Sorting Models in Discrete Choice Fisheries Analysis

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Abstract

One of the greatest challenges facing empirical fisheries researchers is to endogenize fishing effort in bioeconomic models in a way that accounts for fleet heterogeneity. Such heterogeneity can manifest in a wide range of both observable and unobservable characteristics of fishing vessels and individual fishermen. Without accounting for heterogeneity, we simply have an incomplete understanding of how pressure on fish resources responds to policy instruments that are available, the states of fish stocks, and exogenous shocks to the system. Largely due to data limitations, the discrete choice fisheries literature has focused on modeling unobserved heterogeneity through random parameters. In this paper, we draw on the industrial organization literature on product differentiation and the public economics literature on spatial sorting to estimate sorting models of observable heterogeneity. Models of this type estimate individual-specific structural coefficients based on observable individual characteristics and choice-specific constants using contraction mapping. We apply the methods to location choices and target species choices in the Gulf of Mexico reef-fish fishery. For this application, we have an unusual data set that couples daily observations from logbooks with demographic information from a mail survey of captains. We use contraction mapping to control for spatially-, and species-explicit stock information. The models are used to explore spatial and inter-temporal species effort substitution in response to two marine reserves, which are implemented in sample.

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Introduction

Effective fishery management requires understanding fish stocks and fishing behavior; fish biology and behavior of the harvest sector jointly determine fishery outcomes (Clark 1990). Improving our understanding of fishing behavior requires a systematic analysis of heterogeneity in the harvest sector. Such heterogeneity can manifest in a wide range of both observable and unobservable characteristics of fishing vessels and individual fishermen. Observable characteristics include vessel size and type, gear type(s), number of crew, and past behavior (fishing effort, location choices, and species targets). Unobservable characteristics include fishing skill, risk preferences, willingness to relocate, vessel-specific information about abundance, and the opportunity cost of time. All of these features can vary substantially across a fishing fleet. Managers ultimately would like to understand the aggregate impacts of policy on behavior, but these impacts cannot meaningfully be understood without individual-level modeling. Will a model of a representative individual or vessel reasonably reflect the aggregate behavior of the fleet? Or, will such a model miss important nuances that are essential for understanding the aggregate impact of fishing behavior on the resource base?

In this paper, we draw on the industrial organization literature on product differentiation (Berry 1994; Berry, Levinsohn, and Pakes 1995) and an emerging literature on spatial sorting in public economics (Bayer and Timmins 2005; 2007; Timmins and Murdock 2007) to estimate sorting models of observable heterogeneity. Models of this type estimate individual-specific structural coefficients based on observable individual characteristics and choice-specific constants using contraction mapping. We apply the methods to location choices and target species choices in the Gulf of Mexico reef-fish fishery. For this application, we have an unusual data set that couples daily observations from logbooks with demographic information from a mail survey of captains. We use contraction mapping to control for spatially- and species-explicit stock information. The models are used to explore spatial and inter-temporal effort substitution in response to two marine reserves, which were implemented during our sample period.

Background and Motivation

Because spatial fishery management tools—e.g. marine reserves and territorial use rights in fisheries (TURFs)—aim to manage people spatially, it is fundamental to understand individual preferences across locations. These spatial preferences can be inferred from locational sorting behavior. A spatially-explicit fishery policy then leads to re-sorting across locations. With spatial preference information, fishery managers can predict the redistribution of fishing effort. This is important to avoid some unintended outcomes of a policy such as increasing fishing pressure in other areas when reducing fishing effort in a protected area.

Different individuals respond to fishery management differently, and these responses often hinge on individual attributes. If the distribution of individual attributes is constant over time, it may be appropriate to model a representative fisherman. However, this scenario is not generally true. In the short run, fishermen choose between fishing and other job opportunities, but in the long run, entry and exit occur in the fishery. Thus, the distribution of individual attributes is not constant over time. The predicted policy outcome using a representative fisherman could differ substantially from the true outcome solely due to individual heterogeneity.

Managers would like to avoid surprises (Wilen et al. 2002), but failing to account for heterogeneity could ultimately compound existing management challenges. For example, a season closure might increase fishing intensity before and after the closure for fishermen without other employment but may dampen fishing effort for those with other sources of income. In a conceptual model, Anderson (2004) shows that diverse behavioral objectives of fishermen can lead to different levels of fishing effort for the same stock levels and affect bioeconomic equilibria. In the broader behavioral economics literature, Camerer et al. (1997) presents a hypothesis that cab drivers in New York attempt to meet income targets rather than maximize profits. In many ways, owner-operator fishermen have similar constraints; they make labor-leisure tradeoffs, they need certain flows of income to make boat payments, and these constraints may trump the incentives to pursue pure profit maximization across time. It is an empirical question as to whether these hypothetical examples will show up in real behavioral fisheries data.

