel length for the inshore fleet. I find that the average length of vessels in the inshore fleet has increased steadily as the auction has progressed. This is due in part to the propensity of the TPWD to grant bids for smaller boats.

In all but 4 of the 14 rounds at least 70% of the buyout offers were made to boats smaller than the median vessel length for the entire fleet in that round. Likewise, in 7 of the 14 rounds over half of the buyout offers were made to boats in the first quartile of the age-vessel length distribution. The result has been a 5% increase in the average vessel length of the fleet since 1995. Figure A.2 in Appendix A shows the trend in average vessel length for the fleet over time. Without a counterfactual scenario it is impossible to tell whether such a trend would have occurred in the absence of the buyback program. However, by purchasing the smaller vessels, it is safe to say that the program has exacerbated this trend.

The question that arises naturally then is, “are the trends in age of the owners and the length of the vessels two separate trends or a single one?” This question can be answered somewhat informally by examining the age/vessel length distribution for the fishery.

At first glance, vessel lengths seem to be distributed fairly evenly across age classes. In 1997, 56% of vessels below the median length were owned by fisherman above the median age. So about half of the small vessels are owned by old fishermen and about half are owned by young fishermen. Among vessels above the median length, 45% were owned by fishermen above the median age. The average vessel length for all license holders above the median age in 1997 was 37.2 while the average vessel length for license holders below the median age was 40.3. From these figures it does not appear that older fishermen necessarily own smaller boats. In fact, the correlation between age and vessel length for all bidders is very weak (-0.094). However, as shown in Figure 3.3, younger fishermen owned a disproportionate number of the largest vessels. At the start of the program, among vessels in the fourth quartile of the distribution (from 45 – 94 ft), 60% were owned by fishermen below the median age. Among the largest 10% of boats in the fishery in 1997 (those 50 ft or greater), only 35% were owned by license holders above the median age. So, while most of the vessels in the fishery are distributed fairly evenly among age classes, the largest vessels belong almost exclusively to young fishermen.

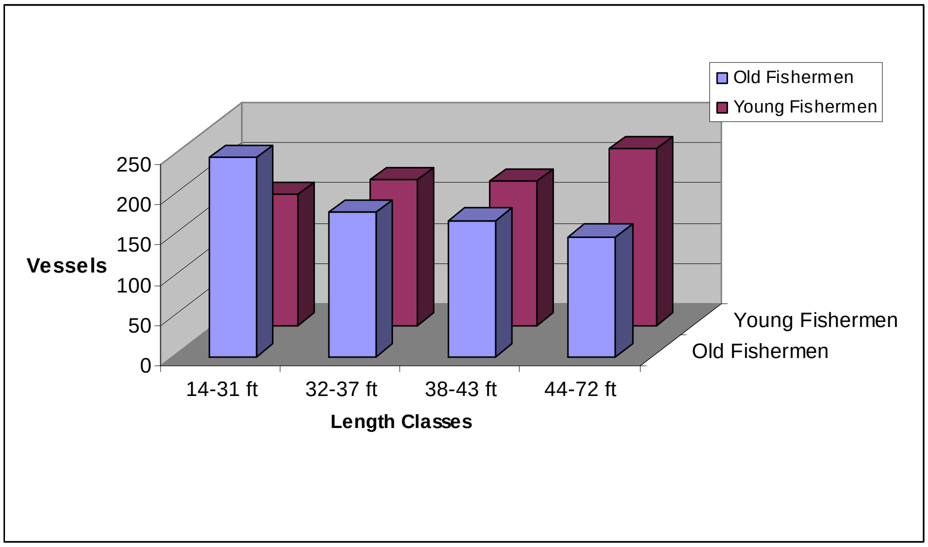

Figure 3.3. Vessel Length Distribution by Age of Owner in 1996[18]

Effects on Bidding

In Chapter IV I will develop a formal dynamic econometric model to estimate parameters of the bidding function that will allow us to identify variables affecting the underlying value of the licenses. In particular, I suspect that vessel length, shrimp price, and license holder age will influence the size of the bid submitted to the auction. In this section I propose a simple model to test the hypothesis that these three independent variables help explain bids.

Here I propose a Heckman two-stage estimation model as a first attempt at modeling the fisherman's bidding function. A two-stage model is appropriate in this case because I suspect that there may be significant differences in the underlying license

[18] Here we use two age classes and four length classes. The age classes are defined as fishermen above the median age for all license holders (old fishermen) and those below (young fishermen). The length classes are separated by quartiles of the distribution of lengths for all vessels in the fishery in 1997.

valuation between those owners who chose to participate in the auction and those who do not. In this auction average bid per foot of boat length[19] is higher for bidders older than the median age. However, we also observe that the average age of all fishermen who submit bids is higher than the average age for all license holders. This suggests that there may be a sample selection bias. To solve the problem of discerning the effects of our suspected drivers on bidding while also accounting for their effects on the participation decision I first estimate the following Probit model for the participation decision:

$$P(BidYN = 1|x) = G(\beta_0 + \beta_1 AGE + \beta_2 LENGTH + \beta_3 P + \beta_4 GULFOWN)$$ [20]

In the equation above *BidYN* is a binary variable indicating whether a fisherman submitted a bid for that license or not. *AGE, LENGTH,* and *P* are continuous independent variables indicating the age of the license holder, length of the vessel to which the license is attached, and shrimp price respectively. *GULFOWN* is a binary variable indicating whether the vessel is also licensed to shrimp in offshore areas. The function $G(\cdot)$ is the cumulative density function of the standard normal distribution.

Our sample includes observations of several thousand licenses over 14 time periods (rounds). There are a total of 38,671 observations in our sample, in 2,676 of these the dependent variable takes a value equal to 1. The results of the Probit regression are shown in Table 3.4 below.

[19] Here we are talking about all bids placed, which does not necessarily mean they were granted.
[20] Here we use the notation of Woolridge 2003.

From Table 3.4 one can see that age, length, and price all appear to be significant factors in the participation decision, though the overall explanatory power of the regression is quite low. License holder age enters positively, suggesting that older license holders are more likely to participate in the auction, while the coefficient on vessel length suggests that fishermen owning larger boats are less likely to participate.

Table 3.4

Probit Regression to Explain Auction Participation

Variable	**Coefficient**	**Std. Error**	**z-Statistic**
C	-0.59	0.10	-5.796
LENGTH	-0.02	0.00	-21.338
AGE	0.01	0.00	9.061
GULFLICOWNER	-0.20	0.02	-8.867
P1	-0.07	0.02	-3.264
McFadden R-Squared	0.047		
Obs with Dep=0	35,995		
Obs with Dep=1	2,676		
Total Obs	38,671		

In the second stage I use OLS to estimate coefficients of the bid function. The OLS equation is given in the equation below.

$$BID = \beta_0 + \beta_1 AGE + \beta_2 LENGTH + \beta_3 ROUND + \beta_4 P + \beta_5 GULFOWN + \beta_6 MILLS$$

The dependent variable here is bid in dollars and independent variables are vessel length (*LENGTH*), bidder age (*AGE*), bidding round (*ROUND*), and shrimp price lagged one period (*P1*). In addition, I also include the inverse mills ratio (*MILLS*)[21] from the first stage regression as a sample selection correction. The results of this regression are displayed in Table 3.5.

Table 3.5

OLS Estimation of Fisherman's Bidding Function[22]

Variable	Coefficient	Std. Error	t-Statistic	probability
C	4589.76	3156.83	1.45	0.146
LENGTH	107.97	52.652	2.05	0.040
AGE	60.21	17.38	3.46	0.001
ROUND	-533.08	48.47	-10.99	0.000
P1	-1877.8	416.08	-4.51	0.000
MILLS	4772.22	2180.25	2.19	0.028
Adjusted R-Squared	0.059			
Observations	2,676			

[21] The inverse Mills ratio is the ratio between the standard normal pdf and standard normal cdf.
[22] We experimented with several different models for this second stage regression. Using the Adjusted R-squared as our primary model fitting criteria we settled on this one. In particular we found that the presence of the dummy variables for gulf license holders exhibited degrading collinearity with the length variable. Because they came out to be statistically insignificant, we dropped them from the model.

From Table 3.5 two effects become clear immediately. The first is that age still has an impact on bid size even after controlling for differences in participation through the inverse mills ratio. In particular, it appears that, holding all else constant, a one-year change in age equates to about a $60 increase in bid size. When combined with the information that older fishermen tend to be more likely to participate, this is an interesting result. It suggests that, overall, younger fishermen are less likely to bid in the auction, but those young license holders that bid do so with a stronger intent to leave the fishery. It is possible that this result reflects a difference in effort between these two groups. That is, among fishermen who chose to participate, the auction attracts young bidders who shrimp only part-time or not at all and older bidders who are full-time shrimpers possibly looking to retire.

Second, the inverse mills ratio comes out as a statistically significant variable in the regression, which can be interpreted as validation for the two-step procedure. In other words, the significance of the mills ratio confirms that there are systematic differences in participation across age classes.

In this section I have examined the effects of age, price, and vessel length on auction behavior and auction outcomes. Here I have proposed a Heckman 2-Stage procedure as a first attempt at estimating parameters of the bidding function. I find that on average bids increase by $107 for each foot of length of the vessels. Since one of the underlying objectives of this research is to identify the value of a license, this relationship provides a first estimate of the reservation price function.

There are, however, some limitations to this approach. First, I find that on average, and controlling for length and age of owner, bids are declining from round to round. This immediately calls into question the ability to infer from the bids evidence about the reservation price of the vessels. Economic intuition would suggest that lower valued bids would tend to be bought out earlier so that the average value of licenses in the fishery would rise over time. Since the results from the second-stage regression runs exactly counter to this result, it calls into question the ability to infer directly from the bids evidence about the underlying value of licenses. Secondly, I find that, even after a sample selection correction, the model had very little explanatory power.

In Chapter IV I provide an alternative to this static estimation that is capable of capturing the dynamic elements of the bidder's decision process. In particular, the sequential auction allows bidders the opportunity to gather information about the agency's willingness to pay for a license. This informational effect is largely ignored in the model presented here. The OLS estimation used here implicitly assumes a 1:1 relationship between the bid and the fisherman's reservation price. In the next chapter I propose an econometric model which relaxes this assumption by incorporating the fisherman's subjective expected probability of success in the auction. The 2-Step estimation procedure carried out here suggests that license holder age, shrimp price, and vessel length are important elements of the bid function. In Chapter IV I will attempt to incorporate these factors into a dynamic econometric model which will also be capable of capturing the learning that goes on in a sequential auction. In the next section I take an initial look at how bidding behavior has changed over time.

Information Effects

The sequential nature of this auction allows bidders to use information from past successes or failures to form optimal bids in the current round. Each round they are allowed to extract information from the agency and update their expectations regarding the probability for success in the auction. In this section I present auction trends illustrating the importance of learning.

One can observe evidence of this learning by referring to Figures 3.4 – 3.6[23]. In the early rounds, bids are widely dispersed. But by the 14th round of the auction, they become very concentrated around the average buyback price. These data suggest that bidders are learning about the probabilities of having particular bids granted as the auction progresses and using this information to revise bids for later rounds.

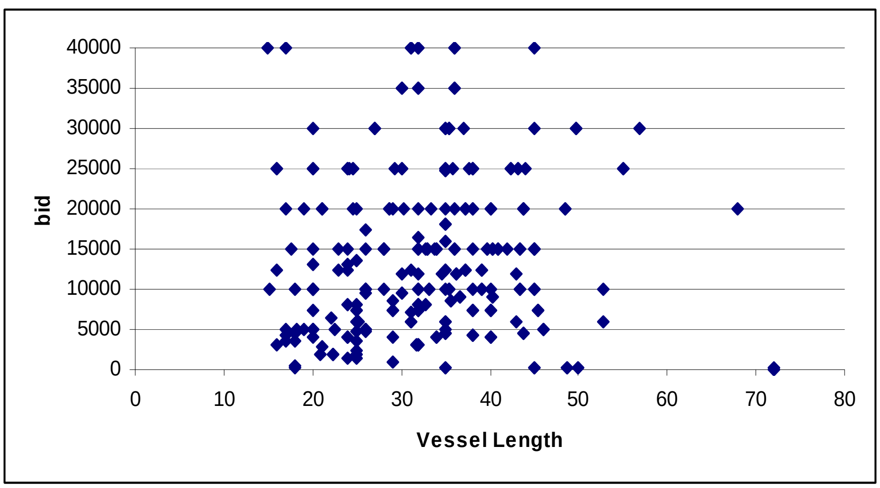

Figure 3.4. TX License Buyback Auction Round 1 Bids

[23] For illustrative purposes, bids above $40,000 are not shown.

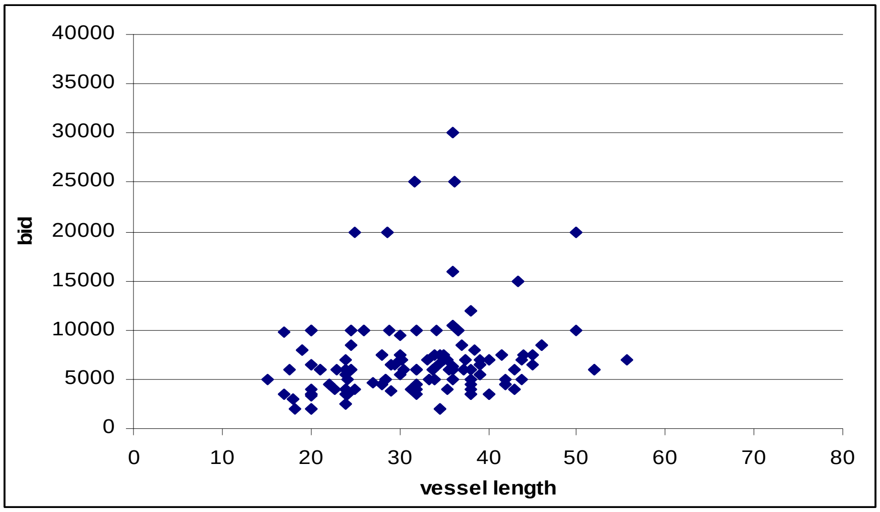

Figure 3.5. TX License Buyback Auction Round 6 Bids

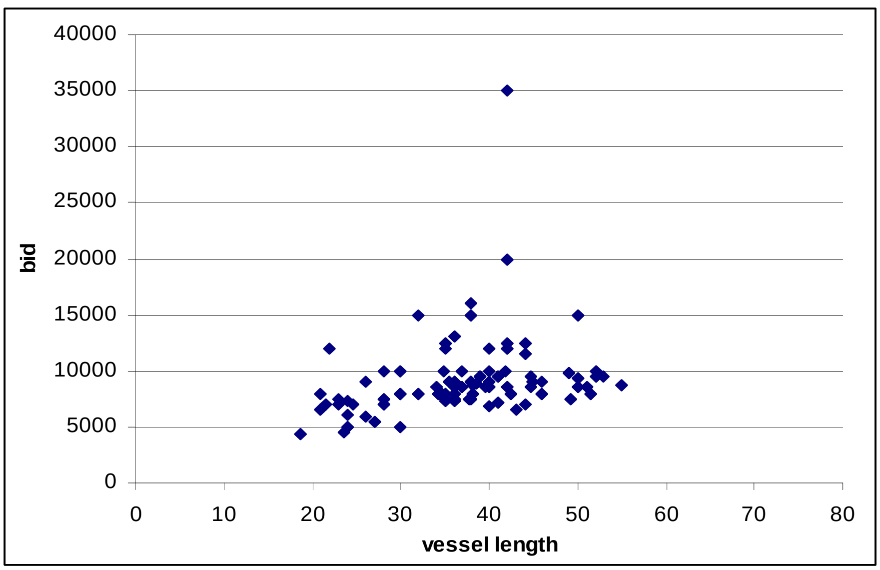

Figure 3.6. TX License Buyback Auction Round 14 Bids

To gauge how bidders take advantage of this sequential auction in preparing their bids we can look at the bidding histories of auction participants. There are roughly 800 unique owners in the data set who have submitted bids in the auction. Of these unique owners, 406 have submitted bids in multiple rounds. That is, about half of all bidders in the auction have participated in multiple rounds.

Our data on whether bids were granted or not tells an interesting story that is consistent with the idea that the sequential auction may induce a speculative motive. Of the almost 1,700 unique licenses in the auction, 796 have been bid on unsuccessfully (not granted) at least once. In percentage terms this means that around 47% of all the assets offered for sale in this auction were offered at a price greater than that which the agency was willing to pay. Among the 1,177 licenses that were sold from round 2 through the 14th round, 363 of these had a prior bid rejected by TPWD before selling. This means that roughly one out of every three licenses surrendered through the buyback auction was bid on in a round prior to that in which it was ultimately sold.

I find that most bidders who sell a license after repeated bidding use a strategy of bidding high early and lowering their bids monotonically in subsequent rounds, zeroing in on their sell-out price from above. Two-thirds of the repeat bid licenses have been sold using this approach.

The No Sale Option

A unique feature of this auction is that it offers fishermen an opportunity to withdraw their bids after observing whether the bid was granted. Once the agency decides to grant a bid they inform the license holder and, at this time, the fisherman can decide to either execute the sale of the license or withdraw the bid. If the bid is withdrawn, the license holder can continue fishing and possibly participate in the auction again later. About 6% of the licenses that have been bid on through round 14 have rejected an offer from TPWD at least once. Most of these licenses remained in the fishery as of the 14th round of the auction but 32 of them had been sold. Seven of these were sold for less than the originally rejected offer. Of the ones which collected positive returns, the average return on exercising the no-sale option was about $1,700.[24]

Although it may sound irrational to sell a license for less then a higher bid which was granted earlier in the auction, there is a plausible explanation for this behavior which hinges on risk aversion: consider a fisherman who is experiencing a good return on his license and is not strongly considering leaving the fishery. The fisherman decides to submit a bid of $6,000 just to see if the agency will take it. The agency does but on further reflection the fisherman decides to keep the license. Two years later returns have become quite poor for the fisherman and he is desperate to sell back his license. He knows that the agency was once willing to pay $6,000 for his license, but also knows that the price the agency pays depends on all other bidders in the market and, therefore, reasonably fears that a bid of $6,000 may not be granted. This plausible situation might lead a fisherman to actually reduce his bids below a price that was previously accepted.

As stated earlier, these fishermen selling for a price below one that was previously granted are anomalies. Most bidders who sell after rejecting an offer from the agency do so at a price higher than that which was previously granted. If such withdrawals were common the agency would be spending much more to buy out the same number of licenses than would be retired if all bids were binding. And this is a concern since the

[24] Return was calculated as the difference between the bid that was granted then rejected and the bid that was ultimately granted then accepted. These figures are net of license cost.

no-sale option as this gives bidders the ability to reject an offer in order to find the highest price the agency would pay for their license. After all, when a fisherman observes that bid *b* is granted, they know that the agency is willing to pay at least $*b* for the license and might be willing to pay more.

In fact, relatively few fishermen exercise this option and the cost to agency has been small. Summing the return to future bidding of all 32 individuals that sold a license after rejecting an earlier round offer, I calculate that the agency spent an extra $44,000 dollars to buy out these licenses, an increase of 26% over the total of the initial bids from these fishermen and only 0.5% of the total cost of the program through round 14. However, one cannot necessarily say that TPWD would have purchased these licenses for $44,000 less if all auction bids were binding because we don't know if these license holders would have participated without the option to withdraw or that their bids would be unchanged. It may be that the no-sale option serves an important function: convincing those who would normally be nervous about or intimidated by the auction to participate and allowing them to correct obvious mistakes in their bids.[25]

Figure 3.7 below shows the returns captured on exercising the no-sale option. As discussed, the impact of this auction feature is almost trivial. Only 32 sales out of over 1,200 were executed after previously rejecting an offer and $44,000 out of over $8 million spent to purchase these. Interestingly, seven bidders actually sold their licenses for an amount less than the price that was offered and rejected in earlier rounds.

[25] The authors would like to thank Stuart Whitten of CSIRO for this insight. We know of at least one case where the no-sale option was used to correct an obvious mistake. One bidder, whose first bid of $900 in round 13 did not accept the buyback offer and then in the 14th round, just 2 months later, placed a bid for $9,000, apparently correcting an erroneous bid.

Finally, I present evidence of speculation in the comparison of the two types of rejections. Recall that there are two ways in which a bid can fail to result in a sale: 1) the agency can choose not to grant the bid or 2) the agency may grant the bid and the fisherman can choose not to accept the offer. The questions that naturally arise then are when would a fisherman choose not to accept an offer? And when would the agency choose not to grant a bid?

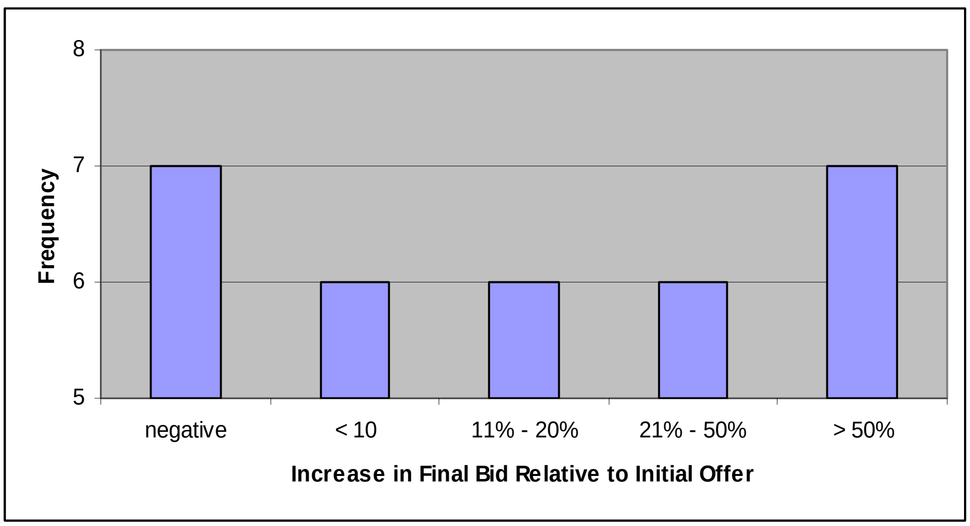

Figure 3.7. Returns to Rejecting an Offer After It Was Granted

Presumably, an offer from TPWD would be rejected if the fisherman feels like they bid too low. Likewise, the agency would choose not to grant a bid if they believe that the fisherman bid too high. In this auction we observe that there are relatively few cases where the bidder bids too low. Out of roughly 2,500 total bids over 14 rounds, there are only 151 cases where an offer was rejected by the fisherman. In contrast, cases where the bidder bid too high are plentiful. In 1,169 cases the agency has chosen not to grant the bid. This means that the TPWD has deemed almost half of all bids to be too high.

Information Effects Summary

In this section I have presented statistics related to the sequential nature of the buyback auction in order to illustrate the importance of learning. Three results in particular paint an especially clear picture of the role of information in this auction. First, I have shown that bids as a function of vessel length are becoming tightly condensed over time. Next, about half of all auction participants have submitted bids in multiple rounds. And finally, I have shown that, among bidders who have bid in multiple rounds, most do so because they bid too high not too low. Taken together these three findings suggest that there is probably an element of speculation at play in this auction.

Summary of Lessons from the TX Shrimp License Buyback

In this chapter I have presented trends from the Texas Inshore Shrimp License Buyback Program as a means for further understanding sequential buyback programs. Using license holder data on the inshore shrimp fleet over the first 7 years of the buyback, I find an increase in the average length for vessels in the fleet and a noticeable propensity for older license holders to sell out. In examining how individual agents respond to the auction mechanism I find that a large portion of auction participants bid in multiple rounds, suggesting that learning may play a role in the bidding process.

