ABSTRACT

Title of Document: TO BID OR NOT TO BID: AN INVESTIGATION INTO ECONOMIC INCENTIVES UNDERLYING AUCTION PARTICIPATION

Geret Sean DePiper, Doctor of Philosophy, 2012

Dissertation Directed By: Associate Professor Douglas W. Lipton
Department of Agricultural and Resource Economics

This dissertation investigates the individual characteristics correlated with auction participation decisions using data from two commercial fishing license buybacks. I use the joint empirical analysis of stated and revealed preferences, with two major findings emerging. First, the results of my analysis suggest that individuals with relatively low willingness to accept values and low engagement in the fishery faced problems with the participation decision which prevented them from tendering bids in the auction. This has serious policy implications given that the efficiency of reverse auctions relies on buying goods back from individuals who value them the least. The low participation rate suggests that the licenses bought back represent between 47 – 64 percent of the maximum achievable with the same funds under a first best outcome.

Second, fishermen are frequently modeled as strict profit maximizers and harvest histories are often assumed to serve as a good proxy for expected future

profits in many circumstances. I find evidence against both of these assumptions. Indicators for bequest and enjoyment values are associated with an increased bid equivalent to that of a $6,500 - $20,000 increase in annual profits. Indicators of bequest and enjoyment values are also significantly correlated with the decision of whether to tender a bid at all. Expected future usage patterns are an important consideration in the participation decisions, and the expected usage can differ significantly from past usage patterns. These results suggest that market experience plays an important role in auction participation decisions, and the problems which develop from inexperience should be addressed explicitly through the auction design.

TO BID OR NOT TO BID: AN INVESTIGATION INTO ECONOMIC INCENTIVES UNDERLYING AUCTION PARTICIPATION

By

Geret Sean DePiper

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2012

Advisory Committee:
Professor Douglas W. Lipton, Chair
Professor Anna Alberini
Professor Kenneth E. McConnell
Professor Michael Paolisso
Dr. Eric Thunberg

Dedication

To Jill and Leah, the two best parts of my life.

Acknowledgements

I thank my dissertation committee for their comments, advice, and time throughout this project. Special thanks to my advisor, Dr. Douglas Lipton, for all that he has done to nurture my work over the past five years.

I gratefully acknowledge the support of the National Marine Fisheries Service through a 2010 grant funding a survey of individuals eligible for the Maryland and Virginia license buybacks. I also gratefully acknowledge the support of the National Marine Fisheries Service/Sea Grant Graduate Fellowship in Marine Resource Economics.

I am indebted to the faculty and fellow students in the Department of Agricultural & Resource Economics at the University of Maryland, for their companionship, mentoring, and insight. I thank Michael Currie, Qing Lin, Alexander Meo, and John Porcelli for their data entry and survey phone calls.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction and Policy Background

The benefits of a reverse auction as a procurement market rely on efficient allocation of the good. For a good differentiated only in price this efficiency depends on the buyer purchasing from those individuals with the lowest value, or willingness to accept (WTA), for the good. But what happens when those individuals with the lowest WTA values do not participate? Evidence suggests that just this issue occurred in the Maryland and Virginia's license buybacks. Maryland was dissatisfied with the low participation in their auction for licenses, rejected all bids, and offered a fixed price roughly equal to the 25th percentile of the bid distribution. Ultimately more people accepted that fixed price offer than the total number of bidders in the original auction. This result indicates that problems with the participation decision for the auctions kept some people who would otherwise be willing to sell their license from tendering bids.

The importance of participation decisions on auction outcomes has recently been illustrated within the auctions literature (Bajari and Hortacsu, 2003; Kjerstad and Vagstad, 2000; Li and Zhang, 2010). The low participation rates in the Maryland and Virginia license buybacks highlight the importance of participation in terms of achieving management goals—in this context, the cost-effective removal of licenses from the fishery.

This dissertation looks to answer three questions in order to better understand the license buyback participation decisions. First, how are the Maryland and Virginia crabbing licenses valued? Second, who bid in the auction and why? Third, what do these results indicate about buyback design? I link actual bids submitted by watermen in the above mentioned reverse auctions with hypothetical, open-ended WTA responses from a survey of individuals eligible for the license buybacks in order to generate a more complete picture of the participation decisions surrounding the Maryland and Virginia buybacks. The resulting dataset is a combination of revealed and stated preference information that links buyback data with historical catch histories and stated preferences at the individual level, and provides a unique opportunity to investigate both the buyback participation decisions and the underlying value of the licenses themselves.

Chapter 2 outlines the theoretical models of optimal bidding and participation decisions for individuals eligible for the Maryland and Virginia license buybacks, and provides an empirical approach to estimating the theoretical models. I pay special attention to the values that have been identified by license holders themselves in motivating participation decisions.

Chapter 3 provides an overview of the dataset used in the empirical investigation. The results of the economic analysis are presented in Chapter 4. My study suggests that commercial fishermen are *not* strict profit maximizers. Indicators for the importance of a bequest motive and the enjoyment of crabbing are significantly correlated with license values, with these indicator variables associated with an increase of between 30-40% above the baseline bid amount. This bid increase is equivalent to that associated with an increase in annual profits of between $6,500 and $20,000, and suggests that non-pecuniary factors of utility could underlie the bulk of a license's value for some individuals. My analysis also highlights that past usage patterns are not necessarily good indicators of expected future profit streams, an important finding given that this assumption underlies most fishery buybacks.

Chapter 5 presents buyback simulations based off of the WTA survey data, and investigates outcomes under full participation, and varying market designs. The Markov Chain Monte Carlo simulations indicate that both Maryland and Virginia fell far short of the number of licenses which could have been bought with the existing budget, primarily due to the non-participation of individuals with relatively low WTA values.

Chapter 6 presents a discussion of the results and draws policy implications for the design of both license buybacks and other management instruments. In particular, the most probable cause of the low participation rates is the increased costs of information gathering for inframarginal crabbers. I explore potential steps by which these costs might be defrayed.

1.1 The Chesapeake Bay Blue Crab Fishery

The Blue Crab (Callinectes sapidus) fishery is the most valuable fishery in the Chesapeake Bay, with a dockside value of just under $109 million in 2010 (National Oceanic and Atmospheric Administration, 2010). This is a single stock fishery managed in coordination by Maryland, Virginia, and the Potomac River Fisheries Commission. Both Maryland and Virginia manage their crab fisheries as limited access, which provides transferability to the license holder, but not exclusivity to any fraction of the harvest. Table 1.1 provides an overview of Maryland and Virginia crab pot licenses. Although other blue crab licenses exist, the majority of the harvest in each state is landed with the use of pots, and this study focuses on policy instruments aimed specifically at pot licenses. The crab population was severely depressed in comparison to historical numbers between the early 1990's and 2009, although it has since rebounded.

Table 1.1: Pot licenses in Maryland and Virginia Blue Crab fisheries

	Maryland			Virginia	
	Recreational	LCC	Large Pot	Hard	Peeler
Pots Allowable	2	50	300, 600, 900	85, 127, 170, 255, 425	210
Trotline	1,200 ft	Unlimited	Unlimited	None	None
Traps & net rings	30 total	Unlimited	Unlimited	None	None
Annual Fee ($)	5	50	150, 170, 190	48, 79, 79, 79, 127	36
Catch sale	Prohibited	Allowed	Allowed	Allowed	Allowed
License sale	Prohibited	Allowed	Allowed	Allowed	Allowed
Licenses	Unknown	3,676	231, 222, 404	456, 81, 38, 762, 135	764
Catch Limits[a]					
Hard male	1	Unlimited	Unlimited	51[d]	None
Hard female	None	2[b]	10, 15, 20[c]	51[d,e]	None
Peeler & soft	2 dozen	Unlimited	Unlimited	None	51[d,e]

[a]Bushels, unless otherwise noted
[b]10 bushels Sept. 1 - Nov. 10
[c]6, 10, & 15 bushels June 16- Aug. 31; 25, 35, & 45 bushels Sept. 1 - Nov. 10
[d]March 17 - May 31, 51 bushels is the combined limit for male and female crabs
[e] Female harvest prohibited after November 20

Thunberg (2000) defines latent effort as a continuum running from no use up to, but not including, full use of the allowable gear and human capital within a fishery. In general it can be thought of as a pool of potential effort or the unused portion of capital within a fishery, and directly corresponds to overcapitalization. Both the Maryland and Virginia portions of the crab fishery exhibit large pools of latent effort, with anywhere between one third and one half of pot licenses completely unused in any given year. Even so, stock assessments have indicated that the existing effort represented overfishing of the resource prior to 2009 (Virginia Marine Resources Commission, 2009).

The large pool of latent effort induces management uncertainty, in that it is unclear when, or whether, effort could flow back into the fishery. Maryland and Virginia share a management goal of rebuilding the crab population, for both conservation and economic objectives. The economic objective is to return the crab populations to levels which can more effectively sustain watermen, processors, wholesalers, and other businesses dependent on the crab. The major issue from the management perspective is whether effort is likely to re-enter the fishery as the crab population is successfully rebuilt. If a large amount of latent effort re-enters, the fishery will act like an open access resource, with the corresponding dissipation of potential rents. This influx of effort could also directly erode any conservation gains that would otherwise accrue to the population. Maryland and Virginia view the decrease in potential effort through the direct removal of licenses as the most effective manner in which to achieve sustainability in the fishery. To achieve this, the states implemented commercial license buybacks in 2009. Maryland's buyback was instituted in the Limited Crab Catcher (LCC) license category, while Virginia's buybacks targeted both the Hard and Peeler pot categories of licenses.

1.2 Fishery Exit Inertia and Buybacks

1.2.1 Fishery Exit Inertia

This dissertation provides additional insight into the issue of exit inertia. This phenomenon consists of individuals continuing to fish long after a profit maximizing framework indicates exit from the fishery is optimal. Exit inertia has been linked to numerous underlying causes over the years. Clark, Clarke, and Munro (1979) attributed exit inertia to an issue of imperfectly malleable capital, where the salvage value of fishing gear is near zero despite its high acquisition costs. Fishermen then become locked into a fishery as they are unable to recoup the high fixed entry costs upon exit. This argument does not seem to play a role in Maryland and Virginia, where fixed costs represent roughly 23% of total crabbing costs (Rhodes et. al, 2001).

Weninger and Just (1997) show how delayed exit strategies can serve as the dominant strategy within an individual transferrable quota (ITQ) system. The Maryland and Virginia fisheries are managed as limited entry, and lack the exclusivity to a portion of the overall harvest which is critical in Weninger and Just's argument, and thus precludes it as the explanation for the buyback results studied here.

Commercial fishermen are traditionally assumed to derive all their utility from the profit they generate fishing. Although other paradigms such as constrained revenue maximization (e.g. Kirkley & Strand, 1988) and risk aversion (e.g. Mistiaen & Strand, 2000; Opaluch & Bockstael, 1984) exist, commercial fishermen are often modeled as strict profit maximizers (e.g. Bjørndal & Conrad, 1987; Eggert & Tveterås, 2007; Gordon, 1954; Mistiaen & Strand, 2000; Scott, 1955; Tidd et al., 2011; Ward & Sutinen, 1994; Weninger & Just, 1997). Many other values have also been postulated as important components of the employment decisions surrounding fishing (Anderson, 1980; Gatewood and McCay, 1990; Opaluch and Bockstael, 1984). In this paper I investigate what license holder characteristics are correlated with the unobservable drivers of the buyback participation decision, in order to better understand the economic incentives at work in these fisheries. Use and non-use values are considered as potentially underlying both the value of licenses and the decision to participate in the buybacks. For example, Opaluch and Bockstael (1984) suggest that exit from a fishery could induce "psychic costs" due to breaking with family tradition, and researchers have long indicated the important role family tradition plays in commercial fishing (e.g. Chaves et al., 2002; Horobin, 1957; Miller & Van Maanen, 1979). Anderson (1980) and others (e.g. Berman, Haley, & Kim, 1997; Pollnac & Poggie, 1988) espoused the idea of a worker satisfaction bonus, in which fishermen gain non-monetary benefits directly from the act of fishing. Other researchers have postulated that the fisherman identity itself can generate utility (e.g. Davis, 2000; Gatewood & McCay, 1990; Pollnac & Poggie, 2006). Results of a series of open house meetings held by Maryland prior to the buyback suggest that all of these are important considerations, along with bequest value and a life-cycle argument[1], in which the expected future use differs significantly from past usage.

[1] These components of license value were repeatedly mentioned by watermen in MD DNR open house meetings regarding LCC crabbing licenses. Discussions with the VMRC revealed similar feelings expressed by crabbers in VA. For the purpose of this research the bequest value is theoretically modeled as paternalistic altruism (McConnell, 1997) and lifecycle value suggests extenuating circumstances, such as another job or young children, which preclude the current, but not the future, use of the license.

1.2.2 Commercial Fishery Buybacks

Although their ability to produce welfare gains has been called into question (Clark, Munro, & Sumaila, 2007, 2005; Holland et al., 1999; Weninger & McConnell, 2000), buybacks are an important tool for fishery managers in dealing with the detrimental effects of overcapacity. In the United States, buybacks have been instituted within the New England groundfish fishery (Thunberg, Kitts, & Walden, 2007), the Texas bay and bait shrimp fishery (Riechers, Griffin, & Woodward, 2007), the Washington state commercial salmon fishery (Muse, 1999), and the Bering Sea Pollock Buyback in Alaska (United States General Accounting Office, 2000). Fishery buybacks have expended significant sums of money, with the Bering Sea buyback alone costing $90 million. Buyback targets, budgets, and anticipated bid values in the case of auctions are often based solely as a function of the fishermen's anticipated profit streams, often proxied by harvest histories. However, my analysis suggests that a significant portion of a license's value can lay both in other determinants of utility and expected usage patterns which differ starkly from past harvest histories. Further, I find evidence that marginal and inframarginal fishermen have problems formulating a bidding strategy. This means the individuals most often targeted by buyback policies are exactly those least prepared to engage in the process of submitting a bid for their holdings.

Recent economic experiments suggest that, although theoretically equivalent, bids within sealed bid auctions and participation in posted offer markets can differ significantly (Jack, 2011). Specifically, bids tend to be significantly above an individual's true valuation and auction participation levels tend to be significantly lower than can be theoretically justified when compared to participation decisions in what should be an equivalent alternative market. One potential explanation for such results is value uncertainty, defined here as unfamiliarity with either the auctioned good or the act of explicitly developing a bid for that good.

This uncertainty could directly interfere with formulating a bidding strategy, particularly with inexperienced bidders (DePiper et al., 2011). In this paper I provide a more detailed investigation into what individual characteristics underlie the divergence in outcomes. In particular, I find that individuals whose license value lies primarily in non-pecuniary factors face value uncertainty in the bid-formulation process. The greatest effect of this uncertainty is observed in individuals holding relatively low WTA values. Participation costs associated with either information gathering during the bid formulation process or the bidding itself then makes non-participation optimal for these individuals, leading to lower participation rates than otherwise anticipated.

This dissertation is not the first research to investigate buyback participation decisions. Kitts et al. (2000) investigated participation in the first New England Groundfish fishery buyback. This buyback was structured as a vessel buyout, and retired the vessel as well as all associated federal fishing permits. Kitts et al. utilize a Heckman two-step analysis to investigate both the probability of bidding in the auction, and bid function. Their research finds that participation was directly correlated with the age of the vessel and revenue dependence on the groundfish fishery. However, as Kitts et al. themselves state, the research lacked demographic and other economic variables which likely help explain the participation decisions.

Further, Kitts et al. do not investigate the effect of a depressed participation rate on outcomes, in terms of increased costs of the buyback to the fishery manager.

Avila-Forcada et al. (2012) study participation in a conservation buyout program aiming to protect a small porpoise, Vaquita marina (*Phocoena sinus),* in the Northern Gulf of California. This buyout was somewhat unique as it combined a traditional buyout program with switch out and rent out options. Each category was implemented as a posted offer buyback. Individuals under the buyout program received the highest compensation, as it corresponded with a complete cessation of all fishing activities. The switch out option required fishermen to switch to vaquita safe gear, with compensation depending on the type of gear and temporal length of the switch out. The rent out option represented a suspension of fishing activities within a designated zone of the vaquita's critical habitat. A multinomial logit model was used to estimate an individual's propensity to participate in each category of the buyback. The participation decision is modeled as a function of economic variables including age, education, conservation attitude, profits, alternative income sources, financial liabilities, and wealth for a random sample of eligible fishermen, all of which are significant in the participation decision to some extent. Although the important variables corresponding to the participation decision are identified, these results are not used to investigate how the buyback outcomes compare to a first-best scenario.

Mamula (2009) investigates participation in the Texas bay and bait shrimp fishery. This buyback was structured as a dynamic sequential auction, in which license holders decided whether to bid or not in each year over a 13 year period. If the bid was accepted by the state, the license holder was provided a final opportunity to accept or reject the sale of the license. Mamula starts his analysis by estimating a Heckman two-step model of the joint decision of whether and how much to bid. His analysis suggests that the probability of bidding in any round of the buyback correlates positively to the age of the fisherman and negatively to the length of the fisherman's vessel, price of shrimp, and an indicator as to whether the fisherman has an offshore shrimping license in addition to the inshore license eligible for the buyback. However, the final simulation of alternative buyback designs which Mamula undertakes does not explicitly consider the participation decision, and therefore a first best outcome is not compared against outcomes due to depressed participation rates.

My analysis differs significantly from this previous research in that it uses WTA values gathered directly from fishermen to understand both the economic value of fishing at an individual level and the buyback participation decision. This WTA data is combined with subjective beliefs on expected usage and indicators for the importance of both use and nonuse values, which are also missing from previous studies. All of these are found to be important considerations in the participation decision surrounding the Maryland and Virginia buybacks.

Conditioning the participation decision on an individual's WTA value allows the identification of potential issues associated with the bidding process which might otherwise be transparent. For example, the relationship between value uncertainty and low WTA values does not become apparent until WTA is directly controlled for. The low participation rates for individuals with relatively low WTA values suggests that the number of licenses actually bought represent between 47 and 64 percent of the first best scenario. This disparity highlights the importance of the participation rate in achieving management goals.

1.3 Maryland and Virginia License Buybacks

This section provides an overview of the rules and regulations governing the license buybacks in Maryland and Virginia. It also provides a summary of the results of each state's buyback efforts. The Maryland and Virginia buybacks were underwritten through Federal emergency disaster relief funding, which was awarded to the states in recognition of the dire straits faced by the blue crab fishery (Maryland Department of Natural Resources, 2009).

An important note is that both Maryland and Virginia allow watermen to sell their commercial licenses in the open market. A survey of classified ads indicates that the median asking price for a Maryland LCC license was just under $5,000 at the time of the buyback. However, these asking prices are imperfect signals for a license's true market value due to a thin market, unpublished clearing prices, and the regulatory imperative to transfer the fishing business, including gear, with the license. The exact gear that needs to be transferred is not defined by Maryland Department of Natural Resources (DNR), and thus the exact degree to which the license value is overstated is unclear. Market data for licenses in Virginia are unavailable.

1.3.1 Maryland Buyback Design and Outcomes

The Maryland LCC license buyback began as a reverse auction, with each license equal in terms of buyback priority. The buyback had a total budget of $3 million, with the only criterion for eligibility being the possession of an LCC license. A total of 3,676 license holders were eligible for the buyback, and each was sent a letter detailing the buyback rules. The letter stated the following:

1. The license holder should submit a bid for the value (s)he determines the license is worth.
2. Maryland DNR will accept the lowest bids first, and continue buying licenses until all available funds are exhausted.
3. The range of bids received by Maryland DNR would be used to determine a maximum price to be paid in the auction and any bids above this maximum price would be rejected.
4. The Maryland DNR had previously conducted an independent economic analysis of the value of an LCC license, and any bids unrealistically high when compared to this value would be excluded from determining the maximum price to be paid for an LCC license.[2]
5. The bid value should be for the license alone, and not for any associated assets such as boats or crabbing gear.

[2] The economic analysis undertaken prior to the buyback was intended to highlight the potential drawbacks of a posted offer in comparison to an auction format specifically because of the lack of information regarding the license value. This statement from the Maryland DNR can thus be viewed as gamesmanship aimed at incentivizing competitive bidding rather than being grounded on actionable data.

The total budget available for the buyback was not made public in the buyback announcement, although a target of purchasing 2,000 licenses was publicized by Maryland. Individuals who held a license between April 1, 2004 and December 15, 2008, but recorded no crab catch during that time were advised that their license would be subject to new regulations for the 2010 season if their bid was not accepted. These proposed regulations greatly decreased the profit generating capacity of the licenses, restricting both their use and transferability. The goal of the proposed regulations was to induce buyback participation for those individuals not currently engaged in the fishery. A total of 1,058 individuals were classified as latent by Maryland.

Table 1.2 provides summary statistics for the Maryland reverse auction. All the Maryland statistics are broken down between active and latent classifications to reflect the differing profit generating capacity of these two groups, though the bids were not ranked by these categories in the buyback itself. Latent license holders participated in greater numbers and with lower bids than those not classified as such. Of note is the strikingly low participation rate, given that license holders were able to name their own price for the license. Even the 27% participation rate for latent license holders is unexpectedly low, given the serious value implications of the proposed restrictions these license holders faced.

Table 1.2: Maryland LCC auction bids

Status	Obs	Mean	Median	SD	Min	Max	Bid
		($)	($)	($)	($)	($)	(%)
Active	210	16,749	5,000	40,077	250	300,000	8.02
Latent	282	7,667	3,675	16,761	30	150,000	26.65
Total	492	11,543	4,950	29,405	30	300,000	13.38

Note: Results drop obvious protest bid of $425,000,000.

At $4,950, the median bid of all bidders in the auction is very similar to asking prices on the open market at around the same time. However, anecdotal evidence suggests that these asking prices are significantly inflated above market clearing prices (DePiper et al., 2011), and include the transfer of business capital. In a private values setting, large variations in individuals' WTA is to be expected. Nonetheless, past usage patterns do not suggest that the licenses have historically generated a profit stream even remotely justifying the $4,950 license value. Basic calculations indicate that even in years of high crab populations roughly half of all active license holders fail to generate positive profits (DePiper & Lipton, 2009). Although past usage patterns might not represent an individual's expected future crabbing, the additional restrictions proposed for individuals categorized as latent would severely curtail their potential profit stream. However, it is unclear how seriously crabbers considered the proposed regulations, given that roughly six months prior to the auction very similar proposals were retracted in the face of strong political opposition (Maryland Department of Natural Resources, 2009b).

The participation rate was much lower and bids were much higher than Maryland DNR anticipated. In light of this, Maryland rejected all bids and offered a flat price of $2,260 to anyone willing to sell their license at that price. Table 1.3

presents summary statistics for take-up of the posted price offer. The most striking feature of the posted offer is again the participation rate, which is much higher than the auction and driven primarily by the increase in participation within the latent license category. Of the 285 latent crabbers who bid in the auction, 210 (~74%) accepted the posted price. A total of 372 individuals accepting the posted offer (~54%) did not previously bid in the auction.

Table 1.3: Maryland LCC posted offer buyback results

Status	Accepted	Acceptance	Bid	Mean Bid	SD Bid
		(%)	(%)	($)	($)
Active	249	9.51	40.56	4,928	6,798
Latent	434	41.02	48.39	4,602	9,100

The proposed regulations for latent license holders were enacted between the auction and posted price offer, which confounds the direct comparison of participation in these two markets. However, individuals classified as active were not subject to the additional restrictions, and thus their participation decisions are more aptly comparable. Of particular interest is that only 41% of active individuals participating in the posted offer buyback had previously submitted a bid in the auction. This suggests some major issues associated with the bid formulation process. Eight percent of the individuals who bid in the Maryland reverse auction bid below the $2,260 posted offer and subsequently rejected the posted offer itself. Further, 27% of those active individuals who bid and ultimately accepted the $2,260 bid at least double that amount in the auction, which is an unexpectedly high amount of bid shading given the market structure.

1.3.2 Virginia Buyback Design and Outcomes

In contrast to Maryland, Virginia had a very specific formula for prioritizing licenses for their buyback. Two major categories of licenses exist in Virginia, hard pot and peeler pot licenses. Within these, individuals were segmented into three distinct groups based on their average harvest history during the 2004 – 2007 seasons: full time, part time, and wait list. Full time fishermen were defined as having reported an average of at least 100 days of harvest in the hard shell fishery and at least 60 days within the peeler fishery. Part time fishermen are defined as having reported less than 100 days of harvest in the hard shell fishery and less than 60 days of harvest in the peeler fishery. Fishermen were placed on the wait list in either the peeler or hard shell fishery if they reported no harvest days for that respective fishery for the years between 2004 and 2007. Waitlisted licenses are not allowed to be transferred, sold, or used for crabbing until the population of crabs older than one year is estimated to be above 200 million for three consecutive years. At the time of the buyback, the crab population had not surpassed the 200 million threshold since the early 1990's, although it has been surpassed in all three years since 2009. The rules of the Virginia buyback were as follows:

1. The Virginia Marine Resource Commission (VMRC) had a budget of $6,724,470 for the buyback program.
2. Funds were dedicated to full-time, part-time, and waiting listed fishermen for the buyback such that 50 percent, 30 percent, and 20 percent of the budget were available for each group, respectively.

3. Each bid would be divided by the maximum number of pots allowed by the specific license and the average number of reported days of harvest between 2004 and 2007 in order to calculate a bid per pot day.[3] For individuals who received the license for the first time in 2008 or 2009, that year's crabbing effort would serve to calculate the bid per pot day value.
4. Bid per pot day would be ranked in ascending order within each category (full time vs. part time vs. wait list), and purchased from lowest to highest until all funds allocated to that category were exhausted.
5. The VMRC reserves the right to reject any excessive bids, with an excessive bid being defined after all bids have been submitted.
6. Individuals selling their license through the buyback are eligible to re-enter the fishery by purchasing a license from another fisherman.

The results of the Virginia license buyback are summarized in Table 1.4. Participation rates are quite a bit higher than those in the Maryland auction across all license categories. Bids are also much higher in Virginia, a function of the larger number of pots which the Virginia licenses allow in comparison to Maryland, directly corresponding to larger profit earning potential, coupled with a much smaller total supply of licenses in Virginia. Also in contrast to Maryland, licenses categorized as wait listed in Virginia were already frozen at the time of the auction. Ultimately the VMRC spent a total of $6,725,161 buying 359 licenses back, and expended their budget completely.

[3] Although not explicitly indicated in the auction instructions, the bids of individuals on the waitlist, who have no harvest history between 2004 and 2007, were ranked in ascending order by dividing the bid by the total number of pots allowed by the license being bid upon.

Table 1.4: Virginia commercial pot license auction bids ($ thousands)

Status	Obs	Mean	Med	SD	Min	Max	Bid
Hard Pot		($)	($)	($)	($)	($)	(%)
Full time	49	114.41	98.00	116.83	6.00	600.00	25.26
Part time	232	59.10	30.00	73.30	0.50	634.00	24.29
Waitlist	141	20.33	10.00	29.44	1.00	220.00	43.65
Peeler Pot							
Full time	27	40.36	20.00	58.53	2.00	200.00	24.11
Part time	126	38.48	15.25	50.99	0.50	300.00	29.44
Waitlist	89	19.01	8.00	23.20	1.00	125.00	59.73

The buyback summary statistics indicate some intriguing participation patterns. In particular, the apparent preference reversals between Maryland's reverse auction and fixed price offer suggest that value uncertainty could be playing a role in individual's participation decisions. The next section lays out the process by which this information will be utilized in order to better understand participation decisions, and more formally investigate the role of value uncertainty in the buybacks.

Chapter 2: A Model of Bidding

In this section I develop models of the bid function and the participation decision surrounding Maryland and Virginia's license buybacks. Two key differences exist between my model and much of the existing literature on auctions. The first is my specific interest in what individual characteristics are correlated with the decision to bid or not, and its implications for the realization of management objectives. Maryland's buyback indicates that a large number of individuals with relatively low WTA values did not bid in the auction. Understanding who bid is the first step in understanding why the divergence in participation rates between the posted price and auction markets occurred. The second difference that sets my model apart is my interest in the non-monetary motives for both whether and what to bid. I have already provided casual evidence that profits do not explain the variation in bids. In order to provide empirical evidence I begin my discussion of this section with a simple model of bidding.