Let us consider a specific example from the Gulf of Mexico gag fishery. Gag is a long-lived grouper and one of 62 species in the Gulf of Mexico reef fish complex. Gag is a sequential hermaphrodite that aggregates to spawn, so managers have particular concerns about its reproductive viability in the presence of heavy fishing pressure. The reef fish complex is managed with a wide array of policies that target individual species, collections of species, and the reef fish complex in aggregate. The entire fishery is managed with limited entry, but total catch quotas apply to different subsets of reef fish. In recent years, quotas for groupers have been divided into shallow-water grouper quota—which includes gag, black, and red grouper among others— and deep-water grouper quota—which includes snowy and yellowedge groupers among others. There is a 24 inch size limit on gag, and commercial gag fishing is also affected by a seasonal closure and two marine reserves.

In Smith et al. (2006b), we find that aggregate annual effort targeting gag **increases** in response to a seasonal shallow-water grouper closure implemented in 2001 (a one-month closure from February 15 to March 15, which is in the middle of the gag spawning season). This rather shocking result can be explained by imposing income constraints on the household utility maximization problem of individual fishermen. However, formal statistical testing of the underlying cause of this aggregate result requires more examination of who is fishing more, and what their particular economic circumstances are (e.g. income level, boat ownership, access to other fishing permits, home port location, size of the household, etc.).

Now, let us consider an example about spatial choice that our modeling can explore. In June of 2000, the GMFMC formed two marine reserves in the northeastern Gulf. We found that after 4.5 years, the aggregate effect of these reserves was a decrease in reef-fish yield (Smith et al. 2006a). However, the aggregate effect may be masking substitution across target species. Did fishermen respond to the reserves by switching to other statistical areas, changing their gear configurations, or targeting different species? Alternatively, were behavioral responses minimal, in which case the yield decreases directly reflect losses in fishable biomass? This is a hugely important question for Gulf managers and for the broad debate about the effectiveness of marine reserves. We begin to explore heterogeneous behavioral responses to marine reserves in this paper.

The tools for understanding heterogeneity in the determinants of individual fishing behavior have only recently begun to emerge in the broader fisheries economics and econometrics literature. For quite some time, authors have used discrete choice models to study broad fishery choice (Bockstael and Opaluch 1983), entry and exit decisions (Ward and Sutinen 1993), and choice of fishing grounds (Eales and Wilen 1986; Dupont 1993; Larson, Sutton, and Terry 2000; Curtis and Hicks 2000; Hicks and Schnier 2006). Recent work has emphasized the importance of two types of behavioral heterogeneity: state dependence and preference heterogeneity. Habit persistence, i.e. fishermen tend to do what they have been doing (Holland and Sutinen 2000), is one form of state dependence. Variation in individual preferences is another source of heterogeneity that can be modeled with McFadden and Train's (2000) Mixed Logit. Mistiaen and Strand (2000) analyze location choice; Eggert and Tveteras (2004) analyze gear choice; and Strand (2004) looks at spatial variation in risk preferences of Gulf of Mexico longliners. Smith (2005) combines these two strands of the literature (state dependence and heterogeneity), adding more dimensions to the random parameter vector in a Mixed Logit model of location choice. Finally, Smith and Wilen (2005) examine preference heterogeneity in fishing by estimating separate probit models for each individual and bootstrapping standard errors to test hypotheses about the population of fishermen. They demonstrate that behavioral responses to physical risk, financial risk, and other aspects of the economic environment are heterogeneous.

Understanding fishing behavior for managers also requires understanding how multiple individual discrete decisions simultaneously unfold over space and time. Three examples in Gulf of Mexico are participation (when to go fishing), species target, and fishing location choice. All of these, combined with the amount and type of gear deployed, are critical determinants of fishing effort. Nested logit models have been used to study joint participation and location choice in fisheries (Berman, Haley, and Kim 1997; Smith 2002; Smith and Wilen 2003), but these models still impose a very restrictive substitution pattern. A model that has more flexibility in substitution patterns and that can incorporate a rich parameterization of heterogeneity is essential to learning more about fishing behavior. We depart from the emphasis in the literature on unobserved heterogeneity and instead model observed heterogeneity.

The Model

We model the choice of fishing location choice and species target jointly in a random utility framework. The utility of individual *i* choosing the species-location alternative *j* at time *t* is:

(1) $$u_{ijt} = v_{ijt} + \varepsilon_{ijt} .$$

Following Bayer and Timmins (2005), the deterministic term is decomposed into effects of choice-specific attributes and a choice-specific constant:

(2) $$v_{ijt} = \left(\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}_\mathbf{1}\right) Reserve_{jt} + \left(\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}_\mathbf{2}\right) P_{jt} + \left(\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}_\mathbf{3}\right) CPUE_{jt} + \left(\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}_\mathbf{4}\right) D_{ij} + \delta_j ,$$

where $\boldsymbol{\beta}_\mathbf{k} = \left(\beta_{k1}\ \beta_{k2} \cdots \beta_{kI}\right)$, and the number of individual characteristics in $\mathbf{x}_\mathbf{i}$ is I (including a '1' for the constant term). The observed individual heterogeneity is thus a function of individual attributes. As such, the effect of each choice-specific attribute has a mean effect (β_{k1}) and an effect of individual-specific attributes. The model setup is comparable to a Mixed Logit model with random parameters (McFadden and Train 2000). However, assuming that the parameter heterogeneity is observable, this model significantly reduces the computational intensity. The following summarizes the nomenclature in (2):

$\mathbf{x_i}$: individual attributes (speed, vessel length, income, income from commercial fishing, age, and a '1' for the constant term);

$Reserve_{jt}$: marine reserve policy. $Reserve_{jt} = 1$ if individual i chooses alternative j when and where a marine reserve is present.

