Fishing Behavior Across Space and Time

Luc Pierre Veyssiere, Quinn Weninger

Working Paper No. 09032
August 2009

IOWA STATE UNIVERSITY
Department of Economics
Ames, Iowa, 50011-1070

Fishing behavior across space and time

Luc Veyssiere
Iowa State University

Quinn Weninger*
Iowa State University

Revised: August 10, 2009

Abstract

Models of fishing behavior rarely incorporate the complexities of marine ecosystems, multiple-stock harvest technologies, and regulations present in real world marine fisheries. We introduce a structural model of a multi-species, weak-output-disposability harvest technology. A latent target-cost-minimizing share vector is estimated to link the technology to a spatially and temporally heterogeneous fish stock. Data from the Gulf of Mexico reef fish fishery is used to estimate the model. The results provide a robust characterization of harvest and discard behavior across space and time. Our approach considerably improves methods used to study fishing behavior and evaluate alternative fisheries management policies.

JEL Classification: Q2
Keywords: Spatial fishing behavior, multiple-stock fisheries, costly targeting, at-sea discarding.

*Send correspondence to Quinn Weninger, Department of Economics, Iowa State University, Ames IA 50011-1040, USA; Phone: 515-294-8976; E-mail: weninger@iastate.edu. We thank Larry Perruso for providing the Gulf of Mexico reef fishing data, and seminar participants at UC Santa Barbara, and NAAFE for helpful suggestions. Funding from the Environmental Defense Fund, Grant 40-198, and the National Marine Fisheries Service is greatly appreciated.

1 Introduction

Fisheries management problems have recently been linked to a reliance on overly simplistic models of marine ecosystems. Single-species management principles that ignore complex biological interactions among multiple species, or multiple age cohorts, and treatment of spatially heterogeneous fish metapopulations as a spaceless whole stocks are examples.[1] A similar critique can be leveled at models of fishing behavior which often exhibit a considerable disconnect between fundamentals, prices, technologies, stock conditions and regulations, and the fishing outcomes that are of interest to managers. At the least, effective management of fisheries requires information on stocks-specific harvests across space and time, information on bycatch and at-sea discarding, behavioral responses to prices and regulations, and tools to evaluate biological and economic performance of alternative regulatory policies. An essential requirement is that behavioral models be capable of examining the counterfactual, i.e., the behavioral responses of fishermen to regulations that have yet to be adopted. The problem calls for a structural approach that can link management-relevant fishing outcomes to the complex ecological, institutional and economic conditions in marine fisheries.

This paper introduces a novel approach to study the policy-relevant aspects of fishing behavior within a biologically and spatially heterogeneous fishery.[2] Commercial fishermen decide where and when to fish jointly with choices of factor inputs to employ in the harvesting process and the quantity and mix of individual fish species or sub-stocks to harvest. These choices are constrained by the available technology, the composition of the fish stocks and often by various harvest regulations. We introduce a structural economic model that takes as the unit of analysis the spatial harvest and discard choices of fishermen. The model draws heavily on the neo-classical theory of the firm, but is modified to account for the role of the *in situ* fish stocks in the technology. We consider multiple-species, and/or multiple age cohort stocks that are spatially and temporally heterogeneous, and therefore make considerable

[1] A growing view among fisheries scientists and marine ecologists is that a more holistic approach will improve the management of ocean fisheries resources (Brodziak and Link, 2002; Pikitch et al., 2004; U.S. Commission on Ocean Policy, 2004). The challenges and opportunities that accompany spatial fisheries management are discussed in Wilen (2004).

[2] Berrmann (2007) discusses the various limitations of the random utility model for analyzing spatial fishing behavior. See also Curtis and McConnell (2004).

progress toward incorporating the ecological complexity of real world fisheries.

A key element of our model is a latent vector of target-cost-minimizing harvest shares. This vector summarizes spatial-temporal stock conditions and importantly the spatial-temporal profit opportunities for fishermen. The latent cost share vector provides the crucial link between the technology and the spatially and temporally heterogeneous fish stock. A second key feature is the technology itself, which we assume exhibits a weak-output disposibility property consistent with costly targeting in multiple-species fisheries (Turner, 1995; Singh and Weninger, 2009). Third, our approach controls directly for effects of regulations common in managed fisheries on fishing behavior.

An application to the Gulf of Mexico reef fish fishery is presented to demonstrate the key attributes. The Gulf of Mexico reef fish fishery is a multiple-species fishery that is managed with seasonal closures for some species stocks, per-trip catch limits, spatial closures, gear restrictions and catch quotas. These regulations along with the weak output disposibility technology lead to a complex decision environment which interacting constraints on the harvest choices of fishermen. Our econometric model incorporates these constraints, in the form of unique Kuhn-Tucker necessary conditions, in the estimation of a parametric multiple-product cost function. The system of estimating equations identifies further the latent stocks conditions that determine the cost structure across space and time. A Gibbs sampler is used to fit the model (see Casella and George, 1992 and Geweke et al., 1999).

Our analysis of reef fish harvest behavior demonstrates several of the model's strengths. We are able to show how prices, and regulation such as per-trip landings limits used to reduce fishing mortality, redirect fishing efforts toward unregulated species and across space and time. Spatial-temporal discard patterns are also impacted by price and regulatory changes. Our model predicts that when the price of fuel rises, reef fish fishermen are less inclined to target higher priced reef fish species, and instead are more inclined to land a harvest mix with low targeting costs. The preferred harvest strategy under higher fuel prices also involves fewer at-sea discards.

Before we present the model and empirical results, it is instructive to compare our approach with related literature. Our model is similar in spirit to state space modeling (see Geweke and Tanizaki, 2001 and for ecological applications see Punt and Hilborn, 1997).

Ecologists have long relied on state-space models to estimate latent fish biomass and its underlying dynamics. We do not explicitly model stocks dynamics here; extensions of the model in this direction are discussed in the concluding section. We do adopt some of the econometric techniques used in the ecology literature. Recent advances have shown that Bayesian state space models perform better in the estimation of highly non linear dynamic such as the logistic growth function, which features many fish ecosystems (Wang, 2007).

Current methods for analyzing spatial fishing patterns rely almost entirely on the discrete choice random utility construct.[3] A standard application of random utility models (RUMs) to spatial fishing behavior assumes that on each trip from port, the fisherman selects, from among a set of spatially disjoint (discrete) fishing opportunities or sites, the opportunity that yields the highest utility.[4] Our model also exploits the heterogeneity of the ocean environment for determining spatial behavior, but we do not discretize space or time. The number of sites at which fishermen might deploy gear in a fishery is typically far too large to be estimated via a multinomial probit or multinomial logit specification. This places artificial limits on the number of sites for which preferences may be estimated and forces researchers to assume coarse geographical divisions of the fishing grounds, with coarse descriptions of spatial fishing patterns (Berman, 2007).[5] Our approach of treating space and time continuously is therefore an important advance.

Moreover, application of the RUM to fishing data takes as the unit of analysis the spatial location of a *fishing trip*. A second-stage model of input and output choices on each trip is required by the researcher in order to complete the link between fundamentals and harvests, bycatch revenues and costs. Our model considers the choice of spatial location jointly with the input and harvest choices that are made on the trip. As we demonstrate, this allows us

[3] The random utility model (RUM) was developed by Daniel McFadden to study transportation choices. The original set up assumes that a particular transportation choice yields utility U which is known fully by the decision maker. Utility is decomposed as $U = V + e$, where V is observable by the researcher, while e captures an unobserved component. In empirical applications V may be conditioned on observables such as distance to a destination, average traffic patterns, road conditions, etc.

[4] Numerous applications of the RUM to spatial fishing data have appeared in the resource economics literature. We do not attempt a review of this literature. A special issue of Marine Resource Economics (Volume 19, Number 1, 2004) is dedicated to analysis of spatial fishing behavior. Smith (2000) provides an overview of the RUM method for analyzing spatial fishing data.

[5] Branch et al. (2005) discusses a related problems where the spatial grid used to divide fisheries geographically—typically latitude and longitude designations determined by political considerations—may be unrelated to the locations of productive fishing sites.

to directly predict management-relevant fishing behavior which is crucial for management purposes.

Estimation procedures that incorporate Kuhn Tucker necessary conditions are common in the analysis of consumer demand systems, and valuation of non-marketed goods (see von Haefen, and Phaneuf, 2007 for a review of this literature). Kuhn Tucker estimation is less common in applied production analysis (an exception is Lee and Pitt, 1987). Whereas in demand systems consumer utility is not observable, in our fishing profit maximization problem we observe costs but do not observe the composition of the fish stock at the locations chosen for fishing. We incorporate species-specific KT necessary conditions for optimal harvesting, along with the trip-level cost function. Estimating the system of equations improves parameter identification and directly accommodates the impacts of regulations, e.g., landing constraints that impact our data.

We choose to use Bayesian methods as they present computational advantages over frequentist methods in both fitting non linear equations and estimating random parameters. Markov Chain Monte Carlo (MCMC) methods simulate the posterior but do not maximize the likelihood function (Chernozhukov and Hong, 2003). Bayesian estimation approaches are capable of estimating models for which extremum-based estimators fail to converge. Furthermore in Bayesian frameworks random parameters are accommodated by the appropriate choice of priors. These hierarchical priors introduce an additional structure in the model which eases estimation (Chib and Carlin, 1999).[6,7]

Our model allows for random vessel skipper effects. We adopt a hierarchical prior and use a Metropolis Hasting algorithm to draw from the posterior of our non linear systems of equations (Kim, et al., 2002).[8] Our structural approach unlike Kim, et al. (2002) accommodates not only for lower binding constraints, zero harvests, but also for upper binding

[6]Remark that data augmentation methods (Tanner and Wong, 1987) used for Bayesian inference in RUM greatly eases the computational burden of these models and can significantly extend the location choice set considered (see McCulloch and Rossi, 1994 and Imai and van Dyk, 2005).

[7]While there is no clear advantage in estimating KT systems with either Bayesian or frequentist methods, in the presence of random parameters the Bayesian methods are often preferred (von Haefen and Phaneuf, 2007).

