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Rational ecosystem-based fisheries management: An application to the GOM commercial reef fish fishery

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Keywords

Ecosystem-based fisheries management, rational fishing, model validity

Disciplines

Agricultural and Resource Economics | Aquaculture and Fisheries

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JEL Classification: Q2
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1 Introduction

Proponents of ecosystem-based fisheries management (EBFM) argue that policy designs that take a more holistic view of marine ecosystems and affront their real world complexity will more effectively meet management goals.[1] Researchers are addressing added complexity with the help of computer-based ecosystem process models, hereafter, EPM's (see review below). EPM's can track numerous ecosystem components, such as multiple fish species and marine mammal populations, spatial and temporal habitat variation, varying temperature, chemical composition, and water salinity and currents, and competing anthropogenic uses of ecosystem resources, among other factors, across space and time at fine spatial-temporal scale. EPM's are used to simulate outcomes of stakeholder interest across competing management scenarios and varying model specifications.[2] Simulation may assist managers and stakeholders in identifying and quantifying ecological and economic tradeoffs implicit in a specific management action, thus leading to improved EBFM policy designs.

Fishing mortality is the principal determinant of stock abundance across species, space, and time in most marine ecosystems. It is therefore essential that models of the fishing sector be integrated into EPM's, and that these models generate a robust and unbiased characterization of fisheries-ecosystem interaction. It has become common practice when building the EPM fishery sector component to: (1) adopt restrictive and empirically unsupported assumptions for fishing technologies; (2) assume fishermen employ myopic, *ad hoc* decision rules when conducting fishing operations; (3) ignore the role of regulations and market clearing conditions that constrain fishery outcomes and, due to a pervasive and unresolved identification problem in bioeconomic fisheries analysis; (4) rely on empirically unverifiable theories of the crucial stock effect property of fishing technologies when predicting/simulating bioeconomic outcomes. Throughout this paper I will refer to assumptions/practices (1)-(4) as the *standard* fishing sector assumptions, and fishing sector components of EPM's that utilize assumptions (1)-(4) as standard fishing models. This paper evaluates the validity

[1] EBFM is described in Patrick and Link (2015) as one that "Recognizes the combined physical, biological, economic and social tradeoffs for managing the fisheries sector as an integrated system, specifically addresses competing objectives and cumulative impacts to optimize the yields of all fisheries in an ecosystem." See also NMFS, 2016.

[2] See Punt et al., 2016 for a review of a practice known as management strategy evaluation that simulates the entire fisheries management process wherein EPM's and submodels of the fisheries sector component play a crucial role.

of standard fisheries models and proposes and implements an alternative rational expectations model of multiple-species fishing under a real world regulatory constraint that address the shortcomings.

Standard fishing models score low on a criteria of ecological validity (i.e., the extent to which the assumed setting approximates the real world) with regard to multiple-species fishing technologies and the role of regulations in a decentralized production setting. I show how missing elements of real world decision making by commercial fishing operations can obtain a misleading characterization of fishing outcomes. Predictions derived under restrictive standard assumptions confound biological and economic forces into a reduced form effect that cannot predict fishing sector outcomes under changing model fundamentals, such as regulations, dockside prices, and stock abundance. Moreover, reliance on ad hoc rules to describe and predict fishing behavior ignores shadow prices that are key drivers of fishing outcomes in regulated fisheries. Lastly, in lieu of the missing stock effect property, common practice inserts a conceptual *stand in* for the *stock effect* property of the fishing technology. Predictions of fishing behavior derived under this stand in approach may offer heuristic description of possible behavior and outcomes but are void of empirical content.

Singh and Weninger (2018), hereafter SW, study rational ecological-economic equilibrium fishing outcomes in a decentralized multiple-species commercial fishery that exhibits spatial- and temporal-heterogeneity across both ecological and economic dimensions. SW relax several of the standard model assumptions. This paper implements an abbreviated version of the approach empirically to the US Gulf of Mexico (GOM) commercial reef fish fishery. The paper makes several contributions.

First, I highlight and contrast ecological validity in the SW versus the standard fisheries models in the context of a major US fishery. Following Weninger et al., (2019) I estimate a flexible multiple-species harvesting technology under which commercial reef fish fishermen are assumed to engage in costly, endogenous targeting of individual reef fish species. This step generalizes the fixed output proportions assumption popular in standard models, e.g., the F-cube model of Ulrich et al. (2008, 2009). The calibration demonstrates the importance of estimating the deep structural properties of fishing technologies (among other model components). Results contrast the effects of the endogenous targeting decisions of GOM reef fish fishermen which, I show become masked within the ubiquitous catchability coefficients in standard harvest function specifications (Gordon, 1954; Schaefer, 1954; see additional discussion in section 2).

Second, the application to the GOM reef fish fishery demonstrates the implications of adopting ad hoc behavioral assumptions and utilizing naive prediction of fishery sector outcomes in bioeconomic fisheries analysis. Ad hoc behavioral rules are easily incorporated into computer-based EPM's. Fishing effort allocation rules, for example, can be specified as a simple functions of contemporaneous or lagged model elements such as stock abundance and/or landings prices. On the contrary, deriving rational expectations equilibrium fishing outcomes under a quota regulation requires solution of a multi-state variable dynamic programming problem. The approach I implement is data intensive and computationally demanding. My analysis and results show, however, that the payoff in terms of improved model validity can be substantial.

The application to the GOM reef fish demonstrates these gains. I estimate equilibrium fishing outcomes, including regional-temporal quota utilization, landings and discards across individual reef fish species, fleet revenue, cost, and quota rent, and importantly, the equilibrium (fishery wide) quota trading prices, or regulatory *shadow* prices that govern rational equilibrium fishing activity. Equilibrium outcomes are derived under varying total annual quotas, under a simulated region-wide fishery closure, and under changing factor input prices. The results address, quantitatively, a key question for GOM fishery managers and stakeholders, how will changes in annual quotas, closures, and other economic fundamentals change regional harvests, landings, crew employment, and fishing sector profits?

A third contribution of the paper is to highlight a currently unresolved empirical limitation of fisheries bioeconomic models. Ekervold and Gordon (2013) and Weninger et al., (2019) show how unobservability of the *in situ* fish stock creates an empirical identification problem that precludes estimation of the fishing *stock effect*, i.e., the structural property of harvest technologies that determines the productivity of allocated factor inputs (fishing effort). Absent knowledge of this key driver of fishing behavior, it is impossible to predict fishing sector response to changing abundance. Bioeconomic models thus lack external validity in the realm in which they are most often used to inform policy design. Until methods to defensibly calibrate stock effects emerge, simulations using standard fishery sector models are likely to mislead policy designs. The problem may be more pronounced in multiple-species settings. My application to the GOM reef fish fishery makes clear which aspects of fishing behavior are consistently calibrated, and thus external valid. The exercise highlights the limitations of simulation exercises in the context of EBFM.

The remainder of the paper is organized as follows. Section 2 surveys some popular EPM's and further highlights the prevalence and role of standard assumption (1)-(4) introduced above. Section 3 presents the main elements of SW model. Section 4 presents the application to the GOM commercial reef fish fishery. Data and accompanying estimation challenges/limitations are indicated. Section 5 reports results from an abbreviated policy evaluation exercise emphasizing the role of the GOM quota regulation in the determination of equilibrium fishing outcomes. Section 6 summarizes my main findings and discusses future directions to further advance EBFM.

2 Background

In this section briefly reviews methods currently used to implement EBFM with particular focus on the structure and integration of the fishery sector model components.[3] A necessarily informal assessment of model validity follows. I use the term *ecological validity* to describe the extent to which a model approximates the real world setting that is being studied. *Internal validity* references the ability of a model and empirical calibration to identify a causal factor in the presence of confounding forces/factors. *External validity* refers to the property by which a calibrated model or key behavioral driver can be used to predict outcomes outside of a particular environmental-economic setting. Finally, I to describe the common practice of relying on the theoretical but empirically untestable components of standard fisheries models in lieu of their consistently calibrated counterparts.

Ecosystem process models

Ecopath with Ecosim (EwE) combines ecosystem trophic mass balance analysis with a dynamic modeling capability for exploring past and future impacts of fishing and environmental disturbances (Christensen and Walters, 2004). The model user can specify either the species-specific fishing mortality rate or utilize a Fleet and Effort Dynamics module to predict fishing mortality across species,

[3] A comprehensive survey of ecosystem process models is available in Plagányi (2007) and Prellezo et al. (2010).

space, and time. The Fleet and Effort module utilises a primal model of the fishing technology with user specified rules for effort allocation, and investment/divestment in fleet-specific effort capacity.[4] The mix of harvested species in the model is determined exogenously by the species composition of fish stock in the period and location in which harvesting takes place. The model accommodates heterogeneous fishermen whose effort allocations respond differently to spatial-temporal economic incentives, which are operationalized as fishing income differentials.[5]

Atlantis (Fulton et al., 2007) includes a "Socioeconomic Model" module of commercial fishing fleet behavior that tracks monthly, yearly and spatial fishing effort allocations, landings, and profits across multiple species, subfleets (defined as separate gear types), space, and time.[6] Fishing effort, which is operationalized as days fishing, is allocated to high expected profit opportunities at an exogenously determined rate which is specified by the model user. The socioeconomic module determines an "Annual Effort Plan" for individual subfleets under various assumptions for the role of regulations, dockside fish prices, fleet investment, and quota trading. The plan allocates effort proportionally to *expected* profits, which are assumed proportional to expected harvests. Empirical calibration generally uses naive prediction e.g., expected harvest in month t is estimated from month $t-1$ outcomes. The Atlantis socioeconomic module includes additional submodules to predict investment and divestment in vessel capital using ad hoc investment rules.

Atlantis evaluates fishing activity either directly or indirectly. An example of a direct approach sets spatial-temporal harvests to a level chosen by the model user. The model can simulate fish stock dynamics under different fishing *intensities*, and/or spatial-temporal fishing patterns. The indirect approach relies on the predictions of the socioeconomic module that constructs the annual effort

[4]The fisheries management and economics literatures often use days at sea to proxy for the factors of production that are allocated to fish harvest. In this approach, assumptions are added to limit total days at sea (capacity) during a specified calendar period.

[5]EwE includes an optimization routine to predict spatial-temporal, species-specific fishing mortality rates that maximize a user-specified management objective function. Christensen and Walters (2004) offer, as an example, an objective that maximizes the weighted sum of (1) the logarithm of the net present value of fishing profits earned, (2) the existence value of the biomass stock and (3) a variance measure to penalize uncertainty about predictions that involve large deviations from the Ecopath baseline (the idea here is to caution the user against selecting policies that lead to extreme, relative to the Ecopath baseline, net present value and biomass outcomes).

