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Abstract

This paper analyzes the bias in fishermens predicted participation rates in the target fishery associated with ignoring the multi-species aspect of labor supply decisions in spatial bio-economic fishery models. Recent advancements have been made to simultaneously model the biology of a marine species and the strategic behavior of harvesters over both time and space in order to more accurately predict the effect of regulatory policies on harvester effort and resource population. These models assume a nested choice structure in which the harvester first faces a dichotomous decision between fishing for the target species or not on a given day and then chooses a location to fish conditional on participation. This structure implicitly groups all non-target species options together in the first nest forcing participation-specific coefficients to be the same for all outside options, including fishing for an alternative species and staying home, two very different choices. Using a complete 15-year panel of all fishing trips made by fishermen possessing a Florida spiny lobster license, including non-lobster trips, I show that the simplifying assumption of a dichotomous choice structure in the first nest is not innocuous and that the participation probabilities can change substantially with the addition of another species as an outside alternative.

1 Introduction

Many fishermen participate in more than one fishery on a daily or seasonal basis. Despite this behavior, bio-economic fishery models do not typically address the multi-species aspect of fishermen's daily participation decisions. Instead, when modeling participation, these models posit a dichotomous choice between fishing for the target species and not fishing for the target species on a given day. This assumption implicitly groups all non-target species options together, including staying home and participating in other fisheries, which are two very different choices. Using data from the Florida lobster and stone crab fisheries, I examine and compare the predictive power of a model that ignores the multi-species aspect of fishermen's participation decisions with that of a model that explicitly allows for participation in a second fishery. I find that a model of the first type over predicts the effect of management policies on participation compared with a model of the second variety, suggesting the importance of incorporating the multi-species decision structure into future bio-economic fishery studies.

Fishery managers have used a variety of policy instruments to promote the viability of fisheries, including input controls, such as gear restrictions, output controls, such as total allowable catches (TACs), and access limitations, such as entry restrictions, season closures, and area closures. In spite of their attempts, many fish stocks around the world are in decline.[1] An emerging literature attributes the failure of management, in part, to a disconnect between biological and economic processes in modeling fish stocks. While management models often involve detailed modeling of the biology of a marine resource, fishing effort is typically boiled down to a constant rate that does not respond to economic incentives. This new literature, which models both the biology of a marine resource and fishermen's strategic harvesting behavior together, demonstrates that there can be large differences in predicted policy outcomes between models that endogenize fishing effort and those that do not, highlighting the importance of incorporating the behavior of the harvesting sector in

[1] See, e.g., Botsford et al. (1997), Jackson et al. (2001), and Pauly et al. (1998).

effective resource management.

One of the first and most heavily cited papers in this literature is Smith and Wilen's (2003) spatial bio-economic model of the Northern California red sea urchin fishery. This paper addresses the biological and economic impacts of creating marine reserves (area closures), which have gained substantial popularity and practice as a means to manage fisheries.[2] Indeed, many preceding studies support their effectiveness.[3] However, as Smith and Wilen discuss, these previous studies make unrealistic assumptions about fishing effort and the distribution of effort. The authors find that once fishing effort is allowed to respond dynamically and spatially to changes in relative profits resulting from area closures, marine reserves become much less biologically and economically favorable.

In a similar study, Kahui and Alexander (2008) develop and estimate a spatial bio-economic model of the Abalone fishery off of Stewart Island, New Zealand. While they do not explicitly compare policy simulations of the bio-economic model with a simple population model, their results are very similar to Smith and Wilen and suggest that once fishing effort is endogenized only in specific situations can marine reserves outperform conventional management practices.

Another notable paper by Smith (2008) examines the effectiveness of a season closure in the Gulf of Mexico gag grouper fishery, the purpose of which is to decrease total fishing effort and promote spawning, thereby increasing the stock of gag. However, simulations of the bio-economic model developed by Smith show that the behavioral response of fishermen to the season closure is so strong that total fishing effort can actually increase. This is in sharp contrast to the predictions of biological models and again stresses the importance of incorporating fishermen's behavior in management models.

While this literature has made huge advances in bio-economic modeling, each study has analyzed the fishery of interest predominantly in isolation of other fisheries, which is a poor characterization of many fisheries. In these models, fishermen have two choices: fish

[2] Allison et al. (1998).

[3] See, e.g., Halpern (2002).

for the target species or don't on a given day. In a multi-species fishery, this means that observations of non-participation consist of both participation in other fisheries and days spent at home. The implication of this grouping is that factors that influence participation are forced to have the same effect on the decision to stay home and the decision to fish for another species. This can be problematic since the decision to fish for a non-target species is likely to be much more similar to the decision to fish for the target species than it is to the decision to stay home.

For example, when the weather is calm fishermen may be more likely to fish for any species and less likely to stay home. Therefore, we expect to find a positive effect of calm weather on the probability of participating in the target fishery and the probability of participating in non-target fisheries. However, if participation in alternative fisheries is grouped with staying home, the effect of calm weather on the probability of participating in the target fishery will be biased towards zero. Similar biases may occur with other factors that affect participation as well. The result is a model that underestimates the effect of the explanatory variables, which may do a poor job of predicting participation rates.

The purpose of this paper is to examine the bias that is generated from assuming a simple dichotomous participation structure. To do so, I estimate three separate models and compare the predictive powers of each. The first model follows previous studies in which fishermen either participate in the target fishery or do not. The second uses the same structure as the first, but adds covariates that describe the profitability of an alternative fishery as a simple means of controlling for opportunity costs. The third explicitly models the choice to fish for an alternative species so that there are now three alternatives. The management tools that I analyze with these three models are a 5% landings tax and the re-designation of one of the areas in the fishermen's choice sets as a marine reserve.

In general, I find that the typical model (Model 1), which does not control for participation in an alternative fishery, predicts a stronger participation response to both management tools as compared to a model than explicitly allows for participation in a second fishery

(Model 3). Specifically, Model 1 predicts an increase in non-participation in response to a 5% landings tax that is 2.5 times the prediction of Model 3. Similarly, Model 1 predicts an increase in non-participation that is almost twice that of Model 3 following the re-designation of Area 2 as a marine reserve.

The next section provides a historical overview of the spiny lobster fishery and the current economic and political situation. Section 3 introduces a model of individual choice describing the way in which fishermen make daily discrete decisions and section 4 discusses a biological model which may be integrated with the behavioral model described in section 3. Description of the data and the criteria used to determine the effective sample is discussed in section 5. Section 6 presents empirical results and section 7 discusses policy simulations. Finally, section 8 concludes.

2 Description of the Florida Spiny Lobster Fishery

Commonly referred to as the Florida spiny lobster, panulirus argus is a warm-water clawless lobster found in the western Atlantic waters from North Carolina to Brazil.[4] In the United States, spiny lobster are primarily harvested in Floridas southernmost counties, Monroe and Dade, both in Atlantic waters and the Gulf of Mexico. This industry constitutes one of Floridas most important commercial fisheries with an average annual value in excess of 30 million U.S. dollars.

The fishery consists of a recreational sector and a commercial sector of trappers, divers, and bully netters.[5] Commercial fishermen collect and sell live whole lobsters to fish houses, which are usually located at their homeport. Fish houses remove the lobster tails and sell only this portion to restaurants and distributors. The tail usually constitutes slightly more than a third of the total weight of a lobster. As such, there is quite a discrepancy between

[4]Background information on this fishery is taken from Shivlani, et al., SEDAR 08 U.S. Stock Assessment Panel and the Florida Fish and Wildlife Conservation Commission: Division of Marine Fisheries Management.

[5]Bully netters harvest lobster with hand nets. This requires fishing in very shallow waters so that lobster are visible from the boat. Although this technique used to be popular, bully netters currently contribute less than one percent of annual commercial lobster landings.

the price paid to commercial fishermen for whole lobster and the price at which fish houses sell tails. Over the sample period, the average per pound price paid to fishermen was $5.67 in 2007 dollars and total commercial landings in the state of Florida averaged approximately 6 million pounds per year. Recreational fishermen generally contribute another 1.5 million pounds each year.

There are general restrictions that apply to the entire industry as well as sector-specific regulations. The carapace length of the lobster must be a minimum of three inches in length, a size reached at approximately two years of age. Harvesting females carrying eggs is prohibited regardless of size. Spawning occurs between March and August giving rise to a season closure from April 1 to August 5. However, to boost tourism, the recreational sector enjoys an additional two-day sport season that falls on the last consecutive Wednesday and Thursday in July. While commercial fishermen must wait until August 5 to harvest lobster, trappers may drop traps as early as August 1 to allow them to accumulate lobster before the start of the season.

In Monroe County, recreational fishermen must possess a valid saltwater products license and a crawfish stamp and are subject to a six lobster per person per day bag limit, or 24 lobster per boat, whichever is greater. Until recently, commercial divers needed only to hold a saltwater products license and to abide by a per day boat limit that was set high enough that the restriction was rarely binding.

Since the 1950s, the commercial trap fishery has been responsible for the bulk of annual landings and the number of traps in the fishery steadily increased for the next 40 years. In the early 1960s, the number of traps was estimated to be less than 100,000, which rose to approximately 250,000 by the mid-1970s and may have been as high as 900,000 by 1990. However, the increase in trapper's fishing effort out-paced the growth in annual landings and so catch per unit effort (CPUE) steadily decreased from 1970 to 1990.

At this time, the fishery came under heavy scrutiny by the Florida Fish and Wildlife Conservation Commission (FWC). Because the commercial trap sector dominated the industry and because problems other than decreased CPUE were associated with the increase in the number of traps fished, such as increased by-catch mortality rate, FWC focused its restructuring of the fishery on this sector only. The FWCs solution was a transferable trap certificate program (TCP), which was implemented at the start of the 1993/94 fishing season. The goal of the program was to reduce the number of traps to 400,000, although research suggested that this would still be twice the level that would achieve economic efficiency.

Trappers were issued certificates based on the number of pounds landed the previous two out of three seasons. The program stipulated a blanket 10% reduction in the number of traps four different times between 1993 and 1999 bringing the number of traps down to approximately 550,000. In 2000, the guidelines were relaxed to passive reductions.[6] With the exception of the 1999 season, total commercial landings fell from approximately seven million pounds in 1994 to three million pounds in 2001. During the same period, trappers' percentage of commercial landings steadily fell from 95% to 85%. So that trappers were not further injured from a potentially flawed program, the TCP reductions were suspended in 2004.

The FWC and both the recreational and commercial sectors are currently in mediation with the intent to better regulate the industry and promote biological and economic efficiency. The TCP is under review as well as methods to regulate the fishery as a whole, such as marine reserves, and each sector of the fishery individually.