[8]The Bayesian inference approach in Kim, et al., (2002) identifies parameters of consumers preferences for varieties of yogurt. Their procedure remains a reduced form approach because of the absence of data on consumer preferences and thereby only partially identifies behavioral parameters. On the contrary our structural model uses data on the cost function for identification.

constraints on choice variables. In our case the upper-bound constraint is due a per-trip landings regulations imposed by the fisheries management program. To our knowledge this paper is the first to incorporate both types of corner solutions.

The next section presents a multiple-factor input, multiple-species behavioral model in a landings-regulated fishery. Our empirical estimation strategy is also presented. Section 3 presents a brief overview of the Gulf of Mexico reef fish fishery, the available data and a discussion of the regulations used to protect reef fish stocks. Section 4 reports results and demonstrates use of the model for designing regulatory policies. Section 5 summarizes the main insights of the paper and discusses extensions.

2 Model

We consider a representative, profit maximizing fisherman who harvests from $i = 1, ..., m > 1$ differentiated fish stocks. Individual stocks can differ by species, age cohort or sex. Denote the non-negative harvest vector as $h = (h_1, ..., h_m)$. The optimization problem is analyzed in two stages; a cost minimization stage followed by a profit-maximizing harvest choice.

2.1 Multiple-stocks harvest technology

In a fishery, the cost of harvesting h will depend on factor input prices, but also on the composition, i.e., the absolute and relative abundance of individual fish stocks. We allow the spatial and temporal distribution of the stocks to be heterogenous. Stock composition at a particular location and time can vary depending on the spatial-temporal microhabitat. Abundance at spatial location $s \in S$ and date t is denoted $x_{st} = (x_{1,st}, ..., x_{m,st})$, where $x_{i,st}$ is stock i abundance, and S is the set of all fishing locations on the fishing ground.[9] We assume that harvest h is small relative to stock abundance and treat x_{st} parametrically.

Date t minimum costs are defined as

$$c(h, w, x_{st}) = \min_{v,s}\{w'v|\ v \text{ can harvest } h \text{ given } x_{st},\ \ s \in S\}, \tag{1}$$

[9] The spatial location index s may for example, indicate the lattitude, longitude and depth of water column.

where v is a vector of factor inputs (e.g., fuel, bait, ice, labor, and capital), that is purchased competitively at price vector, $w > 0$. We assume the cost function is convex in h and non-decreasing, concave and linearly homogeneous in w. These are *standard* structural properties of multi-product technologies. Additional structural properties unique to fishing technologies are discussed next (see Singh and Weninger, 2009 for further details).

Minimizing the cost of harvesting h will in general involve selecting fishing locations where the composition of the stock is *well-suited* given the harvest target h. To be more precise, if a fisherman chooses to harvest a relatively large quantity of stock i fish he will likely select a location at which x_i is abundant in absolute terms and abundant relative to other stocks. At this location, the fishing gear can be expected to intercept stock i in roughly the same proportion as the target vector h. Moving vessels and gear across space utilizes costly inputs. Therefore the fishing location must be optimally chosen jointly with the target harvests to balance costs and benefits of targeting a particular mix of stocks.

Notice that the optimization problem in (1) is defined over locations s, whereas the spatial index remains attached to our stock measure, x_{st}. Commercial fishing involves steaming from port to a preferred location and then returning to port to off-load and sell the catch. Vessel operations are mobile and regularly operate from different ports. However, each fishing trip must depart from, and return to some land-based port, and thus the production process is spatially linked to land.[10] Our model allows the costs of accessing a particular stock composition to differ across coarse regions of the fishing ground.

We assume the technology exhibits the non-standard structural property of weak output disposibility (Turner, 1995, 1997; Singh and Weninger, 2009). An important implication of this property is that costs can be non-monotonic in h and specialization, i.e., selecting a harvest mix with $h_i = 0$ for some i and $h_j > 0$ for $j \neq i$, can be costly. To see why this property is reasonable in multiple-stock fisheries, compare the costs associated with the following harvest vectors. The first, denoted h^+, has strictly positive quantities for each species ($h_i^+ > 0$, for all i). The second h^0 is identical with the exception that harvest of the species i stock is zero; $h^0 = (h_1^+, .., h_{i-1}^+, 0, h_{i+1}^+, .., h_m^+)$. Well-suited fishing locations, given

[10] Researchers have conditioned the location choice on the port from which the vessel departs (Haab et al., 2008). The choice departure and landing port is likely part of a dynamic optimization problem that is a topic of future research.

the target h^0, may be quite limited since it is likely difficult, maybe impossible, to avoid intercepting some stock i when it is present at a location.[11] Adjusting factor inputs, e.g., changing the mesh size on fishing nets, altering bait and hook configurations, could enhance gear *selectivity* and avoid intercepting stock i when it is present at a location. However these adjustments are expected to be costly.

Next compare the costs of harvesting strictly positive vector h^+. It is reasonable that the subset of fishable locations will expand. More generally, fewer factor inputs will be utilized in avoiding stock i fish. The implication is $c(h^+, w, x_{st}) < c(h^0, w, x_{st})$. Although ultimately an empirical question, weak output disposibility, or non-monotonicity of the cost function under stock condition found in most multiple-stock fisheries, is distinctly possible.

Let $c_i \equiv \partial c(h, w, x_{st})/\partial h_i$ denote the marginal cost of harvesting the species i stock at (s, t). The weak output disposibility property is summarized with the following condition.

Condition 1 *Set $h_j > 0$ for some $j \neq i$, then $c_i(h, w, x_{st}) < 0$ at harvest quantity $h_i = 0$ is permitted.*

The above condition implies that there can exist a strictly positive harvest quantity at which marginal cost is zero. Marginal costs are negative at smaller harvests because factor inputs that would otherwise be used to avoid intercepting stock i are saved. Condition 1 implies that marginal rate of output substitution can be positive over a range of harvest levels. It is this property that underlies the bycatch problem in fisheries and under certain regulations provides an incentive to discard fish at sea.

2.2 Targeting behavior

We next consider the profit maximizing harvest choices. In many fisheries harvesting activities are subject to stock-specific regulations designed to control total fishing mortality. Following Singh and Weninger (2009), we assume that regulations are directed at the quantities of fish landed at port. Denote landings and discards of stock i as $l_i \geq 0$ and $d_i \geq 0$,

[11] If the mix of stocks is distributed homogeneously across the fishing ground, and gear is less than fully selective, the set of fishable locations with $x_{i,st} = 0$ and $x_{j,st} > 0$, $j \neq i$ will be empty and $c(h^0, w, x_{st}) = \infty$.

respectively. It should be emphasized that the minimum cost function in (1) is defined over harvested fish, $h = (l_1 + d_1, ..., l_m + d_m)$.

The regulations we consider are landings constraints that are strictly enforced at the fish dock. We assume that at-sea harvests are unobserved by the manager and are not subject to penalty. Let $\bar{l} = (\bar{l}_1, ..., \bar{l}_m)$ denote the maximum legal landings quantity for stock i fish; $\bar{l}_i = 0$ simulates a closed harvest season for stock i.

The Lagrangian for the profit maximization problem is given as

$$\mathcal{L} = p \cdot l - c(l + d, w, x_{st}) - \lambda \cdot (l - \bar{l}), \tag{2}$$

where $p \in \Re^m_+$ is the output price vector and $\lambda \in \Re^m_+$ is a vector of Lagrange multipliers (vector conformability is assumed). Necessary conditions for optimal landings and discards, denoted l^* and d^*, respectively, are given as

$$p_i - c_i(l^* + d^*, w, x_{st}) - \lambda_i \leq 0, \quad \text{if } l_i^* > 0; \quad \lambda_i \left(l_i^* - \bar{l}_i\right) = 0, \quad i = 1, ..., m, \tag{3a}$$

$$-c_i(l^* + d^*, w, x_{st}) \leq 0, \quad d_i^* c_i(l^* + d^*, w, x_{st}) = 0, \quad i = 1, ..., m, \tag{3b}$$

$$l_i^* \leq \bar{l}_i, \quad i = 1, ..., m, \quad d_i, \lambda_i \geq 0 \quad i = 1, ..., m, \tag{3c}$$

Suppose that prices at the dock are strictly positive for the moment, and that the landings constraint does not bind. In this case $\lambda^* = 0$ and the necessary condition in (3a) indicates the optimal harvest vector satisfies a familiar condition with the price of stock i equal to its marginal cost. We see also that at h^* marginal cost is positive (since $p_i > 0$). Equation (3b) implies therefore that $d^* = 0$ or alternatively $h^* = l^*$; all harvested fish is landed at port. Under strictly positive prices and no regulation, discarding is not part of a profit maximizing fishing strategy (Turner, 1995).

Now suppose one or more landings constraints bind. Consider first an extreme case where landing stock i is prohibited, $\bar{l}_i = 0$, for example in the case of a stock-specific closure. Assume fishing remains profitable, i.e., $l_j^* > 0$ for some j. Profit maximization requires, $c_i^* = 0$ as indicated in (3b). An optimal fishing strategy will involve positive discards if marginal costs are negative at zero harvest quantity. Under the weak output disposibility technology it may be less costly to harvest and discard species i fish than take costly efforts to avoid intercepting it with the fishing gear. The implication is that harvests and mortality, unless discarded fish are unharmed, are strictly positive under a stock-specific landings closure. A final observation is that the behavioral implications for a zero dockside price and a landings constraint $\bar{l}_i = 0$ are identical.

Notice further that $c_i^* = 0$ from the necessary condition (3a). This implies that $\lambda_i^* = p_i$; the shadow price of the stock i landings constraint is equal to the dockside price.

Next consider the case with $\bar{l}_i > 0$ and suppose the landings constraint binds, $l_i^* = \bar{l}_i$. From (3a) we see that $\lambda_i > 0$ and $p_i > c_i^*$. If discards are positive, $d_i^* > 0$, equation (3b) requires $c_i^* = 0$, and from (3a), we see that $\lambda_i^* \geq p_i$. Alternatively, suppose $\bar{l}_i > 0$ and that $d_i^* = 0$. Equation (3b) requires $c_i^* > 0$, which occurs at strictly positive harvest level, and since $d_i^* = 0$ we have $0 < h_i^* = l_i^* < \bar{l}_i$. However, if the landing constraint does not bind, $\lambda_i^* = 0$, and therefore $p_i - c_i^* = 0$.