[6]In an application of the Atlantis model to the GOM, Ainsworth et al. (2015) specifies 66 distinct spatial polygons, and considers time steps as small as 12 hours. Atlantis utilizes age cohort models to track abundance of vertebrate populations.

plan, coupled with periodic updates/adjustments that respond to *unforeseen changes in economic conditions*. The annual effort plan is re-evaluated monthly and adjustments are made based on unforeseen contingencies, e.g., if actual cumulative catches have fallen below a planned benchmark, effort levels can be increased.

FishRent (Salz et al., 2011) is a computer-based bioeconomic model designed to assess potential resource rents in a multiple-species and multiple-fleet-segment fishery over multiple time periods. FishRent combines several modules − Biological, Policy, Interface, Economic, Behavioral, and Price − to track components of the fishery environment. Fishrent simulates biological and economic outcomes under a set of starting conditions for a user-supplied parameterization of the model. The Economic module tracks total catches, revenues and costs across multiple species and fleet segments. The Behavior module contains an investment/divestment function that tracks/predicts changes in fleet size.

The Policy module of FishRent allows the user to vary regulations between input and output controls. Input controls limit the quantity of fishing effort, defined as fleet-segment days at sea, that are allocated during each production period. Output controls take the form of a species-specific total allowable catch (TAC) regulation. An option within the Policy module allows the user to increase the resource exploitation *intensity* by adjusting annual TACs above or below a maximum sustainable yield benchmark.

Per-period harvest of individual species is determined by a user-parameterized Cobb-Douglas production (harvest) function. Harvest of each species by each fleet segment is a function of the segments total effort allocation and the species-specific stock abundance. If harvest of one or more species exceeds its respective TAC, the excess catch is assumed discarded. The decision problem for mock fishing industry participants is a choice of how many capital units to allocate to each fleet sector and the number of days at sea to operate each capital unit. Capital investment is assumed to follow a myopic rule whereby capital enters (exits) at a user-specified rate when returns to capital are positive (negative).

The FishRent model assumes that days at sea are controlled directly by regulation (under the input control policy option). If an output based regulation is selected, the model inverts the Cobb-

Douglas harvest function to identify the days required to harvest the allowable catch.[7]

DISPLACE (Bastardie, et al., 2013) is an agent-based bioeconomic fisheries model. A strength of agent-based models is the ease with which individual decision heterogeneity, along almost any dimension deemed important by the model user, can be incorporated. Bastadie, et al., 2013, consider individual vessels that differ in terms of fishing power or productivity. An application in Bastardie, et al., 2014, simulates the effects of various behavioral/management scenarios, including a fisherman's decision to "Reduce the vessel speed", "Choose a port closer to the fishing grounds" and, "Displace effort toward a high expected profit area." Model structure and assumptions, relationships between key variables, parameter values, and the initial conditions must be specified by the model user. Flexibility with regard to spatial and temporal resolution is virtually unlimited, as is the set of policy options that might be evaluated.

The Fleets and Fisheries Forecast model, or F-cube, (Ulrich et al. 2008, 2009) is designed for the evaluation and management of "mixed fisheries" a term used in the fisheries management literature to describe fisheries in which multiple species are concurrently harvested by a particular gear type.[8] F-cube assumes fishing mortality is proportional to allocated fishing effort, e.g., days or hours fishing. The model allows the scale and mix of per unit effort catch to vary across métiers which partition commercial fishing operations into relatively homogeneous subsegments, with the goal of simplifying the analysis of heterogeneous commercial fishing activity.

TEMAS (technical management measures) is a fleet-based bioeconomic software model designed for simulation of short and long term bioeconomic outcomes in multiple-species fisheries (see Ulrich et al., (2007)). The model adopts the fixed output proportions assumption and allows for "flexibility of fishers to adopt their activity to changes in resources, management, and market conditions." Fishing effort allocations and capital investment decisions are predicted by a fleet adaptation module that allocates effort based on spatially heterogeneous cost structures, prices, and management. The fleet behavior module's is operationalized (see Ulrich et al., 2007) using naive predictors where fishing effort is assumed allocated based on differences in "the average value per unit of effort

[7] Documentation claims that the FISHRENT model can be used "to determine optimum value of resource rent and other variables." It is not clear to me how this feature operates.

[8] The consonant term from the production economics literature is a joint-in-inputs technology.

during a previous time step (as proxy for economic attractiveness of alternate choices), and information on the fleet's fishing pattern during the previous time step (as proxy for recent knowledge) and one year earlier (as proxy for seasonality and tradition)."

In sum, two key commonalities arise in fishery sector models: (1) restrictive assumptions for the structure of the multiple-species harvest technology in the form of fixed output proportions and (2) use of user-specified and *ad hoc* rules to characterize fishing behavior which are commonly estimated by naive prediction, i.e., next period behavior will be equal to last period behavior. I next argue that robust prediction of commercial fishing outcomes in complex and decentralized fishery environments requires less restrictive assumptions for multiple-species harvesting technologies and adoption of rational decision rules that are consistent with regulatory instruments used to manage real world fisheries.

2.1 Standard assumptions: validity and other attributes

Multiple species fishing technologies

Representations of commercial fishing technologies are rooted in the early work of H. Scott Gordon (1954) and Schaefer (1954) (see Hannesson (1983) for a review). The ubiquitous Gordon-Schaefer (G-S) single-species harvest function takes the form, $h = qEX$, where h denotes the harvest quantity, q is a scaling parameter known as the *catchability* coefficient which measures the proportion of the stock, X, that is harvested per unit of the (scalar) factor input, E, known as fishing *effort*. Harvest functions map physical quantities of factor inputs to physical quantities saleable output; E is in fact a composite of multiple factors of production, e.g., vessel capital services, crew labor, fuel, nets, hooks, bait, and electronic equipment used on board, miscellaneous supplies, etc. utilized in harvesting operations. In applications, fishing effort is often measured with input proxies such as the number of boats in a fishery, days fishermen spend at sea (which assumes physical quantities flow in proportion to time), or as a consistent aggregate index of the array of factor inputs allocated (Squires, 1987). The implications of using proxies to measure effort is not a focus of this paper. I instead consider the role of the G-S harvest model for characterizing and predicting the behavior of multiple-species fishermen.

Extensions of the G-S framework to the case of multiple-species has followed two paths. The first assumes a technology that is nonjoint in inputs (e.g., Flaaten, 1991). Nonjointness implies the existence of species-specific harvest functions, e.g., $h_i = q_i E_i X_i$, where i indexes individual fish species. Under the nonjoint property, fishermen are assumed able to direct fishing effort toward the production of a single fish species (observe the subscript notation, E_i). This specification rules out *public* factors of production, i.e., capital, labor, nets and hooks are assumed allocatable to a single targeted fish species. Importantly, the non-joint assumption implies that the choice of species i harvest can be made independently of the input/harvest choice for other species. This characterization of multiple-species harvesting is not supported empirically (Branch and Hilborn, 2008; Weninger et al., 2019) or conceptually (Abbott et al., 2015; Ulrich et al., 2017).

A second extension of the G-S harvest model to multiple-species takes the form,

$$\vec{h} = \vec{q} E \vec{X}, \tag{1}$$

where above-arrows have been added to distinguish vectors with dimension equal to the number of species under consideration. The specification in 1 assumes the technology is joint-in-inputs and exhibits fixed output proportions. Note that the effort variable is specified as a scalar.

Fixed output proportions assumes that fishermen do not control the mix of species that are intercepted by their gear while fishing. Equation (1) is consistent with behavior wherein fishermen organize factor inputs to form the effort composite input independently of the mix of species they harvest, and independently of the level and mix of the species' stocks. The internal structure/organization of E may vary with factor input prices, although rarely are prices included in its measurement.[9]

Under the technology in equation (1) the mix of harvested species is determined by the exogenous stock abundance vector. The model rules out targeting of individual species. With no control over the mix of harvested species, the specification in (1) assumes that fishermen either stop fishing

[9]Primal models of multiple-species fishing technologies have additional limitations. Multi-output production functions or transformation functions can be formed only if the technology exhibits the property of strong (also called free) output disposability (Diewert, 1973). Turner (1995) and Singh and Weninger (2009) show that the free output disposability property is inconsistent with the pervasive problem of bycatch and discarding in commercial fisheries.

when an individual species quota binds, or continue to fish (apply effort) and discard the overage of the binding quota species catch.

The métier adaptation of (1) is more general in that is allows the harvest species mix to vary across gear types and/or the spatial region of fishing. The model maintains the fixed output proportions assumption within métiers. Let $k = 1, \ldots, K$ index a finite set of métiers. The F-cube model assumes the decision problem for fishermen is involves two choices (in addition to the formation of the effort aggregate); fishermen first choose the métier(s) in which they operate and then choose the quantity of effort, E_k, applied to each. Discarding behavior follows as above.

Harvest outcomes under the G-S model are determined by the effort choice and the catchability coefficient $\vec{q}_k$ for métier k. To demonstrate the crucial role of this parameter for prediction in bioeconomic models, it is instructive to review a typical application/calibration of equation (1). Ono et al., 2018 build an EPM of the BSAI multiple species groundfish fishery with the goal of evaluating alternate management strategies. The model presented includes a fish population dynamics module, a fleet harvesting/dynamics module, and a module to predict quota allocations across heterogeneous users of the groundfish resource. The goal is evaluation and prediction of fishing and biological outcomes under alternate regulatory scenarios.[10]

Ono et al., 2018, define a métier as a "group of fishing operations targeting a specific assemblage of species using a specific gear, at a specific time and in a specific area." Onboard observer data across a 5 year data period (2010-14) that recorded species composition at the level of a vessel trawl tow is used in a cluster analysis to identify a set of métiers. Note that the data used in this exercise proxies for $\vec{h}_n/E_n$ in equation (1) where the n subscript indexes observations in the data. It should be emphasized that the data are generated by individual fishermen operating in different regions at different dates within the 2010-14 data period. Clusters, or métiers, are identified through similarity in observed groundfish catch composition. Importantly, the groundfish stock abundance in the regions and time periods of the data is unobserved by the researcher.

For expositional purposes denote $\hat{q}_k$ as the estimated catchability vector for métier $k = 1, \ldots, K$

[10] The scenarios investigated in the paper include competing assumptions for the harvest control rule used to set annual quotas, changes in a target species and a bycatch species quota, a change in the structure of the fishing technology and accompanying fishing behavior, and a change in the information available to the regulator when setting annual quotas.