2.1 Theory of Bidding and the Participation Decision

2.1.1 A Simple Model of Bidding

In the neoclassical framework, commercial fishermen are traditionally assumed to derive all their utility from the profit they generate fishing, and are very often modeled as strict profit maximizers. In particular, fishermen look to maximize the net present value of expected future profit streams. Assuming risk neutrality this can formally be represented in discrete time as:

$$(2.1) \qquad EU(\pi_i) = E[\sum_{t=0}^{T} \pi_{i,t}\, \delta^t]$$

In this formulation $\pi_{i,t}$ represents individual i's profits in time t and δ^t is the discount factor. The value of the license, and thus an individual's bid in the license buybacks, is then simply the expected discounted flow of profits that can be generated from crabbing (plus a non-negative amount of bid shading due to the pay-as-bid structure of the auction).

A regression of an individual's bid amount on the flow of expected future profits should then explain most of the bid variation within the Maryland and Virginia license buybacks. Table 2.1 presents simple regressions of the natural log of an individual's bid amount on their average historical annual profits in order to investigate whether profits alone can explain bidding patterns. This is a functional representation of equation 2.1 and assumes that historical profits provide a good proxy for expected future earnings, a common assumption in the literature. The results indicate that, although highly significant with a p-value of 0.000 in both states, profits alone fail to explain a great deal of the variance in individual bids within Maryland and Virginia's auctions. This in turn suggests that a more complex model of behavior is necessary in order to better explain the decisions surrounding the license buybacks.

Table 2.1: Regression of bid amount on profits
(standard error)

	Maryland	**Virginia**
Constant	-3.1784*	-1.7179*
	(0.0572)	(0.0505)
Profits	0.5542*	0.7195*
	(0.1231)	(0.0734)
R-squared	0.0397	0.1267
Prob > F	0.0000	0.0000
Observations	492	664

*Significant < 10% level

2.1.2 A More Complex Model of Bidding

Given that fishermen derive non-pecuniary utility from fishing, an individual fisherman is assumed to have a utility function of the following form:

$$U(\pi_i, Z_i). \tag{2.2}$$

Here π_i defines fisherman i's profits from crabbing. Vector Z_i is composed of indicators for the previously mentioned non-pecuniary factors of utility, as well as demographic variables.

Individuals bid in an auction only if they expect to gain from doing so. Given the utility function in equation 2.2, the choice of whether to participate in the auction depends on whether the utility from participation is greater than the utility from not participating in the auction. Formally, a waterman participates if:

$$(2.3) \qquad pr(bid \leq cutoff\ price)U\left(bid_i, C, Z_{i,bid}\right) + \left[1 - pr(bid \leq cutoff\ price)\right] U\left(\pi_i, C, Z_{i,license}\right) \geq U\left(\pi_i, Z_{i,license}\right).$$

Here pr represents probability, bid_i is individual i's bid value, $cutoff\ price$ is the state's exogenous cutoff price in the auction, C represents the cost of participating in the auction,[4] and all other terms are defined as before. The cutoff price is the largest bid accepted within the auction. The probability $pr[bid_i \leq cutoff\ price]$ represents individual i's subjective probability of winning the auction. Thus the individual participates in the auction if the expected payoff from participation (left hand side of equation 2.3 is greater than the reservation value of the license (right hand side of equation 2.3).

After rearranging equation 2.3, an individual participates if:

$$(2.4) \qquad pr[bid_i \leq cutoff\ price]\left[U\left(bid_i, C, Z_{i,bid}\right) - U\left(\pi_i, C, Z_{i,license}\right)\right] - \left[U\left(\pi_i, Z_{i,bid}\right) - U\left(\pi_i, C, Z_{i,license}\right)\right] \geq 0.$$

The first and second terms in equation 2.4 represent the expected utility and disutility from participating in the auction, respectively.

Individual i's subjective probability of winning the auction is a function of their beliefs over the cutoff price such that:

[4] This cost can be thought of as either monetary or psychological cost of participation. Psychological costs could stem from a distrust of any interactions with the state, a lack of understanding as to the exact rules of the auction, or any other issue which makes participation in the buyback costly.

$$(2.5) \qquad pr[bid_i \leq cutoff\ price] = 1 - F(bid_i) = \int_{bid_i}^{\infty} f(b)db.$$

In this framework $F(\cdot)$ and $f(\cdot)$ are respectively the cumulative distribution and probability density functions of the subjective belief over the cutoff price. The probability of winning the auction thus depends on a fisherman's expectations over the distribution of the cutoff price. In what follows, it is assumed that fishermen face an exogenous cutoff price within the auction. I use an exogenous cutoff for two reasons. First, the instructions for the Maryland buyback expressly state that an independent economic evaluation of a license value had been undertaken, and any bids substantially greater than this value would be summarily rejected. Similarly, the instructions in Virginia state that VMRC reserves the right to reject any bid that it determines to be excessive. Both states also indicated that the exact cutoff price would be calculated from the distribution of bids received in the auction itself. Thus, although the exact cutoff price is endogenous, there is an exogenous upper bound on that cutoff price. Second, in both the MD and VA license buybacks there were a large number of potential participants (3,676 in MD and 1,835 in VA). It is likely that, with such a large group of potential bidders, individuals will take the value below which bids will be accepted as exogenous, suggesting a decision-theoretic rather than a game-theoretic framework is appropriate. Thus, although the cutoff price is endogenous to the system, any given individual will treat the cutoff price as exogenous.

The auction environment can be characterized as a multi-unit, sealed, pay-as-bid auction with singleton supply, an entry cost, and endogenous participation.

Structural models of similar auctions have recently been developed (T. Li, 2005; Menezes & Monteiro, 2000). However, the license buybacks in Maryland and Virginia differ significantly from these frameworks in important ways. First, the license buybacks are reverse auctions, such that bidders were sellers and not buyers within the auction. This suggests that license holders should already have some sense as to the value of the license prior to the auction, and thus make the participation decision with a sense of what their WTA is. This is in contrast to many structural auction models, in which the participation decision is made prior to an individual's draw from the value distribution. Second, as previously mentioned the size of the pool of participants is large enough that a decision theoretic framework is appropriate.

To proceed, functional forms for equation 2.4 must be specified. Ultimately, a license provides an expected flow of services throughout the lifetime of individual i. Formulated over discrete time, the expected utility of this service flow can be represented as:

$$(2.6) \qquad EU(\pi_{i,t}, Z_i) = \sum_{t=0}^{T} (V(\pi_{i,t}) + use(Z_{1,i,t}) + nonuse(Z_{2,i,t}))\delta^t + \sum_{t=T+1}^{D} k(R_{b,t})\delta^t.$$

Both profit and license use is assumed to be random, and expectations are made over these components of utility. Utility is assumed to be increasing in all arguments, with decreasing marginal returns. The flow of utility in equation 2.6 is broken into two distinct time periods. The first summation encapsulates the utility generated while a fisherman holds a license; and T represents the final time period in which individual i personally uses the license. Here $V(\cdot)$ represents utility over income, $\pi_{i,t}$ is annual fishing profit, $use(Z_{1,i,t})$ is a function defining non-pecuniary use value derived from crabbing, $nonuse(Z_{2,i,t})$ is a function which represents non-use values associated with the ownership of a license, and δ^t is the discount factor.

The second summation in equation 2.6 represents the bequest value of the license, $k(R_{b,t})$, accrued from the time the license is passed on to the beneficiary until the end of the benefactor's lifetime. If bequest value is in the form of paternal altruism (McConnell, 1997), then this utility is generated from the expected flow of services provided to the license beneficiary. This service flow will be a function of expected revenue that a beneficiary will earn, $R_{b,t}$, a random variable. If a beneficiary does not exist, the second term in equation 2.5 is replaced with the discounted salvage value, or market price, of the license at time period $T+1$.

An individual deciding whether to participate in the auction forecasts the expected future flow of utility encapsulated in equation 2.6. This expected flow then feeds into equation 2.4, which captures the participation decision itself. Assuming risk neutrality,[5] an individual is interested solely in the expected value of future profits. Further, given the use of indicator variables to capture the importance of non-pecuniary factors of utility in the bidding decision, these also enter the model linearly. With these assumptions, a functional representation of equation 2.6 is:

$$(2.7) \qquad EU(\pi_i, Z_i) = \beta\mu_{\pi,i} + \theta Z_i,$$

[5] I estimated an alternative linear mean-standard deviation specification for the functional form of utility over profits, which indicated no significant sensitivity of the bidding decision to the variance of profits, and thus leads credence to the assumption of risk neutrality.

with both β and θ as parameters to be estimated, $\mu_{\pi,i}$ representing mean future profits, and Z_i is a vector of variables capturing non-monetary arguments of utility. Substituting equations 2.5 and 2.7 into 2.4, and assuming that the cost of participation, C, enters the utility function linearly, individuals will bid in the auction if:

(2.8) $$[1 - F(bid_i)][\alpha bid_i - \beta\mu_{\pi,i} - \theta Z_i] - C \geq 0.$$

The fact that we only observe the decision to participate in the auction as an indicator of the underlying difference in expected utility suggests a latent variable construct. The latent variable y_i^* is the change in utility that an individual fisherman expects from bidding in the auction. Formally:

(2.9) $$y_i^* = [1 - F(bid_i)][\alpha bid_i - \beta\mu_{\pi,i} - \theta Z_i] + \varepsilon_{bid,i} - C - \varepsilon_{c,i}.$$

In this representation, $\varepsilon_{bid,i}$ and $\varepsilon_{c,i}$ are factors governing utility which are known to the individual but not to the researcher. Instead of y_i^*, the researcher only observes a binary outcome y_i, which maps to the latent variable as follows:

(2.10) $$y_i = 1 \text{ if } y_i^* \geq 0, \text{ otherwise } y_i = 0.$$

The indicator $y_i = 1$ denotes that individual i participated in the auction.

As previously noted, the subjective probability of winning the auction is determined by an individual's expectations over the distribution of the auctions' exogenous cutoff prices. A negative exponential function is used to model this expectation.[6] From equation 2.5 we then have:

$$(2.11) \qquad pr[bid_i \leq cutoff\ price] = [1 - F_i(bid_i)] = e^{-\exp(\varphi W_i) bid_i}$$

Here W_i is a vector of the variables governing an individual's expectations of the state's cutoff price. These variables look to capture the familiarity an individual has with the distribution of license values. The parameter vector φ is to be estimated. The subscript on the cumulative distribution function indicates that this distribution is an individual's subjective believe, and varies from person to person.

Substituting 2.11 into 2.9 results in the following empirical specification:

$$(2.12) \qquad y_i^* = -C + \psi D_i + \left[e^{-\exp(\varphi W_i) bid_i}\left[\alpha bid_i - \beta \mu_{\pi,i} - \theta Z_i\right]\right] - \eta_i.$$

The constant C captures the costs of participation, among other factors driving the baseline participation rate. D_i is a vector of demographic characteristics which influence participation in the auction, and ψ is a parameter vector to be estimated. All other variables and parameters are as previously defined. The η_i term is equal to $\varepsilon_{bid,i} - \varepsilon_{c,i}$. Assuming that η_i is distributed $N(0,1)$, we have from equation 2.12 that the probability of bidding is equal to the probability that $y_i^* \geq 0$, which can be estimated within a probit framework. More formally the log-likelihood function is:

[6] The negative exponential is a Weibull distribution with the shape parameter restricted to 1. A Weibull distribution with no restriction on the shape parameter was also estimated, but likelihood ratio tests indicated that it provided no gains in model fit as compared to the negative exponential functional form.

$$(2.13) \qquad lnL = \sum_{i=1}^{n} \mathrm{y_i} \ln\Phi(-C + \psi D_i + e^{-\exp(\varphi W_i) bid_i}[\alpha bid_i - \beta\mu_{\pi,i} - \theta Z_i])$$

$$+\sum_{i=1}^{n}(1-\mathrm{y_i})\ln\left(1-\Phi(-C+\psi D_i+\left[e^{-\exp(\varphi W_i) bid_i}[\alpha bid_i - \beta\mu_{\pi,i} - \theta Z_i]\right]\right)).$$

$\Phi(\cdot)$ is the standard normal cumulative distribution function, and n equaling the number of individuals eligible for the buyback.

2.2 Empirical Strategy

A complication with equation 2.13 is that the bid is only observed for individuals who actually submitted a bid in the auction. Additionally, equation 2.13 does not specify the determinants of individuals' bids themselves. For this reason, I need to develop predicted bids for everyone eligible for the buyback. I estimate a Heckman two-step model, which allows me to recover the parameters of subjective probability that can be coupled with the WTA data from the survey in order to predict an individual's bid, regardless of whether they participated in the auction or not. I then use these predicted bids in order to estimate the likelihood in equation 2.13. The Heckman also allows an investigation into the bid function, and whether incidental truncation might bias OLS estimates. The estimation proceeds as follows.

Stage 1 – Estimate a Heckman two-step model for two primary reasons. First, I recover the parameters of subjective probability that are used in stage 2 in order to predict an individual's bid. Second, the Heckman allows me to understand whether incidental truncation might otherwise bias the OLS estimation of the bid function, and what individual characteristics explain bid variation.

Stage 2 – Use the parameters of subjective probability of winning the auction and an individual's WTA value from the survey in order to predict optimal bids for individuals, regardless as to whether or not they actually bid in the auction.

Stage 3 – The predicted bids are then incorporated into the full model in order to understand what individual characteristics are correlated with the decision of whether to bid or not. I am particularly interested in what variables of the utility function are correlated with the participation decision. I use an E-M algorithm to iterate between estimating equation 2.13 and generating predicted bids based off of an individual's WTA in stage 2, until convergence.

2.2.1 Stage 1: Heckman Selection Correction for the Bidding Model

If risk neutral, individual i's optimal bid is the solution to the following maximization problem:

$$(2.14) \qquad max_{bid_i}[1 - F(bid_i)][bid_i - WTA_i] - C.$$

Here WTA_i is individual i's WTA value for the license. The FOC of equation 2.14 can be rearranged as:

$$(2.15) \qquad bid_i^* - \frac{1-F(bid_i^*)}{f(bid_i^*)} - WTA_i = 0.$$

Given the pay-as-bid market design of the auctions, the individual's optimal bid is thus their WTA plus an additional shading term specifically composed of the Mill's ratio $\frac{1-F(bid_i^*)}{f(bid_i^*)}$. Using the exponential distribution for the Mill's ratio, equation 2.15 is then:

$$(2.16) \qquad bid_i^* - \frac{1}{exp(\varphi W_i)} - WTA_i = 0.$$

Following Greene (2003, p. 782-785) and making changes in the notation for consistency with my previous specifications, the equation of interest in the Heckman model is the bid function:

$$(2.17) \qquad \ln\left(bid_i^* - \frac{1}{exp(\varphi W_i)}\right) = -C + \psi D_i + \beta\mu_{\pi,i} + \theta Z_i + \nu_i,$$

which is observed only if individuals bid in the auction. The truncation of the distribution of bids affects the expectation of equation 2.17, and must be controlled for. To do this, a selection model is first estimated. This selection model is an alternative specification of the latent variable model in equation 2.12, given the limitations of the data at this stage of the analysis:

$$(2.18) \qquad \dot{y}_i^* = -C + \psi D_i + \beta\mu_{\pi,i} + \theta Z_i + \frac{1}{exp(\varphi W_i)} + \dot{\eta}_i.$$

The $\frac{1}{exp(\varphi W_i)}$ term is the conditional mean of the subjective probability of winning the auction, $\dot{y}_i^*$ takes the value of one if an individual bid in the auction and zero otherwise, $\dot{\eta}_i$ is an error term, and all other arguments are as previously specified. The mean of the subjective probability of winning the auction is used to gain a more accurate starting estimate for the parameters of the negative exponential function. Assuming $\dot{\eta}_i$ and ν_i follow a bivariate normal distribution with zero means and correlation coefficient ρ, equation 2.18 can be estimated within a probit framework, maximizing the log-likelihood function $lnL = \sum_{i=1}^{n} \mathrm{y_i} \ln\Phi(-C + \psi D_i + \beta\mu_{\pi,i} + \theta Z_i + \frac{1}{exp(\varphi W_i)}) + \sum_{i=1}^{n}(1 - \mathrm{y_i})\ln(1 - \Phi(-C + \psi D_i + \beta\mu_{\pi,i} + \theta Z_i + \frac{1}{exp(\varphi W_i)}))$. Once this selection model is estimated, its parameters are used to correct equation 2.17 by inserting $\hat{\lambda}_i = \frac{\phi(\hat{\dot{y}}_i^*)}{\Phi(\hat{\dot{y}}_i^*)}$ as a regressor, with $\phi(\cdot)$ and $\Phi(\cdot)$ representing the standard normal probability density and cumulative distribution functions, respectively, and $\hat{\dot{y}}_i^*$ representing predictions generated from the estimates of equation 2.18. The specification of the bid function equation now becomes:

$$(2.19) \qquad \ln\,(bid_i^* - \frac{1}{exp(\varphi W_i)}) = -C + \psi D_i + \beta\mu_{\pi,i} + \theta Z_i + \beta_\lambda \hat{\lambda}_i\left(\hat{\dot{y}}_i^*\right) + \nu_i,$$

with $\beta_\lambda = \rho\sigma_{\eta_i}$ as a parameter to be estimated, and this specification now the conditional expectation of an incidentally truncated bivariate normal distribution, correcting for the potential selection bias. Ultimately, cross-equation restrictions on the parameters of the subjective probability of winning the auction $\frac{1}{exp(\varphi W_i)}$ are necessary.

2.2.2 Stage 2: Generating Predicted Bids

The identity in equation 2.16 defines an individual's optimal bid, and calculating this bid is straightforward once the parameters of the subjective probability of winning the auction are combined with an individual's WTA value. This process generates predicted bids for all individuals, regardless as to whether they bid in the auction, and serves as the starting point of the E-M algorithm in Stage 3.

2.2.3 Stage 3: E-M Algorithm

The predicted bids in Stage 2 are then substituted into equation 2.13 and the log-likelihood is maximized with respect to the observed data. This maximization provides new estimates for the parameters in the subjective probability of winning the auction, which serves as the maximization step in the E-M algorithm. These parameter estimates can then be substituted into equation 2.16, in order to provide a new predicted bid. The estimation and maximization steps are then iterated, until convergence. I define convergence as predicted bids differing by no more than 1·e-14 between iterations.

The importance of Stage 3 is as follows. WTA is defined as the smallest amount of money an individual would willingly accept as compensation for the loss of their commercial fishing license. Through equation 2.16 the bid amount is this WTA plus a non-negative amount of money, which depends on how likely an individual feels it is that they will win the auction. The non-negative amount of money above an individual's WTA value is termed bid shading. The more likely an individual feels it is they will win the auction, the larger the shading of their bid amount above their WTA. Thus the entire value of the license should be captured within the bid value, and the only parameter of significance in the utility function should be that associated with the bid amount itself. The significance of parameters associated with indicators of non-pecuniary factors of utility in the bidding decision, despite conditioning on the bid amount, then provides evidence consistent with value uncertainty with respect to these non-monetary factors. The next chapter provides a description of the data used in estimating the empirical strategy outlined here.

Chapter 3 : Data

The primary equation of interest is the latent variable model of equation 2.12:

$$y_i^* = -C + \psi D_i + \left[e^{-\exp(\varphi W_i) bid_i}\left[\alpha bid_i - \beta\mu_{\pi,i} - \theta Z_i\right]\right] - \eta_i.$$

Vector D_i contains variables capturing individual license holder demographic characteristics. The W_i vector consists of variables identifying characteristics which govern an individual's subjective probability of winning the auction. Vector Z_i contains variables serving as indicators of use and non-use values. The $\mu_{\pi,i}$ variable is expected future profits, in this analysis represented by an individual's mean annual historical profits. The bid_i is an individual's bid amount, which is predicted through the three step process previously outlined using a individual's self reported WTA values. The C is a constant term and ψ, α , β, θ are either parameters or vectors of parameters, all of which are to be estimated. Table 3.1 identifies the exact variables used in the analysis, and the source of the data. The core variables originate from a survey I designed and implemented specifically to support this research. An important exception is the mean historical profits, which links individual catch histories[7] to crab price data, both of which are gathered by the states of Maryland and Virginia, and crabbing cost data from an independent survey of Chesapeake Bay crabbers (Rhodes et al., 2001).

---

[7] In calculating mean annual profits I use ten years of harvest histories (1999 – 2008) for Virginia and thirteen years of harvest histories (1996 – 2008) in Maryland. I calculate profits for all individuals eligible for the buybacks based on their activity in the fishery, with individuals reporting no historical harvest receiving a profit value of zero.

Table 3.1: Variables for empirical specification

Argument	Variables	State	Notes
D_i - Demographic Characteristics	Age	MD	Date of birth, provided by MD DNR.
	Recreational, Commercial, Both Recreational and Commercial	MD, VA	Indicator variable self-identification as a recreational or commercial crabber. Survey data.
	Multiple licenses at address	MD, VA	Indicates multiple license holders share the same mailing address.
	Probably Crab	MD, VA	Indicates individual felt it very likely they would crab in 2010, the year after the buyback. Survey data.
	Distance	MD, VA	Straight line mileage from Maryland DNR and VMRC offices.
	Within 35 miles	VA	Indicates if individual's mailing address is within 35 miles of the VMRC offices.
	Large pot licenses	VA	Indicates whether individual holds a large ($\geq$ 255) hard pot license. Provided by VMRC.
	Non-crabbing license	VA	Indicates whether individual holds non-crabbing fishing licenses. Provided by VMRC.
	Full time, Part time, Wait List	VA	Indicates how individual was categorized by state. Provided by VMRC.
	Latent	MD	Indicates if individual was classified as latent. Provided by MD DNR.
	Stopped crabbing	MD	Indicates whether individual stopped crabbing in four years prior to buyback, but was not classified as Latent. Provided by MD DNR.

Table 3.1 (continued): Variables for empirical specification

Argument	Variables	State	Notes
W_i - Subjective probability	Late reporting	MD	Indicates whether individual filed fewer late reports in 2009 than 2008 (months prior to buyback). Provided by MD DNR.
	High Education	MD	Indicates whether individual completed at least some college coursework. Survey data.
	Heard	VA	Indicates whether individual heard of other crabbing licenses being sold. Survey data.
	Two pot licenses	VA	Indicates whether individual owns both a hard and peeler pot license. Provided by VMRC.
μ_i – monetary utility	Average annual profits	MD, VA	Represents expected profits. Generated from individual catch history and price data gathered by the MD DNR and VMRC, and joined to cost data gathered by a 1999 cost survey of Chesapeake Bay crabbers (Rhodes et al., 2001).
	Mean earnings	MD	Mean earnings for an individual's zip code, from the 2000 U.S. Census.
Z_i – Non-monitary utility	Identity, Family History	MD, VA	Self-reported indicator for which contributes the most to the value of an individual's license. Survey data.
	Bequest, Enjoy Crabbing	MD, VA	Indicates if a bequest value or the enjoyment of crabbing was considered in the participation decision. Survey data.

It is these profits used in the regression of Table 2.1. Figure 3.1 and Figure 3.2 are kernel density plots of the profits for each state. As can be seen from these graphs, most crabbers are barely covering the costs of crabbing. Additionally, when compared to the distribution of actual bids in Figure 3.3 and Figure 3.4, the bid distributions exhibit a much thicker tail than the distribution of profits.

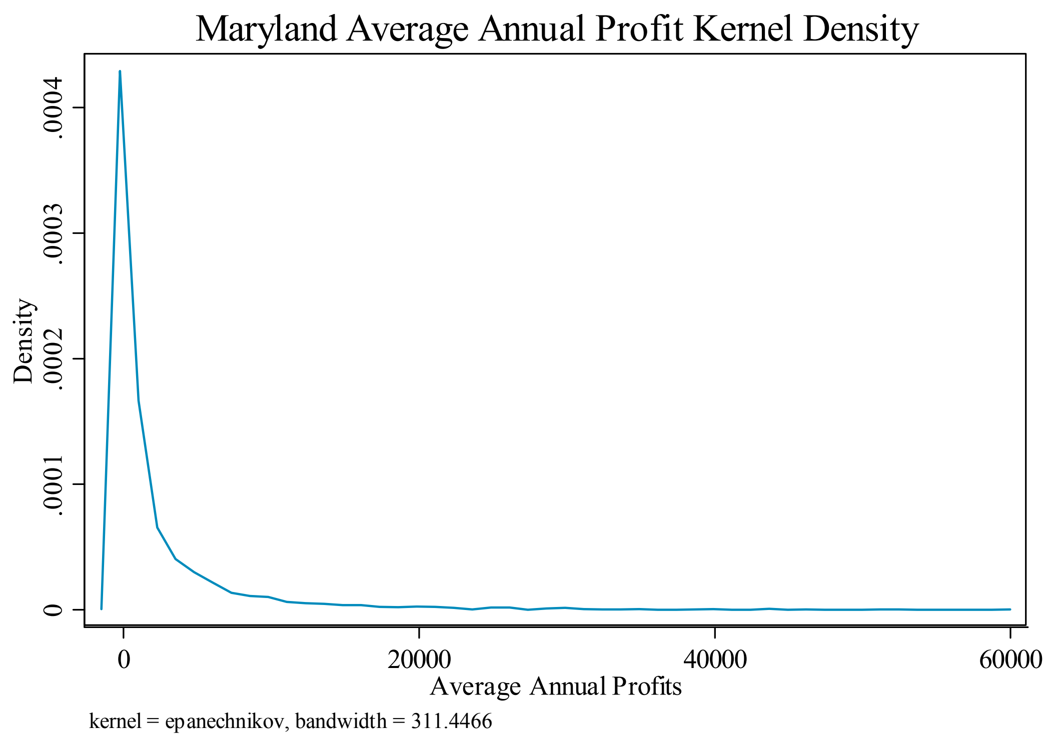


Figure 3.1: Kernel density of average annual profits for Maryland LCC license holders

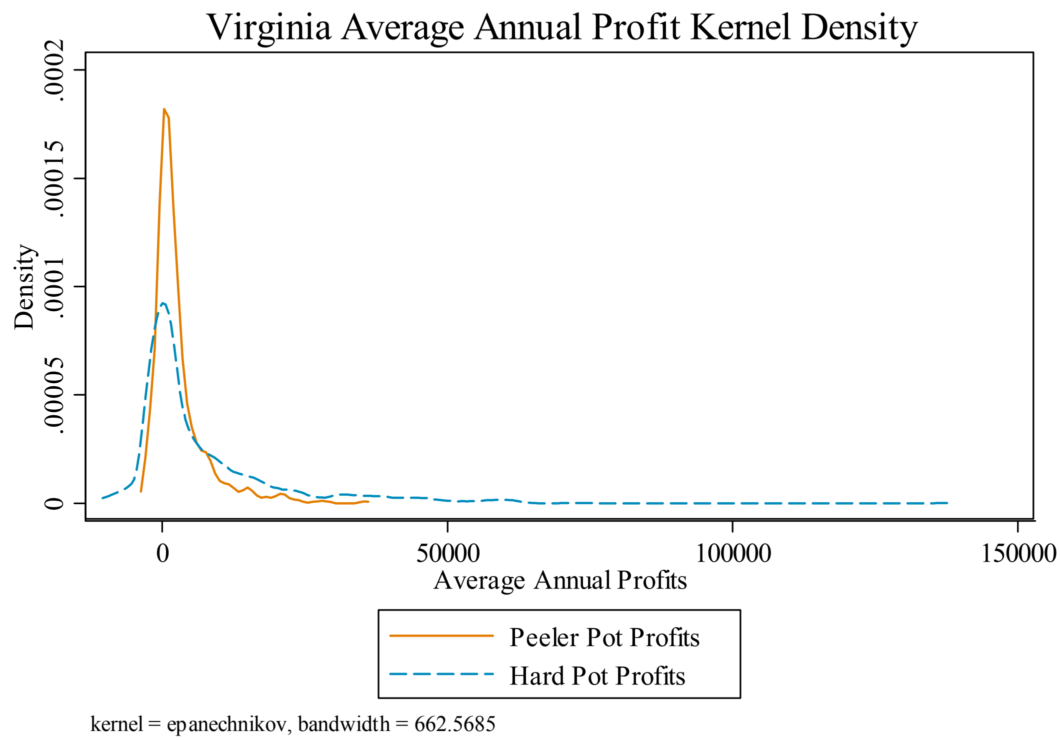


Figure 3.2: Kernel density of Virginia license holder average annual crabbing profits