P_{jt} : species-specific monthly price (red snapper, grouper and other reef);

$CPUE_{jt}$: species- and location-specific catch-per-unit-effort;

D_{ij} : distance;

δ_j : alternative-specific constant; and

ε_{ijt} : i.i.d. error term with a Type I Extreme Value distribution.

The unobservable alternative-specific constant not only captures location- and species-heterogeneity such as carrying capacity, but also controls agglomeration and congestion effect. Omitting these information leads to biased estimators. The probability of individual i choosing alternative j at time t is,

(3) $$p_{ijt} = \frac{v_{ijt}}{1 + \sum_{s \in J_t} v_{ist}}.$$

The choice set J_t varies over time due to the seasonal closure policy for red snapper and grouper species. The alternative of non-reef fish is estimated as the baseline. The utility of participating in the non-reef fish fishery is normalized to one. The alternative-specific constants are estimated through Berry Levinsohn and Pakes (1995) contraction mapping (hereafter, BLP):

(4) $$\delta^{new} = \delta^{old} + \ln(s) - \ln\left[\hat{s}\left(\delta^{old}\right)\right],$$

where s is the observed share vector for alternatives and

(5) $$\hat{s}_j = \frac{1}{N}\sum_{i,t}\hat{p}_{ijt}\ .$$

N is the total number of choice occasions. The routine starts with a guess at the δ's, estimates the β's, in (2) conditional on this guess using maximum likelihood, and then updates the δ's according to (4) and (5). The iterative routine stops when all of the parameter values have settled.

Some notes on the motivation for using BLP contraction mapping are in order here. Given the large data sets that are common in fishing logbooks and the large number of choices (J=40) when crossing three species aggregates with 13 fishing locations (and including a choice for non-reef fishing normalized to zero), the BLP contraction is computationally more feasible and stable than putting in choice-specific dummy variables. Still, with just 40 choices, it is possible to estimate these coefficients with dummy variables using conventional maximum likelihood. The more compelling motivation for this approach is that BLP uses population level information to exactly identify the choice-specific constants. When we link our analysis to the survey data, we necessarily exclude individuals who did not respond to the survey. We are able to include non-respondents in the population. The asymptotic properties of BLP stem from the use of population shares, though often researchers end up using sample data for the contraction. Here we are able to use the sample to estimate coefficients on the covariates and the population data to pin down the fixed effects.

For comparing models that incorporate heterogeneity and choice-specific fixed effects, we are interested in the "marginal" effect of forming a marine reserve. The effect, strictly speaking, is not "marginal" because locations either contain a reserve or they do not. Thus, the definition of the marginal effect is:

(6) $$\Pr\left\{ y = j \mid \bar{X}, Reserve = 1 \right\} - \Pr\left\{ y = j \mid \bar{X}, Reserve = 0 \right\},$$

where y is the choice variable and $\bar{X}_{ijt}$ is the mean of all variables except the reserve dummy. The estimated marginal effect is the mean across individuals. It is also possible to estimate the individual-specific marginal effect. This is particularly useful when this model is used to predict the location and species distribution of effort in the case of heterogenous fishing vessels.

Data

We constructed a unique data set that we believe is unprecedented in previous research in fisheries economics. The data set combines: 1) daily choice records from federal logbook data on the Gulf of Mexico reef fish fishery, 2) federal commercial fishing permit data, 3) species-level price data from Florida landings tickets, 4) a social survey of reef fish captains, 5) NOAA weather buoy data, 6) county-level unemployment statistics (from Bureau of Labor Statistics), and 7) publicly-available census data. For this paper, we use just the first four of these data sources. It is the integration of a social survey with repeated choices from logbooks that is unique.

The logbook data report fishing location by National Marine Fishery Service fishing zones (depicted in Figure 1) and catch by species. Our data set contains a complete set of records for 1993-2004. For purposes of analyzing discrete location choices and species target decisions, we aggregate the 62 reef fish species into three groups: grouper, snapper, and other reef fish. Permit data provide information about vessel length for each of the unique vessels that appear in the logbook data. Florida landings tickets were provided by the Florida Marine Research Institute (FMRI), a division of the Florida Department of Fish and Wildlife. We use these data to develop weighted average price time series for each of our species aggregates.

We conducted a social survey of reef fish captains by mail in 2005. A unique aspect of our survey was the ability to link repeated fishing choices to the individual survey respondents. This entailed cooperation with both state and federal agencies to enable us to track individual vessels over space and time, associate the survey responses with these records, obey confidentiality rules, and limit access to the survey data to our team. To this end, NOAA Fisheries provided FMRI with a complete permit data base with vessel codes and names and addresses of permit holders. FRMI generated a unique survey identifier associated with each vessel code and stripped the identifying information about reef fish captains (e.g. names and addresses) from the version of the file sent to us. We prepared the mail surveys with the unique survey codes, and FMRI did the mailing on our behalf. The pre-paid return envelopes were addressed to us. In this way, we were able to assure reef fish captains that their survey responses would not be made available to state or federal regulators (a significant concern of many commercial fishermen).

