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Fishing technologies: Specification and estimation

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Aquaculture and Fisheries | Behavioral Economics | Econometrics

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This paper consistently estimates the structural properties of a multiple-species fishing technology. Our approach overcomes two ubiquitous features of fisheries data generating processes that invalidate classical ordinary least squares estimators: (1) unobservability, by the researcher, of the *in situ* fish stock and its effect on productivity, and (2) endogenous production decisions that vary with fishermen's private information about stock abundance and other economic variables. Our estimations obtain consistency by exploiting the timing of production decisions and the information available to fishermen when endogenous production scale and scope, i.e., targeting of individual species', decisions are made. Our estimator adopts methods used in fisheries stock assessment to control for the effects of abundance on productivity. A nonlinear instrumental variables estimator controls for endogenous scope adjustments. We present an application of our model to the Gulf of Mexico commercial reef fish fishery. Comparison with an estimator that ignores latent stock abundance effects and endogeneity in production indicates substantial bias, which can be linked to past fishery management failure.

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Introduction

Effective management of fisheries resources requires knowledge of the growth potential of the fish stock and the benefits and costs of extracting the resource (Clark, 1990). Empirical measurement of stock growth and extraction costs is complicated by unobservability of the *in situ* fish stock and endogenous, stock-dependent production decisions of fishermen. Fishermen have much better information about stock conditions and thus the productivity of their harvesting efforts than do fisheries researchers. This ubiquitous feature of fisheries data generating processes creates an omitted variable problem that has impacted previous empirical measurement of fishing technologies, with potentially serious implications for fisheries management. This paper introduces a model and estimation strategy to consistently estimate the structural properties of a multi-species harvesting technology when stock abundance is unobserved by the researcher. An application of the model to the Gulf of Mexico commercial reef fish fishery is presented to illustrate the approach and the potential magnitude of the omitted variable problem.

The abundance of fish in the sea has long been considered a key determinant of the productivity of inputs such as labor, fuel, bait, and capital allocated to harvesting the resource (Gordon, 1954; Schaefer, 1954; Smith, 1978). True stock abundance, however, is unobservable.[1] Identifying these separate effects empirically, i.e., the contribution of fishermen-supplied inputs versus natural stock growth and recruitment, is particularly challenging. Empirical measurement of fishing technologies is further complicated by its multi-product or multi-species nature, i.e., public factors of production such as nets, hooks and bait simultaneously intercept multiple-fish species, even as different combinations of nets, traps, hooks and bait are used to *target* different mixes of species. Stock abundance is, in addition, spatially and temporally heterogeneous, and variable due to natural fluctuations in the marine environments.

While local abundance, i.e., the size and species' composition of the fish stock at spatial-temporal scales at which harvesting operations take place is unobserved by the researcher, fishermen can amass extensive knowledge of stock conditions and may directly observe the productivity of their gear as it is allocated and retrieved from the water. These conditions introduce an omitted variable problem similar to that which arises in the estimation of standard neo-classical production functions; fishing firms make endogenous factor input choices in lieu of a private signal about their own productivity (e.g., Marschak and Andrews, 1944).

We introduce a model and strategy to consistently estimate the properties of a multi-species harvest cost technology. Our estimations share features of a growing literature that addresses similar problems in estimating neo-classical production functions in the presence of unobserved productivity shocks (e.g., Olley and Pakes, 1996; Levinson and Petrin, 2003; Ackerberg et al., 2015; Wooldridge, 2009). This literature exploits lagged input decisions and assumptions on the economic environment to construct an instrument for an unobserved, firm-specific productivity shock. We cannot apply this approach directly because fishermen endogenously choose the location of fishing and thus the local stock conditions that determine fishing productivity. We instead generate a proxy for unobserved abundance using methods developed and used in the fisheries stock assessment literature. We use a catch-effort model to create an index of abundance to control for

[1] In addition to wildlife populations, oil, natural gas, and mineral reserves are similarly difficult to measure. What creates an additional challenge for measuring fish stocks is the fact that they move in space, in some cases across international borders, and are constantly dying and regenerating naturally.

the component of harvest productivity that is observed by fishermen (but not the researcher). The technique addresses one important source of omitted variable bias in our data.