Because commercial trappers have been responsible for between 72% and 95% of total lobster landings during the past fifty years, I focus my analysis of fishing effort on this sector only. Prior to the TCP, the commercial trap sector was comprised of both part-time and full-time fishermen. Vessels ranged in size from 20ft to 60ft. Most had power operated pullers with which to pull traps, although some fishermen still pulled traps by

[6]Under passive reductions, reductions are first applied to certificates purchased by someone outside the sellers immediate family. If these types of reductions do not constitute an annual four percent reduction in total certificates, the remainder is reduced equally across all certificate owners in the fishery.

hand. Since the TCP was implemented, many of the marginal fishermen have sold their certificates leaving the sector with a much more homogenous group of fishermen. In the 2001-02 season, the average fisherman set 1,463 traps, fished from a 21 year old, 36 foot boat with 433 horsepower inboard engine, automated puller and a crew of two.

Many lobster fishermen also partake in the stone crab fishery. Stone crab are found along the coast of South Florida, especially in the Gulf of Mexico. The season opens on October 15th and closes May 15th. Although stone crab are almost exclusively harvested with traps, different traps are used for stone crab and lobster. Stone crab traps are smaller and, unlike lobster traps, are usually baited with cowhide or pigs' feet. However, the same vessel, puller, and crew may be used to harvest either. Therefore, fishermen participating in both fisheries can easily switch between species from day to day. Because of the substantial overlap in seasons, the ability to switch easily between species, and the fact that lobster fisherman are often observed to participate in the stone crab fishery, these two fisheries provide a good opportunity to model fishing effort in a multi-species framework.

3 An Empirical Model of Participation

For the base model, I follow Smith and Wilen (2003). I assume that fishermen make daily discrete decisions regarding participation and fishing location that maximize a random utility function

$$U_{ijt} = v_{ijt} + \epsilon_{ijt} = f(\mathbf{X}_{it}, \mathbf{Z}_{i1t}, \mathbf{Z}_{i2t}, ..., \mathbf{Z}_{iMt}; \boldsymbol{\theta}) + \epsilon_{ijt} \quad (1)$$

where i subscripts the fisherman, t the time period, and j the fishing location. Thus, $\mathbf{X}_{it}$ consists of fisherman- and time-specific characteristics that are constant across locations, such as the fisherman's age and the day of the week, while location-specific characteristics, such as distance from port, are included in $\mathbf{Z}_{ijt}$. Notice, location-specific characteristics may also be fisherman- and time-specific. $\boldsymbol{\theta}$ is a vector of parameters, and ϵ_{ijt} is a random unobservable utility component. According to this model, fisherman i in period t will choose location j if the utility he gains from choosing j is greater than the utility he would receive from choosing any other location or from not fishing for the target species.

For econometric analysis, I use a nested logit framework to model this choice structure. This framework presumes that fishermen first decide whether or not to participate in the target fishery and then, conditional on participation, decide in which area to fish so that decisions are nested. The nested logit framework is often adopted because it is computationally less burdensome than many other formulations. [7] Importantly, the nested logit model also avoids making the assumption of independence from irrelevant alternatives (IIA). In this context, IIA would imply that the ratio of the probability of visiting area j to the probability of not fishing for lobster is independent of the number of other areas in the fisherman's choice set and the characteristics of these areas. Consequently, if an area is removed from the fisherman's choice set, as we would do to simulate the effect of an area closure, IIA requires that fishing effort be redistributed proportionately to the remaining alternatives, which includes all other fishing areas and non-participation. Since one of the goals of developing a spatial bio-economic fishery model is to determine how effort is redistributed in response to the creation of a marine reserve, we cannot use a model that has the answer already built in.

The error term, ϵ_{ijt}, is assumed to be independently and identically distributed generalized extreme value and utility is assumed to be linear in fisherman- and location-specific variables. Under these assumptions the random utility model can be formulated as follows[8]

$$Pr(\text{Go to } j) = \frac{\exp\left\{\frac{\mathbf{z}'_{jt}\boldsymbol{\gamma}}{(1-\sigma)} + \mathbf{x}'_t\boldsymbol{\beta} + (1-\sigma)I\right\}}{\sum_{k=0}^{5}\left[\exp\left\{\frac{\mathbf{z}'_{jt}\boldsymbol{\gamma}}{(1-\sigma)}\right\} + \exp\left\{\frac{\mathbf{z}'_{jt}\boldsymbol{\gamma}}{(1-\sigma)} + \mathbf{x}'_t\boldsymbol{\beta} + (1-\sigma)I\right\}\right]} \tag{2}$$

and

$$\begin{aligned} Pr(\text{Do not go}) &= 1 - \sum_{k=0}^{5} Pr(\text{Go to } k) \\ &= \frac{1}{1 + \exp\left\{\mathbf{x}'_t\boldsymbol{\beta} + (1-\sigma)I\right\}} \end{aligned} \tag{3}$$

[7] See Smith and Wilen (2003) and Smith (2002).

[8] Equations (2) - (4) are taken from Smith and Wilen (2003).

where

$$I = \ln \left[\sum_{k=0}^{5} \exp \left\{ \frac{\mathbf{z}_{jt}^{'} \gamma}{(1-\sigma)} \right\} \right]. \tag{4}$$

Because none of the explanatory variables used in estimation are fisherman-specific, the i subscripts have been suppressed from the above equations. $\boldsymbol{\beta}$ corresponds to the parameter vector for location-independent characteristics while $\boldsymbol{\gamma}$ denotes the parameter vector for characteristics that vary across location. $(1-\sigma)$ is the coefficient on the nested logit inclusive value. Maximum likelihood estimation is used to derive the vectors $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\gamma}}$, the nested logit estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$.

Once we obtain consistent estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, equations (2) - (4) can be used to calculate the probabilities of visiting each location as well as the probability of not participating in the target fishery on each day given a vector of values for all of the explanatory variables. In this way, the effect of regulatory policies on total effort and the distribution of effort can be simulated by manipulating the values of the explanatory variables or changing the location choice set.

4 Integrating Harvester Spatial Behavior with a Biological Model

While it is beyond the scope of this paper to integrate the the spatial fishing effort model described in Section III with a biological model in order to simulate the effect of regulatory policies on the stock of lobsters and not just fishing effrt, the following section describes the manner in which this can be accomplished.

SEDAR 8's 2005 stock assessment of the Florida spiny lobster uses an Integrated Catch-at-Age model to predict catch rates. While this model is fairly detailed, it assumes that lobster mortality due to fishing is a function of lobster age and the fishing season only. This is given by

$$F_{a,y} = Sel_a F\_full_y \tag{5a}$$

where Sel_a is the selectivity of a lobster of age a, or ease with which a lobster of age a can be caught, and F_full_y is the mortality rate from fishing on a fully recruited lobster in a given fishing year. A lobster is predicted to be of fully recruited legal size by age three. The selectivity of a lobster as a function of age tends to be dome shaped since younger lobster do not meet the size limit and so are not harvested and older lobster tend to be too big to fit inside the traps and are less sociable.[9] Both Sel_a and F_full_y are parameters estimated by the model. In no way is equation (5a) able to predict the effect of effort response to changes in regulation on fishing mortality.

The remaining equations in SEDAR's Integrate Catch-at-Age Model are given below. Size of population by age and fishing year (solved backwards) is given by

$$N_{a-1,y-1} = N_{a,y}\exp(F_{a-1,y-1} + M_{a-1,y-1}) \tag{6}$$

where M is the natural rate of mortality assumed to a constant of .34 across all ages and years. Average population during the fishing year is given by

$$\bar{N}_{a,y} = \frac{N_{a,y}}{F_{a,y} + M_{a,y}}(1 - \exp(-F_{a,y} - M_{a,y})) \tag{7}$$

and predicted catch-at-age is

$$\hat{C}_{a,y} = F_{a,y}\bar{N}_{a,y}. \tag{8}$$

Predicted index values used to tune the model are

$$\hat{I}_{a,y,j} = q_j \sum_a N_{a,y}\exp(Fraction_j(-F_{a,y} - M_{a,y})) \tag{9}$$

where q_j is the catchability coefficient and $Fraction_j$ accounts for when the survey is conducted during the fishing year. The objective function minimizes the sum of squared errors and is given by

$$SS = \sum_a \sum_y \lambda_{a,y}\ln\left(\frac{C_{a,y}}{\hat{C}_{a,y}}\right) + \sum_a \sum_y \sum_j \lambda_j \ln\left(\frac{I_{a,y,j}}{\hat{I}_{a,y,j}}\right)^2. \tag{10}$$

Minimization of equation (10) results in 47 parameter estimates.

[9] However, since shorts, or sub-legal sized lobster, are often used to bait traps, which can lead to their demise for several reasons, their mortality rate due to fishing is likely nonzero, which would tend to flatten out the dome shape.

In contrast to the mortality equation given in (5a), the following, taken from Smith and Wilen (2003), incorporates fishing effort

$$f_{jt} = (Trips_{jt})\, q = \left(o_t \sum_{p=1}^{M} T_p p_{pjt} \right) Sel \tag{5b}$$

where j is location, t is the time period, and the subscript p is the port. Sel is the catchability coefficient, which represents the average harvest per trip. T is the number of commercial trappers in port p and p_{pjt} is the probability that a trapper from port p will go to location j in time t. o is the number of possible days at sea during the time period t. Estimates of p_{pjt} are obtained from equations (2) - (4) described above.

Replacing equation (5a) with (5b) essentially modifies SEDAR 8's model so that the resulting parameter estimates, such as population by age and year, will be based on the estimates obtained from the fishing effort model developed in this study. Unfortunately, SEDAR 8's model is not spatially explicit so it is better equip to address the impacts of the policies that affect total fishing effort or age-specific effort, such as size limit changes and seasonal closures, rather than policies that affect the distribution of effort, such as the creation of marine reserves.

5 Data Description & Sample Selection

Since 1978, fish houses have been required to fill out trip tickets for each sale made. Records of these trip tickets are maintained by the FWC. An example is shown in Figure 1. These tickets record the fisherman's unique license number, the date of the trip, the location of the trip, the gear used, and, if relevant, the number of traps pulled and the length of time traps soaked since the last pull. These tickets also record each species that was sold and the number of pounds and the price paid per pound for each species.

The FWC provided me with all trip ticket records from the 1986/87 fishing season through the 2006/07 season for which *any* amount of lobster or stone crab was recorded as sold. From this set of trips tickets, the FWC compiled a list of fishing licenses and additionally provided any remaining trip tickets that matched on fishing license. Using the license number, fishing behavior may be tracked over time. As a result, the data constitute a complete panel of all fishing trips made in Florida between the 1986/87 and 2006/07 fishing seasons by fishermen that ever sold spiny lobster or stone crab. For each fisherman in the sample, I observe each and every day they sold *any* species of marine life as well as the composition of species sold.