Survey administration followed the Dillman (1978) method. We first developed a draft survey and ran a focus group with reef fish captains in the northeastern Gulf. As a result of the focus group, we removed many of the questions about risk preferences (particularly gambling activities, which clearly struck a nerve with some fishermen in our focus group). We then conducted a very limited pre-test with the revised survey (n = 3) and extensive phone debriefings with each of the pre-test participants. See Appendix A for the full survey. We administered five separate mailings: 1) a pre-notification post card, 2) the survey along with a gift, 3) a follow-up reminder post card, 4) a second copy of the survey, and 5) a third copy of the survey. With the initial mailing of each survey, we included a gift of a DVD with video footage from inside the Madison-Swanson Marine Reserve. At this stage, we are using a very small portion of the information that we collected. Table 1 reports a summary of the survey response rate (46 - 47%).

One drawback of using survey data in conjunction with logbooks is that we are limited by both survey non-respondents and non-responses to particular survey questions. As a first step, we use a small subset of the available survey data, including questions on vessel speed, total income, captain's age, and percentage of income derived from commercial fishing. This leaves us with 373 individuals and 28,399 total choices.

Results

Table 2 reports mean coefficient results from the discrete choice model. These are interpretable as the standard coefficients of a conditional logit model. All parameters are highly significant. Price, CPUE, and distance all have their expected signs; a higher species price increases its attractiveness for fishing, a higher CPUE increases the probability of fishing for a species in a specific location, and longer travel distances decrease the probability of fishing at a particular site. The ex ante expected sign of the reserve effect is less obvious. On the one hand, we expect that the reserve eliminates some of a fishing ground and thus reduces the profitability of fishing in the surrounding zone (Smith et al. 2006a). But on the other hand, from our survey 33% of fishermen report that marine reserves in the Gulf of Mexico have increased fishing yields of groupers and other reef fish. Empirically, the mean coefficient for reserves is negative.

Table 3 reports the interaction effects from the discrete choice model. These can be interpreted as how individual observable heterogeneity modifies the mean response to the structural covariates. Most of the interactions are statistically significant, suggesting that the observable sources of heterogeneity are partly driving the observed behavior in the fishery. One interesting finding is that vessel speed has a negative effect on the tendency to fish in a zone that contains a reserve and also has a negative effect on the distance. Vessel length, on the other hand, has positive effects on both, though the distance interaction is not significant. These results point to an interesting source of heterogeneity in the fishery. The smaller vessels tend to be faster, but by virtue of being smaller, have less hull capacity and tend to make shorter trips. They may be designed to get to a fishing site quickly and return to port within the same day. Faster vessels thus are more averse to longer travel distances. The opposite is true for large vessels.

Though not all of the income interactions are significant, the CPUE and distance interactions suggest a troubling problem in the reef fish fishery. Lower income individuals are less responsive to changes in CPUE and less responsive to travel distance. This naturally raises a question about the direction of causality. Are lower income fishermen poor because they are not as good at fishing? Or, alternatively are their prospects in other fisheries or outside of fishing so small that they can less afford to adjust fishing effort to economic conditions than wealthier fishermen?

Captain age is another interesting finding. We find that older fishermen are less responsive to marginal changes in all of the economic opportunities. That is, the signs of the captain age interactions are all opposite of what we find in the mean coefficient levels. Holland and Sutinen (2000) suggest that "old habits die hard" for New England fishermen. One interpretation of our model is that older fishermen have formed strong fishing habits and thus are less responsive to changes in the economic environment.

Figure 2 depicts the choice-specific fixed effects solved for in the BLP contraction mapping. Moving along the x-axis, geographically, is moving counter-clockwise through the Gulf of Mexico starting from the southern tip of Florida until Louisiana. This figure provides an average picture of the relative abundance over space of the three species aggregates in our model. Unlike a traditional stock assessment model, these stock indices are derived implicitly from the observed behavior of the fishing fleet alone.

Table 4 summarizes our analysis of the reserve effect. Here, we take the model estimates reported above as the full model and derive individual net effects of the reserves on the probability of each choice as described by equation (6). We average across individuals to produce a mean net effect (hereafter mean effect). Note that this differs from the mean coefficient on reserves in Table 2, which is just the size of the individual effect assuming all variables that capture heterogeneity take on a value of zero. Beyond the full model, we run the econometrics three different ways: 1) excluding the choice-specific constants, 2) excluding the observable heterogeneity, and 3) excluding both constants and observable heterogeneity. We derive the individual net effects and the corresponding mean effects for each of these models. We then take the ratio of each mean effect to the mean effect from the full model. Thus, a ratio of 1.0 would indicate that the models do not produce a different mean effect.