(notation differs slightly in Ono et al., 2018 application). Conditional on the identification of K, $\vec{q}_k$, for $k = 1, \ldots, K$ is calibrated from historical catch data (see also Hoff et al., 2010; Sølgaard Andersen, et al., 2010; many others that apply similar methods). Under the implicit assumptions of the model in (
refGS Multiple) the estimates of $\vec{q}_k$ derived from historical data will embody the unobserved stock conditions during the data period. Extrapolating $\vec{q}_k$ estimates to different stock conditions requires additional assumptions as recognized by the authors.

Recall that the G-S characterization of multiple-species fishing behavior does not include endogenous targeting if distinct fish species. If endogenous targeting is a possibility, the internal and the external validity of the G-approach will be low. To appreciate this point, contrast the G-S characterization of fishing behavior with behavior implied in a model of flexible, costly targeting in a multiple-species fishery.

Singh and Weninger (2009, 2018), Weninger et al. (2019), and the results presented below (see also Branch and Hilborn, 2008; Abbott et al., 2015) assume fishermen influence the mix of species that are intercepted and harvested by their gear. For example, adjusting the micro-locations of fishing, the depths of gear deployment, time of day that gear is set, the type of gear and bait used, among other possibly subtle behaviors, alters the "catchability" of fishing gear. Such endogenous targeting actions are assumed driven by economic motives such as profit maximization. Under the flexible costly targeting assumption realized harvest at the trip level or over a discrete calendar period becomes an endogenous choice that depends jointly on economic and regulatory fundamentals such as fish and fuel prices, and annual catch limits, and on the abundance and composition of the multiple-species fish stock that is exploited. In this production setting, and acknowledging that space and time are continuous as most likely are stock conditions, catchability is a continuous property of the multiple-species technology, or in other words, the number of possible métiers, K, is infinite. Perhaps the most important point of contrast is that with flexible and endogenous targeting, the implicit catchability of individuals species becomes a complex function of all model fundamentals including the management policy and regulations that are the focus of the bioeconomic analysis.[11] Policy

[11] Singh and Weninger (2009, 2018) present necessary conditions for profit maximizing factor input choices, harvest choices and at-sea discards which occur under specific technological and regulatory conditions.

recommendations derived under the restrictive G-S assumptions, if they do not hold, will exhibit low external validity.

Stark differences in implied decision making processes and model calibration methodology exist between the G-S specification and the flexible, costly targeting model of SW. However, unobservability of the *in situ* fish stock negates empirical test of competing models. The internally and external validity of competing models is thus unknowable. It should be emphasized further that the effect of changes in stock abundance and species mix on the productivity of effort in the G-S framework, and on harvest costs in the SW model cannot be empirically identified when the stock is unobserved. Thus, bioeconomic simulation to predict fishing behavior under changing stock conditions may be particularly unreliable. I return to this issue below.

Weninger et al., (2019) introduce a parametric functional form and a strategy to estimate a trip level cost function that captures the structural properties of jointness and weak output disposability (costly targeting) when spatial-temporal stock conditions are unobserved by the researcher. The approach is used below to consistently calibrate key aspects of the GOM reef fish harvesting technology and address several important questions related to management design.

Regulations

Commercial fishing takes place in a decentralized production environment; a manager/regulator sets rules by which harvesting operations can legally proceed; autonomous agents (fishermen) carry out harvesting operations to address privately optimal objectives. Regulations limit fishing mortality to what are deemed sustainable levels. Historically, regulations have restricted factors of production that are allocated to the fishery or imposed constraints on production practices, e.g., limits on numbers of participating vessels and their size, gear restrictions, spatial and/or temporal fishery closure, vessel trip catch or landings limits. More recently output control approaches including individual transferable quotas (ITQs) which grant a right to harvest a specified quantity of fish during a set production period, usually a single calendar year, have become popular. An ITQ regulation places a bound on seasonal harvests, or landings in the case where at-sea vessel monitoring is absent. ITQs do not force fishermen to harvest the entire quota, nor do they dictate where across the fishing ground, or when within the regulatory cycle harvests occur.

Regulations are constraints on harvesting operations. Such constraints effectively change, depending on their specific form, the implicit prices that harvesters face when organizing production. The ability to predict fishing behavior in a regulated production setting hinges critically on understanding the private economic objectives of fishermen and incorporating the correct regulatory shadow prices into fishing behavioral models.

Input-control regulations alter prices of the factors of production. For example, a regulation that limits vessel length, if binding, will raise the effective price of vessel capital potentially leading a profit maximizing fisherman to adjust all factor inputs and harvested outputs. An ITQ regulation when binding introduces a virtual supply price, i.e., the price at which a profit maximizing fisherman would supply a quota-constrained harvest vector if the constraint did not exist. Predicting behavior of commercial multiple-species fishermen under an ITQ regulation thus requires calculation of these virtual quota trading prices.

This principle applies to the red snapper and the grouper-tilefish ITQ regulations in the GOM commercial reef fish fishery. Each year the regulator (with stakeholder input) sets species-specific quotas that cap total *landings* of major reef fish species during a calendar year. All landings, by species, must be matched against quota. Quota is freely tradeable. There are no spatial or within-season restrictions on quota use except to protect sea turtles. Commercial fishermen decide when and where species-specific quota is utilized. Discarding fish at sea is neither prohibited or observed by the regulator and discards do not need to be matched against quota.

To characterize and predict outcomes in a decentralized fishery, SW assume commercial fishermen are rational economic agents who choose factor inputs, harvests and discards by species, and within-season quota purchases/leases with the goal of maximizing their private single-season profit. Fishermen are assumed to have full knowledge of the ecological-economic environment in which harvesting operations take place, i.e., they understand the ecological, economic, and regulatory forces and the decision making of all GOM commercial fishermen. Ecological-economic equilibrium outcomes correspond to the privately optimal choices of all fishermen throughout the full regulatory cycle. Equilibrium stock conditions are determined jointly with equilibrium economic choices.

It is again instructive to contrast the rational behavioral assumption of SW with the assumptions of standard fishery models. Note that a rational seasonal profit maximizing fishermen must plan the entire season's harvesting operations such that no adjustments to factor input use or redistribution of quota utilization across space or within-season can increase seasonal profit. Because quota is freely tradeable, this profit maximization condition extends to the level of the entire reef fish fleet. The solution to the fishermen's problem will depend on all fundamentals: the available technology, fish and factor input prices, and spatial-temporal stock abundance.

A common behavior rule used to characterize and predict fishing behavior in standard model are that fishermen are myopic and follow *ad hoc* rules such as "effort is allocated across regions and species in response to profit opportunities at rates set by the model user. Profit opportunities one period ahead are typically assumed equal to current profit opportunities. Seasonal quota constraints or other regulatory constraints may be included but in *ad hoc* ways, e.g., fishing stops when the quota for the most valuable species in the multiple-species complex has been landed by the fleet.

Fishing patterns predicted by standard model do not adhere to the seasonal profit maximization objective or other directed objective, thus the label, *ad hoc*. For example, the module determining the seasonal effort allocation in Atlantis adjusts the rate of effort allocated if it appears that quota constraints will be met too early or too late in the season. The implication is that the initial rate of effort application was incorrect. One problem with the *ad hoc* approach is there are an infinite number of early season effort allocation rates and within season adjustments that could be inserted into a standard model, each of which will generate a different prediction of spatial-temporal fishing outcomes. The choice of a particular beginning season effort allocation rate becomes arbitrary, and in practice is estimated from past data.

Stock effects

A central purpose of EPM development and fisheries sector modeling is to predict and evaluate outcomes of interest to stakeholders under alternative management policies. Internal and external model validity are crucial for this endeavor.[12] Assessing and achieving internal validity in bioeconomic fisheries models is complicated by missing or imprecise measures of stock abundance. The problem is illustrated simply in the context of the G-S harvest model, equation (1).

Notice that the fish stock the catchability coefficient, fishing effort and stock abundance enter multiplicatively in equation (1). Suppose that cost expenditure data exist so that a consistent index of fishing effort can be formed (Squires, 1987). The G-S harvest model includes two unobserved components, $\{\vec{q}, X\}$. The catchability coefficient maps abundance to the productivity of fishing effort and is therefore the key driver of the effort allocation decision. If X changes, the quantity of effort chosen by the profit maximizing fishermen must also be expected to change. The parameter $\vec{q}$ determines the magnitude of effort adjustment. Precise knowledge of the parameter $\vec{q}$ is therefore crucial for predicting fishing sector response to changing stock abundance. Weninger et al., 2019 show how unobservability of absolute and relative species stock abundance prevents identification of the stock effect structural property of a multiple-species fishing technology.

Unobservability of the *in situ* fish stock further precludes statistical testing of the internal validity of the harvest model. This problem is made concrete by contrasting the standard and SW assumptions for the structure of multiple-species technologies. Under the fixed output proportions assumption (equation 1 and Fcube), variation in catch composition that is observed in data is attributed, solely, to variation in the species mix, conditional on factors that distinguish métiers, e.g., gear, space, date of season. Under the costly targeting technological assumptions of SW, variation in observed catch composition is assumed to vary with the profit maximizing targeting choices of fishermen, and thus potentially all model fundamentals including dockside fish prices, factor input prices, the scale and scope properties of the technology, regulations, as well as the spatially- and temporally- (continuously) varying fish stock. Absent data on spatial-, temporal- and species-specific abundance, formal testing for the true cause of observed catch is not possible. It is not surprising therefore that a consensus as to which technological specification is appropriate in analyses of multiple-species fisheries has not emerged.

[12] Shmueli (2010) compares statistical methods in the context of different scientific objectives of either explaining and predicting economic phenomenon. See Ferraro et al., (2018) for a discussion of causal inference in coupled human and natural systems.

If the stock effect property cannot be estimated, how does EPM simulation proceed? The missing stock effect property is commonly replaced with additional assumptions often which derive from the G-S harvest model. A recent application to a Bearing Sea Aleutian Island (BSAI) groundfish fishery demonstrates.[13] Ono et al., (2018) assume the métier specific catch composition is fixed in the 2011-15 data that is available for analysis. Simulations of stock dynamics, TACs, catch by métier are projected over a 15 year period in which annual recruitment is assumed given as a log-normally distributed recruitment shock. The simulation therefore considered changes in absolute abundance and species mix during the simulation. Predicting fishing behavior in this environment thus requires knowledge of ground fishermen's factor input allocation responses to absolute and relative groundfish abundance. In lieu of the missing stock effect property, Ono et al. (2018) assume that the métier-specific catch of species i fish increases proportionally to relative abundance of the (simulated) species i stock. This assumption is consistent with fixed output proportions technology but is clearly *ad hoc* and cannot be tested or calibrated empirically.