While it is difficult to make causal statements without first trying to establish a counterfactual scenario, a few policy relevant observations can be made on the basis of this analysis. First, there is evidence that the sequential auction framework has tended to induce speculation among its participants, probably inflating bids. This result could have important implications for managers hoping to get the most “bang for their buck” from a buyback scheme.

I have also shown that systematic differences exist in both auction participation rates and bidding behavior across age classes. For managers concerned with social implications of buyback programs, this result will also be important. In particular, I showed that older license holders were more likely to participate in the auction and were exiting the fishery through the buyback program faster than young ones. This result may be seen as favorable or unfavorable depending on where the agency falls with respect to the three goals of buyback programs quoted from Holland et al. (1999) in the introduction. If the buyback program is seen as a vehicle for providing transfer payments to the industry then it may perfectly acceptable to buyout older license holders faster as it could signal that the money is going to the “most deserving.” However, if the overriding goal of the program is remove the most effort for the least money then the propensity to buyout older license holder may be a concern as it suggests the agency is buying out fishermen that were likely to retire anyway.

Finally, I have presented in this chapter an elementary econometric model of the fisherman’s bid function. While parameter estimates from this model suggest that vessel length, shrimp price, and license holder age are important drivers of bids submitted to the auction, the counterintuitive coefficient on the round parameter and the low explanatory power of the model suggests that something is missing. The Heckman procedure presented in this chapter is not capable of capturing the learning that is made possible when the same fisherman is allowed to bid on the same asset in multiple rounds of the auction. In particular, I suspect that in any particular round of the auction a fisherman's bid will be based not only on factors affecting the underlying value of the license (vessel length and shrimp price for example), but also on the fisherman's perceived probability of success for any particular bid. In the next chapter I will present an econometric model capable of estimating the primitive variables of the fishermen's reservations price function by incorporating into the estimation the fact that bidding decisions take into account the sequential auction and over time bidders learn more and more about the probabilities of success for particular bids.

CHAPTER IV

AN EMPIRICAL MODEL OF BIDDING IN SEQUENTIAL AUCTIONS

Introduction

In 1995 the Texas State Legislature granted authority to the Texas Parks Wildlife Department (TPWD) to begin purchasing inshore (bay and bait) shrimp licenses from permit holders. In doing so they created a rich and complex decision making environment for inshore shrimpers. In this chapter I present a dynamic econometric model capable of describing the fisherman's decision making process inside this environment and use the model to estimate the effects of key variables, such as vessel length and shrimp price, on the bidding function.

The sequential auction format used by TPWD offers participants the opportunity to engage in strategic bidding for the purpose of gaining information about the agency's willingness to pay for a license. Therefore, I model the bidding decision as a dynamic optimization problem. In order to estimate effects of key variables on the bidding function I nest this dynamic optimization algorithm inside of a hill-climbing routine, which will locate likelihood maximizing parameter estimates for the model.

The remainder of this chapter is organized as follows: The next section will review the auction rules as motivation for our approach[26]. The following section will discuss the contributions of this chapter in the context of two distinct bodies of literature. I then present the empirical model and apply it to data collected from the auction from

[26] Readers interested in a full discussion of the institutional setting should refer back to Chapter III.

1997 to 2004 and present the results of our estimation. Finally, I offer some interpretation of these results and conclusions.

Motivation

The Texas Inshore Shrimp License Buyback Program purchases bay and bait shrimp permits via a sequential, first price auction. At the start of each bidding round license holders may state a price at which they are willing to sell their license. TPWD then scores these bids[27] and makes formal offers to buy as many of the top scored bids as their budget for that round allows. At that point the license holder has an opportunity to withdraw his or her bid and keep the permit or sell the permit for the bid price. For this reason one must distinguish between a bid that is accepted by TPWD and a bid that is accepted by the fisherman. In the language of this program a bid is “granted” if it is accepted by TPWD and a bid is said to be “accepted” if the offer from TPWD is accepted by the fisherman. In order for a license to be bought back it must be granted and accepted. Once a license is bought back it is retired from the fishery.

Literature Relevant to the Estimation of Dynamic Decision Processes

This chapter makes a contribution to the literature on estimation of dynamic models. More specifically, our estimation procedure is an important methodological contribution to the literature on dynamic decision processes.

[27] Bids are scored based on the length of the vessel being bid on, under the assumption that catch is positively correlated with length.

Dynamic Decision Processes

The starting point for our estimation procedure is the seminal 1987 paper by John Rust. Rust (1987) developed the nested fixed point algorithm allowing the estimation of parameters of an optimal stopping problem and in Rust (1988) he provided a guide to maximum likelihood estimation of dynamic optimization problems. Also, in his chapter in *The Handbook of Econometrics* (1994), Rust lays out quite clearly the details of and assumptions necessary for maximum likelihood estimation of dynamic decision processes. Prior to Rust's paper, estimation approaches for dynamic decision problems required highly restrictive functional form assumptions that would not be suitable in the current setting.

Some other helpful applications and discussions of the estimation techniques for dynamic decision processes have come from Miranda and Schnitkey (1995), Provencher and Bishop (1997) and Schjerning (2005). Our problem contains two notable differences from those previously considered. First, work in this area has traditionally focused on problems containing a binary control variable while our key "control" variable, the bid made by fishermen, is continuous over a range. Second, I consider "state" variables which include the parameters of a subjective probability distribution and allow them to evolve following a Bayesian updating process as the fishermen get information from auction outcomes. Thus our state transition is notably more complex than those models previously considered.

Model

Here I am proposing a model capable of estimating the magnitude of speculation present in a sequential auction. The approach can be summarized as follows. The function *R*( ) captures the benefit, to the fisherman, of holding a license in the current period. This function captures the financial returns on holding a license as well as the fisherman's preferences for holding a license. By estimating parameters of this function it is possible to identify differences in observed bids and the benefit function. I label this difference the *speculative premium*. In this section I present in detail the empirical model by which I will estimate the parameters of the function *R*.

Data Generating Process

Because observed bids come from a sequential auction I use a dynamic framework as the basis to describe the data generating process. I assume that the bids from the auction are the result of license holders solving a dynamic optimization problem. In this section I will present the details of this optimization problem.

At the beginning of each round a fisherman chooses a bid, $b \in \Re^{+}$. If the bid is granted by the TPWD then the fisherman must choose whether to accept the agency's offer. A is a binary variable defined as:

$$A = \left\langle \begin{array}{ll} 0 & \text{if bidder rejects offer} \\ 1 & \text{if bidder executes sale} \end{array} \right.$$

If the bid is not granted or is rejected[28], the fisherman uses the license to fish in the current period and collects returns equals to R, a function to be estimated. Define R as a function of vessel characteristics, which are contained in the vector of state variables, x_t, a parameter vector ϕ, and an error term ε. It is worth noting that $R(x_t;\phi,\varepsilon)$ includes the economic returns to fishing but is sufficiently general to include individual specific preferences and opportunity costs as well.

A fisherman who does not sell his license in the current period collects benefits equal to R in that period but also has the opportunity to participate in the auction again next period. Denote by $V_{t+1}(x_{t+1};\theta)$ the value of arriving in the next period in state x_{t+1} with parameter vector θ. The state vector x_{t+1} captures vessel characteristics and the fisherman's expectation as to whether a bid will be accepted. Hence, for the fisherman who does not sell his or her license in the current period, the discounted present value of the stream of expected net benefits is $R+\beta V_{t+1}$, where β is the discount factor.

Since the fisherman cannot know with certainty which bids will be granted, the decision process is not deterministic. Fishermen must submit their bids based on expectations about their probability for success. I define $\pi(b,x_t;\theta)$ as the subjective probability that bid b will be granted this round. The vector θ contains the parameters of this subjective probability distribution which are themselves state variables.

[28] In this chapter I am concerned with modeling bids submitted in the sequential auction and factors affecting those bids. I do not consider those license holders that declined to participate in the auction. Although this treatment was necessary in order to estimate the desired effects, it does impose some limitations on the model. The model at present is not capable of picking up idiosyncratic differences between bidders and non-bidders.

All the pieces are now present to formally define the fisherman's decision problem. In each round the fisherman chooses a bid in order to maximize his or her expected payoff. This optimization problem can be stated formally as,

$$\begin{aligned} V(x_t;\phi,\theta) = \max_{b,A}\, & A\cdot\{\pi(b;\theta)\cdot b + (1-\pi(b;\theta))\cdot[R(x;\phi,\varepsilon)+\beta V_{t+1}]\} \\ & + (1-A)\cdot\{R(x_t;\phi,\varepsilon)+\beta V_{t+1}(x_{t+1};\phi,\theta)\}. \end{aligned} \tag{4.1}$$

Learning

The sequential format allows bidders to gather information as the auction progresses. I model this learning through the state equation of our dynamic optimization problem. The state equation of the dynamic programming (DP) algorithm, which is spelled out above, describes how fishermen use observed outcomes in one round of the auction to form expectations about their probability for success in the next round.

Our approach to dealing with the learning that takes place inside of a sequential auction framework is a Bayesian updating process consistent with a uniform prior on the agent's probability of success. Bayesian updating occurs when an agent combines a prior probability with an observed outcome to form a posterior probability. In the context of a sequential auction we can imagine that, before submitting a bid in the first round, the bidder forms an expectation regarding his or her probability of success with a particular bid. The bidder then observes success or failure in the auction and updates the prior probability for the next round.

In the sequential buyback auction the information available to the bidder in each round is limited. Suppose the bidder submits a bid *b* which the agency does not grant. The bidder learns only that the agency's reservation price for his or her license is somewhere below *b*. Learning takes place in our algorithm as fishermen combine prior expectations about the reservation price with observations from the auction to form new expectations regarding the range in which that agency reservation price falls. Each time a license holder places a bid he or she gets a step closer to uncovering this price. Here I examine the details of how information about this reservation price is transmitted in our model.

Start by assuming that, in any round, the agency has a reservation price for each vessel in the auction. This price is denoted as $\hat{p}$ and it represents the agency's maximum willingness to pay for a license. Also assume that this reservation price may increase over time. The bidder's priors in each round are captured by *RPLo* and *RPHi*. *RPLo* represents the highest bid that the agent believes will be granted with certainty and *RPHi* represents the bid at which the agent believes the probability of being granted is zero.

When a license holder decides to place a bid in the auction there are two possible outcomes, each of which reveals a different piece of information. If the bid, *b*, is granted by the agency then the fisherman knows that the actual *RPLo* is at least as large as *b*, so *RPLo* is revised upward. If the bid is not granted then the fisherman knows that *RPHi* is at least as small as *b*, so *RPHi* is revised downward.

The inclusion of growth parameter, *g*, and spread parameter, *sigma*, allow for the possibility that the agency's reservation price rises over time. The agency's reservation price for a vessel of particular length may be increasing with time to keep up with a natural rate of inflation but also because the supply of available licenses is diminishing.

This effect is captured by the parameter *g*. The spread parameter adjusts the endpoints of the distribution according to the information received by the bidder. It should be noted that these parameters are estimated by the model and no assumptions are made *a priori* about their values.

For illustrative purposes we can imagine the updating process occurring in three steps. These are pictured below in Figure 4.1. The first stage depicts a prior subjective distribution with *RPLo*, *RPHi*, and a bid that falls inside the range. Suppose that a bid, *b* is granted by the agency. The first step in the updating process moves *RPLo* up to *b* since the fisherman now knows the agency is willing to pay at least *b* for the license. When a bid is granted the fisherman doesn't learn anything directly about *RPHi* so it remains unchanged for the moment. In the next step both *RPHi* and the new *RPLo* are adjusted by the growth factor *g* and the parameter *sigma*.

In practice the fisherman's subjective distribution is updated in a single step. The following equations define the state transition of our DP algorithm:

$$RPLo_{t+1} = \begin{cases} b*(1+g)/(1+sigma) & \text{if bid is granted} \\ RPLo_t*(1+g)/(1+sigma) & \text{if bid is not granted} \end{cases}$$

and,

$$RPHi_{t+1} = \begin{cases} (RPLo_t + RPSpread_t)*(1+g)/(1+sigma) & \text{if bid is granted} \\ b*(1+g)(1+sigma) & \text{if bid is not granted} \end{cases} \tag{4.2}$$

Using these values the value of $RPSpread_{t+1}$ is defined as $RPHi_{t+1} - RPLo_{t+1}$. With these parameters, the posterior distribution is fully defined and the grant probability of a bid, *b*, in round *k* can be calculated using,

$$\pi(b, RPLo_k, RPSpread_k) = 1 - \frac{(b - RPLo_k)}{RPSpread_k}$$

With the state transition defined, next period's value function, $V_{t+1}(x_{t+1};\theta)$ can be approximated conditional on current values of the state variables. Now with an approximation of the one period ahead value function we have all the pieces necessary to solve the decision problem in (4.1) for the optimal bid, *b** for any state.

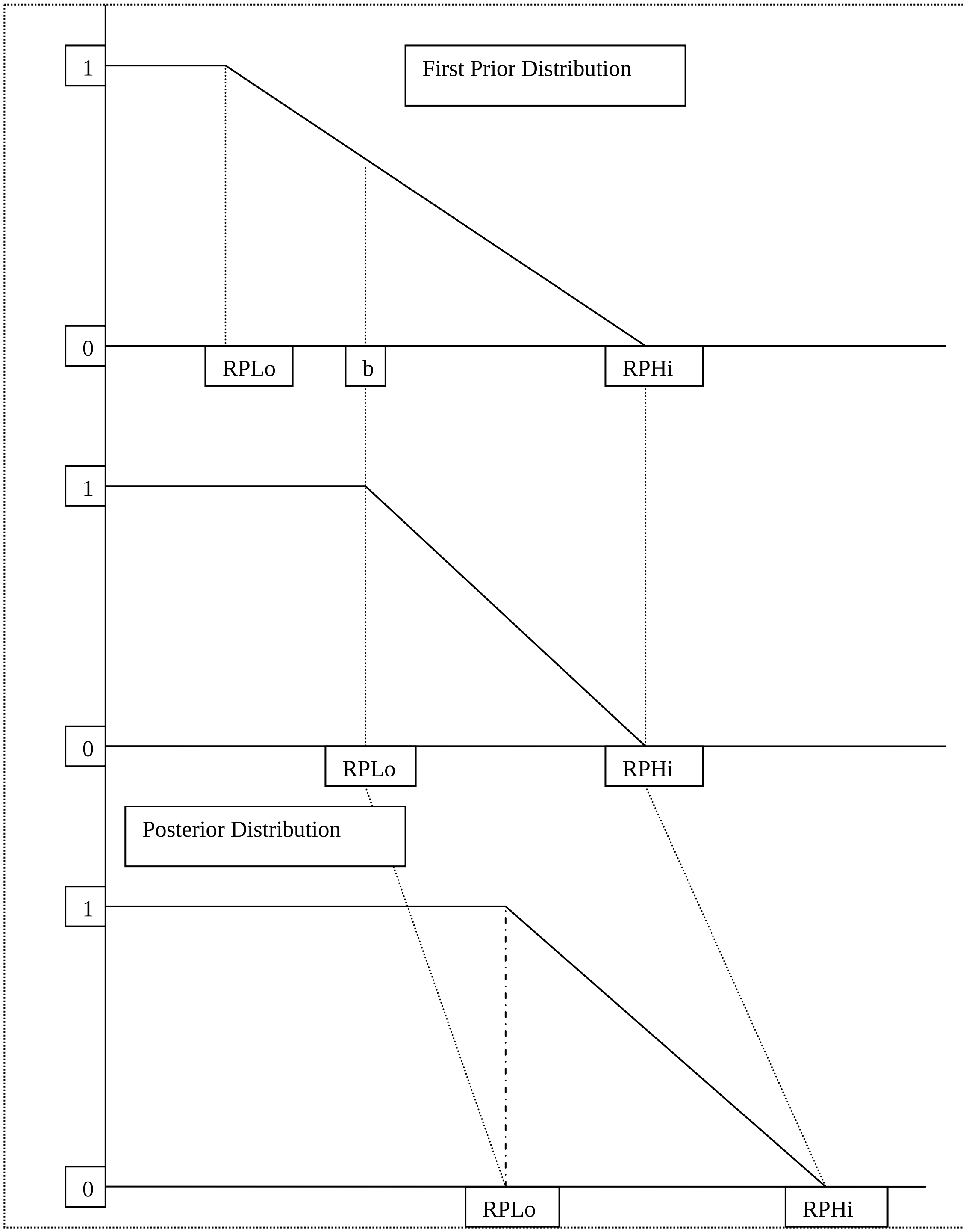

Figure 4.1. Prior and Posterior Expected Probabilities in the Sequential Bidding Problem

When a Bid Is Granted

Now consider the following simple numerical example of probability updating in the sequential auction. Suppose a fisherman with a 32 foot vessel submits a bid of $10,000 in the first round. The fisherman observes that the bid is not granted and therefore knows that the agency's reservation price is less than $10,000. In the second round this fisherman bids $4,000 and has that bid granted. If the fisherman then rejects this grant, he or she enters the third round with the knowledge that the agency's reservation price for her license is somewhere between *RPlo*= $4,000 and *RPHi*=$10,000. In each round the fisherman observes whether a bid was granted and updates his or her expectations about the true reservation price accordingly.
Figure 4.2 illustrates the prior subjective distribution for this fisherman.

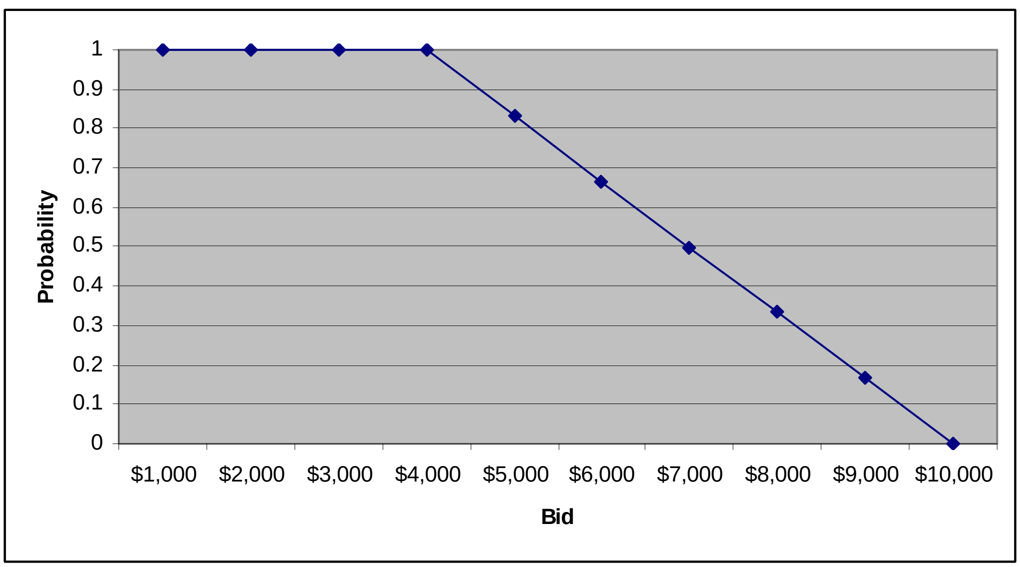

Figure 4.2. Prior Subjective Distribution for *RPLo* = $4,000 and *RPHi*= $10,000[29]

---

[29] *RPLo* and *RPHi* are defined in equation (4.2)

Practical Considerations

The normative decision rule arising from the structure of our data generating process says that bidders chose their bid such that,

$$b^* = \arg\max\left\{\pi\left(b_t\right)[b_t + (1-A)(R+\beta V_{t+1})] + (1-\pi\left(b_t\right))(R+\beta V_{t+1})\right\}$$

I find however that very few bidders ever exercise their right to reject an offer[30]. Because the number of actual observations in which $A = 0$ is so small and because this second control variable would expand the dimensions of a problem which is already pushing the limits of our numerical capabilities, I treat these observations as outliers and discard them. This leads to a new, more practical statement of our problem,

$$\max_{b_t} v_t = \{[\pi(b;\theta)\cdot b] + (1-\pi(b;\theta)[R(x_t;\phi)+\beta V_{t+1}]\}$$

and this is the model which will actually be implemented.

However, because the model is attempting to explain a rich decision environment with only a few parameters we must account for deviations from this normative rule. To account for these deviations an error term is included and the decision problem can be written in estimable form as,

$$\begin{aligned} b_{it}* &= \arg\max_{b_{it}} \{\pi(b;\theta)\cdot b + (1-\pi(b;\theta))[R(x_t;\phi)+\beta V_{t+1}(\varepsilon_{t+1})]\} + \varepsilon_{it} \\ b_{it} &= b_{it}* + \varepsilon_{it} \end{aligned} \tag{4.3}$$

That is, the error for observation *i* is the difference between the actual bid and that which would be dynamically optimal for a given set of parameters.

---

[30] We find that the total number of times that a fisherman rejected an offer from TPWD is less than 1% of total number of bids from the auction.

The Estimator

From this expression for the optimal bidding problem one can see that ε is the difference between actual and predicted bids. Given this expression, parameter estimates for the model are obtained by finding the value of θ that minimizes the sum of squared errors, i.e, $\theta *$, is that which solves the problem, $\min \sum_i \sum_t \varepsilon_{it}$.

The task of calculating the error term for each observation is a critical step in our estimation process. Because understanding this process may aid an overall understanding of our algorithm I provide some detail on this calculation here. Suppose that one observes bidder *i* arriving in round 2 of the sequential auction with a 32 foot vessel. The solution to the dynamic optimization problem provides an optimal bid, *b** for this bidder conditional on the parameters in θ. Suppose we observe that this individual actually bids *b* in round 2. We can then calculate the error for this agent in round 2 of the auction for parameter vector θ, as $\varepsilon_{it} = b_{it} - b_{it} *$.

There are two important conditions imposed on the model which effect the calculation of the error term. The first is that all bidders are repeat bidders. That is, the sample is restricted only to those agents who have participated in the auction in more than one round. Second, I assume that information is gained only through bidding. That is, I assume that a bidder will learn about the probability of future bids being accepted by hearing how the agency responds to his or her bids.[31] So bids can be thought of as being

[31] The assumption that this is the only source of information for the fishermen is obviously quite restrictive. Nonetheless, for reasons of computational limits, it was the most complex specification that we were able to estimate.

numbered sequentially rather than being associated with a particular round. A short numerical example will help illustrate this point.

The infinite horizon DP will solve for a *b** in each round of the auction. Recall that *b** will be a function of the parameters in θ. In particular, vessel length and the initial *RPLo* will help determine *b** in the first period of the DP, b_1*. Equation (4.2) shows how the distributional parameters are revised and these parameters will then influence b_2*. For a given starting value of *PLo* (determined by the parameter vector) the DP algorithm will produce a *b** for each round of the auction and one can think of each of these as being associated with an *RPLo* for that round. Now suppose that we observe an individual that submits the following bids in three rounds:

$$\begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} 7{,}000 \\ 6{,}000 \\ 5{,}000 \end{bmatrix}$$

The DP module has produced the array $b = [b_1*, b_2*, ..., b_{14}]$ and I would like to compare these values to observed values in order to calculate the errors for individual *i*. To do this I compare b_1 to b_1*, regardless of whether b_1 actually took place in round 1 or round 10.

The sum of squared errors (SSE) approach is very intuitive. In essence I am simply defining a dynamically optimal solution and trying to minimize the distance between that solution and observed behavior. However, as will be shown, solving this minimization problem in practice is quite difficult.