The remaining sections estimate a parametric cost function consistent with the structural properties of a costly-targeting technology and the KT necessary conditions for profit-maximizing harvest behavior.

2.3 Empirical model

We adopt the following empirical cost function for estimation:

$$c(h, w, s, \varphi_{st}|\gamma, \pi, \beta)= \left[1 + \sum_{i=1}^{m} \gamma_v \left(\theta_i - \varphi_{i,st}\right)^2\right] \cdot g(h, w, s|\beta). \tag{4}$$

The function in (4) decomposes cost into targeting costs, which are measured by the first bracketed term and non-targeting cost, measured by the function $g\,(.)$. An explanation of the structure and notation used in each component is presented next.

Targeting costs: Notice first that the stock variable, x_{st} has been replaced with the vector $\varphi_{st} = (\varphi_{1,st}, ..., \varphi_{m,st})$, where $\varphi_{i,st} \in [0, 1]$, $i = 1, ..., m$. The vector φ_{st} is a minimum-target-cost share vector for location s and date t. The term $\theta_i = h_i / \sum_{i=1}^{m} h_i$ in (4) is the share of stock i fish in the harvest vector. The parameter, $\gamma_v \geq 0$ is a targeting cost parameter for fishermen v. We use V to denote the set of fishermen.

If a fisherman chooses harvest h such that $\theta_i = \varphi_{i,st}$, for all i, the square-bracketed term in (4) will equal unity, and harvest costs are given as $g(h, w, s|\beta)$. In this case no *targeting* efforts are necessary to harvest the vector h. This is admittedly a stylized construct, since explicit separation of costs into targeting and non-targeting components is difficult to envision in practice. The no-target-cost vector φ_{st} is simply a means to summarize the targeting-relevant features of the fish stock at various $(s,\ t)$ combinations. Notice that if $\gamma_v > 0$ the term $\sum_{i=1}^{m} \gamma_v \left(\theta_i - \varphi_{i,st}\right)^2$ increases with the Euclidean distance between θ and φ_{st}. Therefore harvesting costs rise with the added effort that is required to harvest a mix os species that differs from the mix implicit in φ_{st}.

We allow targeting costs to vary across skippers to allow for heterogeneity in targeting ability which is likely linked to such factors as skipper experience. The parameter γ_v measures the rate at which costs increase for skipper v as the harvest share θ deviates from φ_{st}.

Non-targeting costs: The function $g(h, w, s|\beta)$ is assumed to be strictly positive for $h > 0$, non-decreasing and convex in h, and non-decreasing, concave and linearly homogeneous in w. For our empirical application to the Gulf reef fish fishery g is specified as

$$g = \exp(\beta_0 + \beta_1 h_1 + ... + \beta_m h_m + \beta_s s + \beta_{ss} s^2) \cdot K^{\beta_K} w^{\beta_w}; \tag{5}$$

K denotes vessel length and will proxy for the capital endowed to the fishing operation, and w will hereafter denote the price of fuel.

Inclusion of a proxy for capital reflects the short run nature of the harvest problem that we analyze below. Prices for other factor inputs such as bait, ice and groceries, could not be constructed from our data. The crew wage is discussed shortly.

Inclusion of the space index in (5), which we enter quadratically, is intended to capture non-targeting cost differences over the fishing ground. Changes in absolute stocks abundance, fishing depths or crew labor quality across regions of the fishery are examples.

The specification in (5) is convex in individual stock harvest levels if $\beta_1, .., \beta_m$ are positive. The function is jointly convex in h if $\sum_i \beta_i > 0$. The function g is increasing and concave in w if $\beta_w \in (0, 1]$. Linear homogeneity could be easily imposed if multiple-input prices were available. Our data include a single price and therefore the linear homogeneity property is not considered below. If vessel length is a normal input in the production process, harvest costs will be non-increasing and concave in K.

Special cases of the multi-stock targeting technology arise under particular values of γ_v.

As $\gamma_v \rightarrow \infty$ the technology exhibits fixed output proportions, i.e., costs become infinite unless $\theta = \varphi_{st}$. This case can represent an harvest technology whereby fishermen cannot influence the mix of harvested stocks. Independence across harvested stocks occurs if $\gamma_v = 0$ and $g(h, w, s|\beta)$ is chosen appropriately (see May et al., 1979; Clark, 1990; Boyce, 1996). A test of the null hypothesis, $\gamma_v = 0$ is therefore a test of the structural property of costly targeting (weak output disposibility).

Minimum-target-cost share vector: Estimates of stock specific abundance across space and time is not available in our data, or for any fishery that we are aware of. Therefore the minimum-target-cost share vector is treated as a latent variable that must be estimated. We require a parsimonious specification of the vector φ_{st}. Since s and t are continuous variables, our state space is infinitely large. A curse of dimensionality must be overcome in order to summarize the cost impacts of φ_{st} over space and time. One approach is to discretize the state space, i.e., divide the fishery into subregions and time intervals and assume φ_{st} is constant within each subregion/calendar period combination. This approach has several flaws: (1) the choice of sub-regions and time intervals requires considerable information about spatial-temporal habitat variation; (2) there is no reason to expect φ_{st} changes abruptly at the spatial and temporal boundaries that are chosen, and (3) the number of subregion/calendar period combinations, and therefore unique values of φ_{st} that must be estimated, is likely to be excessive in most fisheries.

Our approach is to assume that spatial and temporal changes in the composition of the fish stocks can be represented by a smooth and continuous function of s and t. We adopt the following functional specification for our estimation:

$$\varphi_{i,st} = \frac{\exp(f_i(s, t|\pi_i))}{1 + \exp(f_i(s, t|\pi_i))}, \quad i = 1, ..., m. \tag{6}$$

where π_i are parameters to be estimated. The function $f_i(s, t|\pi_i) \in \Re$. The transformation in equation (6) ensures $\varphi_{i,st} \in [0, 1]$.[12]

In our empirical application f is specified as;

$$f_i(s, t, y|\pi_i) = \pi_{i,0} + \pi_{i,s}s + \pi_{i,ss}s^2 + \pi_{i,y}y + \pi_{i,yy}y^2 + \pi_{i,t}(t - t^2). \tag{7}$$

[12] Our assumptions for (6) do not guarantee that $\sum_i \varphi_{i,st} = 1$ at each (s, t) combination. This does not detract from the model's ability to summarize the minimum targeting costs over space and time.

In our empirical application s is a spatial index denoting the geographical subregion of fishing, and t is the day of the year that a fishing trip begins. The variable y is cumulative days since the beginning of our data period. The latent stock share model is therefore capable of capturing spatial and seasonal variation, as well as longer term changes in the composition of the fish stock. The function in (7) addresses the dimensionality problem; in our case, characterizing $\varphi_{i,st}$ requires that we identify seven parameters for each of the m fish species/stocks harvested by the fishermen in our data.[13] Note also that the specification in (6) provides a framework to test for spatial and temporal variation in the composition of the stocks, e.g., tests of the null hypotheses that f_i is constant across space or time or both (i.e., $f_i(s,t|\pi_i) = \pi_{i,0}$) is easily implemented.

Crew shares: A final consideration is labor remuneration in fisheries data. The lay system by which hired captains and crew are paid a share of trip revenues is ubiquitous in marine commercial fisheries. As pointed by McConnell and Price (2004) the lay system can have implications for fishing behavior. If we denote by η_c the share of trip revenue that is paid to the crew, variable trip profits in (2) become:

$$\eta pl - c(l + d, w, x_{st}) - \lambda \cdot (l - \bar{l}).$$

In the above $\eta = 1 - \eta_c$ denotes the residual share of the trip revenue that accrues to the vessel skipper, who we assume is responsible for trip-level harvests decisions. Information on crew shares in our data is incomplete, and we therefore estimate the parameter $\eta = 1 - \eta_c$.

2.3.1 Error structure

We assume that the fishermen in our data are aware of φ_{st}, i.e., are knowledgeable about the spatial-temporal composition of the fish stock over the fishing ground.[14] The stock composition is however unobserved by the researcher. Similarly, vessel skipper know their

[13] Higher-order polynomials and cross terms would increase the flexibility of the model. The added flexibility was deemed to be unnecessary in our application.

Discretizing the *state space* would be problematic with over 21 subregions and roughly 3.75 years of data. For example, if we assume stock conditions are constant during each quarter (year) there would be 345 (92) distinct values of $\varphi_{i,st}$ for $i = 1, ..., m$ to be estimated.

[14] We do not require the assumption that individual fishermen possess knowledge of x_{st} over the entire fishing ground.

own target cost parameter γ_v. Target costs are unobserved by the econometrician. We assume γ_v is distributed normally in our sample with mean $\bar{\gamma}$ and variance σ_γ^2.

$$\gamma_v \sim N\left(\bar{\gamma}, \sigma_\gamma^2\right).$$

The estimating equations of our model include the empirical cost function introduced in equation (4), and corresponding Kuhn Tucker necessary conditions for optimal targeting. To simplify notation, we collect the observed data for a representative fishing trip into the row vector $z = [1, h_1, ...h_m, s, w, K, t, y]$. Moreover let $A(z|\gamma, \pi) = [1 + \gamma_v \left(\theta_i - \varphi_{i,st}\right)^2]$, the marginal cost of harvesting stock i is given as

$$c_i\left(z|\gamma_v, \pi, \beta, \varphi\right) = \left[\frac{\partial A}{\partial h_i} + A\frac{\partial g}{\partial h_i}\right] g\left(.\right) + \varepsilon_i.$$

In the above, ε_i, is an error term associated with KT necessary conditions $i = 1, ..., m$. A random term, ε_0 which we assume is distributed $N(0, \sigma_0^2)$ is also appended to our cost function equation (4). The random vector $\varepsilon = (\varepsilon_0, \varepsilon_1, ..., \varepsilon_m)$ is assumed normally distributed with zero mean and diagonal covariance matrix Σ.[15] Hereafter, σ_0^2 and σ_i^2 will denote the variance of ε_0 and ε_i, respectively.