A second concern in the simulation exercise is that shadow prices accompanying the BSAI quota regulation are absent. In other words, predictions of fishing behavior responses generated by the model are not disciplined by a directed behavioral objective for groundfish fishermen (e.g., profit-maximization) nor are they governed by the regulatory constraint under which groundfish fishermen operate (see Fissel et al., 2016).

Summarizing, this section as argued that standard fisheries models lack ecological, internal, and external validity, the latter problems arising in particular due to unobservability of fish stock abundance at spatial and temporal scales typically specified in EBFM models. Unobserved abundance further precludes measurement of the stock effect structural property of harvesting technologies forcing reliance on circular *ad hoc* assumptions when predicting fishing behavioral outcomes under changing stock conditions. The next sections relax the standard model assumptions and overcomes several but not all of these limitations.

[13] The Ono et al., 2018 model is used to conduct, through simulation, management strategy evaluation that encompasses various aspects of the actual fisheries management process. Four main model components are included: (i) a stock growth model, (ii) a stock assessment model that utilizes a CPUE index and other data along with the stock model to estimate abundance in year t, (iii) a management model that applies a harvest control rule to set year $t+1$ annual total allowable catch by species and, (iv) a fleet dynamics model that predicts the year $t+1$ catch of each species for each métier.

3 A model of rational multiple-species fishing

Let s index the spatial regions of the GOM fishing ground. Regions are delineated based on coarse commonality in ecological habitat and presumed stock growth and economic characteristics, e.g., costs of accessing the resource from ports in each region, regional differences in habitat quality, water depth, demand conditions, etc. Individual fish species are indexed with subscript $\imath = 1, \ldots, I$. A region may support some or all species of reef fish in the multiple-species complex. I consider a single representative calendar year which corresponds to a regulatory cycle, i.e., the period over which aggregate quota is set by the regulator and utilized by the industry. I divide the year into quarters which I index with subscript t. Stock and economic conditions can vary across (s, t) combinations. I assume for simplicity that stock and economic conditions are fixed within (s, t) pairs.

The regulator announces annual species-specific quotas prior to the commencement of harvesting operations. Let $\bar{Q}$ denote the I-vector of species-specific quotas. (To ease notation, above arrows are no longer used to denote vectors.) The regulation caps the seasonal *landings* of each species. There is no cheating in the model and therefore seasonal landings cannot exceed $\bar{Q}$. The regulator can only limit the landing, actual landings may fall below $\bar{Q}_i$ for some i if it is not profitable to land the entire species i quota. Consistent with the ITQ regulation in the GOM reef fish fishery, discarding is not illegal and is unobserved by the regulator on most trips.[14] Thus while the regulation caps landings it does not limit at sea discards. Finally, there are no restrictions on the regions or date that species i quota may be landed within the regulatory cycle; spatial-temporal quota utilization is decided by industry.

I assume fishermen have access to a common harvesting technology. Per-trip harvest costs depend on factor input prices, the quantity of reef fish harvested and the absolute and relative abundance of individual reef fish species stocks within the region of fishing. The assumption of a common technology avoids the need to track individual fishing operations. I instead consider a *representative* operation with technology given by the trip-level harvesting cost function $c(h_{st}, w_{st}|X_{st})$, where w_{st} denotes a vector of factor input prices and X_{st} denotes the stock abundance in region s

[14] Some trips carry on board observers to collect information used for management purposes.

and quarter t. Notice that harvest costs are defined over the quantity of fish *harvested*, $h_{st} = l_{st}+d_{st}$, where $l_{st} \geq 0$ denotes landings and $d_{st} \geq 0$ discards. Harvest costs are assumed to be increasing and convex in h_{st}, and non-decreasing and concave in w_{st}. The joint in inputs and weak output disposability properties are assumed. The reader is referred to Weninger et al., (2019) for a detailed discussion of the relationship between harvest costs and the multiple-species abundance, X_{st}.

I assume factor inputs are purchased competitively. Reef fish fishermen are further assumed to be price takers at the dock. Prices for landed reef fish are assumed to depend on the total quantity landed in a region during a subperiod. I use $L_{s,t}$ to denote the I-vector of region s, quarter t aggregate landings (all fishermen, all trips). The dockside fish price vector then follows $p(L_t)$ where $p(\cdot)$ is the inverse demand for landed fish.

I use K_{st} to denote the number of fishing trips taken in region s and quarter t. Aggregate harvest is denoted $H_{st} = L_{st} + D_{st}$.

I assume that quota trading is frictionless, i.e., there are no trading transactions costs.

A fishing vessel is appropriately viewed as a quasi-fixed factor of production. I however do not model the capital investment decisions of reef fish fishermen. Many fisheries, including GOM reef fish, are characterized by an oversized fishing fleet (see Weninger et al., 2019). I therefore assume the capital embodied in the reef fish fleet is sufficient to accommodate a perfectly elastic supply of fishing trips during a regulatory cycle. Finally, to simplify the model I assume that harvest, landing, and discard choices are identical on each trip taken within each (s, t) pair.

Rational expectations equilibrium fishing

SW derive conditions for equilibrium species-specific quota utilization across species, space and time. The allocation satisfies an intuitive condition wherein the marginal profit from utilizing a unit of species i quota (landing a unit of species i fish) is equal across all trips and all (s, t) pairs. I solve for this equilibrium in two steps.

The first step solves for the profit maximizing trips, and per-trip landings and discards, given prices, stock conditions, and quota in each (s,t) pair:

$$v(X_{st}, Q_{st}) = \max_{\{K,l,d\}} K\Big(p_{st}(L)l - c(l+d|w_{st}, X_{st})\Big). \tag{2}$$

subject to,

$$KL \leq Q_{st}.$$

The problem in (2) must be solved for all feasible reef fish stock abundance and quota levels. $v(X_{st}, Q_{st})$ is thus a multivariate function of the state space which in the most general case includes I stocks and I quota quantities. Multivariate functional approximation methods are used to approximate $v()$ over its domain. Note that the domain of interest is bounded. Possible values of the fish stock are determined from beginning season stock conditions and stock growth properties. The quota available in (s,t) pairs, i.e., the quota that remains unfished at date t is bounded above by the beginning season quota, which is determined by the model user.

The second step of the solution algorithm solves the (s,t) quota allocation problem:

$$V(X_1, \bar{Q}) = \max_{\{Q_{st}\}} \sum_{t=1}^{4} \sum_{s=1}^{4} v(X_{st}, Q_{st}|s,t). \tag{3}$$

Subject to,

$$\sum_{t=1}^{4} \sum_{s=1}^{4} Q_{st} \leq \bar{Q}, \tag{4a}$$

$$X_{s,t+1} = G(X_t - L_t - \lambda D_t), \tag{4b}$$

where $G(\cdot)$ is the stock transition function that governs growth and spatial migration of the reef fish stock. Abundance in region s and quarter $t+1$ is specified as a function of the period t escapement across the entire fishery. Note that $X_t = \{X_{st}\}_{s=1}^{S}$ is the $I \times S$ matrix of beginning quarter stock levels, $L_t = \{L_{st}\}_{s=1}^{S}$ denotes landings and $\lambda D_t = \{\lambda D_{st}\}_{s=1}^{S}$ denotes dead discards, with λ representing the discard mortality rate (vector conformability is assumed).[15]

[15]Observe that the solution to (2) also determines landings and discards at all values of the state space; L_t =

4 Calibration and implementation

To implement the model I divide the GOM reef fish fishery into four regions: a WEST region extends from the Mexico border in west Texas to the Mississippi river delta; the AL-MS region extends from the eastern Mississippi river delta to Cape San Blas, Florida (near Panama City, Florida). A third northern Florida region (FL-North) extends from Cape San Blas south to roughly Fort Myers, Florida. A fourth region (FL-South) is the Florida Key region.

Practical considerations require aggregation across some reef fish species. I form eight harvested outputs based on regulations and the importance of individual species in commercial landings and revenue. Species designations include: (1) red snapper; (2) vermilion snapper; (3) red grouper; (4) gag grouper; (5) shallow water groupers, which included black grouper, scamp, yellowfin grouper, and yellowmouth grouper; (6) deep-water groupers, which included snowy grouper, speckled hind, warsaw grouper, and yellowedge grouper; (7) tilefish, which included blueline tilefish, golden tilefish and goldface tilefish; and an (8) Other species category which includes coastal pelagic species (mackerel, tuna, and dolphin species) and all remaining reef fish species. Quantities in output groups that consist of multiple fish species are formed as linear aggregates.

Four components of the model require calibration: (1) the dockside inverse fish demand function; (2) the trip-level harvest cost function; (3) stock growth transition equations; and (4) starting values for model state variables, which include the beginning season abundance, by species and region, and the vector of annual quotas (a choice variable for the model user). Challenges involved in calibrating stock growth and initial stock abundance are not discussed here. I focus on the estimation of the fishing behavioral components, (1) and (2).[16]

Weninger et al., (2019) show that under reasonable assumptions for the form taken by the harvest cost stock effect (even thought it is not estimated), absolute and marginal reef fish harvest costs can be consistently estimated from trip-level harvest and expenditure data. The authors expose why identification of reef fish stock effects across space and time require additional strong and untestable assumptions. Absent a defensible estimate of the stock effect for reef fish, the analysis

$L(X_T, Q_t)$ and $D_t = D(X_T, Q_t)$. These relationship can be used in the second step of the solution algorithm to determine fishing mortality and thus the spatial-temporal evolution of the fish stock.

[16]Note that the following is not a comprehensive guide to the econometric analysis of fisheries data.

that is feasible is limited. The results I present below will be interpreted as "short run" scenarios during which changes in the reef fish stock abundance are either assumed minimal, or assumed to have minimal effects on reef fish harvest costs and thus fishing behavior. There is no way to test this assumption. The results reported in the sequel are interpreted accordingly. Note that the unmeasured stock effect property does not prevent use of the model to inform frequently asked management questions as I demonstrate shortly.

Further empirical considerations

Aggregating across different gear types may mask differences in fishing technologies and behavior; on the surface, disaggregation would appear to be a sensible empirical strategy. The trip cost functional form I estimate includes shift parameters to accommodate potential cost differences among longline and vertical line gear types. Note however that type of gear used by commercial fishermen is an endogenous choice. Modeling gear choice decisions can further complicate fishing behavioral models and will likely increase data requirements. The theory of quota regulated fishery production requires all profit opportunities and thus cost efficiencies be exhausted in a quota trading equilibrium (Singh and Weninger, 2018). I exploit this principle and focus my estimation on the cost function for vertical line reef fishing gear, the most prevalent gear type in my data. The implicit assumption I make is that all quota users, irrespective of gear type, must match the cost efficiency of vertical line gear.