Estimation

In the data set we have observations for roughly 800 fishermen over 14 rounds of bidding. For each fisherman in each round we know the number of assets they hold, the size of their bid, whether TPWD granted that bid and, if the bid was granted, whether the bidder accepted the offer. Additionally, the data include individual vessel characteristics such as length. Although horsepower and location were also included in the data, these are excluded from the analysis here for several reasons. First, in personal communications, TPWD staff indicated that they do not place much confidence in the horsepower data. Secondly, our computational limits impose significant limitations on how many variables can be incorporated in the model. Finally, in work cleaning the data it was found that horsepower data frequently changed from year to year (for the same vessel) in ways that appeared arbitrary and more indicative of data error than true variation in the underlying variable, which might also be the reason that TPWD does not trust the data on horsepower variable. The task here is to estimate parameters which show the effects of these variables on the bidding function.

Parameters

Before proceeding further with the discussion of the estimation routine, let's review the parameters in our model that will be estimated. The estimable parameters are those related to the bidder's subjective probability distribution and parameters of the benefit function.

Distributional Parameters

First, the initial values of the two state variables must be estimated, $RPLo_0$ and $PSpread_0$. Recall that $RPLo_0$ and $RPSpread_0$ define the first prior subjective distribution that the bidder faces. In each subsequent period $RPLo_{t+1}$ and $RPSpread_{t+1}$ are derived from $RPLo_t$ and $RPSpread_t$ using actual bids in *t*, the growth parameter g and the spread parameter *sigma*. Hence, g and *sigma* are also estimated.

The Benefit Function

Up to this point I have been rather general about the benefit function, *R*. Previously *R* was defined as a function of parameters ϕ, and independent variables, *x*. The theoretical model does not impose any restrictions on the functional form of *R*. However, because of the numerical intensity of our estimation algorithm there is a heavy penalty for non-parsimony. Therefore, in practice I use a relatively simple linear model for the benefit function *R*.

In any year the benefit of holding a license is assumed to be equal to the net revenue generated by the asset, say-*M*–*C*, where *M* indicates gross revenue and *C* indicates gross costs. If individual agents' landings were available then gross revenue could actually be calculated,

$$M = total\ lbs\ of\ \ shrimp \times shrimp\ \ price(\$/lb).$$

However, since there is no data on individual landings, I use vessel length, *L*, as a proxy for catch. The gross revenue function can be written as,

$$M(L,p) = p \cdot y(L)$$
$$\text{where } y(L) = y_1 + y_2 \cdot (L).$$

Here $y(L)$ may be thought of as the pounds landed function, where there is some autonomous portion of landings, y_1, and a portion, y_2 ,that depend on the size of the vessel. Likewise, *C(L)* is written as a linear function of vessel length:

$$C(x) = c_1 + c_2 L$$

Expanding the benefit function using the pieces above we have,

$$R(L,p) = py_1 + py_2 L - c_1 - c_2 L. \qquad (4.4)$$

giving the parameter vector ϕ=(y_1, y_2, c_1, c_2).

In sum the parameter vector I am seeking to estimate contains four parameters which define the bidder's subjective probability distribution and four parameters of the benefit function *R*: $\theta = [PLo_0, PSpread_0, g, \sigma, \phi]$.

Estimation Algorithm

In the previous section I discussed the estimator that will be used for the model. The problem now is to find the values of the parameter vector, θ, which minimize the sum of squared errors (SSE). The algorithm used to carry out this minimization was programmed using Fortran 90. A short discussion of a few of the programming details will help illustrate some important details of our estimation procedure and also illuminate some of the challenges in attempting to estimate this type of model.

First I provide a brief overview of the algorithm. The general structure of the program works as follows: the main program chooses parameter values for the model, the Dynamic Programming (DP) modules use these parameters to solve the infinite horizon DP. The DP model yields an optimal policy function, $b^*(\cdot)$, which can be used to predict the "optimal" bids for each observed bidder. The econometric modules use observed data points and optimal state dependent bids from the DP to calculate the Sum of Squared Errors, where ε_{it} is defined in (4.3). The algorithm then returns to the main program which chooses new parameters. The program operates according to the flow as presented in Figure 4.3.

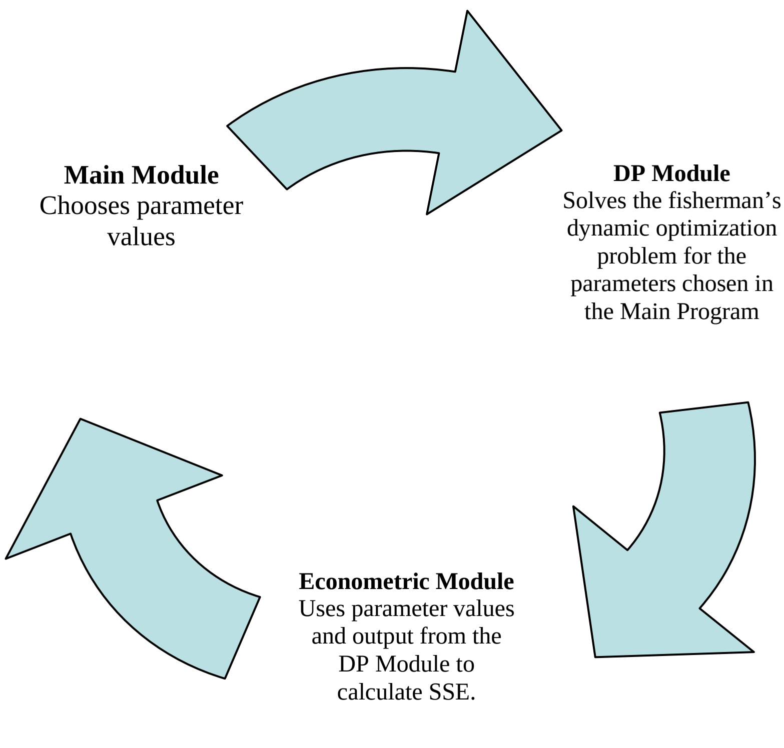

Figure 4.3. Flow of the Econometric Model

It should be noted that the overall set up of the program is general enough to accommodate different approaches to finding the optimal set of parameters. The method I use to find the minimum SSE parameter vector is an adaptive grid. Using the adaptive grid search algorithm a sparse grid is first chosen and then, after observing actual values found, the grid is refined until the "best possible" parameters are identified. Each time a grid search is implemented, grids for the parameter are defined in the main module and the program runs until the SSE for each possible parameter combination has been evaluated. The combination of parameters with the lowest SSE is the best estimate based on the optimization criterion. Because of the highly non-linear nature of the objective function I found the simplicity of the grid search to be quite advantageous. Further, although more sophisticated nonlinear hill-climbing algorithms might yield more precise estimates of the parameters, given the parsimonious model specification, such precision is inconsistent with the true precision of the econometric model.

Grid Search

Using the grid search method, the program evaluates the sum of squared errors at a number of pre chosen points in order to find that vector which minimizes the chosen distance measure. This is a computationally intense process but, given the shape of our objective function, a necessary one. In each iteration of the grid search algorithm, grids are defined for each of the estimated parameters. A grid is defined by a minimum value, a maximum value and a number of points between the two to evaluate. For example, if the y_1 grid is defined as having a minimum at 0, a maximum at 10 and 10 grid points then it can be illustrated by the following vector,

$$y1Grid = \begin{bmatrix} 0 \\ 1.111 \\ 2.222 \\ 3.333 \\ 4.444 \\ 5.555 \\ 6.666 \\ 7.777 \\ 8.888 \\ 10 \end{bmatrix}$$

The ith grid point in the this grid for example is given by,

$$y1Grid(i) = y1\min + (i-1) * (y1\max - y1\min)/(n-1),$$

where n is the total number of grid points. Once grids have been defined for each of the parameters, the algorithm will search for the value of the parameter vector θ, which minimizes the sum of squared errors by evaluating the SSE at every possible combination of grid points.

Practical Restrictions

As mentioned previously, the solution algorithm is computationally very intense. For example, with only 10 points in each parameter grid the program still must undergo 10^8 iterations. And inside each of theses iteration the infinite horizon dynamic programming problem must be solved. As a practical matter, there are a number of steps that have been taken to reduce the computational intensity of this algorithm.

The first of these is to evaluate the DP only inside those iterations where it is necessary. Although the econometric subroutines must be evaluated at every parameter change, the outcome of the DP will only change with changes in the distributional parameters, g and *sigma*, which affect the state equation in the DP model. A short discussion of why this is so follows.

The optimal bid, *b**, is a function of the state variables *RPLo, RPSpread,* and *R.* In practice, the DP is actually solved for a small number of possible states and Chebychev polynomial approximation is used to smooth the value function over the full range of state variables. The solution to the DP problem yields a *b** matrix which contains an optimal bid as a function of each combination of the possible states. The econometric subroutine uses linear interpolation to determine which element of this *b** matrix is relevant for a particular bidder. This means that changes in the parameters of the *R* function (*y1, y2, c1, c2*) don't affect the *calculation* of the *b** matrix, they determine which element of that matrix is used for a particular bidder. The parameters *g* and *sigma*, because they affect the state transition of the DP, have an affect on the one-period ahead value function V_{t+1}. Therefore, changes in these parameters will affect the calculation of the *b** matrix. It is therefore possible to economize on run time by calling to the DP module only for values of θ which contain changes in *g* or *sigma*.

Another way efficiency is promoted in the algorithm is by imposing a theoretical restriction on the parameter c_2. Recall that the benefit function in our model is written as

$$R(x, p) = py_1 + py_2 x - c_1 - c_2 x \,,$$

and that the parameter c_2 reflects that portion of costs that are dependent on vessel length. In the estimation I impose the restriction $c_2 \geq 0$ which saves run time by only searching for optimal values of c_2 in the positive direction. In the adaptive search algorithm, the approach was to focus first on those parameters for which the value function seemed to be responsive to small changes in the parameter values. Although all possible care was taken to ensure that the final estimates were robust, the possibility that this iterative approach ended with suboptimal parameter vectors cannot be ruled out. On the other hand, this would also be true if a nonlinear hill-climbing algorithm were used – because the optimization problem is not convex, there is no numerical algorithm that will guarantee that a global optimum is found.

Results

The main objective of the empirical model is to estimate the speculative premium induced by the sequential auction. The speculative premium is a quantity derived from parameter estimates of the benefit function. In this section I will present the estimated parameter values and use these estimates to derive the speculative premium.

Data

One of the primary goals this study is to identify the way in which learning, as allowed by the sequential auction, influences bidding behavior. For this reason the model is estimated using a subset of our data containing only those bidders who participated in more than one round. There were a total of 1,642 observations used in the estimation. The average vessel length for observations in the sample was 33 feet. The average bid for the sample is shown in Figure 4.4 below. Average shrimp price for the Texas bay system is also shown in the table below.

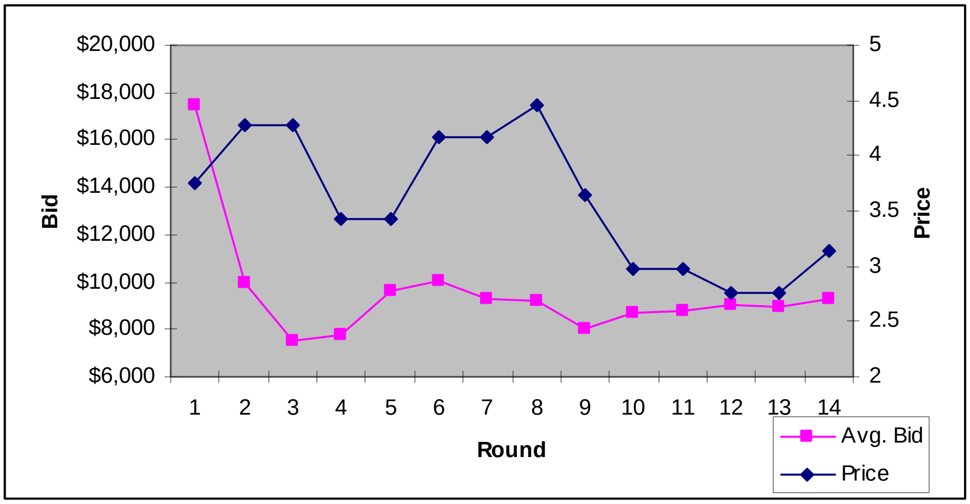

Figure 4.4. Average Bid and Price by Round in the TX Shrimp License Buyback Auction

Source: TPWD

Parameter Estimates

Parameter estimates were obtained through the grid search algorithm by running the estimation program many times and tightening the bounds of selected grids on each run. In practice it simply was not feasible to chose wide bounds for each grid and allow the algorithm to search over a large number of grid points for the optimal solution. With 8 parameters even evaluating the model at ten grid points in each dimension would require 8^{10} iterations. At the current rate of 0.03 seconds per iteration, running the model with 8 parameters and 10 grid points would require roughly 833 hours of computing time. For this reason we carried out several experiments to find the range in which optimal parameter values could be expected to fall. This allowed us to keep the grids used to obtain the final estimates relatively small. The final model was estimated with the following grids:

Table 4.1

Final Parameter Grids and Estimates[32]

	Grid points	Min	max	Optima
y1	8	95	105	101.25
y2	8	0	5	2.5
c1	1	0	0	0
c2	1	0	0	0
RPLoStart	5	0	5,000	1,000
RPSpreadStart	5	5,000	25,000	15,000
G	5	0	0.25	0
Sigma	5	0	0.25	0
Observations	1,642			
R-squared	0.139			

Parameter estimates obtained from the model are also shown in Table 4.1. Here I present these estimates and discuss their importance to our analysis. Recall that the function *R* was previously defined as, $R(x, p) = py_1 + py_2 x - c_1 - c_2 x$. Combining the estimated parameters with 2005 prices for an average sized vessel (32 feet) results in a predicted *R* value of around $570, which is consistent with information obtained from industry experts.[33]

[32] The distributional parameters RPLoStart, RPSpreadStart, G, and Sigma are defined in equation (4.2). The parameters of the benefit function y1, y2, c1, and c2 are described in equation (4.4)

In addition to this informal model validation we also have a goodness of fit statistics. The measure chosen for this model is the R^2 statistic. R^2 measures the proportion of the sample variation in actual bids which is explained by the model and is calculated as,

$$R^2 = \frac{\left(\sum_i \sum_t (b_{it} - \bar{b})(b*_{it} - \bar{b}*)\right)^2}{\left(\sum_i \sum_t (b_{it} - \bar{b})^2\right)\left(\sum_i \sum_t (b*_{it} - \bar{b}*)^2\right)}$$

The R^2 statistic shows that our model explains almost 14% of the sample variation in the bids. Considering the parsimonious specification of the model and complexity of the decision making environment $R^2 = 0.139$ is promising.

Model Validation

The structure of this model – a dynamic programming problem nested within an outer minimization algorithm – does not lend itself easily to conventional hypothesis testing. However, the quality of the empirical model can be analyzed by consulting a variety of somewhat primitive measures.

---

[33] In personal conversations with Robin Reichers of the Coastal Fisheries Division of Texas Parks and Wildlife he has relayed his feeling that many of the bidders in this auction were suffering from poor returns.

Model Performance

I have shown that the optimal parameter estimates obtained from the grid search method explain roughly 14% of the total sample variation in bids. In addition to the R-squared measure, examining the difference between actual and predicted bids will also give a sense of how well the model fits.

In Table 4.2 below I show the mean absolute error (MAE) by bid number. Because it is assumed that information is gained only through bidding, it makes sense to express the deviations between observed bids and predicted bids in terms of bid number rather than round.[34]

Although the difference in actual versus predicted bids is initially quite high, the model performs relatively well after the first bids. The overall MAE for the entire sample is 50.1% of observed bids, which may seem high, however it should be remembered that the computational intensity of this estimation procedure forces us to search for optima over very course grids.

[34] To reiterate: the model treats a bidder participating in the auction for the first time as an uninformed bidder, even if this first bid is placed in the 13th round.

Table 4.2

Mean Absolute Error by Bid Number

Bid Number	Observations	MAE	MAE (%)
1	624	$6,225.91	65.8%
2	624	$2,995.60	47.0%
3	220	$2,813.91	37.0%
4	89	$2,136.33	28.2%
5	37	$3,291.09	27.8%
6	19	$3,869.09	31.7%
7	9	$4,071.67	43.2%
8	7	$4,622.62	28.3%
9	5	$3,880.24	24.3%
10	5	$2,324.53	23.9%
11	2	$3,676.99	32.7%
12	1	$926.19	14.2%

One of the principal objectives of this chapter was to develop an empirical model capable of incorporating the learning made possible by the sequential auction format. Given that objective one must judge model quality not only on how the model fits overall but also how well it fits the dynamics of the bidder's decision problem. Figure 4.5 shows that our model systematically predicts in excess of observed first bids. Given the uninformed nature of the bidders at this stage, this is not surprising.[35] However, in Figure 4.6 note that the model fit improves substantially in the 2^{nd} round, suggesting that the model is capturing the bidders' updating process.

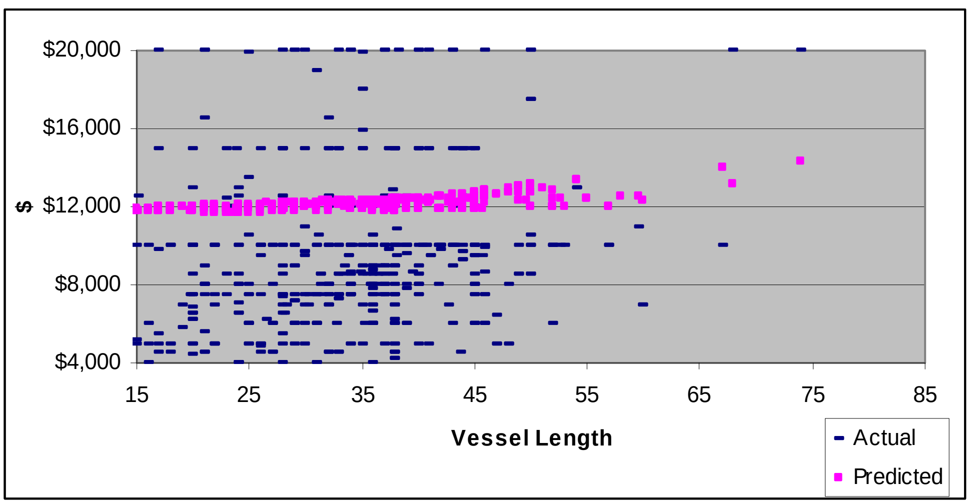

Figure 4.5. Actual and Predicted 1^{st} Bids[36]

[35] The reader may want to refer to Figure 3.4 from the previous chapter and note the dispersion among bids. Fitting a model to this particular subset of data would certainly be a near impossible task.
[36] Figure 4.5 is truncated at $4,000 and $20,000 for illustrative purposes.

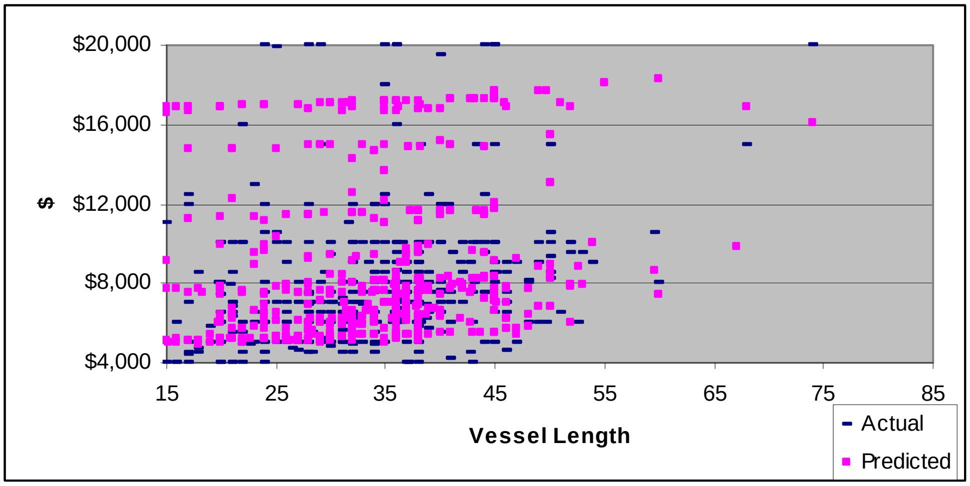

Figure 4.6. Actual and Predicted 2nd Bids

Standard Errors of the Point Estimates

A complicating feature of this model is that the DP must be re-run for each change in *RPLo*, *RPSpread*, *g, or sigma.* Because of this structure it is very costly (in computing time) to improve the precision around estimates for these parameters. As a result, estimates for these distributional parameters are not likely to be robust to small changes in the sample and little meaning could be attached to standard errors.

To ensure that the best estimates for these parameters within the feasible search range have been selected I perform a check on the objective function values in the *RPLo* and *RPSpread* dimensions. Figures 4.7 and 4.8 show the top 200 objective function values and the associated *RPLo* and *RPSpread* values.

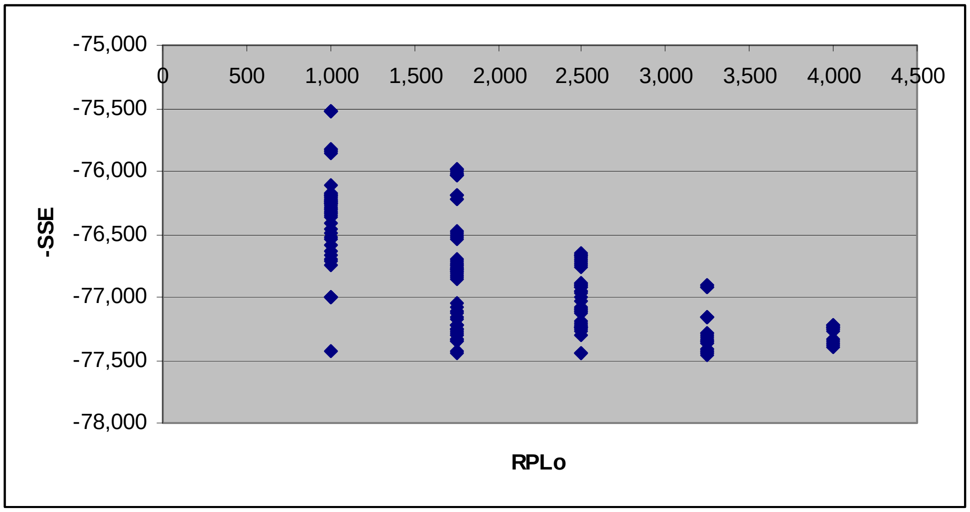

Figure 4.7. Objective Function Values in the *RPLo* Dimension

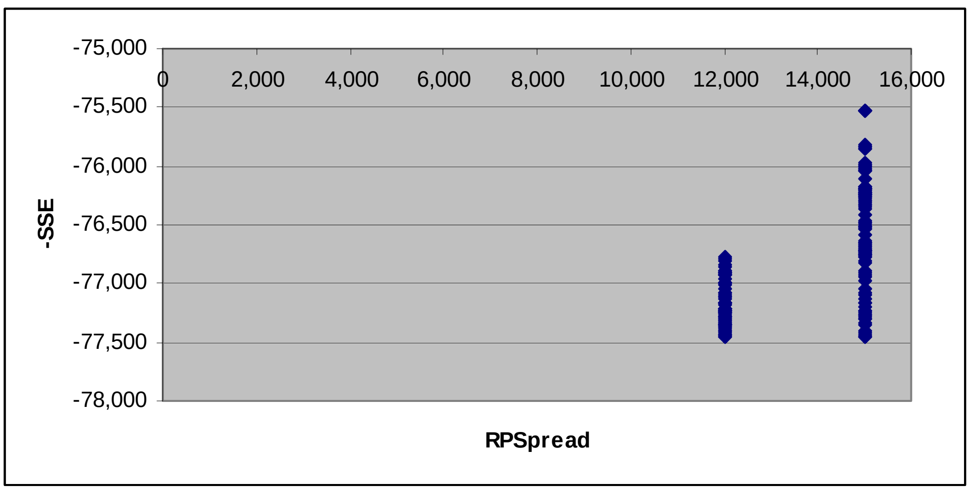

Figure 4.8. Objective Function Values in the *RPSpread* Dimension[37]

In Figure 4.7 the top 200 objective function value and their associated values for the parameter *PLo* are shown. From the figure it is clear that the best objective function

[37] For Figures 4.7 and 4.8 the parameters *RPLo* and *RPSpread* are defined in equation (4.2)

values occur at low *RPLo* values. Among the grid points that were evaluated in the *RPLo* dimension, 1,000 and 1,500 clearly yield the best objective function values.