The technology we seek to measure exhibit the properties of jointness-in-inputs, i.e., capital, labor, fuel, nets and hooks are public factors of production that harvest multiple fish species, and weak output disposability. This latter property imparts a costly targeting feature of fisheries data generating processes (Turner, 1995; Singh and Weninger, 2009). The implication for our estimations is that fishermen endogenously influence the mix of distinct fish species that are intercepted with their gear.[2] We control for this second source of bias by exploiting the timing of productions decisions, available information, and natural variability in the marine environment. Stock abundance varies at fine spatial and temporal scale due to varying currents and tides, fluctuating water temperature, unobserved predator-prey interactions, and harvesting pressure of other fishermen. The stock that is exposed to fishing gear is uncertain at the time production decisions are planned. Realized harvest is therefore only partially controlled by endogenous harvest/targeting decisions. Our estimations exploit exogenous fluctuations in harvest to identify model parameters.

We analyze trip-level cost and harvest data from the US Gulf of Mexico commercial reef fish fishery. Gulf of Mexico reef fish fishermen target five major species, and harvest roughly 90 minor reef fish species, across a spatially and temporally heterogeneous marine habitat. Our application shows how estimations that ignore the two sources of omitted variable bias can significantly miss-measure the structural properties of fishing technologies. Estimates of the species-specific marginal harvesting costs obtained under naive least squares estimation, i.e., where latent stock effects and endogenous harvesting and targeting are ignored, are between 41.3% - 87.7% larger than estimates obtained from our model. The extent to which bias of this magnitude has misdirected reef fish management policy is a worthy topic of investigation.

Our paper is the first to link harvest costs to latent, multiple-species stock abundance across space and time. It is also the first to estimate a weak output disposability or *costly targeting* harvest technology (Turner, 1995; Singh and Weninger, 2009). These contributions facilitate *ex ante* evaluation of fisheries regulations that were not previously possible. We demonstrate by evaluating the effects of varying regulations on costs and wasteful discarding in the reef fish fishery.

The rest of the paper is organized as follows. The next section reviews existing empirical models of harvest technologies, emphasizing the empirical challenges that arise particularly in applications with spatially and temporally varying stock abundance. Section 1 outlines features of commercial fishing that guide our cost function specification and estimation. Section 2 presents the model. Section 3 describes the our data and section 4 presents the estimation results, including a demonstration of how the model might be used as a prescriptive management tool. Section 5 summarizes the main findings and discusses extensions.

[2]Endogenous targeting actions include, for example, decisions to set gear at different micro-locations and varying depths, employ different hook sizes and baits, set gear at different times of the year and day. Evidence of targeting behavior in multiple-species fisheries is reported in Abbott et al. (2015), Branch and Hilborn (2008), Singh and Weninger (2017).

1 Background

1.1 Related literature

Models of commercial fishing technologies are rooted in early work by Gordon (1954) and Schaefer (1954) (see Hannesson (1983) for a review). The ubiquitous Gordon-Schaefer model specifies a dynamic stock growth equation and a harvest function of the form $h = qEX$, where h is the harvest quantity, q is a *catchability* coefficient that determines the proportion of fish stock X that is harvested per unit of *fishing effort*, E. Fishing effort is in actuality a composite (index) of factors of production such as capital, crew labor, fuel, nets, hooks and bait.[3] Dual models of harvest technologies are also common, e.g., a harvest cost function may be specified as $c(h, w, X)$ where h and X are as above, and w is a vector of factor input prices (e.g., Smith, 1968).[4] The distinguishing feature of resource extracting technologies is inclusion of the *common* resource stock, X. The maintained but virtually untested hypothesis is that the productivity of allocated factors of production increase or the costs of harvesting the resource decrease with higher stock abundance.

Models of fishing technologies have been generalized to consider the harvest of multiple fish species. This literature has followed the theory of the multiple-product firm. Applications of duality theory to investigate the structural properties of multiple-species fishing technologies are common (e.g., Squires, 1987, 1988; see Jensen (2002) for a review). Turner (1995) introduced the property of weak output disposability to better capture and understand the problem of bycatch and discarding in multiple-species fisheries. Singh and Weninger (2009) link a weak output disposability technology to multiple-species stock abundance to derive stock and regulatory conditions under which discards are likely to occur.

A second branch of the fisheries literature emphasizes the importance of spatial stock heterogeneity in fisheries and the question of where fishermen choose to fish (Sanchirico and Wilen 1999, 2005; Smith, 2000, 2002). The focus of this literature is the location decision for a fishing *trip*; less emphasis is placed on the structure of the harvest technology or the role of unobserved fish stock in the trip location choice.