The behavioral model introduced above implies the following KT restriction on ε_i:

$$R_i = \begin{cases} \varepsilon_i = c_i\left(z|\gamma_v, \pi, \beta, \varphi\right) & \text{if } \bar{l}_i = 0 \text{ and } d_i > 0 \\ \varepsilon_i < c_i\left(z|\gamma_v, \pi, \beta, \varphi\right) & \text{if } l_i = 0 \text{ and } d_i = 0 \\ \varepsilon_i = c_i\left(z|\gamma_v, \pi, \beta, \varphi\right) - \eta p_i & \text{if } 0 < l_i < \bar{l}_i \\ \varepsilon_i > c_i\left(z|\gamma_v, \pi, \beta, \varphi\right) - \eta p_i & \text{if } l_i = \bar{l}_i \end{cases} .. \tag{8}$$

We index the trip level observations with subscript $n = 1...N$. From the KT restrictions in (8) and our assumptions for the error terms, the likelihood function for $Z_n = (c_n, z_n)$ is given as

$$L\left(Z_n|\Gamma\right) = \phi_0\left(\varepsilon_{n0}|0, \sigma_0^2\right) \prod_{i=1}^{m} \int_{R_{ni}} \phi_i\left(\varepsilon_{ni}|\sigma_i^2\right) d\varepsilon_{ni},$$

where $\Gamma = \{\beta, \gamma_v, \eta, \pi, \Sigma\}$, and R_{ni} reflects the regulatory constraint for stock i on trip n. Letting $Z = \{Z_n\}_{n=1}^N$ we have the following likelihood for our data

[15] Specification of a general covariance matrix (e.g., Kim, et al., 2002) is reserved for future work.

$$L(Z|\Gamma) = \prod_{n=1}^{N} L(Z_n|\Gamma) \tag{9}$$

3 The Gulf of Mexico reef fish fishery

The Gulf of Mexico reef fish fishery is a complex of bottom-dwelling species consisting of snappers, groupers, tilefishes, amberjacks, triggerfishes, grunts, porgies, and a host of others. Reef fish fishermen also intercept coastal pelagic species such mackerel, dolphin (wahoo), sharks and tuna. The two major gear types in the fishery are vertical hook and line gear and longline gear. The US portion of the fishery extends from the US border with Mexico in the western Gulf to the Florida Keys. Figure 1 below shows the 21 subregions of the fishery. Hereafter subregions 13-21 will be referred to as the western region, and subregions 1-12 as the eastern region of the reef fish fishery.

The composition of the reef fish stocks varies across western and eastern regions. Groupers are the most important species, by landed pounds and revenue, in the east, with red and gag groupers dominating landings and revenue. National Marine Fisheries Service log book data indicate that red and gag grouper account for 44% of total annual landings, and 50% of annual revenue in the eastern Gulf region (pounds are reported as gutted weight, and prices, revenues and costs are in first quarter 2008 US dollars.) The largest volume and revenue species in the western Gulf region is red snapper which accounts for roughly 49% of the total landed pounds and 59% of total revenue annually.

3.1 Data

The data available for analysis are from the National Marine Fisheries Service log book reporting system and a survey of annual operating expenses that was conducted by the Southeast Fisheries Science Center. Regulations require that following each reef fish trip, vessel operators record harvests by species, gear type used, primary subregion of fishing, number of crew on board the vessel and other trip characteristics. In 2003, a "Trip Expense & Payment Section" was added to the logbook form which recorded revenue by species, and expenses for fuel, bait, ice, and food. Beginning in 2005, expense and payment data

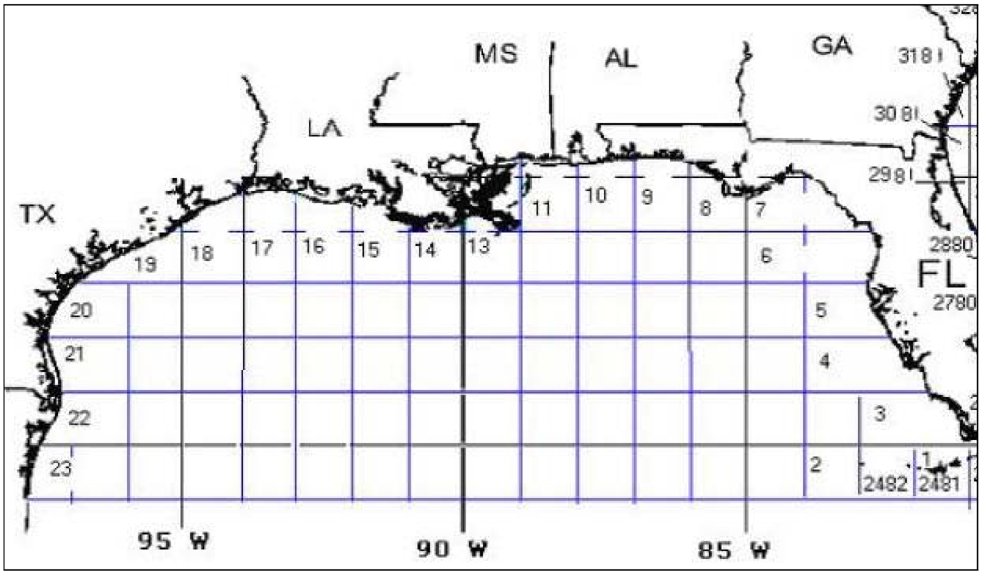

Figure 1: The Gulf of Mexico Reef Fish Fishery.

collection became mandatory for a stratified sample of the permitted reef fish vessels. A second stratified sample of reef fish fishermen record discards by species. The data that we use in our analysis consists of the set of vessel operations that record both expenses and discards .

Our data are from January, 2005 through August, 2008. There are 1,753 trip-level observations with complete information on trip expenses and discards. Of these, 75 records included entries that we deemed to be outliers. Trips that recorded extreme costs per landed pound were deemed outliers; observations with costs less than \$0.04 per pound and in excess of \$2.50 per pound were dropped. Furthermore we removed fishing trip in subregion 12 which corresponds to the New Orleans estuary. Finally we deemed landings of more than 10,000 pounds of one particular species to be non-typical (the average landings of all species for vertical line gear is 1,854.61 pounds) .Remaining data includes 1,518 vertical line gear trips and 170 longline trips. The empirical results that follow are for vertical line gear.

Tractability requires that individual reef fish species be aggregated to form output groups. The four major species harvested include: h_1- red snapper; h_2- vermilion snapper; h_3- red grouper; and h_4- gag grouper. The remaining species were aggregated into output groups based on similarity in harvesting practices, e.g., fishing locations, depths, bait, and capture methods, used to in harvesting.[16] This resulted in three additional outputs: h_5- Deep water groupers and tilefishes; h_6- Coastal pelagics and sharks, and h_7- Other reef fish species. Descriptive statistics for trip-level costs, prices and harvest per trip are reported in an appendix.

We take as our spatial index, the coarse geographical region that yielded the bulk of the each trip's catch (Figure 1). The index takes the value of 1 on trips taken in the Florida Keys and 21 for trips taken in waters off the southern Texas coast. It should be emphasized that additional and finer-grained information on fishing location (e.g., latitude, longitude and fishing depth) if available could be incorporated into the model described above. Our data lists the date that the catch is landed at port. We specify a time index t which indicate the day of the year that landings are recorded, and an index y which is set equal to the cumulative days since January 1, 2005; y therefore ranges from 1 through 1,380. We impose the restriction that the seasonal effect on January 1 equal the effect on December 31 of each year. Both t and y are normalized to line on the unit interval.

3.2 Regulations

The Gulf of Mexico Fisheries Management Council is responsible for the management of Gulf reef fish. A host of regulations including vessel entry (fleet size) restrictions, gear and area restrictions, seasonal closures, per-trip catch limits and recently individual fishing quotas are used to limit the aggregate harvest of the commercial fleet. Possibly the most regulated species in the reef fish complex is red snapper. Prior to December 2007 red snapper was managed under controlled access regulations. Under this system an annual total allowable catch (TAC) was selected by managers and enforced with fishery closures and a per-trip *endorsement* program.[17] The endorsement program restricts landings of red snapper on each fishing trip, during red snapper openings. Vessel operators held either a class 1 permit

[16] Harvested quantities within each output category are aggregated linearly. The aggregation procedure assumes that optimal input choices and aggregate output levels can be chosen independently of the mix of species within each output category. The harvest technology is thus assumed to exhibit weak output separability. Linear aggregation implies a constant rate of transformation among species within each output group. These assumptions are consistent with fishing practices as described to us by reef fish fishermen. Nonetheless, it should be noted that output aggregation could bias the results that follow.

[17] The red snapper TAC was set at 4.65 million pounds in 2005 and 2006. Stock concerns led to reductions in the TAC in 2007, to 3.315 million pounds, and a further reduction in 2008, to 2.55 million pounds.

to land 2,000 pounds per trip, a class 2 permit to land 200 pounds per-trip, or no permit at all. Vessels that do not own an endorsement permit are prohibited from landing red snapper at any time.

In an effort to spread the annual red snapper harvest more evenly throughout each year, red snapper landings were permitted during the first 10 days of each month. When the cumulative fleet harvest reached the annual TAC, the fishery was closed until the following year. The implications for fishing behavior during the controlled access management period (1/1/05-12/31/06) are summarized in the following table.[18]

Regulation	Opt. landings/discards	KT necess. cond.
1. $\bar{l}_i = 0$	$l_i^* = 0,\ d_i^* > 0$	$c_i^*(h^*, x) = 0$
2. $\bar{l}_i = 200\ (2,000)$	$l_i^* > 0,\ d_i^* = 0$	$\eta p_i - c_i^*(h^*, x) \geq 0$
3. $\bar{l}_i = 200\ (2,000)$	$l_i^* > 0,\ d_i^* > 0$	$c_i^*(h^*, x) = 0$

Beginning in January 2007 red snapper controlled access regulations were replaced with individual fishing quotas (IFQs). Under the IFQ program, vessel operators can legally land any quantity of red snapper as long as they possess quota to cover landings. The IFQ program was begun by issuing red snapper quota *gratis* to qualifying fishermen. The amount of quota that was distributed was based on historical participation, i.e., history of red snapper landings during designated qualifying years. Therefore, vessels that held class 1 endorsement permits under the controlled access regime tended to receive larger shares of red snapper IFQ. The implications for fishing behavior during the IFQ management period (1/1/07-08/31/08) are summarized in the following table.