Fishing vessel capital is appropriately viewed as quasi-fixed, and specific factor of production. The specificity label reflects the property wherein the value of a fishing boat when allocated to a non-fishery use in the economy is likely to be discretely lower and may in fact be zero (Singh et al., 2006). Vessel capital investment/divestment decisions are complicated by costly investment reversibility and uncertainty in managed fisheries (deriving from random stock abundance and regulatory adjustements). A robust and well-calibrated model of capital investment is therefore difficult to conceive, and is not attempted here.

Dockside fish demand

Estimates of GOM reef fish inverse demand are provided in Keithly Jr. and Tabarestani (2017). Keithly Jr. and Tabarestani (2017) estimate a system of inverse demand equations for GOM red snapper, red grouper, other grouper species, GOM and South Atlantic Dolphin, and three import substitute species.

Own-price flexibility estimates are -0.725 for red snapper, -0.643 for red grouper, and -0.436 for other grouper species. Dolphin makes up an insignificant share of trip revenue in my data. I assume therefor that the Dolphin dockside price is constant. Cross-price flexibility estimates for the three reef fish species provided in Keithly Jr. and Tabarestani (2017). These estimates are small but nonzero at conventional levels of statistical significance.

The demand analysis of Keithly Jr. and Tabarestani (2017) has implications for modeling fishing behavior in multiple-species fisheries. First, nonzero price flexibilities imply that reef fish prices vary with landings. Second, nonzero cross-price flexibilities suggest a potential source of harvest interdependency across reef fish species that is often overlooked in multiple-species bioeconomic fisheries models.

I adopt two simplifying assumptions in my application. First, I specify the dockside fish price at each (s, t) combination as function of (s, t) landings only. The assumption here is that markets for landed reef fish are independent across (s, t) pairs. Note that if this independence does not hold, equilibrium dockside prices become a function of species-specific landings across all regions and perhaps across multiple quarters. Such dependence would increase the dimension of the state space of my model to unmanageable levels, e.g., with regional price interdependence, $2 \times I \times S$ state variables determine price in each (s, t) and are thus relevant for solving the problem in (2). A second assumption is that cross-species price effects at the regional level are zero. This latter assumption further simplifies the model and importantly allows me to isolate the role of technological interdependence in equilibrium fishing outcomes.

Harvest costs and specification tests

My estimations of trip harvesting costs follow Weninger et al., (2019). Region-specific cost functions are estimated using date from the 2005-14 harvest seasons. Trip level landings and cost are obtained from the National Marine Fisheries Service (NMFS) log book reporting system. Log book records include trip start and end dates, landings by species, the quantity and type of gear deployed, the primary region of fishing, the depth at which the bulk of the gear was deployed, the number of crew on board, among other infromation (see Weninger et al., 2019 for additional details). A survey of annual capital and fixed operating expenses conducted by the Southeast Fisheries Science Center supplements the logbook data. Discard information is obtained from post trip surveys. The full data set contains 21,491 observations; of these, 12,422 (57.8%) include harvesting cost information.

Table 1 reports descriptive statistics at the level of individual fishing trips, and across the four regions of the GOM. The table reports average values and standard deviations for trip characteristics including days at sea, crew size, landings, revenue, variable costs, cost shares for individual factor inputs, and species-specific revenue shares.

The descriptive statistics show regional variation across all trip characteristic. Differences in factor input expenditure shares are small, but perhaps revealing of potential differences in the regional reef fish harvesting costs. What is not apparent is the underlying cause of these costs difference. It is reasonable to expect that distance from ports within a region to the regions productive fishing locations vary geographically. Such difference would impact fuel-harvest transformation relationships. For example, a reef fish trip involves steaming from port to a chosen location where the gear is deployed; no fish are harvested during the steaming portion of the trip. This suggests further that a non-linear relationship between factor inputs deployed and harvest may exist, e.g., that the fuel input-output transformation relationship is likely nonlinear. Estimation results confirm this intuition.

Estimation of cost function structural properties are consistent with regional heterogeneity exhibited in table 1. The fuel price-cost elasticity estimate is 0.66 in the WEST region, 0.28 in the AL-MS region, 0.26 in the FL-North region, and 0.30 in the FL-South region of the fishery. The crew wage cost elasticity estimate increases moving from the west to east regions from 0.30 in the

	WEST (N=2,742)		AL-MS (N = 4,321)		FL-North (N=3,438)		FL-South (N=2,191)	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Days	4.11	3.50	3.85	2.78	5.18	3.60	2.88	3.24
Crew size	2.68	1.41	2.81	1.20	2.36	0.91	1.93	0.78
Landings	3,702.52	4,826.73	2,245.50	2,191.43	2,325.03	2,765.45	1,193.94	1,847.49
Revenue	11,349.60	16,565.01	6,261.29	6,723.64	7,076.53	8,988.60	3,315.28	5,576.92
Var. Cost	4,397.07	4,826.73	2,245.50	2,191.43	3,839.73	3,350.35	2,089.65	2,812.07
Labor exp.	2,192.04	2,589.76	1,944.11	1,690.35	2,216.56	1,871.93	1,160.19	1,578.04
Fuel exp.	856.86	896.56	604.49	583.43	631.13	539.45	375.46	465.45
Other exp.	1,195.84	1,568.03	829.13	1,009.56	858.00	1,070.73	480.04	824.28
Capital Exp.	148.65	217.88	124.79	178.27	134.04	144.85	73.96	117.72
Factor Expenditure Shares								
Labor	0.51	0.12	0.57	0.12	0.59	0.11	0.57	0.14
Fuel	0.23	0.09	0.20	0.09	0.20	0.09	0.22	0.11
Other	0.23	0.11	0.20	0.11	0.18	0.10	0.18	0.11
Capital	0.03	0.01	0.03	0.02	0.03	0.01	0.04	0.01
Revenue Shares by Species								
Red snap.	0.36	0.41	0.26	0.34	0.09	0.17	0.01	0.05
Verm. snap.	0.10	0.20	0.32	0.33	0.04	0.12	<0.01	0.05
Red group.	<0.01	0.02	0.06	0.14	0.54	0.36	0.10	0.26
Gag group.	<0.01	0.02	0.03	0.09	0.12	0.19	0.01	0.05
OSW group.	0.01	0.04	0.02	0.04	0.03	0.11	0.03	0.10
DW group.	0.04	0.13	0.02	0.09	0.02	0.12	0.03	0.13
Tilefish	0.01	0.05	0.01	0.08	<0.01	0.03	0.01	0.09
Oth. spec.	0.49	0.47	0.28	0.38	0.16	0.32	0.85	0.37

Table 1: **Regional Trip-level Cost and Revenue Descriptive Statistics.** Landings are reported in pounds. Revenues and expenses are reported in \$2014.

WEST to 0.51 in the FL-South.

Table 1 shows variation in species-specific revenue shares across regions. Red and vermilion snapper account for 46% of trip revenue on average on WEST trips. In the AL-MS region, these same two snapper species make up an even larger share, 58%, of average trip revenue due primarily to large vermilion snapper harvests. Red and vermilion snapper comprise a small share of trip revenue in the eastern GOM; 13% in FL-North, and roughly 1% in FL-South. Grouper species combined account for roughly 5% of average trip revenue in the WEST. The combined grouper share of trip revenue exceeds 70% in FL-North. Groupers account for roughly 17% of average trip revenue in the FL-South region.

It is instructive to examine the descriptive statistics in table 1 in context of a fixed output proportions technology assumptions. A first question is whether fishing effort, which I measure as total trip cost[17] is linear in days at sea. I regress trip costs on days at sea entered in polynomial form. These regressions soundly reject the linearity specification in all regions.

I next test the hypothesis that harvested pounds are linear in effort, measured either as days at sea or as trip cost. For these regressions I select harvest shares of prominent species from each region as the left hand side variable and, as above, consider linear and higher-order polynomials of my effort measures as regressors. Linear specifications are soundly rejected for most reef fish species across all regions. The linear in effort harvest function specification is not supported with my data.

A question remains as to which technological assumptions, the fixed output proportions G-S specification, or a flexible technology with endogenous targeting best characterizes the GOM reef fish fishing technology? As noted, a formal test of competing assumptions is not possible given unobservability of the reef fish stock. Considerable indirect evidence however supports the flexible costly targeting assumption. Singh and Weninger (2017) find a strong link between catch composition, trip level catch limit regulations and fishery closures. Weninger et al., (2019) link reef fish catch composition to the economic targeting incentives implicit in the quota regulation. Examination of the catch composition in my data, as reported in figure 1, further supports the flexible technological specification.

Figure 1 shows a box and whisker plot of quarterly average per trip red grouper harvest shares (landings plus regulatory discards) on vertical line gear trips during the 2005-14 data period. Average values are indicated by a rectangle; 25%-75% percentile values are indicated by the vertical whiskers. The dashed vertical demarcation shows the start of the Grouper/Tilefish IFQ program which began in January, 2010.

The catch composition shown in the figure is informative of the true structure of the reef fish harvest technology. Notice first that the 25%-75% range in red grouper harvest shares indicate considerable heterogeneity within and across quarters. If the technology satisfied the fixed output

[17]The problem of constructing meaningful aggregates for factors of production and nonlinearity in effort-harvest relationships are problems that can be addressed with better data and consistent methods of aggregation (see Squires, 1987).