Models that link the harvests of multiple fish species to the multiple-species fish stock abundance, either in the primal or the dual format, are rare (Singh and Weninger (2009, 2017) are exceptions). Equally rare are methods to estimate fishing technologies in settings where stock abundance is spatially and temporally heterogeneous, and unobserved by the researcher. We next demonstrate the omitted variable bias problem in empirical measurement of fishing technologies in the context of a slightly generalized Gordon-Schaefer model. We also review methods that have been proposed to control for stock abundance when estimating fishing technologies.

1.2 Omitted stock abundance and bias in estimation

For simplicity we discuss the omitted variable problem in the context of a single-species G-S model. The arguments are easily extended and apply to the case of multiple-species. We consider a Cobb-

[3] A consistent aggregate input index can be formed only if the technology exhibits the property of homothetic separability of inputs (Squires, 1987).

[4] Alternative dual models of harvesting technologies appear in Squires (1987), Kirkely and Strand (1988), Weninger (1998), among others.

Douglas functional form. The two properties of the technology to be estimated are the input-output and the stock-output elasticity. We maintain the assumption that the stock is heterogeneous across space and time. We therefore denote abundance as $X = X_{st}$, where $s \in S$ denotes the fishing location and t the date at which fishing takes place. S is a finite set of fishing locations.

The assumed goal is to consistently estimate the structural properties of the technology. If stock varies across space and time it will be important to conduct the analysis at fine spatial and temporal scale. An analysis carried out at the level of a single fishing trip may be appropriate. In this case, as we will assume throughout the paper, s will denote the spatial area that is accessible on a single fishing trip.

The Cobb-Douglas harvest function takes the form:

$$h = qE^{\alpha}X_{st}^{\delta},$$

where notation is as above; α and δ are the parameters of interest.

The fisherman's problem given a time and location is to choose effort E to maximize trip profit. It is reasonable to assume that the decision maker, who we take to be the vessel skipper, chooses effort conditional on observed prices and some knowledge of the stock abundance. For simplicity assume the skipper has complete knowledge of abundance X_{st} (we relax this assumption below). The skipper's problem is then,

$$\pi(p, w|X_{st}) = \max_{E}\{pqE^{\alpha}X_{st}^{\delta} - wE\}, \text{ for given } s \text{ and } t, \tag{1}$$

where w is the unit price of effort. An interior solution to (1) satisfies $E^* = \left[\frac{p}{\alpha wqX_{st}^{\delta}}\right]^{\frac{1}{\alpha-1}}$. Inserting this expression into 1 obtains an expression for profit as a function of exogenous variables (p, w, X_{st}) and model parameters (α, δ).

Identification of (α, δ) in the primal framework requires data on harvest, effort, prices, and spatial-temporal stock abundance. Invariably, stock abundance is unobservable to the researcher, particularly at the spatial-temporal scale of an individual fishing trip. Fishermen, on the other hand, may have considerable information about *local* (s, t) stock abundance and, as we argue below, learn about its effect on productivity as fishing proceeds. If X_{st} is not included as a covariate in the harvest or profit regression model, it necessarily enters the error term. In this case, ordinary least squares regression obtains consistent estimates of the parameters (α, δ) only if the optimal effort choice, E^* is independent of X_{st}. If a dual cost function model is specified for estimation, consistency requires the optimal harvest choice to be uncorrelated with stock abundance. In either case, failing to control for stock abundance introduces omitted variable bias in the estimation (Ekerhovd and Gordon, 2013).

Several approaches to address the problem of omitted stock abundance have been used in the analysis of fisheries production data. The two-equation model of Gordon (1954) and Schaefer (1954) has been used extensively (see Zhang and Smith (2011) for a review). A recent adaptation of this approach in Zhang and Smith (2011) uses panel data from the Gulf of Mexico reef fish fishery to estimate latent stock abundance and the Cobb-Douglas harvest-effort elasticity parameter, α. The harvest-stock elasticity is not estimated. The authors form a multiple species output aggregate and assume that stock abundance is spatially homogeneous, i.e., all fishermen harvest from a common stock, i.e., $X_{st} = X_t$ for all $t = 1, \ldots, T$. A first step regression exploits within-period variation in fishing effort (measured as crew-days per trip) to identify α, and a period t fixed effect that serves as the proxy for abundance. A second regression inserts the estimated stock proxy into a logistic stock growth function.

Identification in Zhang and Smith (2011) relies on: (1) a spatially homogeneous stock abundance, (2) fishing effort allocations that are made independently of X_t, and (3) within-period variation in effort sufficient to identify the harvest-effort elasticity.[5] Below we will argue that conditions (1)-(3) do not characterize most commercial fisheries data generating processes.