Although the data to which I have access spans from the 1986/87 fishing season to the 2006/07 season, many of the trip tickets in the earlier years did not record the price paid per pound. Table 1 shows the percentage of trip tickets that are missing lobster prices by fishing season. These numbers are quite large between the 1986/87 and 1995/96 seasons, climbing as high as 76%. However, in the period from 1996/97 to 2006/07, no more than 1.67% of trip tickets are missing prices. Because price is likely to be an important factor explaining participation, I restrict my analysis to begin in the 1996/97 season so that I do not have to rely on sparse records of prices to generate expectations.

In order to determine the relevant sample, several terms must be defined: 1) what constitutes a lobster or a stone crab trip; 2) what constitutes a trapper; and 3) what constitutes a lobster fisherman. Since I do not know which specie(s) was targeted on a given day, I infer the intent of the fisherman based on observed catch. There are 251,560 trips made by fishermen on which some amount of lobster was sold. The contribution of lobster to the total value of the trip varies.[10] On average, the sale of lobster constitutes 91% of the total value of a trip and 75% of all trips that record any amount of lobster consist solely of lobster. So, for the bulk of trips, inference about intent to fish for lobster seems clear. However, for several thousand other trips this distinction is less clear. Figure 2 displays a histogram of the contribution of lobster to the total value of the trip once trips consisting solely of lobster are removed. With the exception of a small spike near zero, the distribution is fairly flat until around 60% when it starts to increase sharply. For the purposes of this study, I classify a trip as a lobster trip if at least 50% of the total value

[10]XXXXXX Discuss computation of values and imputation of prices

of the trip is from lobster sales. This classification re-designates 7.6% (or approximately 19,300) of the trips in the sample as non-lobster trips. After dropping a couple hundred other trips due to inconsistencies with the fisherman's social security number or license, the total number of lobster trips in the sample is 232,089.

The main methods of harvesting lobster are with traps and by diving. 84% of lobster trip tickets report the use of traps, 16% report diving, and 3% report some other kind of gear.[11] Of the 2,249 unique fishers in the current sample that make at least one lobster trip, 578 never report using traps and 721 always report using traps. The remaining 950 fishermen report a mix of gear use throughout their tenure in the sample. Figure 3 displays a histogram of the percentage of lobster trips reporting the usage of traps for each fisherman once those that always use traps or never use traps are removed. The spikes are at either end of the distribution with few fishermen falling in the gray middle ground. I restrict the sample to include only fishermen that report using traps to harvest lobster at least 90% of the time. This drops 1,142 fisherman, bringing the sample down to 1,107.

While the remaining fishermen have all made at least one trip in which lobster was the primary species sold, whether or not all of these fishermen should be considered lobster fishermen solely on this basis is left to be determined. This is an important distinction since I am assuming that fishing for lobster is a viable option for each fisherman in the sample on each day in the season and for all seasons observed. If a fisherman makes few lobster trips throughout the sample relative to other non-lobster trips or makes a handful of trips in a relatively short period of time with no trips made during the rest of the time he is observed in the data, fishing for lobster may not regularly be in the fisherman's choice set. To better ensure that it is, I further reduce the sample based on absolute and relative participation in the lobster fishery.

Of the remaining 1,107 trappers, 161 participate in the lobster fishery no more than once per fishing season during the entire time they are observed. After removing these fishermen

[11] Just over 3% of trip tickets in the sample report more than one gear type so that gear usage does not have to sum to 100%.

from the sample, there are 6,024 unique fisher-fishing season pairs. For 180 of these pairs, 0% of trips made are lobster trips.[12] For 1,386 pairs, 100% of trips made are lobster trips. For the remaining 4,458 fisher-fishing season pairs, the composition of trips is a mix of lobster and non-lobster trips. Figures 4 and 5 display histograms of the percentage of total trips that are lobster trips and the percentage of total earnings contributed by lobster trips, respectively, by fishing season. I drop from the sample all fisher-fishing season pairs for which percent participation in the lobster fishery is below 5% or for which percent earnings from lobster trips is below 5%. This removes 567 fisher-fishing season pairs and 19 fishermen from the sample. Finally, I remove fishermen that are observed to fish for lobster less than ten times over the entire sample period. This removes another 108 fishermen, leaving a sample of 819 fishermen, 5,321 fisher-fishing season pairs, 1,267,363 possible lobster trip opportunities, and 184,918 actual lobster trips.

The FWC divides the waters adjacent to the Florida coastline into 18 fishing areas. Figure 6 provides a detailed diagram of the zoning. Although some trip tickets indicate more detailed location information, most do not.[13] Thus, these zones constitute the spatial resolution of fishing effort. Table 2 shows the number of visits to each area by the fishermen still in the sample between the 1996/97 and 2006/07 fishing seasons. 98.6% of all lobster trips made lie within areas 1, 2, 3, 744, and 748, the five southernmost areas. Because almost the entire industry is contained within these five fishing areas and to reduce the computational burden of estimating a model with 18 areas, I further restrict the sample by dropping fishermen that ever fished outside these five areas so that I can plausibly assume that areas 1, 2, 3, 744, and 748 constitute each fisherman's location choice set. The final sample includes 754 trap fishermen, 4,804 fisher-fishing season pairs, 1,144,221 possible lobster trip opportunities, and 164,963 actual lobster trips.

Table 3 provides summary statistics for the final sample of fishermen. The weighted

[12]These fisher-fishing season pairs remain in the current sample because these fishermen are observed to fish for lobster during a different fishing season

[13]Some reference a quadrant indicating whether the trip was in the northwest, northeast, southwest, or southeast of a square latitude-longitude degree. Others reference a decimal attached the zone number indicating federal or state waters and other information.

averages weight each fisherman's statistics by the number of times he is observed in the data. Fisherman that participate more frequently make slightly more revenue per trip, which might reflect a premium for experience. In general, participation rates are fairly low. The average unweighted participation rate is about 13%. The standard deviations for each variable are all quite high relative to their means indicating the diversity in participation and earnings of the fishermen in the sample.

In addition to the information provided in the trip ticket database, a variety of other sources are used to collect information on factors that may influence fishermen's participation and location decisions. Daily weather conditions, the moon cycle, and the day of the week are factors that may affect participation. High wind speed tends to reduce vessel speed and make fishing less efficient. Particularly high winds may even make fishing dangerous. We would, therefore, expect high current wind speed to deter participation. However, rough water from high winds also tends to stir lobsters out of reefs and gets them moving across the ocean floor and into traps. In addition, rough water tends to shift traps around making it difficult to locate traps. The first effect suggests that catches may be greater following high wind speeds. The second suggests that fishermen may be inclined to go out fishing following high wind speeds in order to locate traps that have shifted before they are permanently lost. For these reasons, we expect high *lagged* wind speed to encourage participation.

Daily wind speed data is available through the National Oceanic and Atmospheric Administrations (NOAA) historical weather buoy database. I use data from ten weather buoys spanning the geography and timeline of the sample.[14] NOAA records weather conditions every hour and wind speed is measured in meters/second. To determine daily wind speed, hourly wind speed is averaged from midnight until noon of the fishing day. The rationale is that fishermen wake at 6am and base daily decisions on the previous six hours of observed weather conditions and the forecast for the next six. Lagged wind speed is calculated as a

[14] Archives of daily weather conditions can be found on NOAAs National Buoy Data Center website: http://www.ndbc.noaa.gov.

two-day lag of current wind speed.

A lobster's natural habitat is in reefs and other dark enclosed areas, which is why trapping is effective. During the new moon, lobster tend to emerge from their hideouts and relocate, while during the full moon they tend to remain in hiding. This results in greater lobster abundance in traps especially around the new moon. For this reason, I include an explanatory variable to capture the effect of the the moon cycle on participation. A value of 1 indicates a full moon and a value of 0 indicates a new moon. The variable also takes on 13 values in between 0 and 1 to capture daily stages of the moon cycle.

Many fish houses are closed on Sundays making it difficult for fishermen to sell their catch on Sunday. In addition, opportunities may be different for fishermen on Sundays due to family, church, and so on. For these reasons, we might expect participation to systematically vary on Sundays. To account for this, a dummy variable for Sunday is included in the model.

Expected revenue per unit effort and the distance fishermen must travel to arrive at each location are two important determinants of the location decision. The first provides a measure of the profit of fishing in each area and the second provides a measure of the cost. Expected revenue per unit effort (RPUE) is defined as the product of the daily price per pound and the expected catch per unit effort (CPUE) and catch per unit effort is defined as total trip landings in pounds divided by the number of traps pulled. RPUE is calculated using observations on prices, landings, and the number of traps pulled from the trip ticket database.

Because the spatial variation in prices and CPUE are innately different - prices are offered by fish houses and vary across land and CPUE varies across the ocean - they are calculated and matched to fisherman observations using different methods. In addition to the trip ticket database, the FWC also provided a license database that, among other things, includes the zip code associated with each fisherman's license. Linking this zip code to each observation on lobster price in the trip ticket database, I group prices into five areas according the latitude and longitude of the zip code. For the first week of the season, a three-day unweighted average is computed for each of the five areas using price observations from the previous, current, and next day. A seven-day backward-rolling weighted average is used to compute expected prices through October, a ten-day backward-rolling weighted average through January, and a 14-day backward-rolling weighted average through the end of the season, where observations are weighted according to their proximity to the current day.[15] In addition to these weights, observations on prices are also weighted by the associated number of pounds sold on that trip ticket. Daily price averages are then linked to daily fishing opportunities according to the zone in which the zip code associated with the fisherman's license falls. Note that expected prices vary across days and fishermen (due to differing home port zip codes), but not across fishing areas.

I group observations on CPUE according to the fishing area reported on each trip ticket and only compute averages for CPUEs within the five southernmost fishing areas since all other areas have been removed from the location choice set. Unlike prices, I calculate CPUE using only observations from trip tickets that have been designated as lobster trips (i.e. trips for which at least 50% of the total value of the trip came from lobster). Since only one number for traps pulled can be indicated on a trip ticket, non-lobster trips are more likely to contribute lower-than-actual CPUE values and thereby downward bias CPUE averages. For the same reason, I also exclude observations with "unusual" values for traps pulled (i.e. *very* small or *very* large). Finally, I exclude observations with extremely high and implausible values for CPUE. I follow a similar averaging method for CPUE as prices, with the exception of using a five-day unweighted average for the first week of the season due to fewer observations on CPUE after the aforementioned exclusions. The five-day average consists of the current day, the two preceding days, and the next two days. Daily CPUE averages are then linked to daily fishing opportunities by matching on day and fishing area.