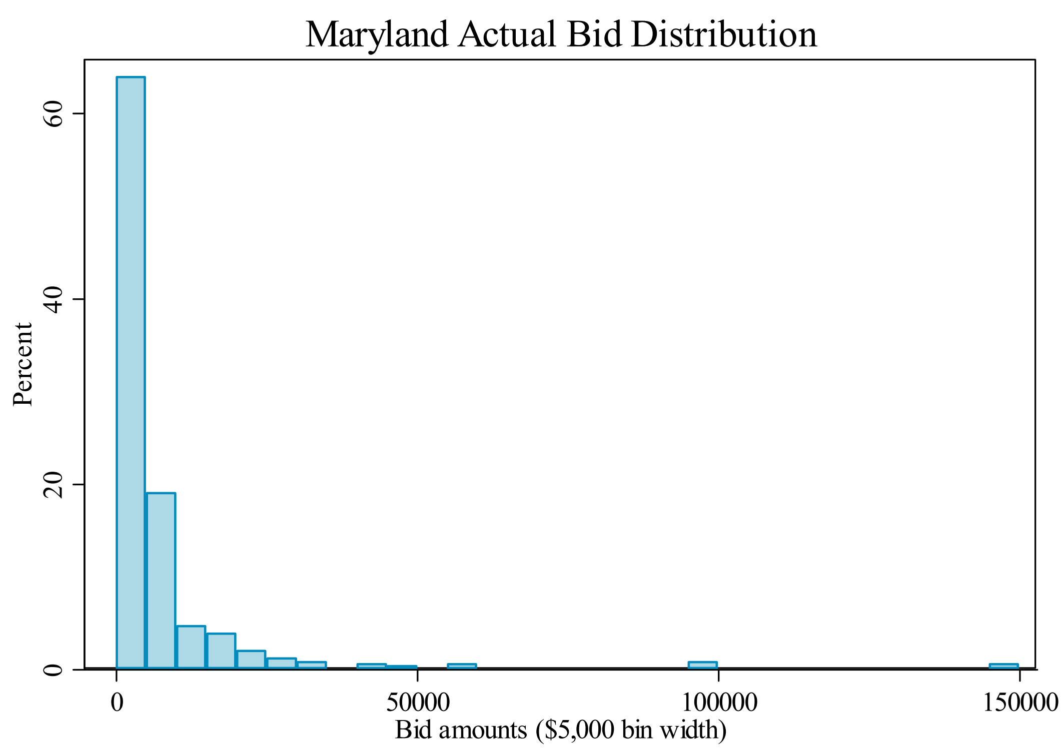


Figure 3.3: Histogram of actual bid values for Maryland licenses < $200,000

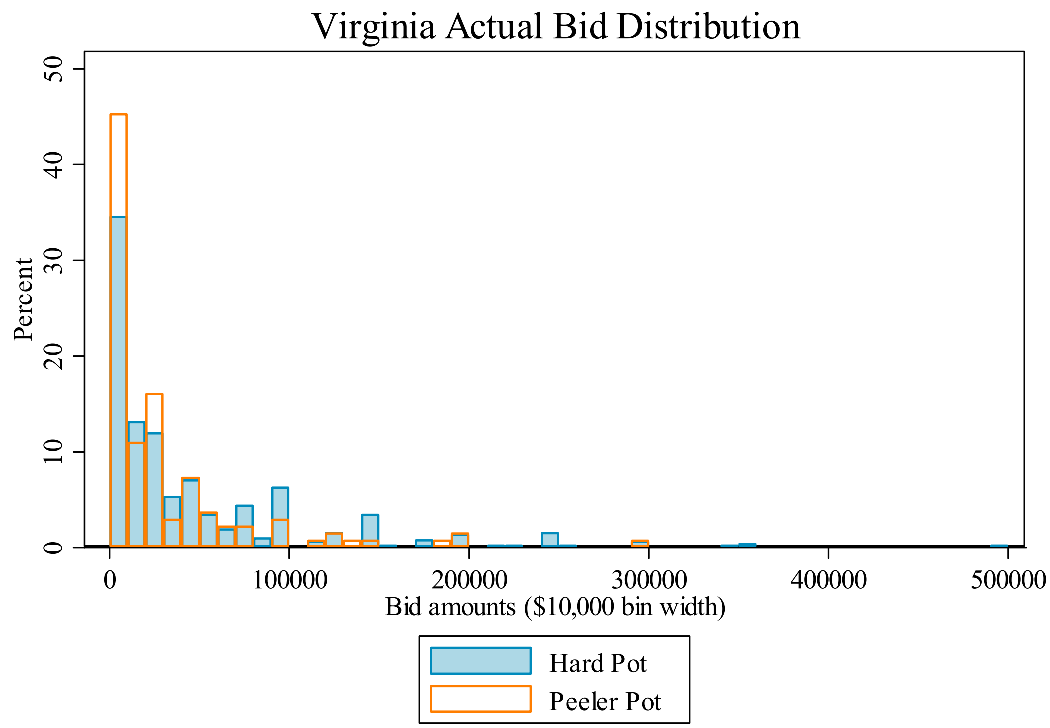


Figure 3.4: Histogram of actual bid values for Virginia licenses < $600,000

The majority of the remaining data were gathered from a survey mailed in April 2010, shortly after the auctions closed, to nearly all individuals eligible for the buyback. The exception is a small number of individuals in each state that acquired licenses after the beginning of the buyback. Because these individuals could have acquired licenses for the specific purpose of bidding in the auction, and thus could bid in patterns significantly different than the general population of license holders, they were excluded from the survey. In Maryland this restriction excluded 85 individuals, or 2.3 percent, and in Virginia I excluded 64 individuals, or 3.5 percent of all license holders eligible for the buyback.

The survey garnered response rates of roughly 33% in Maryland and 25% in Virginia, and the surveys themselves are presented in Appendices E and F. Figure

3.5 and Figure 3.6 provide histograms of the WTA values submitted as part of this survey. A comparison of the WTA histograms with those of the actual bids indicates that the tail of the WTA distribution is thicker, which is to be expected given that people with high WTA values are less likely to win the auction, and thus less likely to participate. I excluded WTA values greater than $1 million from the analysis, as a cutoff for what would be deemed a protest bid. This cutoff excluded six individuals from Maryland, or 0.5 percent of survey responders, and 14 individuals from Virginia, or 3.2 percent of responders.

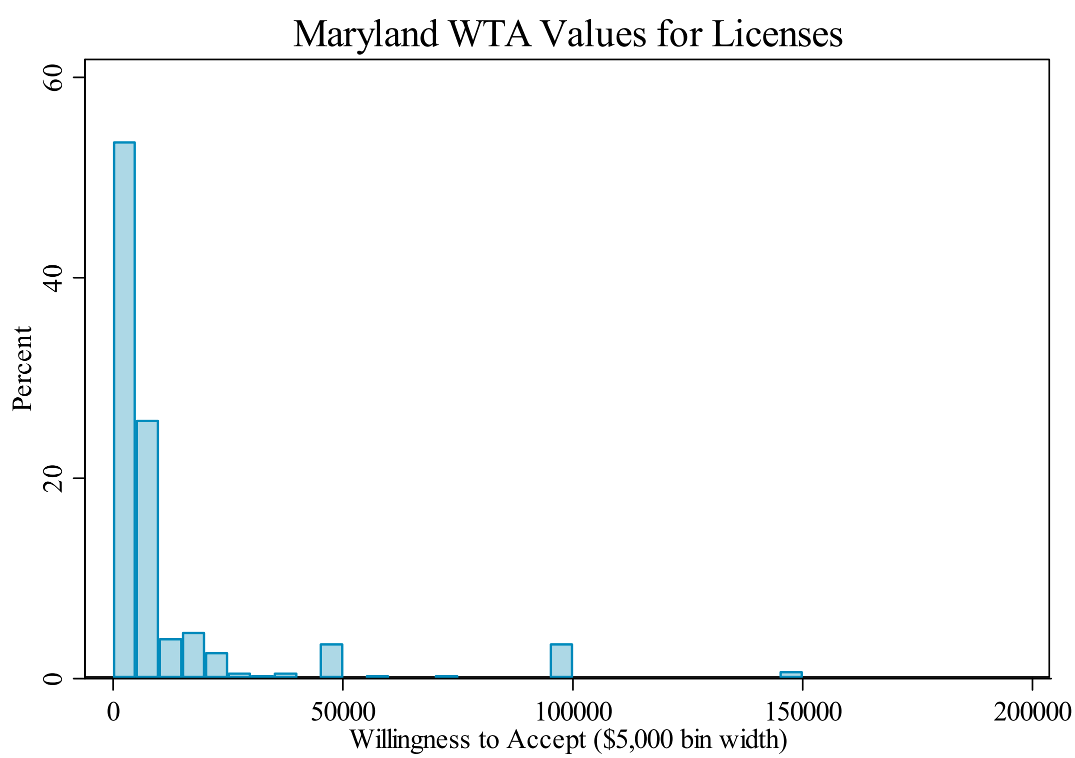


Figure 3.5: Histogram of WTA value < $200,000 for Maryland LCC licenses

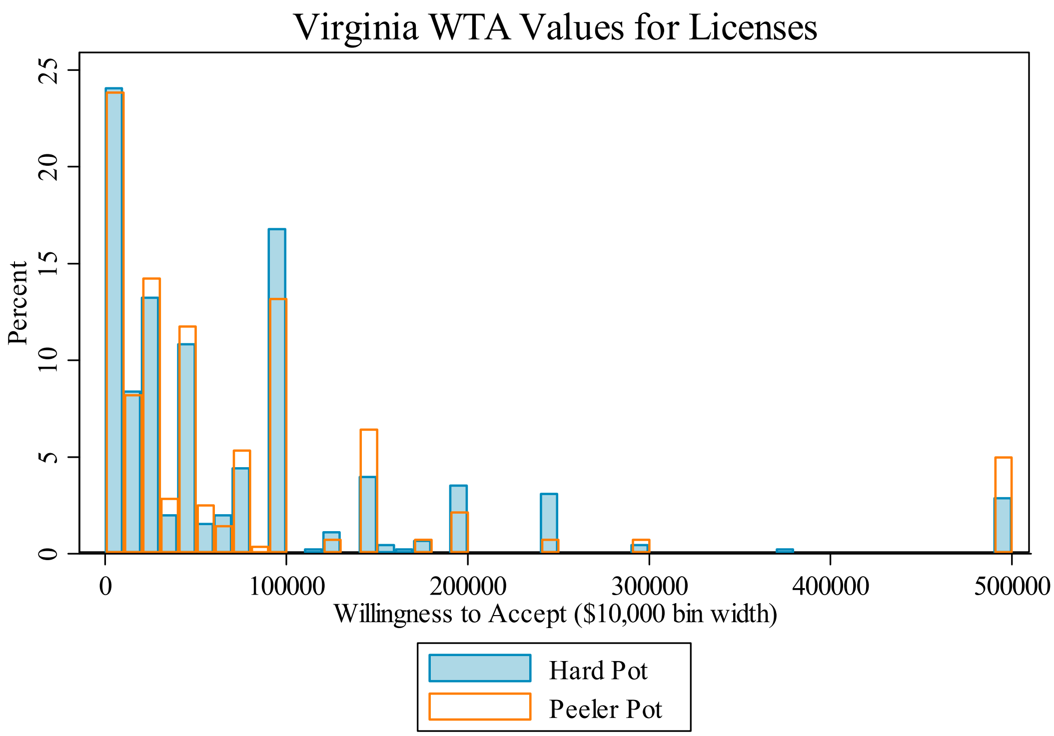


Figure 3.6: Histogram of WTA values < $600,000 for Virginia crabbing licenses

Table 3.2 and Table 3.3 respectively provide summary statistics for the indicator and continuous variables used in my analysis. These statistics represent the sample of individuals used within the analysis of Sections 4.1 through 4.4, with 1,035 observations in Maryland, and 463 observations in Virginia. The exception to this is the WTA variables, which suffered from a roughly 30% item nonresponse rate. In Maryland and Virginia there are respectively 743 and 390 WTA observations. I investigate the deviation of these statistics from the universe of license holders due to nonresponse and other issues in Section 4.5.

Table 3.2: Summary statistics for indicator variables

	Maryland		Virginia	
Variables	**Mean**	**SD**	**Mean**	**SD**
Stopped Crabbing	0.15	0.36		
Latent	0.23	0.42		
Late Reporting	0.74	0.44		
High Education	0.43	0.50		
Bequest	0.57	0.50	0.24	0.43
Family History	0.32	0.47	0.37	0.48
Identity	0.47	0.50	0.52	0.50
Enjoy Crabbing	0.61	0.49	0.47	0.50
Commercial	0.27	0.44	0.76	0.43
Both rec. and comm.	0.48	0.50	0.18	0.38
Probably Crab	0.84	0.37	0.74	0.44
Mult holders at address	0.03	0.17	0.11	0.31
Peeler Pot License			0.32	0.47
Within 35 mi			0.38	0.49
Two Pot licenses			0.51	0.50
Heard			0.72	0.45
Non-crabbing licenses			0.65	0.48
Large pot license			0.39	0.49
Full Time			0.12	0.33
Wait List			0.16	0.37

Table 3.3: Summary statistics for continuous variables

Variable	Mean	SD	Median	Min	Max
Maryland					
Age (years)	58	14	59	18	89
Profits ($1,000)	1.97	54.87	0.22	-10.36	59.66
WTA ($1,000)	36.50	137.08	5.00	0.20	1,000
Mean Earnings	59.94	13.92	59.81	23.96	111.82
Total Distance	36.00	20.16	34.72	0.52	221.21
Virginia					
WTA ($1,000)	100.29	169.08	50.00	0.50	1,000
Profits ($1,000)	3.97	9.61	0.00	-10.40	59.48
Total Distance	50.42	29.86	50.27	2.84	149.12

In what follows the effect of variables on the probability of bidding is assumed to be a function of the value of the license, and the corresponding sign of the latent variable in equation 2.12. All else equal, the larger the value of the license, the less probable that the latent variable is greater than zero, and thus less likely an individual is to bid in the auction. This is because a larger value is less likely to be accepted by either the Maryland DNR or VMRC, and thus the expected payoff from participation is low. The discussion also presents expected effects without controlling directly for the WTA in the models, as the WTA should capture the full value of a license by its definition.

I begin a discussion of the expected effect of variables on both the value of the license and probability of bidding with the indicator variables of Table 3.2. The Stopped Crabbing, Latent, and Wait List indicators control for recent inactivity in the fishery and should be inversely correlated to the value of a license, and positively correlated with the bidding decision. Intuitively this is a result of the value of the license lying in something other than current profits or usage. Any use values will thus be based off of expected future usage patterns, which are discounted. Conversely, the Probably Crab variable corresponds to expected crabbing in the near future. This represents an increase in value, and decreased probability of participation when compared to the baseline in which individuals felt it was less likely they would crab. The increased value associated with the expected crabbing in the near future is a result of either a continuation of historical usage patterns for those individuals who have been crabbing, or a re-entry into the fishery for those individuals who have not recently been crabbing. Similarly the Full time designation corresponds to increased recent use intensity in Virginia, and should provide for increased value as compared to the Part time baseline. However, it is unclear what effect this designation should have on participation. The raw participation rates between the Full time and Part time auctions, presented in Table 1.4, do not seem to indicate a large difference. Given that the higher valued licenses in the Full time classification were only ranked against similarly high valued licenses, there is no theoretical reason to believe that this classification should induce a significant effect on participation.

Given the baseline recreational designation, the Commercial and Both rec. and comm. indicators should correspond to higher license values, and lower participation in the buybacks. For individuals currently crabbing, the significance of these designations is questionable given that profits and usage patterns are already controlled for. However, for individuals not currently engaged in the fishery, these variables are likely directly correlated with the expected usage intensity, and thus could be important control variables.

As compared to the baseline profit importance, the additional use and non-use motives indicated by the Bequest, Family History, Identity, and Enjoy Crabbing variables should correspond to an increased value of licenses. This is because these are values in addition to profits, which are already controlled for in the models. The increased value should thus correspond to a decreased probability of bidding in the auction. The Large pot and Peeler Pot license indicators should also correspond to an increased value of licenses. This is due to the increased potential profits represented by these license types when compared to smaller hard crab licenses. The effect of this increased value should again be a decrease in the probability of bidding.

The variables of the subjective probability of winning the auction have unclear effects on the value of the license and the probability of bidding. Theoretically these variables govern the expectation over the exogenous cutoff price for the auctions. The Late Reporting, Two Pot licenses, and Heard variables look to capture engagement in the fishery, and thus familiarity with either the distribution of values within the population of license holders or the market price of these licenses. The High Education indicator looks to capture familiarity with concepts of probability, as well as the opportunity costs of crabbing. The effect on the bid amount is always non-negative, as these variables act through the bid shading term. However, the relative magnitude of these effects will depend on the relationship of the conditional expectation of the cutoff price with an individual's value. The variables of the subjective probability should facilitate the decision by providing more accurate expectations over the cutoff price. The relative effect on the participation will again depend on the expectation in conjunction with an individual's license value.

The relationship between the Mult holders at address variable and both the value of the license and the probability of crabbing is also ambiguous. More than one license holder at a single address could capture economies of scale that increase the profitability of the licenses, and thus an increase in the comparative value of the license. Conversely, the multiple licenses could signal excess capacity, which would then decrease the value of any single license in the household. The Non-crabbing license variable also represents an ambiguous impact on both the value of a license and the probability of bidding. The blue crab fishery is seasonal, and complementarities across fisheries are likely. An individual holding other commercial licenses could then be expected to increase the value of the crab license. Conversely, the additional licenses might represent increased opportunity costs of crabbing and a corresponding decrease in the value of the crabbing license. Given that the blue crab fishery is the most valuable in the bay the latter interpretation is unlikely, but cannot be ruled out.

The most likely channel by which the Age variable of Table 3.3 affects the value of the license is through the time horizons governing the flow of values derived from an individual's license. Given that this variable captures an individual's date of birth, the effect should be positive as an increase in the variable suggests longer use horizons. However, the Age variable could also represent an increased opportunity cost, in that younger fishermen could have more occupational flexibility corresponding to a decreased economic value of the license (Gimeno et al., 1997).

Increased profits from crabbing should correspond to an increase in the value of the license, given that these licenses are, at their core, profit generating assets. This suggests an inverse relationship between profits and participation rates.

The Mean Earnings variable looks to control for non-fishing household income. In general this variable can be thought to represent the opportunity cost associated with holding the license, and should be negatively correlated with the license value. This suggests a positive correlation with the probability of bidding in the auction.

An exclusion restriction is necessary for identification purposes within the Heckman Two Step model. Specifically, at least one variable needs to appear in the selection model that does not, and theoretically should not, appear within the second step bid function model. I thus need a variable which affects the decision of whether or not to bid in the auction, but not the amount bid. I use the distance of each individual's postal address from the MD DNR and VMRC offices as instruments for the Maryland and Virginia specifications. Specifically, the straight line distance from the postal address to the state offices is included in the selection model, along with a dummy variable indicating whether the mailing address is within 35 miles of VMRC office for Virginia's specification, but excluded from the bid function. The distance from the state office should not realistically affect the value bid for a license, but there are valid reasons to believe that they could affect the participation decision. [8] Specifically, the further the distance from the state offices, the longer mail delivery is likely to take. In Maryland the bid submission window was less than a month from the mail date of the announcement, and thus delayed delivery could greatly affect the participation decision of eligible individuals. This reasoning would suggest that distance is negatively correlated with participation in the auction.

[8] An exception to this argument would be if the distance from the office were correlated with travel costs to the fishery. However, this does not seem to be the case, given that out-of-state residence, which should be correlated with the highest travel costs, was not a significant factor in the amount bid in the auction. Additionally, the geography of the area provides for shoreline at a significant distance away from the state offices of both Maryland and Virginia in numerous directions, and the mailing addresses of license holders are by and large clustered around the shoreline.

Chapter 4 : Estimation Results

Maryland's auction failed to induce participation for a large number of individuals who ultimately sold their license through the posted price offer. The bids in the auction are also much higher than many individuals ultimately accepted in the posted price offer. In the results I focus on the most important individual characteristics explaining the Maryland and Virginia participation decisions, with a particular interest in non-monetary motives. My analysis looks to understand the differences in participation rates between the two Maryland buyback designs, and whether similar participation patterns presented themselves in Virginia.

4.1 Heckman Model

The first step of my analysis is the Heckman model, detailed in Table 4.1. Model results including insignificant parameter estimates can be found in Table A.A.1 of Appendix A. Significant parameter signs are generally consistent with theory, when an unambiguous relationship exists. In both states past and expected future usage patterns are significantly correlated with the decision of whether or not to bid, as can be noted from the parameters estimates on the Stopped Crabbing and Latent variables in Maryland and the Probably Crab variable in both states. The Stopped Crabbing and Latent variables are associated with an increased probability of participating in the auction, while the Probably Crab variable is associated with a decreased probability of bidding. In each state the parameters associated with the subjective probability of winning the auction are significant at the one percent level.

Table 4.1: Heckman selection models estimating auction participation and bid function (standard error)

	Selection model		Bid function	
	Maryland	**Virginia**	**Maryland**	**Virginia**
Constant	-2.3231*	-0.1159	-4.4105*	-2.2562*
	(0.4009)	(0.4005)	(0.3826)	(0.3668)
Demographics				
Age	-0.1489		0.6993*	
	(0.1144)		(0.1742)	
Stopped Crabbing	0.5537*			
	(0.1618)			
Latent	0.7988*			
	(0.1364)			
Probably Crab	-0.4868*	-0.5845*	0.5723*	0.6737*
	(0.1334)	(0.1931)	(0.1762)	(0.2699)
Commercial	-0.3049*	0.2305	0.9949*	0.7381*
	(0.1643)	(0.1837)	(0.2505)	(0.2156)
Both Rec. and Comm.	-0.4087*		0.6932*	
	(0.1313)		(0.1944)	
Mult holders at address	0.6514*	-0.0235		-0.6132*
	(0.3057)	(0.2335)		(0.2884)
Wait List		-0.2441		-0.2639
		(0.2232)		(0.2618)
Full Time		0.0977		0.5972*
		(0.2540)		(0.2886)
Large pot license		0.1938		0.7808*
		(0.1506)		(0.1736)
Non-crabbing licenses		-0.2596		0.4820*
		(0.1653)		(0.2218)
Utility indicators				
Profits	-0.0069	-0.2456*	0.3783*	0.1910
	(0.1237)	(0.0981)	(0.2161)	(0.1474)
Mean Earnings	0.0252		1.2202*	
	(0.4290)		(0.5745)	
Family History	-0.2704*			
	(0.1298)			
Bequest	-0.3961*		0.3344*	
	(0.1137)		(0.1761)	
Identity		-0.2645*		
		(0.1454)		
Enjoy crabbing		-0.4271*		0.4560*
		(0.1455)		(0.2035)
Subjective Probability				
Late Reporting	-0.3145*			
	(0.0938)			

Table 4.1 (continued): Heckman selection models estimating auction participation and bid function (standard error)

	Selection model		Bid function	
	Maryland	**Virginia**	**Maryland**	**Virginia**
High Education	-0.2389*			
	(0.0729)			
Heard		-0.3935*		
		(0.1234)		
Two pot licenses		0.4491*		
		(0.1626)		
Instruments				
Distance	0.5576*	-1.4150*		
	(0.2794)	(0.4422)		
Within 35 miles		-0.7679*		
		(0.2561)		
Inverse Mills			0.0718	-0.4626
			(0.1835)	(0.3596)
Observations	1035	463	132	109

*Significant < 10% level

The variables of primary interest are those of the utility function. Profits are inversely correlated with the probability of bidding in the auction, although the effect is not significant in Maryland. The indicators for the importance of Family History and Bequest value are both significant in Maryland, and correspond to a decreased probability of bidding in the auction. In Virginia, the importance of the joy of crabbing and Identity value both correspond to a significant decrease in the probability of bidding in the auction. At this point there are no departures from expectations. This is because without controlling for the value of the bid itself in the participation decision, we would expect a correlation between factors of utility and the decision to bid.

The bid function provides insight into what individual characteristics are correlated with the licenses' value. The semilog specification of equation 2.17 means that coefficients in the bid function can be viewed as the percent increase in a bid over the base value given a one unit increase in the independent variable. The only significant indicators of utility are Profits, Mean Earnings, and Bequest in Maryland and Enjoy crabbing in Virginia. Of interest is that the Mean Earnings variable corresponds to an increased license value, when theoretically a negative relationship should exist. This might suggest household complementarities, in which the wife works to subsidize the husband in his fishing career (Binkley, 2000). There does not seem to be selection bias in the bid equation, with the coefficient on the Inverse Mills ratio not significant at any conventional level.

4.2 Parsimonious Bid Function

Given that selection bias does not seem to be an issue the OLS estimation of a more parsimonious bid function is presented in Table 4.2. Results, including insignificant point estimates, are presented in Table A.A.2 of Appendix A. The Bid model specifications are an estimation of equation 2.17, while the WTA specifications substitute the natural log of an individual's WTA values in place of the dependent variable in equation 2.17. Point estimates can again be interpreted as the percent change in the dependent variable given a one unit change in the associated independent variable. In the Maryland WTA specification the bequest motive is associated with just under a 30% increase in the value of a license; roughly equivalent to a $6,500 increase in expected annual profits. Given survey respondents' median annual profits of $220, this suggests that the bequest motive could correspond to a large portion of the license's value for many individuals. In Virginia the enjoyment of crabbing is associated with over a 40% increase in license value; larger than the effect of a $20,000 increase in annual profits, and again suggests non-monetary sources of utility could underlie the bulk of a license's value for some individuals.

Table 4.2: Parsimonious bid function estimation. The Bid specification is an estimation of equation 2.17, while the WTA specification substitutes the natural log of WTA for the left hand side of equation 2.17 (standard error)

Coefficient	MD Bid	MD WTA	VA Bid	VA WTA
Constant	-4.1543*	-2.8138*	-2.3664*	-2.8014*
	(0.3803)	(0.1273)	(0.2010)	(0.2017)
Profits	0.3911*	0.4513*	0.2057*	0.1658*
	(0.2046)	(0.0856)	(0.1169)	(0.0502)
Probably crab	0.5389*	0.2836*	0.5963*	0.3940*
	(0.1726)	(0.1177)	(0.1877)	(0.1550)
Commercial	0.9089*		0.9419*	0.7368*
	(0.2463)		(0.1955)	(0.1473)
Both rec. and comm.	0.6174*	0.1753*		
	(0.1900)	(0.0870)		
Mean earnings	0.9517*			
	(0.5612)			
Age	0.6072*	0.4968*		
	(0.1672)	(0.0837)		
Bequest	0.3520*	0.2909*		
	(0.1726)	(0.0863)		
Latent		-0.3098*		
		(0.1060)		
Enjoy crabbing			0.3564*	0.4394*
			(0.1723)	(0.1138)
Large pot license			0.6423*	0.8683*
			(0.1596)	(0.1487)
Wait list			-0.7919*	-0.3887*
			(0.2065)	(0.1852)
Mult holders at address			-0.7351*	
			(0.2792)	
Peeler Pot License				0.5898*
				(0.1493)
Non-crabbing license				0.4185*
				(0.1325)
Observations	138	768	128	431

*Significant < 10% level

4.3 Full Participation Decision Estimation

Table 4.3 presents the primary results of this paper, the investigation of the decision to bid or not controlling for each individual's predicted bid. All model specifications estimate the conditional probability of bidding in the auctions through a probit framework. In the linear specification the variables and parameters enter the standard normal cdf linearly, while the full model specifications are estimates of equation 2.12. A specification including insignificant variables, once the optimal bid is controlled for in the model, is presented in Table A.A.3 of Appendix A.