A second common approach in the empirical fisheries literature is to include, when available, an *estimate* of stock abundance as a control in a primal or dual regression model. The presence of an abundance estimate introduces measurement error and may reduce omitted variable bias, but only under special conditions. As noted, abundance estimates are rarely available at fine spatial-temporal scale. If the true abundance is heterogeneous, inserting a seasonal or regional *average* estimate will not address the problem, since in any region or subperiod fishermen will be harvesting actual stock abundance that is either above or below the estimated mean value.

A related concern is that stock assessment methods often rely on fishery-dependent data. Catch and effort methods in particular are regularly used to construct indices of changes in abundance over time (see Maunder and Punt, 2004; SEDAR, 2014). We highlight below the assumptions that must hold for such methods to provide consistent estimates of abundance and thus consistent estimates of fishing technologies when used as controls.

Virtual population analysis (VPA) is an alternative method for estimating unobservable fish stock abundance. This approach tracks the number and age of fish that are removed from the fishery over time. Observed fishing mortality is combined with an estimate of natural fish mortality to place a lower bound on the number of fish of each age that must have been present in the fishery in past years. Summing across age cohorts obtains a back-prediction of abundance. As the name implies, VPA estimates a virtual rather than the actual fish population. It is the latter, we claim, on which fishermen base their endogenous production decisions. Including VPA-based stock estimates in harvesting technology regressions therefore does not appear to be a promising approach for addressing the problem of omitted variable bias.

We contend that the problem of unobserved and/or omitted fish stock abundance impacts all previous estimations of fishing technologies. To address the omitted variable bias problem we propose an estimation that exploits both the natural and economic processes that underlie most commercial fisheries data generating processes (DGPs). The next section reviews these processes and their role our empirical specification and estimations.

1.3 The production setting

Heterogeneity and randomness in local abundance: Fish move across space and time in search of food, cover, and/or to avoid predators, and to breed. Habitat quality is linked to marine struc-

[5]Consistent effort aggregation requires homothetic separability of inputs and outputs. Note that linear output aggregation assumes perfect substitutability among individual reef fish species. Zhang and Smith (2011) do not discuss the source of within-period variation in fishing effort that enables identification of α.

ture, e.g., coral reefs, bottom substrate, and water depth, currents, which is heterogeneous across space and time. Individual fish species have unique habitat requirements, with individual species concentrated in their preferred or *niche* habitats (see MacCall, 1990).

The abundance and mix of species that habituate a particular location, time of day, and day of the year is subject to random, exogenous shocks due to fluctuations in tides, water temperature, own and cross-species competition, predation and harvest mortality, among other random factors. Even if a fisherman knows the spatial distribution of habitat type and quality, natural variation in marine conditions imply that the fish present at given location and date will be partially random. The decision of where and when to set gear is therefore made under uncertainty about the actual stock abundance and species mix that will be intercepted by gear when fishing begins.[6]

Hereafter, we use $F(X|s,t)$ to denote the distribution of the random stock (vector) X at location s and date t. The habitat quality at a given (s,t) can be assumed fixed during the duration of a single fishing trip, which are usually in the range of 1-10 days depending on the fishery under consideration. We assume that fishermen know $F(X|s,t)$.

Fishing trips: Harvesting operations are conducted from the deck of a vessel whose main function is to transport the captain, crew, gear, catch, and supplies to and from at-sea fishing locations. Fishermen take multiple trips to sea and back during a regulatory cycle, typically a calendar year. The capacity of the vessel to carry fuel and supplies links harvesting operations to land-based ports where the catch can be offloaded, supplies can be replenished, and the crew rested in preparation for the next trip to sea.

Costly targeting of individual fish species: Multiple-species fishing technologies exhibit the property of jointness-in-inputs, i.e., capital, labor, fuel, nets, and hooks are public factors of production that contribute to the harvest of multiple fish species simultaneously. Commercial fishermen however can influence, surprisingly proficiently, the mix of species that are encountered by their gear and thus harvested.[7] Actions that can be taken to control the harvest species mix include, for example, the choice of micro-location at which the gear is set, e.g., proximity to known reef structure or bottom substrate; fishing specific tides and/or at times of day; modification of gear, e.g., the size and type of hook used (J-hook versus circle hook), spacing between hooks, the number of fishing lines deployed, soak time; the type of bait used, among other actions.