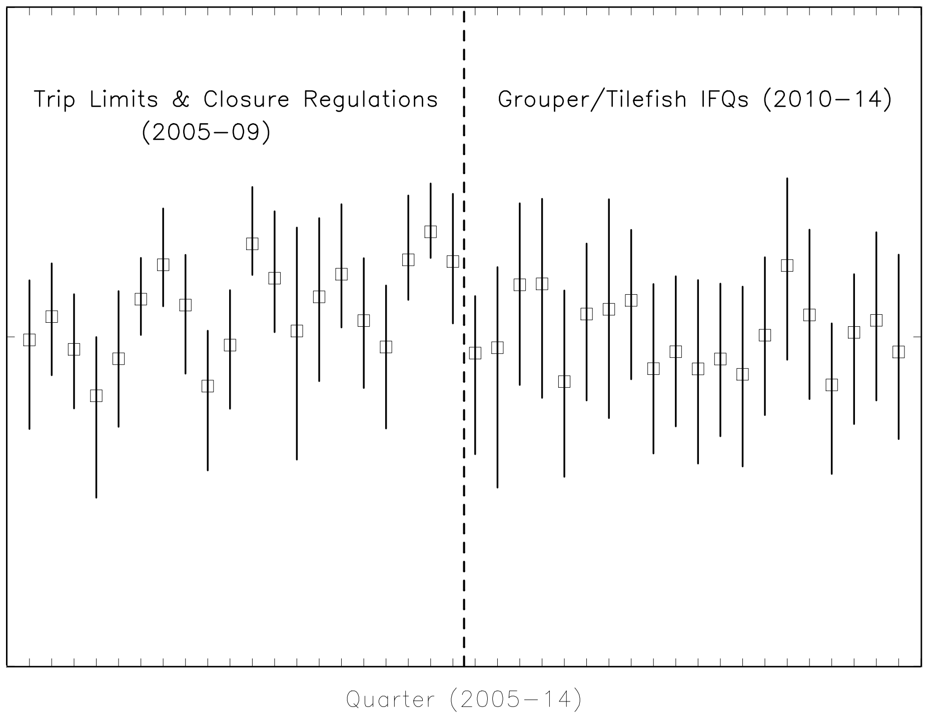

Figure 1: Red Grouper Harvest shares: 2005-14.

proportions assumption, and all fishermen in the FL-North region fish a common reef fish stock, the share of red grouper in trip catch would be constant. The heterogeneity shown in the figure, although not conclusive, does not support the fixed output proportions assumption. It is possible the reef fish stock abundance is spatially heterogeneous within the FL-North region or that individual fishermen target different species mixes. As noted, unobservability of the reef fish stock precludes a formal test of competing hypotheses regarding the structure of the multiple-species technology.

A second observation is the cyclical pattern shown during the pre-IFQ regulation, which disappears when the quota regulation is introduced. Low red grouper harvest share quarters during 2005-09 coincide with grouper fishery closures which were used to limit fleet catch and meet conservation goals. The observed pattern is consistent with the hypothesis that reef fish fishermen avoided grouper species and targeting other species (under presumably the same stock conditions) when grouper landings were prohibited. This supports a flexible costly targeting specification for the reef fish technology. Observed patterns in the harvest mix of other reef fish species across other regions and gear types find similar support. To conserve space these results are not reported.

Implementation

In the absence of consistently estimated regional stock transition equations,[18] equation (4b), and cost-stock effects, the impacts of changing stock conditions, in terms of absolute abundance, species mix and spatial migration, on fishing costs and thus equilibrium fishing outcomes are unknowable. To move forward additional assumptions are needed. The approach I follow here is to use the two calibrated model components to simulate equilibrium outcomes that can be viewed as credible given the stock conditions during the 2005-14 data period. In other words, an evaluation of management scenarios in which reef fish stock abundance is maintained *near* 2005-14 levels can provide important and reliable management advice. It should be emphasized that because there is no way to evaluate bias due to a no-stock-change assumption, the results that follow are interpreted with some caution.

The dimension of the state space in the most general application to the GOM reef fish fishery is 14, with 8 reef fish species and 6 species' quotas (recall that landings of vermilion snapper and the Other species group are not included under the regulation).

Ignoring stock dynamics allows me to reduce the dimension of the state space further to 6. I simplify the model and drop reef fish species in regions where they have a particularly small role in landings and revenue. Table 3 in the appendix reports average quarterly landings and revenues during 2014 which is the year of my baseline calibration. Shallow water groupers account for roughly 1% of landings and revenue in the WEST region. Red and vermilion snapper make up 2%-3% of landings and revenue in FL-South. Other shallow water groupers make up 2% or less of landings and revenues in all regions. I drop shallow water groupers in the WEST, red and vermilion snapper in FL-South, and other shallow water groupers in all regions. For these species and regions I fix quarterly landings to their 2014 average quarterly values (see table 3).

[18] Growth and migration patterns of GOM reef fish species can in principle be calibrated and summarized with surplus stock production models. Attempts to calibrate a stock transition model and initial stock abundance did not produce results that were deemed sufficient for credible bioeconomic simulation.

Chebychev polynomial interpolation is used to approximate $v(X, Q|s)$ for each $s \in S$ and for a representative quarter (see Judd, 1998; Miranda and Fackler, 2002). I assume that dockside demand conditions and factor input prices are constant across quarters. Under these assumptions, and with not stock effects in the model, the annual quota will be distributed equally across quarters. This simplification allows me to solve the quota allocation problem, equation (3), for a single representative quarter.[19]

5 Results

Table 2 reports quarterly and regional equilibrium quota utilization, harvesting costs, fishing sector profits (quota rent), consumer surplus, and fishery-wide quota trading prices under four management scenarios. Scenario 1 sets annual red snapper, grouper and tilefish quotas and economic conditions (fish demand and factor input prices) equal to their counterparts in my 2014 data. Scenario 2 maintains 2014 economic conditions but reduces the red and gag grouper quota by 25% relative to 2014 levels. Scenario 3 maintains 2014 quotas and economic conditions but simulates a fishery closure. The scenario is intended to approximate the 2010-11 Deepwater Horizon oil spill disaster. The disaster led authorities to close large portions the AL-MS subregion to commercial fishing. The closures began in May 2010 and ended in March 2011. Regional landings of groupers and tilefish dropped considerably during this period. Scenario 3 simulates the closure event by removing the entire MS-AL region from the quota allocation problem in equation (3).

Finally, scenario 4 maintains 2104 snapper, grouper and tilefish quotas but changes a key economic fundamental. I consider the effects of a 20% increase in the price of fuel, relative to the 2014 average fuel price. Note that studying changes in annual quotas requires that I solve the problem in equation (3) under different quota constraints. Evaluating a change in an economic fundamental requires re-approximation of the regional quota constrained value functions in equation (2) before re-solving equation (3).

Scenario 1 results provide a check on the model's ability to replicate outcomes observed in the

[19] Regional value functions are strictly concave in quota which ensures that maximized seasonal quota value involves repeating quarterly production plans throughout the year.

GOM reef fish fishery data. The results indicate that the annual red snapper quota of 5.054 m. lbs. in 2014 is binding with a positive equilibrium quota lease price of \$0.485/lb. In actuality, 91.6% of the 2014 red snapper quota was landed in 2014. NMFS (2015) reports that average quota lease prices during this period averaged \$3.03 per pound. When I reduce the red snapper quota to the levels observed during 2010-12 (on average, 3.402 m. lbs. per year) my model predicts an equilibrium red snapper lease price of \$2.838/lb., which is much closer to reported lease prices (NMFS, 2015).

Scenario 1 predicts WEST region red snapper landings and quota use at 731.514 pounds per quarter. Actual 2014 WEST region quarterly landings of red snapper averaged roughly 9% less at 666.119 pounds per quarter. If I adjust for the fact that 0.916% of the fishery wide red snapper quota was utilized in 2014, my model predicts that 57.9% of the red snapper quota will be fished in the WEST where in actuality 57.3% of the red snapper was landed in the WEST region in 2014.

Scenario 1 results indicate that the West region harvesting activity is, in equilibrium, organized into 119 fishing trips per quarter. The GOM data indicate that, on average, 659.250 WEST region trips were taken per quarter in 2014. This discrepancy is not unexpected. The solution to the problem in (3) organizes the reef fish harvest into fully cost efficient representative fishing trips, which include larger per trip harvest than observed in the data (there is also considerable variation in per-trip harvest among actual vessels). Whereas the model assumes equilibrium representative trips fully exploit the available returns to size in harvest, actual reef fish fishing the GOM does not achieve this standard. Per-trip harvests/landings in the range predicted by the model are observed in the 2014 GOM reef fish data.

Comparison of the scenario 1 predictions with their observed counterparts in 2014 finds similarities but also discrepancies. The results highlight the challenges of calibrating models of complex coupled human natural systems. Results that follow should be interpreted in light of these calibration limitations.

Management scenario 1 outcomes indicate slack annual quotas for red and gag grouper and binding quotas for the remaining species. As required, equilibrium quota lease prices are zero (positive) when the species-specific annual quota is slack (binding). Scenario 2 results indicated binding quotas and positive quota prices for all species; the red grouper quota lease price rises to

$0.84/lb. and the gag grouper quota leases to $ 1.53/lb. under the reduced grouper quotas.

The results highlight the role of quota shadow prices for predicting fishing behavior. Equilibrium quota allocation across regions and quarters is determined by the marginal profit from landing a unit of quota, which is derived as the virtual landings price, $p_i - r_i$, less the species-specific marginal harvest cost. Note that marginal costs depend on and must be evaluated at the equilibrium trip-level harvest vector. Under the flexible costly targeting technology, a change in the annual quota for a single reef fish species can cause adjustments to all endogenous variables of the model. Results in table 2, for example, indicate that quota utilization, quarterly trips, the trip level mix of harvested species and landings, quota rent, consumer surplus, and the quota lease prices are all impacted by a reduction in red and gag quotas (management scenario 2).

Additional red and gag grouper quota scenarios were examined. The results are not reported to save space. This analysis finds that modest reductions in the red and gag grouper quotas, in the range of 5% - 10% declines relative to 2014 quotas, and quota increases above 2014 levels have no effect on equilibrium outcomes. The reason is that for modest quota adjustments both red and gag quotas remain slack and therefore predicted equilibrium outcomes are unchanged. On the contrary, marginal adjustments to binding species quotas result in changes to all endogenous variables.

Comparison of the results of scenario 3 with the baseline results yields several insights. First, a closure of the AL-MS region loosens quota constraints in the remaining *open* regions. Scenario 3 results show that only the Tilefish quota binds when the AL-MS region is closed. Quarterly red snapper quota use in the WEST GOM increases from 731,514 to 795,842 pounds. The number of fishing trips, total cost, quota rent, and consumer surplus all increase in the WEST, FL-North, and FL-South. Interestingly, tilefish quota use declines in the WEST but increases in FL-North and FL-South. This finding suggests differences in cost complementarity across regions. The results indicate that cost complementarity between tilefish and other reef fish species is stronger in FL-North and FL-South than in the WEST. As a result, the model predicts a redistribution of Tilefish quota away from the WEST and toward the two Florida regions when the AL-MS region is closed to fishing.