[15] For example, the seven-day backward-rolling weighted average assigns a weight of 7 to price observations on the current day, a weight of 6 to price observations on the previous day, and so on so that a weight of 1 is assigned to observations a week preceding the current day.

Therefore, expected CPUE varies across days and fishing areas, but not across fishermen. Expected RPUE is then simply calculated as the product of the daily price and the daily CPUE and will vary across days, fishermen, and fishing locations.

I calculate the distance that fishermen must travel to visit each fishing area as the distance from the center of the zip code associated with the fisherman's license to the closest "fishable" portion of each area. Areas may include marshy land, marine reserves, and other portions not typically inhabited by lobster. "Fishable" portion refers to the remainder of each area. While the fisherman's actual homeport would be more ideal, the center of the zip code is the best approximation available. For zip codes located from the southern tip of Florida and farther south through the Keys, I use the direct distance between zip code and each fishing area. For zip codes located on the east and west coasts, I use an indirect measure to calculate distances to areas on the opposite coast which requires fishermen to travel around the southern tip of Florida. For zip codes located within areas (e.g. the zip code for Key West, 33040, is located within area 1) I designate the distance as 1 nautical mile in order to somewhat differentiate between staying home (distance = 0 miles) and going out fishing (distance > 0 miles). Distances varies across fishermen and fishing locations, but not across days.

In addition to these variables, I propose that changes in opportunities in other fisheries also affect participation in the lobster fishery. Because many lobster fishermen also participate in the stone crab fishery, I focus on opportunities in this fishery. Not all lobster fishermen posses a stone crab permit which means that changes in stone crab opportunities do not affect all fishermen in the sample. I use a similar criteria to determine which fishermen are stone crab fishermen as I used to determine which are lobster fishermen. After pooling all of the trip tickets associated with each fisherman in the sample, I calculate the number of times each fisherman participated in the stone crab fishery in each fishing season observed and the total value of earnings from selling stone crab. As with lobster, I only consider a trip to be a stone crab trip if at least 50% of the total value of the trip came from stone crab. For each fishing season, I designate a fisherman as a stone crab fisherman if more than one stone crab trip was observed that year and if at least 5% of all trips made were stone crab trips and at least 5% of total earnings that year originated from the sale of stone crabs. A dummy variable captures whether or not a fisherman in a given fishing season holds a stone crab permit, based on the above criteria, and so whether or not opportunities in the stone crab fishery are available to that fisherman. Note that a fisherman's stone crab permit status may change from fishing season to fishing season. Of the 716 fishermen in the sample, 500 hold a stone crab permit at some point in the sample period. During fishing years in which they hold a permit, average participation in the stone crab fishery is 18 days with a standard deviation of 20 days, a minimum of 1 day, and a maximum of 125 days.

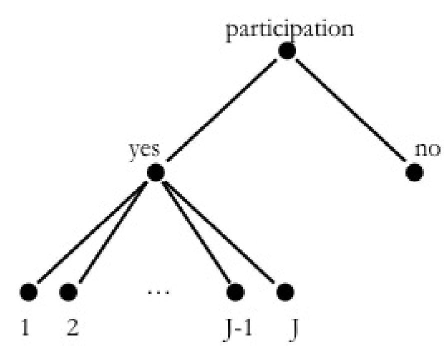
Another dummy variable indicates whether or not the stone crab season is open, which begins October 15th and ends May 15th. This variable turns on beginning October 15th only for those fishermen that hold a stone crab permit. Therefore, the permit dummy captures the effect of holding a stone crab permit prior to the beginning of the stone crab season on participation in the lobster fishery and the season dummy captures the effect of holding a stone crab permit once that season opens on participation in the lobster fishery.

Daily price and CPUE averages in the stone crab fishery are calculated in the same manner as they are for lobster. Prices are matched to daily fishing opportunities according to zip code zones. However, since stone crab RPUE is used as a predictor of participation and not location choice in the lobster fishery, it can take on only one value per fisher per day. In order to match area-specifc CPUE averages to fisher-day observations, I calculate the mode area fished for each stone crab fisherman at the month- and fishing season-level using observations on stone crab trips only. When possible, the mode at the month level is used first to match daily CPUE averages. The assumption is that, when considering fishing for stone crab, fishermen are more likely to visit the area they frequent most so CPUE averages for that area are a best approximation of current stone crab profits.

Expected stone crab RPUE is calculated as the product of the daily price and the daily CPUE. It is interacted with the season dummy so that RPUE is only non-zero for fishermen that hold a stone crab permit and during open season days. It varies across fishermen, according to permit status, home port zip code, and the fishing area most frequented, and it varies across days, according to seasonality. Stone crab RPUE captures the effect of an additional dollar of revenue per trap on the probability of participating in the lobster fishery, given that a stone crab permit is held and the stone crab season is open.

6 Empirical Results

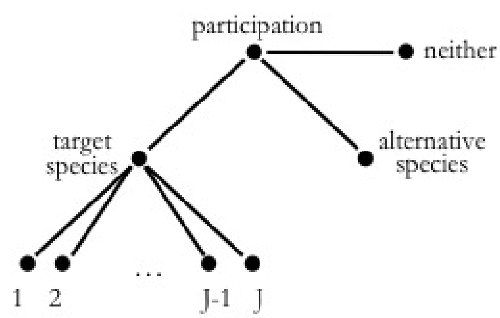
Three models are estimated and compared. The first and second have the same structure as previous spatial bio-economic models. Participation is modeled as a two-pronged choice between fishing for the target species or not fishing for the target species on each possible fishing occasion. Conditional on participation, fishermen then decide which area to visit. This choice structure is shown to the right.



The $\mathbf{X}_{it}$ covariates consist of factors that influence the participation decision and the $\mathbf{Z}_{it}$ covariates consist of factors that influence the location decision.

The difference between the first and second model is the set of $\mathbf{X}_{it}$ covariates. The first includes daily wind speed, a two-day lag of daily wind speed, a measure of the moon cycle, and a dummy variable for Sunday. In addition to these covariates, the second model also includes variables that describe opportunities in the stone crab fishery. These include a dummy indicating whether or not the fisherman currently holds a stone crab permit, a dummy indicating if the stone crab season is open, and a measure of expected stone crab RPUE. The $\mathbf{Z}_{it}$ covariates are the same for both models and consist of the distance each fisherman must travel from their homeport to arrive at each area and the expected lobster RPUE of each area.

The third model is structurally different than the first two. Instead of a two-pronged choice in the first stage, fishermen choose between fishing for the target species, fishing for an alternative species, and participating in neither of these fisheries. This choice structure is shown below. The covariates are the same for this model as model 2. $\mathbf{X}_{it}$ and $\mathbf{Z}_{it}$ However, because the choice to participate in the stone crab fishery is now explicitly modeled, the $\mathbf{X}_{it}$ covariates are allowed to have different effects on the decision to participate in the stone crab fishery and the decision to participate in neither fishery. Presumably, this more flexible structure will also affect the estimates for lobster participation.



6.1 Nested Logit Results

The empirical results from the three nested logit models are shown in Tables 4, 5, and 6. In all three models, participating in neither fishery serves as the base case so participation-specific coefficients should be compared to this decision. The coefficients in Model 1 all achieve the expected sign and are all statistically significant. Fishermen are less likely to participate in the lobster fishery when wind speeds are high, more likely when wind speeds were high two days ago, less likely when the moon is full or near full, and less likely on Sundays. The negative coefficients on the area constants reflect the overall low participation rates. All else equal, fishermen are less likely to visit areas that are far away and more likely to visit areas with higher RPUE. The inclusive value parameter for the participation branch is positive, statistically significant, and between 0 and 1.[16] This suggests that the model is

[16]The inclusive value parameter for the non-participation branch is constraint to 1 due to the fact that it is a degenerative branch.

consistent with random utility maximization.

The coefficients on the variables that Models 1 and 2 share also retain the predicted sign and are statistically significant in Model 2. Model 2 includes three additional variables that describe the opportunities in the stone crab fishery. The positive coefficient on permit status indicates that fishermen that hold a stone crab permit are more likely to fish for lobster before the stone crab season begins than are fishermen that do not hold a stone crab permit. This might be because fishermen with stone crab permits have higher participation rates in general. The coefficient on stone crab season is negative, indicating that once the season opens, fishermen holding stone crab permits are less likely to fish for lobster than they were before the season began, presumably because some fishing effort shifts into the stone crab fishery. The overall effect of the stone crab season opening on lobster participation is captured by the sum of these two dummies, which is negative as we would expect. Contrary to what might be expected, the coefficient on stone crab RPUE is positive, suggesting that fishermen holding stone crab permits are more likely to fish for lobster when the expected profits in the stone crab fishery are high. There are a couple of possible explanations for this. One explanation is that fishermen targeting lobster may often end up with a species mix that includes stone crab - i.e. lobster and stone crab may, to some extent, be compliments so that increases in expected revenue in either fishery would encourage participation in the lobster fishery. Another explanation has to do with the strong correlation between lobster and stone crab revenues.

The coefficients on wind speed, lagged wind speed, and Sunday in Model 3 obtain the same signs as Models 1 and 2 and achieve statistical significance. They also obtain the same sign for lobster participation as for stone crab participation, indicating the similarity between these two alternatives. However, full moon is no longer statistically significant. Because participation in the stone crab fishery can only happen once the season is open, the coefficients on the dummies for stone crab permit and stone crab season must be combined to determine the effect of holding a permit on participation in the stone crab fishery. This combined effect is positive by definition since permit status was determined based on positive observed participation. As we would expect, participation in the stone crab fishery increases with expected revenue. This effect is approximately 60% greater than the effect of stone crab revenue on lobster participation.

6.2 Marginal Effects

Table 7 provides marginal effects which allows the estimates from the three models to be compared. Marginal effects are calculated using the following method. A small increment is added to one of the covariates to modify the sample. Predicted participation probabilities are calculated using the original sample and this modified sample. The difference between these predicted participation probabilities divided by the small increment provides an estimate of the marginal effect of the modified covariate on the probability of choosing alternative j for fisherman i on date t. These marginal effects are then averaged across all fishermen and days within each alternative in the first node (fish for lobster, fish for stone crab, if relevant, or fish for neither species) to derive an estimate of the marginal effect of each covariate on the probability of choosing each alternative.