We follow Turner (1995, 1997), Singh and Weninger (2009) and others and assume the multiple-species harvest technology exhibits weak output disposability. This assumptions implies that specialization in the harvest of single species and more broadly targeting a particular species' mix is costly.[8]

Regulations: A central goal of fisheries management is to maintain a sustainable harvest. Regulations intended to prevent overfishing are generally of two forms: (1) controls on inputs allocated to harvesting operations and (2) controls on the quantity of fish harvested during a regulatory cycle.

[6]Bottom dwelling demersal fish targeted in the GOM commercial reef fish fishery are not easily detected with sonar equipment. The productivity of gear that is set at a chosen location is therefore revealed only after gear is set, retrieved, and the catch observed.

[7]See Branch and Hilborn (2008), Abbott et al., (2015), and Singh and Weninger (2017) for empirical evidence.

[8]Since otherwise fishermen could costlessly avoid species prohibited by regulation and the pervasive problem of bycatch and at-sea discarding in fisheries would not exist.

Both forms of regulation were used in the Gulf of Mexico commercial reef fish fishery during the period of our data, 2005-14. From 2005-07, red snapper landings were capped at either 0, 200 or 2,000 pounds per trip depending on the class of permit held by individual vessel operators. Shallow water grouper landings were capped at 6,000 pounds per trip from 2005-10. Closure regulations which prohibited any landings (of a specific reef fish species) were used in the earlier years of our data; from 2005-07 for red snapper and from 2005-10 for groupers and tilefish species.[9]

Input control regulations were replaced with individual fishing quota (IFQs) in 2007 for red snapper and in 2010 for grouper and tilefish species. Under the IFQ regulation, fishermen hold shares of an aggregate quota for an individual species or species group. Quota shares translate to quota landings permits that allow fishermen to legally land specified quantities of reef fish. Quota can be leased annually and/or sold in perpetuity. At-sea discards are discouraged but not prohibited and do not count against permit holdings.

We next introduce a model of the trip-level harvesting technology in the form of a dual, parametric multiple-species harvest cost function. The functional form chosen exhibits the jointness and weak output disposability properties under certain parameter values. A strategy to consistently estimate the model parameters follows.

2 Model

Hereafter, we interpret the spatial index $s \in S$ as the coarse location that can be accessed by a vessel during a fishing trip. The choice of micro-location(s) within s at which gear is set is considered part of a set of costly actions that can be taken to target a mix of individual fish species. We define t as the trip date, and X_{st} as the true abundance at location s and date t.

We separate the fisherman's trip-level production problem into a pre-trip planning stage and an at-sea harvest operations stage, hereafter the *planning* and *operations* stages, respectively. We assume the optimizing agent, the vessel skipper, organizes production to maximize expected trip profits given available information on prices, regulations, and expected stock conditions.

Pre-trip planning activities include replenishing vessel supplies, configuring the gear, scheduling the crew, and selecting the coarse location and date of the trip. We do not model the choice of (s, t) but rather focus on optimizing behavior, given that the decision to take a trip has been made. The harvest operations stage begins when the vessel departs port and ends when the vessel returns. Once on the water, adjustments to inputs and changes in the targeting actions are assumed limited. For example, hook types and bait cannot be adjusted once the vessel has left port. A change in the coarse trip location is also not practical given the fixed quantity of fuel onboard.

We however allow one particular modification to the pre-trip plans during the at-sea operations phase. Random stock conditions imply that planning decisions be based on expectations of the abundance that will be encountered on the trip, as summarized by $F(X|s, t)$. As gear is set and retrieved the skipper and crew observe productivity and thus learn about the true or *realized* stock abundance, X_{st}. Fishing thus provides a real-time signal about the realized productivity of factor inputs applied on the trip. It is reasonable to expect that the skipper will make adjustments to pre-

[9]Closures were staggered throughout each the year to spread the harvest and avoid supply gluts and low dockside prices.

trip plans in response to this productivity signal. For example, if gear productivity is higher than anticipated, the skipper may choose to extend the trip (within limits dictated by on-board supplies). If gear productivity is below pre-trip expectations, the skipper may decide to cut the trip short and reduce inputs relative to the pre-trip plans.