Comparing the scenario 4 results with baseline values finds not surprisingly that trips taken, quota rent, and consumer surplus, are lower when fuel prices increase. Equilibrium quota lease prices decline for red snapper, tilefish and DW grouper species, and remain at $0/lb. for the slack quota species, red and gag grouper. Declines in quota utilization relative to the baseline are indicated across most species and regions, with the magnitudes of these changes varying regionally. Interestingly, the model predicts that DW grouper quota is redistributed from the WEST region to the AL-MS, FL-North, and FL-South regions of the fishery when fuel prices rise. This result is explained by regional differences in the harvest technology. As noted above, the fuel price-cost elasticity in the WEST region is more than twice that of other regions. The result is a redistribution of quota to the now *relatively* lower cost regions.

It should be emphasized that the changes in equilibrium outcomes reported in table 2 derive from changes in regulations and economic fundamentals, i.e., stock conditions do not vary in the model. Yet, non-trivial changes in reef fish targeting at the trip level are indicated. Under a fixed output proportions harvest technology, changes in the harvest mix are assumed to derive exclusively from changes in stock abundance. If the fixed output proportions assumption is imposed, when in fact the technology is flexible as assumed here, the targeting adjustments in table 2 will be missed.

Zero reef fish discarding is predicted under all scenarios considered in table 2. Under a flexible technology, discarding fish at sea is part of a profit maximizing plan under quite special stock, quota, and economic conditions. Note that when discarding fish due to insufficient quota, trip revenue derives only from non-quota-constrained species. This revenue must be sufficient to compensate for the costs of harvesting both discarded and retained species. Further examination of equilibrium outcomes (not reported to save space) find that positive discards arise when quotas for relative high price and low marginal cost species are set to particularly low levels, while remaining reef fish quotas are maintained at levels are sufficient to maintain a profitable fishing trip. If regulators avoid setting quotas in the *discard set* as defined in Singh and Weninger (2009), over-quota discards do not arise in the model.

An exercise of further contrasting the predicted outcomes in table 2 with those obtained under a standard fishery sector model was not informative. Suppose a model of multiple métiers under a fixed output proportions harvest technology is specified for GOM reef fish. Implementation would require rules governing the allocation of regional fishing effort (which would also require definition and measurement), rules to determine discards when one or more reef fish species quotas bind (e.g., Hoff et al., 2010; Ulrich, et al., 2017). Unless quota prices are derived endogenously, effort allocations would follow *ad hoc* rules as functions of revenue or profit differentials that are calculated from the wrong prices, i.e., quota shadow prices would be absent from the model. Métier-specific cathabilities would remain fixed under simulated management and economic scenarios. Additional assumptions for constraints on annual effort (days at sea), vessel capital investments, may also be required (e.g., Sølgaard Andersen et al., 2010). Without sound basis to select among the large set of candidate assumptions, all of which would impact model predictions, comparison of competing model predictions, do not provide further insight.

6 Conclusion

Fisheries sector models are often used within complex ecosystem process models to inform the design of ecosystem-based fisheries management (EBFM) policy. For reasons of simplicity and to maintain model tractability, standard practice maintains restrictive assumptions for the structure of multiple-species fishing technologies and *ad hoc* rules to predict fishing behavior and fisheries-ecosystem interaction. Regulatory shadow prices that emerge in decentralized and regulated production settings are ignored. Due to a pervasive empirical identification problem in fisheries bioeconomic models, empirically unverifiable assumptions are used to represent the fisheries sector response to changing stock conditions. Fishing sector models that invoke these assumptions/methods score low on criteria of ecological, internal, and external validity. EBFM policy designs that derive from such models are unlikely to meet EBFM goals.

This paper proposes a model of rational, flexible multiple-species fishing under an individual transferable quota regulation as an alternative. An application to the Gulf of Mexico (GOM) commercial reef fish fishery demonstrates the improved ecological validity. The application further highlights empirical challenges in calibrating fisheries bioeconomic models, and demonstrates the types of policy questions that can and cannot be quantified using currently available data and calibration methods. Simulations are presented that predict equilibrium outcomes of interest to managers and fishery stakeholders under varying annual reef fish quotas, in a scenario that replicates a regional fishery closure, and under changing economic fundamentals (fuel prices). Results inform and quantify bias that may obtain from restrictive standard fishery models.

Deriving rational expectations equilibrium outcomes in managed marine ecosystems is not without limitation; the proposed methodology is data intensive and computationally demanding. The state space that can be accommodated using numerical recursive dynamic programming methods limit model generality, e.g., the number of fish species included in the application was reduced.

Managers and stakeholders should nonetheless be aware of the role of simplifying assumptions in bioeconomic simulation exercises. New empirical methods and perhaps enhanced fisheries data collection may allow consistent estimation of the stock-effect structural property of commercial fishing technologies. Until such estimates are available, a "stock-constant" simulation such as the on presented in this paper offers a defensible policy evaluation tool. Absent the stock-effect component, however, long-term prediction of fisheries sector outcomes under changing stock conditions will lack external validity and are likely to mislead EBFM.

References

Abbott, J. K., A. C. Haynie and M. N. Reimer. 2015. Hidden Flexibility: Institutions, Incentives, and the Margins of Selectivity in Fishing, *Land Economics*, 91: 169-195.

Ainsworth, C. H., M. J. Schirripa, and H. Morzaria-Luna, eds. 2015. An Atlantis Ecosystem model for the Gulf of Mexico Supporting Integrated Ecosystem Assessment. NOAA Technical Memorandum NMFS-SEFSC-676, 149 p. doi:10.7289/V5X63JHV.

Bastardie, F., J. R. Nielsen and T. Miethe. 2014. DISPLACE: a dynamic, individual-based model for spatial fishing planning and effort displacement - integrating underlying fish population models. *Canadian Journal of Fisheries and Aquatic Science*, 71: 366-386.

Branch, T. A., and Ray Hilborn. 2008. Matching catches to quotas in a multispecies trawl fishery: targeting and avoidance behavior under individual transferable quotas, *Canadian Journal of Fisheries and Aquatic Sciences*, 65: 1435-1446.

Christensen, V., and C. J. Walters. 2004. Ecopath with Ecosim: methods, capabilities and limitations. *Ecological Modeling*, 172: 109-139.

Diewert, W. E. 1973. Functional Forms for Profit and Transformation Functions, *Journal of Economic Theory*, 6: 284-316.

Ekerhovd, N. A., and D. V. Gordon. 2013 Catch, Stock Elasticity, and an Implicit Index of Fishing Effort, *Marine Resource Economics*, 28: 379-95.

Ferraro, P. J., J. N. Sanchirico, and M. D. Smith. 2018. Casual inference in coupled human and natural systems, available at https://doi.org/10.1073/pnas.1805563115.

Fissel, B., M. Dalton, B. Garber-Yonts, A. Haynie, S. Kasperski, J. Lee, D. Lew, A. Lavoie, C. Seung, K. Sparks, and S. Wise. 2016. Stock Assessment and Fishery Evaluation Report for the Groundfish Fisheries of the Gulf of Alaska and Bering Sea/Aleution Islands Area: Economic Status of the Groundfish Fisheries Off Alaska, 2016, National Oceanic and Atmospheric Administration.

December 20, 2017.

Flaaten, O. 1991. Bioeconomics of Sustainable Harvest of Competing Species, *Journal of Environmental Economics and Management*, 20: 163-180.

Fulton, E. A., A. D. M. Smith and D. C. Smith. 2007. Alternative Management Strategies for Southeast Australian Commonwealth Fisheries: Strategy 2: Quantitative Management Strategy Evaluation. Australian Fisheries Management Authority, Fisheries Research and Development Corporation, June 2007.

Fulton, E. A., A. D. M. Smith, D. C. Smith, and I. E. van Putten. 2011. Human behavior: the key source of uncertainty in fisheries management, *Fish and Fisheries*, 12: 2-17.

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

Hannesson, R. 1983. Bioeconomic Production Functions in Fisheries: Theoretical and Empirical Analysis, *Canadian Journal of Fisheries and Aquatic Science*, 40: 968-82.

Hoff, A., H. Frost, C. Ulrich, D Damalas, C. D. Maravelias, L. Goti, and M. Santurtún. 2010. Economic effort management in multispecies fisheries: the FcubEcon model, Open access article available at Oxford University Press.

Judd, K. L. 1998. Numerical Methods in Economics, The MIT Press, Cambridge, MA.

Keithly Jr., W. R., and M. Taberestani 2018. The Gulf of Mexico Grouper/Tilefish Fishery After Introduction of an Individual Fishing Quota Program: The Impact on Ex-vessel Prices. unpublished manuscript.

Miranda, M. J., and P. L. Fackler. 2001. Applied Computational Economics and Finance, MIT Press, Cambridge, MA.

National Marine Fisheries Service (NMFS, 2015). 2014 Gulf of Mexico Red Snapper Individual Fishing Quota Annual Report, National Marine Fisheries Service, Southeast Regional Office, St.

Petersburg, FL, November 5, 2015.

National Marine Fisheries Service (NMFS) 2016. Ecosystem-Based Fisheries Management Policy of the National Marine Fisheries Service, NOAA
(available at http://www.nmfs.noaa.gov/op/pds/index.html).

Ono, K., A. C. Haynie, A. B. Hollowed. J. N. Ianelli, C. R. McGilliard, and A. E. Punt. 2018. Management strategy analysis for multispecies fisheries, including technical interactions and human behavior in modeling management decisions and fishing, *Canadian Journal of Fisheries and Aquatic Science*, 75: 1185-102.

Patrick, W. S., and J. S. Link. 2015. Myths that Continue to Impede Progress in Ecosystem-Based Fisheries Management, *Fisheries*, 40: 155-160.

Pindyck, R. S. 2013. Climate Change Policy: What Do the Models Tell Us?, *Journal of Economic Literature*, 51: 860-872.

Plagányi, E. E. 2007. Models for an ecosystem approach to fisheries. FAO Fisheries Technical Paper. No. 477. Rome, FAO. 108 p.

Prellezo, R., A. Little, R. Nielsen, J. Levring Andersen, Ch. Rockmann, P. Accadia, E. Buisman and J. Powell. 2010. Survey of Existing bio-economic models. Final report. Available at https://webgate.ec.europa.eu/maritimeforum/en/node/1075.

Punt, A. E., D. S. Butterworth, C. L. de Moor, J. A. A. De Oliveira, and M. Haddon. 2016. Management strategy evaluation: best practices, *Fish and Fisheries*, 17: 303-334.

Salz, P., E. Buisman, H. Frost, P. Accadia, R. Prellezo and K. Soma. FISHRENT; Bio-economic simulation and optimisation model for fisheries. 2011. LEI Report 2011-024, ISBN/EAN 978-90-8615-514-9.