For continuous participation-specific covariate (wind speed, lagged wind speed, and stone crab revenue), the small increment is defined as the standard deviation of the covariate in the sample divided by 1000. Note that observations on stone crab revenue are only modified for those fishermen holding stone crab permits and for those days during which the stone crab season is open. For indicator participation-specidic covariates (full moon, sunday, stone crab permit, and stone crab season), the small increment is defined as switching the covariate from 0 to 1. Note that stone crab season is only switched to 1 for fishermen that hold a stone crab permit. For the two location-speficic covariates (distance and lobster revenue), the same definition is used to determine the small increment as is used for continuous participation-specific covariates. However, observations on each of these covariates are only modified for Area 1. Therefore, the marginal effects should be interpreted as the change in the probability of choosing alternative j given an increase in distance or revenue associated with Area 1.[17]

The marginal effect of lagged wind speed, full moon increases in absolute value moving from Model 1 to Model 3. Similarly, all three marginal effects describing the opportunities in the stone crab fishery increase in absolute value moving from Model 2 to Model 3. The marginal effect of Sunday on the probability of participating remains the same across all specifications. Interestingly, the marginal effect of wind speed does not increase in absolute value, but falls by 11%.

The bottom third of Table 7 shows the marginal effects of an increase in distance and lobster revenue associated with Area 1 on the probability of choosing each alternative. An increase in the distance a fisherman must travel to arrive at Area 1 decreases the probability of visiting that area and increases the probability of choosing all other alternatives, including fishing for stone crab and not fishing for either species. The decrease in the probability of visiting Area 1 gets smaller in absolute value as we move from Model 1 to Model 2 to Model 3, although the difference between the marginal effect in Models 1 and 3 is fairly small (7.7%). What is interesting is that the probability of not fishing in response to an increase in the distance to Area 1 is cut in half from Model 1 to Model 3. Some of this difference is coming from a smaller response in the own effect (the 7.7% difference in the probability of visiting Area 1 between the two models), but most of the difference (75%) is coming from fishermen moving from Area 1 to Areas 2 - 5 in Model 3 rather than from Area 1 to non-participation. Compared with Model 1, Model 3 suggests that changes in distance are more likely to affect a fisherman's location choice than his participation decision.

In all three models, and as anticipated, an increase in expected revenue in Area 1 increases the probability of visiting that area and decreases the probability of visiting all other areas, fishing for stone crab, or not fishing at all. With the exception of fishing for stone crab, which is only an explicit option in Model 3, all marginal effects shrink in absolute value moving from Model 1 to Model 2 to Model 3, suggesting that fishermen are generally

[17] I have not yet calculated standard errors.

less responsive to changes in revenues in Model 3. Less effort is drawn to Area 1, less effort is drawn from other areas, and less effort is drawn from non-participation. However, the proportion of effort that is drawn from other areas relative to non-participation is much greater in Model 3 than Model 1 (68% compared with 42%). Compared with Model 1, Model 3 again suggests that fishermen are more likely to move between areas in response to changes in relative area profits rather than move into non-participation. The propensity to switch at the lower nest rather than the upper nest will become important when evaluating the effect of implementing various management tools.

6.3 Predicted Participation Rates

Tables 8 and 9 provide participation and location predictions of the three models both in an out of sample.[18] In each table, observed participation is given in the first column followed by predicted participation based on the estimates from each of the three models. The percent deviation from the observed value is provided beneath each prediction. The first row of each table shows the number of non-lobster trips. The portion of non-lobster trips that are observed and predicted as stone crab trips are shown in the second row of columns 1 and 4, respectively.

Each model nails total overall lobster participation in sample. Model 1 appears to outperform Models 2 and 3 in predicting location choice, but the difference is only slight. Out of sample, Model 3 generally outperforms Models 1 and 2, but, again, the difference is fairly small. Model 1 under predicts non-participation by 4.4% while Model 3 under predicts non-participation by 3.4%.

7 Policy Simulations

Tables 10 and 11 provided policy simulations for implementing a 5% landings tax and turning Area 2 into a marine reserve (i.e. closing this area). Simulations are done out of

[18]The models are estimated using fishing seasons 1996 - 2003. This allows me to calculate out of sample predictions using seasons 2004 - 2006 for which actual participation rates are known and can be used for comparison

sample and tables provide both predicted participation pre- and post- the policy change. Changes in participation rates from the base case are provided under each prediction. Model 1 predicts the largest impact of implementing a landings tax on participation, followed by Model 2, and then Model 3. Model 1 predicts a drop in participation more than 2.5 times that of Model 3.

Similarly, Model 1 predicts the largest increase in non-participation once Area 2 is closed, followed by Model 2, and then Model 3. In response to closing Area 2, Model 1 predicts that approximately 20% of displaced Area 2 effort is redistributed to other areas, while approximately 80% of this effort moves into non-lobster opportunities. In contrast, Model 3 predicts that displaced Area 2 effort is redistributed almost equally between other areas and non-participation. The result is that Model 1 predicts an increase in non-participation almost twice that of Model 3.

8 Conclusion

Bio-economic fishery management models do not typically address the multi-species aspect that characterizes the participation decision that many fishermen face on a daily basis. In this paper, I develop and compare three models that vary in their incorporation of an alternative fishery in order to determine the importance of the multi-species aspect of fishermen's decisions on management model predictions. The management tools that I analyze are a 5% landings tax and the re-designation of one of the areas in the fishermen's choice sets as a marine reserve.

In general, I find that the typical model (Model 1), which does not control for participation in an alternative fishery, predicts a stronger participation response to both management tools as compared to a model than explicitly allows for participation in a second fishery (Model 3). Specifically, Model 1 predicts an increase in non-participation in response to a 5% landings tax that is 2.5 times the prediction of Model 3. Similarly, Model 1 predicts an increase in non-participation that is almost twice that of Model 3 following the re-designation of Area 2 as a marine reserve. If we believe Model 3 to be a better representation of fishermen's behavior, then ignoring the multi-species aspect of daily participation decisions may lead to poor predictions of the effect of management policies, something we can no longer afford to do.

References

[1] – Assessment of Spiny Lobster, *Panulirus Argus*, in the Southeast United States. SEDAR 08 U.S. Stock Assessment Panel: Stock Assessment Report (2005).

[2] – A Report to the Spiny Lobster Advisory Board. Florida Fish and Wildlife Conservation Commission: Division of Marine Fisheries Management (2005).

[3] Allison, G. W., Lubchenco, J., Carr M. H. "Marine Reserves are Necessary but not Sufficient for Marine Conservation." *Ecological Applications* Vol. 81 (1998) pp. S79 - S92.

[4] Botsford, L. W., Castilla, J. C., and Peterson, C. H. "The Management of Fisheries and Marine Ecosystems." *Science*, Vol. 277 (1997), pp.509-15.

[5] Halpern, B. "The Impact of Marine Reserves: Do Reserves Work and Does Reserve Size Matter?" *Ecological Applications* Vol. 13 (2003) S117-S137.

[6] Hicks, R. L. and Schnier, K. E. Dynamic Random Utility Modeling: A Monte Carlo Analysis. *American Journal of Agricultural Economics*, Vol. 88 (2006), pp. 816-835.

[7] Jackson, J. B. C., Kirby, M. X., Berger, W. H., Bjorndal, K. A., Botsford, L. W., Bourque, B. J., Bradbury, R. H., Cooke, R. E., Erlandson, J., Estes, J. A., Hughes, T. P., Kidwell, S., Lange, C. B., Lenihan, H. S., Pandolfi, J. M., Peterson, C. H., Steneck, R. S., Tegner, M. J., Warner, R. R. "Historical Overfishing and the Recent Collapse of Coastal Ecosystems." *Science*, Vol. 293 (2001) 629-37.

[8] Pauly, D., Christensen, V., Dalsgaard, J., Froese, R., Torres, F. Jr. "Fishing Down Marine Food Webs." *Science*, Vol.279 (1998) 860-63.

[9] Sanchirico, J. N. and Wilen, J. E. Optimal Spatial Management of Renewable Resources: Matching Policy Scope to Ecosystem Scale. *Journal of Environmental Economics and Management*, Vol. 50 (2005), pp. 23-46.

[10] Sanchirico, J. N. and Wilen, J. E. A Bio-economic Model of Marine reserve Creation. *Journal of Environmental Economics and Management*, Vol. 42 (2001), pp. 257-76.

[11] Shivlani, M., Ehrhardt, N., Kirkley, J. and Murray, T. Assessment of the Socioeconomic Impacts of the Spiny Lobster Trap Certificate Program, Spiny Lobster Fishery Management Efforts, and Other Spiny Lobster User Groups on Individual Commercial Spiny Lobster Fishers. Division of Marine Biology and Fisheries, Rosenstiel School of Marine and Atmospheric Science, University of Miami (2004).

[12] Smith, M. D. Two Econometric Approaches for Predicting the Spatial Behavior of Renewable Resource Harvesters. *Land Economics*, Vol. 78 (2002), pp.522-538.

[13] Smith, M. D. State Dependence and Heterogeneity in Fishing Location Choice. *Journal of Environmental Economics and Management*, Vol. 50 (2005), pp. 319-340.

[14] Smith, M. D. and Wilen, J. E. Economic Impacts of Marine Reserves: The Importance of Spatial Behavior. *Journal of Environmental Economics and Management*, Vol. 46 (2003), pp. 183-206.

[15] Smith, M. D., Zhang, J., and Coleman, F. C. Effectiveness of Marine Reserves for Large-Scale Fisheries Management. *Canadian Journal of Fisheries and Aquatic Science*, Vol. 63 (2005), pp.153-164.