The above characteristics of the harvesting process and technology are formalized in the following assumptions:

Assumption 1 (Random stock abundance)**.** *Due to exogenous fluctuations in the marine environment, X_{st} at location s and date t is a random variable with distribution function $F(X|s,t)$. The moments of $F(X|s,t)$ vary smoothly across space and time. $F(X|s,t)$ is known to fishermen and unobserved by the researcher. The realization, X_{st}, is unknowable.*

Assumption 2 (Costly targeting)**.** *Fishermen choose targeting actions during the pre-trip planning phase to influence the mix of harvested species. Targeting actions are chosen conditional on information set $\Omega = \{p, w, R, k, F(X|s,t)\}$, where p and w denote output and factor input prices, respectively, R denotes regulations, k is the quasi fixed vessel capital, and $F(X|s,t)$ is the stock distribution.*

Assumption 3 (At-sea information)**.** *The vessel skipper receives a signal χ of realized stock abundance X_{st} and therefore realized productivity during the operations stage. Operations stage adjustments to pre-trip plans are limited to increasing or decreasing harvest scale; no adjustments to endogenous targeting occur during the operations stage.*

The cost function

We specify the following functional form for trip-level harvest costs (Singh and Weninger, 2009):[10]

$$C(h, w|X_{st}, k) = \underbrace{\left[1 + \frac{\gamma}{2}\sum_{i=1}^{I}(S_i(h) - \varphi_i(X_{st}))^2\right]}_{A} exp\Big(\delta(X_{st}) + \beta_0 + \beta_h h\Big) G(w, k) exp(u). \quad (2)$$

The first right-hand term, labeled A, imparts the stock-dependent weak output disposability property of the technology. Term A depends on species-specific harvest shares, which are denoted $S_i(h) = \frac{h_i}{\sum_j h_j}$ for species i, and a stock-dependent term, $\varphi_i(X_{st}),\ i = 1, \ldots, I$. Singh and Weninger (2009) refer to $\varphi(X_{st}) = [\varphi_1(X_{st}), \ldots, \varphi_I(X_{st})]$ as a *no-targeting-cost* share vector. The idea is that when the mix of harvested species exactly matches $\varphi(X_{st})$ the costs that arise due to the targeting actions of the producer are in fact zero.

The targeting cost component A increases with the Euclidean distance $|S(h) - \varphi(X_{st})|$ for $\gamma > 0$. Thus as the targeted harvest share vector deviates from $\varphi(X_{st})$, costs rise. Such cost increases may of course be part of a profit maximizing strategy if, as is likely the case, some species earn higher returns at the dock.

[10]Prices may vary across space and time. We exclude (s, t) subscripts to simplify notation.

Singh and Weninger (2009) assume a the no-targeting-cost vector follows $\varphi_i(X_{st}) = \frac{X_{i,st}}{\sum_j X_{j,st}}$. Under this specification targeting costs attain their lowest value when the mix of harvested species exactly matches the mix of individual species stock abundance. We do not take a stand on precisely how $\varphi(\cdot)$ maps to relative abundance. We assume simply that the no-targeting-cost vector exists, and is unique for given local abundance X_{st}.

It is worth repeating that A is defined over harvest and stock *shares*; its role in the model is to capture scope (dis)economies associated with endogenous targeting actions. Note also that term A is homogeneous of degree zero in the harvest scale. Thus harvest scale effects on costs operate through the second right hand term in equation (2) only.

With $\beta_h > 0$ harvest costs are increasing and convex in h. The second right hand term includes a second stock-dependent term, $\delta(X_{st})$ that is intended to capture *stock level* effects on harvesting costs, i.e., the (untested) assertion that higher abundance lowers the costs of harvesting a given vector h (Smith, 1968; Clark, 1990). The form for $\delta(X_{st})$, and its identification is addressed below.

The third right hand term in (2), $G(w, k)$, measures factor input price effects and the effects of vessel capital, k on costs. Below we specify a parametric form for G that is non-decreasing and linear homogeneous in w. Our inclusion of k in equation (2) implicity treats vessel capital as a fixed input. Thus, (2) is interpreted as a short run cost function.[11] We assume that factor input prices are exogenous.

The regression error term u is assumed to have zero mean and finite variance, and satisfies the following assumptions:

$$\mathbb{E}(u|\Omega) = \mathbb{E}(u|\chi) = 0.$$

Two challenges must be overcome to obtain consistent estimates of the model parameters. The first arises from the endogenous targeting actions chosen during the planning phase. The second from potential adjustments in the harvest scale in response to the at-sea signal of the trip's productivity, χ. These challenges derive from, respectively, the expected and unanticipated stock conditions, both of which are unobserved by the researcher. Failing to control for their effects results in inconsistent parameter estimates. The next sections exploit our assumptions (1)-(3) for fisheries data generating processes to overcome these estimation challenges.