Figure 4.8 shows the top 200 objective function values and their associated *RPSpread* values. Here, the dominance of the *RPSpread* estimate (over the alternatives) is pronounced. Note that among the top 200 objective function values only two of the five points in the *RPSpread* grid appear (12,000 and 15,000). All other values for *RPSpread* evaluated by the grid search algorithm were associated with objective function values outside the top 200.

In the current set up it is imperative to keep the dimensionality of the problem as low as possible. To address this need we use very course grids in our search for optimal values of *RPLo* and *RPSpread*. This approach imposes some important limitations in terms of our ability to express confidence in the quality of estimated parameters. Since we only evaluate 5 possible values for *RPLo* and *RPSpread* we cannot say with certainty that we have found the best estimates of the true *RPLo* and *RPSpread*. With finer evaluation grids we would almost certainly find *RPLo* and *RPSpread* parameters which offered an improvement over the current estimates. However Figure 4.7 and 4.8 illustrate that, although it may be possible to find better estimates by increasing the precision of the search algorithm, one would expect these "better" estimates to occur in a neighborhood around the current estimates. That is, due to the limitations associated with the nested DP structure of our model, I cannot say that our *RPLo* and *RPSpread* estimates are necessarily the best, however the estimates are certainly the best *among all evaluated alternatives*.

Because the model involves solving a DP problem for changes in the parameter space the precision around estimates of *RPLo*, *RPSpread*, *g*, or *sigma* cannot be increased without increasing run-time dramatically. For estimates of the parameters of the *R* function however, it is possible to use finer grids in the search algorithm at low cost, making it possible to calculate standard errors around the estimates for *y1* and *y2*.

Greene (2003) shows how standard errors can be calculated for Maximum Likelihood estimates. Although the estimator used here is the minimization of the sum of squared errors and not the maximization of a likelihood function, I will show that the following approach can be used to derive standard errors for this model as well.

The general approach is to use the inverse of the information matrix to calculate these standard errors. The asymptotic covariances are given by the expected values of the second-derivitives of the likelihood function.

$$[I(\theta)]^{-1} = \left[-E\left(\frac{\partial^2 L(\theta)}{\partial\theta\partial\theta'} \right) \right]$$

where θ represents the parameter vector

The estimator for the asymptotic covariance matrix is computed by evaluating the actual second derivatives at the optimal parameter values.

$$\left[\hat{I}(\hat{\theta}) \right]^{-1} = \left(-\frac{\partial^2 L(\hat{\theta})}{\partial\hat{\theta}\partial\hat{\theta}'} \right)$$

Conceptually, standard errors provide us with a measurement of how robust point estimates are. The second derivatives, contained in the information matrix, tell us how the slope of the likelihood function changes as we move slightly away from the optimal point. Intuitively, if the slope is changing rapidly we know the likelihood function is very steep in the neighborhood of the optimum. If this is the case then we are likely to be more confident in our point estimates. However, the flatter the likelihood function around the neighborhood of the optimum, the less confident we are likely to be in our estimates.

Since I use a minimum distance measure as the criteria for finding optimal parameters of the model, the calculation of standard errors is slightly different from Greene's Maximum Likelihood presentation. However, the calculations serve the same basic function. In this model estimates are obtained by minimizing an objective function which is the sum of the squared distance between observed and predicted bids. The standard errors of the estimates can be approximated by observing how the objective function changes with slight movement away from the optimum.

In practice, the model is essentially a discrete approximation to a continuous process. From the model estimation we obtain the optimal parameter vector,

$$\theta^* = \begin{bmatrix} y1^* \\ y2^* \end{bmatrix} = \begin{bmatrix} 101.25 \\ 2.5 \end{bmatrix}.$$

Because the optima are both interior grid points, it is possible to move one grid step in either direction around this optimal point and observe the likelihood function value at a total of 9 points. Figure 4.9 below shows the points of evaluation and the numerical derivatives associated with each.

In the figure below we have $y1_1 = 99.5$, $y1_2 = 101.25$, and $y1_3 = 103$. The three points for *y2* are $y2_1 = 1.25$, $y2_2 = 2.5$, and $y2_3 = 3.75$. At each of these points we have an objective function value, which is the sum of squared errors. Using the standard expression for the log likelihood function of estimator θ with error variance σ^2,

$$LL(\theta, \sigma^2) = -\frac{n}{2}\log(2\pi\sigma^2) - \frac{(y - X\theta)(y - X\theta)'}{2\sigma^2} \qquad (4.5)$$

we can transform objective function values into log likelihood values and use the inverse of the information matrix to calculate standard errors.

First note that in the classic linear model the sum of squared errors associated with estimator θ is $(y - X\theta)(y - X\theta)'$. Also, an unbiased estimator of σ^2 is given by

$$s^2 = \frac{\sum_i \varepsilon_i}{n - K},$$

where ε_i is the error associated with observation *i*, *n* is the number of observations and *K* is the degrees of freedoms. By substituting the quantities s^2 and SSE into (4.5) it is possible to transform the SSE values at each grid point into log likelihood values.

Looking along the rows of the matrix in Figure 4.7, one can see the partial derivatives with respect to *y1*. Starting in the first cell and moving across the first row, one can see the 3 values of *y1* which are used – one value on either side of the optimal point (101.25). Moving across this row, *y2* remains constant and 2 partial derivatives can be calculated from these three points. Starting in the first cell and moving down the first column, one can see the representations for two partial derivatives with respect to *y2*, evaluated at the first *y1* value.

Finding the second derivatives $\frac{\partial^2 LL}{\partial y1^2}$ and $\frac{\partial^2 LL}{\partial y2^2}$ in this case is a simple matter of taking a second difference around the optimal points, holding all other parameters at their optimal levels. Denote $\frac{LL(2,2) - LL(1,2)}{y1^2 - y1^1}$ from above as $\left(\frac{dLL}{dy1}\right)^1$ and $\frac{LL(3,2) - LL(2,2)}{y1^3 - y1^2}$ as $\left(\frac{dLL}{dy1}\right)^2$, then the second derivative $\frac{\partial^2 LL}{\partial y1^2}$ is approximated by,

$$\frac{\left(\frac{dLL}{dy1}\right)^2 - \left(\frac{dLL}{dy1}\right)^1}{y1^2 - y1^1}$$ [38].

The same process is used to approximate $\frac{\partial^2 LL}{\partial y2^2}$.

[38] The reader should note that, because we use uniform grids the distance between any two neighboring points in the grid is equal.

	y1				
y2	LL(1,1) = -7,768.286	$\frac{\Delta LL}{\Delta y_1} = 0.0152$	LL(2,1) = -7,768.259	$\frac{\Delta LL}{\Delta y_1} = 0.0147$	LL(3,1) = -7,768.234
	$\frac{\Delta LL}{\Delta y_2} = 1.1722$		$\frac{\Delta LL}{\Delta y_2} = 1.1527$		$\frac{\Delta LL}{\Delta y_2} = 1.1318$
	LL(1,2) = -7,766.821	$\frac{\Delta LL}{\Delta y_1} = 0.0013$	LL(2, 2) = -7,766.818	$\frac{\Delta LL}{\Delta y_1} = -0.0001$	LL(3,2) = -7,766.819
	$\frac{\Delta LL}{\Delta y_2} = -2.74811$		$\frac{\Delta LL}{\Delta y_2} = -3.03$		$\frac{\Delta LL}{\Delta y_2} = -3.320$
	LL(1,3) = -7,770.256	$\frac{\Delta LL}{\Delta y_1} = -0.2004$	LL(2,3) = -7,770.607	$\frac{\Delta LL}{\Delta y_1} = -0.2070$	LL(3,3) = -7,770.969

Figure 4.9. Numerical Derivatives of the Implied Likelihood Function Around the Optimum

Deriving the cross-partial derivatives for the information matrix, $\frac{\partial^2 LL}{\partial y1 \partial y2}$ and $\frac{\partial^2 LL}{\partial y2 \partial y1}$, is slightly more complex. To calculate these values I use the change in the average partial derivatives. For example, to get the cross-partial derivative of *y1* with respect to *y2* I use the following procedure:

With 3 values for both parameters there are 2 numerical partial derivatives at each value of *y2* – for *y2* = 1.25 the partials are $\frac{LL(2,1) - LL(1,1)}{y1^2 - y1^1}$ and $\frac{LL(3,1) - LL(2,1)}{y1^3 - y1^2}$.

Averaging these slopes gives an approximation to $\frac{\partial LL}{\partial y1} | y2 = 1.25$, which measures the change in the likelihood function with a change in *y1*, holding *y2* = 2.5. Averaging in this manner again for *y2* = 2.5 and *y2* = 3.75, gives 3 partial derivatives which can be differenced to provide an estimate for the cross-partial derivative, $\frac{\partial^2 LL}{\partial y2 \partial y1}$.

$$\frac{\left(\frac{LL(3,1)-LL(2,1)}{y1^3-y1^2}\right)-\left(\frac{LL(2,1)-LL(1,1)}{y1^2-y1^1}\right)}{2}=\frac{\partial LL}{\partial y1}(y2=1.25)\equiv\left(\frac{\partial LL}{\partial y1}\right)^1$$

$$\frac{\left(\frac{LL(3,2)-LL(2,2)}{y1^3-y1^2}\right)-\left(\frac{LL(2,2)-LL(1,2)}{y1^2-y1^1}\right)}{2}=\frac{\partial LL}{\partial y1}(y2=2.5)\equiv\left(\frac{\partial LL}{\partial y1}\right)^2$$

$$\frac{\left(\frac{LL(3,3)-LL(2,3)}{y1^3-y1^2}\right)-\left(\frac{LL(2,3)-LL(1,3)}{y1^2-y1^1}\right)}{2}=\frac{\partial LL}{\partial y1}(y2=3.75)\equiv\left(\frac{\partial LL}{\partial y1}\right)^3$$

$$\frac{\partial^2 LL}{\partial y1\partial y2}\approx\frac{1}{2}\left[\frac{\left(\frac{\partial LL}{\partial y1}\right)^2-\left(\frac{\partial LL}{\partial y1}\right)^1}{\Delta y2}+\frac{\left(\frac{\partial LL}{\partial y1}\right)^3-\left(\frac{\partial LL}{\partial y1}\right)^2}{\Delta y2}\right]$$

Here I have provided some technical details of our numerical approach to deriving the information matrix. As an inherently numerical process the notation deviates somewhat from the standard textbook presentation of standard error calculations. However, the reader should understand that this approach serves the same purpose as traditional standard error reporting – namely, to understand how the objective function is behaving in a neighborhood around the optimal parameter estimates.

The table below provides estimates of the asymptotic covariance matrix of *y1* and *y2*. The matrix of second derivatives contains very large values, suggesting that the objective function is steep in the neighborhood of the optimal estimates. This gives estimated standard errors for *y1* and *y2*.

Table 4.3

Standard Errors of the Parameter Estimates[39]

	Y1	y2
Y1	701.09	
Y2		0.18

The standard errors shown in Table 4.3 suggest that the estimate for *y2* is very robust, while the estimate for *y1* is not robust at all. Figure 4.10 shows the 200 best objective function values in the *y1* dimension. From the figure it is clear that the objective function is not at all responsive to changes in y1 around the optimum.

Figure 4.11 however, shows that the objective function is responsive to changes in *y2*. Much like the difficulties discussed previously with attaching confidence to the grid search estimates of *RPLo* and *RPSpread*, it is difficult to say how robust the estimate of 2.5 for *y2* would be to small changes around the value. From Figure 4.11, it is clear that the best objective function values occur around the point estimate for *y2*. So again, although it is not possible to say that the *y2* estimate is the true objective function maximizing value, it is clear that the *y2* estimate is the best *among all values in the set which made estimation feasible.*

[39] The reader may refer to equation (4.4) for definitions of the variables y1 and y2.

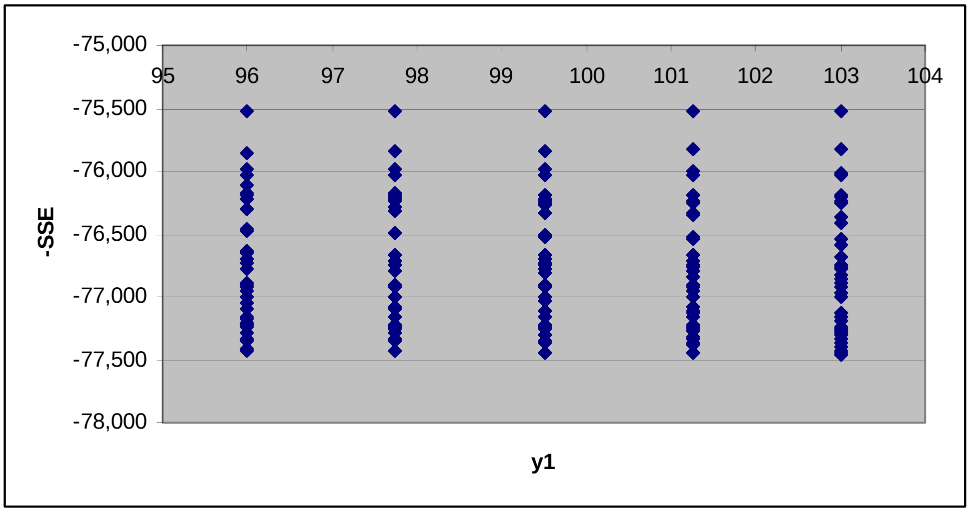

Figure 4.10. Objective Function Values in *y1* Dimension

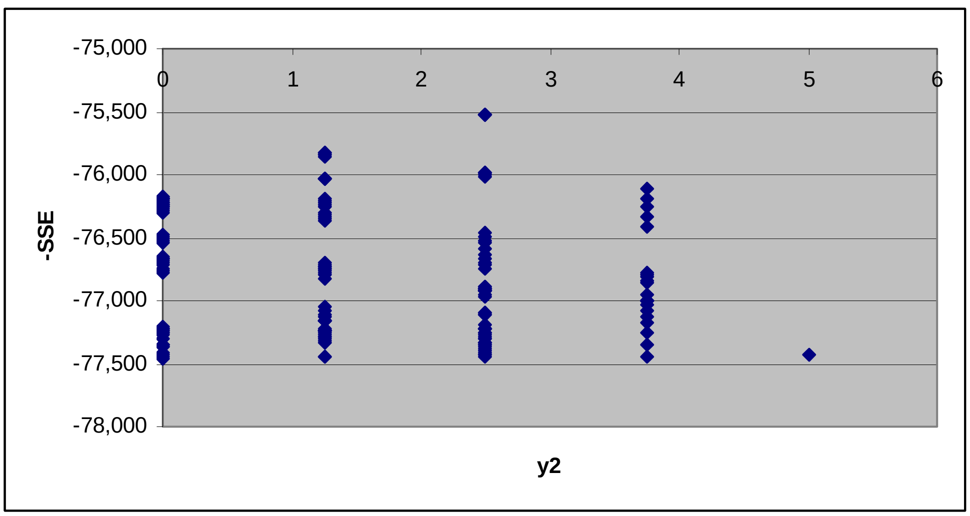

Figure 4.11. Objective Function Values in the *y2* Dimension[40]

[40] For Figures 4.10 and 4.11 the parameters *y1* and *y2* are defined in equation (4.4)

In particular, it is important to understand the effect that the grid search algorithm has on the calculation of these errors. Referring back to Figure 4.4, one can see that the grid steps for *y1* and *y2* are 2 and 1.25 respectively. The extent to which the parameter estimates can be labeled robust, or "good", is limited by how significant one considers a 2 unit change. That is, we observe that the slope of the objective function changes dramatically as we move from the optimal *y1* value of 101.25 down the grid to 99.5 or up the grid to103. Therefore, I can state confidently that the estimate for *y1* is robust relative to the alternatives. However, the model lacks the precision to state confidently whether 101.25 is a better estimator than 101.26.

Heteroskedasticity

Although there are well know formal tests for heteroskedasticity, Kennedy (2003) recommends preceding these with a visual inspection of residuals. Figure 4.12 shows the model errors as a function of the independent variable vessel length. The figure shows no evidence that the error variance is correlated with vessel length.

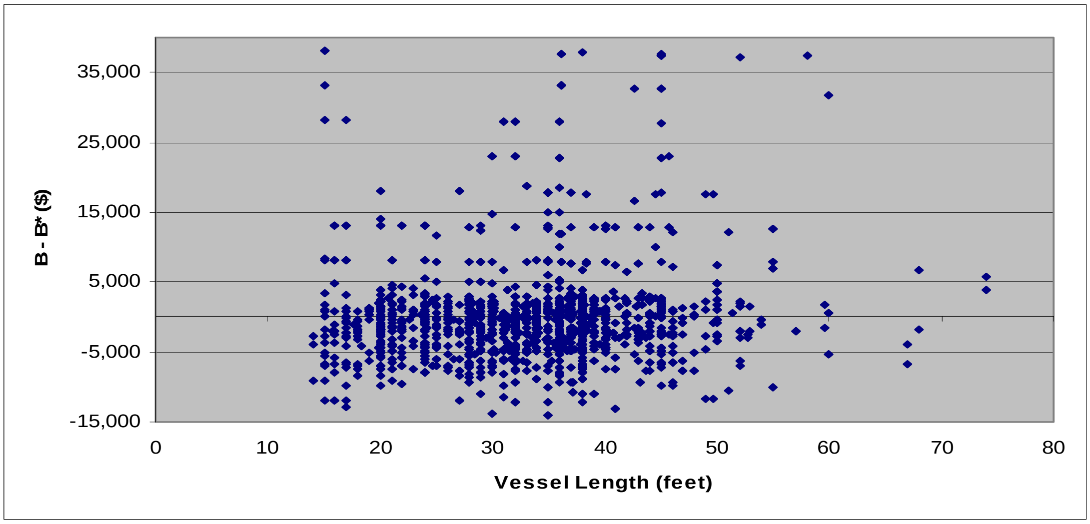

Figure 4.12. Prediction Error by Vessel Length

Figure 4.13 shows the model errors as a function of the independent variable price. For the price variable, prediction errors tend to be higher at the higher price levels. From figure 4.14, one also notes that the number of observations in the sample appears to be correlated with the price. This suggests a possible extension to the model. Since 46% of the total observations in the sample come from the 5 rounds in which shrimp price exceeded $4/lbs, a sample selection correction may be in order here. Unfortunately, the numerical intensity of the current model prohibits the introduction of more structure.

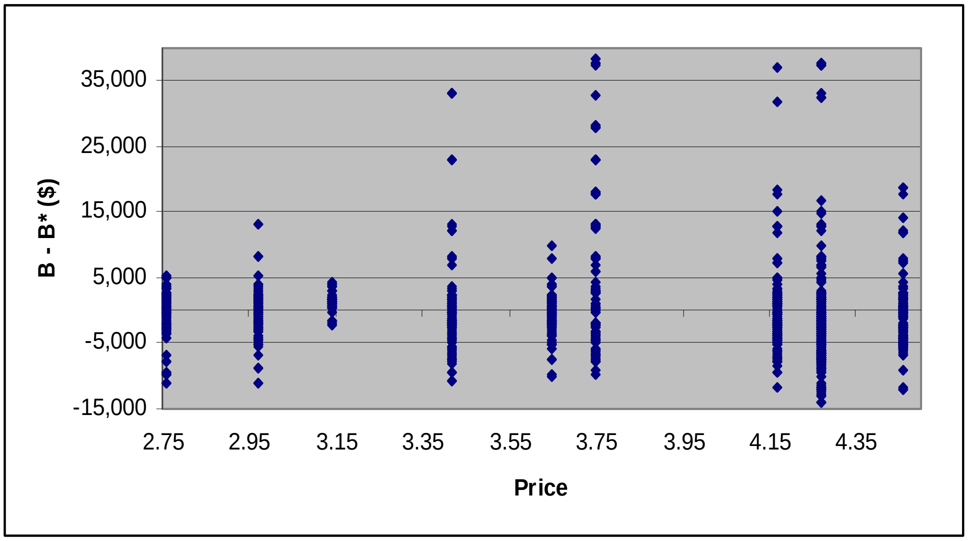

Figure 4.13. Prediction Error by Shrimp Price

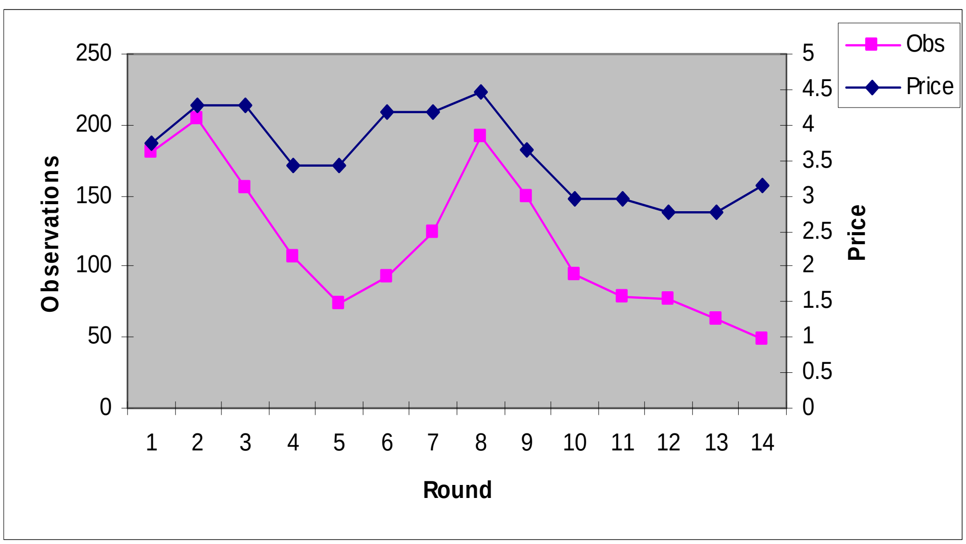

Figure 4.14. Sample Observations and Price

Identification

Estimates of the parameters *c1* and *c2* from our model are both 0. This can probably be attributed to an identification problem rather a reflection of true parameter values. Recall that the specification used to define the function *R* led to the reduced form equation,

$$R(x, p) = py_1 + py_2 x - c_1 - c_2 x\,.$$

In this equation the *y2* and *c2* parameters are both interacting with vessel length. Likewise *y1* and *c1* are both providing intercept terms, although *y1* is scaled by the price variable. The fact that *c1* and *c2* are estimated to be 0 is likely indicative of the fact that the model simply cannot distinguish between the competing effects of these coefficients. I have derived an expression for *R* using a gross revenue less cost approach. However, it appears that what the model is really picking up is a single set of coefficients defining a net revenue function.

Identification in the econometric sense is a problem usually encountered with systems of equations. As Kennedy[41] (2003, p. 182) states:

> If you know that your estimate of a structural parameter is in fact an estimate of that parameter and not an estimate of something else, then that parameter is said to be identified: identification is knowing that something is what you say it is.

If this analysis relied heavily on estimates of separate cost and revenue parameters then the identification problem discussed here might certainly be concerning. However, the primary objective is to uncover the *speculative premium,* which is expressed as the

[41] The reader may also want to refer to Kennedy (2003, p.184) for an intuitive discussion of the identification problem using a supply and demand example.

difference between observed bids and capitalized value of the asset. This objective does not necessarily require that *y1*, *y2*, *c1*, and *c2* all be econometrically identified and for this reason I do not address the identification problem here.