It goes without saying that the individual effects will differ, but what is interesting about Table 4 is that there are major differences in some of the mean effects. That is, accounting for observable heterogeneity and choice-specific fixed effects leads to very different conclusions about the mean behavioral response of the reef fish fleet to the formation of two marine reserves. These differences appear both in zones that contain the reserves (6 and 8) and in the other zones. With the exception of groupers, the model that excludes observed heterogeneity but still includes choice-specific constants comes close to estimating the mean behavioral effect of the reserve from the full model. The results do not hold for grouper most likely because the reserves were formed in part to protect gag and other shallow-water groupers, and thus the overall behavioral response is more pronounced.

Discussion

We present results form a unique data set that allows us to explore the effect of observable heterogeneity on behavioral responses to marine reserves. Collecting survey data and linking it with logbook information is both costly and bureaucratically complicated. Our statistical estimates and comparisons across models indicate that this sort of activity may be worth the effort. Without conducting a survey, an intermediate step for other applications would be to exploit vessel information that exists in permit files together with repeated choices in logbooks. Our results also show that including choice-specific constants has an even more pronounced effect on behavioral responses to reserves than observable heterogeneity. Thus, there is strong support for using the BLP contraction to estimate these choice-specific effects, especially if the number of choices is large and the population information is available. Both of these conditions are likely to be true for federally managed fisheries, particularly as we move towards using more spatial management tools.

The spatial resolution of our data is not sufficient to exploit the power of the sorting model to its fullest potential. One of the strengths of this econometric modeling approach is the ability to decompose the estimation into two stages and use the second stage to disentangle agglomeration or congestion effects from the alternative-specific constant. We can easily imagine both features existing in fisheries. Agglomeration could arise from some common information about spatially explicit abundance that is not observed by the analyst. Congestion externalities, in contrast, occur when boats fish in close proximity to one another, compete for the same fish, and increase the risks of fishing lines becoming entangled or even boat collisions. Spatial choice in Alaskan groundfish fisheries—see Berman 2006; Berman et al. 2007; Haynie and Layton 2006; Abbott and Wilen 2007— is potentially a fruitful area for future research. In that context, the spatial resolution of fishing data is higher, and there is substantial interest in understanding the effects of micro-spatial closures (mostly to protect critical habitat of threatened steller sea lions).

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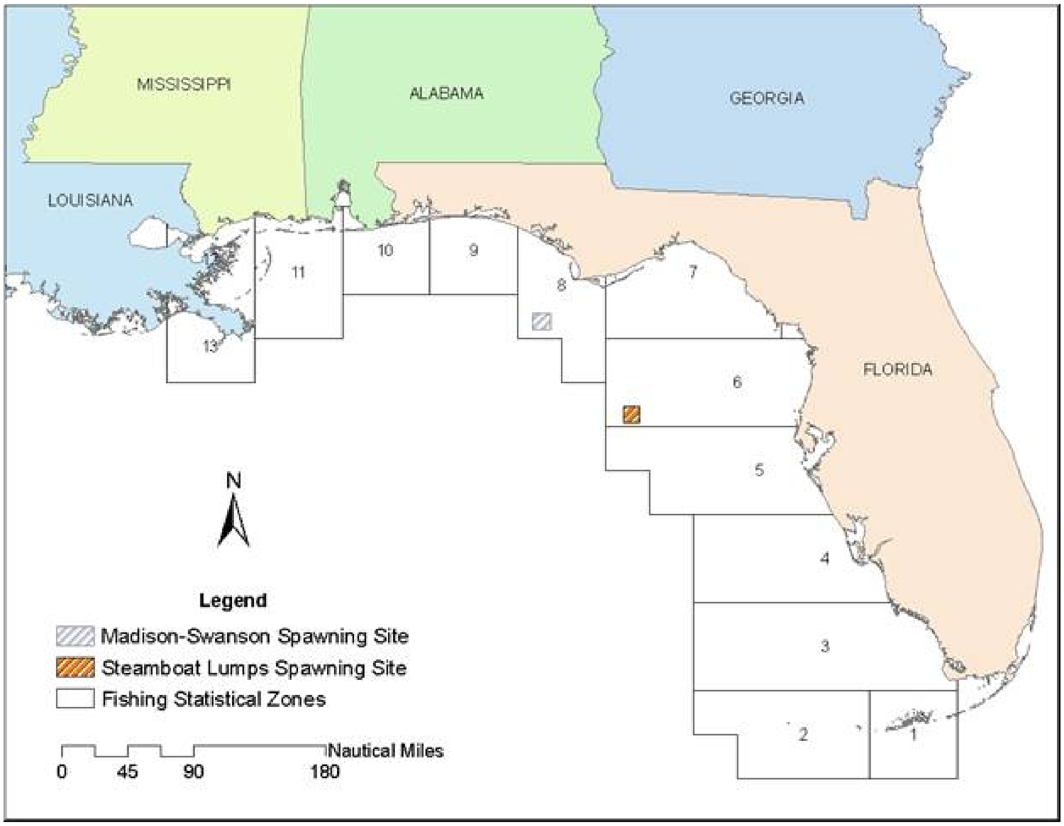

Figure 1 – National Marine Fisheries Service Fishing Zones and the Two Marine Reserves Formed in 2000