To ease notation in what follows we will use $n = 1, \ldots, N$ to index individual trip observations. Note that n summarizes a unique combination of trip location (s), date (t), and identity of a vessel skipper (f). We utilize series function approximations in our estimations below. We adopt the convention of denoting parameters of these approximations with the Greek symbol, θ.

Catch and effort stock assessment model

We begin by applying principles from catch and effort stock assessment methodology to construct an index of relative stock abundance over space and time and, importantly, to construct an estimate of the at-sea information, χ_n , for each trip in our data. Catch and effort stock assessment hinges on the assumption that at small spatial scale the catch of fish, typically measured as the number of

[11]The size of k may increase (decrease) costs if capital and variable factors (fuel, labor, gear, bait) are complements (substitutes) in production. Larger vessels require more fuel and a larger crew to operate but can take longer trips from port, transport more fish per trip, and can operate in more severe weather conditions.

fish harvested, will be proportional to the product of fishing effort and the unobserved stock density (e.g., Maunder and Punt, 2004; Campbell, 2015). It should be noted that when used for stock assessment, the *effort* construct is defined as the units of gear, such as nets, or baited hooks, that are deployed while fishing. In our empirical application, we follow SEDAR (2014) and measure effort as the number of hooks times the hours the hooks are soaked. We will use this definition of fishing effort throughout the remainder of the paper.

Stock assessment proceeds by specifying a catch per unit of effort (CPUE) equation, $h/E = qX$. We now have to address the multispecies nature of the catch in our data. To that end, let $\overline{h}_n = h_n'\omega$ and $\overline{X}_n = X_n'\omega$ denote, respectively, linear aggregates across species of trip n harvest and abundance. In data on catch, harvest is typically measured in pounds of each specific species, so we set $\omega_i = \frac{1}{wgt_i}$, where wgt_i is the average weight of species i fish such that $\overline{h}_n$ is a measure of fish density as required. Considering the catchability coefficient, q, we note that by assumption 2 it may be endogenously influenced by targeting actions chosen during pre-trip planning.[12] Recall that all planning decisions are made conditional on the information set Ω_n, which includes the abundance density $F(X|s,t)$ and implicitly, its moments. By assumption 1, moments of the abundance distribution vary smoothly with (s,t). The implication is that catchability potentially also varies smoothly with space and time. Using the indexes defined above and our assumptions on q, our CPUE model takes the form $\overline{h}_n/E_n = q(\Omega_n)\overline{X}_n$.

We next decompose $\overline{X}_n$ into the product of a deterministic component, denoted $\mu(s,t)$, and a deviation χ_n. Finally, we introduce a (multiplicative) fisherman-specific fixed effect to the CPUE model to capture any unobserved, time- and space-invariant components of catchability for fisherman f. Making all substitutions and taking natural logs obtains:

$$ln\left(\frac{\bar{h}_n}{E_n}\right) = \alpha_f + ln\; q(\Omega_n) + \ln\left(\mu(s,t)\right) + \ln\left(\chi_n\right). \tag{3}$$

We approximate the catchability function and the deterministic component of stock abundance with a semi-parametric series estimator:

$$ln\; q(\Omega_n) + \ln \mu(s,t) = \sum_{j=1}^{J} \theta_j b_j(\Omega_n, s, t) + e_n \tag{4}$$

where e_n is an approximation error. For compactness define $\sum_{j=1}^{J} \theta_j b_j(\Omega_n, s, t) = B_J(\Omega_n, s, t)'\theta_J$, where $B_J(\Omega_n, s, t) = (b_1(\Omega_n), \ldots, b_J(\Omega_n, s, t)$ is a $1 \times J$ vector of known basis functions of the elements of (Ω_n, s, t), and θ_J is a conformable parameter vector. Cross validation can be used to determine J (Li and Racine, 2007).

[12] Maunder and Punt (2004) and Maunder et al., (2006), argue that catchability may depend on harvest efficiency, targeting behavior, environmental factors, fleet dynamics, and perhaps stock conditions. Our primary interest is the consistent estimation of χ_n and therefore we follow this level of generality.

Making this final substitution obtains our CPUE estimating equation:

$$ln\left(\frac{\bar{h}_n}{E_n}\right) = \alpha_f + B_J(\Omega_n, s, t)'\theta_J + \ln(\chi_n) + e_n. \tag{5}$$

The unknown parameters (α_f, θ_J) can be estimated with ordinary least squares. An estimate of χ_n is then obtained as:

$$\hat{\chi}_n \approx exp\left(ln\left(\frac{\overline{h}_n}{E_n}\right) - \hat{\alpha}_f - B_J(\Omega_n, s, t)'\hat{\theta}_J\right), \tag{6}$$

where we are relying on the approximation in (4) to be good enough (i.e. J to be large enough) to render e_n small enough to not be important.