Regulation	Opt. landings/discards	KT necess. cond.
1. $\bar{l}_i = 0$	$l_i^* = 0,\ d_i^* > 0$	$c_i^*(h^*, x) = 0$
2. $\bar{l}_i = \infty$	$l_i^* > 0,\ d_i^* = 0$	$\eta p_i - c_i^*(h^*, x) \geq 0$

Grouper species are also heavily regulated. Red grouper is managed as part of a shallow water grouper complex, which includes Black, Gag, Red, Yellowfin, Scamp, Yellowmouth groupers, Rock Hind and Red Hind. The shallow water grouper fishery is closed when a red

[18] A minimum size restriction of 15" total length was in place during 2005-06. The length restriction was reduced to 13" total length in 2007-08.

grouper TAC of 5.31 million pounds is reached, or when a TAC of 8.80 million pounds for all shallow water groupers is reached (the closure occurs at the first date either constraint is met). In addition, measures are used to protect fish during heightened spawning activity. The red and gag grouper fisheries are closed from February 15 through March 15 of each year. An aggregate trip limit of 6,000 pounds of shallow water and deep water groupers combined was introduced for the 2006 fishing season.

Deep water groupers and tilefishes, hereafter DWG, are also managed under controlled access regulations. Fishermen face a per-trip limit of 6,000 pounds and the fishery is closed when the annual TAC is reached. The commercial deepwater grouper TAC is currently set as 1.02 million pounds. The commercial tilefish TAC is currently set at 440,000 pounds. There are no size limits for deepwater grouper species or tilefish since these fish do not survive retrieval from the depths in which they are caught. The behavioral implications of regulations on groupers and other species are summarized in an extended appendix available from the authors upon request.

4 Results

Tables 2, 3, and 4 of the appendix report median values, standard deviations, and 95% confidence intervals of the posterior parameter distribution The individual parameter distributions are consistent with our assumptions for the structure of the harvest technology, and profit maximizing harvest choices under a costly targeting technology.

The results suggests that trip-level costs are increasing and concave in the fuel price; the posterior median value of β_w is 0.504, with 95% confidence interval [0.488, 0.526]. The posterior distribution for β_K has median value 1.119, and 95% confidence interval, [1.095, 1.156]. The result is consistent with trip-level costs that are increasing and convex in vessel length. At first glance this result seems counterintuitive. One would expect capital to be a normal input in production. However, larger boats tend to harvest more fish per trip, i.e., have a larger hold capacity, which can yield a return to scale. Moreover, larger vessels are better-able to fish in sever weather conditions. They can harvest more fish annually than smaller boats, and therefore incur lower average fixed operating costs.[19] This advantage is not reflected in the trip-level data. It is also possible that our proxy for capital services, which is a stock variable, does not fully reflect the capital services available for production on a fishing trip.

The posterior median for $\overline{\gamma}_v$ is 3.090 (c.i. [2.953, 3.247]), and the posterior median for σ_v^2 is 4.686 (c.i. [3.655, 6.029]). The results indicate considerable variation in targeting ability across skippers in our data, which is not uncommon in the analysis of harvesting performance (e.g., Squires and Kirkley, 1999).

The latent harvest share parameters π_i are generally well-identified (Table 3 in the appendix). The fitted minimum target cost-shares vectors are reported in in Figure 3, also in the appendix. Simulations that follow below suggest that the fitted values of φ_{st} are generally consistent with landing patterns and available biological information on stock abundance across space and time. Although it is tempting to view φ_{st} as an index of absolute stock abundance, we feel this interpretation is premature.

Finally the posterior median for η is 0.5461 which means that crews receive roughly 45% of the trip revenue. The posterior median is very close to the value from the log book data; the median crew share reported in the 2005-08 log book data is 44.21%.

Further interpretation of the results may be best-accomplished by examining their implications for fishing behavior. Space constraints do not permit a comprehensive demonstration. The following simulations highlight some of the more interesting aspects of fishing (targeting) behavior, and the influence of regulations in the reef fish fishery, that are implied by our estimation results.

4.1 Simulations

This section reports the results from several simulation exercises. In each simulation we draw with replacement a random sample of 1,000 vectors from the posterior parameter distribution.[20] For each draw, we use a numerical optimization routine to solve for the profit maximizing harvest and discard vectors for a representative vessel operation (equation (2)).

[19] A 1% increase in vessel length correlates with a 3% increase in harvest size per trip.

[20] We do not incorporate optimization error in our simulations.

We solve the optimization problem for each subregion of the reef fish fishery thus obtaining optimal landings and discards for (s,t) combinations, prices p, w and landing restrictions, $\bar{l}$. Variable profits, also quasi-rent to the vessel capital, captain and crew labor shares, marginal costs etc. are also calculated in our investigation and predictions of fishing behavior.

Our baseline simulation assumes a 40 foot vessel and prices equal to the mean of the sample data (see Table 1 in the appendix). We impose a per-trip landings of constraint of 5,000 pounds. The date chosen for the baseline simulation is the midpoint of the 2006 fishing season. Regulations in 2006 included red snapper landing limits under the endorsement program and closures for grouper species. Our baseline scenario assumes a 2,000 pound red snapper landings constraint. The effects of a grouper closure are considered separately.

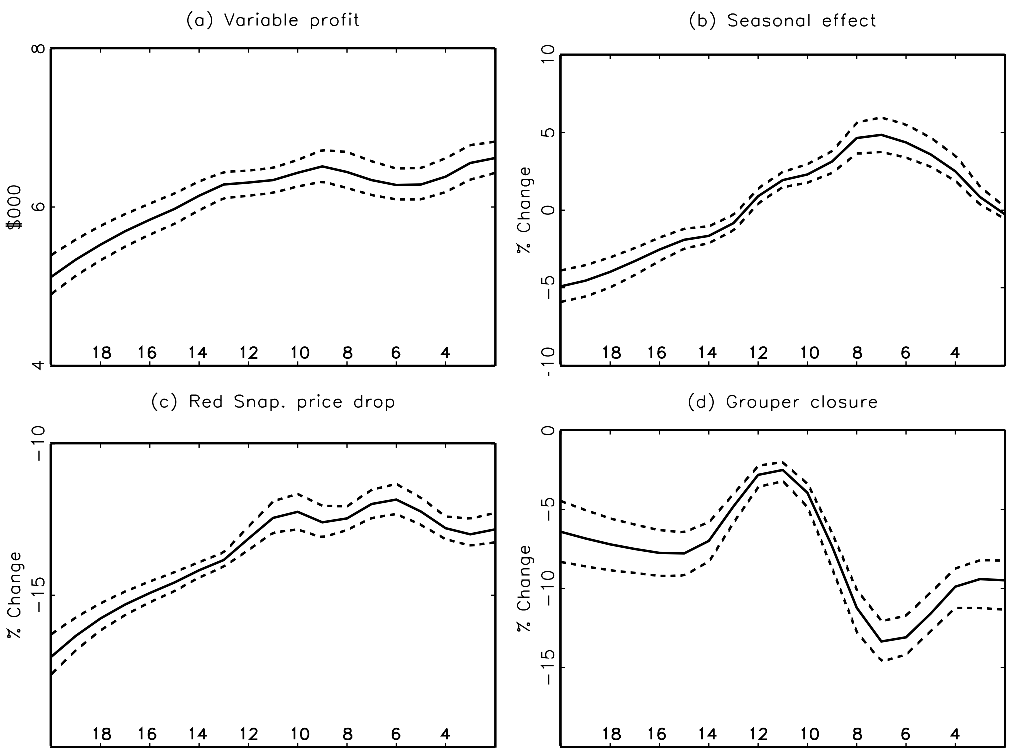

Figure 2: Profits simulations. Solid lines in panels (a)-(c) denote median values, dashed lines indicate 95% c.i.'s. Panel (a) is per-trip profits on a 10,000 pound summer trip; (b) is percent change in profit between summer and winter; (c) is percent change in profit with low red snapper price; (d) is median targeting cost under mean and 25% higher fuel price.

Panel (a) of Figure 2 reports median variable trip profits (solid lines) and 95% c.i.'s (dashed lines) under our baseline conditions. Variable profits per trip vary around $5,000-$7,000 over much of the Gulf. Lowest variable profits are indicated in the far western regions of the fishery. Red snapper is a key species in the western region, and is the highest priced among the seven targeted species, averaging $3.19 per pound landed. The 2,000 pound landings limit however constraints the profit potential for this species.[21] If we run the model without the 2,000 pound limit on red snapper landings, the variable profits flatten out at roughly $10,000 per trip across all subregions of the fishery.

The model predicts that the 2,000 pound red snapper landings constraint binds in all subregions of the fishery. In the western and central subregions the remaining 3,000 pounds of landed fish is made up of vermilion snapper and gag grouper, with a smaller amount of Other Species landed in subregions 18-21. In eastern subregions a smaller amount of vermilion snapper is landed and no landings of Other species are recorded. Remaining landings are comprised largely of gag grouper and red grouper in subregions 3-7. Targeting of red snapper and gag grouper is explained by the relatively high dockside prices for these species, which are set a $3.19 and $3.10 per landed pound respectively in the baseline case. The remaining variation in targeting behavior is due to spatial variation in targeting costs as measured, as measured by φ_{st}. The fitted lowest-target-cost share for red snapper exceeds 0.70 in the far western subregions of the fishery, and declines monotonically toward the eastern subregions. Interaction between the 2,000 pound red snapper landing limit and φ_{st} explains the decline in variable profits for $s > 14$.

The model predicts median red snapper discards that range from 200 pounds in subregion 16 to 550 pounds in subregion 20. Discarding red snapper occurs when *optimal* harvests exceed the 2,000 pound landing limit. Under the weak output disposibility technology, discarding avoids the targeting costs that would otherwise be required to harvest only what is landed. With fitted values of $\varphi_{i,st}$ in western subregions $s = 16 - 20$ well above 0.50 (see Figure **??** in the appendix), harvesting 2,000 pound of red snapper on a 5,000 pound trip

[21] Fishing vessels are mobile and we would expect to see only small variation in per-trip profits across space. The higher returns in the eastern region do not reflect the impacts of periodic grouper closures. Moreover a vessel with a 200 pound endorsement permits, or no red snapper landings permit will have a different earning profile. Taking these considerations into accout, we can conclude that profit opportunities do not vary substantially with s..

requires costly targeting. The model suggesting discarding overages is preferred.