[16] Smith, M. D., Zhang, J., and Coleman, F. C. Structural Econometric Modeling of Fisheries with Complex Life Histories: Avoiding Biological Management Failures, Revise-and-Resubmit (conditional acceptance), *Journal of Environmental Economics and Management* (2006) (See Smiths website for working paper)

Table 1: Percentage of Trip Tickets Missing Prices by Fishing Season

Season	% Missing Prices	Season	% Missing Prices
1986	73.36	1996	1.67
1987	76.18	1997	1.38
1988	67.14	1998	0.66
1989	71.63	1999	0.15
1990	58.74	2000	0.00
1991	61.97	2001	0.00
1992	66.35	2002	0.30
1993	56.47	2003	0.22
1994	46.60	2004	1.51
1995	12.69	2005	0.15
		2006	0.09

Table 2: Frequency of Visits to Each Fishing Area

Area	# of Trips	Area	# of Trips
1	44,216	10	-
2	14,757	717	-
3	5,059	722	-
4	83	728	4
5	7	732	32
6	59	736	26
7	9	741	2,382
8	1	744	37,859
9	-	748	80,424

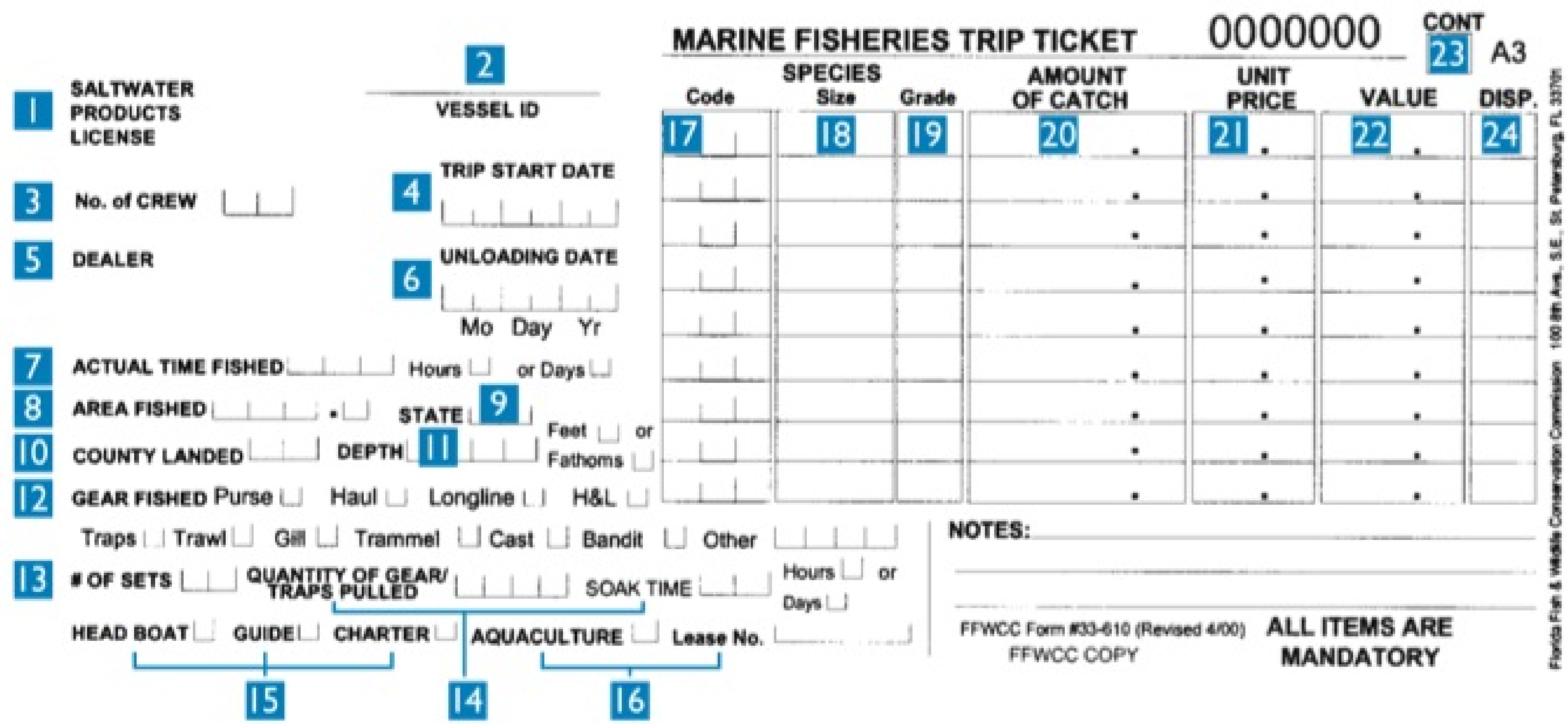


Figure 1: Florida Fish and Wildlife Conservation Commission Marine Fisheries Trip Ticket

of Lob Value to Total Value.pdf

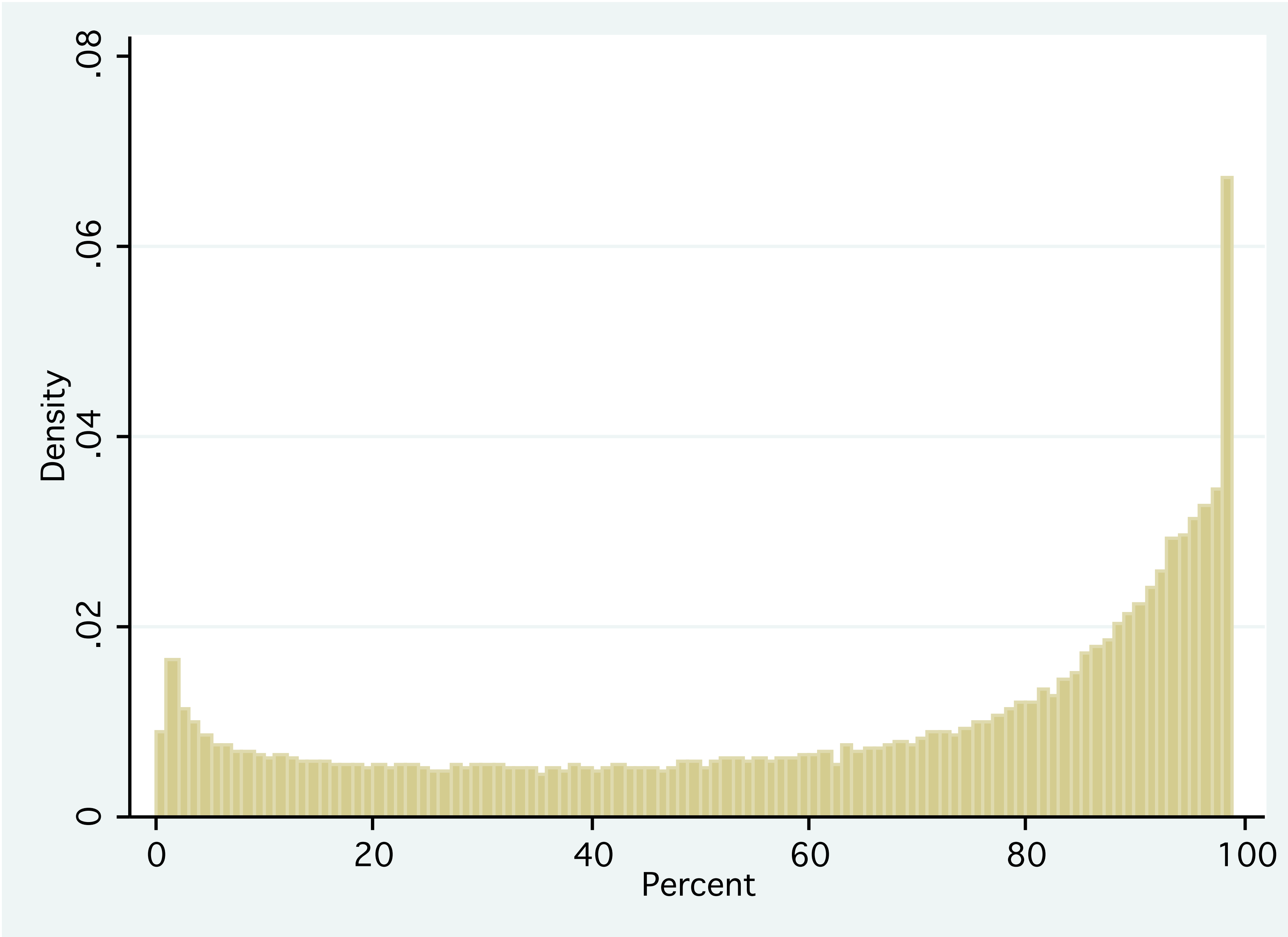


Figure 2: Histogram of the Contribution of Lobster to the Total Value of the Trip Once Trips Consisting Solely of Lobster are Removed