Table 4.3: Probit models of the participation decision, with an indicator for bid or not as dependent variable. Bid amount measured in thousands of dollars for Maryland, and tens of thousands of dollars for Virginia (standard error)

	MD Linear	MD Full	VA Linear	VA Full
Constant	-1.2505*	-1.3397*	0.8791*	0.4728
	(0.2714)	(0.2341)	(0.3410)	(0.3631)
Demographics				
Stopped Crabbing	0.5587*	0.4626*		
	(0.1767)	(0.1717)		
Latent	0.9594*	0.8919*		
	(0.1535)	(0.1503)		
Probably Crab	-0.3757*	-0.3386*		-0.3842*
	(0.1544)	(0.1541)		(0.1797)
Commercial	-0.4586*	-0.4423*		
	(0.1717)	(0.1703)		
Both Rec. and Comm.	-0.5140*	-0.5049*		
	(0.1456)	(0.1452)		
Mult holders at address	0.6781*	0.6111*		
	(0.3478)	(0.3506)		
Distance	0.5917*	0.6507*	-1.1050*	-1.1116*
	(0.2906)	(0.2895)	(0.4430)	(0.4570)
Within 35 miles			-0.5057*	-0.6182*
			(0.2593)	(0.2655)
Non-crabbing licenses			-0.5114*	-0.4699*
			(0.1513)	(0.1729)

Table 4.3 (continued): Probit models of the participation decision, with an indicator for bid or not as dependent variable. Bid amount measured in thousands of dollars for Maryland, and tens of thousands of dollars for Virginia (standard error)

	MD Linear	MD Full	VA Linear	VA Full
Utility indicators				
Bid amount[a]	-0.1322	0.8332*	-0.5103*	1.2553*
	(0.0819)	(0.2865)	(0.1434)	(0.5715)
Bequest	-0.3436*	-2.7399*		
	(0.1271)	(1.1094)		
Family History	-0.2783*			
	(0.1472)			
Identity				0.9753
				(0.6012)
Enjoy crabbing			-0.3502*	-1.4736*
			(0.1507)	(0.6961)
Subjective Probability				
Late Reporting	0.4295*	-0.8620*		
	(0.1566)	(0.2362)		
High Education	0.3668*	-0.4231*		
	(0.1252)	(0.1953)		
Heard				-0.8252*
				(0.3003)
Two pot licenses				1.5121*
				(0.8321)
Observations	743	743	390	390
AIC	546.28	543.27	403.48	407.09

*Significant < 10% level

[a]WTA used in place of the predicted bid amount for the linear specifications.

The point estimates for the demographic variables are relatively stable across specifications within each state, and are quite similar to the results of the probit estimated as part of the Heckman model. Exceptions to the general agreement between specifications lie with the indicators of utility and variables of subjective probability. The difference in magnitude and signs of the coefficients primarily stem from the differences in specifications themselves. In Maryland the bid amount becomes statistically significant at the 1 percent level, and the indicator for family history is no longer significant at any conventional level (p-value > 0.3), when moving from the linear to the full model specification. In Virginia, both indicators of subjective probability are significant in the full specification but not in the linear specification.

In Maryland Akaike's Information Criterion (AIC) suggests that the full model fits the data better than the linear specification, with the opposite true in Virginia. The full model is the preferred specification given its theoretical basis and the ambiguity in terms of best fit between the two states. I use the full model specification to derive the marginal effects discussed below.

Given the optimal nature of the bid, a marginal increase in the bid amount should decrease the probability of bidding in the auction. Figure 4.1 and Figure 4.2 graph the actual marginal effects associated with bid values in each state against the respective individual's WTA. In both states these marginal effects vary both in magnitude and sign across observations. The mean and median marginal effects are 0.0028 and -0.0002 respectively in Maryland, with 72% of observations presenting a negative marginal effect. Virginia has a similar trend, with mean and median marginal effects of 0.0150 and -0.00004 respectively, and 81% of individuals associated with a negative marginal effect. In both states the positive marginal effects are associated the lowest relative WTA values, and are the first suggestion of potential problems in the bidding process.

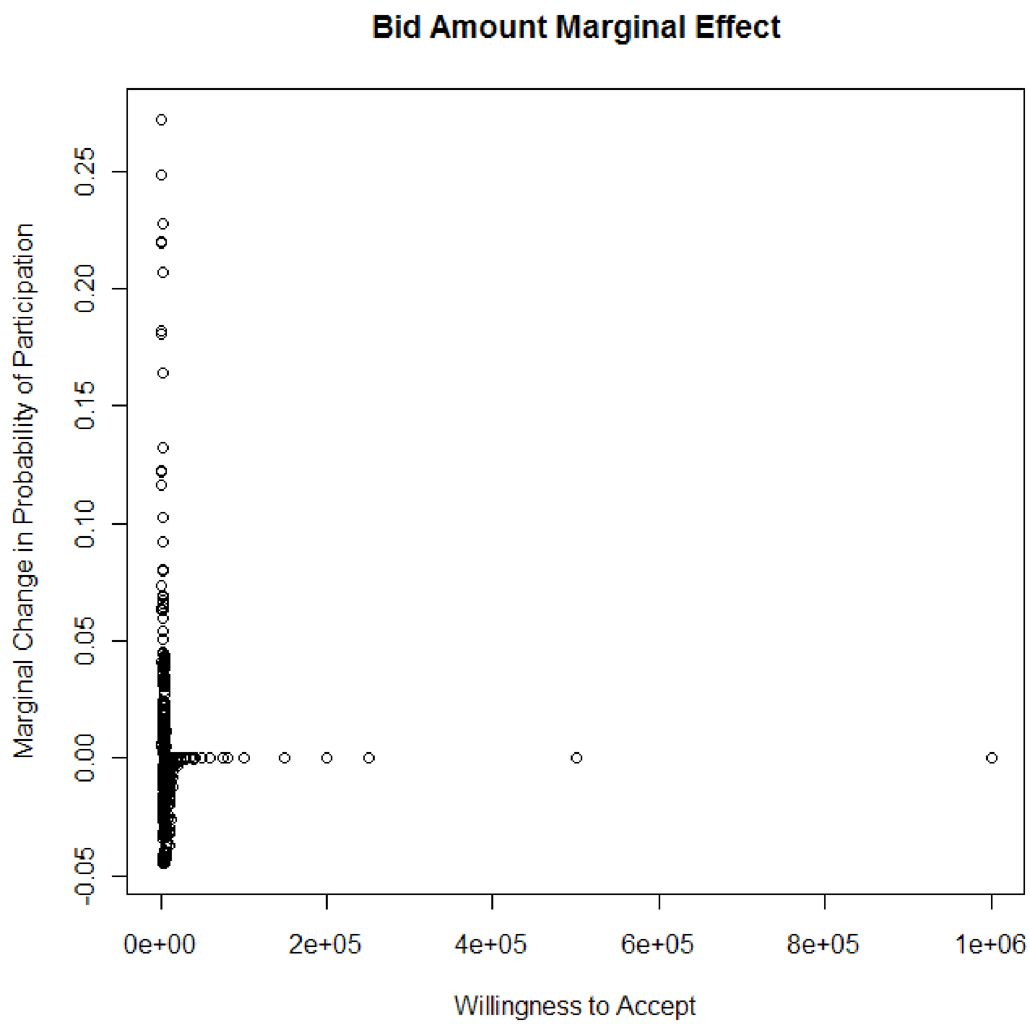


Figure 4.1: Marginal effect of the bid amount on the probability of bidding in Maryland's auction, graphed against each individual's WTA

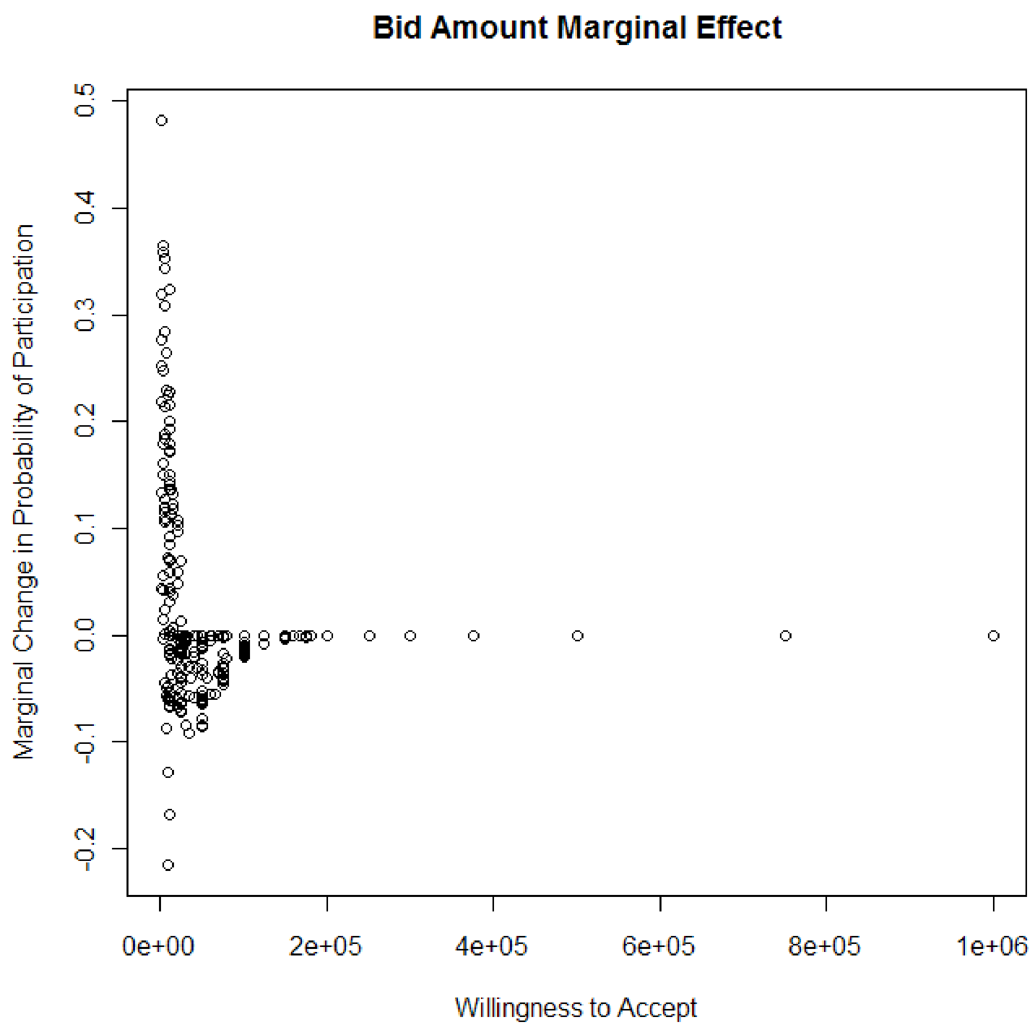


Figure 4.2: Marginal effect of the bid amount on the probability of bidding in Virginia's auction, graphed against each individual's WTA

Theoretically you would expect to see the bid amount as the only significant determinant of utility in the model specification. Instead, the indicators of a bequest value in Maryland and enjoyment value in Virginia are significantly correlated with the decision to bid in the auction, as is evident from Table 4.3. Figure 4.3 and Figure 4.4 graph the effect of these variables in the participation decision across WTA values. The magnitude of the marginal effect is again greatest for those individuals with relatively low WTA values. This is further evidence consistent with license value uncertainty for those individuals least engaged in the fishery. This is particularly true given the previous findings of Table 4.2, which suggest that the bequest motive and the joy of crabbing could be associated with the majority of a license's value for these individuals.

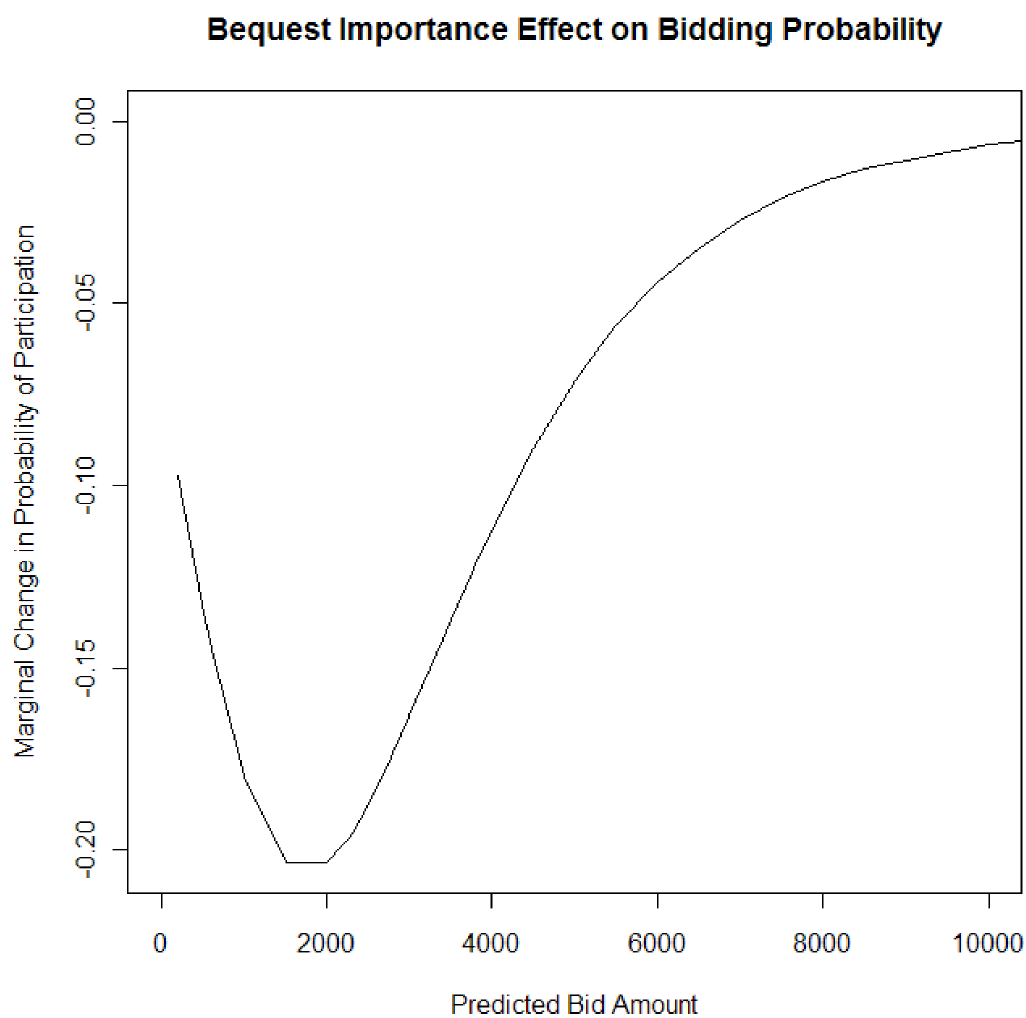


Figure 4.3: Effect of indicating the importance of a bequest motive on the probability of bidding in Maryland's license auction

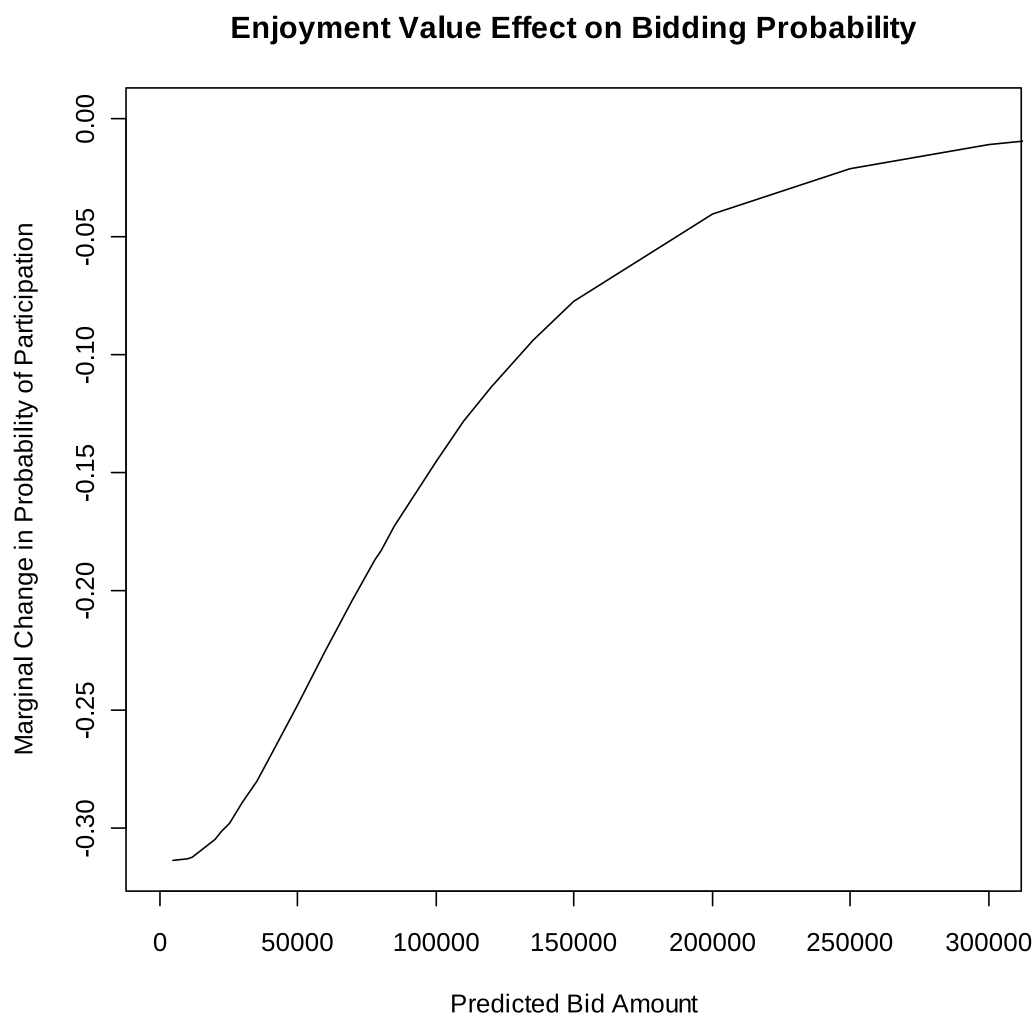


Figure 4.4: Effect of indicating the importance of enjoyment of crabbing on the probability of bidding in Virginia's license auction

4.4 Posted Offer Participation

Further insight can be gained by investigating participation in Maryland's posted price offer. The participation decision for the posted offer should be a simple one. If an individual's WTA value is below the $2,260 offer, that individual should accept the posted offer. Conversely, if the WTA value is above $2,260, the posted offer should be rejected. However, seeming preference reversals between the auction and posted price offer indicate additional complexity in the decision.

Table 4.4 presents probit models of the participation decisions surrounding the posted price offer. Results including insignificant point estimates can be found in Appendix A, Table A.A.4. Models 1 and 2 investigate the decision of whether to accept or reject the posted price, with the dependent variable equal to 1 if the individual accepted the offer and 0 otherwise. Model 1 uses the raw WTA score submitted by individuals, while Model 2 uses a dummy variable equal to 1 if an individual's submitted WTA value is below $2,260, and zero otherwise. The remaining components of the two models are equal. Parameter estimates are relatively consistent between the two models. Theoretically the only variable which should be of importance here is the WTA value.

A good portion of this incongruity could stem from the enforcement of additional restrictions on individuals classified as latent between the auction and posted price phases of the buyback. As is to be expected, the coefficient on the latent classification is significant, and is associated with a median 22% increase in the probability of accepting the offer.[9] Conversely, an individual indicating they were very likely to crab in 2010 is associated with a 22% decrease in the probability of accepting the posted price, suggesting that an option value is an important motivator in the decision to sell a license. The other large median marginal effect stems from the indicator for a bequest motive, with an associated 17% decrease in the probability

[9] At median values all the marginal effects are significant at greater than the 1 percent level except WTA, Stopped Crabbing, Commercial, and Both rec. and comm., which are significant at greater than the 5% level. All but the Latent, Stopped Crabbing, and Late Report coefficients are associated with a negative effect on the probability of taking the offer. All of these marginal effects are calculated using the Model 1 specification from Table 9.

of accepting the posted price offer. Interestingly, the effect associated with late reporting is an increase of 6 percent, indicating that the more engaged an individual is in the fishery, the more likely they are to accept the posted price offer, all else being equal. This additional evidence is consistent with the value uncertainty argument, in that potential participants are able to use the information provided by the posted price offer to update the expected value of their license.

Table 4.4: Maryland probit models of the posted offer participation decision (standard error). WTA measured in $10,000

	Model 1	**Model 2**	**Model 3**	**Model 4**
Dependent variable	Accepted	Accepted	Reversal	Reversal
Constant	-0.7160*	-1.1120*	0.8896*	0.8442*
	(0.2582)	(0.2601)	(0.3101)	(0.4703)
Stopped Crabbing	0.5288*	0.5545*		
	(0.2076)	(0.2055)		
Latent	0.9227*	1.0131*		
	(0.1615)	(0.1602)		
Probably Crab	-0.9008*	-0.8240*	-0.8188*	-0.6969*
	(0.1568)	(0.1571)	(0.2843)	(0.3136)
Commercial	-0.6218*	-0.6132*	-0.6798*	
	(0.2039)	(0.2006)	(0.3588)	
Both Rec. and Comm.	-0.5230*	-0.5324*	-0.5474*	
	(0.1574)	(0.1555)	(0.3075)	
Age	-0.5315*	-0.6081*	-0.6955*	-0.6811*
	(0.1490)	(0.1443)	(0.2900)	(0.3212)
WTA	-0.2385*	0.8375*		-1.9914*
	(0.0766)	(0.2779)		(0.5530)
Bequest	-0.7574*	-0.7507*	-0.6044*	
	(0.1441)	(0.1423)	(0.2758)	
Late Reporting	0.8871*	0.8929*		0.8442*
	(0.1956)	(0.1971)		(0.3906)
Observations	768	768	108	100[a]

*Significant < 10% level

[a]Drops one individual who provided WTA > $50,000 but accepted posted price of $2,260.

Models 3 and 4 of Table 4.4 investigate those seeming preference reversals between the auction and posted offer. The binary dependent variable in these two models takes a value of 1 if the individual bid above $2,260 in the auction and subsequently accepted the posted price of $2,260, and a value of 0 if the individual bid above $2,260 in the auction and rejected the posted price.[10] The only difference between Model 3 and Model 4 is whether the WTA is controlled for. As can be seen from Model 4, the WTA is highly correlated with the preference reversal. Calculated at the sample median, a marginal increase of $10,000 in WTA is associated with a 79% decrease in the probability of exhibiting the reversal between the auction and posted price offer, an effect significant at greater than the 1 percent level. An individual indicating they were very likely to crab in 2010 is associated with a median decrease of 24% in the probability of exhibiting the reversal. Again, the more engaged individuals seem more likely to have made the reversal, with a median 28% increase in its probability if an individual's late reporting decreased between 2008 and 2009. It thus seems that the reversals were made by individuals with relatively low beginning WTA values but relatively more engagement in the fishery, and low expectation of actually using the license in the coming year.

4.5 Model Sensitivity

A number of assumptions regarding the model and data have the potential to greatly influence the analysis in this research. In this section I explore the sensitivity of my results to some of the key assumptions made.

[10] Unfortunately, the small number of observations for individuals bidding below $2,260 but subsequently rejecting the posted offer price precludes a more formal investigation into these reversals.

4.5.1 Missing WTA Values

Approximately 30% of survey respondents in Maryland and 20% of respondents in Virginia did not provide WTA values. Given the central role that WTA values play in my analysis I investigate the bias due to item non-response through the use of multiply-imputed (MI) datasets. Rubin (1987) provides the canonical reference for MI as a manner to address missing data. The strength of the MI process lies in its ability to specifically address the uncertainty due to imputations being modeled predictions and not observations. In this analysis I employed a predicted means matching (PMM) algorithm using the MICE package (van Buuren & Groothuis-Oudshoorn, 2011) in R (R Development Core Team, 2011). The PMM imputation process is outlined in Appendix B.

Table 4.5 provides a comparison of the estimation of equation 2.12 for the complete case versus multiply-imputed datasets. The complete case analyses are labeled MD CC and VA CC in the table, and utilize only those cases for which no missing data exist. The MD MI and VA MI specifications are the results of the multiply imputed datasets, combined as outlined in Appendix B. In both states the complete case and MI results correspond quite strongly. Parameter signs are consistent across each state's specifications. Although some fluctuation in the point estimates occurs, both their magnitudes and significance levels are also relatively stable. In Maryland the parameters of most interest, those associated with the bid amount and bequest value of the license, differ by 11 and 12 percent of the complete case estimate respectively. In Virginia the bid amount, identity, and enjoy crabbing parameters differ by 7, 17, and 11 percent respectively.

Table 4.5: Probit models of the participation decision comparing complete case and Multiple Imputation analysis (standard error)

	MD CC	MD MI	VA CC	VA MI
Constant	-1.3397*	-1.3901*	0.4728	0.3988
	(0.2341)	(0.2176)	(0.3631)	(0.3455)
Demographics				
Stopped Crabbing	0.4626*	0.4889*		
	(0.1717)	(0.1600)		
Latent	0.8919*	0.7619*		
	(0.1503)	(0.1353)		
Probably Crab	-0.3386*	-0.4749*	-0.3842*	-0.4500*
	(0.1541)	(0.1372)	(0.1797)	(0.1702)
Commercial	-0.4423*	-0.3190*		
	(0.1703)	(0.1540)		
Both Rec. and Comm.	-0.5049*	-0.3980*		
	(0.1452)	(0.1337)		
Mult holders at address	0.6111*	0.6153*		
	(0.3506)	(0.3020)		
Distance	0.6507*	0.5840*	-1.1116*	-1.1750*
	(0.2895)	(0.2606)	(0.4570)	(0.4320)
Within 35 miles			-0.6182*	-0.7220*
			(0.2655)	(0.2558)
Non-crabbing licenses			-0.4699*	-0.3140*
			(0.1729)	(0.1645)
Utility indicators				
Bid amount	0.8332*	0.7404*	1.2553*	1.1670*
	(0.2865)	(0.2895)	(0.5715)	(0.0359)
Bequest	-2.7399*	-2.4192*		
	(1.1094)	(0.9934)		
Identity			0.9753	0.8071
			(0.6012)	(0.5764)
Enjoy crabbing			-1.4736*	-1.3148*
			(0.6961)	(0.6809)
Subjective Probability				
Late Reporting	-0.8620*	-0.9559*		
	(0.2362)	(0.2520)		
High Education	-0.4231*	-0.4005*		
	(0.1953)	(0.1937)		
Heard			-0.8252*	-0.9603*
			(0.3003)	(0.3375)
Two pot licenses			1.5121*	1.5368*
			(0.8321)	(0.8870)
Observations	743	1013	390	456

*Significant < 10% level

Table 4.6 summarizes predicted versus actual participation decisions for Maryland and Virginia under the complete case and MI specifications. All individuals with a predicted participation probability greater than 0.5 are predicted to bid, and all others as predicted to not bid in the auction. The MI values are the average prediction across the five imputed dataset models. The complete case specification predicts auction participation more accurately than the MI specification in Maryland, though there is no clear dominance in the Virginia models.

Table 4.6: Predicted auction participation for the complete case versus Multiple Imputation specifications, in percentages

	CC Predictions		**MI Predictions**	
	Bid	**No Bid**	**Bid**	**No Bid**
MD Actual Bid	0.2437	0.7563	0.1413	0.8587
MD Actual No Bid	0.0754	0.9246	0.0327	0.9673
VA Actual Bid	0.2647	0.7353	0.2422	0.7578
VA Actual No Bid	0.1563	0.8438	0.1230	0.8770

Table 4.7 presents the differences in individual predicted outcomes between the complete case and multiply-imputed specifications. In both states the participation probabilities and optimal bids predicted by each specification differs significantly as determined by a paired t-test for the equality of means ($p = 0.0000$) and non-parametric Wilcoxon signed-rank test ($p = 0.0000$). However, the magnitude of the difference between predictions is very small. The mean difference in predicted bids is less than 0.001 percent of the mean bids in both Maryland and Virginia. In both states the complete case specification generally provides for larger predicted probabilities and smaller bids than the MI specification.