The model predicts fairly substantial discards of Other species, h_7 (as high as 1,500 pounds in subregions 1-4). These discards arise because of the per-trip landings constraint assumed in the baseline simulation. At 5,000 pounds total landings, estimated variable profit margins for landed species at roughly \$1.12 per pound, whereas marginal profits for Other species is less than \$1.

When we simulate harvest behavior without the 2,000 pound red snapper landings constraint optimal landings are comprised almost entirely of red snapper. Only in subregions 5-8 are positive landings of gag grouper indicated. Red snapper discards are zero in the absence of the red snapper landings constraint, although discards of Other species and vermilion snapper are indicated. It should be emphasized that the predicted discards arise due to the total trip landings constraint assumed in the baseline model.

Our second simulation examines seasonal effects on harvest behavior and variable trip profits. We solve for optimal harvests and discards on a trip that originates January 1, 2006. Prices are unchanged from the baseline levels, and the 2,000 pound limit on red snapper landings remains in place.

Economic and regulatory conditions are unchanged in the second simulation. The model predicts differences in the landings mix, discards, and profits due to the seasonal variation in the minimum-target-cost harvest vector φ_{st}. Panel (b) of Figure 2 reports the percentage difference in variable profits between a winter and a summer trip, in other words, the gain from fishing in winter (solid curve denotes the median value and dashed lines indicate 95% c.i.'s). We find that winter fishing earns slightly lower variable profits in the western subregions, but yields between 2-5% higher profits in the eastern subregions. We also find that optimal landings mix in the winter includes larger shares of vermilion snapper in the central subregions and larger shares of gag grouper throughout the Gulf.

Our empirical estimation reveals that $\varphi_{i,st}$ for red snapper and gag grouper exhibit summer troughs or winter peaks. Thus the harvest vector that minimizes targeting costs will be comprised of larger shares of red snapper and gag grouper during winter fishing. The model also predicts an increase in the *harvest* of red snapper. However, under the 2,000 pound landings limit, overages are discarded at sea. The model predicts that in the western subregions of the fishery, winter discards of red snapper are 200-700 pounds higher than during summer fishing.

In a third simulation we reduce the red snapper price by 25% below the baseline value (of \$3.19 per pound). Panel (c) reports the percentage change, decline, in variable profits across subregions. The results indicate variable profit declines in the range of 14%-18% in western subregions and 12%-13% in eastern subregions. The mix of landed species is unchanged in western subregions 13-21. This is explained by the importance of red snapper in the western Gulf. In the east however the model predicts that a 25% drop in the red snapper price has important implications for targeting behavior. Under the lower red snapper price, red snapper landings decline in subregions 1-12. Eastern Gulf fishermen land instead larger quantities of vermilion snapper, red grouper, and gag grouper. Our model predicts that the red snapper price decline does not significantly alter discarding behavior.

A fourth simulation considers the effects of a closure of the red and gag grouper fisheries. Panel (d) in Figure 2 reports the percent profit decline for the case of $p_3 = p_4 = 0$. The results find that the closure policy causes reductions in variable profits vary widely across subregions. Losses are greatest, in excess of 10%, in subregions 4-9 which is considered to be the heart of the grouper fishery. Losses are smaller in the central region where shallow water groupers are a less important target species, and increase again in the western region where high-priced gag groupers comprise a important share of landings. The results indicate that when the red and gag grouper fisheries close, landings of vermilion snapper (h_2) and deep water groupers and tilefishes (h_5) increase. Not surprisingly, the model predicts positive discards of red grouper in subregions 5-7, i.e., when red grouper landings are prohibited fishermen can either incur added costs to avoid them or discard the red grouper intercepted by their gear.

The results reported above by no means exhaust the economic and regulatory impacts that can be examined by our model. We consider in a fifth simulation exercise the impact of an increase in the price of fuel. The annual average fuel price in our data rose from \$2.27 in 2005 to \$3.75 in 2008, and it is therefore reasonable to expect that fuel prices affected the reef fish targeting behavior in our data. The simulations find that a 40% fuel price increase reduced per-trip variable profits by 5%-10% relative to baseline levels. The model predicts that higher fuel prices impact targeting behavior. We find that the median targeting cost component, $\left[1+\sum_{i=1}^{m}\gamma_v\left(\theta_i-\varphi_{i,st}\right)^2\right]$ decline by 2%-5% depending on the subregion under the higher fuel price. Intuitively, targeting efforts will be dampened under higher fuel prices and the optimal harvest share will more closely mirror the minimum-target-cost vector φ_{st}. This is because adjusting the harvest mix in response to price differentials at the dock becomes more costly when the fuel price rises. Our simulations indicate, for example, that landings of gag are reduced by 200-300 pounds across the fishery. Landings of vermilion snapper increase primarily in the central subregions and landings of red grouper increase under in subregions 2-7. The model predicts, also rather intuitively, that at-sea discards decline under high fuel prices.

Recall that the empirical specification for φ_{st} includes a time index y to capture longer term trends in stocks conditions in the fishery. This allows us to examine longer term trends in targeting behavior. Simulations that varied y for example, from 2005 through 2008, indicated only minor changes in variable profits and targeting behavior. The results are not reported here.

We construct a final simulation to examine the changes in fishing behavior that accompanied a switch from controlled access to individual transferable quotas (ITQs) for red snapper. To represent this policy switch we introduce a quota user cost which we assume arbitrarily to be equal to 50% of the baseline red snapper price, and drop the 2,000 pound landing constraint. Under ITQs trip limits on landings are no longer required; landings are restricted only at the seasonal level by the aggregate ITQ holdings of the vessel operation. We evaluate optimal harvests and discards for a mid 2007 season trip, which was the first year of the red snapper ITQ program.

First, the results indicate a reduction in trip variable profits ranging from 15% in eastern subregions and increasing to 33% in western subregions.[22] The reduction in variable profits or capital quasi rents conforms with theoretical predictions, that property rights-based management programs provide incentives to reduce oversized fishing fleets. An important results for managers, however relates to the stark variability in losses across regions. Because tar-

[22] Looses in variable profits are offset by increases in resource rents generated under the red snapper ITQ program. These rents would be determined as the quota rental times the total red snapper landings.

geting costs vary across subregions, substitute target species and red snapper fishing costs do as well. Our model suggests that introducing ITQ for a single species in a multiple-species fishery can significantly alter harvests and discards of species managed under the status quo. In particular, our model predicts that red snapper landings increase above the 2,000 pounds in the far western subregions. Vermilion snapper landings also increase in subregions 10-17 where these two species tend to be harvest complements. The addition of the red snapper quota rental substantially lowers the residual price for fishermen at the dock. Our model predicts that eastern landings of red snapper fall to zero when a quota rental is introduced; optimal landings instead include substantially higher shares of vermilion snapper, gag grouper and red grouper.

A less anticipated impact on fishing behavior is a predicted increase in red snapper discards. Results indicate positive red snapper discards in subregions 7-16, ranging from 150 pounds per trip to over 1,000 pounds per trip (subregions 13 and 14). This result is due to the 5,000 pound per-trip landings constraint. At a substantially reduced red snapper price and a 5,000 pound trip limit on landings, the marginal profit from landing red snapper falls below marginal profits from landing other species such as vermilion snapper and red and gag groupers.

5 Conclusions

We have introduces a new approach for studying spatial-temporal fishing behavior in marine fisheries. We estimate a structural behavioral model that provides a direct link from the *in situ* fish stock, prices and species-specific regulations, to outcomes of interest to managers, e.g., species-specific harvests, discards and fishing profits. A parametric cost function and Kuhn Tucker necessary conditions for profit maximizing targeting of multiple fish species under landings restrictions is specified for estimation. Markov Chain Monte Carlo methods are used to simulate the posterior likelihood function. We estimate a latent, *lowest-target-cost* harvest share vector that summarizes the costly targeting technology and corresponding profit opportunities for fishermen across space and time. The fitted model is used to predict the effects of changes in economic conditions and regulations on spatial and temporal landings, discards, and fishing profits in the Gulf of Mexico reef fish fishery.

Our results demonstrate complex interactions between the economic and regulatory environment and the multiple-species harvesting behavior of Gulf reef fish fishermen. Not surprisingly, we find that per-trip landings limits used to control aggregate fishing mortality redirect fishing effort toward unregulated species, in pattern that vary spatially with stock conditions. We are also able to investigate the effects of model fundamentals on the incentives to discard fish at sea.

Several policy lessons emerge from our analysis of the Gulf reef fish fishery. For example, replacing controlled access management with individual fishing quotas for a single species, is likely to redirect effort toward species without a quota rental, and may enhance incentives to discard fish at sea. We also find, not surprisingly, that closures for individual species cause fishermen to substitute toward unregulated species, and can enhance incentives to discard fish. Less obvious findings relate to the impact of increased fuel prices on targeting and discard behavior. Our model predicts that when the price of fuel rises, Gulf reef fish fishermen may be inclined to target higher priced species, and more willing to land a mix of species that moderates targeting costs. On the flip side, targeting is enhanced and at-sea discards will increase when fuel prices decline. Overall the results demonstrate the need to consider behavioral responses and policy design inclusive of the complete biological, economic and regulatory environment of marine fisheries.

An important attribute of our model is that optimal responses of fishermen to varying economic and other regulatory conditions is incorporated explicitly. Our results demonstrate clearly the benefits of a structural approach for policy analysis. Moreover, because we are able to link fishing behavior directly to stock conditions, prices and regulations, the model is ideally suited to investigate *ex ante* impact of alternative forms of regulations. Methods based on the discrete choice RUM framework require a second layer model to complete the link from fundamentals to trip-level behavior. Our approach avoids discretizing the fishing ground and/or the choice set of fishing inputs and outputs; our approach provides a rich framework to characterize fishing behavior at any spatial or temporal scale. Taken together these attributes suggest that our model can be a powerful tool to improve the design of fisheries management policies.