Discussion

Benefit Function

Using the parameter estimates to calculate the implied values of *R*, it is clear that the bidders in this fishery are getting very low returns on their licenses. Figure 4.15 shows the value of *R* for the average vessel in the sample for each round. From the figure, one can see that values of *R* range from a high of just over $800 in 2000 (round 8) to just above $500 in 2004 (round 13).

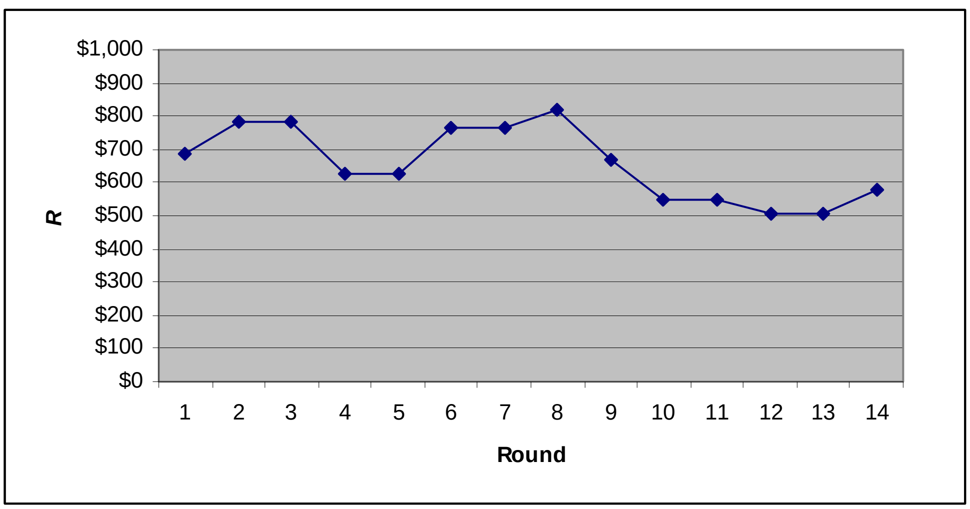

Figure 4.15. Implied *R* Values for Average Vessel[42]

[42] The function *R* is defined in equation (4.4)

The Speculative Premium

The parameters of the *R* function allow calculation of the speculative component present in bidding behavior in the sequential auction. Here I present the derivation of the speculative premium and discuss its significance.

By solving the dynamic decision problem stated in (2) the bidder learns his or her b^* conditional on a set of parameters. And by comparing those conditional b^*s with observed decision the parameter vector θ^* which minimizes the sum of squared errors was found. With these parameter estimates, we can calculate the implied value of *R* which, when compared to observed bids gives the speculative premium.

Figure 4.16 shows the average speculative premium by round for all vessels in the sample. Figure 4.17 shows the average speculative premium for four representative vessel lengths based on quartiles of the distribution of all vessel lengths in the fishery.

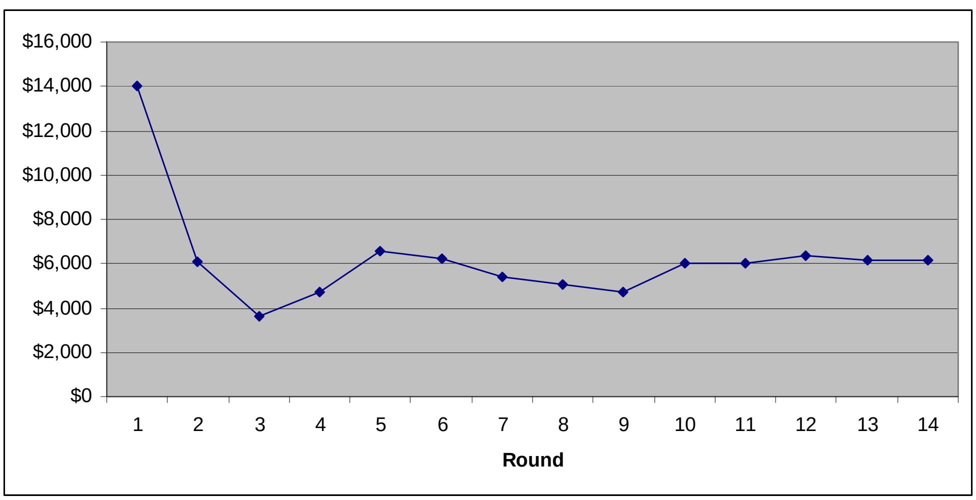

Figure 4.16. Average Speculative Premium by Round for All Vessels

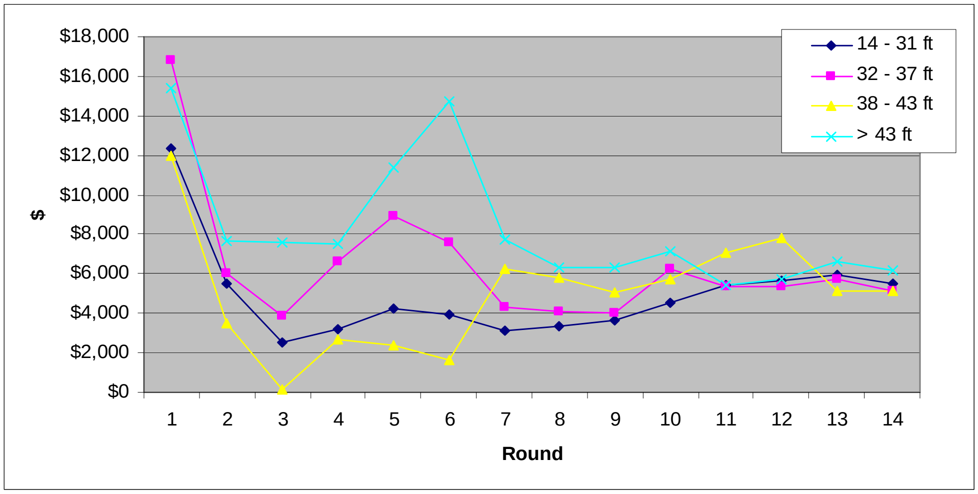

Figure 4.17. Average Speculative Premium by Round and Length Class

From Figure 4.17 one can see that the difference between bid amount and the capitalized value of the asset (the license) is initially quite volatile. This is consistent with the hypothesis of agent learning. In the early round, when bidders are still learning about the agency's willingness to pay relative to their own valuations, the speculative component is highly variable. By about halfway through the sample however, it appears that bidders have settled in to a steady state level of speculation around $6,000.

Summary of Empirical Work

The overarching goal of this chapter was to estimate the magnitude of speculation present in this sequential buyback auction. This quantity plays a vital role in our cost benefit analysis of sequential versus one-time auctions, which I present in the next chapter. However, in defining and estimating a model capable of measuring this speculative component I have also presented several important empirical and methodological contributions.

One important methodological contribution of this work is the estimator itself. As was discussed previously, models of this type are often estimated using a maximum likelihood approach where the likelihood function appears similar to that of a multinomial logit model. When the control variable is discrete this approach is appropriate and its use is well documented in the literature (Rust, 1988; Provencher and Bishop, 1997; Schjerning, 2005 among others). However, in this model the control variable, bid, is continuous. The difference highlights an important contribution of this work. Here I have presented a feasible estimator for a dynamic decision model with a continuous control variable.

The model is also unique in that it incorporates the learning made possible by the sequential auction into the decision process. I have shown here how a Bayesian updating procedure can be used to transmit information acquired in the current round and inform next period's bidding. The state equation provides a guide for how learning can be modeled inside of a nested dynamic optimization estimation routine.

Although I have shown some large prediction errors present in the model, in estimating this model, I believe sufficient evidence has been provided to validate this approach. In particular, the R-squared measure is higher than might otherwise be expected, considering the rich decision environment that is explained with only a few variables. Furthermore, the model's predictions improve greatly after one realized outcome, suggesting that the agent's learning is being appropriately model. And finally, standard errors for the two parameters of the *R* function are low, suggesting that these estimates are relatively robust.

In short, although further refinements are necessary to achieve greater precision on the point estimates, I believe that the results of the estimation are sufficient both to validate this dynamic econometric approach and provide reasonable estimates for use in the next chapter's policy simulation. With respect to this last point, in achieving reliable estimates for parameters of the *R* function, I have found that bidders in the sequential auction do inflate their bids by a speculative premium. This is certainly an important result for fisheries managers considering using a buyback program for capacity reduction. However, more generally, it can be stated that the repeated game format of the sequential auction seems to offer agents an incentive to over bid relative to their true valuation.

CHAPTER V

A COST-BENEFIT ANALYSIS OF SEQUENTIAL VERSUS ONE-TIME BUYBACK AUCTIONS

Introduction

In their extensive survey of buyback programs Holland, Gudmundsson and Gates (1999) show that license buyback programs have been a popular management tool for addressing a range of fisheries management issues including overfishing and overcapacity. Given the popularity of license buyback programs, it is important to understand the design and implementation issues of these programs as they relate to management goals. In this chapter, I study how the key design issue of auction method will affect the ability of a buyback program to reduce capacity and generate rents in the fishery.

Once the management authority has decided to implement a license buyback, they must consider how that program will be carried out, specifically, deciding how these licenses will be purchased. The two most likely competing candidates here are via an agency stated price offering or a buyback auction. Under a price offering system, the agency would simply state a price at which it is willing to buyback licenses and then buy permits back from as many willing sellers as the budget allows. Under an auction system, the agency solicits bids from license holders and decides, based on bids and the management goals, how to allocate the budget among collected bids. Although there are a number of interesting implications surrounding the auction versus pricing decision, they are beyond the scope of this analysis. The point of departure for this study will be an agency that has decided to implement a license buyback auction. Readers interested in a discussion of the relative merits of an agency stated price buyout versus an auction mechanism should refer to Latacz-Lohmann and Van der Hamsvoort (1997).

The next key design issue that the agency faces is whether the auction will take place in a single year or over time. The current literature on buybacks exhibits a notable lack of discussion of this particular issue and there does not seem to be a clear preference among fisheries managers in the U.S. for one auction type over the other. Of the two U.S programs discussed in Curtis and Squires (2007), one is a sequential buyback auction and the other a one-time buyback auction.

Intuitively speaking, from the perspective of the managing agency, an advantage to one-time license buybacks (OTBs) over sequential buybacks (SBs) is that they remove the possibility of gamesmanship from the process of buying back permits. By completing the buyout in a single year the agency does not allow participants to learn about the agency's willingness to pay. Intuition and economic theory suggest that this type of buyback auction should lead to stated buyout prices (bids) that are close to the individual's true value.

A notable disadvantage of the OTB relative to the SB is that the OTB requires all funding up front. With a SB program the agency has the option of generating funds each year, through a tax for example[43], and thereby funding itself. A one-shot program, however, requires a much larger initial investment. The relative importance of this will be the focus of our analysis here. Another advantage of a SB program, which will not be

[43] The Texas program funds buyouts partially through a fee assessed to the saltwater fishing stamp.

evaluated in this chapter, is that it provides the opportunity for managers to learn as the program proceeds. I discuss that aspect in the concluding comments, but do not formally evaluate its significance here.

In this chapter I compare two buyback programs with an equivalent pot of money spent two different ways. I model a SB program with an annual budget that is exhausted each year over a ten year period and contrast this with a OTB program that has a budget equal to the present value of the SB's stream of payments. The setting for these policy comparisons will be the Gulf of Mexico's shrimp fishery.

In the next section I provide brief clarification of some terms that will be important to understand for this analysis. Then I discuss the methodology for this study and introduce the General Bioeconomic Fisheries Simulation Model (GBFSM) which is used to simulate policy paths for our analysis. The details of the scenarios considered for the policy comparisons are then presented. Finally, I present the results of the simulation and conclusion that can be drawn from the analysis.

Important Terms and Concepts

"License" vs. "Permit"

In this chapter it will be important to understand the distinction between the terms "license" and "permit." In the Gulf of Mexico a shrimp license is an asset which confers on its holder the right to shrimp in state waters only. A permit allows the holder to fish for shrimp in federal waters. When referring specifically to an asset allowing the holder to shrimp in federal waters the term "permit" will be used. In all other instances the general term “license” will be used, but will refer to a general license to participate, rather than a specific limited right to fish in state waters. This is done since the term “license” (e.g. sequential license buyback), is the term conventionally used in the fisheries economics literature. However, the reader should understand that comments about licenses in general also apply to a program buying back permits to fish in federal waters. When referring specifically to state licenses, I will indicate this.

The Fishery

The Magnuson-Stevens Fishery Conservation and Management Act defines a fishery as:

> one or more stocks of fish which can be treated as a unit for purposes of conservation and management and which are identified on the basis of geographical, scientific, technical, recreational, and economic characteristics.

In this chapter I use the term “fishery” to apply to the various regional shrimp stocks throughout the Gulf of Mexico as well as the Gulf as a whole. In each of our simulated programs, “the fishery” will be defined by the management’s authority. For example, when referring to the Texas Inshore Shrimp License Buyback Program, the term “fishery” will be used to refer to the inshore shrimp stock in Texas and those licensed to harvest that resource. In this chapter I will also analyze simulated programs for capacity reduction in the Gulf of Mexico as whole. The boundaries of “the fishery” will be assumed to extend as far as the authority of the program in question. Moreover, I use the term “fishery” to apply only to the harvesting sector. There are no effects on the processing sector, consumer, or any other direct or indirect impacts modeled here.

Methodology

The overarching goal of the analysis in this chapter is to simulate a buyback program implemented with a SB auction and a program carried out via a OTB auction and compare their relative abilities to achieve the management goals of reducing capacity, increasing productivity, and increasing fishery rents. To achieve this goal, I use results of the analysis of the SB auction that has been used by the Texas Parks and Wildlife Department (TPWD) to buy back Bay and Bait licenses in the Texas inshore shrimp fisheries. The TPWD program is an ongoing auction that has been purchasing bay and bait licenses from inshore shrimpers since 1995.[44] Using data from this auction, certain behavioral patterns can be identified which characterize how fishermen respond to the incentives of a SB auction. In Chapter IV I estimated a model of bidding behavior using a dynamic econometric model. The model included an estimate of the speculative premium. In the previous chapter I also presented the details of that econometric model and the nested dynamic optimization algorithm used to obtain parameter estimates of that model.

In this chapter I use the results from Chapter IV to simulate bidding behavior in a buyback program for large vessel permits throughout the Gulf of Mexico using both a SB and OTB auction. With these simulations it is possible to compare the cost and effectiveness of each. The speculative premium is the key variable in this chapter as it

[44] Further background on the Texas Program can be found in the third chapter of this dissertation as well as Funk et al. (2003).

establishes a behavioral relationship between the value that a fisherman attaches to their license and the bids that he or she will offer for the sale of that asset.

A GBFSM Introduction

To conduct the simulations necessary for this study I developed a policy module which operates inside of the General Bioeconomic Fisheries Simulation Model (GBFSM). GBFSM has been discussed at length in the fisheries economic literature and a detailed discussion of the model is beyond the scope of the current analysis. In this section we will provide a very general overview of GBFSM and discuss the placement of the Gulf of Mexico license buyback module within the overall structure. For a more detailed discussion of GBFSM the reader should consult Grant and Griffin (1979) and Grant, Isakson, and Griffin (1981).

GBFSM is a multi-species, bioeconomic simulation model developed by Dr. Wade Griffin. A summary of the major functionality of the simulation model is provided in the GBFSM manual:

> The biological sub-model represents the recruitment of new organisms into the fishery by species, sex, and fishing area. Recruitment may be in one or all depth zones, and movement may be to greater or lesser depths and between fishing areas. Organisms grow and move from one size class to another, and mortality results from both natural causes and fishing…
>
> … The economic submodel represents the fishing effort (nominal days fished converted to real days fished) exerted on each species and on by-catch. Monetary costs of fishing, value of harvest, and rent to the fishery are calculated.

Fleets

This simulation model divides the Gulf of Mexico into four regions as shown below in Table 5.1.

Table 5.1

Four Gulf Regions of Shrimp Landings in the General Bioeconomic Fisheries Simulation Model [45]

Region 1	Region 2	Region 3	Region 4
Florida	Alabama[46], Mississippi, & Eastern Louisiana	Western Louisiana	Texas

Each region includes two vessel classes: vessels less than 60 feet in length and vessels 60 feet or greater in length. In the model, small vessels (those less than 60 feet) generally shrimp in inshore areas in state waters and offshore state waters.[47] Large vessels shrimp both in offshore state waters and federal waters, including the Exclusive Economic Zone (EEZ). The model is calibrated so that the initial size of each large vessel fleet is equal to the number of federal permits requested from each region in 2005.

[45] Regions are where shrimp are landed and areas are where shrimp are caught. Areas are adjacent to each region. It is assumed that vessels land fish in only one region but can catch fish in any of the four areas where shrimp are caught.

[46] In the results section of this chapter I will refer to each region by its proper name. For example, I will refer to “Texas” instead of “region 4.” As a convenience to the reader however, I will refer to region 2 as “East Gulf.”

[47] There are only a few small vessels that have permits to fish in federal waters, however for convienence it is assumed that small vessels do not have permits.

An important assumption of the model is that large vessels selling back their federal permits do not continue fishing in offshore areas in state waters[48].

Finally, it deserves mention that GBFSM is a homogenous fleet model. Revenue and cost figures are calculated by region and vessel class. This means that all vessels within a particular fleet are treated as if they have the same revenue and cost structure.

The buyback policy module works in four basic steps. First, using the estimated speculative premium in the SB program and fishery rents, which are calculated in GBFSM's economic submodel, the distribution of bids that will be submitted to the auction in a given year is predicted. Next, the budget determines how many of these bids can be accepted. The size of the fleet is then adjusted to reflect the number of licenses or permits exiting the fishery due to the buyout. Finally, effort in days fished is adjusted according to the new fleet size. The next section will explore these steps individually.

The GBFSM Buyback Policy Module

The buyback policy module was written in Fortran 90 for this analysis and functions as one of several GBFSM policy options. The module operates inside of GBFSM and uses information obtained from GBFSM's biological and economic submodels, along with data from outside the model, in order to simulate the effects of different buyback programs. This section discusses the details of the buyback policy module.

---

[48] From personal communication with Mike Travis of NMFS I understand that it would not be economically viable for large vessels to operate without access to the EEZ. Therefore, I believe it is reasonable to assume that large vessels forfeiting their federal permits are not continuing to shrimp in offshore state waters.

Data

The data required of GBFSM for our simulations can be broken into two classes. The first class of data provides the policy module with a complete description of the programs it must simulate. The second class of data deals with parameters estimates and other data obtained from outside of GBFSM and used by the buyback policy submodel.

The program description data starts with a specification of the number of programs to be simulated. Next, the region/vessel class combinations eligible to participate in each program must be defined. Then each program is assigned a type (either sequential or one-time). Finally, the total budget for each program is declared. The second class of data includes estimated values from outside the simulation model. The first of these is the speculative premium. This value can be calculated using the parameters of the function estimated in Chapter IV for each region, vessel class, and year. Next, the actual number of vessels in each region/vessel class combination must be input.

Initial Values

GBFSM is set up to analyze percent changes in fleet size. The simulation model treats each region as if it were initially composed of 100 representative vessels. For the offshore fisheries, the buyback policy module keeps track of the representative fleet (percent of original vessels) in each year as well as the actual fleet and this translates into a corresponding percentage reduction in the total effort available to fish in each region. For the inshore fisheries, the model only tracks percentage changes in each fleet. I do not track changes in actual vessels for the inshore fisheries because of the lack of reliable data on the number of inshore vessels for each region. However, the absence of actual vessel numbers for the inshore fisheries should not qualitatively limit the analysis.

Because offshore fishing in state waters is a relatively minor part of the fishery, in all of the analysis in this chapter it is assumed that any program that retires the federal permits will effectively also retire the state off-shore license. No program explicitly for state offshore fishing is modeled. In the model, vessels are assumed to land shrimp in a single region. For calibration, individual vessels are not identified, so there is a one-to-one relationship between the landings in the region and the vessels.

Predicted Bids

The first major task carried out in the buyback policy submodel of GBFSM is to determine a distribution of bids for each fleet. Bids are determined based on the profitability of the fishery and type of buyback under analysis. To present this calculation completely it will be informative to back-up and briefly discuss order of operations.

Figure 5.1 illustrates the important steps to understand for this analysis. When a simulation run begins, the model initializes several key variables, including fleet size. The simulation then runs through the biological submodel, which calculates recruitment, mortality, and other important biological relationships. Once the biological variables are calculated, the simulation then calculates economic variables such as cost and fisheries rents. Of particular interest for this analysis are fishery revenues and the cost structure. After calculating the key economic variables, the simulation enters the license buyback submodel.

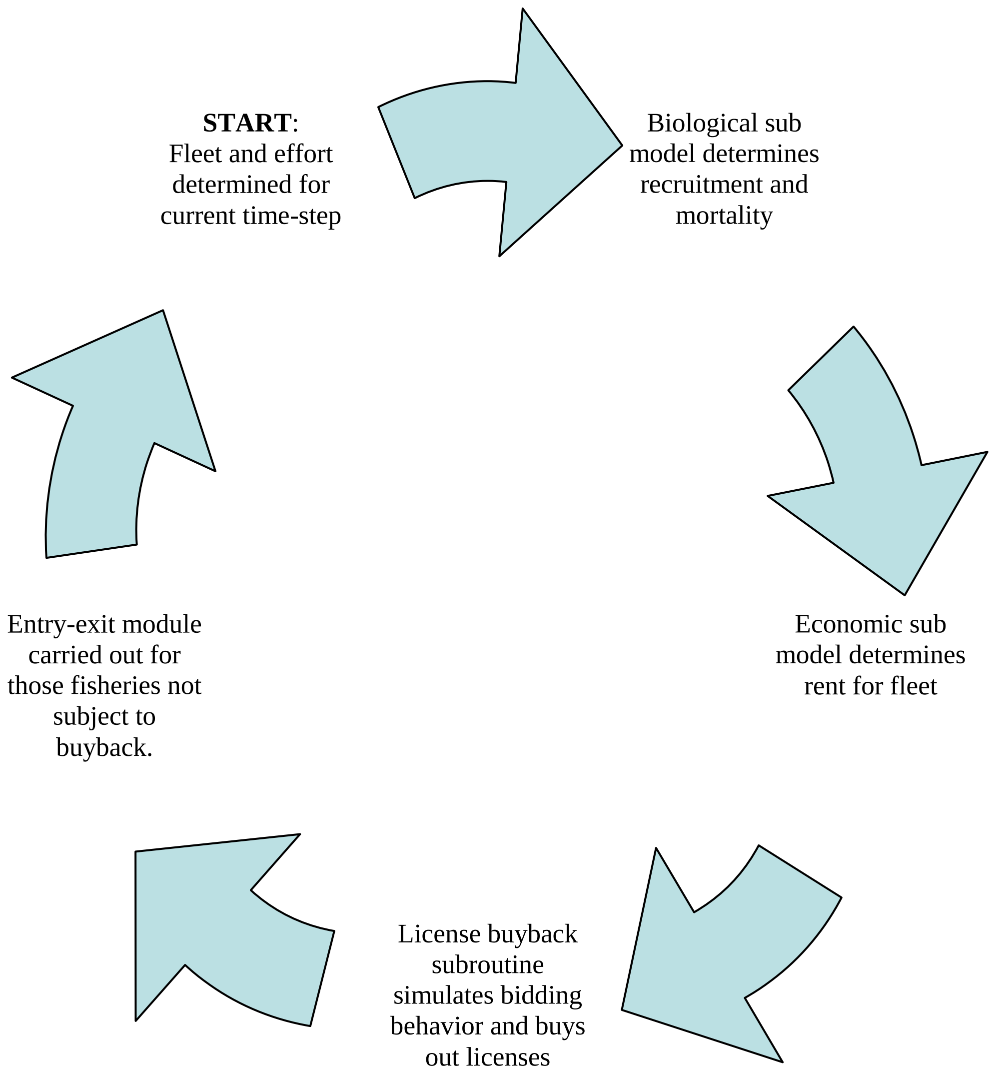

Figure 5.1. An Illustration of the General Bioeconomic Fisheries Simulation Model

In a given year, the model enters the buyback policy module with values for the crucial variables, fleet size and net revenue. To predict the bids that will be submitted for license buyout in a SB auction I use the net revenue combined with the estimated value of the speculative premium. And to predict bids in a OTB auction I use the present value of net revenues. Net revenues are defined as revenues net of all variable costs.