Table 4.7: Difference in predictions between complete case and Multiple Imputation specifications

Prediction Difference	Mean	SD	Minimum	Maximum
MD Optimal Bid ($)	-0.18	0.12	-0.29	0.05
MD Bid Probability (%)	1.24	2.34	-2.70	12.01
VA Optimal Bid ($)	-0.13	0.14	-0.33	0.019
VA Bid Probability (%)	2.00	3.14	-7.17	13.14

Wilcoxon signed-rank tests between actual and predicted bids in Maryland indicate no significant difference for either the complete case or multiple imputation specifications, with p-values ~ 0.50 for both specifications. The distributional equality of predicted and observed bids is statistically rejected at the five percent level in Virginia, with Wilcoxon signed-rank p-values ~ 0.02 for both specifications. However, the equality of medians is not rejected at any significant level using a two-tailed sign test based off of the binomial distribution, with a p-value > 0.20 for both specifications.

There is a strong similarity in the results of the complete case and MI specifications. However, given that it provides for participation predictions and optimal bids at least as good as the MI specification, the complete case specification is preferred.

4.5.2 Virginia's Two Licenses

A difference between the Maryland and Virginia buyback structure warrants discussion. Whereas Maryland license holders had only one license eligible for the buyback, some Virginia license holders had both a hard pot and peeler pot license eligible. The participation decisions surrounding these two licenses could be jointly determined, and thus a joint distribution should be used to model them. However, the overwhelming majority of individuals holding two licenses made the same decision for both, such that either two bids were submitted, or none at all. For this reason, a bivariate probit model of the joint decision returns a correlation coefficient of 1, which suggests that estimating the joint decision provides no additional information regarding participation. For this reason, a univariate probit was estimated in preceding sections, dropping those few individuals whose participation decision varied between the peeler and hard pot auctions and without any correction for the correlation between the participation decisions for dual license holders. In order to investigate the sensitivity of my results to this uncontrolled correlation I compare the original specification to specifications that drop one of the two licenses for individuals holding both.

Table 4.8 presents a comparison of Virginia's estimation of equation 2.12, with the Full results representing the original specification, the Hard specification dropping the peeler license observations for individuals who have two eligible licenses, and the Peeler specification dropping the hard pot license observations for individuals who have two eligible licenses. The point estimates in the Hard and Peeler specifications differ by an average of 28 percent and 35 percent of a standard deviation respectively from the Full specification. The p-values tend to become larger as observations are dropped, as would be expected. A notable exception is the indicator for the importance of identity in the value of a license, which is statistically significant in all specifications excepting the Full model.

Table 4.8: Virginia probit models of the auction participation decision investigating model sensitivity to uncontrolled correlation in the data (standard error)

Selection Model	Full	Hard	Peeler
Constant	0.4728	0.1846	0.3273
	(0.3631)	(0.4070)	(0.4170)
Probably Crab	-0.3842*	-0.3480*	-0.5004*
	(0.1797)	(0.2042)	(0.2068)
Non-crabbing licenses	-0.4699*	-0.4635*	-0.3442*
	(0.1729)	(0.1918)	(0.1969)
Bid amount	1.2553*	1.2566*	1.1556*
	(0.5715)	(0.5085)	(0.4715)
Enjoy crabbing	-1.4736*	-1.4840*	-1.4382*
	(0.6961)	(0.6759)	(0.6729)
Identity	0.9753	0.9899*	1.1060*
	(0.6012)	(0.5589)	(0.5370)
Heard	-0.8252*	-0.8460*	-0.9006*
	(0.3003)	(0.2725)	(0.2772)
Two Pot licenses	1.5121*	1.3329*	1.8229
	(0.8321)	(0.7286)	(1.2020)
Within 35 mi	-0.6182*	-0.4294	-0.5614*
	(0.2655)	(0.2982)	(0.3095)
Total Distance	-1.1116*	-0.7675	-0.9234*
	(0.4570)	(0.5159)	(0.5316)
Observations	390	293	282

*Significant < 10% level

These results suggest no strong bias in the analysis due to uncontrolled correlation between observations for individuals holding two eligible licenses. Given that the Hard and Peeler selection models use around 25 percent fewer observations than the Full specification, the Full specification is preferred.

4.5.3 Unit Nonresponse

Unit nonresponse, or the fact that 33 percent of individuals mailed in Maryland and 25 percent of individuals mailed in Virginia responded to the survey, is another source of bias with potential ramifications for my analysis. A random sample of individuals that did not respond to the mail component of the survey were contacted by phone and asked a subsample of questions as a first step in gauging whether unit nonresponse poses an issue. A total of 61 mail nonrespondents responded to the Maryland phone survey and 56 mail nonrespondents responded to the Virginia phone survey.

Table 4.9 presents the results of tests for equalities of responses from the mail and phone components of the survey. In Maryland both age and the frequency with which individuals self-reported being commercial watermen differ between mail respondents and phone respondents. The phone respondents are significantly older and more likely to self-report as commercial. In Virginia, the frequency with which individuals self-report both being commercial and the importance of an identity value associated with the license, as well as the WTA for peeler pot licenses, differ significantly between the mail and phone respondents. Phone respondents are significantly more likely to self-report as a commercial waterman, are less likely to state the importance of identity, and have significantly higher WTA values for peeler licenses than mail respondents. These results suggest that, although most of the variables are similar across populations, some potential for nonresponse bias at the unit level exists.

Table 4.9: P-values for tests of equality between mail and phone survey responses. Dichotomous variable comparisons are two-tailed t-tests for the frequency of positive responses. Continuous variable comparisons are Mann-Whitney U tests for the equality of the distribution

Variables	Maryland	Virginia
Categorical Variables		
Commercial	0.0026	0.0952
Probably Crab	0.3251	0.1794
Mult holders at address*	0.8081	0.6006
Stopped Crabbing*	0.1470	
Latent*	0.1486	
Both rec. and comm.	0.1498	
Late Reporting*	0.8514	
Bequest	0.1243	
High Education	0.8866	
Identity		0.0025
Peeler Pot License*		0.6554
Enjoy Crabbing		0.1888
Peeler Wait List*		0.9983
Hard Wait List*		0.8832
Within 35 mi*		0.4219
Two Pot licenses*		0.9446
Non-crabbing licenses*		0.8860
Large pot license*		0.8941
Continuous variables		
Age*	0.0222	
Profits*	0.9708	
WTA	0.6486	
Total Distance*	0.1442	0.5737
Peeler WTA		0.0539
Hard WTA		0.2018
Hard Profits*		0.6840
Peeler Profits*		0.4355
Ratio*		0.9997

*Observed for everyone eligible for the buybacks

Although some of the data used in this paper is available only for survey respondents, there are a large number of variables which are available for all individuals who were eligible for the buybacks in Maryland and Virginia, and some of these variables are indicated with an asterisk in Table 4.9.

Table 4.10 presents the results of a logistic regression which further investigates potential nonresponse bias in the analysis by identifying which variables are significantly correlated with unit nonresponse. Table A.A.5 in Appendix A provides model results including insignificant point estimates. The dependent variable is an indicator equal to one if an individual responded to the survey, and zero otherwise. The average licenses variable is the average number of non-crabbing licenses held by each individual over the 13 years of harvest data available for Maryland license holders. The bid variable is an indicator equal to one if an individual bid in the auction and zero otherwise. Personal and Retail are the percentages of the harvest respectively held for personal use or sold to a retailer, averaged over the harvest history of an individual. The Buyback variable is an indicator equal to one if an individual accepted the fixed price offer, and zero otherwise. The number of years fished is the total number of years within the harvest history in which the individual actively crabbed. All other variables are as previously defined.

It is apparent from Table 4.10 that individuals who responded to the survey differ significantly from those who did not respond to the survey. Further, the differences are in variables which are likely to be important to the participation decisions that are the primary interest of this paper. Of note is that the majority of the variables which differ between the two groups are consistent with the observed differences between mail and phone respondents. The Personal, Retail, Number of years fished, and Average licenses are likely to be strongly correlated with whether an individual self-identifies as a commercial fisherman. Age is controlled for directly in the estimate for the propensity to respond to the mail survey in Maryland. In addition, the Distance, Latent, Stopped Crabbing, and Mult holders at address variables are significant in the propensity to respond to the mail survey, although they were not found to be significantly different between the mail and phone respondents. Likelihood ratio tests suggest that the Stopped Crabbing and Latent variables are jointly, though not independently, significant. I have previously shown that profits are significantly correlated with WTA values, and thus controlling for profits in the propensity model should help control for differences in this variable. The identity value indicator is the one variable for which no obvious control exists.

Table 4.10: Logit regressions of the response to the mail survey, with the dependent variable equaling one if an individual responded to the mail survey and zero otherwise (standard error)

Selection Model	Maryland	Virginia
Constant	-0.4190*	-1.4542*
	(0.1922)	(0.0907)
Average licenses	-0.2661*	
	(0.0684)	
Bid	0.3285*	
	(0.1235)	
Personal	0.0029*	
	(0.0014)	
Retail	0.0123*	
	(0.0057)	
Age	-0.4970*	
	(0.0726)	
Buyback	-0.6556*	
	(0.1196)	
Distance	0.3596*	
	(0.1670)	
Stopped Crabbing	-0.2035*	
	(0.1065)	
Latent	-0.1760	
	(0.1146)	
Number of years fished	0.0240*	0.1001*
	(0.0109)	(0.0149)

Table 4.10 (continued): Logit regressions of the response to the mail survey, with the dependent variable equaling one if an individual responded to the mail survey and zero otherwise (standard error)

Selection Model	Maryland	Virginia
Mult holders at address	-0.4791*	-0.4932*
	(0.2037)	(0.1685)
Profits		-0.1129*
		(0.0517)
Observations	3588	1772
Model Likelihood Ratio	0.0000	0.0000

*Significant at < 10% level

The above analysis suggests that nonresponse bias could present an issue. I undertook MI analysis in order to further investigate this issue, creating imputations for each individual with missing observations. Imputation methods, along with results of the MI analysis can be found in Appendices B and C. Rubin (1987) provides a simple calculation for the fraction of an estimate's information missing, γ_m,due to nonresponse. This formula is $\gamma_m = \frac{r_m + 2/(\nu+3)}{r_m+1}$, with $r_m = (1 + \frac{1}{m})\frac{B_{MI}}{W_{MI}}$ representing the relative increase in variance due to nonresponse, B_{MI} equaling the between imputation variance and W_{MI} the within imputation variance, and ν equal to the parameter's calculated degrees of freedom. Exact definitions for B_{MI}, W_{MI}, and ν can be found in Appendix B. The fraction of missing information calculated in this manner is extremely large for both Maryland and Virginia. For example, the average missing fraction of information in Maryland's bid function is 0.69 percent, while in Virginia this average is 0.59. Thus, the majority of the simulation variance is generated between imputations.

The survey which generated the nonresponse was specifically targeted towards gathering information on WTA, and the variables most likely to correlate to those values. It is unclear whether predictors for variables such as the importance of a bequest motive and identity value are strong enough in order to provide valid imputations, in stark contrast to the WTA item nonresponse issue. Coupled with the significant amount of information missing due to nonresponse, any correction to the complete case estimation seems haphazard. For this reason, although I acknowledge that nonresponse bias could be an issue in this analysis I do not correct for it in the estimations[11].

4.6 Hypothetical Bias

An obvious question is how well the hypothetical WTA data represents the unobserved license values underlying actual bidding decisions in the Maryland and Virginia auctions. In this section I investigate the convergent validity of the data in order to answer this question statistically. Convergent validity is the statistical comparison of two variables which purport to represent the same underlying value. In this analysis I will directly compare the actual bids and hypothetical WTA values in order to understand whether they converge in their statistical representation of individuals' actual license values.

Table 4.11 compares the actual bid and hypothetical WTA data for those individual who both submitted a bid in their respective auctions and WTA values

[11] I also estimated an inverse propensity score weighted (IPW) regression to investigate the potential bias due to nonresponse, with the results presented in Appendix D. The IPW uses the inverse predicted propensity to respond to the mail survey, generated from the logit model of Table 4.10 to weight each individual's response in order to represent the underlying population. Point estimates were very similar to the unweighted complete case specification. However, both the IPW estimator and the MI specification provided for conditional WTA values significantly smaller than the unweighted complete case specification. In Maryland the mean nonresponse bias is calculated at roughly 2.5% of the OLS estimate, or $250, while in Virginia the mean bias is 4%, or $2,100.

through the survey. In Maryland and Virginia, between 20 and 36 percent of respondents submitted WTA values greater than their actual bid values, suggesting some potential for hypothetical bias. However, upon closer inspection these numbers are not as troubling as they might first appear for the following reasons.

Table 4.11: Difference between actual bids and hypothetical WTA values for individuals submitting both

	Maryland		**Virginia**	
	Full	**Outliers Removed**	**Peeler**	**Hard**
Observations	131	128	49	82
Mean ($)	-1,044	900	400	25,067
Median ($)	0	0	0	2,000
SD ($)	25,363	4,639	23,626	50,483
Inconsistent (%)	36	35	19	22

First, both the mean and median differences in Virginia are consistent with theoretical expectations. Though the median difference in Maryland is consistent with expectations, the mean score is not. However, 23 of the 47 individuals who provided WTA values above their original bids in Maryland had bids below the $2,260 posted offer price. Given the common value component of the licenses, and the nature of the information revealed through Maryland's posted offer price, it is logical for these individuals to have updated their WTA values in a positive direction after the buyback. Second, after discarding the three individuals whose difference between actual bid and WTA values were greater than two standard deviations away from the mean, and thus could be argued to be protest responses, the distribution of differences in Maryland becomes much better aligned with expectations. Third, the raw Pearson correlation coefficient between the Maryland WTA and bid values is

0.8833, suggesting a very strong linear correlation between the two, as would be theoretically expected. The correlation coefficient for the pooled licenses in Virginia is 0.7382, which also very high. Interestingly, hard pot licenses seem to correspond with much higher amounts of bid shading than peeler licenses in Virginia.

Section 4.5.1 statistically compares predicted optimal bids with actual bids in the auction, with mixed results. Using a Wilcoxon signed-rank test Maryland's predicted and actual bids are not significantly different at any conventional level, while Virginia's are (p-values of 0.5174 and 0.0210 respectively). Figure 4.5 graphs the predicted and actual bids in Virginia. The predicted bids are tightly grouped around the 45 degree line for the lower end of the distribution. However, at the upper end of the distribution the predictions tend to be significantly smaller than the actual bids. This suggests that the model is much better at controlling for bid shading at the lower end of the WTA distribution.

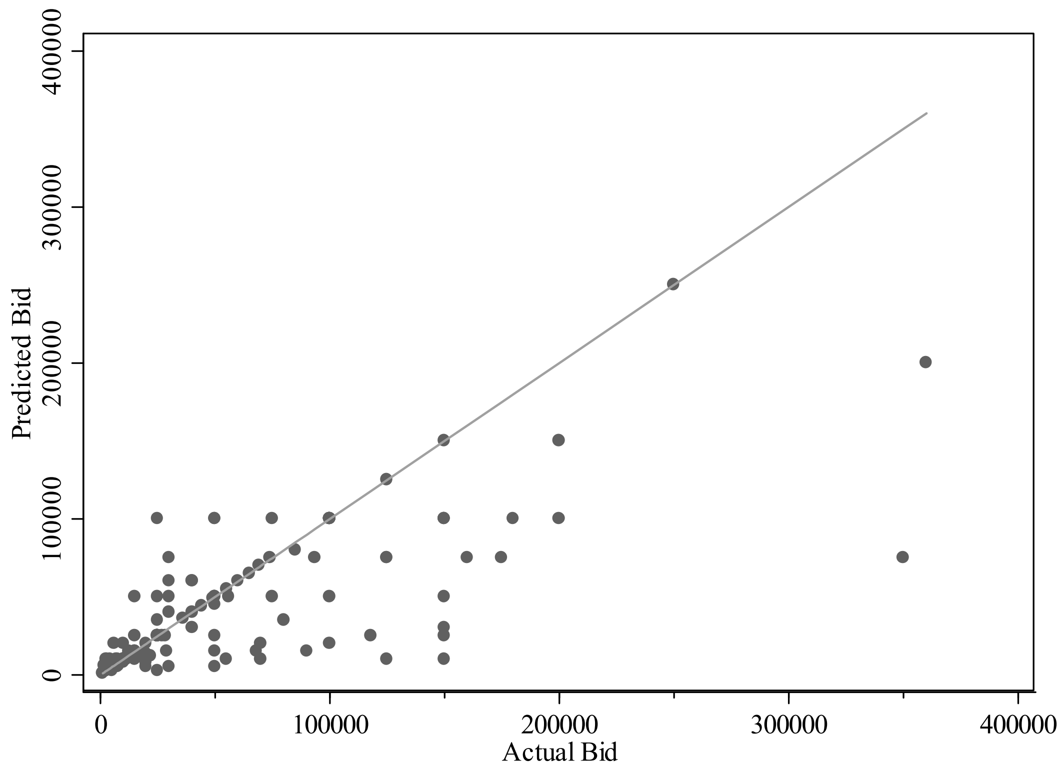


Figure 4.5: Predicted versus actual bids in Virginia

In Table 4.2 we had previously estimated the bid function of equation 2.17 using both the actual bid and hypothetical WTA values. In Table 4.12 we revisit these estimations holding the observations to only those individuals who both bid in the auction and provided WTA values. This is done to further investigate whether hypothetical bias is a concern in the analysis. The average difference between point estimates in Maryland is 1.05 standard deviations[12], while in Virginia it is 1.03 standard deviations. The Wait List (2.40 SE), Peeler (1.38 SE), and Constant (1.89 SE) parameters provide the greatest differences between specifications in Virginia,

---

[12] The Bid specification standard errors (SE) are used to compute the point estimate differences.

while in Maryland the Age (1.70 SE), Commercial (2.01 SE), and Both rec. and comm. (1.63 SE) parameters differ most.

Table 4.12: Comparison of regression results for actual and predicted bids (robust standard error)

	Maryland		Virginia	
Coefficient	**Bid**	**WTA**	**Bid**	**WTA**
Constant	-4.2548*	-3.8769*	-2.2524*	-2.7180*
	(0.4105)	(0.4315)	(0.2466)	(0.2063)
Profits	0.3958*	0.4209*	0.1536*	0.1911*
	(0.1806)	(0.1625)	(0.0556)	(0.0428)
Mean earnings	1.0877*	0.5351		
	(0.5729)	(0.5276)		
Age	0.4932*	0.2380*		
	(0.1503)	(0.1400)		
Bequest	0.2311	0.3946*		
	(0.1678)	(0.1598)		
Commercial	0.9402*	0.4399*	0.9089*	0.8077*
	(0.2495)	(0.2222)	(0.2244)	(0.2079)
Both rec. and comm.	0.7842*	0.4582*		
	(0.1996)	(0.1757)		
Probably crab	0.4658*	0.4835*	0.5509*	0.5980*
	(0.1697)	(0.1439)	(0.2036)	(0.2201)
Large pot license			0.7515*	0.7934*
			(0.2091)	(0.1931)
Wait list			-0.9684*	-0.4931*
			(0.1982)	(0.2385)
Peeler Pot License			0.0396	0.3331*
			(0.2125)	(0.1961)
Observations	124	124	120	120
R-squared	0.386	0.271	0.560	0.474
Prob. > F	0.0000	0.0000	0.0000	0.0000

*Significant at < 10% level

Where the models do seem to differ substantially in Maryland, the Bid specification suggests a larger effect than the WTA estimate. This results in a larger conditional bid than conditional WTA value. This in turn suggests that the bid shading is not controlled for completely by the parameters of the subjective probability, and some residual shading is correlated with the Age, Commercial and Both rec. and comm. parameters. There is thus no apparent support for hypothetical bias in the Maryland specifications.

In Virginia, the differences in the Wait List and Peeler parameter estimates could again suggest differences in the bid shading for these individuals when compared to other participants. This is plausible given the different manner in which the bid rankings were conducted for waitlisted individuals in comparison with full time and part time classifications, and the evidence from Table 4.11.[13] The difference in constant estimates provides for a larger baseline value in the Bid specification when compared to the WTA specification and does not provide an indication of hypothetical bias.

A comparison of actual and hypothetical results for individuals who provide both thus suggests that hypothetical bias is not a major concern. Where the data do diverge, the actual values are consistently larger than their hypothetical counterparts, which is theoretically expected when comparing bids and WTA values if shading is imperfectly controlled for.

[13] The waitlisted bids were divided by the maximum number of pots that individual's license allows, whereas the full time and part time bids were divided by the maximum number of pots multiplied by the average number of days crabbed, to generate a bid per pot day value.

Chapter 5: Buyback Simulations

The imputations in section 4.5.3 do not provide reliable results for the statistical analysis of the bid formulation and auction participation models. However, as Markov-Chain Monte Carlo (MCMC) simulations, the imputations provide an opportunity to compare alternative auction outcomes under different market designs and with full participation. This allows investigation into the variation in simulations and comparisons of simulated and observed market outcomes in order to gauge the overall impact of low participation.

A first best outcome is defined here as one in which the state buys the largest number of licenses possible with the available budget. This first best outcome occurs when individuals accept their WTA in exchange for their license, under the specific rules of the auction, and everyone participates, or is amenable to sell. In the simulations I compare these first best outcomes against observed outcomes, in order to better understand the impact of low participation rates on buyback results.

In all simulations 1,000 MI draws are made for each missing WTA observation, as outlined in Appendix B and C. These imputations are undertaken in the exact same manner as section 4.5.3, with the added step that all missing variables of the WTA function were imputed, not just the WTA. These variables are imputed to address both unit and item nonresponse.

5.1 Maryland Simulations

The major drawback of using a posted price offer to buy licenses stems from the fact that the price can easily lead to outcomes that diverge from management objectives and expectations. In Maryland's case, the $2,260 price lead to 646 individuals selling their licenses for a total expenditure of $1,459,960. However, the DNR only expended 49% of their available $3 million budget. This money could have been used to buy back additional licenses, and further decrease the management uncertainty induced by latent effort. I use the simulations to understand how far from a first best outcome the observed results lay.

In section 5.1.1 I simulate the number of licenses which could have been bought with the $1,459,960 under the assumptions of full participation and individuals bidding their WTA. The simulations in 5.1.1 give a sense as to how well the MI WTA values are characterizing the actual WTA values underlying participation decisions. In section 5.1.2 I then look at the total number of licenses which could have been bought with the entire $3 million budget, again assuming full participation and individuals receiving their WTA value in exchange for their license. This provides an understanding of the maximum number of licenses which could have realistically been bought given Maryland's available budget.

5.1.1 Simulation Under $1,459,960 Budget

Figure 5.1 provides results of the simulation, which indicate that an average of 607 licenses could be bought with the restricted budget, with a 15.40 standard deviation. This is 94% of the actual 646 licenses bought, which suggests some inflation of the MI WTA over true values. However, only 3,592 individuals were simulated out of the total 3,676 population eligible for the auction. The 84 individuals not simulated bought the licenses after the buyback were announced. As previously stated these individuals were excluded from the analysis in order to avoid potential issues dealing with individuals who obtained a license solely to bid in the auction.

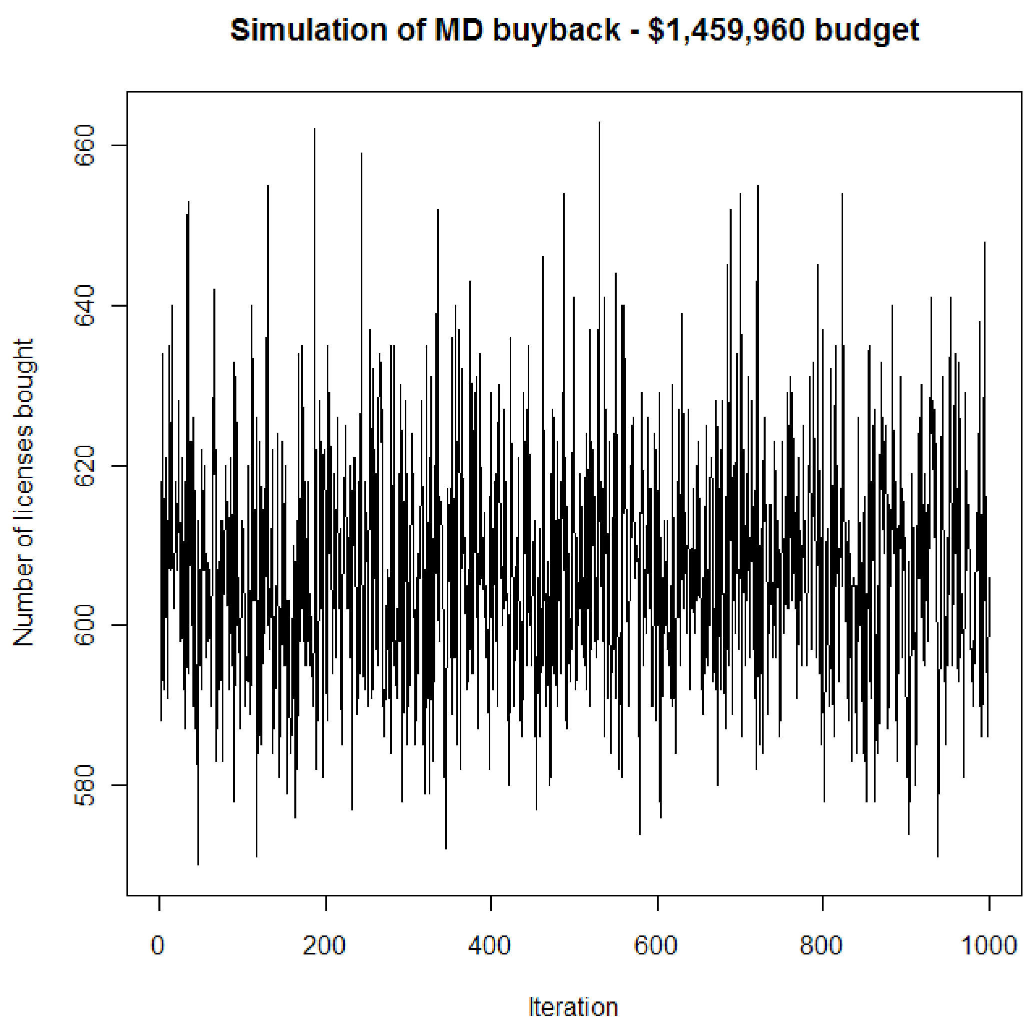


Figure 5.1: Maryland simulation of first best outcome utilizing $1,459,960 budget

Given these results, the simulated WTA values are conservative, in that they are somewhat larger than would be expected given the observed outcomes. This suggests that the simulations with the full $3 million budget should also provide conservative predictions on the number of licenses which could be bought under a first best scenario.

5.1.2 Simulation Under Full $3 Million Budget

Figure 5.2 graphs the number of licenses bought in each iteration of the simulation. By expending the entire $3 million budget, the mean simulation allowed for 1007 licenses to be bought back, with a 23.47 standard deviation.

These simulations suggest that the actual posted offer fell far short of a first best scenario. The 646 licenses represent 64% of the total licenses which could have been bought given full participation and total budget expenditure, even in what are likely conservative simulations. This result clearly underscores the issue faced by fishery managers in Maryland. An auction format is much more efficient, but only if bidding rates approach full participation. In reality the 646 licenses bought back from the posted price offer using $1,459,960 greatly exceeds the 470 licenses which could have been bought if the original auction had been honored, and all $3 million was expended. These simulations highlight the importance of the participation rate as a market design issue that warrants close attention by fishery managers.