For example, our model can guide the design of fishery closure policies, property rights-based management, marine reserves, etc. Designing a system of marine reserves requires knowledge of trade-offs between ecological preservation across a spatially heterogeneous fishing ground and pursuit of economic rents. Our model measures directly, the short term cost, or foregone profits of closing subregions of a fishery. A useful extension of our model would link our costly targeting technology, and our lowest-target-cost share vector, to measures of absolute stock abundance. This would allow a fully dynamic analysis of spatial behavior and spatial management policies. Evaluating changes in stock abundance in areas surrounding marine protected areas, and stock effects due to large scale redistribution of fishing effort across space and time are examples.

6 References

Berman, M.. Modeling Spatial Choice in Ocean Fisheries. *Marine Resource Economics*, 21 (2007): 375-394.

Boyce, J. R., An Economic Analysis of the Fisheries Bycatch Problem. *Journal of Environmental Economics and Management*, 31 (1996): 314-336.

Brodziak, J., and J. Link, Ecosystem-Based Fisheries Management: What is it and how can we do it?, *Bulletin of Marine Science*, 70 (2002) 589-611.

Branch, T. A., R. Hilborn, and E. Bogazzi. Escaping the tyranny of the grid: a more realistic way of defining fishing opportunities. *Canadian Journal of Fisheries and Aquatic Sciences*, 62 (2005): 631-642.

Casella, E. and E. I. George. Explaining the Gibbs Sampler. *The American Statistician*, 46 (1992): 167-174.

Clark, C. W., Mathematical Bioeconomics: The Optimal Management of Renewable Resources, Second Edition, John Wiley & Sons, Inc. New York, 1990.

Chernozhukov, V. and H. Hong. An MCMC approach to classical estimation. *Journal of*

Econometrics, 115 (2003): 293-346.

Chib, S. and B. P. Carlin, On MCMC sampling in hierarchical longitudinal models. *Statistics and Computing*, 9 (1999): 17-26.

Chib, S. and E. Greenberg, Understanding the Metropolis-Hastings Algorithm. *The American Statistician,* 49 (1995) 327-335.

Curtis, R. and K. E. McConnell. Incorporating information and expectations in spatial decisions. *Marine Resource Economics*, 19 (2004): 131-144.

Gelfand, A. E. and A. F. M. Smith. Sampling based approaches to calculating marginal densities. Journal of American Statistics Association. 85 (1990): 398-409.

Gelman, A., Roberts, G. and W. Gilks. Efficient Metropolis Jumping Rules in Bayesian Statistics 5 (1995): 599-607.

Geweke, J., Using Simulation Methods for Bayesian Econometric Models: Inference, Development and Communication. *Econometric Reviews*, 18 (1999): 1-73.

Geweke, J. and H. Tanizaki, Bayesian estimation of state-space models using the Metropolis–Hastings algorithm within Gibbs algorithm. *Computational Statistics and Data Analysis* 37 (2001): 151–170.

Haab, T. C., M. Hamilton, and K. E. McConnell, Small Boat Fishing in Hawaii: A Random Utility Model of Ramp and Ocean Destinations. *Marine Resource Economics*, 23 (2008): 137-151.

Imai K. and D. A. van Dyck, A Bayesian analysis of the multinomial probit model using marginal data augmentation. *Journal of Econometrics*, 124 (2005): 311-334.

Kim, J. Allenby, G. E. and P. E. Rossi, Modeling consumer demand for variety. *Marketing Science*, 21 (2002): 223–228.

Lee, L. and M. M. Pitt. Microeconometric models of rationing, imperfect markets and non-negativity constraints. *Journal of Econometrics*, 36 (1987): 89-110.

May, R., M., J. R. Beddington, C. W. Clark, S. J. Holt, R. M. Laws, Management of Multiple-species Fisheries. *Science* 279 (1979): 267-277.

McConnell, K. E. and M. Price, The lay system in commercial fisheries: Origin and implications. *Journal of Environmental Economics and Management*, 31 (2006): 295-307.

McCulloch, R. and P. Rossi, An exact likelihood analysis of the multinomial probit model. *Journal of Econometrics.*, 64 (1994): 207-240.

Pikitch, E. K., C. Santora, E. A. Babcock, A. Bakun, R. Bonfil, D. O. Conover, P. Dayton, P. Doukakis, D. Fluharty, B. Heneman, E. D. Houde, J. Link, P. A. livingston, M. Mangel, M. K. McAllister, J. Pope, K. J. Sainsbury, Ecosystem-based fisheries management. *Science*, 305 (2004): 346-347.

Punt, A. E. and R. Hilborn, Fisheries stock assessment and decision analysis: the Bayesian approach. *Reviews in Fish Biology and Fisheries*, 7 (1997): 35-63.

Singh, R. and Q. Weninger, Bio-economies of scope and the discard problem in multiple-species fisheries. *Journal of Environmental Economics and Management*, 58 (2009): 72-92.

Squires, D., and J. Kirkley, Skipper skill and panel data in fishing industries. *Canadian Journal of Fisheries and Aquatic Science*, 56 (1999): 2011-2018.

Tanner, M. A. and W. H. Wong, The Calculation of Posterior Distributions by Data Augmentation: Rejoinder. *Journal of the American Statistical Association*, 82 (1987): 548-550

Turner, M. A., Economics without Free-Disposal: The problem of Quota-induced Discarding in Heterogeneous Fisheries. Mimeo, University of Toronto, 1995.

Turner, M. A., Quota-Induced Discarding in Heterogeneous Fisheries. *Journal of Environmental Economics and Management*, 33 (1997): 186-195.

U.S. Commission on Ocean Policy, Preliminary Report of the U.S. Commission on Ocean Policy, Governor's Draft., U.S. Commission on Ocean Policy, Washington, DC, April, 2004.

von Haefen, R. H. and D. J. Phaneuf, Continuous Demand System Approaches to Nonmarket Valuation, in Applications of Simulation Methods in Environmental and Resource Economics, Riccardo Scarpa and Anna Alberini, editors, (2007).

Wang, G., On the latent space estimation of nonlinear population dynamics using Bayesian and non-Bayesian state-space models. *Ecological Modelling*, 200 (2007): 521-528.

Wilen, J. E. Spatial management in fisheries. *Marine Resource Economics*, 19 (2004): 7–19.

7 Appendix

7.1 Prior specifications

With the exception of the targeting skill parameter, all priors are assumed to be diffused. A hierarchical prior captures heterogeneity in fishing skill. We assume

$$\gamma_v \sim N\left(\bar{\gamma}, \sigma_\gamma^2\right).$$

Following standard methods (e.g., Chib and Carlin, 1999) we use conventional conjugate priors for the hyperparameters of this distribution, i.e.,

$$\begin{aligned} \sigma_\gamma^2 &\sim IG\left(2.5, 3\right), \\ \bar{\gamma} &\sim N\left(0, 1000\right); \end{aligned}$$

in the above $IG(.)$ and $N(.)$ denote the inverse gamma and normal distribution, respectively.

7.2 Random Walk M-H Algorithm

Here we simply present the Random Walk Metropolis Hastings (RWMH) algorithm. For further details on the Metropolis-Hastings (M-H) algorithm we refer the reader to (Chib, and Greenberg, 1995). The M-H algorithm is similar in spirit to acceptance/rejection sampling and consists in three steps:

1. At iteration ω, sample a candidate value for the parameters from a candidate density

$$q_\omega^* \sim \delta\left(q|q_{\omega-1}\right)$$

2. Draw a random number u such that

$$u \sim U\left(0, 1\right)$$

3. Accept or reject the candidate based on the following decision rule. Let

$$a = \frac{\phi\left(q_\omega^*|.\right)\delta\left(q_{\omega-1}|q_\omega^*\right)}{\phi\left(q_{\omega-1}|.\right)\delta\left(q_\omega^*|q_{\omega-1}\right)}$$

where $\phi(q|.)$ denotes the posterior distribution of q according to the data. Then if $u \leq a$, set $q_\omega = q_\omega^*$ otherwise $q_\omega = q_{\omega-1}$.

In the RWMH algorithm the candidate density is normal so that

$$q_\omega^* \sim N\left(q_{\omega-1}, \sigma_q^2\right).$$

In the above, σ_q^2 is the variance os spread of the normal distribution. The main idea behind the M-H algorithm is to replicate the stationary property of the Markov chain. Indeed a can be interpreted as the "jump" probability from one candidate to the next. This probability is pending on the value of the spread. The art of the RWMH algorithm dwells in setting the value of this spread. We follow the recommendation of Gelman and Gilks (1995) and specify the spreads of our candidate generating density so that the acceptance rate is close to 50 percent for single valued parameters and between 25 and 50 percent for multi-valued parameters.

7.3 Estimation algorithm

We use a Gibbs sampler to simulate draws from the posterior of the joint posterior density. The following algorithm describes the procedure.

Using the Gibbs sampler we repeatedly cycle through each conditional density, drawing from each one in turn. When the number of cycles grows large, the draws converge in distribution to that of the complete joint posterior (Gelfand and Smith, 1990). Our Gibbs sampler consists of seven steps or "blocks".

Step 1: $\beta|\Gamma_{-\beta}, Z$ As this posterior conditional is of unknown form we use the RWMH algorithm explained above. For further reference $\Gamma_{-\beta}$ indicates the entire set of parameters less the parameter β.

Step 2: $\Sigma|\Gamma_{-\Sigma}, Z$. Likewise the form of the conditional posterior for Σ is unknown. We again use the RWMH algorithm to draw from this unknown posterior.

Step 3: $\gamma_v|\Gamma_{-\gamma_j}, Z$ The vector of vessel specific skills is drawn using a RWMH algorithm. Unlike other parameters the prior on these parameters is non diffuse. Hence the value of the prior has to be accounted for in computing the acceptance probability (see Kim, et al., 2002).