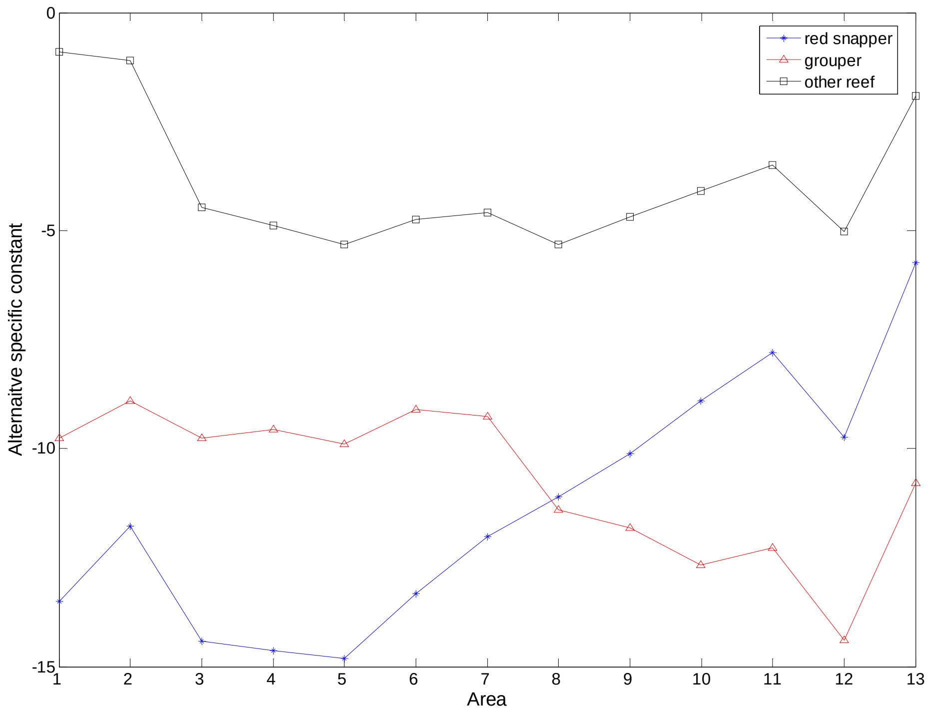

Figure 2 – Choice-specific Constants from the BLP Contraction Mapping, Based on Logbook Population Data

Table 1 – Summary of Survey Response Rate

	Surveys Mailed	Surveys Returned	Response Rate
Total	1079	495	45.9%
Adjusted*	993	464	46.7%

*Removes blanks with 'No Longer Fishing in Gulf', incorrect address, or duplicate permit holder.

Table 2 – Mean Coefficients from the Discrete Choice Model

	Estimate	St. Error	
Reserve	-1.08	0.219	**
Price	9.82	0.145	**
CPUE	0.79	0.120	**
Distance	-4.03	0.079	**
# Choices	28,399		
# Individuals	373		
# Alternatives	40		

** Indicates significant at the 5% level.

Table 3 – Interaction Coefficients from the Discrete Choice Model

		Estimate	St. Error	
Reserve	**Speed**	-1.113	0.3272	**
	Vess. Length	1.928	0.3422	**
	Income < $35K	-0.029	0.0628	
	Commercial > 60% Income	-0.154	0.0535	**
	Cap. Age	2.437	0.2634	**
Price	**Speed**	-2.507	0.2006	**
	Vess. Length	-2.871	0.2101	**
	Income < $35K	0.026	0.0398	
	Commercial > 60% Income	-0.004	0.0352	
	Cap. Age	-3.074	0.1729	**
CPUE	**Speed**	-0.735	0.1878	**
	Vess. Length	2.004	0.1639	**
	Income < $35K	-0.365	0.0399	**
	Commercial > 60% Income	-0.143	0.0317	**
	Cap. Age	-0.726	0.1429	**
Distance	**Speed**	-0.537	0.1151	**
	Vess. Length	0.155	0.1092	
	Income < $35K	0.965	0.0276	**
	Commercial > 60% Income	0.165	0.0185	**
	Cap. Age	2.605	0.0917	**

** Indicates significant at the 5% level.

Table 4 – Comparing the Effect of the Marine Reserve on Mean Choice Probability Reports the Share of the Reserve Effect from the Full Model that Each of the Other Three Models Finds (1.0 indicates no difference)

Species	Area	No Constants	No Survey	Conditional Logit
1	1	1,355.31	6.89	1,562.95
1	2	206.72	4.79	235.65
1	3	1,836.67	4.05	2,019.43
1	4	1,344.84	3.54	1,415.59
1	5	1,193.76	3.64	1,226.49
1	**6**	**280.14**	**3.38**	**295.74**
1	7	81.51	2.77	84.28
1	**8**	**43.00**	**2.43**	**46.42**
1	9	20.02	2.01	21.51
1	10	9.48	2.14	10.53
1	11	5.10	2.03	5.88
1	12	58.44	3.03	70.39
1	13	1.13	2.28	1.36
2	1	1.55	1.48	1.77
2	2	0.58	1.25	0.65
2	3	0.98	1.04	1.07
2	4	0.45	0.82	0.47
2	5	0.47	0.85	0.48
2	**6**	**0.22**	**0.87**	**0.23**
2	7	0.27	0.79	0.27
2	**8**	**2.83**	**0.99**	**3.03**
2	9	5.18	0.88	5.52
2	10	17.64	0.96	19.46
2	11	19.34	0.98	22.18
2	12	271.86	0.98	325.37
2	13	7.61	1.05	9.11
3	1	0.04	0.93	0.04
3	2	0.04	0.96	0.04
3	3	0.71	0.98	0.78
3	4	0.59	0.84	0.63
3	5	0.69	0.92	0.71
3	**6**	**0.39**	**0.92**	**0.41**
3	7	0.36	0.82	0.37
3	**8**	**0.94**	**0.96**	**1.02**
3	9	0.65	0.84	0.70
3	10	0.53	0.83	0.59
3	11	0.47	0.87	0.54
3	12	3.79	0.95	4.59
3	13	0.17	1.07	0.21