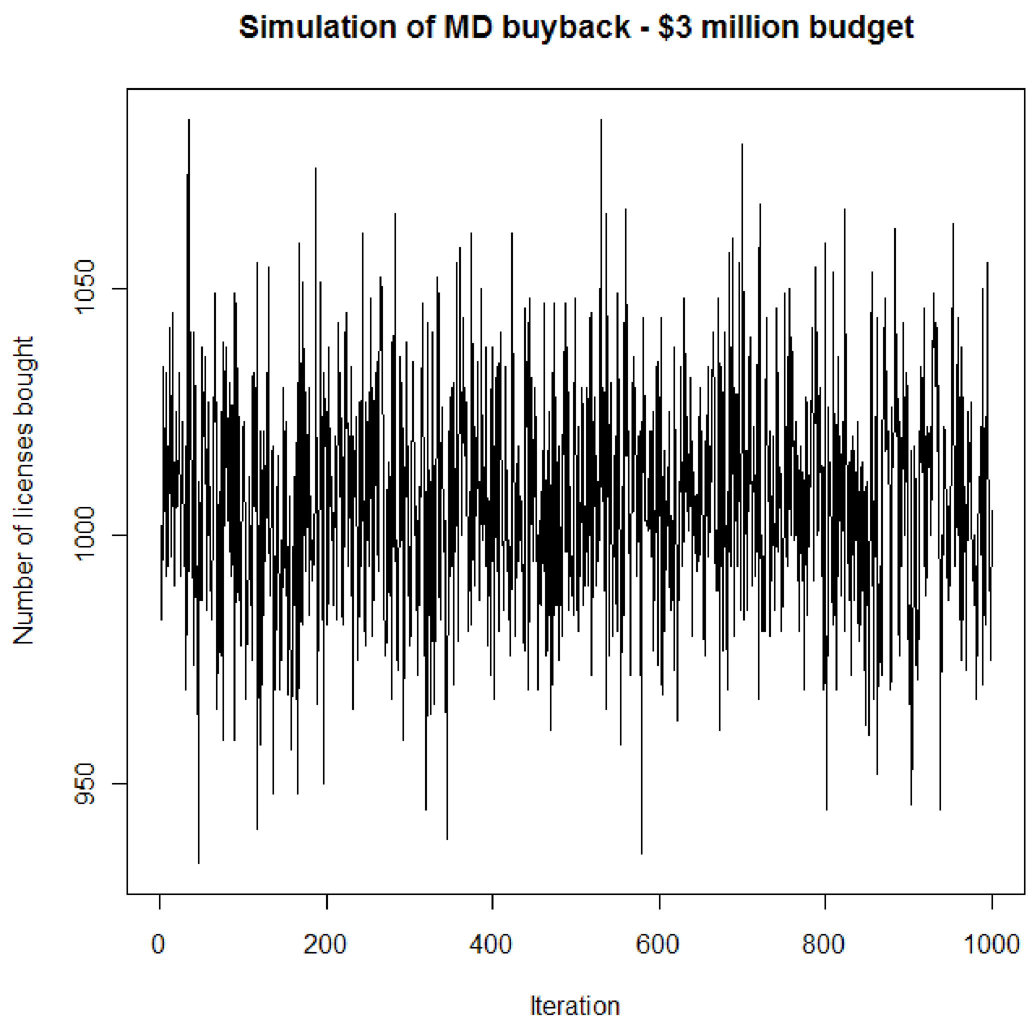


Figure 5.2: Maryland simulation of first best outcomes under $3 million budget

5.2 Virginia Simulations

Having followed through with the auctions as original designed; Virginia's problem was the opposite of Maryland's. Whereas Maryland's posted price offer induced additional participation but failed to expend the budget, Virginia's shortcoming lies specifically in the low participation rate of the auction format.

Section 5.2.1 contrasts Virginia's actual auction outcomes against a first best scenario under the implemented market design. Section 5.2.2 then contrasts these results with a simulation which ranks by bid per pot, but does not differentiate between the Wait List, Part Time, and Full Time classifications of the actual auction.

5.2.1 Simulations Under Actual Market Design

Figure 5.3 presents the first best simulations of Virginia's buybacks under the actual buyback rules. The rules ranked licenses by a bid amount per pot day (bid divided by the product of the average number of days fished and the license's maximum allowable pots) for the full time and part time classifications, and bid per pot (bid divided by the license's maximum allowable pots) for wait listed individuals. The budget was divided between license classifications in the exact manner as the actual buyback, with the full time, part time, and wait list classifications respectively receiving \$3,320,397, \$2,036,131, and \$1,368,633.

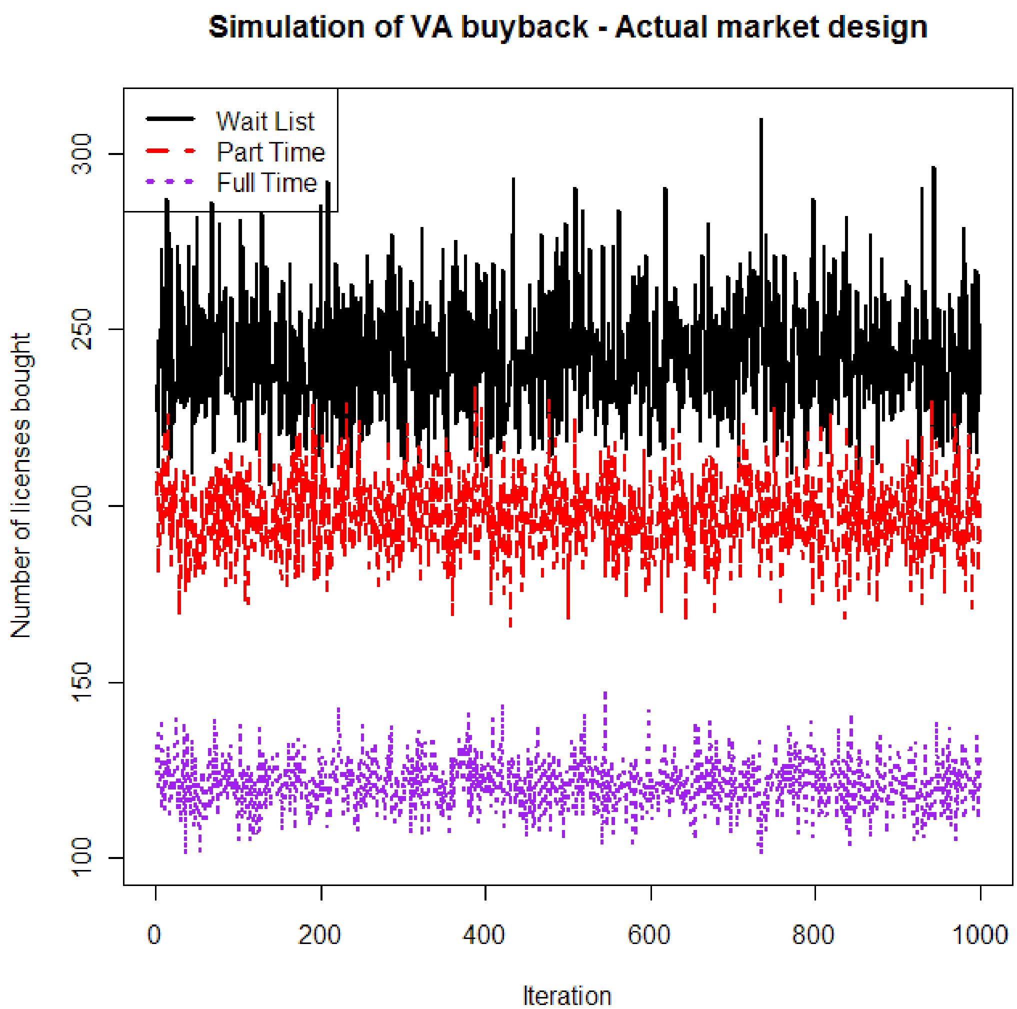


Figure 5.3: Virginia first best buyback simulation under actual auction rules

The simulations average 242 wait listed (16.13 sd), 121 full time (7.40 sd), and 197 part time (11.40 sd) licenses bought back with available funds, for a total of 560 licenses. The 359 licenses actually bought back in the auction represents 64% of the potential licenses which could have been bought with full participation in the auction. The actual auction retired 75,441 licensed crab pots, for a 20% reduction in potential gear capacity. The simulated first best results remove an average of 123,071 licensed pots from the fishery, an increase of 63% over the observed outcome. These results again suggest that specific attention must be paid in designing markets that minimize participation costs, and maximize participation rates, in order to effectively and efficiently attain management goals.

5.2.2 Uncategorized Simulations

Virginia's auction format specifically targeted active effort. A sizeable portion of the budget was used to buy the licenses of individuals who ultimately re-entered the fishery. This final simulation investigates what total potential effort could have been removed from the fishery if the prioritization of active watermen's licenses was not part of the market design. In this uncategorized simulation, it is assumed that the manager's objective is to remove the largest amount of potential effort from the fishery given their budget constraint. As such, bids are ranked on a dollar per pot basis, and licenses are bought from lowest to highest ranking until the entire budget of $6,725,160.93 is expended. Thus, in terms of priority no weight is given on the full time, part time, and wait list classifications.

Figure 5.4 graphs the results of the uncategorized simulations. These results can be thought of as the maximum potential effort that could have been retired from the fishery given Virginia's budget, versus the actual auction design that prioritized the removal of active licenses. The average number of licenses retired through these simulations is 771 (30.16 sd), a 115% increase over the 359 licenses actually bought, and 38% greater than the simulations of section 5.2.1. The average total number of pots retired through the uncategorized buyback is 157,208, a 108% increase over the actual number of licenses retired through the auction as it was implemented, and 28% more pots than the simulations of 5.2.1.

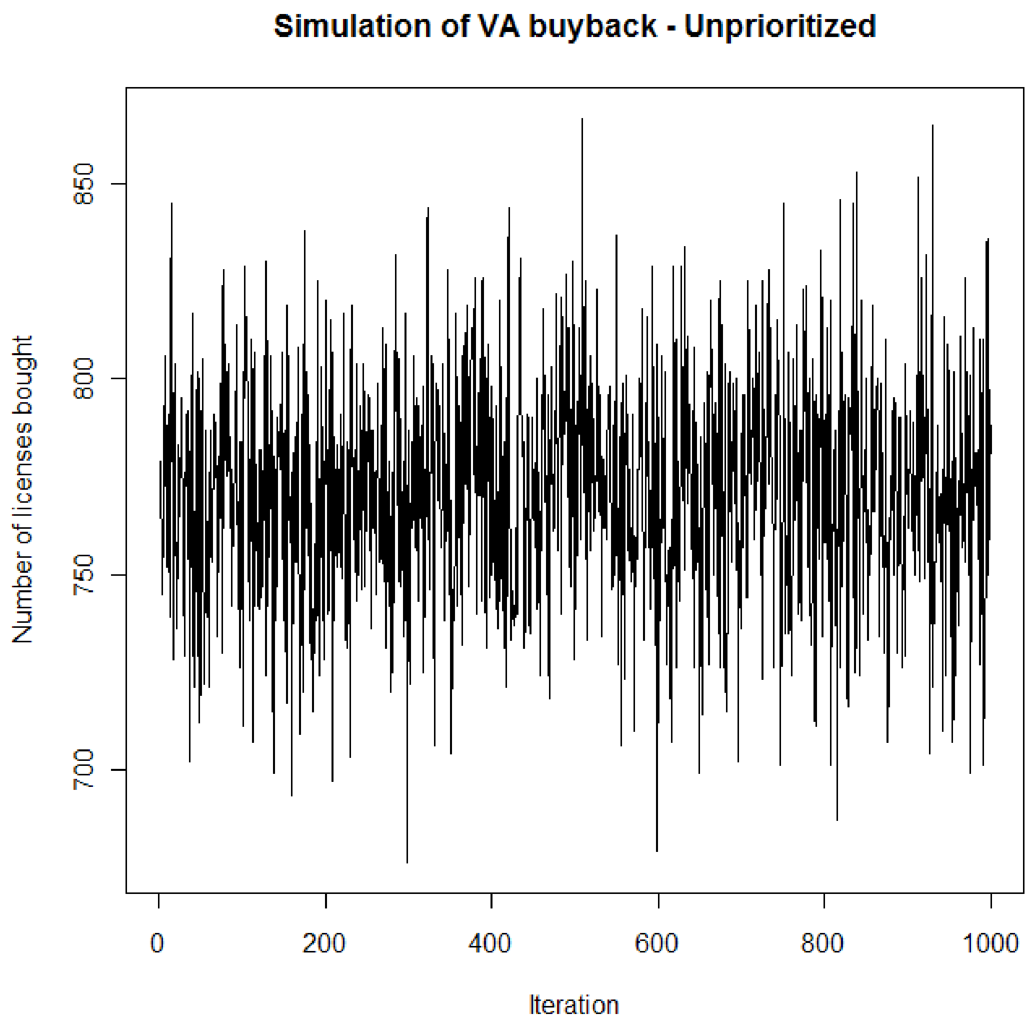


Figure 5.4: Simulated Virginia buyback putting no priority on license categories

5.3 Discussion of Simulation Results

The results of the simulation clearly highlight the central role played by participation decisions in the Maryland and Virginia auction outcomes. In both states the simulations suggest that low participation rates in the auction, particularly within the low end of the WTA distribution, severely hindered the effectiveness of the buybacks. Maryland was able to partially address this issue by switching to a posted price offer, which induced additional participation within the lower tail of the WTA distribution. However, Maryland's posted price buyback utilized only 49% of the available budget, meaning the 646 licenses actually bought back represents roughly 64% of the total which could have been bought back with a more efficient outcome.

In Virginia both the low participation rate of individuals in the lower tail of the WTA distribution and the categorization and prioritization used to target active licenses severely decreased the total potential effort, in the form of licensed pots, which could have been removed. The VMRC faces management challenges which are not considered in this research, which lead to the prioritization of active effort. However, 24% of Virginia's total budget, or $1,614,315, was used to acquire licenses from individuals who promptly reentered the fishery. A number of individuals who re-entered the fishery had a single license prior to the buyback, but bought two licenses upon re-entry. This evidence suggests that, as implemented, the Virginia license was ineffective in reducing active effort. Removing the maximum number of potential pots from the fishery using the given budget could well have served as a more attainable and effective goal.

Chapter 6: Discussion

In both states the value uncertainty interpretation finds support through all steps of my analysis. A consistent argument is that value uncertainty was a major issue in the auction, leading to low participation rates and high variability in the bids tendered. This uncertainty could have stemmed from numerous sources including the thin alternative market for licenses and the outstanding policy initiatives. The switch to the posted price format in Maryland provided additional information to license holders; both through the announcement of the posted price offer itself, and what Maryland deemed a fair market value for the license, and through the implementation of additional restrictions on those individuals classified as latent. The more engaged an individual, the more likely these signals were used to update the expected value of their license, all else being equal.

This difference in updating between individuals with low and high WTA values has a logical explanation in the nature of the value stemming from the license itself, which is a mix of common and private values. The profits which can be generated from selling the license on the open market should serve as a lower bound for WTA values. For individuals with relatively low WTA values this common value could easily comprise the bulk of the license's value, along with more amorphous values than current license usage. However, the open market for these licenses is thin, and clearing prices are not general public knowledge. A strong signal on the common value component of the license would provide a great deal of information. At relatively higher WTA values, the bulk of the license's value stems primarily from private value components. This suggests that signals for the value of the license are more likely to be used in updating by individuals with low starting WTA values, for which the common value component of the license is relatively more important. This description holds with the findings of Milgrom and Weber (1982), who espouse the full reporting of available information about the common value component of the auctioned item in mixed common-private value settings and first price auctions, in order to increase efficiency and decrease the effect of the winner's curse. Groves and Squires (2007) similarly suggest the important role common information plays in the efficiency of the price formation process for fishery buybacks, although the magnitude of this inefficiency is not specifically investigated or detailed.

Given that an individual's WTA value is significantly correlated with engagement in the fishery, as judged by historical profits, future expected usage, self-classification, etc., these results suggest that marginally engaged crabbers could face difficulty in formulating bids. Marginally engaged individuals are often targeted for this type of policy intervention, which suggests that additional care in the design and execution of the intervention is warranted. For buybacks, this additional care could include a dry-run of the auction as suggested by Groves and Squires (2007), much in the manner of practice rounds in experimental economics.

Alternatively, an auction format designed specifically to address problems in the bid formulation process could facilitate participation in buyback auctions. As an example, DePiper et al. (2011) tested what they termed a facilitated auction in an experimental setting. This facilitated auction draws attention to the most salient issues in the bid formulation process by asking potential participants to consider the smallest amount of money they would be willing to sell the item for, and the largest amount of money they believe the auctioneer will pay for the item. The auction instructions then suggest that the individual's bid should fall somewhere between these two values, and implicitly focuses attention on the trade-off between the probability of and profits from winning the auction. By walking through the steps of formulating a bid, this design specifically addresses issues stemming from unfamiliarity with the auction format, much in the same manner as practice rounds.

The inefficiency due to nonparticipation also lend more weight to license auctions of the form proposed by Garber and Bromley (2003), who suggest that fishermen should tender bids to purchase the right to stay in the fishery, as opposed to the state buying licenses and capital from fishermen. Although this could prove politically problematic, Garber and Bromley's policy instrument has the benefit of ensuring participation from everyone wanting to remain active in a fishery. This would mitigate any allocation inefficiencies directly due to decreased participation rates. This type of auction has been implemented in Chilean fisheries including the Squat Lobster (*Pleuroncodes monodon*), yellow prawn (*Cervimundia johni*), black cod (*Dissostichus eleginoides*), and orange roughy (*Hoplostethus atlanticus*) (Cerda-D'Amico & Urbina-Véliz, 2000), among others.

More generally, market information could play a decisive role in buyback participation decisions. The reversals associated with Maryland's change from an auction to a posted price offer suggest that individuals incorporated new information into their decision-making process between the two market designs. A strong signal from the Maryland DNR on the fair market value of a license seems to have played a large role in the participation decision surrounding the buyback, consistent with the theory for mixed private and common value goods. In Maryland, the proposed regulations faced by individuals classified as latent most assuredly complicated the participation decision for those individuals, and this source of uncertainty should have been addressed prior to initiating the auction.

The most likely reason that this value uncertainty translated into lower auction participation rates for marginally engaged fishermen is the increased costs of information gathering for these individuals. The value of their licenses tend to be generated not from current usage, but more amorphous sources such as a bequest value or expected future usage which differs significantly from past usage patterns. One could easily imagine that these individuals lack the social networks which would facilitate an understanding of the current economic reality of the fishery and its future outlook. The results indicate that expected usage patterns and alternative sources of utility must be understood when ex-ante values are generated for auction design and budgeting purposes. These results are also consistent with List's (2003) finding that market experience attenuates anomalies in field experiments.

Simulations of alternative outcomes suggest that the number of licenses actually bought represent between 47% and 64% of what could have been bought with higher participation rates. Likewise, the total licensed pots removed represent between 48% and 64% of the most efficient outcomes in each state. The magnitude of these results indicates that the low auction participation rates severely impacted each state's ability to achieve stated management goals.

The underlying issues highlighted in this paper could extend to the design of other fishery management tools, such as individual transferrable quota (ITQ) systems.

Generally, ITQ systems assign what amounts to individual property rights over a fraction of the total allowable harvest in a fishery. Fishermen are then free to harvest their individual quota at any time throughout the season, or to trade it to others. This market-based approach should provide efficiency gains over both open access and limited access management regimes. However, my analysis suggests that transaction costs likely exist, in the form of information search costs. These costs could hamper the efficiency of the ITQ system. For example, the speed and extent of efficiency gains could correlate negatively with the quantity of quota provided to individuals least prepared to undertake the trades necessary for efficiency to be achieved. The results of this paper suggest that initial allocation could be an important concern for fishery managers when transitioning to an ITQ system and this potential warrants additional investigation. The potential for this type of inefficiency could warrant additional research into the role of quota brokerage services, such as implemented by the Australian South East Trawl Fishery (Fox, Grafton, Kompas, & Che, 2007).

The research within this dissertation could also explain similar intransigence observed in the agricultural sector. Like fishing, small scale and family run agricultural enterprises have long been viewed as an important contributor to rural culture and society, beyond their profit-generating potential (Commission of the European Communities, 2002). Direct subsidies (Commission of the European Communities, 2002; Ilbery et al., 2009; Internal Revenue Service, 2010), tax breaks (Internal Revenue Service, 2010), and payment programs aimed at inducing farm exit (Botterill, 2001) have all looked to influence the entry and exit decisions surrounding small farms. Small scale farming enterprises have been noted to continue operations in the face of negative profits, and non-pecuniary factors of utility have been cited reasons for this exit inertia (Hoppe et al., 2010; Jack et al., 2009). The optimality of policies aimed at these entry and exit decisions relies not only on understanding the magnitude of the value generated from these enterprises, but also whether value uncertainty is a potential concern for marginal and inframarginal farmers.

APPENDIX A: Results Including Insignificant Estimates

Table A.A.1 presents the Heckman selection model of Table 4.1, retaining insignificant parameter estimates. The results suggest that most of the value indicators correspond to insignificant point estimates. The exceptions are the Bequest and Family History indicators and Mean Earnings in Maryland, and the Enjoy Crabbing indicator and Profits in Virginia. Significant point estimates are consistent with those presented in Table 4.1.

Table A.A.1: Heckman selection models estimating auction participation and bid function, including insignificant point estimates (standard error)

	Selection model		**Bid function**	
	Maryland	**Virginia**	**Maryland**	**Virginia**
Constant	-2.2426*	-0.4067	-4.3195*	-2.2177*
	(0.4060)	(0.4803)	(0.4276)	(0.5493)
Demographics				
Age	-0.1253		0.6802*	
	(0.1163)		(0.1698)	
Stopped Crabbing	0.5288*		-0.1723	
	(0.1633)		(0.2542)	
Latent	0.7754*		-0.2757	
	(0.1377)		(0.2000)	
Probably Crab	-0.4615*	-0.6067*	0.4063*	0.6636*
	(0.1364)	(0.1957)	(0.1845)	(0.2678)
Commercial	-0.2880*	0.5398	1.0477*	0.7644*
	(0.1677)	(0.3341)	(0.2493)	(0.4513)
Both Rec. and Comm.	-0.3856*	0.4161	0.6780*	-0.0442
	(0.1326)	(0.3535)	(0.1920)	(0.4601)
Mult holders at address	0.6424*	-0.0744	0.7176	-0.6575*
	(0.3046)	(0.2394)	(0.5554)	(0.3029)
Full Time		0.1344		0.6184*
		(0.2562)		(0.2848)
Wait List		-0.2236		-0.2901
		(0.2247)		(0.2562)
Non-crabbing license		-0.2774*		0.4544*
		(0.1676)		(0.2299)
Large pot license		0.1869		0.7898*
		(0.1532)		(0.1726)
Utility indicators				

Table A.A.1 (continued): Heckman selection models estimating auction participation and bid function, including insignificant point estimates (standard error)

	Selection model		Bid function	
	Maryland	**Virginia**	**Maryland**	**Virginia**
Profits	-0.0164	-0.2434*	0.1664	0.1810
	(0.1231)	(0.0993)	(0.2582)	(0.1450)
Mean Earnings	0.0398		1.3815*	
	(0.4296)		(0.5712)	
Family History	-0.2348*	-0.1842	0.1371	-0.0136
	(0.1326)	(0.1616)	(0.1977)	(0.2094)
Identity	-0.1443	-0.1995	-0.2002	-0.2365
	(0.1224)	(0.1579)	(0.1867)	(0.2014)
Bequest	-0.3793*	0.2501	0.3054*	0.0335
	(0.1145)	(0.1679)	(0.1777)	(0.2069)
Enjoy crabbing	-0.1057	-0.4902*	0.2459	0.4587*
	(0.1195)	(0.1511)	(0.1736)	(0.2173)
Subjective Probability				
Late Reporting	-3.1289*			
	(0.9488)			
High Education	-2.2521*			
	(0.7421)			
Heard		-0.4064*		
		(0.1235)		
Two pot licenses		0.4144*		
		(0.1573)		
Instruments				
Distance	0.5852*	-1.4370*		
	(0.2800)	(0.4475)		
Within 35 miles		-0.8110*		
		(0.2597)		
Inverse Mills			0.0954	-0.4050
			(0.1834)	(0.3626)
Observations	1035	463	132	109

*Significant < 10% level

Table A.A.2 details the models of Table 4.2, retaining insignificant point estimates. Estimates are consistent with Table 4.2, though Mean Earnings and Profits are respectively no longer significant in Maryland and Virginia's Bid specifications.

Table A.A.2: Parsimonious bid function estimation of Table 4.2, including insignificant point estimates (standard error)

Coefficient	MD Bid	MD WTA	VA Bid	VA WTA
Constant	-4.0137*	-2.7772*	-2.5105*	-2.7814*
	(0.4095)	(0.2359)	(0.2316)	(0.2018)
Profits	0.3690*	0.4054*	0.1885	0.1664*
	(0.2061)	(0.0905)	(0.1186)	(0.0502)
Probably crab	0.5047*	0.2342*	0.5353*	0.4168*
	(0.1766)	(0.1191)	(0.2100)	(0.1556)
Commercial	0.8766*	0.2026	0.9089*	0.7389*
	(0.2489)	(0.1313)	(0.2009)	(0.1471)
Both rec. and comm.	0.5986*	0.2944*		
	(0.1912)	(0.1063)		
Mean earnings	0.8975	-0.1795		
	(0.5645)	(0.3041)		
Age	0.5984*	0.4391*		
	(0.1675)	(0.0852)		
Bequest	0.3627*	0.2821*		
	(0.1731)	(0.0865)		
Latent	-0.1611	-0.3356*		
	(0.1734)	(0.1067)		
Enjoy crabbing			0.3681*	0.4598*
			(0.1730)	(0.1145)
Large pot license			0.7775*	0.8540*
			(0.2008)	(0.1488)
Wait list			-0.7755*	-0.3934*
			(0.2074)	(0.1849)
Mult holders at address			-0.7220*	-0.2688
			(0.2803)	(0.1822)
Peeler Pot License			0.1939	0.5831*
			(0.2040)	(0.1491)
Non-crabbing license			0.1527	0.4035*
			(0.1860)	(0.1327)
Observations	138	759	128	431

*Significant < 10% level

Table A.A.3 presents the Full model specifications from Table 4.3, retaining insignificant parameter estimates. In Maryland the indicator for Family History and in Virginia Profits lose significance when the bid amount is directly controlled for.

Table A.A.3: Probit models of the auction participation decision from the Full specification of Table 4.3, including insignificant point estimates (standard error)

	MD	VA
Constant	-1.3244*	0.4113
	(0.2348)	(0.3644)
Demographics		
Stopped Crabbing	0.4696*	
	(0.1720)	
Latent	0.8978*	
	(0.1507)	
Probably Crab	-0.3616*	-0.3733*
	(0.1565)	(0.1809)
Commercial	-0.4466*	
	(0.1706)	
Both Rec. and Comm.	-0.5060*	
	(0.1451)	
Mult holders at address	0.6373*	
	(0.3496)	
Distance	0.6330*	-1.0967*
	(0.2898)	(0.4554)
Within 35 miles		-0.5967*
		(0.2657)
Non-crabbing licenses		-0.4326*
		(0.1743)
Utility indicators		
Bid amount	0.7853*	1.4177*
	(0.2638)	(0.5996)
Bequest	-2.4237*	
	(1.0264)	
Family History	-0.0668	
	(0.0757)	
Profits		-1.3289
		(0.8334)
Identity		1.1399*
		(0.6401)
Enjoy crabbing		-1.5660*
		(0.7259)

Table A.A.3 (continued): Probit models of the auction participation decision from the Full specification of Table 4.3, including insignificant point estimates (standard error)

	MD	VA
Subjective Probability		
Late Reporting	-0.9476*	
	(0.2484)	
High Education	-0.4143*	
	(0.1962)	
Heard		-0.8224*
		(0.2896)
Two pot licenses		1.3997*
		(0.7079)
Observations	743	390

*Significant < 10% level

Table A.A.4 presents results of the posted offer participation decision model in Maryland. Models 1 and 2 investigate the decision of whether to accept or reject the posted price, with the dependent variable equal to 1 if the individual accepted the offer and 0 otherwise. Models 3 and 4 of Table A.A.4 investigate those seeming preference reversals between the auction and posted offer. The binary dependent variable in these two models takes a value of 1 if the individual bid above $2,260 in the auction and subsequently accepted the posted price of $2,260, and a value of 0 if the individual bid above $2,260 in the auction and rejected the posted price. The only difference between Model 3 and Model 4 is whether the WTA is controlled for.