From the econometric model discussed in Chapter IV we have estimates for the speculative component. The following details how the estimates of speculation are used to predict bids for the simulation model.

Denote the benefit function for an individual with vessel length **x** facing price **p** as $R(x,p)$ and the optimal bid as b^* then the speculative ratio for vessel length **x** in time **t** is,

$$specratio(x,t) = \frac{b^*}{R(x, p_t)}.$$

This ratio is used to calculate the average bid for a vessel class for the SB programs in the license buyback submodel.

At the point in the overall simulation when the program enters the buyback policy module, a value for net revenue by region and by vessel class has already been calculated. Under the assumption that revenues and costs are distributed evenly throughout the fleet the expected net revenue for individual *i* can be calculated as,

$$netrevenue_i = \frac{netrevenue(region, vessel\ class)}{fleet(region, vessel\ class)}.$$

In a OTB auction theory suggests that an individual's minimum willingness to accept payment for a license will be the present value of that asset. So for the OTB auction the average bid is calculated as,

$$bid_i^{OTB} = \frac{netrevenue_i}{1-\beta}, \text{ where } \beta = \text{ the discount factor.}$$

In the SB auction however the average bid will contain a speculative component. We calculate the average bid for the SB auction as,

$$bid_i^{SB} = \frac{netrevenue_i}{1-\beta} * (1 + specratio_i).$$

The average bid shown above is the bid per vessel for each region and vessel class. This is converted to a bid per percent of the fleet by adjusting the per vessel bid by the ratio of actual vessels to representative units.

Once the mean bid per percent of the fleet has been calculated, bids for the vessels in that fleet are determined by generating a distribution around the average as follows. I assume that bids from the fleet will be distributed logistically around the average bid, which gives a closed form expression for the cumulative density function (cdf),

$$D(b) = \frac{1}{1 + e^{\frac{-(b-m)}{k}}}.$$

Here, the parameter *m* represents the mean of the distribution and *k* is a distributional parameter related to the variance (the parameter *k* is defined below).

With this assumption about the distribution of the bids, it is possible to calculate the bid at a given percentile of the fleet, *p*, by inverting the cdf,

$$b = m - k \ln\left(\left(1 - p\right)/p\right).^{49} \tag{5.1}$$

The parameter *k* defines the standard deviation of the distribution as follows

$$\sigma^2 = \frac{1}{3}\pi^2 k^2$$
$$k = \sqrt{\frac{3\sigma^2}{\pi^2}}$$
$$\text{where } \pi = 3.14159.$$

The variance, σ^2, is estimated based on data from the TPWD program as is discussed in section entitled "*Bidding Assumptions*" below.

Table 5.2 shows a sample distribution for a fleet with 100 vessels. Here the average bid is $10,000 and standard deviation is $3,000. The table shows predicted bids from this fleet.

Bid Acceptance

Once the distribution for bids submitted to the buyback auction has been simulated, we must determine what percent of the fleet can be purchased. In the simulations this decision is based on available funds (recall that the funds available are exogenous and predetermined). The simulation model can accommodate a variety of different combinations of region and vessel classes eligible to participate in the program and one or several programs can be operating simultaneously. For example, it is possible to simulate one program for the entire gulf or a program for each region in the gulf. Each region-vessel class combination in a program is called a *group* and for each group there

[49] For example, the 90th percentile, *p*=0.9, would refer to the vessel whose bid is higher than 90% of the bids in the fleet.

is a separate distribution of bids. The bids from all groups in a program are sorted from lowest to highest and the lowest bids are accepted until the available funds are exhausted.

Table 5.2

Sample of a Simulated Distribution of Bids

Vessel	**P**	**Bid**[50] $b = m - k\ln\left(\frac{1-p}{p}\right)$
1	0.01	$2,399.73
2	0.02	$3,562.98
3	0.03	$4,250.58
4	0.04	$4,743.54
5	0.05	$5,129.94
6	0.06	$5,449.00
7	0.07	$5,721.65
8	0.08	$5,960.39
9	0.09	$6,173.28
10	0.1	$6,365.82
98	0.98	$16,437.02
99	0.99	$17,600.27

To provide an example of the bid/buyout portion of the algorithm, suppose one wanted to simulate the capacity reduction achieved by extending the current Texas program (call this program 1) and also adding a buyback program for all large, federally permitted vessels in the gulf (call this program 2). The current Texas program applies only to the Texas Bay System, therefore, this program would have one group (Region

[50] Bid, as used here, is defined in equation 5.1.

4/vessel class 1). The second program, operating in the gulf, would have 4 groups (Region 1/vessel class 2, Region 2/vessel class 2, Region 3/vessel class 2, and Region 4/vessel class 2).

For program 1 the buyout process is simple. The simulated distribution gives a dollar amount at each percent of the fleet that is required to buyout that percent. With only one group in the program one could simply integrate along this distribution until the budget is exhausted.

For program 2, however, the buyout process is more complex. With 4 groups eligible to participate there are 4 separate distributions of bids. The model will pool these bids and sort them in ascending order. It will then begin purchasing the cheapest license until the budget is spent. It is interesting to note here that with this type of program it is possible to have regions from which no licenses are purchased.

Fleet/Effort Updating

The last step in the buyback module is to update the fleets and return these values back to the main GBFSM model for use in the next time step. After the bid acceptance portion of the buyback module is complete we know the percent of each fleet that was bought out via the simulated programs. The fleet is then adjusted by this percent. Fleet updating is a simple matter of multiplying the fleet at the beginning of the year by one minus the percent reduction. Likewise, effort, measured in days-fished, is adjusted by the percent change in the fleet.

Important Assumptions of the Simulation Model

The simulation model in general and the policy module in particular impose some important limitations on the results. It is important to be transparent about these in order for the reader to understand what this model is and is not capable of analyzing. What I believe to be the most important assumptions underlying our model are discussed below.[51]

Unit Costs and Prices

One important assumption relating to the fleet rent function is that unit prices within a size category and unit costs are unchanging. The model holds prices and unit costs constant at 2005 levels throughout the 10-year simulation. This is an important assumption because as licenses are bought back capacity leaves the fleet, which may affect shrimp supply. One possible effect of this shift in the supply curve is higher shrimp prices. This movement is not captured in our model.[52]

Bidding Assumptions

In applying the bidding distribution there are two assumptions that deserve some discussion. This first is that there exists a minimum price, below which nobody will bid regardless of rents. The second is that the standard deviation of the distribution is declining through time.

---

[51] A discussion of the assumptions that are maintained in GBFSM can be found at the GBFSM website: http://agecon2.tamu.edu/people/faculty/griffin-wade/gbfsm/

[52] It should be noted however that prices do rise during the 10-year simulation. The price rise is due to a rise in the average size of shrimp harvested as effort decreases. Since prices are positively related to shrimp size, average shrimp price does rise over the 10-year simulation.

The assumption of a minimum bid stems from the estimation work and is empirically justified. The estimation of the bid function for Texas fishermen includes a variable for the minimum point in the bidder's subjective expected grant distribution. This is the lowest value for which bidders in that auction believe the probability of having the agency accept their bid is 1. In this study the value is captured by the variable *PLoStart*, which is a variable to be estimated. This variable is the first prior expectation over the lowest point in the grant distribution. The estimate of this variable (from Chapter IV) was $1,000. This suggests that bidders in the Texas auction who have, as of yet, no knowledge of prices paid for licenses are behaving as though $1,000 is the minimum license price.

In order to use this estimate to inform the simulations, it is converted to a bid per unit length figure then multiplied by a factor representing each region's rents in relation to Texas. The data from the Texas program included bidding behavior almost exclusively from small inshore vessels. Since the simulations in this chapter deal with large offshore vessels, the observed bid floor was converted to a bid floor in terms of dollars per foot of vessel length by scaling up. The bid floor is applied to large vessels by multiplying by 60, the lower bound for length of large boats in GBFSM. The regional rent factor is calculated simply as the ratio of fishery returns in region i to fishery returns in Texas. This is meant to try and capture some of the regional differences in bidding that may arise because of differing economic conditions.

Another key component of the calculation of the distribution of bid is the standard deviation. I have shown that over time the distribution of the bids from the

Texas auction condensed considerably. Over the life of that auction the standard deviation in the distribution of bids went from around $20,000 down to $6,000. I use this trend in the standard deviation for the Texas auction to help form assumptions about the standard deviations for the simulated bid distributions.

At $20,000 the standard deviation in the Texas inshore auction is about 5.3 times the average bid in that auction. This deviation declines by an average of 7% per year through the 8th year. Therefore, in the first period of each simulation the standard deviation of the bidding distribution in each region is set equal to 5 times the average bid for that region. For each year thereafter, the standard deviations decline by 7%. It is assumed that by the 8th year learning is complete and the standard deviation in the bidding distribution does not change.

Participation

In the Texas Inshore Shrimp License Buyback Program, in each year, only a small percent of the total licenses in the fishery are bid on. In 1997 only 18% of the licenses eligible for buyback were bid on. In particular, as described in Chapter III, the participation decision seems to be significantly influenced by the age of the license holder and length of the licensed vessel. Because of the homogeneous fleet structure, the simulation model is not able to incorporate these factors. Hence, it is assumed that in each period there will be a bid for each license in the fishery.

This assumption will likely have an impact on the distribution of bids across regions. In Chapter III I showed that demographic factors have an influence on the bids and the participation decisions, and that these factors will differ between regions.

Specifically, if age could be incorporated into the calculation of bids the predictions would likely be more accurate.

Bid Grant/Acceptance

For the SB auction run by Texas Parks and Wildlife the decision to grant or reject a particular bid is a complicated one. Bids are ranked based on the size of the bid and the agency's estimate of that vessel's effort, which was based on vessel length[53]. The bids that result in the largest effort retirement per dollar spent are ranked highest and granted first. This analysis assumes simply that bids are granted in order from lowest to highest until the budget is exhausted.

I also make an important assumption regarding the fisherman's acceptance of buyout offers. In the Texas program after having a bid granted the license holder may choose whether to accept the offer. This creates a unique decision making environment where the bidder potentially has the ability to bid "too low" without penalty. The estimates of parameters of the bidding function from Chapter IV were derived under the assumption that once a bid is granted the license is retired. Although this is not strictly accurate, the number of bidders who actually rejected a bid once granted is small, suggesting that most bids are offered on the assumption that if granted they will be accepted and their licenses will be retired. This assumption is carried over to the policy simulations as well. This assumption should not significantly impact our ability to compare the two auction designs.

[53] Through personal communication with Robin Riechers of TPWD I learned that the formula for ranking bids originally included vessel length and number of years the owner has been in the fishery. The formula was amended early on to rank bids primarily on vessel length.

Scenario Analysis

The focus of this chapter is on using GBFSM to compare the effectiveness of SB programs relative to OTBs. This comparison is carried out by seeking to answer two important questions. First, what would be the effects of instituting in the entire Gulf of Mexico a SB program similar to the one used to buyback licenses in the Texas Inshore Shrimp fishery? And second, how would the costs and effectiveness of this proposed policy differ if, a OTB auction were used to buyback licenses?

Baseline

The Baseline Scenario assumes that Texas keeps its inshore license buyback program, that there is open access for all small vessels in the gulf and limited entry for large vessels in the gulf. This is a reasonably accurate depiction of current regulations in the Gulf of Mexico's shrimp fisheries. Large vessels operating in federal waters in each region are currently subject to limited entry while small vessels operating inshore and near shore are not. Moreover, the Texas buyback program is entering its 12th year with no plans to end.[54]

Scenario 1: Gulf-wide SB

In Scenario 1 I still consider open access for small vessels in the gulf and a SB operating for small vessels in Texas but I add a SB program for large vessels in all gulf

[54] After completing the analysis I learned that the Texas program is being brought to a conclusion (personal communication, Robin Riechers). Because of the relatively small size of this fishery I believe that halting this program would not significantly alter the simulation results.

regions. This scenario explores the effects of extending a program like the one used to retire licenses in Texas to federal waters in the Gulf of Mexico.

This scenario imposes two buyback programs. The first program applies to one group which includes Texas small vessels only. The second program applies to 4 groups which include large vessels in each of the four regions.

Scenario 2: Gulf-wide OTB

Scenario 2 explores what would happen if a OTB were used in Scenario 1 instead of a SB auction. It again considers open access for small vessels in the gulf and a continuation of the Texas program but it adds a OTB program for federal waters in the Gulf of Mexico.

Scenario 3: Multiple Regional SB Programs

This scenario is similar to Scenario 1, but instead of including large vessel from the four gulf regions in a single program, four programs are specified for large vessels. Here I explore the impact of allowing each region a budget for large vessel buyout. Scenario 3 includes five programs and each program applies to only one group. The first program is a SB program for Texas small vessels. Programs 2 – 5 are SB programs for large vessels in each of the four gulf regions.

Scenario 4: Multiple Regional OTB Programs

Scenario 4 explores what would happen if a OTB auction were used in Scenario 3 instead of a SB auction. It again considers open access for small vessels in the gulf and a continuation of the Texas program but it adds multiple regional OTB programs for large vessels in each of the four regions.

Results[55]

Fleet reductions achieved via buyback programs produce both biological and economic benefits for the fishery. Because biological effects often impact the economics as well, it is informative to further subdivide these effects into stock effects, price effects, and cost effects.

Removing capital and decreasing competition among resource users may affect the size and abundance of the resource stock. Less harvesting pressure on the stock allows shrimp to reach a larger size. Because larger shrimp generally fetch higher prices the buyout may increase the value of landings. A buyout will also have a fleet rationalization effect which provides economic benefits for the fishery. With a buyback in place, the least profitable producers will be the ones most eager to sell their licenses. With these relatively high cost producers purged from the fleet the result is a streamlined fleet with a more favorable revenue/cost relationship.

In this section I will focus on concise measures of program success, which include not only biological and economic benefits but costs as well. In the following section I present the results of our policy simulations. The key outputs will be permit reductions, average permit price, landings, effort, the effects of these changes on fishery

[55] The results in this chapter are based on an early version of the simulation model. The model has since been recalibrated. Interested readers may consult Woodward and Griffin (2008) for an updated results derived from the final parameterized model.

rents, and cost. The results indicate that OTB programs are capable of retiring permits at a much lower cost than SB programs. Because of this, OTB auctions are able to retire more licenses and generate greater rents for the fisheries then the SB programs.

Baseline

The Baseline Scenario is the current status quo for the Gulf of Mexico shrimp fisheries and the base year for our simulations in 2005. The baseline assumes that Texas keeps its sequential buyback program for the inshore fishery, that offshore fisheries in the other four regions have limited entry, and that there is no limited entry for the small vessels in W.LA, AL-MS-E.LA, and FL.

Table 5.3 provides a summary of fleet and rent changes over the 10-year simulation run for large vessels. From the table one can see that, even in the absence of a buyback program, there are noticeable large vessel fleet reductions in each region. This attrition can be explained by the negative rents present in each fishery initially. However, referring to the ending rents column, one can see that these reductions were only sufficient to generate positive rents in two of the four fisheries. This suggests that, although there are fleet reductions without instituting any buyback programs, there is room for improvement.

Table 5.3

Baseline Scenario Results for Large Vessels

	Fleet (Vessels)			Rents ($1,000s)		
	Initial Fleet	Ending Fleet	Percent Reduction	Initial	Ending	Change
FL	627	444	29.16	-$6,640	-$392	$6,247
AL-MS-E.LA	1233	1071	13.17	-$15,717	-$2,237	$13,480
W.LA	588	447	23.90	-$16,987	$3,904	$20,891
TX	1497	1031	30.7	-$40,150	$724	$40,874

Table 5.4 provides a summary of the Baseline Scenario for small vessels. Like the large vessel fleets, we see that rents are initially negative for each small vessel fleet. However, the fleet reductions resulting from this state are much greater than the reductions in the large vessel fleets. From the table we can see that conditions in the small vessel fisheries are extremely poor. Positive rents arise in Western Louisiana and Alabama-Mississippi-Eastern Louisiana only after 30 and 49% of the respective fleets have exited. Moreover, the rents for Florida and Texas small vessels remain negative even after 99 and 70% of the respective fleets have left the fishery.

Table 5.4

Baseline Scenario Results for Small Vessels

	Fleet			Rents ($1,000s)		
	Initial Fleet	Ending Fleet	Percent Reduction	Initial	Ending	Change
FL	100%	1.17%	98.83	-$1,185	-$10	$1,175
AL-MS-E.LA	100%	69.91%	30.09	-$3,527	$349	$3,876
W.LA	100%	51.13%	48.87	-$9,869	$2,084	$11,953
TX	100%	28.57%	71.43	-$7,950	-$1,802	$6,148

Table 5.5 shows a summary of the change in landings and catch per unit of effort (CPUE) under the Baseline Scenario for the large vessel fleets included in the simulations. Here one can see very large changes in landings for the small vessel fleets (especially in Florida and Texas), while changes in landings for large vessel fleets are much less drastic. Conversely, the increases in the CPUE are greater for large vessel than small because a reduction in small vessel harvests benefits large vessels as shrimp are able to migrate to offshore waters.

Table 5.5

Baseline Landings and Catch per Unit Effort Summary for Large Gulf Vessels

	Landings (1,000 lbs)			CPUE (lbs/day fished)		
	Initial	Ending	% Change	Initial	Ending	% Change
FL	7,771.64	6,885.70	-11.4	743.84	937.85	26.08
AL-MS-E.LA	20,224.96	21,572.69	6.66	1,162.56	1,437.03	23.61
W.LA	27,259.19	27,783.31	1.92	1,154.56	1,546.18	33.92
TX	43,625.14	39,977.23	-8.36	1,066.24	1,410.83	32.32

Scenario 1: Gulfwide SB Program

I now present several policies options that will be compared with the baseline presented above. The first policy scenario is that of a single gulfwide SB program for large vessels in addition to the SB program in effect for Texas small vessels. The large vessel SB program applies to all regions and we assume a budget of $4 million per year. This budget is chosen arbitrarily, but the qualitative properties of the results would not change much if the program were scaled up or down depending on the resources available.

Table 5.6 provides a snapshot of important results of the large vessel SB program. The program retired 40% of the original capacity, a 20% improvement over the baseline reductions. Although landings and effort both dropped, the former fell less than the latter and CPUE rose by 35% over the 10-year simulation horizon. Finally, the fleet rationalization achieved by this program prompted an $88.8 million increase in fishery rents.

Table 5.6

Gulfwide Sequential Buyback Snapshot (Large Gulf Vessels)

	Vessels	Landings (1,000 lbs)	Effort (1,000 Days-Fished	CPUE (Lbs/Day-Fished)	Rents ($1,000)
Initial	3945	98,880.96	92.37	1,070.49	-$79,493
Ending	2402	84,475.94	58.18	1,451.98	$9,375
% Change	-39.10	-14.57	-37.01	35.64	

As a concise measure of the costs and benefits of this SB program the rents generated by the program are shown in Table 5.7. From the table one can see that in years 2 and 3 total gulf rents remain negative. In the fourth year the program starts to payoff in the form of positive fishery rents. The total cost of the program in present value terms (using a 7% discount rate) is about $28 million. In comparison, the sum of the present value of total gulf rents in years 2 – 10 is about $28 million. This is a $38 million improvement over the Baseline Scenario, giving a return on investment for the gulfwide SB program of $1.85 for every dollars spent.

Scenario 2: Gulfwide OTB program

Scenario 2 simulates the effects of a gulfwide OTB program for large vessels in addition to the SB program for Texas small vessels. This policy scenario differs from

Scenario 1 only in the type of auction used for the large vessel buyback. In this section I present the effects of a OTB program on the Gulf of Mexico's offshore shrimp fishery.

Table 5.8 provides a summary of results from this simulation. The OTB program was able to cut the offshore fleet by 61%, increasing fishery rents to $27 million by the 10th year. The fleet reductions pushed CPUE up by 52%. These fleet reductions represent a substantial improvement over the baseline reduction of 24%. Additionally, the increase in CPUE is a significant improvement over the 30% increase in CPUE under the Baseline Scenario.

Table 5.7

Gulfwide Sequential Buyback Annual Rents (7% Discount Rate)

Year	Vessels	PV Rents ($1,000s)
1	3,945	-$79,493.36
2	3,451	-$30,536.90
3	3,138	-$7,844.48
4	2,829	$837.17
5	2,688	$3,935.23
6	2,629	$4,633.87
7	2,562	$5,004.71
8	2,503	$5,212.96
9	2,453	$5,244.03
10	2,418	$5,099.47
11	2,402	
Total (Relative to Baseline)		$38,364.00

Table 5.8

Gulfwide One-time Buyback Snapshot (Large Gulf Vessels)

	Vessels	Effort (1,000 Days Fished)	Landings (1,000 lbs)	CPUE	Rents ($1,000)
Initial	3,945	92.37	98,880.96	1,070.49	-$79,493
Ending (year 10)	1,547	35.84	58,574.33	1,634.74	$26,898
% Change	-60.79	-61.20	-35.71	52.70	

Table 5.9 illustrates the present value of the stream of rents generated by the gulfwide OTB program. The budget for this program is a single payment of $28 million. The reductions afforded by the gulfwide OTB program generate over $92 million in total rents, a huge improvement over the Baseline Scenario, which resulted in a $126 million loss for the fishery. Relative to the status quo, the gulfwide OTB program has a rent/cost ratio of $7.79 meaning that for each dollar spent the gulfwide program, there was a $7.79 increase in rents relative to the the status quo.

Table 5.9

Gulfwide One-time Buyback Rents

Year	Vessels	PV Rents ($1,000)
1	3,945	-$79,493.36
2	1,614	$10,748.01
3	1,614	$26,154.39
4	1,550	$24,510.75
5	1,547	$22,476.58
6	1,547	$20,622.35
7	1,547	$18,944.27
8	1,547	$17,343.94
9	1,547	$15,918.41
10	1,547	$14,630.77
Total (Relative to Base)		$218,127[56]

Comparison: Scenario 1 vs. Scenario 2

From the tables presented in the previous sections it is clear that Scenarios 1 and 2 offer an improvement over the Baseline. Here we compare the policy options to one another using total permit reductions, change in rents, change in CPUE, and average cost.

Table 5.10 summarizes the important changes to the offshore fishery from the two simulated policy options. From the table it is immediately clear that the OTB auction was able to retire more capacity at a lower unit price. As a result of the superior

[56] The program generated a total present value stream of rents of $92 million. Since the baseline scenario resulted in a present value stream of rents of -$126 million, the $92 million generated by the Gulfwide OTB is a $218 million improvement.

capacity reductions, the OTB program improved productivity in the fishery by a much greater margin, pushing catch per unit of effort up by an additional 182.76 pounds per day fished.