Appendix A – Survey of Reef Fish Captains
(Note Pagination and Formatting Has Changed)

Survey #

Survey for Captains in the Gulf of Mexico Reef Fish Fishery

Fishing and Employment

This survey is mostly concerned with commercial fishing but has some questions about charter fishing. We define commercial fishing as catching fish to sell, and charter fishing as running recreational charters for hire.

1. How many total years have you been a captain in commercial fishing?
_____ 1 year or less _____ 2 to 5 years _____ 6 to 10 years
_____ 11 to 15 years _____ 16 to 20 years _____ More than 20 years

2. How many years have you worked in commercial fishing?
_____ 1 year or less _____ 2 to 5 years _____ 6 to 10 years
_____ 11 to 15 years _____ 16 to 20 years _____ More than 20 years

3. How many years have you been the captain of your current vessel?
_____ 1 year or less _____ 2 to 5 years _____ 6 to 10 years
_____ 11 to 15 years _____ 16 to 20 years _____ More than 20 years

4. What is the maximum speed of your vessel? ______________ knots
5. What types of fishing gear do you use on your vessel?
Please check all that apply.
_____ Traps _____ Handline _____ Gill Net
_____ Longline _____ Trolling _____ Diving Gear
_____ Bandit Reel _____ Other, please specify ____________________________

6. What types of fish-finding equipment do you have on board?
7. Do you commercial fish in areas outside of the Gulf of Mexico, for instance along the East Coast of Florida or in other parts of the country?

_____ Yes _____ No

7a. If yes:
What percentage of your annual commercial fishing effort do you spend in areas outside of the Gulf of Mexico ?
_____ 0% to 20% _____ 21% to 40% _____ 41% to 60%
_____ 61% to 80% _____ 81% to 100%

7b. Besides the Gulf of Mexico, in what other general areas do you commercial fish?

7c. What species do you target in areas outside of the Gulf of Mexico?

8. What other forms of employment are you engaged in besides commercial fishing?
Check all that apply.
_____ Charter Fishing
_____ Food processing or food services
_____ Retail sales
_____ Construction
_____ Farming
_____ Manufacturing
_____ Financial, legal, medical, or other professional services
_____ Other, please specify ______________________________________

9. After subtracting the costs of fishing, what percentage of your annual household income comes from commercial fishing?
_____ 0% to 20% _____ 21% to 40% _____ 41% to 60%
_____ 61% to 80% _____ 81% to 100%

10. If you do charter fishing, after subtracting the costs of fishing, what percentage of your annual household income comes from charter fishing?
_____ 0% to 20% _____ 21% to 40% _____ 41% to 60%
_____ 61% to 80% _____ 81% to 100%

11. If you have other forms of employment, on an annual basis what percentage of your total work hours do you spend in commercial fishing?
_____ 0% to 20% _____ 21% to 40% _____ 41% to 60%
_____ 61% to 80% _____ 81% to 100%

12. If you have non-fishing employment, is this employment seasonal?
_____ Yes _____ No

12a. If yes:
What months of year do you have the most non-fishing employment? Check all that apply.
_____ Jan. _____ Feb. _____ Mar. _____ Apr. _____ May _____ Jun.
_____ Jul. _____ Aug. _____ Sep. _____ Oct. _____ Nov. _____ Dec.

13. At how many different ports do you land fish?
_____ 1 _____ 2 _____ 3 _____ 4 _____ more than 4

14. To how many different fish houses or retailers do you sell fish?
_____ 1 _____ 2 _____ 3 _____ 4 _____ more than 4

15. Do you always keep your boat at the same dock?
_____ Yes _____ No

15a. If yes, do you have a long-term contract with the dock owner?
_____ Yes _____ No

15b. What is your monthly dock rent? ________

16. What are the most important weather indicators that affect your decision of whether or not to take a fishing trip? Please rank from 1 (most important) through 7 (least important).

_____ Wave height _____ Wave period _____ Wind speed
_____ Wind direction _____ Storm warnings _____ 5-day weather forecast
_____ Other, please specify ____

17. When weather conditions are bad, what other factors influence your decision to go fishing? Check all that apply.
_____ Personal safety
_____ Potential damage to your boat
_____ Fish market conditions (high or low prices)
_____ A seasonal closure of the fishery is coming soon.
_____ A seasonal closure of the fishery just passed.
_____ Your earnings in fishing over the past few months were high (or low).
_____ You have (or do not have) other sources of income.
_____ Other, please specify ____.