Step 4: $\sigma_\gamma^2|\gamma_v, \bar{\gamma}$. Given our conjugate prior for $\sigma_\gamma^2|\gamma_v, \bar{\gamma}$, the posterior conditional follows:

$$\sigma_\gamma^2|\gamma_v, \bar{\gamma} \propto IG\left(c, d\right),$$

where,

$$\begin{aligned} c &= 2.5 + V \\ d &= \left[\frac{1}{3} + \frac{1}{2}\sum_{v}^{V}\left(\gamma_v - \bar{\gamma}\right)'\left(\gamma_v - \bar{\gamma}\right)\right]^{-1}. \end{aligned}$$

Recall V denotes the number of skippers.

Step 5: $\bar{\gamma}|\gamma_v, \sigma_\gamma^2$. The conditional posterior of $\bar{\gamma}$ follows

$$\bar{\gamma}|\gamma_v, \sigma_\gamma^2 \propto N\left(D_\gamma d_\gamma, D_\gamma\right),$$

with

$$D_\gamma = \left[V/\sigma_\gamma^2 + (1000)^{-1}\right]^{-1}$$

and

$$d_\gamma = \sum_{v}^{V} \gamma_v/\sigma_\gamma^2.$$

Step 6: $\pi|\Gamma_{-\pi}, Z$. These coefficients are drawn using a RWMH step.

Step 7: $\eta|\Gamma_{-\eta}, Z$. For this parameter we also use the RWMH step. Since η enters multiplicatively a change of variable is requried.

Variable	Mean	Std. dev.	Min.	Max.
Var. costs (non-labor)	799.89	700.05	20.43	3,997.43
Red snapper (p_1)	3.19	0.28	1.61	4.03
Verm. snapper (p_2)	2.40	0.15	1.70	3.14
Red grouper (p_3)	2.42	0.18	1.94	2.91
Gag grouper (p_4)	3.10	0.21	2.55	3.80
DWG/Tilefishes (p_5)	2.32	0.32	0.83	3.42
Coastal pelagic/sharks (p_6)	1.76	0.33	0.16	3.42
Other species (h_7)	1.81	0.64	0.51	4.68
Fuel price	2.67	0.66	1.47	5.08
Vessel length	35.66	9.26	20	67
Red snapper (h_1)	469.39	1,243.46	0	16,131.80
Verm. snapper (h_2)	280.13	814.43	0	6,395.21
Red grouper (h_3)	366.06	768.97	0	8,619.08
Gag grouper (h_4)	157.30	472.25	0	6,921.44
DWG/Tilefishes (h_5)	69.83	385.25	0	6,917.91
Coastal pelagic/sharks (h_6)	78.56	382.02	0	4,000.00
Other species (h_7)	406.34	767.30	0	9,024.62
Total trip harvest	1,854.61	2,102.17	31.60	17,267.73

Table 1: Sample data descriptive statistics. Table reports mean, standard deviation (Std. dev.) minimum and maximum values for the sample data. There are 1,508 observations on 149 separate vessels.

Variable description	Parm.	Median	Std. dev.	95% c.i.
Constant	β_0	-2.292	0.021	[-2.334, -2.253]
Fuel price	β_w	0.504	0.009	[0.488, 0.526]
Vessel length	β_K	1.119	0.015	[1.095, 1.156]
Sub-region	β_s	1.170	0.012	[1.146, 1.194]
Sub-region^2	β_{ss}	-0.080	0.019	[-0.116, -0.037]
Red snapper	β_1	0.109	0.004	[0.102, 0.116]
Verm. snapper	β_2	0.132	0.008	[0.120, 0.148]
Red grouper	β_3	0.251	0.007	[0.239, 0.265]
Gag grouper	β_4	0.249	0.012	[0.220, 0.269]
DWG/Tilefishes	β_5	0.231	0.010	[0.208, 0.245]
Coastal pelagic/sharks	β_6	0.269	0.011	[0.246, 0.291]
Other species	β_7	0.138	0.007	[0.126, 0.153]
Crew shares	η	0.546	0.005	[0.536, 0556]
Targ. cost (mean)	$\bar{\gamma}$	3.090	0.074	[2.953, 3.247]
Targ. cost. (var.)	σ_γ^2	4.686	0.603	[3.655, 6.029]

Table 2: Posterior parameter distribution. Table reports the median, standard deviation (Std. dev.) and 95% confidence intervals of the posterior parameter distribution.

	Red. snp.	**Verm. snp.**	**Red grp.**	**Gag grp.**
Const.	-2.415 [-2.670,-2.197]	-29.515 [-31.359, -26.999]	-4.619 [-5.529, -4.028]	-8.419 [-9.905, -6.904]
s	3.606 [2.882, 4.645]	118.057 [107.384, 126.184]	39.112 [33.940, 45.253]	52.150 [42.046, 61.485]
s^2	0.919 [-0.005, 1.714]	-122.049 [-131.372, -110.715]	-85.761 [-96.180, -73.394]	-86.897 [-103.396, -72.352]
y	0.635 [0.323, 1.036]	0.619 [0.339, 0.925]	0.227 [-0.056, 0.556]	-1.118 [-1.346, -0.739]
y^2	-0.960 [-1.263, -0.397]	0.524 [0.098, 0.936]	0.182 [-0.368, 0.752]	0.464 [-0.081, 0.850]
$t - t^2$	-3.305 [-3.683, -2.864]	3.151 [2.601, 3.599]	1.710 [1.210, 2.639]	-2.706 [-3.179, -2.035]

	DWG/Tile.	**CP/Sharks**	**Other**
Const.	-5.868 [-10.125, -4.739]	-4.709 [-5.114, -4.291]	1.299 [1.110, 1.449]
s	1.522 [0.766, 2.698]	$0^{\dagger}$ [0,0]	-10.484 [-11.355, -9.085]
s^2	$0^{\dagger}$ [0,0]	0.343 [0.000, 0.731]	7.974 [6.500, 9.059]
y	1.491 [0.703, 2.240]	-0.300 [-0.937, 0.725]	-0.566 [-0.870, -0.366]
y^2	-2.248 [-5.351, -1.131]	0.199 [-0.774, 0.812]	0.104 [-0.199, 0.433]
$t - t^2$	8.464 [3.315, 24.927]	4.980 [3.802, 6.740]	-0.683 [-1.124, -0.161]

Table 3: Posterior parameter distribution: Latent stock share model Table reports median values, and 95% confidence intervals (in square brackets). † - a value of zero was imposed during estimation.

Equation	Parm.	Median	95% c.i.
Cost equation	σ_0^2	0.512	[0.485, 0.543]
Red snapper	σ_1^2	1.009	[0.967, 1.058]
Verm. snapper	σ_2^2	2.365	[2.168, 2.516]
Red grouper	σ_3^2	1.017	[0.973, 1.061]
Gag grouper	σ_4^2	1.347	[1.269, 1.407]
DWG/Tilefishes	σ_5^2	0.765	[0.735, 0.794]
Coastal pelagic/sharks	σ_6^2	3.247	[2.945, 3.561]
Other species	σ_7^2	1.009	[0.964, 1.059]

Table 4: Posterior parameter distribution: Variance matrix. Table reports the median, and 95% confidence intervals of the posterior parameter distribution.

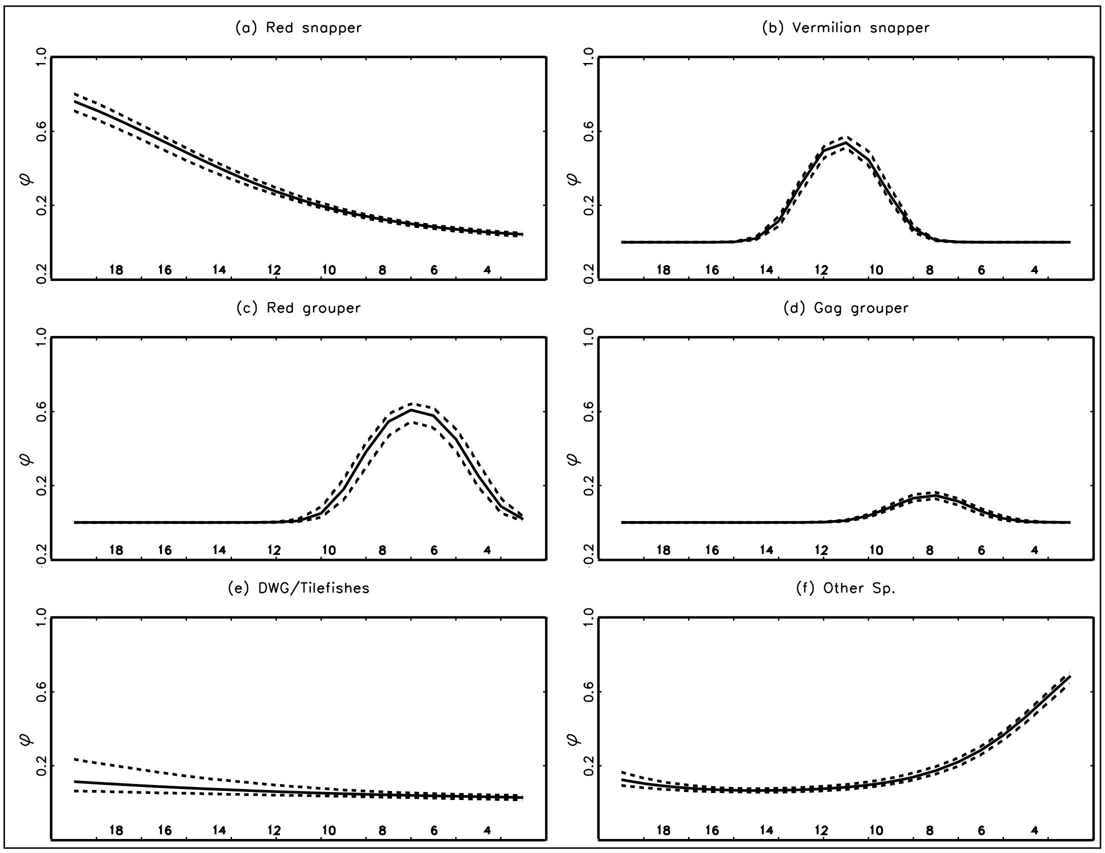

Figure 3: Panels (a)-(f) report the median values (solid line) and 95% confidence intervals for $\varphi_{i,st}$ where $s = 1 - 21$, and t is the midpoint of the 2006 fishing season.