Table 5.10

Gulfwide Sequential and One-time Buyback Auction Comparison

	Fleet Reductions	Cost ($1,000)	Avg. Permit Price ($1,000)	CPUE Change (lbs/unit effort)
SB	1,543	$28,094	$26	381.49
OTB	2,398	$28,094	$12	564.25

Speculative Premium and Permit Prices

In the previous chapter I explored the role of learning in the SB auction and found that this type of auction leads bidders to attach a speculative premium to their bid. This speculation, and the dynamic purchasing of the SB auction in general, creates some interesting differences in prices between the SB and OTB auctions. Table 5.10 shows a permit price difference between the SB and OTB auctions of around $14,000, when calculated as total reductions divided by total cost. However, average permit prices by round for the sequential auction shows a much larger discrepancies between the two auction formats. Table 5.11 shows the average price by round for the SB program.

Table 5.11

Gulfwide Sequential Buyback Auction, Average Price by Round

Year	Vessels	Reductions	Avg. Price ($1,000s)
1	3,945		
2	3,451	494	$8.10
3	3,138	313	$12.78
4	2,829	309	$12.93
5	2,688	141	$28.35
6	2,629	59	$67.73
7	2,562	67	$59.84
8	2,503	59	$68.03
9	2,453	50	$79.97
10	2,418	35	$115.34
11	2,402	16	$252.53

From Table 5.11 it is clear that the SB auction pays a large premium for permits in later rounds. The bulk of the reductions for this scenario are concentrated in periods during which the fishery is losing money, resulting in low buyout prices and a relatively low overall average permit price. However, as the auction progresses and capacity is retired, permit prices begin to rise sharply.

The speculative premium has a compounding effect on permit prices in the SB program. The average simulated bid in any year is based on the net revenues in the fishery. As the fishery becomes more profitable, the average bid for the fleet rises. The speculative component also rises through time reflecting the improved state of the fishery. So, as vessels are removed from the fishery, we note two effects on the distribution of bids. The first is that the average simulated bid is rising as a function of increased profitability. The second is that the speculative component is rising in conjunction with rising rents. These two effects lead to some extremely high permit prices in the later years of our simulation.

Regional Simulations

In addition to the two gulfwide scenarios, two regional scenarios were simulated. In Scenarios 3 and 4, I simulate separate buyback programs for large vessels in each of the four gulf regions. For comparative purposes the total budget of $4 million annually is used here just as in the gulfwide programs. However, the budget is allocated to each region based on its share of total gulf effort in the initial period. Allocation in this manner is only one of many reasonable ways by which the budget might be divided up between the regions and I am not advocating this approach over any other. Though quantitatively the results would vary depending on the allocation rule, I believe that the qualitative features of these results would be reasonably robust to different allocation rules.

Aggregate Effects

This section compares the regional programs with their gulfwide counterparts. The main metrics for comparison are fleet reductions, change in CPUE and change in fishery rents. In the previous discussion of the gulfwide programs, I explored how these programs affect the gulf as a whole. In this section results will also be aggregated in order to compare them to gulfwide results.

Table 5.12 summarizes the results of the regional and gulfwide SB programs. From the table, one can see that the gulfwide SB program categorically dominates its regional counterpart. Because the gulfwide program seeks out the cheapest permits throughout the gulf, it is able to achieve much greater fleet reductions than the regional program. As a result the gulfwide program offers greater increases in both fishery rents and CPUE.

A particularly interesting fact regarding the comparison of the gulfwide and regional SB programs is that, although the regional program targets effort, the gulfwide program actually resulted in a greater effort reduction. This is due in part to the fact that the region responsible for the greatest portion of total gulf effort (Texas) is also the region with the cheapest permits initially. So, while the regional SB program allocates 44% of the $4 million budget to buy out permits in Texas, there are so many cheap permits in Texas that the gulfwide program spends all $4 million in this region in the first year.

Table 5.12

Aggregate Effects - Regional Sequential Buyback vs. Gulfwide Sequential Buyback Programs

	Gulfwide SB			Regional SB		
	Vessels	CPUE	Rents ($1,000)	Vessels	CPUE	Rents ($1,000)
Initial	3,945	1,070.49	-$79,493	3,945	1,070.49	-$79,493
Ending	2,402	1,452	9,375	2,562	1,435.60	$8,654
% Change	-39.1	35.64		-35.06	34.1	

Table 5.13 shows the impact of the regional and gulfwide SB programs on fishery rents over the 10-year simulation. From the table, three interesting effects of fleet reductions on the aggregate rent function are visible. The first is a timing effect. The gulfwide program retires more vessels faster, which has a profound impact on fishery rents. Next, there is a declining marginal impact of fleet reductions on the rent function illustrated in Table 5.13. From years 1 to 2, the change in rents with respect to the change in vessels (measured in thousands of dollars) was -$94.8 for the gulfwide program and -$98.8 for the regional program. By year 10 in the simulation, the fleet level under the gulfwide SB program is such that the change in rents with respect to fleet is -$10.5. This illustrates the declining marginal value of fleet reductions. Finally, there is a geographic effect of fleet reductions on aggregate rents that deserves mention. Because the gulfwide program targets the cheapest permits in each year, it makes very few reductions to the fleet in Western Louisiana.

Table 5.13 also shows the total present value of rents generated by the regional SB and gulfwide SB programs. With these totals we can calculate a rent/cost ratio of $0.85 for the regional SB program and $1.37 for the gulfwide SB program. In short, relative to the status quo, each dollar spent in the gulfwide program generates $1.37 more in rents in the fishery, while the regional program generates $0.85.

Table 5.13

Rents Under Sequential Buyback Programs

	Gulfwide SB			Regional SB		
Year	Fleet	Rents ($1,000)	PV Rents ($1,000)	Fleet	Rents ($1,000)	PV Rents ($1,000)
1	3,945	-$79,493	-$79,493	3945	-$79,493	-$79,493
2	3,451	-$32,674	-$30,537	3488	-$34,271	-$32,029
3	3,138	-$8,981	-$7,844	3243	-$11,453	-$10,003
4	2,829	$1,026	$837	3001	-$2,703	-$2,206
5	2,688	$5,158	$3,935	2869	$1,600	$1,221
6	2,629	$6,499	$4,634	2793	$3,773	$2,690
7	2,562	$7,511	$5,005	2717	$5,673	$3,780
8	2,503	$8,371	$5,213	2663	$6,956	$4,332
9	2,453	$9,010	$5,244	2608	$8,098	$4,713
10	2,418	$9,375	$5,099	2578	$8,654	$4,707
11	2,402					
Total			-$87,907			-$102,289
Total less Baseline			$38,364			$23,981

Just as in the SB programs, the gulfwide OTB program was more effective at reducing capacity than the regional OTB. A summary of effects is shown in Table 5.14 below. From the table one can see that the gulfwide OTB program retired 84 more vessels than the regional program. Since the aim of the gulfwide program is to remove the most vessels per dollar, it is not surprising to see the gulfwide program dominate its regional counterpart in terms of vessel reductions. Furthermore, because the programs are operating with identical budgets the greater fleet reduction under the gulfwide program means that this program also paid a lower average price per vessel. The gulfwide program paid $11,715 per permit on average, while the regional OTB program paid an average of $12,138 for each permit that it retired.

The table also shows that the regional OTB program removed more effort than the gulfwide program. This is not unexpected. Recall that the gulfwide program removes the cheapest permits without regard for which region they come from. The regional program distributes the total budget across the regions based on each region's share of total gulf effort in the initial period. Hence the regional OTB program directs larger portions of the total budget to high effort regions. Although the gulfwide program retires more total vessels, the regional OTB program retires more from Texas and Western Louisiana. These two regions collectively are responsible for 70% of total gulf effort in the initial period. Thus, it is not surprising to see greater effort reductions under the regional OTB program.

Table 5.14

Aggregate Effects – Regional One-time Buyback vs. Gulfwide One-Time Buyback Programs

	Gulfwide OTB				Regional OTB			
	Vessels	Effort (1,000 days fished)	Landings (1,000 lbs)	CPUE (lbs/day fished)	Vessels	Effort (1,000 days fished)	Landings (1,000 lbs)	CPUE (lbs/day fished)
Initial	3,945	92.37	98,880.96	1,070.49	3,945	92.37	98,880.96	1,070.49
Ending	1,547	35.83	58,574.33	1,634.74	1,631	35.00	56,882.34	1,625.35
% Change	-60.79	-61.21	-40.76	52.71	-58.67	-62.11	-42.47	51.83

The superior effort reductions under the regional program also mean that the regional OTB program paid slightly less on average per unit of effort. The regional program paid an average of $489 per unit of effort retired, while the gulfwide program paid an average of $496 for each unit of effort it retired.

It is interesting to note that, although the regional OTB program removed more effort than the gulfwide program, the gulfwide OTB actually resulted in a greater increase in productivity (as measured by CPUE). The gulfwide program retired much more effort from Florida than the regional program. Because FL was initially the least productive region, the gulfwide program had a greater impact on aggregate productivity in the gulf than the regional OTB program.

Finally, from Table 5.15 below, one can see that the gulfwide program was able to generate more rents in the gulf over our 10-year simulation than the regional OTB program. Relative to the Baseline Scenario, the gulfwide program was able to generate $7.76 in rents for each dollar spent, while the regional program produced $7.66 in rents for each dollar spent.

Table 5.15

Rent Comparison – Gulfwide One-time Buyback vs. Regional One-Time Buyback

	Gulfwide OTB		Regional OTB	
Year	Vessels	PV Rents ($1,000)	Vessels	PV Rents ($1,000)
1	3,945	-$79,493	3,945	-$79,493
2	1,614	$10,748	1,993	$10,228
3	1,614	$26,154	1,996	$25,740
4	1,550	$24,511	1,945	$24,162
5	1,547	$22,477	1,952	$22,179
6	1,547	$20,622	1,965	$20,342
7	1,547	$18,944	1,978	$18,668
8	1,547	$17,344	1,991	$17,133
9	1,547	$15,918	2,003	$15,727
10	1,547	$14,631	2,014	$14,430
Total		$91,856		$89,115
Total Less Baseline		$218,127		$215,386

Through the comparison of the gulfwide and regional OTB programs I find that the gulfwide program retired more vessels and resulted in a lower average cost per vessel. The gulfwide program also resulted in a greater increase in CPUE and generated more rents than the regional program. The regional program did retire more effort and resulted in a lower average cost per unit of effort. This distinction highlights an important normative issue: if the goal of the buyback program is increasing productivity and profitability in the fishery then a gulfwide OTB program is the best choice. However, if the goal is to retire the most effort for the least cost then the regional OTB program would be preferred. However, I find that with the budget distributed based on the initial levels of effort, the difference between the regional and gulf-wide OTB programs is relatively slight. In contrast, under a SB program, the regional program is much less effective than the gulf-wide program.

Regional Effects

The analysis in this chapter has shown that, among SB programs, a gulfwide program retires more effort at a lower unit cost, generates more rents for the fishery, and increases productivity by a greater margin than a regional SB program. However, among OTB programs, the relative ranking depends on the preferred evaluation criteria.

Up to this point I have focused the evaluation on the aggregate benefits of each program without regard for how these benefits are distributed. In this section I explore program impacts by region and discuss distributional implications.

Expenditures

Table 5.16 shows the amount spent in each region by each of the four programs. It is evident that the gulfwide SB program spends considerably more in regions 2 and 4 than in regions 1 and 3. Interestingly, the gulfwide SB program spends very little money at all in Western Louisiana, Region 3. By design, the regional programs spend according to each region's initial effort level so there are no real surprises in the spending patterns for the regional SB and OTB programs. However, in the gulfwide OTB program one again sees that the program spends a disproportionate amount in the

East Gulf[57] and Texas. In the following sections I examine changes in CPUE and fishery rents by region in order to analyze whether these spending differences are also consolidating the benefits of capacity reduction.

Table 5.16

Expenditures by Region ($1,000s)

	Gulfwide Sequential Buyback	Regional Sequential Buyback	Gulfwide One-Time Buyback	Regional One-Time Buyback
FL	$9,755	$4,522	$4,640	$3,176
AL-MS-E.LA	$15,381	$7,534	$8,736	$5,292
W.LA	$3,879	$10,225	$4,170	$7,181
TX	$10,985	$17,719	$10,549	$12,445

[57] Recall that "East Gulf" refers to the region containing Alabama, Mississippi, and Eastern Louisiana.

CPUE Changes by Region

One of the potential benefits of removing vessels from the fisheries is improved productivity as measured by CPUE. Table 5.17 shows the percent change in CPUE in each region, under each of the four programs. Previously, it was shown that the gulfwide programs spend a disproportionate amount of money in Texas and the East Gulf . From the table below one can see that, in Texas at least, this appears to be money well spent. Texas experiences the greatest increase in CPUE under all four of the programs.

Interestingly, the percentage increase in CPUE in the East Gulf is low relative to the other regions. East Gulf has the lowest CPUE increase under all programs considered here. Focusing on the gulfwide SB program, one can see that expenditures for East Gulf are much higher than for any other region yet the productivity increase there is smaller than in any other region. The CPUE change is, in fact, the cause of the high expenditure level. Because productivity stays relatively low in East Gulf, permit prices remain cheap compared to other regions. The gulfwide SB program purchases more permits from East Gulf than Florida and Western Louisiana combined.

Table 5.17

Change in Catch per Unit Effort by Region (% Change)

	Gulfwide SB	Regional SB	Gulfwide OTB	Regional OTB
FL	41.49	30.10	57.38	48.23
AL-MS-E.LA	28.98	29.30	44.31	43.02
W.LA	33.50	38.20	52.17	55.44
TX	35.36	33.93	56.63	60.27

Although there are some large differences in spending by region among the four simulated programs, Table 5.17 shows that the changes in productivity across regions is fairly even within each program. The largest spread (as measured by the maximum increase less the minimum increase) in productivity increase is 17.25% under the regional OTB program. And even under this program the lowest productivity change was a 43.02% increase in CPUE.

Rents

To determine how rents are distributed across the various regions, I examine the rents generated by each program and each region's share of that total. Table 5.18 shows the 10-year present value total of rents above the baseline[58] generated by each program for each region.

From Table 5.18 it appears that the monetary benefits of each program are heavily concentrated in East Gulf and Texas. In both regional programs as well as the gulfwide OTB program these two regions collect over 75% of the aggregate benefits. Moreover, Texas collects over 40% of the aggregate benefits in all programs with the exception of the Regional SB program. Given the amount of money spent in Texas, it is not surprising to see benefits concentrated in this region.

Table 5.18

Total Rents Above Baseline (Present Value, $1,000)

	Gulfwide SB	Regional SB	Gulfwide OTB	Regional OTB
FL	$4,462	-$216	$27,350	$23,651
AL-MS-E.LA	$24,448	$11,085	$48,876	$53,581
W.LA	-$38,048	$5,736	$27,224	$18,871
TX	$29,243	$7,377	$114,676	$88,036
Aggregate	$20,105	$23,981	$218,127	$184,139
Max – Min	$67,291	$11,301	$87,452	$69,165

[58] To get these figures I sum the present value of rents in each region under each program and subtract the present value sum of rents under the baseline scenario.

Unlike the increase in CPUE, there is a very inequitable distribution of rents among the regions, under all four programs. From the table above one can see that the most even distribution of rents, as measured by the spread between the largest and smallest gain, was provided by the regional SB program. However, this program also generated substantially fewer rents than any other. It is also interesting to note that the gulfwide OTB program generated more aggregate rents than the regional OTB program and these benefits were more equitably distributed.

From Table 5.18 above one can see that Western Louisiana is actually worse off under the gulfwide SB program then under the status quo. This is a unique result and it is worth diverting briefly from the equity discussion to provide an explanation. One assumption of the model is that owners will not voluntarily leave the fishery when a buyback is in place. In Western Louisiana, like each of the other regions, rents are initially predicted to be negative. However, without any capacity reduction, positive rents are generated by the 3rd year. Because the gulfwide SB program spends so little money in Western Louisiana, there are few changes in the fleet. Under the Baseline Scenario, vessels exit the fishery in the presence of negative rents and this eventually leads to increasing rents in Western Louisiana. While this result follows from a modeling assumption that boats will not voluntarily leave the fishery if a buyback program is in place, this assumption may be reasonable. If the government announces that it will be paying for permits, those assets take on an option value that creates an incentive for the fishermen to keep them active even if normal fishery economics is working against them.

Texas Inshore Buyback

From Table 5.18 one immediately notes extraordinary rent levels generated in Texas by both OTB programs. With total rents of $114 million under the gulfwide OTB and $88 million under the regional OTB, Texas is far and away the most profitable region in the gulf. An important factor contributing to this profitability is the presence of the state run buyback program in the inshore fishery. The inshore buyback program in Texas removes vessels from the bay system, allowing more shrimp to migrate to offshore areas.

In all regions total landings and total revenues tend to fall as vessels are removed from the fisheries. This means that the decline in total landings resulting from fleet reduction is not being offset by an equal increase in the value of landings. The result of this pattern for the present analysis is that declining landings have a negative effect on fishery rents. In Texas, fleet reductions have a smaller effect on total landings than in other regions.

To illustrate the impact of buyouts on total landings I show the year-by-year change in landings with respect to changes in effort in Table 5.19. Here I focus on the regional SB Program because it is the only program which led to reductions in every year. Looking at the last five years of the simulation, one can see that the effect of effort reductions on landings was considerably smaller in Texas than in either Western Louisiana or the East Gulf region. During this time large vessel effort was being removed from all fisheries but, since Texas was also removing effort from its inshore fishery concurrently, gulf landings were impacted to a smaller degree.

The comparison between East Gulf and Texas is particularly informative because the CPUE is very similar in these two regions. In Table 5.20 the CPUE was clearly higher in East Gulf than in TX, but only by an average of about 66 lbs/day fished, per year. Looking at the change in landings with respect to changes in effort, one can see a much larger difference: removing 1 unit of effort from East Gulf resulted in an average loss of 750 lbs, while a 1 unit effort reduction in TX costs an average of 786 lbs. From this table it is clear that, while East Gulf was slightly more productive than TX, the difference in the impact of effort reductions on landings between these two regions was well out of proportion to the productivity difference.

Table 5.19

Regional Sequential Buyback Program’s Change in Landings with Respect to Change in Effort (Change in lbs/ Change in Days-Fished)

Year	FL	AL-MS-E.LA	W.LA	TX
1				
2	202.79	-1,091.63	-217.95	214.67
3	151.48	70.41	-191.19	167.52
4	285.94	958.89	758.54	902.11
5	377.22	1,074.94	941.60	886.94
6	304.56	1,072.38	1,630.51	1,027.26
7	458.68	1,060.72	1,408.58	865.45
8	470.41	1,194.99	1,626.00	1,010.76
9	488.78	1,118.84	1,480.72	950.33
10	463.38	1,290.54	1,968.09	1,047.67

Table 5.20

Landings and Effort Comparison for Regions 2 and 4

	AL-MS-E.LA			TX		
Year	Effort (days fished)	CPUE (lbs/day fished)	Change in Landings/ Change in Effort	Effort (days fished)	CPUE (lbs/days fished)	Change in Landings/ Change in Effort
1	17,397	1,162.56		40,915	1,066.24	
2	16,197	1,329.56	-1,091.63	34,936	1,211.98	214.67
3	15,089	1,422.02	70.41	32,126	1,303.33	167.52
4	14,060	1,455.92	958.89	28,772	1,350.10	902.11
5	13,439	1,473.52	1,074.94	27,334	1,374.47	886.94
6	13,190	1,481.10	1,072.38	26,175	1,389.84	1,027.26
7	12,918	1,489.95	1,060.72	25,504	1,403.64	865.45
8	12,684	1,495.39	1,194.99	24,909	1,413.03	1,010.76
9	12,491	1,501.21	1,118.84	24,397	1,422.74	950.33
10	12,374	1,503.20	1,290.54	24,058	1,428.02	1,047.67
Average			750.01			785.86

The primary reason that Texas is able to remove vessels from the offshore fishery with less impact on landings (as other regions) is because of effort reductions in the inshore fishery. From Table 5.21 below, one can see that initially all of the inshore fisheries experience a sharp decrease in landings. This is because the inshore fisheries are unprofitable at the start so many of the vessels exit in the first two years. However, with open access, as profitability improves effort begins to move back into the fisheries and landings increase. In East Gulf and Western Louisiana landings begin to increase steadily after the 3rd year. Meanwhile, landings in the Texas inshore fishery fall by an average of just over 487,000 lbs per year throughout the 10-year simulation.

Table 5.21

Landings and Effort for Inshore Fisheries Under Regional Sequential Buyback

	FL		AL-MS-E.LA		W.LA		TX	
Year	Effort (Days Fished)	Change in Landings (‘000 lbs)	Effort (Days Fished)	Change in Landings (‘000 lbs)	Effort (Days Fished)	Change in Landings (‘000 lbs)	Effort (Days Fished)	Change in Landings (‘000 lbs)
1	1,604		9,921		32,586		12,466	
2	849	-458.11	7,539	-1,149.16	14,352	-12,519.24	11,839	-6.81
3	475	-235.47	6,810	-498.97	14,580	498.67	11,808	115.9
4	281	-127.32	6,816	70.61	14,886	347.88	11,769	49.55
5	172	-72.96	6,846	55.47	15,206	318.05	11,742	22.16
6	109	-43.76	6,884	43.37	15,529	302.31	11,722	11.55
7	70	-27.11	6,924	53.98	15,850	347.66	11,699	10.67
8	45	-17.11	6,967	44.78	16,180	309.52	11,675	1.7
9	30	-10.96	7,010	49.37	16,510	337.15	11,652	3.8
10	20	-7.12	7,055	39.71	16,844	303.92	11,633	-2.51

Here I have presented several statistics on landings and effort in order to analyze the impact of the inshore buyback in Texas on offshore rents. I have shown that the impact on landings of a one unit effort reduction in Texas is small relative to the other regions. This is due, in large part, to the presence of the inshore buyback program which cuts landings from the bay system by an average of close to half a million pounds per year. By reducing inshore effort, the small vessel buyback program helps improve the profitability of the offshore fishery in Texas.

Program Evaluation Summary

There were two main goals for the analysis provided in this chapter. The first was to assess the cost and effectiveness of SB programs relative to OTB programs. And the second was to compare a policy of multiple regional markets for buyback with a single gulfwide market for both SB and OTB programs. Table 5.22 provides a composite of evaluation criteria.

Table 5.22

Four Program Ranking – Rank in Parentheses

	Gulfwide Sequential Buyback	Regional Sequential Buybakc	Gulfwide One-Time Buyback	Regional One-Time Buyback
Reductions				
Vessels	1,543 (3)	1,383 (4)	2,398 (1)	2,314 (2)
Effort	34,190 (3)	32,773 (4)	56,539 (2)	57,373 (1)
Productivity				
CPUE Increase	381.49 (3)	365.11 (4)	654.25 (1)	554.86 (2)
Efficiency				
Cost per Permit	$26,930 (3)	$28,918 (4)	$11,714 (1)	$12,138 (2)
Cost per Unit of Effort	$1,169 (3)	$1,220 (4)	$513 (1)	$668 (2)
Net Profitability				
Present Value of Rents	$38,364 (3)	$23,981 (4)	$218,127 (1)	$215,386 (2)
Benefits/Cost	$1.37 (3)	$0.85 (4)	$7.76 (1)	$7.66 (2)
Equity (Rank Only)[59]				
Equity in Productivity	3	1	2	4
Equity in Rents	2	1	3	4
Average Rank	2.89	3.33	1.44	2.11

[59] The equity measures used here are simply the difference between the region of greatest gain and the region of least gain for each program. Equity in productivity for example is determined by the difference between the region of greatest CPUE increase and the region of least CPUE increase under each program.