Table A.A.4: Maryland probit models of the posted offer participation decision (standard error), including insignificant point estimates. WTA measured in $10,000

	Model 1	Model 2	Model 3	Model 4
Dependent variable	Accepted	Accepted	Reversal	Reversal
Constant	-0.9178*	-1.2004*	0.0171	0.7448
	(0.3254)	(0.3224)	(0.6688)	(0.8323)
Stopped Crabbing	0.5404*	0.5658*	0.5819	0.8624
	(0.2123)	(0.2097)	(0.4841)	(0.6100)
Latent	0.9474*	1.0310*	0.0123	0.4105
	(0.1706)	(0.1699)	(0.3551)	(0.4700)
Probably Crab	-0.7970*	-0.7187*	-0.7984*	-0.5355
	(0.1689)	(0.1688)	(.3426)	(0.4138)
Commercial	-0.6053*	-0.6009*	-0.4544	-0.1879
	(0.2132)	(0.2109)	(0.4059)	(0.5169)
Both Rec. and Comm.	-0.4789*	-0.4799*	-0.5828*	-0.7107*
	(0.1659)	(0.1644)	(0.3398)	(0.4167)
Age	-0.5153*	-0.5723*	-0.7402*	-0.5219
	(0.1587)	(0.1538)	(0.3261)	(0.3907)
Mult holders at address	-0.2354	-0.1298	0.2281	-0.2406
	(0.6142)	(0.5737)	(0.7045)	(1.0379)
Distance	0.1358	0.0455	-0.0923	-0.4811
	(0.3289)	(0.3343)	(0.5334)	(0.6236)
WTA	-0.2192*	0.8901*		-3.2844*
	(0.0769)	(0.2989)		(1.0887)
Bequest	-0.7046*	-0.6918*	-0.7633*	0.1611
	(0.1509)	(0.1485)	(0.3317)	(0.4621)
Family History	-0.0839	-0.1396	0.4805	0.2886
	(0.1743)	(0.1706)	(0.3712)	(0.4899)
Identity	-0.0167	-0.0101	-0.2009	-0.1387
	(0.1552)	(0.1532)	(0.3217)	(0.3804)
Enjoy crabbing	-0.1630	-0.2191	0.4126	0.9321*
	(0.1530)	(0.1511)	(0.3224)	(0.4871)
Late Reporting	0.9440*	0.9315*	0.6735*	0.9609*
	(0.2077)	(0.2084)	(0.4056)	(0.4637
High Education	0.1506	0.1341	-0.1449	0.1927
	(0.1452)	(0.1439)	(0.3120)	(0.4135)
Observations	742	742	100	91[a]

*Significant < 10% level

[a]Drops one individual who provided WTA > $50,000 but accepted posted price of $2,260.

The Logit regression in Table A.A.5 presents the response models of Table 4.10, including insignificant point estimates. Although significant differences appear between survey respondents and nonrespondents, these differences are not across all variables important in the bidding model.

Table A.A.5: Logit regressions of the response to the mail survey, with the dependent variable equaling one if an individual responded to the mail survey and zero otherwise, including insignificant point estimates (standard error)

Selection Model	**Maryland**	**Virginia**
Constant	-0.3383	-1.3953*
	(0.2076)	(0.2029)
Average licenses	-0.2782*	
	(0.0730)	
Bid	0.3300*	0.0694
	(0.1236)	(0.1285)
Personal	0.0030*	
	(0.0014)	
Retail	0.0121*	
	(0.0057)	
Age	-0.5023*	
	(0.0731)	
Buyback	-0.6424*	
	(0.1206)	
Distance	0.3504*	-0.1240
	(0.1666)	(0.2453)
Within 35 mi		-0.0620
		(0.1658)
Number of years fished	0.0230*	0.1008*
	(0.0110)	(0.0173)
Mult holders at address	-0.4876*	-0.4937*
	(0.2043)	(0.1688)
Profits	0.0469	-0.1126*
	(0.0828)	(0.0517)
Latent	-0.1817	
	(0.1154)	

Table A.A.5 (continued): Logit regressions of the response to the mail survey, with the dependent variable equaling one if an individual responded to the mail survey and zero otherwise, including insignificant point estimates (standard error)

Selection Model	**Maryland**	**Virginia**
Stopped Crabbing	-0.2253*	
	(0.1103)	
Late Reporting	-0.0724	
	(0.0877)	
Non-crabbing licenses		0.0574
		(0.1302)
Two Pot licenses		-0.0768
		(0.1237)
Observations	3588	1767
Model Likelihood Ratio	0.0000	0.0000

*Significant < 10% level

APPENDIX B: Multiple Imputations with Predicted Means Matching (PMM)

MI datasets were created using the MICE package (van Buuren & Groothuis-Oudshoorn, 2011) in R (R Development Core Team, 2011). The PMM algorithm was first outlined by Rubin (1987), who details the process as follows.

Assume the need to predict a univariate continuous random variable $Y_i \sim N(X_i\beta, \sigma^2)$, for which some observations are missing. Define n_1 as the number of observed Y_i, n_0 as the number of missing Y_i, and q as the number of parameters to be estimated.

Define:

(A.B.1) $\hat{\sigma}_1^2 = \sum_{i \in n_1}(Y_i - X_i\hat{\beta}_1)^2/(n_1 - q),$

(A.B.2) $\hat{\beta}_1 = [\sum_{i \in n_1} X_i' X_i]^{-1}[\sum_{i \in n_1} X_i' Y_i].$

Predicted means are generated in the following three steps:

1. Draw a $\chi^2_{n_1-q}$ random variable g and calculate $\sigma_*^2 = \hat{\sigma}_1^2(n_1 - q)/g$.
2. Draw q independent variates from the standard normal distribution to form vector Z and calculate $\beta_* = \hat{\beta}_1 + \sigma_*[\sum_{i \in n_1} X_i' X_i]^{-1/2}Z$, with $[\sum_{i \in n_1} X_i' X_i]^{-1/2}$ representing a Cholesky factorization.
3. Independently draw n_0 variates z_i from the standard normal distribution and construct the missing values of Y_i such that $Y_{i*} = X_i\beta_* + z_i\sigma_*$

Match the n_0 variables Y_{i*} to the nearest prediction for an observed Y_i, and set the missing observation equal to the observed value. Repeat the preceding steps m times to create m full datasets. The analysis of interest, in this case the estimation of equation 2.12, is then conducted independently on each of the m datasets.

The results of the analysis are then combined as specified by Rubin (1987). Point estimates for the parameters of interest are simply the average of the point estimates derived from each of the m datasets. For example, the estimated parameter on mean historical profits, β, is combined such that the final estimate, $\bar{\beta}_{MI}$, is calculated as $\bar{\beta}_{MI} = \sum_{l=1}^{m} \frac{\hat{\beta}_l}{m}$, where $\hat{\beta}_l$ is the point estimate in each complete dataset. The combination of results explicitly considers both the within and between dataset variation. The within dataset variation, W_{MI}, is simply the average variance of the m dataset estimates such that $W_{MI} = \sum_{l=1}^{m} \frac{W_l}{m}$. The between dataset variation, B_{MI} is calculated as $B_{MI} = \sum_{l=1}^{m} (\hat{\beta}_l - \bar{\beta}_{MI}) (\hat{\beta}_l - \bar{\beta}_{MI})' / (m-1)$, where $\hat{\beta}_l$ now represents the vector of parameters estimated from each imputed dataset, and $\bar{\beta}_{MI}$ is a vector of parameter means calculated across imputed datasets.

The within and between variance is then combined to calculate a total variance for the analysis, $T_{MI} = W_{MI} + (1 + \frac{1}{m}) B_{MI}$. Inference is conducted under the assumption that $T_{MI}^{-1/2} (\beta - \bar{\beta}_{MI}) \sim t_v$. The degrees of freedom of the t distribution, v, is calculated such that $v = (\frac{1}{v_m} + \frac{1}{v_{obs}})^{-1}$ (Barnard & Rubin, 1999). In this formulation $v_m = (m-1)[\left(1 + \frac{1}{m}\right) tr(\frac{B_{MI}}{T_{MI}})]^{-2}$, $v_{obs} = \frac{v_{com}+1}{v_{com}+3} v_{com} (1 - \left(1 + \frac{1}{m}\right) tr\left(\frac{B_{MI}}{T_{MI}}\right))$, v_{com} is the complete case degrees of freedom under no missing data, and $tr()$ is the trace operator. This degrees of freedom calculation directly considers the fact that the finite m imputations are used to approximate the asymptotically normal distribution of $\beta - \bar{\beta}_{MI}$, as well as the increased uncertainty due to non-response, in the calculation of critical values.

In this paper I impute WTA values for the 30 percent of survey respondents who did not submit them. Following the literature (Schafer, 1997), I use a shifted-log transformation on the WTA values to produce a more normally distributed dependent variable for imputation. The imputed variable is thus $f(WTA) = \ln(z - a)$. The shifter a is used to address skewness in the distribution of the WTA values, and is chosen by Maximum Likelihood estimation to produce zero skewness. The shifter a is calculated to be 0.0020 and -0.0103 respectively for the Maryland and Virginia.

The shifted-log of WTA values are modeled as functions of variables which theoretically could be important components of WTA. These variables include all those present in the empirical specification of equation 2.12, as prescribed by Rubin (1996). In Maryland these variables were supplemented with the natural log of an individual's average annual historical profits, indicator variables for the importance of profits, enjoyment of crabbing, and identity value for the license, the age of the license holder, indicator variables for whether the individual has heard of other licenses being sold, if the individual thought it was either likely or very likely that the crab population would return to higher and more sustainable levels in the next ten years, and the mean earnings from the individual's zip code. Virginia's imputation model was supplemented by the natural log of an individual's average annual historical profits, indicator variables for the importance of profits, family history, identity, and bequest values of the license, whether an individual was classified as wait listed or full time in the auction, whether an individual completed at least some college coursework, whether the license holder was over 60 at the time of the buyback, whether the individual self classified as recreational or both recreational and commercial, whether the individual felt it was very unlikely that the crab population would return to higher sustainable levels in the next ten years, and whether the individual held a large ($\geq$ 255 pot) license. WTA values were retransformed after imputation.

In the investigation of item nonresponse, I imputed 5 different values for each missing WTA observation, with 40 MCMC iterations between each draw. The 40 iterations provide a burn-in period through which any sensitivity to starting values due to autocorrelation of the simulations can be addressed.

The benefit of using a PMM algorithm over alternatives is its ability to hold imputations within the range of observed outcomes. This is an important characteristic when modeling bids, as imputing a negative value for what should be a non-negative bid amount could have adverse consequences for the analysis. The PMM algorithm also allows preservation of nonlinear relationships between predictors and dependent variables.

The largest drawback with the PMM algorithm is the potential to provide insufficient variation in the imputations due to a lack of strong predictors. Figure A.B.1 provides a graph of the distributions of observed and imputed WTA values for Virginia. As can be seen, the PMM algorithm provides for good variation between imputations. As an additional precaution, the results of the analysis presented in

Table 4.5 were compared to imputations generated directly through the third step of the PMM algorithm, such that the imputed WTA value $Y_{i*} = X_i\beta_* + z_i\sigma_*^2$, which provided very similar results.

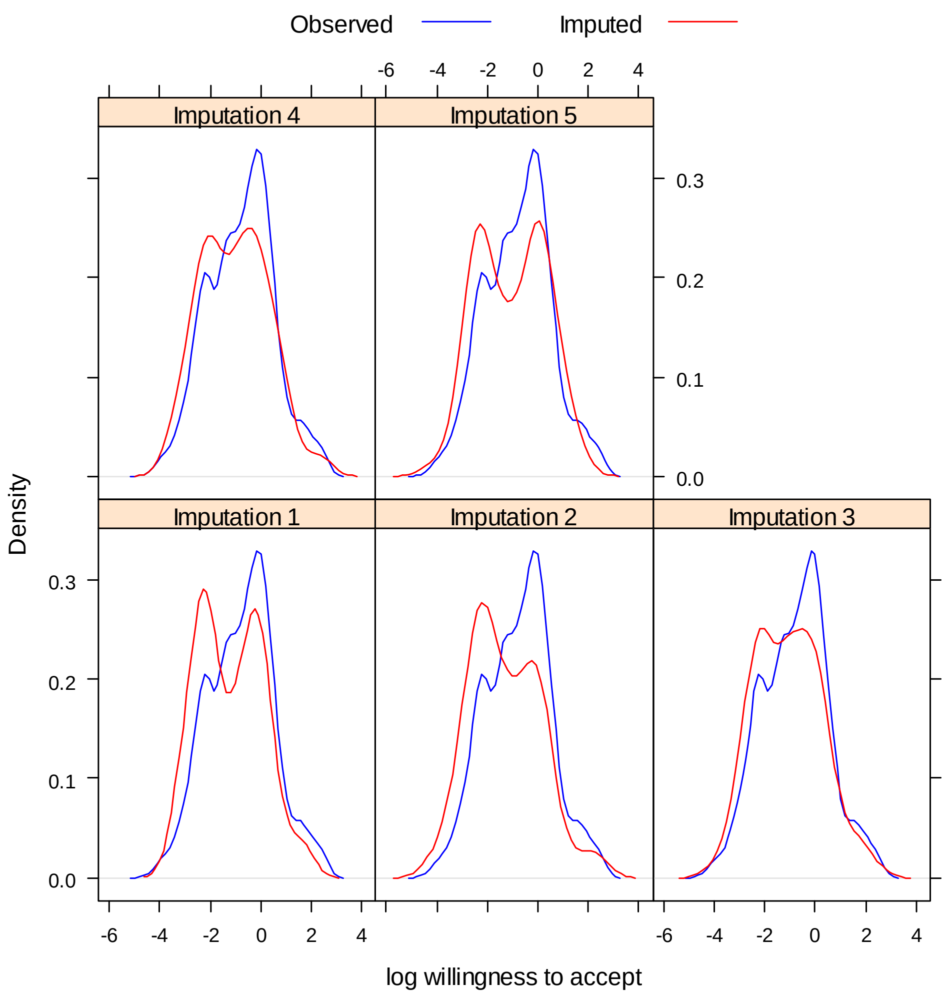


Figure A.B.1: Distribution of observed and imputed WTA values for Virginia

APPENDIX C: Categorical Variable Imputations

In addition to the PMM algorithm implemented for continuous variables, I also utilized two algorithms to impute categorical variables for the simulations presented in Chapter 5, one for dichotomous variables and one for categorical variables for more than two levels.

Dichotomous variables are imputed as follows:

Assume D_i is a dichotomous variable, and that $f(D_i|X_i,\theta) = \Lambda(X_i\theta)^{D_i}[1 - \Lambda(X_i\theta)]^{1-D_i}$, and $\Lambda(a) = \exp(a)/[1+\exp(a)]$. Some of the observations on D_i are missing, such that n_0 is the number of missing observations and n_1 is the number of observed D_i. Estimate, by maximum likelihood, the log-likelihood $ln\ L = \sum_{i \in n_1} D_i \ln\big(\Lambda(X_i\theta)\big) + (1-D_i)\ln(1 - \Lambda(X_i\theta))$ by numerically solving the first order conditions $\frac{\partial lnL}{\partial\theta} = \sum_{i \in n_1}(D_i - \Lambda(X_i\theta))X_i$. The variance is estimated as the negative inverse of the hessian matrix $V(\hat{\theta}) = -(\frac{\partial^2 lnL}{\partial\theta\partial\theta'})^{-1} = \left[\sum_{i \in n_1}\Lambda(X_i\theta)\big(1 - \Lambda(X_i\theta)\big)X_iX_i'\right]^{-1}$.

Imputations are drawn following these steps:

Draw θ_* from $N(\hat{\theta}, V(\hat{\theta}))$.
For each missing observation $i \in n_0$ calculate $\Lambda(X_i\theta_*)$.
Draw n_0 independent uniform (0,1) random numbers, u_i and if $u_i > \Lambda(X_i\theta_*), i \in n_0$ impute $D_i = 0$, otherwise impute $D_i = 1$.

Categorical variables with > 2 levels are imputed as follows:

Assume S_i is a categorical variable with J levels. Under a multinomial logit framework $Prob(S_i = j) = \frac{\exp(X_i\delta_l)}{\sum_{k\epsilon J} exp(X_i\delta_k)}, l \epsilon J$. Normalizing one of the δ vectors to zero means that $J - 1$ parameter vectors need to be estimated. The multinomial logit log-likelihood is then defined as $ln\ L = \sum_{i \in n_1} \sum_{j \epsilon J} s_{ij} \ln\left(\frac{\exp(X_i\delta_j)}{1+\sum_{k \epsilon J-1} \exp(X_i\delta_k)}\right)$. The first order conditions, $\frac{\partial lnL}{\partial \delta_j} = \sum_{i \in n_1}(s_{ij} - \frac{\exp(X_i\delta_j)}{1+\sum_{k \epsilon J-1} \exp(X_i\delta_k)})X_i, j \epsilon J - 1$.

Imputations are drawn following these steps:

1. Draw $\delta_* = \delta_{*1}, \dots, \delta_{*J-1} \sim N(\hat{\delta}, V(\hat{\delta}))$.
2. Calculate $Prob_*(S_i = j) = \frac{\exp(X_i\delta_{*j})}{1+\sum_{k \epsilon J-1} \exp(X_i\delta_{*k})}, j \in J$.
3. Draw n_0 uniform (0,1) random numbers, u_i.
   Calculate a vector of cumulative probabilities,
   $\sum_{k \in 1} Prob_*(S_i = k), \dots, \sum_{k \in J} Prob_*(S_i = k)$, and impute missing value S_{*i} as the first category for which the cumulative probability is larger than u_i.

In Maryland, the following dichotomous variables used directly in the analysis were imputed for individuals who did not respond to the survey: Probably crab, Bequest, Identity, and High Education. The Commercial, Recreational, and Both comm. and rec. indicator variables from the analysis were imputed as a three-level categorical variable. A very small number of individuals lacked the Distance variable, as their address could not be located with GIS software. This continuous variable is imputed using a PMM algorithm. In addition, I imputed the following auxiliary variables used to impute the variables of interest: dichotomous variables indicating the importance of the Enjoyment of Crabbing, Family History, and Profits in the value of an individual's license, and continuous variable Mean earnings. Nonimputed auxiliary variables used in the imputation process include the average percentage of harvest history distributed to retailers, dealers, the public, and for personal consumption, the average percentage of trips using crab traps, scrapes, trotlines, and small pots as their primary gear, the average number of non-crabbing licenses an individual held across their harvest history, whether the individual accepted the posted price offer, the number of years an individual was active in the data, and the average number of hours and the average total annual days crabbed across an individual's harvest history.

In Virginia the variables Heard, Enjoy crabbing, Identity value, and Probably crab, and the indicator variables Commercial, Recreational, and Both comm. and rec. are all imputed for both direct use in the estimations of the paper and for imputing an individual's WTA values. All of these are dichotomous variables, except the last three indicator variables, which are imputed as a three level categorical variable. As in Maryland, a very small number of individuals lacked a distance variable due to their address being unidentifiable with GIS software, and this continuous variable was imputed using a PMM algorithm. Auxiliary variables High Education and an indicator variable for the importance of profits were imputed as dichotomous variables. The auxiliary variables including the size of the license, the average percentage of trips using trotlines, small pots, medium pots and peeler pots as their primary gear, the average number of crabbing and non-crabbing licenses an individual held across their harvest history, whether the individual accepted the posted price offer, the number of years an individual was active in the data, whether an individual had engaged an agent to fish on their behalf at some point over their harvest history, and the average number of trips per year using both hard and peeler pots, were all used in the imputation process.

In Table A.C.1 I investigate the extent to which nonresponse bias effects the estimation by comparing the WTA results of Table 4.2 with results of MI datasets, in which all missing data is imputed. One hundred draws were made for each missing observation, and the results were combined in the same manner as described in Appendix B. All specifications are semilog, with the natural log of an individual's WTA as the dependent variable. Point estimates across Maryland's specifications are generally consistent, with the biggest deviation resting with the Profits, and Commercial parameters. Virginia's parameter estimates diverge to a much greater extent, with the largest differences generally residing in the imputed variables.

Table A.C.1: Estimation of the WTA function comparing results of Table 4.2 with MI regression analysis to control for potential unit nonresponse bias (standard error)

Coefficient	**MD WTA**	**MDMI**	**VA WTA**	**VA MI**
Constant	-2.8138*	-2.8594*	-2.8014*	-2.0284*
	(0.1273)	(0.1134)	(0.2017)	(0.1635)
Profits	0.4513*	0.1781*	0.1658*	0.2202*
	(0.0856)	(0.0792)	(0.0502)	(0.0436)
Probably crab	0.2836*	0.3196*	0.3940*	0.0636
	(0.1177)	(0.0908)	(0.1550)	(0.0879)
Age	0.4968*	0.4785*		
	(0.0837)	(0.0782)		
Bequest	0.2909*	0.2752*		
	(0.0863)	(0.0775)		
Both rec. and comm.	0.1753*	0.1776*		
	(0.0870)	(0.0744)		
Latent	-0.3098*	-0.3230*		
	(0.1060)	(0.1006)		
Commercial		0.2544*	0.7368*	0.2762*
		(0.1310)	(0.1473)	(0.0911)
Enjoy crabbing			0.4394*	0.1028
			(0.1138)	(0.0702)
Large pot license			0.8683*	0.8042*
			(0.1487)	(0.1473)
Wait list			-0.3887*	-0.8583
			(0.1852)	(0.1621)
Peeler Pot License			0.5898*	0.5381*
			(0.1493)	(0.1545)
Non-crabbing license			0.4185*	0.3705*
			(0.1325)	(0.0946)
Observations	768	3584	431	2270

APPENDIX D: Inverse Propensity Weighted (IPW) Estimator

Table A.D.1 presents IPW estimators of the bid function, compared to the unweighted OLS, with the natural log of an individual's WTA as the dependent variable for each state. Maryland and Virginia's point estimates respectively differ by an average of 22 and 18 percent of the unweighted standard error. The only p-value which differs greatly across specifications is the parameter associated with the Both rec. and comm. indicator, which is not significant at any conventional level for Maryland's IPW specification. Although a comparison of point estimates suggest that the two models are not significantly different, a Wilcoxon signed-rank test suggests that the conditional means are, in fact, drawn from different distributions, with a p-value of 0.0000 and an unweighted mean significantly larger that the IPW mean for both states, with a positive suggested bias of roughly 2.5-4% in the OLS estimate for each state.

Table A.D.1: Estimation of the WTA function comparing Table 4.2 results with an IPW regression to control for potential unit nonresponse bias (standard error)

Coefficient	MD WTA	MD IPW[a]	VA WTA	VA IPW[a]
Constant	-2.8138*	-2.8300*	-2.8014*	-2.7898*
	(0.1273)	(0.1315)	(0.2017)	(0.2040)
Profits	0.4513*	0.4523*	0.1658*	0.1385*
	(0.0856)	(0.1350)	(0.0502)	(0.0382)
Probably crab	0.2836*	0.2912*	0.3940*	0.4120*
	(0.1177)	(0.1332)	(0.1550)	(0.1872)
Age	0.4968*	0.4545*		
	(0.0837)	(0.0997)		
Bequest	0.2909*	0.2966*		
	(0.0863)	(0.0907)		
Both rec. and comm.	0.1753*	0.1154		
	(0.0870)	(0.0928)		
Latent	-0.3098*	-0.3179*		
	(0.1060)	(0.1106)		
Commercial			0.7368*	0.7371*
			(0.1473)	(0.1504)
Enjoy crabbing			0.4394*	0.3871*
			(0.1138)	(0.1198)
Large pot license			0.8683*	0.8650*
			(0.1487)	(0.1483)
Wait list			-0.3887*	-0.3634*
			(0.1852)	(0.2039)
Peeler Pot License			0.5898*	0.6018*
			(0.1493)	(0.1574)
Non-crabbing license			0.4185*	0.3959*
			(0.1325)	(0.1536)
Observations	768	766	431	431

*Significant at < 10% level

[a]Robust Standard Errors

APPENDIX E: Survey of Maryland License Holders

Maryland Limited Crab Catcher License Survey

(Image by Wpopp, GFDL, http://commons.wikimedia.org/wiki/User:Wpopp/Image_Gallery)

Please direct questions or comments to:
Geret DePiper
(email) gdepiper@arec.umd.edu (phone) 703-869-5778
or Doug Lipton
(email) dlipton@arec.umd.edu (phone) 301-405-1280

Department of Agricultural and Resource Economics
College of Agriculture and Natural Resources
University of Maryland, College Park
2200 Symons Hall
College Park, Maryland 20742-5535

General Fishing Information

1 What other states or areas do you hold commercial fishing licenses in?

- Virginia ☐
- Potomac ☐
- Other ☐
- None ☐

2 How many years of commercial fishing experience do you have?
Write none if you have never commercially fished.

☐ years

3 **Personal use**: What percentage of the following do you keep for yourself?

Soft crab catch	%
Peeler crab catch	%
Hard crab catch	%

4 In recent seasons the blue crab population has been near historically low levels prompting increased harvest restrictions and regulations by Maryland Department of Natural Resources (DNR). How likely do you think it is that the blue crab population will return to higher, more sustainable levels in the next 10 years?

- Very likely ☐
- Somewhat likely ☐
- Somewhat unlikely ☐
- Very unlikely ☐

Limited Crab Catcher License (LCC) Information

5 Why is the LCC license important to you? **Using each number only once**, please rank the following reasons from 1 (most important) to 4 (least important).

	Most 1	2	3	Least 4
Because of the profit that I can earn from it.	☐	☐	☐	☐
Because of the family history that it represents.	☐	☐	☐	☐
Because of how much I enjoy crabbing.	☐	☐	☐	☐
Because crabbing is part of who I am.	☐	☐	☐	☐

6 For how many generations has your family been crabbing?
If you are the first crabber in your family please write 1.

☐ generations

7 How did you originally get your LCC license? Please check only one.

- It was given to me by a family member. ☐
- I bought it from a family member. ☐
- I bought it on the market. ☐
- I received it through an apprenticeship. ☐
- I received it from the DNR before apprenticeships were needed. ☐
- Other (please explain):

___

___

8 Imagine that a waterman you don't know wants to buy your LCC license from you. What is the **smallest amount of money** you would be willing to sell your license to that waterman for? If you no longer own the license, think back to when you did and answer the question as if you still own an LCC license.

$		.00

9 Check the box next to any family members who have LCC licenses.

- Mother/Father/Grandparent ☐
- Son/Daughter ☐
- Brothers/Sisters ☐
- Aunts/Uncles/Nieces/Nephews ☐
- Other ☐

10 Would you classify yourself as a commercial or recreational crabber?

- Commercial ☐
- Recreational ☐
- Both ☐

LCC License Buyback

You might be aware that the Maryland DNR recently began buying LCC licenses back from license holders. In the first stage, the DNR asked individuals to provide a bid for the amount of money you were willing to sell your license back to the state for in a process known as a reverse auction. In the second stage, the DNR offered $2,260 to anyone willing to trade in their license at that price.

11 Did you sell your LCC license to the Maryland DNR for $2,260?

Yes ☐ No ☐

12 When you were deciding whether to participate in the buyback, how likely did you think it was that you would crab in 2010?

- Very likely ☐
- Somewhat likely ☐
- Somewhat unlikely ☐
- Very unlikely ☐

13 Did you submit a bid in the auction? If you **answer Yes to this question**, please answer the following 3 questions. If you **did not provide a bid** in the auction, please check No and skip to question 17.

Yes ☐ No ☐

14 What was your bid? $ ________ .00

15 How did you come up with this bid? Check as many as apply to you.

- I spoke to other fishermen about what they were bidding. ☐
- I calculated what I have paid in past license fees. ☐
- I calculated what I would have made crabbing if I kept the license. ☐
- I looked at what the license was worth in the open market. ☐
- I included some sentimental value for the license. ☐
- I included some value for the joy I have crabbing. ☐
- I thought of what the license would be worth to my children. ☐
- Other (please explain)

____

____

16 If your bid in the auction was more than $2,260 and you sold your license to the Maryland DNR for $2,260, why did you accept $2,260?

____

____

____

____

____

17 If you **did not bid** in the auction, why didn't you bid? Check any reasons that apply to you. If you **bid** in the auction please skip to question 18.

- [ ] I plan on giving the license to a family member.
- [ ] It was unclear how the reverse auction worked.
- [ ] I am making too much money from the license to sell it.
- [ ] Although I am not currently using the license, I plan to in the future.
- [ ] I enjoy crabbing too much to sell the license.
- [ ] If the economy crashes the license helps me support my family.
- [ ] I would potentially sell my license, just not to the Maryland DNR.
- [ ] I was not aware of the auction.