Background Information
18. Sex

_____ Male _____ Female

19. Age

_____ 18 - 29 _____ 30 - 39 _____ 40 - 49 _____ 50 – 59 _____ 60 or older

20. Marital Status:

_____ Single _____ Married _____ Divorced

21. How many children do you have?
_____ none _____ 1 _____ 2 _____ 3 _____ 4 or more

22. Do you smoke?
_____ Yes _____ No

23. Please indicate the category that best represents your total annual household income after subtracting out the costs of fishing.
_____ Under $20,000
_____ $20,001 to $35,000
_____ $35,001 to $50,000
_____ $50,001 to $65,000
_____ $65,001 to $80,000
_____ $80,001 and over

24. Do you own a home?
_____ Yes _____ No

25. Do you have life insurance?
_____ Yes _____ No

26. Do you have health insurance?
_____ Yes _____ No

Beliefs about Marine Reserves and Other Forms of Fisheries Management

27. Are you familiar with the Madison-Swanson Marine Reserve, Tortugas Ecological Reserve, or the Steamboat Lumps Marine Reserve?
_____ Yes _____ No

28. When these reserves were first proposed, did you believe that they would increase fishing yields of grouper and other reef fish species?
_____ Yes _____ No

28a. If yes, how long did you think that it would take for yield increases to happen?

_____ Less than 6 months_____ 6 months to 1 year _____ 1 to 2 years

_____ 2 to 3 years _____ More than 3 years

29. The Madison-Swanson and Steamboat Lumps reserves took effect in the year 2000, and Tortugas took effect in 2001. Since these reserves took effect, have you changed your beliefs about how they affect fishing yields?

_____ Yes _____ No

30. Do you believe that these marine reserves have increased grouper or other reef fish yields?

_____ Yes _____ No

30a. If yes, how long did it actually take for yield increases to happen?

_____ Less than 6 months_____ 6 months to 1 year ____ 1 to 2 years

_____ 2 to 3 years _____ More than 3 years

31. What do you think are the most important obstacles to the future success of Gulf of Mexico reef fish fisheries? Please rank from 1 (most important) through 6 (least important).

_____ There are too many permit holders.

_____ Some gear types are too efficient.

_____ There is too much bycatch or too many discards of undersized fish.

_____ Some sectors, recreational or commercial, catch too much.

_____ Existing fisheries management does not work.

_____ Other, please specify ____.

32. What do you think are the most effective forms of fisheries management? Please rank from 1 (most effective) through 7 (least effective).

_____ Restrict the number of permit holders

_____ Marine reserves or other types of no-take zones

_____ Seasonal closures

_____ Individual fishing quotas

_____ Size limits

_____ Gear restrictions

_____ Other, please specify ____.

For the following questions, we would like you to consider broad definitions for costs and benefits. Costs may include your boat payment, hiring labor, and purchasing bait, fuel, ice, and fishing and safety equipment. They also include the cost of your time. If a type of management causes you to spend more time fishing to make the same amount of money, we view that as a cost. Similarly, benefits might include the revenue that you earn from selling fish and any savings in time spent fishing. Please indicate whether

you agree or disagree with the following statements.

33. Overall, the Madison-Swanson Marine Reserve created more benefits for fishermen than costs.

☐ Strongly Agree ☐ Agree ☐ Uncertain ☐ Disagree ☐ Strongly Disagree

34. Overall, the Steamboat Lumps Marine Reserve created more benefits for fishermen than costs.

☐ Strongly Agree ☐ Agree ☐ Uncertain ☐ Disagree ☐ Strongly Disagree

35. Overall, the Tortugas Ecological Reserve created more benefits for fishermen than costs.

☐ Strongly Agree ☐ Agree ☐ Uncertain ☐ Disagree ☐ Strongly Disagree

36. In general, marine reserves are a bad way to manage fisheries.

☐ Strongly Agree ☐ Agree ☐ Uncertain ☐ Disagree ☐ Strongly Disagree

37. In general, marine reserves are a better way to manage fisheries than seasonal closures.

☐ Strongly Agree ☐ Agree ☐ Uncertain ☐ Disagree ☐ Strongly Disagree

38. Seasonal closures force fishermen to fish in bad weather.

☐ Strongly Agree ☐ Agree ☐ Uncertain ☐ Disagree ☐ Strongly Disagree

39. Marine reserves impose more costs on fishermen than seasonal closures.

☐ Strongly Agree ☐ Agree ☐ Uncertain ☐ Disagree ☐ Strongly Disagree

40. Permit buyouts will significantly reduce pressure on reef fish in the Gulf of Mexico.

☐ Strongly Agree ☐ Agree ☐ Uncertain ☐ Disagree ☐ Strongly Disagree

41. Please provide any additional comments about reef fishery management in the Gulf of Mexico.
42. Please provide comments about the survey.

Your opinions and the information that you have provided on this survey matter! Please return your completed survey in the self-addressed postage-paid envelope provided.

Thank you again for taking the time to complete this survey!