of Lobster Trips Reporting Trap Usage.pdf

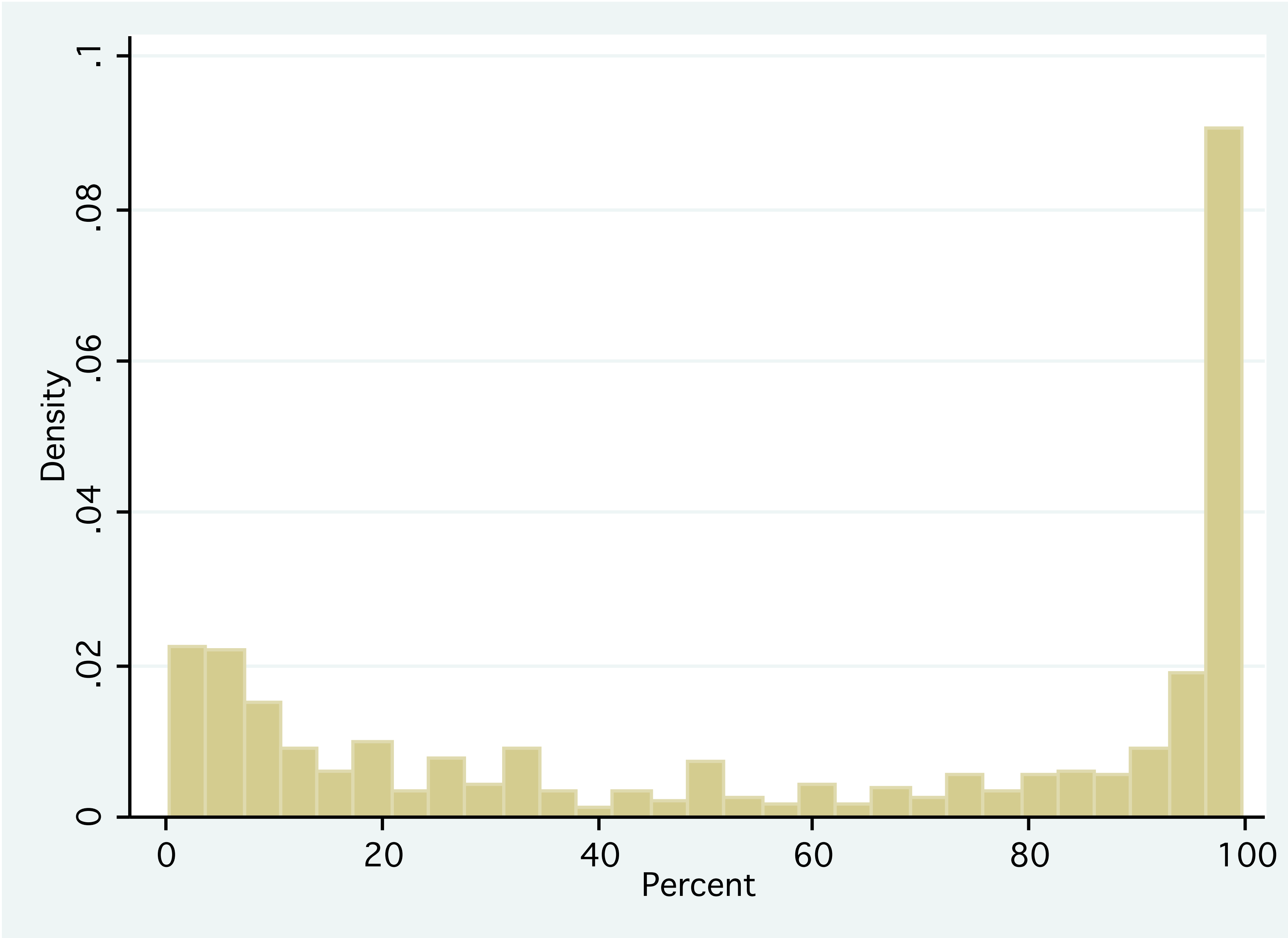


Figure 3: Percentage of Lobster Trips Reporting Trap Usage

of Lob Trips by Fisher-Fishyear.pdf

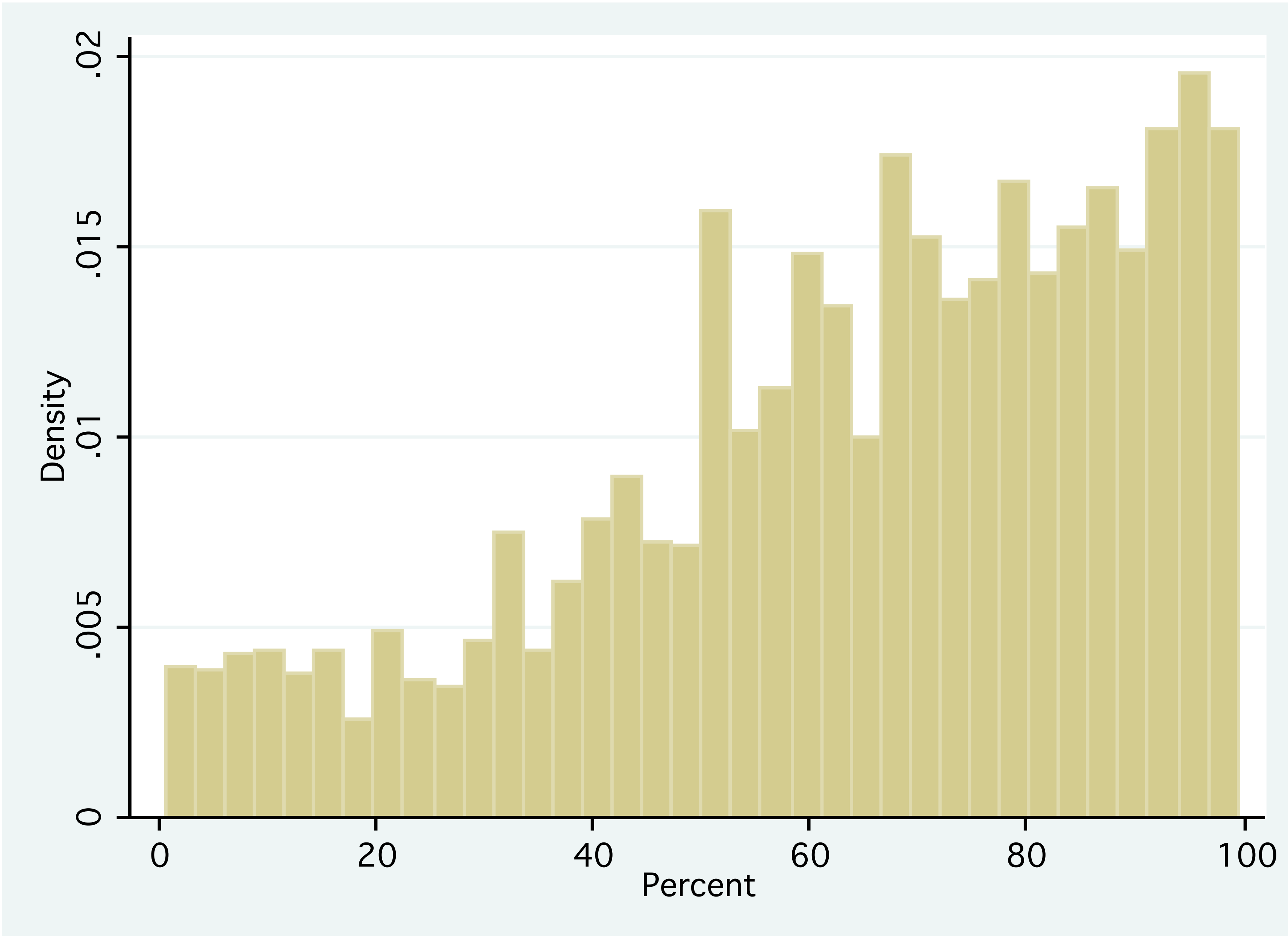


Figure 4: Percentage of Total Trips that are Lobster Trips by Fisher-Fishing Season

of Earnings from Lob Trips by Fisher-Fishyear.pdf

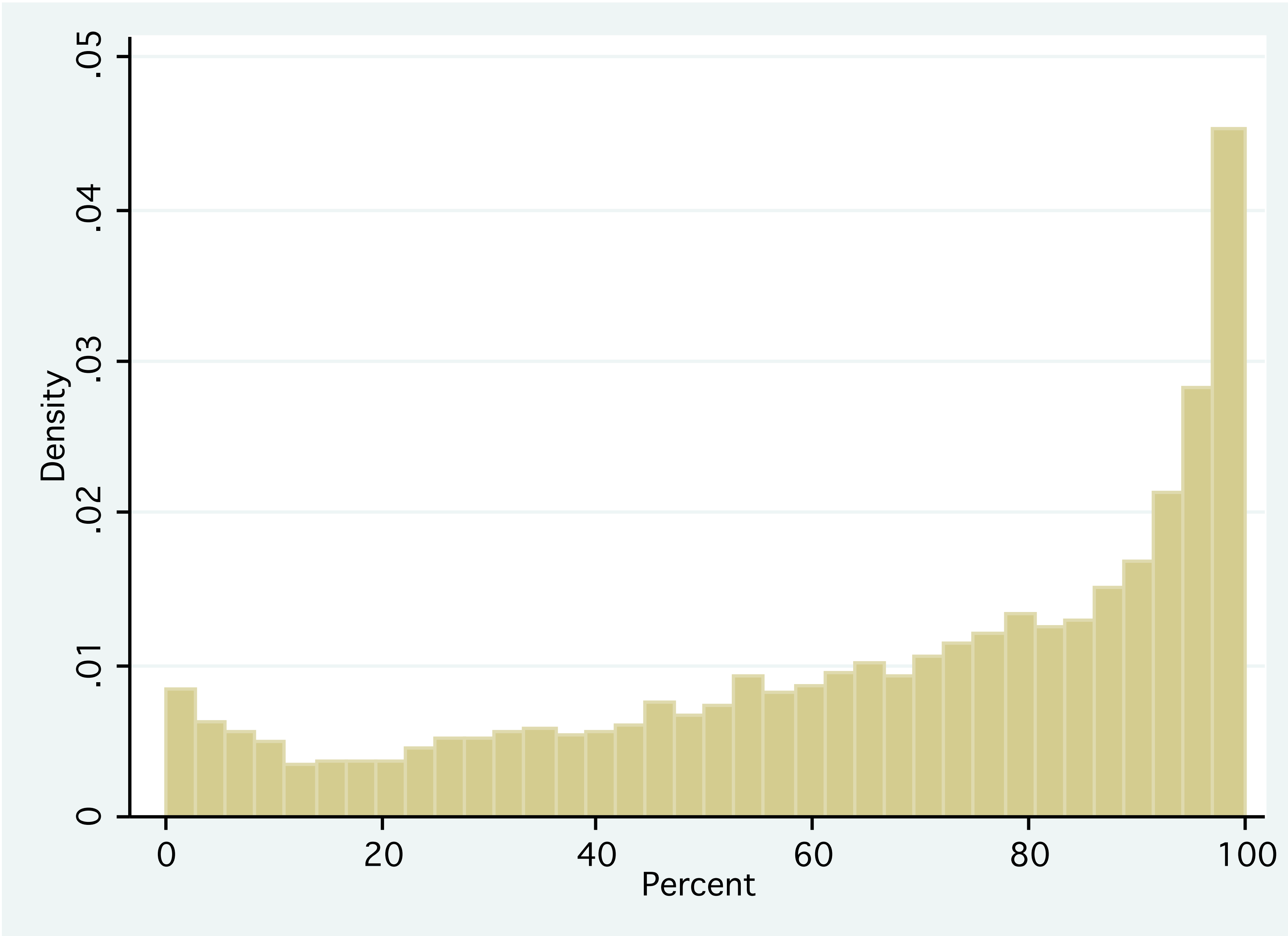


Figure 5: Percentage of Total Earnings from Lobster Trips by Fisher-Fishing Season