Schaefer, M. B. 1954. Some Aspects of the Dynamics of Populations Important to the Management of Commercial Marine Fisheries, *Bulletin of the Inter-American Tropical Tuna Commission*, 1: 26-56.

Shmueli, G. 2010. To Explain or to Predict? *Statistical Science*, 25: 289-310.

Singh, R., Q. Weninger and M. Doyle. 2006. Fisheries management with stock growth uncertainty and costly capital adjustment, *Journal of Environmental Economics and Management*, 52: 582-599.

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

Singh, R. and Q. Weninger. 2015. Harvest efficiency and fishery discards under harvest uncertainty and trading restrictions, *Journal of Environmental Economics and Management*, 70: 72-91.

Singh, R. and Q. Weninger. 2017. Quota flexibility in multi-species fisheries, Iowa State University, Department of economics working paper 17026.

Singh, R. and Q. Weninger. 2018. Rational ecosystem-based fisheries management, Department of economics working paper 17033.

Sølgaard Andersen, B., Y Vermard, C. Ulrich, T. Hutton, and J.J. Poos. 2010. Challenges in integrating short-term behavior in a mixed-fishery Management Strategies Evaluation frame: A case study of the North Sea flatfish fishery, *Fisheries Research*, 102: 26-40.

Squires, D. 1987. Fishing Effort: Its Testing, Specification, and Internal Structure in Fisheries Economics and Management. *Journal of Environmental Economics and Management*, 14: 268-282.

Squires, D. 1988. Production Technology, Costs and Multiproduct Industry Structure: An Application of the Long-Run Profit Function to the New England Fishing Industry. *Canadian Journal of Economics*, 21: 359-377.

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

Ulrich, C., B. S. Anderson, P. J. Sparre, and J. R. Nielsen. 2007. TEMAS: fleet-based bioeconomic simulation software to evaluate management strategies accounting for fleet behavior, *ICES Journal of Marine Science*, 64: 647-651.

Ulrich, C., S. Reeves, and S. Kraak. 2008. Mixed fisheries and the ecosystem approach, *ICES Insight*, 45: 36-38.

Ulrich, C., D. Garcia, J. Castro, D. Damalas, H. Frost, R. Hille Ris Lambers, A. Hoff, et al., 2009. Reconciling single-species management objectives in an integrated framework of avoiding over quota catches: main outcomes of the AFRAME project, ICES Document CM 2009/M: 08. 30 pp.

Ulrich, C., Y. Vermard, P. J. Dolder, T. Brunel, E. Jardim, S. J. Holmes, A. Kempf, L. O. Mortensen. J. J. Poos, and A. Rindorf. 2017. Achieving maximum sustainable yield in mixed fisheries: a management approach for the North Sea demersal fisheries, *ICES Journal of Marine Science*, 74: 566-575.

Weninger, Q., L. Perruso, and H. Bunzel. 2019. Identification of resources extraction technologies when the resource stock is unobservable, Iowa State University, Department of economics working paper 18015.

7 Appendix

7.0.1 Descriptive statistics

Scenario 1: 2014 Quotas (Baseline Calibration)							
	WEST	AL-MS	FL-N	FL-S	Total (m.)	Util.	r_i
Red Snap.	731.514	398.129	120.416	13.441*	1.264	1.000	\$0.487
Red Group.	5.346*	79.841	969.176	235.497	1.407	0.916	0.000
Gag Group.	2.938*	40.224	146.070	15.779	0.209	0.982	0.000
DW Group.	65.442	51.955	107.934	52.170	0.278	1.000	0.561
Tilefish	90.755	35.575	8.065	11.105	0.145	1.000	1.190
Trips	119	187	655	633	1,594		
Cost (\$ m.)	0.770	0.908	2.273	1.203	5.154		
Rent (\$ m.)	4.735	2.702	3.996	2.179	13.612		
Cons. Surp. (\$ m.)	2.132	1.234	1.948	1.072	6.386		
Scenario 2: 25% Decline in Red and Gag Grouper Quotas							
	WEST	AL-MS	FL-N	FL-S	Total (m.)	Util.	r_i
Red Snap.	731.676	398.113	120.270	13.441*	1.264	1.000	0.485
Red Group.	5.346*	62.562	797.122	191.932	1.057	1.000	0.840
Gag Group.	2.938*	29.974	112.585	11.800	0.157	1.000	1.530
DW Group.	65.504	52.003	107.698	52.296	0.278	1.000	1.558
Tilefish	90.746	35.580	8.002	11.172	0.145	1.000	1.190
Trips	119	181	568	616	1,484		
Cost (\$ m.)	0.770	0.877	1.981	1.169	4.797		
Rent (\$ m.)	4.735	2.688	3.898	2.162	18.280		
Cons. Surp. (\$ m.)	2.133	1.178	1.478	0.973	5.762		
Scenario 3: AL-MS Region Closure (Deepwater Horizon Oil Spill)							
	WEST	AL-MS	FL-N	FL-S	Total (m.)	Util.	r_i
Red Snap.	795.842	0.000	134.647	13.441*	0.944	0.744	0.000
Red Group.	5.346*	0.000	969.654	235.444	1.210	0.859	0.000
Gag Group.	2.938*	0.000	145.993	15.217	0.164	0.783	0.000
DW Group.	76.555	0.000	121.343	60.048	0.258	0.930	0.000
Tilefish:	115.433	0.000	13.326	16.741	0.145	1.000	0.487
Trips	127	0.000	662	639	1,428		
Cost (\$ m.)	0.821	0.000	2.295	1.213	4.329		
Rent (\$ m.)	4.770	0.000	4.006	2.186	10.962		
Cons. Surp. (\$ m.)	2.365	0.000	2.012	1.093	5.470		
Scenario 4: 2014 Quota, 20\$ Increase in Fuel Prices							
	WEST	AL-MS	FL-N	FL-S	Total (m.)	Util.	r_i
Red Snap.	731.172	398.527	120.359	13.441*	1.264	1.000	\$0.474
Red Group.	5.346*	77.465	953.910	234.126	1.271	0.903	0.000
Gag Group.	2.938*	39.846	145.579	15.190	0.204	0.975	0.000
DW Group.	61.291	53.180	110.134	52.896	0.278	1.000	0.435
Tilefish	89.970	36.030	8.183	11.318	0.145	1.000	1.133
Trips	118	183	646	622	1,569		
Cost (\$ m.)	0.858	0.937	2.346	1.257	5.398		
Rent (\$ m.)	4.636	2.655	3.887	2.102	13.280		
Cons. Surp. (\$ m.)	2.109	1.216	1.899	1.037	6.261		

Table 2: **Equilibrium Quota Allocation by Species and Region.** Scenario 1 is for 2014 economic conditions and annual quotas: red snapper quota is 5.054 m. lbs.; red grouper quota is 5.630 m. lbs.; gag grouper quota is 0.835 m. lbs.; OSW grouper quota is 0.523 m. lbs.; DW grouper quota is 1.110 m. lbs.; Tilefish quota is 0.582 m. lbs. Scenario 2 increases red and gag grouper quotas 25% above 2014 levels. Scenario 3 closes the AL-MS region. Scenario 4 reports results under 2014 quotas and a 20% increase in fuel prices above 2014 levels. Trips have been rounded to the nearest integer. Total is the sum of regional pounds in millions. Costs, quota rent, and consumer surplus is reported in millions of \$2014. An asterisk indicates a species for which landings are held at 2014 levels.

Region 1: WEST								
	R. Snap.	V. Snap.	R. Grp.	Gag Grp.	SW Grp.	DW Grp.	T. Fish	Other Sp.
Landings	666.12	121.86	5.35	2.94	7.44	76.64	95.55	326.13
Share	0.55	0.10	0.00	0.00	0.01	0.06	0.07	0.21
Revenue	3,147.36	382.48	19.97	13.59	30.81	345.57	291.72	678.31
Share	0.66	0.08	0.00	0.00	0.01	0.07	0.06	0.13
Price	4.73	3.16	3.74	4.62	4.14	4.52	2.99	2.08
Region 2: Al-MS								
	R. Snap.	V. Snap.	R. Grp.	Gag Grp.	SW Grp.	DW Grp.	T. Fish	Other
Landings	364.88	189.65	78.36	28.84	9.99	43.27	36.32	260.92
Share	0.37	0.18	0.08	0.03	0.01	0.04	0.04	0.25
Revenue	1,497.19	569.10	298.88	142.58	46.37	189.84	104.96	465.22
Share	0.45	0.17	0.09	0.04	0.01	0.06	0.03	0.14
Price	4.08	3.02	3.81	4.93	4.65	4.38	2.89	1.71
Region 3: FL-North								
	R. Snap.	V. Snap.	R. Grp.	Gag Grp.	SW Grp.	DW Grp.	T. Fish	Other
Landings	112.71	34.40	1,018.67	94.08	26.74	89.17	14.13	223.80
Share	0.07	0.02	0.63	0.06	0.02	0.06	0.01	0.14
Revenue	490.94	102.77	3,850.55	466.42	122.91	389.66	31.41	454.83
Share	0.08	0.02	0.65	0.08	0.02	0.07	0.01	0.08
Price	4.35	3.00	3.78	4.95	4.58	4.41	2.15	2.04
Region 4: FL-South								
	R. Snap.	V. Snap.	R. Grp.	Gag Grp.	SW Grp.	DW Grp.	T. Fish	Other
Landings	13.44	1.11	207.66	9.60	11.18	42.88	14.88	468.28
Share	0.02	0.00	0.29	0.01	0.02	0.07	0.02	0.57
Revenue	59.19	3.42	779.91	47.63	52.73	183.78	29.79	1,174.73
Share	0.03	0.00	0.34	0.02	0.02	0.09	0.01	0.48
Price	4.46	3.00	3.77	4.95	4.72	4.29	2.11	2.65
All Regions								
	R. Snap.	V. Snap.	R. Grp.	Gag Grp.	SW Grp.	DW Grp.	T. Fish	Other
Landings	4,628.58	1,388.12	5,240.16	541.81	221.37	1,007.88	643.50	5,116.48
Share	0.25	0.07	0.28	0.03	0.01	0.05	0.03	0.27
Revenue	20,778.73	4,231.09	19,797.26	2,680.90	1,011.25	4,435.39	1,831.54	11,092.37
Share	0.32	0.06	0.30	0.04	0.02	0.07	0.03	0.17
Price	4.41	3.05	3.76	4.86	4.52	4.40	2.54	2.12

Table 3: **Quarterly Average Landings, Revenue, and Dockside Price by Species, 2014.** Landings are reported in thousands of pounds, revenues in thousands of 2014 dollars, and dockside prices in 2014 dollars.