Other (please explain):

____

____

18 Did any other members of your family:

Submit a bid in the LCC auction?	Yes ☐	No ☐
Sell a license back to MD DNR for $2,260?	Yes ☐	No ☐

19 Would you have bid if, assuming your bid was accepted, the Maryland DNR made you wait 3 years before getting another LCC license?

Yes ☐ No ☐

20 If the buyback was to be run again, would you prefer an auction or a flat offer?

Auction ☐ Flat Offer ☐

21 Think back to the auction. What bid would you submit if you had a chance to resubmit a bid in the auction? Write none if you would not bid.

$ ______ .00

22 Have you heard of anyone selling their LCC license to another waterman?

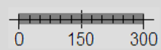
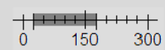
Yes ☐ No ☐

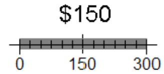
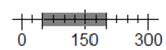
23 If you answered yes to question 22, what price did you hear the license being sold for? If you know of more than one license being sold, please provide the average price of those licenses.

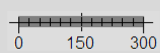
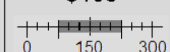
$ ______ .00

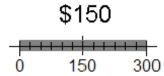
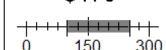
Choose the fishing trip you would prefer to take

Each of the next 4 questions is a choice between two fishing trips. Assume that there is an equal chance of earning any particular amount of money between the lowest and highest profits given for each trip. In each question choose the trip that you would prefer to take. **There are no right or wrong answers**, and we are only interested in your opinions.

24	Fishing Trip A	Fishing Trip B
Lowest and highest profit for trip	$0 - $300	$25 - $175
Average profit on each trip	$150	$100
Graph of possible profits		
Which trip would you choose?	Trip A ☐	Trip B ☐

25	Fishing Trip A	Fishing Trip B
Lowest and highest profit for trip	$0 - $300	$50 - $200
Average profit on each trip	$150	$125
Graph of possible profits		
Which trip would you choose?	Trip A ☐	Trip B ☐

26	Fishing Trip A	Fishing Trip B
Lowest and highest profit for trip	$0 - $300	$75 - $225
Average profit on each trip	$150	$150
Graph of possible profits		
Which trip would you choose?	Trip A ☐	Trip B ☐

27	Fishing Trip A	Fishing Trip B
Lowest and highest profit for trip	$0 - $300	$100 - $250
Average profit on each trip	$150	$175
Graph of possible profits		
Which trip would you choose?	Trip A ☐	Trip B ☐

Vessel Information

Answer the following questions about the boat you use for crabbing most often.

28 Do you own the boat? If you **answer Yes to this question**, please answer the following 6 questions. If you **do not own the boat**, please check No and skip to question 35.

Yes ☐ No ☐

29 Age of boat: ____ years

30 Length of boat: ____ feet

31 Age of engine: ____ years

32 Total boat horsepower: ____ horsepower

33 Estimated market value of boat: $ ____ .00

34 Where is this boat docked?

Nearest Town or City ____

State ____

Demographic Information

35 What is your age?

Under 18 years old	☐
18 – 29 years old	☐
30 – 39 years old	☐
40 – 49 years old	☐
50 – 59 years old	☐
60 + years old	☐

36 What is your sex? Male ☐ Female ☐

37 What is your race?

Caucasian	☐
African American/Black (non-Hispanic)	☐
Hispanic	☐
Asian/Pacific Islander	☐
American Indian/Alaskan Native	☐
Other	☐

38 What is the highest level of education that you completed?

Less than high school	☐
High school graduate/GED	☐
Some College	☐
Bachelor's degree or higher	☐

39 What is your marital status?

Single, never married ☐
Married ☐
Separated/Divorced ☐
Widowed ☐

40 How many children do you have? ☐

41 If you have children, are any watermen?

Yes ☐ No ☐

42 What is your approximate annual household income before taxes? This should include income from spouses or other household members, as well as non-work related income such as rental properties. (check only one)

Under $20,000 ☐
$20,000 - $39,999 ☐
$40,000 - $59,999 ☐
$60,000 - $79,999 ☐
$80,000 - $100,000 ☐
Over $100,000 ☐

43 What percentage of your annual household income is from the following:

Crabbing ___ %
Other fishing activities ___ %
Non-fishing activities ___ %

If you have any additional comments, feel free to write them on another sheet of paper and include them in the return envelope along with the completed survey. Thanks for your help!

APPENDIX F: Survey of Virginia License Holders

Virginia Commercial Crab Pot License Survey

(Image by Wpopp, GFDL, http://commons.wikimedia.org/wiki/User:Wpopp/Image_Gallery)

Please direct questions or comments to:
Geret DePiper
(email) gdepiper@arec.umd.edu (phone) 703-869-5778
or Doug Lipton
(email) dlipton@arec.umd.edu (phone) 301-405-1280

Department of Agricultural and Resource Economics
College of Agriculture and Natural Resources
University of Maryland, College Park
2200 Symons Hall
College Park, Maryland 20742-5535

General Fishing Information

1 What other states or areas do you hold commercial fishing licenses in?

- Maryland ☐
- Potomac ☐
- Other ☐
- None ☐

2 How many years of commercial fishing experience do you have?
Write none if you have never commercially fished.

☐ years

3 **Personal use**: What percentage of the following do you keep for yourself?

Soft crab catch	%
Peeler crab catch	%
Hard crab catch	%

Crab Pot License Information

4 Why is the commercial pot license important to you? **Using each number only once**, please rank the following reasons from 1 (most important) to 4 (least important).

	Most 1	2	3	Least 4
Because of the profit that I can earn from it.	☐	☐	☐	☐
Because of the family history that it represents.	☐	☐	☐	☐
Because of how much I enjoy crabbing.	☐	☐	☐	☐
Because crabbing is part of who I am.	☐	☐	☐	☐

5 For how many generations has your family been crabbing?
If you are the first crabber in your family please write 1.

[ ] generations

6 Did you own a commercial **hard crab pot** license between August and November 2009? If you did not own a commercial hard crab pot license during this time, please check No and skip to question 9.

Yes [ ] No [ ]

7 How did you originally get your commercial hard crab pot license?

It was given to me by a family member. [ ]
I bought it from a family member. [ ]
I bought it on the market. [ ]
I received it from the VMRC. [ ]
Other (please explain):

____

____

8 Imagine that a waterman you don't know wants to buy your commercial hard crab pot license from you. What is the **smallest amount of money** you would be willing to sell your license to that waterman for? If you no longer own the license, think back to when you did and answer the question as if you still own a commercial hard crab pot license.

$ [ ] .00

9 Did you own a commercial **peeler** pot license between August and November 2009? **If you did not own** a commercial peeler pot license during this time, please check No and skip to question 12.

Yes ☐ No ☐

10 How did you originally get your commercial peeler pot license?

It was given to me by a family member. ☐
I bought it from a family member. ☐
I bought it on the market. ☐
I received it from the VMRC. ☐
Other (please explain):

____

____

11 Imagine that a waterman you don't know wants to buy your commercial peeler pot license from you. What is the **smallest amount of money** you would be willing to sell your license to that waterman for? If you no longer own the license, think back to when you did and answer the question as if you still own a commercial peeler pot license.

$ ____________ .00

12 Do any of your family members have **commercial pot licenses** in Virginia? For each person listed please check all that apply.

	Hard Crab license	Peeler license
Father/Mother/Grandparent →	☐	☐
Son/Daughter →	☐	☐
Brother/Sister →	☐	☐
Aunt/Uncle/Niece/Nephew →	☐	☐
Other →	☐	☐

13 Would you classify yourself as a commercial or recreational crabber?

- Commercial ☐
- Recreational ☐
- Both ☐

14 In recent seasons the blue crab population has been near historically low levels prompting increased harvest restrictions and regulations by the Virginia Marine Resources Commission (VMRC). How likely do you think it is that the blue crab population will return to higher, more sustainable levels in the next 10 years?

- Very likely ☐
- Somewhat likely ☐
- Somewhat unlikely ☐
- Very unlikely ☐

Crab Pot License Buyback

You might be aware that the VMRC recently began buying commercial crab pot licenses back from license holders through what is called a reverse auction.

15 When you were deciding whether to participate in the auction, how likely did you think it was that you would crab for each of the following in 2010?

	Hard Crabs	Peeler Crabs
Very likely →	☐	☐
Somewhat likely →	☐	☐
Somewhat unlikely →	☐	☐
Very unlikely →	☐	☐

16 Did you submit a bid for your commercial hard crab pot license?

Yes ☐ No ☐

If you answered No to this question, please skip to question 18.

17 What was your hard crab pot license bid?

$ ______ .00

18 Did you submit a bid for your commercial peeler pot license?

Yes ☐ No ☐

If you answered No to this question, please skip to question 20.

19 What was your peeler pot license bid?

$ ______ .00

20 How did you come up with your bid? Check as many as apply to you. If you did not submit a bid for any of your licenses, please skip to question 21.

- I spoke to other fishermen about what they were bidding. ☐
- I calculated what I have paid in past license fees. ☐
- I calculated what I would have made crabbing if I kept the license. ☐
- I looked at what the license was worth in the open market. ☐
- I included some sentimental value for the license. ☐
- I included some value for the joy I have crabbing. ☐
- I thought of what the license would be worth to my children. ☐
- Other (please explain)

21 If you **did not bid in the hard pot auction, but owned a commercial hard pot license** between August and November 2009, why didn't you bid? Check any reasons that apply to you. Please skip to question 22 if you bid for or didn't own a hard pot license between August and November 2009.

- I plan on giving the license to a family member. ☐
- It was unclear how the reverse auction worked. ☐
- I am making too much money from the license to sell it. ☐
- Although I am not currently using the license, I plan to in the future. ☐
- I enjoy crabbing too much to sell the license. ☐
- If the economy crashes the license helps me support my family. ☐
- I would potentially sell my license, just not to the VMRC. ☐
- I wanted to sell only one of my licenses. ☐
- I was not aware of the auction ☐
- Other (please explain):

____

____

22 If you **did not bid in the peeler pot auction, but owned a commercial peeler pot license** between August and November 2009, why didn't you bid? Check any reasons that apply to you. Please skip to question 23 if you bid for or didn't own a peeler pot license between August and November 2009.

- I plan on giving the license to a family member. ☐
- It was unclear how the reverse auction worked. ☐
- I am making too much money from the license to sell it. ☐
- Although I am not currently using the license, I plan to in the future. ☐
- I enjoy crabbing too much to sell the license. ☐
- If the economy crashes the license helps me support my family. ☐
- I would potentially sell my license, just not to the VMRC. ☐
- I wanted to sell only one of my licenses. ☐
- I was not aware of the auction. ☐
- Other (please explain):

____

____

23 Did any other members of your family:

Submit a bid in the hard pot auction? Yes ☐ No ☐

Submit a bid in the peeler pot auction? Yes ☐ No ☐

24 Would you have bid if the VMRC made you wait for 3 years before harvesting crabs with a similar license? For example, if you sold a hard crab pot license, you would not be able to use a hard crab pot license for 3 years.

Yes ☐ No ☐

25 If the buyback was to be run again, would you prefer an auction or a flat offer?

Auction ☐ Flat Offer ☐

26 Think back to the auction. What bid would you submit if you had a chance to resubmit a bid for your **hard pot license**? Write none if you would not bid.

$ ______ .00

27 Think back to the auction. What bid would you submit if you had a chance to resubmit a bid for your **peeler pot license**? Write none if you would not bid.

$ ______ .00

28 Have you heard of anyone selling the following licenses to another waterman?

Virginia commercial hard crab pot license Yes ☐ No ☐

Virginia commercial peeler pot license Yes ☐ No ☐

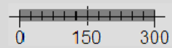
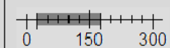
29 If you answered Yes to question 28, what price did you hear the license being sold for? If you know of more than one license being sold, please provide the average price of those licenses.

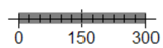
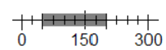
Commercial hard crab pot license $ ______ .00

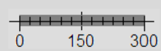
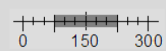
Commercial peeler pot license $ ______ .00

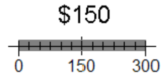
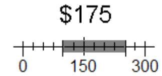
Choose the fishing trip you would prefer to take

Each of the next 4 questions provides a choice between a range of possible profits on two hypothetical fishing trips. Assume that there is an equal chance of earning any particular amount of money between the lowest and highest profits stated in each trip. In each question choose the trip that you would prefer to take. **There are no right or wrong answers.** We are only interested in your opinions.

30	Fishing Trip A	Fishing Trip B
Lowest and highest profit for trip	$0 - $300	$25 - $175
Average profit on each trip	$150	$100
Graph of possible profits		
Which trip would you choose?	Trip A ☐	Trip B ☐

31	Fishing Trip A	Fishing Trip B
Lowest and highest profit for trip	$0 - $300	$50 - $200
Average profit on each trip	$150	$125
Graph of possible profits		
Which trip would you choose?	Trip A ☐	Trip B ☐

32	Fishing Trip A	Fishing Trip B
Lowest and highest profit for trip	$0 - $300	$75 - $225
Average profit on each trip	$150	$150
Graph of possible profits		
Which trip would you choose?	Trip A ☐	Trip B ☐

33	Fishing Trip A	Fishing Trip B
Lowest and highest profit for trip	$0 - $300	$100 - $250
Average profit on each trip	$150	$175
Graph of possible profits		
Which trip would you choose?	Trip A ☐	Trip B ☐

Vessel Information

Answer the following questions about the boat you use for crabbing most often.

34 Do you own the boat? If you **answer Yes to this question**, please answer the following 6 questions. If you **do not own the boat**, please check No and skip to question 41.

Yes ☐ No ☐

35 Age of boat: ☐ years

36 Length of boat: ☐ feet

37 Age of engine: ☐ years

38 Total boat horsepower: ☐ horsepower

39 Estimated market value of boat: $ ______ .00

40 Where is this boat docked?

Nearest Town or City ______

State ______

Demographic Information

41 What is your age?

- Under 18 years old ☐
- 18 – 29 years old ☐
- 30 – 39 years old ☐
- 40 – 49 years old ☐
- 50 – 59 years old ☐
- 60 + years old ☐

42 What is your sex? Male ☐ Female ☐

43 What is your race?

- Caucasian ☐
- African American/Black (non-Hispanic) ☐
- Hispanic ☐
- Asian/Pacific Islander ☐
- American Indian/Alaskan Native ☐
- Other ☐

44 What is the highest level of education that you completed?

- Less than high school ☐
- High school graduate/GED ☐
- Some college ☐
- Bachelor's degree or higher ☐

45 What is your marital status?

Single, never married	☐
Married	☐
Separated/Divorced	☐
Widowed	☐

46 How many children do you have? ____

47 If you have children, are any watermen?

Yes ☐ No ☐

48 What is your approximate annual household income before taxes? This should include income from spouses or other household members, as well as non-work related income such as rental properties. (check only one)

Under $20,000	☐
$20,000 – $39,999	☐
$40,000 – $59,999	☐
$60,000 – $79,999	☐
$80,000 – $100,000	☐
Over $100,000	☐

49 What percentage of your annual household income is from the following:

Crabbing	%
Other fishing activities	%
Non-fishing activities	%

If you have any additional comments, feel free to write them on another sheet of paper and include them in the return envelope along with the completed survey. Thanks for your help!

Bibliography

Anderson, L. G. (1980). Necessary components of economic surplus in fisheries economics. *Canadian Journal of Fisheries and Aquatic Sciences*, *37*(5), 858–870.

Avila-Forcada, S., Martínez-Cruz, A. L., & Muñoz-Piña, C. (2012). Conservation of vaquita marina in the Northern Gulf of California. *Marine Policy*, *36*(3), 613–622.

Bajari, P., & Hortacsu, A. (2003). The winner's curse, reserve prices, and endogenous entry: empirical insights from eBay auctions. *RAND Journal of Economics*, *34*(2), 329–355.

Barnard, J., & Rubin, D. (1999). Miscellanea. Small-sample degrees of freedom with multiple imputation. *Biometrika*, *86*(4), 948 –955. doi:10.1093/biomet/86.4.948

Berman, M., Haley, S., & Kim, H. (1997). Estimating net benefits of reallocation: Discrete choice models of sport and commercial fishing. *Marine Resource Economics*, *12*, 307–328.

Binkley, M. (2000). "Getting by" in tough times: Coping with the fisheries crisis. *Women's Studies International Forum*, *23*(3), 323–332. doi:10.1016/S0277-5395(00)00090-X

Bjørndal, T., & Jon M. Conrad. (1987). The dynamics of an open access fishery. *The Canadian Journal of Economics / Revue canadienne d'Economique*, *20*(1), 74–85. doi:10.2307/135232

Botterill, L. (2001). Policy approaches to farm exit: Some factors influencing the eficacy of Commonwealth programs. *Canberra, Bureau of Rural Sciences*.

Cerda-D'Amico, R. J., & Urbina-Véliz, M. (2000). ITSQ in Chilean fisheries: The case of the squat lobster (Pleuroncodes monodon). *Proceedings of the tenth biennial conference of the International Institute of Fisheries Economics and Trade*. Presented at the IIFET 2000: Microbehavior and macroresults, Oregon State University, Corvallis Oregon.

Chaves, P., Pichler, H., Robert, M., Chaves, P., Pichler, H., & Robert, M. (2002). Biological, technical and socioeconomic aspects of the fishing activity in a Brazilian estuary, Biological, technical and socioeconomic aspects of the fishing activity in a Brazilian estuary. *Journal of Fish Biology, Journal of Fish Biology*, *61, 61*(sA,), 52, 52–59, 59. doi:10.1111/j.1095-8649.2002.tb01760.x, 10.1111/j.1095-8649.2002.tb01760.x

Clark, Colin W, Clarke, F. H., & Munro, G. R. (1979). The optimal exploitation of renewable resource stocks: Problems of irreversible investment. *Econometrica*, *47*(1), 25–47.

Clark, C. W., Munro, G. R., & Sumaila, U. R. (2005). Subsidies, buybacks, and sustainable fisheries. *Journal of Environmental Economics and Management*, *50*(1), 47–58.

Clark, C. W., Munro, G. R., & Sumaila, U. R. (2007). Buyback subsidies, the time consistency problem, and the ITQ alternative. *Land Economics*, *83*(1), 50.

Commission of the European Communities. (2002). *Mid-term Review of the Common Agricultural Policy* (Communication from the Commission to the Council and the Euopean Parliament No. Com(2002) 394 final). Brussels: Commission of the European Communities.

Davis, D. (2000). Gendered cultures of conflict and discontent: Living “the crisis” in a Newfoundland community. *Women’s Studies International Forum*, *23*(3), 343–353. doi:10.1016/S0277-5395(00)00092-3

DePiper, G., Higgins, N., Lipton, D., & Stocking, A. (2011). *Auction design, incentives, and buying back Maryland and Virginia crab licenses*. Mimeo.

DePiper, G. S., & Lipton, D. W. (2009). *Designing a license buy back program for Maryland’s Blue Crab fishery: Limited Crab Catcher Licenses*. Maryland Department of Natural Resources.

Eggert, H., & Tveterås, R. (2007). Potential rent and overcapacity in the Swedish Baltic Sea trawl fishery for cod (Gadus Morhua). *ICES Journal of Marine Science: Journal du Conseil*, *64*(3), 439–445. doi:10.1093/icesjms/fsm019

Fox, K. J., Grafton, R. Q., Kompas, T., & Che, T. N. (2007). Capacity reduction and productivity: A profit decomposition for the Australian south east trawl fishery. In R. Curtis & D. Squires (Eds.), *Fisheries buybacks* (pp. 67–74). Blackwell Publishing.

Garber, D., & Bromley, D. (2003, September 4). *The role of auctions in managing capacity and effort in fisheries*. Presented at the People and the Sea: II, Amsterdam, The Netherlands.

Gatewood, J. B., & McCay, B. J. (1990). Comparison of job satisfaction in six New Jersey fisheries: implications for management. *Human Organization*, *49*(1), 14–25.

Gimeno, J., Folta, T. B., Cooper, A. C., & Woo, C. Y. (1997). Survival of the Fittest? Entrepreneurial Human Capital and the Persistence of Underperforming Firms. *Administrative Science Quarterly*, *42*(4), 750–783. doi:10.2307/2393656

Gordon, H. S. (1954). The Economic Theory of a Common-Property Resource: The Fishery. *The Journal of Political Economy*, *62*(2), 124–142.

Greene, W. H. (2003). *Econometric analysis* (5th ed.). Saddle River, NJ: Prentice Hall Upper.

Groves, T., & Squires, D. (2007). Lessons from fisheries buybacks. In R. Curtis & D. Squires (Eds.), *Fisheries buybacks* (pp. 15 – 53). Blackwell Publishing.

Holland, D., Gudmundsson, E., & Gates, J. (1999). Do fishing vessel buyback programs work: a survey of the evidence. *Marine Policy*, *23*(1), 47–69.

Hoppe, R. A., MacDonald, J. M., & Korb, P. (2010). *Small farms in the United States: persistence under pressure* (No. 63). Economic Information Bulletin. USDA Economic Research Service. Retrieved from http://www.ers.usda.gov/publications/eib63/

Horobin, G. W. (1957). Community and Occupation in the Hull Fishing Industry. *The British Journal of Sociology*, *8*(4), 343–356. doi:10.2307/587980

Ilbery, B., Ingram, J., Kirwan, J., Maye, D., & Prince, N. (2009). Structural change and new entrants in UK agriculture: examining the role of county farms and the Fresh Start initiative in Cornwall. *Journal of the Royal Agricultural Society of England*, *170*, 77–83.

Internal Revenue Service. (2010). *Farmer's tax guide for use in preparing 2010 returns* (No. Publication 225). Department of the Treasury.

Jack, B. K. (2011). Designing markets for carbon offsets: A field experiment in Malawi. *SSRN eLibrary*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1638563

Jack, C. G., Moss, J. E., & Wallace, M. T. (2009). 111 EAAE-IAAE Seminar "Small farms: decline or persistence."

Kirkley, J. E., & Strand, I. E. (1988). The technology and management of multi-species fisheries. *Applied Economics*, *20*(10), 1279–1292.

Kitts, A., Thunberg, E., & Robertson, J. (2000). Willingness to participate and bids in a fishing vessel buyout program: A case study of New England groundfish. *Marine Resource Economics*, *15*(3).

Kjerstad, E., & Vagstad, S. (2000). Procurement auctions with entry of bidders. *International Journal of Industrial Organization*, *18*(8), 1243–1257.

Li, T. (2005). Econometrics of first-price auctions with entry and binding reservation prices. *Journal of Econometrics*, *126*(1), 173–200.

Li, Tong, & Zhang, B. (2010). Testing for affiliation in first-price auctions using entry behavior. *International Economic Review*, *51*(3), 837–850. doi:10.1111/j.1468-2354.2010.00603.x

List, J. A. (2003). Does market experience eliminate market anomalies? *Quarterly Journal of Economics*, *118*(1), 41–71. doi:10.1162/00335530360535144

Mamula, A. (2009). *License buyback programs in commercial fisheries: An application to the shrimp fishery in the Gulf of Mexico* (Ph.D. Dissertation). Texas A&M University.

Maryland Department of Natural Resources. (2009a). *Maryland Department of Natural Resources' grant proposal for Federal blue crab fishery disaster funding.* (p. 9). Maryland Department of Natural Resource, Fisheries Service.

Maryland Department of Natural Resources. (2009b). *Blue crab latent effort & housekeeping*. Easton, MD.

McConnell, K. E. (1997). Does altruism undermine existence value? *Journal of Environmental Economics and Management*, *32*(1), 22–37.

Menezes, F. M., & Monteiro, P. K. (2000). Auctions with endogenous participation. *Review of Economic Design*, *5*(1), 71–89.

Milgrom, P. R., & Weber, R. J. (1982). A theory of auctions and competitive bidding. *Econometrica*, *50*(5), 1089–1122. doi:10.2307/1911865

Miller, M., & Van Maanen, J. (1979). Boats Don't Fish, People Do": Some Ethnographic Notes on the Federal Management of Fisheries in Gloucester. *Human Organization*, *38*(4), 377–385.

Mistiaen, J. A., & Strand, I. E. (2000). Location choice of commercial fishermen with heterogeneous risk preferences. *American Journal of Agricultural Economics*, *82*(5), 1184.

Muse, B. (1999). Washington State commercial salmon fishery buyback programs, 1995-1998. *Alaska Commercial Fisheries Entry Commission, Juneau*.

National Oceanic and Atmospheric Administration. (2010). Annual landings query. *Annual Commercial Landing Statistics*. Retrieved from http://www.st.nmfs.noaa.gov/st1/commercial/landings/annual_landings.html

Opaluch, J. J., & Bockstael, N. E. (1984). Behavioral modeling and fisheries management. *Marine Resource Economics*, *1*(1), 105–115.

Pollnac, R. B., & Poggie, J. J. (1988). The structure of job satisfaction among New England fishermen and its application to fisheries management policy. *American Anthropologist*, New Series, *90*(4), 888–901.

Pollnac, R. B., & Poggie, J. J. (2006). Job satisfaction in the fishery in two Southeast Alaskan towns. *Human organization*, *65*(3), 329–339.

R Development Core Team. (2011). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from http://www.R-project.org/

Rhodes, A., Lipton, D. W., & Shabman, L. (2001). *1999 socio-economic profile of the Chesapeake Bay commercial blue crab fishery*. Bi-State Blue Crab Advisory Committee.

Riechers, R., Griffin, W., & Woodward, R. (2007). The Texas inshore bay and bait license buyback program. In R. Curtis & D. Squires (Eds.), *Fisheries buybacks* (p. 215). Blackwell Publishing.

Rubin, D.B. (1987). *Multiple imputation for nonresponse in surveys*. Wiley Classics Library (Vol. 519). Hoboken, New Jersey: John Wiley & Sons Inc.

Rubin, Donald B. (1996). Multiple imputation after 18+ years. *Journal of the American Statistical Association*, *91*(434), 473–489. doi:10.2307/2291635

Schafer, J. L. (1997). *Analysis of incomplete multivariate data*. Monograph on Statistics and Applied Probability (Vol. 72). Chapman & Hall/CRC.

Scott, A. (1955). The Fishery: The Objectives of Sole Ownership. *Journal of Political Economy*, *63*(2), 116–124.

Thunberg, E. (2000). Latent fishing effort and vessel ownership transfer in the northeast US groundfish fishery. *Biennial conference of the International Institute of Fisheries Economics and Trade* (pp. 10–15). Presented at the IIFET 2000: Microbehavior and Macroresults, Oregon State University, Corvallis, Oregon.

Thunberg, E., Kitts, A., & Walden, J. (2007). A case study of New England groundfish fishing capacity reduction. In R. Curtis & D. Squires (Eds.), *Fisheries buybacks* (pp. 239–248). Blackwell Publishing.

Tidd, A. N., Hutton, T., Kell, L. T., & Padda, G. (2011). Exit and entry of fishing vessels: An evaluation of factors affecting investment decisions in the North Sea English beam trawl fleet. *ICES Journal of Marine Science: Journal du Conseil*, *68*(5), 961–971. doi:10.1093/icesjms/fsr015

United States General Accounting Office. (2000). *Commercial fisheries: Entry of fishermen limits benefits of buyback programs* (No. GAO/RCED-00-120). Report to House Committee on Resources.

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). *MICE: Multivariate imputation by chained equations in R*. Journal of Statistical Software.

Virginia Marine Resources Commission. (2009). *Blue crab fishery management plan.* (p. 52). Virginia Marine Resources Commission.

Ward, J. M., & Sutinen, J. G. (1994). Vessel entry-exit behavior in the Gulf of Mexico shrimp fishery. *American Journal of Agricultural Economics*, 916–923.

Weninger, Q., & Just, R. E. (1997). An analysis of transition from limited entry to transferable quota: non-Marshallian principles for fisheries management. *Natural Resource Modeling*, *10*(1), 53–83.

Weninger, Quinn, & McConnell, K. E. (2000). Buyback programs in commercial fisheries: Efficiency versus transfers. *The Canadian Journal of Economics / Revue canadienne d'Economique*, *33*(2), 394–412.