It is clear from Table 5.22 that the OTB programs were able to retire more effort at a much lower cost than their SB counterparts. These reductions resulted in greater productivity increases and greater increases in fishery rents. The table also shows that the regional programs offered little advantage over the gulfwide programs. The regional SB was almost categorically dominated by its gulfwide counterpart (ranking below the gulfwide SB program in 7 out of 9 measures). And, while the regional OTB program retired more effort at a lower unit cost then its gulfwide counterpart, the gulfwide OTB program generated superior rents resulting in a more favorable rent/cost ratio for the program.

The 2nd Best Policy

In this chapter I have shown that, when offered the choice between buying back permits sequentially over time or spending the present value of a stream of sequential payments to buyback permits in a single year, more effort can be reduced from the fishery with the single upfront payment. However, a prominent advantage to a sequential buyout is that it does not require a large initial investment. Because of this very practical advantage, SB programs may still find a place in the regulator’s toolkit. Although, on the basis of rents, productivity increases and permit reductions, an OTB program would be preferred, for managers who chose the SB program for capacity reduction, understanding how capacity reductions influence fleet rents can help regulators run an SB program more effectively.

Removing vessels from the fleet will have biological and economic impacts on the fishery. However, many of these effects (such as an increase in abundance or increase in size of shrimp landed) will relate back to the rent function. Fishery rents are a compact measure of program success which captures many biological and economic relationships. In the previous sections I have discussed how each of the simulated programs affects the rent function. In this section I briefly discuss how vessel reductions in general impact fishery rents and how this information could be used to improve the efficacy of an SB program.

In GBFSM, vessel reductions influence rents mainly through their effect on landings and the cost structure. Landings affect revenues which, in turn, affect rents while cost has a more direct effect on rents.

Conceptually, one expects that inefficient producers will be the first to sell back their permits. The immediate effect of this exit will be to reduce aggregate cost relative to revenues and increase rents. However, as profitability in the fishery increases remaining vessels have an incentive to expand operations, which tends to eat away at rents. Because GBFSM is a homogeneous fleet model, fleet costs fall in direct proportion to vessel reductions. Furthermore, effort in the fishery is assumed to be directly related to the number of vessels. Therefore, the simulation model is not capable of analyzing these cost issues.

The biological submodel included in GBFSM does, however, allow us to analyze the behavior of landings under buyback regimes. The immediate impact of vessel reductions will be to reduce total landings. But over the longer term, we cannot say *a priori* whether total landings will rise or fall with vessel reductions. If the stock is overfished initially, and if overfishing is severe, then it is possible to see total landings increase over the longer term. Removing vessels, and hence fishing pressure, may improve recruitment, leading to increased abundance in later years. Given the annual nature of shrimp fisheries, however, what the simulations actually show are total landings decreasing with vessel reductions.

The effect of changes in landings on fishery rents comes through the revenue function. Revenues are made up of total landings and value of landings. Declining total landings have a negative impact on revenues. However, this effect may be reduced by the size effect. As total shrimp landings decrease, the expectation is that value per pound will rise as shrimp are allowed to reach a larger size before harvest. While the impact of landings on revenue and therefore rents may be predicted *a priori* (with sufficient information regarding the yield curve), it cannot be know. What the simulations show is that total revenues are decreasing with vessel reductions, meaning that the positive impact on the revenue function of value increase is dominated by the negative impact of volume decrease.

Here I have discussed how vessel reductions relate to fishery rents through their effects on the cost and revenue functions. Focusing on the SB programs, one can see the impact of vessel reductions on rents through time. In simple economic terms one can think of the additional rents generated through vessel reductions as the marginal benefit of the program. By examining the last purchased in each year it is also possible to calculate the marginal cost – the cost required to purchase one additional vessel. These two quantities are shown below in Table 5.23.

Table 5.23

Marginal Benefit and Cost to Purchase One Additional Vessel for Gulfwide Sequential Buyback Program

Year	Vessel Reduction	Marginal Benefit	Marginal Cost
1			$8,100
2	494	$94,810	$8,750
3	313	$75,680	$10,330
4	309	$32,340	$13,470
5	141	$29,290	$58,460
6	59	$22,700	$230,850
7	67	$15,130	$261,090
8	59	$14,630	$259,270
9	50	$12,780	$279,390
10	35	$10,520	$493,840

The table shows that vessel reductions initially have a very large payoff since marginal benefits greatly exceed marginal cost. However, this payoff declines substantially as more and more vessels are removed. By year five the marginal cost exceeds the marginal benefit by a factor of almost four and by the 10th year buying an additional permit under the gulfwide SB program only generates an additional $10,520 but costs almost a half million dollars.

In Table 5.24 below, I present the change in rents per dollar spent in each year of the sequential auction. From the table one can see that by the 6th year the additional rents generated by the programs were less than the amount spent and therefore the change in rents per $ spent falls below 1 in these years. Furthermore, by the final year of the simulation, the change in rents per dollar spent drops to a dismal $0.09 for the gulfwide SB and $0.14 for the regional SB.

Although not as effective as OTB programs, SB programs offer managers an affordable alternative to expensive one-time programs. Managers would have the option of ending the program if they see that the marginal costs are greater than the marginal

Table 5.24

Change in Rents per Dollar Spent for Sequential Buyback Programs

Year	Gulfwide SB	Regional SB
1		
2	$11.70	$11.31
3	$5.92	$5.70
4	$2.50	$2.19
5	$1.03	$1.08
6	$0.34	$0.54
7	$0.25	$0.48
8	$0.22	$0.32
9	$0.16	$0.29
10	$0.09	$0.14

benefits. In this section I have shown that the marginal benefit of vessel reductions declines over time and as such the SB programs generate very few benefits per dollar spent in the later years. One relatively simple rule which may increase the cost effectiveness of the SB programs substantially would be to place a cap on permit price. Managers with a thorough understanding of the economics of the fishery will be better able to place this cap appropriately, though even for the most experienced and knowledgeable managers, the difficulty of the task is significant.

In sum, SB programs, although they do not compare favorably to OTBs based on the criteria presented in this chapter, may provide managers with a more cautious approach to buying back permits. In a highly variable industry, such as shrimping in the Gulf of Mexico, the idea of “optimal” reductions will likely change drastically from one year to the next. A SB program would allow regulators to update their purchasing goals and criteria as economic conditions in the fishery change or as new information becomes available. In this section I have presented some evidence on marginal benefits and marginal costs of reductions. Managers who prefer a cautious approach to reductions in capital may favor a SB program, the analysis presented in this section may help rationalize the use of a sequential program.

Summary of Simulation Work

In this chapter I have shown that OTB programs, by virtue of avoiding the speculative premium, retire more effort faster, and at a lower cost, then SB programs. This produces biological and economic benefits for the shrimp fisheries in the Gulf of Mexico under which are far superior to those generated by SB programs. I have also shown that single market buyback programs perform better in the Gulf of Mexico then programs using multiple regional markets.

CHAPTER VI

SUMMARY AND CONCLUSIONS

This dissertation has provided a thorough analysis of the cost and effectiveness of sequential buyback auctions relative to one-time buyback auctions for renewable resource management. For this study I have developed an empirical model of bidding behavior in a sequential license buyback auction. I used data from the Texas Inshore Shrimp License Buyback Program – a long running sequential buyback auction – to estimate parameters of this model. With these parameters, a model was developed to simulate two hypothetical buyback policies: a sequential license buyback program for offshore shrimp vessels in the Gulf of Mexico and a one-time buyback program for offshore shrimp vessels in the Gulf of Mexico. Simulating two alternative programs for capacity reduction in the same fishery allowed for the comparison of the auction formats.

In Chapter II, a literature review on auctions and bidding was provided to establish some background for our study. The literature on auctions and bidding both from traditional economics and environmental economics is very well developed. Furthermore, the game theoretic foundations of bidding, and in particular the elements of strategy involving one bidder against another, have been explored at length in the auction theory literature. However, the topic of strategy as it applies to sequential auctions has received notably less attention. A contribution of this dissertation is that it provides an in depth study of bidding strategy when participants are allowed to learn about the buyer's value over the course of a repeated game.

Chapter III gave a statistical summary of the Texas Inshore Shrimp License Buyback Program. The objective in this chapter was to provide the basic motivation for our formal dynamic econometric model. In Chapter III I showed that over half of all participants in the buyback auction placed bids in more than one round. I also showed that the distribution of all bids placed in the auction becomes progressively tighter as the auction progresses. In the first round of the auctions bids are distributed very diffusely but by the fourteenth round we see bids clustered very tightly around the average license price. This suggests that bidders are learning about the agency's willingness to pay as the auction progresses and using this informing in submitting bids.

In Chapter IV I presented an econometric model used to estimate parameters of the fisherman's bidding function in a sequential auction. The primary objective of this chapter was to estimate the parameters of the fisherman's underlying benefit function and to distinguish this from the speculative premium induced by the sequential auction format. This was done by first setting up a dynamic programming algorithm to solve the dynamic optimization problem characterizing the fisherman's decision problem. The DP problem was then nested inside of an estimation algorithm which searched for optimal parameters by minimizing the sum of squared errors between actual and predicted bids. The results of the estimation showed a speculative component which was initially very high and volatile over the early years of the auction but which leveled out over the later years. The estimates suggest an initial speculative premium equal to 3.6 times individual benefits in the first round of the auction and a shape decline to 1.3 times individual benefits for the second round. There was very little change in the speculative premium after the 10th round as it stayed consistently between 1.8 and 1.9 times individual benefits.

In addition to providing the estimates needed for effective policy comparison, Chapter IV makes some important methodological contributions. First, I use a Bayesian updating algorithm to introduce learning to our dynamic optimization problem. This represents a contribution in the modeling of bidding under a sequential auction where information transmission is an important part of the decision problem. Next, this analysis considered a control variable (bid amount) that is continuous. This marks an important departure from previous exercises in estimation of dynamic decision problems (Rust 1988, Miranda and Schnitkey 1995, and Provencher and Bishop 1997) which all use a binary decision variable.

The main objective of Chapter V was to use a simulation model to compare the cost and effectiveness of a sequential license buyback program relative to a one-time buyback program for capacity reduction in the Gulf of Mexico shrimp fishery. In this chapter I showed that the sequential buyback program, because of the speculative premium induced by this particular auction format, retires substantially less effort per dollar spent then the one-time buyback program. In this chapter I found that, if faced with the choice of spending a buyout budget over several years or spending the present value of a sequential stream of payments in a single year, fisheries managers would usually be better off choosing the one-time auction format.

As is often the case with complex estimation, it was necessary throughout this dissertation to make some simplifications. Although these were deemed necessary and defensible, future work in this area should concentrate on refining the estimation algorithm. In particular, there may be room to increase the precision of the point estimates by refining the grid search boundaries. The grid search method was deemed the most appropriate algorithm to achieve maximization given the heavy non-linearities in the objective function. However, future research may be able to add some precision to the estimates.

In addition to further refinements in the grid search, a second suggestion for future work is to concentrate on the structure that was imposed on the benefit function. Currently, the benefit function contains the explanatory variables *price* and *vessel length*. There was some evidence presented in Chapter III that license holder age should also be incorporated into the fisherman's benefit function. Because of the computational intensity of the estimation algorithm, it was not possible to add another variable to the structure. However, future research that strives to improve the efficiency of estimation may provide an important extension to this work by making it possible to add more explanatory variables to the *R* function that estimates the value of a fishing license.

It should also be reiterated that the simulation results, presented in the previous chapter, were based on an earlier version of the model. This model was parameterized using the best data available at the time. Since then, data improvements have led to a re-parameterization of the simulation model and updated results can be found in Woodward and Griffin (2008). It should be made clear however, that the updated model bears no qualitative differences from the model used in this analysis. While the results derived from the final simulation model differ quantitatively from those presented in Chapter V, the conclusions presented in this dissertation regarding the performance of sequential auctions relative to one-time buyback auctions remain intact.

NOMENCLATURE

BSAI	Bering Sea Aluetian Islands
CPUE	Catch per Unit of Effort
DGP	Data Generating Process
DP	Dynamic Programming
EEZ	Exclusive Economic Zone
FAO	Food and Agriculture Organization of the United Nations
GBFSM	General Bioeconomic Fisheries Simulation Model
MAE	Mean Absolute Error
Magnuson-Stevens	Magnuson-Steven Fisheries Conservation and Management Act
ML	Maximum Likelihood
NMFS	National Marine Fisheries Service
OLS	Ordinary Least Squares
OTB	One-time buyback
PV	Present Value
RFP	Relative Fishing Power
SB	Sequential buyback
SSE	Sum of Squared Errors
TPWD	Texas Parks and Wildlife Department

REFERENCES

Ashenfelter, O. 1989. How Auctions Work for Wine and Art. *Journal of Economic Perspectives.* 3(3): 23-36.

Curtis, R and D. Squires. 2007. *Fisheries Buybacks*. Ames, IA: Blackwell.

Deltas, G. and G. Kosmopoulou. 2004. Catalogue vs Order-Of-Sale Effects in Sequential Auctions: Theory and Evidence from a Rare Book Sale. *The Economic Journal*, 114(492): 28-58.

Funk, R.D, W.L Griffin, J.W Mjelde, and J.M Ward. 2003. A Simulation Model of License Buyback in the Texas Bay Shrimp Fishery. *Marine Resource Economics* 18(1): 33 – 53.

Ginsburgh, V. 1998. Absentee Bidders and the Declining Price Anomaly in Wine Auctions. *Journal of Political Economy*, 106(6): 1302-1319.

Ginsburgh, V. and J.C van Ours. 2007. On Organizing a Sequential Auction: Results from a Natural Experiment by Christie's. *Oxford Economic Papers*, 59(1): 1–15.

Grant, W.E and W.L Griffin. 1979. A Bioeconomic Model of the Gulf of Mexico Shrimp Fishery. *Transactions of the American Fisheries Society* 108(1): 1 – 13.

Grant, W.E, K.G Isakson, and W.L. Griffin. 1981. A General Bioeconomic Simulation Model for Annual-Crop Marine Fisheries. *Ecological Modeling* 3(3): 195 – 219.

Greene, W.H. 2003. *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.

Griffin, W.L., A.K. Shah, and J.M. Nance. 1997. Estimation of Standardized Effort in the Heterogeneous Gulf of Mexico Shrimp Fleet. *Marine Fisheries Review*. 59(3): 23-33.

Grooves, T. and D. Squires. 2007. Lessons from Fisheries Buybacks. *Fisheries Buybacks*, Curtis, R and D. Squires, eds., pp. 15-55. Ames, IA: Blackwell.

Haby, M.G., R.J. Miget, L.L. Falconer, and G.L. Graham. 2002. A Review of Current Conditions in The Texas Shrimp Industry, an Examination of Contributing Factors, and Suggestions for Remaining Competitive in the Global Shrimp Market. Extension Economics Staff Paper, TAMU-SG-03-701.

Holland, D., E. Gudmundsson and J. Gates. 1999. Do Fishing Vessel Buyback Programs Work: A Survey of the Evidence. *Marine Policy* 23(1): 47-69

Jeitschko, T. 1998. Learning in Sequential Auctions. *Southern Economic Journal* 65(1): 98-112.

Kennedy, P. 2003. *A Guide to Econometrics*. Cambridge, MA: MIT Press.

Krishna, V. 2002. *Auction Theory*. New York: Academic Press.

Larkin, S., W. Keithly, C. Adams, R. Kazmierczak. 2004. Buyback Programs for Capacity Reduction in the U.S. Atlantic Shark Fishery. *Journal of Agricultural and Applied Economics* 36(2): 33-53

Latacz-Lohmann, U. and C. Van der Hamsvoort. 1997. Auctioning Conservation Contracts: A Theoretical Analysis and an Application. *American Journal of Agricultural Economics*, 79(2): 407- 418.

McAfee, P. and J. McMillan. 1987. Auctions and bidding. *Journal of Economic Literature* 25(2): 699-738.

McAfee, P. and D. Vincent. 1993. The Declining Price Anomaly. *Journal of Economic Theory* 60(1): 191-212.

Milgrom, P. 1985. The Economics of Competitive Bidding. A Selective Survey. *Social Goals and Social Organization*, E. Pazner, L. Hurwicz, D. Schmeidler, and H. Sonnenschein eds., pp. 261 - 293. Cambridge: Cambridge University Press.

Milgrom, P. 1989. Auctions and Bidding: A Primer. *The Journal of Economic Perspectives*, vol. 3, pp. 3-22.

Milgrom, P. and R.J. Weber. 1982. A Theory of Auctions and Competitive Bidding. *Econometrica*, vol. 50, pp. 1089-1122.

Miranda, M. and G. Schnitkey. 1995. An Empirical Model of Asset Replacement in Dairy Production. *Journal of Applied Econometrics* 10(0): 41-55.

Mullin, W. 2001. Will Gun Buyback Programs Increase the Quantity of Guns? *International Review of Law and Economics* 21(1): 87-102.

Muse, B. *Washington State Commercial Salmon Fishery Buyback Programs, 1995-1998.* Working paper, 1999. http://www.cfec.state.ak.us/research/buyback/WA_BB.PDF

Neugebauer, T. and P. Pezanis-Christou. 2007. Bidding Behavior at Sequential First-Price Auctions With(out) Supply Uncertainty: A Laboratory Analysis. *Journal of Economic Behavior and Organization*. 63(1): 55-72.

Oren, S., and M.H. Rothkopf. 1975. Optimal Bidding in Sequential Auctions. *Operations Research*, vol. 23(6): 1080-1090.

Perrigne, I. and Q. Vuong. 1999. Structural Econometrics of First-Price Auctions: A Survey of Methods. *Canadian Journal of Agricultural Economics*, 47(3): 203-233.

Provencher, B. and R. Bishop. 1992. An Estimable Dynamic Model of Recreation Behavior with Application to Great Lakes Angling. *Journal of Environmental Economics and Management* 33(2): 107-127.

Reichers, R., W.L. Griffin and R.T. Woodward. 2007. The Texas Inshore Bay and Bait License Buyback Program. *Fisheries Buybacks*, R. Curtis and D. Squires eds., pp. 215-226. Ames, IA: Blackwell Publishing.

Robinson, L., P. Cambell and L. Butler. 1994. Trends in Texas Commercial Fishery Landings, 1972 – 1993. Management Data Series No. 111. Austin, TX: Texas Parks and Wildlife Department, Fisheries and Wildlife Division,

Rust, J. 1987. Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher. *Econometrica* 55(5):999-1033.

Rust, J. 1988. Maximum Likelihood Estimation of Discrete Control Processes. *Journal on Control and Optimization* 26(5): 1006-1024.

Schjerning, B. 2005. Structural Estimation of Markov Decision Models with Continuous State Variables, Multiple Alternatives and Unobserved Heterogeneity. *Working Paper*: http://www.cebr.dk/upload/sp_2005-03.pdf

Texas Parks and Wildlife Department. 2002. Executive Summary: The Texas Shrimp Fishery. In: *A report to the Governor and the 77th Legislature of Texas,* September 2002.

Texas Parks and Wildlife Department (TPWD). 2005. *Texas Commercial Fishing Guide*, 2005-2006.

Townsend, R. 1985. On “Capital Stuffing” in Regulated Fisheries. *Land Economics* (61)2: 195-197.

van den Berg, G., J.C. van Ours and M.P. Pradhan. 2001. The Declining Price Anomaly in Dutch Rose Auctions. *American Economic Review* 91(4): 1055-1062.

Weninger, Q. and K.E McConnell. 2000. Buyback Programs in Commercial Fisheries: Efficiency Versus Transfers. *Canadian Journal of Economics*, 33(2): 394-412.

Wilson, R.B. 1987. Game-Theoretic Analyses of Trading Processes. *Advances in Economic Theory*: *Fifth World Congress*, Bewley, T.F ed., pp. 33–70. Cambridge: Cambridge University Press.

Woodward, R.T and W.L Griffin. 2008. Final Report on Marfin Grant #NA04NMF4330080, Cost and Effectiveness of Sequential License Buyback Program in the Gulf of Mexico. Unpublished report. Texas A&M University, College Station, TX.

APPENDIX A

APPENDIX TO CHAPTER III

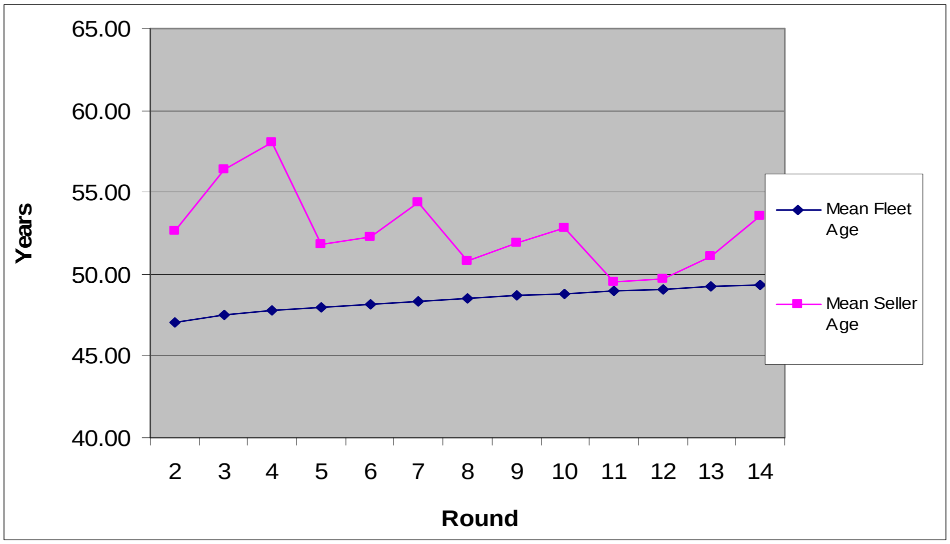

Figure A.1 License Holder Age by Round of the TX Shrimp License Buyback

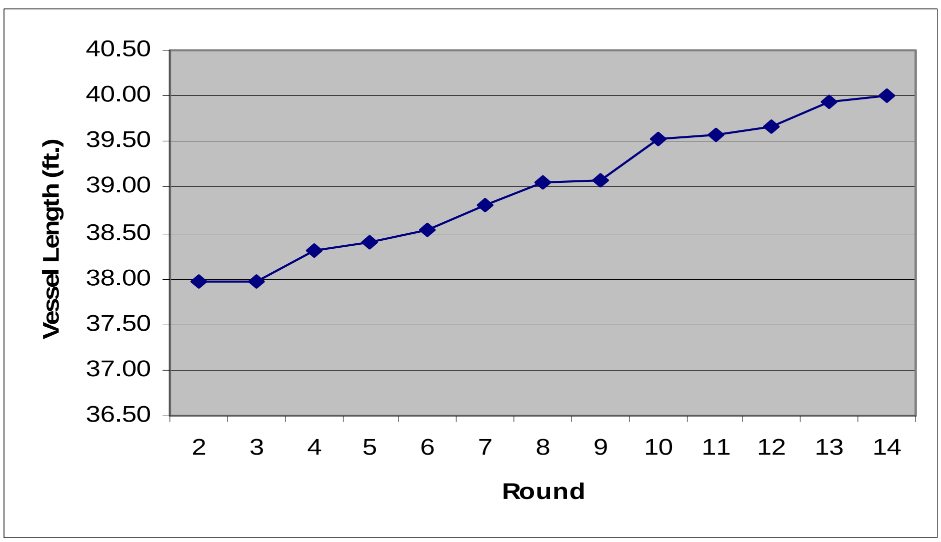

Figure A.2 Average Vessel Length of TX Inshore Shrimp Fleet by Auction Round

VITA

Name:	Aaron T. Mamula
Address:	National Marine Fisheries Service Southwest Fisheries Science Center 110 Shaffer Road Santa Cruz, CA 95060
Email Address:	aaron.mamula@noaa.gov
Education:	B.A., Economics, Oregon State University, 2000 M.A., Economics, Southern Methodist University, 2003 Ph.D, Texas A&M University, 2009