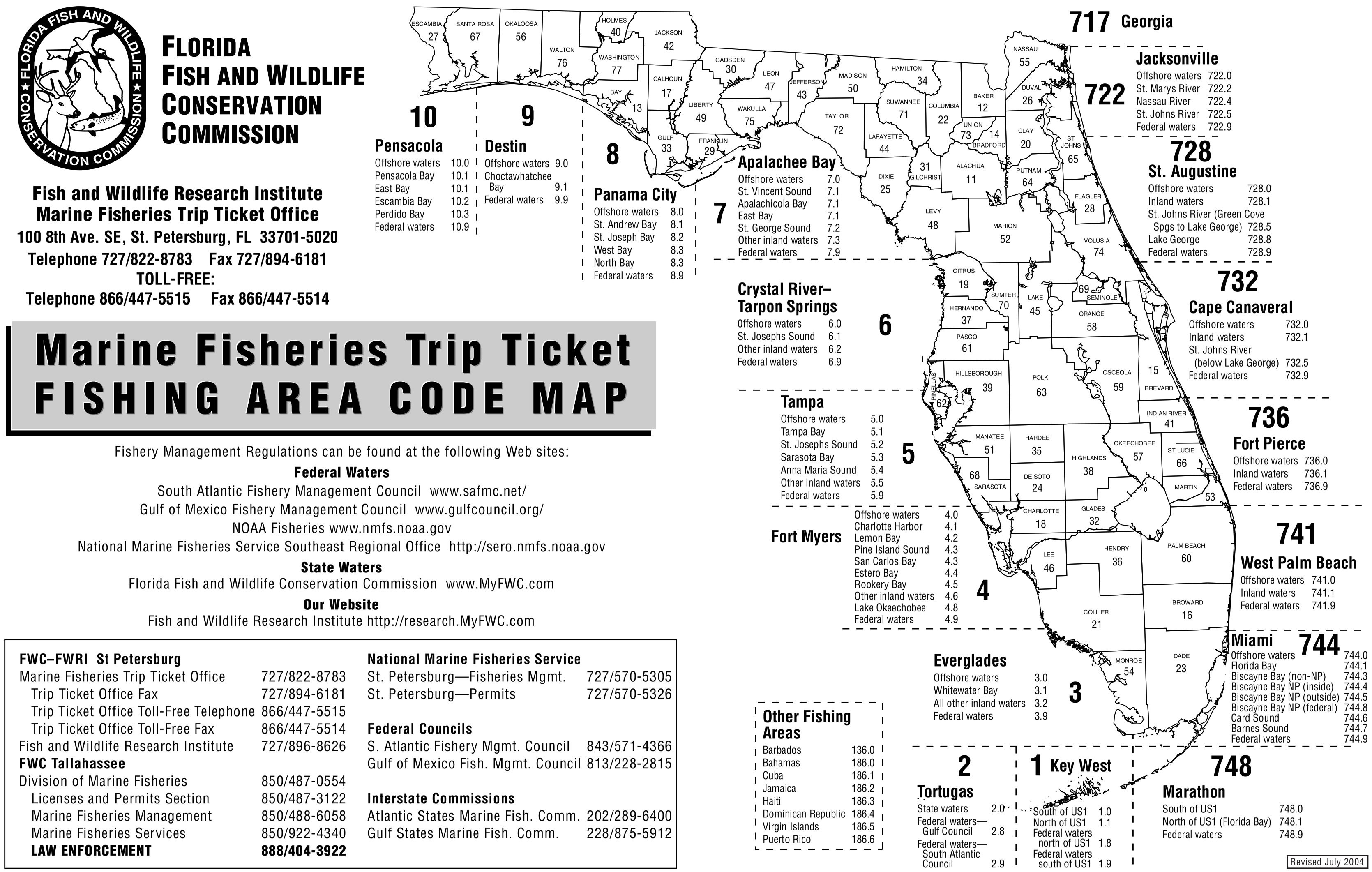


Figure 6: FWC Trip Ticket Fishing Areas

Table 3: Summary Statistics

	Unweighted		Weighted			
Variable	Mean	Std Dev	Mean	Std Dev	Min	Max
Possible days at sea	1,518	863	2,148	648	238	2,620
Actual days at sea	220	219	439	262	10	1,267
Participation rate	0.129	0.084	0.198	0.093	0.006	0.483
Lifetime revenue	271,753	397,736	526,480	499,638	1,073	3,794,820
Per trip revenue	1,152	1,405	1,235	1,252	65	15,375

Table 4: Nested Logit Estimates - Model 1

Variable	Coefficient	Standard Error	Z-statistic
Participation-Specific			
Constant	0	*Restricted for Identification*	
Wind Speed	-0.1564	0.0018	-89.23
Lagged Wind Speed	0.0110	0.0016	6.72
% Full Moon	-0.1220	0.0141	-8.65
Sunday	-0.7142	0.0150	-47.62
Location-Specific			
Area 1	-1.8462	0.0284	-64.91
Area 2	-2.0753	0.0347	-59.76
Area 3	-2.6024	0.0415	-62.69
Area 4	-1.7205	0.0256	-67.14
Area 5	-1.1798	0.0204	-57.90
Distance	-0.0245	0.0004	-62.44
Revenue	0.1086	0.0025	44.33
Inclusive Value (1-σ)	0.5728	0.0096	59.58
Log-likelihood			
Observations			

Table 5: Nested Logit Estimates - Model 2

Variable	Coefficient	Standard Error	Z-statistic
Participation-Specific			
Constant	0	*Restricted for Identification*	
Wind Speed	-0.1415	0.0018	-79.79
Lagged Wind Speed	0.0317	0.0017	18.97
% Full Moon	-0.1488	0.0142	-10.46
Sunday	-0.7226	0.0151	-47.91
Stone Crab Permit	0.6112	0.0114	53.69
Stone Crab Season	-1.3296	0.0178	-74.75
Stone Crab Revenue	0.0828	0.0029	28.62
Location-Specific			
Area 1	-1.5105	0.0299	-50.56
Area 2	-1.5954	0.0346	-46.17
Area 3	-2.0029	0.0440	-45.51
Area 4	-1.4686	0.0274	-53.61
Area 5	-1.1005	0.0201	-54.80
Distance	-0.0165	0.0005	-33.66
Revenue	0.0495	0.0025	19.88
Inclusive Value (1-σ)	0.3747	0.0115	32.53
Log-likelihood			
Observations			

Table 6: Nested Logit Estimates - Model 3

Variable	Coefficient	Standard Error	Z-statistic
Lobster Participation			
Constant	0	*Restricted for Identification*	
Wind Speed	-0.1484	0.0018	-83.19
Lagged Wind Speed	0.0335	0.0017	19.95
% Full Moon	-0.1496	0.0143	-10.49
Sunday	-0.7491	0.0151	-49.64
Stone Crab Permit	0.6294	0.0113	55.62
Stone Crab Season	-1.3515	0.0181	-74.68
Stone Crab Revenue	0.1297	0.0031	42.22
Stone Crab Participation			
Constant	-5.6911	0.0599	-94.99
Wind Speed	-0.1441	0.0031	-46.48
Lagged Wind Speed	0.0426	0.0030	14.41
% Full Moon	0.0393	0.0260	1.52
Sunday	-0.7966	0.0279	-28.52
Stone Crab Permit	-18.3792	-	-
Stone Crab Season	21.9158	0.0545	402.03
Stone Crab Revenue	0.2070	0.0028	73.11
Location-Specific			
Area 1 Constant	-1.2984	0.0275	-47.23
Area 2 Constant	-1.3477	0.0309	-43.60
Area 3 Constant	-1.6842	0.0410	-41.07
Area 4 Constant	-1.2772	0.0257	-49.67
Area 5 Constant	-0.9871	0.0187	-52.81
Distance	-0.0131	0.0005	-26.29
Revenue	0.0312	0.0021	15.11
Inclusive Value (1-σ)	0.2941	0.0114	25.70
Log-likelihood	-296,410.57		
Observations	3,105,109		

Table 7: Marginal Effects

Variable		Model 1	Model 2	Model 3
Lobster Participation				
Wind Speed		-0.01962	-0.01736	-0.01736
Lagged Wind Speed		0.00138	0.00389	0.00386
% Full Moon		-0.00765	-0.00907	-0.00923
Sunday		-0.06469	-0.06403	-0.06381
Stone Crab Permit		-	0.04407	0.04578
Stone Crab Season		-	-0.02795	-0.02929
Stone Crab Revenue		-	0.00277	0.00318
Stone Crab Participation				
Wind Speed		-	-	-0.00451
Lagged Wind Speed		-	-	0.00139
% Full Moon		-	-	0.00118
Sunday		-	-	-0.01866
Stone Crab Permit		-	-	-0.00084
Stone Crab Season		-	-	0.01044
Stone Crab Revenue		-	-	0.00681
Location-Specific				
Distance	Neither	0.00082	0.00055	0.00041
	Area 1	-0.00143	-0.00135	-0.00132
	Area 2	0.00012	0.00018	0.00020
	Area 3	0.00004	0.00005	0.00005
	Area 4	0.00006	0.00008	0.00008
	Area 5	0.00038	0.00050	0.00055
	Stone Crab	-	-	0.00002
Revenue	Neither	-0.00364	-0.00164	-0.00099
	Area 1	0.00633	0.00405	0.00315
	Area 2	-0.00055	-0.00053	-0.00047
	Area 3	-0.00016	-0.00015	-0.00013
	Area 4	-0.00029	-0.00023	-0.00019
	Area 5	-0.00169	-0.00151	-0.00132
	Stone Crab	-	-	-0.00005

Table 8: In Sample

		Predictions		
Choice	Observed	Model 1	Model 2	Model 3
Non-Lobster	209,316	209,316	209,316	209,316
		0.00%	0.00%	0.00%
(Stone Crab)	(10,829)	-	-	(10,829)
		-	-	(0.00%)
Area 1	9,144	9,200	9,293	9,352
		0.61%	1.63%	2.27%
Area 2	3,003	3,032	3,022	3,040
		0.96%	0.64%	1.22%
Area 3	954	964	985	998
		1.08%	3.20%	4.59%
Area 4	9,016	8,632	8,448	8,348
		-4.26%	-6.30%	-7.41%
Area 5	14,671	14,960	15,040	15,051
		1.97%	2.52%	2.59%

Table 9: Out of Sample

		Predictions		
Choice	Observed	Model 1	Model 2	Model 3
Non-Lobster	61,944	59,215	59,714	59,833
		-4.41%	-3.60%	-3.41%
(Stone Crab)	(2,953)	-	-	(3,604)
		-	-	(22.04%)
Area 1	1,786	3,136	3,003	2,993
		75.60%	68.15%	67.58%
Area 2	1,513	1,174	1,120	1,104
		-22.41%	-26.00%	-27.06%
Area 3	123	324	312	313
		163.62%	153.60%	154.07%
Area 4	1,572	3,201	3,033	2,941
		103.64%	92.96%	87.11%
Area 5	4,700	4,587	4,456	4,454
		-2.40%	-5.19%	-5.23%

Table 10: Implementation of 5% Landings Tax

	Model 1		Model 2		Model 3	
Choice	Pre	Post	Pre	Post	Pre	Post
Non-Lobster	59,215	59,626	59,714	59,957	59,833	59,996
		0.69%		0.41%		0.27%
Stone Crab	-	-	-	-	3,604	3,564
		-		-		-1.10%
Area 1	3,136	3,029	3,003	2,938	2,993	2,949
		-3.43%		-2.16%		-1.49%
Area 2	1,174	1,105	1,120	1,075	1,104	1,070
		-5.90%		-4.00%		-3.02%
Area 3	324	313	312	305	313	308
		-3.47%		-2.20%		-1.51%
Area 4	3,201	3,069	3,033	2,953	2,941	2,886
		-4.12%		-2.64%		-1.88%
Area 5	4,587	4,496	4,456	4,409	4,454	4,429
		-1.99%		-1.05%		-0.57%

Table 11: Closure of Area 2

	Model 1		Model 2		Model 3	
Choice	Pre	Post	Pre	Post	Pre	Post
Non-Lobster	59,215	60,316	59,714	60,482	59,833	60,437
		1.86%		1.29%		1.01%
Stone Crab	-	-	-	-	3,604	3,592
		-		-		-0.32%
Area 1	3,136	3,271	3,003	3,267	2,993	3,329
		4.30%		8.80%		11.24%
Area 2	1,174	0	1,120	0	1,104	0
		-100.00%		-100.00%		-100.00%
Area 3	324	336	312	336	313	344
		3.68%		7.82%		10.05%
Area 4	3,201	3,094	3,033	2,981	2,941	2,915
		-3.36%		-1.73%		-0.90%
Area 5	4,587	4,621	4,456	4,571	4,454	4,613
		0.73%		2.58%		3.56%