The series function approximation in (5) controls for the effect of endogenous targeting actions on catchability and for the deterministic and thus predictable component of the abundance index. As apparent in equation (5), space and time enter $\mu(s,t)$ and the catchability coefficient through $F(X|s,t) \in \Omega_n$. The effect of space and time on both terms cannot be separately identified under the most general assumptions of the CPUE model. More generally, the catch-and-effort model cannot be used for stock assessment if catchability varies with stock abundance, or as in our case, if q varies with (s,t) (Maunder, et al., 2006). This dependence does not impair identification of the unanticipated abundance; by construction $\hat{\chi}_n \perp \Omega_n$, and conditional on the assumption that CPUE is proportional to stock abundance, the left hand side of 6 proxies for the at-sea information received on trip n at the operations stage. In subsequent regressions we use $\hat{\chi}_n$ to control for endogenous adjustments to harvest scale following assumption (3).

The conditions under which catch-and-effort stock assessment methods can consistently estimate changes in unobserved stock abundance are clear from the above. Equation (5) controls for the non-(s,t) elements of Ω_n, a step known as effort *standardization* in the stock assessment literature (see Maunder and Punt, 2004). Under the assumption that $q \perp (s,t)$, the estimated parameters from the CPUE model can be used to construct an index of relative abundance, $\hat{\mu}(s,t|\hat{\alpha},\hat{\theta})$. It should be emphasized that the restriction that q is independent of (s,t) cannot be tested. Moreover, our description of fisheries data generating processes suggests reasons to question the $q \perp (s,t)$ assumption. We will return to this matter in our estimation of latent stock abundance effects below.

Cost function estimation: Step 1

Let $y_n = (h_n, w_n, X_n, k_n)$ denote the trip n cost function arguments. Let $G(w_n, k_n) = \beta_w' ln(w_n) + \beta_k ln(k_n)$, where β_w is an factor price-cost elasticity parameter vector.[13] Taking logarithms in equation (2) and making substitutions obtains:

$$ln\, C(y_n) = ln\,(A_n) + \delta(X_n) + \beta_0 + \beta_h' h_n + \beta_w' ln(w_n) + \beta_k ln(k_n) + u_n. \tag{7}$$

[13]The log-log form allows the property of linear homogeneity in factor input prices to be imposed through the restriction $\sum_j \beta_{w,j} = 1$.

Estimation of (7) requires that we specify the stock level effect term, $\delta(X_n)$. We add the following assumption:

Assumption 4 (Stock Effects). *(i) The effect of the stock abundance mix on harvest costs operates through the no-targeting-cost share vector $\varphi(X_n) \in A_n$. (ii) The effect of the stock level on harvest costs can be represented by a scalar measure $\delta(X_n) = \delta(s,t)$.*

Assumption 4(ii) suggests an approach to estimate stock level effects. We can separate the stock level effect $\delta(s,t)$ into a deterministic component, $\overline{\delta}(s,t) = \mathbb{E}[\delta(st)]$, and a component that is unanticipated. The unanticipated component is naturally specified as χ_n, which was estimated by $\hat{\chi}_n$ in the previous step.

Our specification of $\overline{\delta}(s,t)$ follows from the assumptions for the CPUE model. Under the assumption that catchability is $(s,t)-$invariant, the deterministic component $\overline{\delta}(s,t)$ can be specified as a function of the constructed abundance index, $\hat{\mu}(s,t)$. If $q \perp (s,t)$ cannot be justified, $\overline{\delta}(s,t)$ remains latent. We consider two additional possibilities for our estimation. We can specify $\overline{\delta}(s,t)$ as a polynomial of (s,t) and rely on our trip cost data for its estimation. Recall, however, that both the stock species mix effects and stock level effects may vary with space and time. Separately estimating $\delta(s,t)$ and $\varphi(s,t)$ from trip-level cost data alone may not be possible. A third possibility is to assume stock level effects are insignificant in our data, i.e., set $\overline{\delta}(s,t) = \delta$, a constant. These three estimation options are investigated further in section 4.

Before proceeding further, it should be emphasized that CPUE methods produce an index of *relative* stock abundance over space and time. Neither setting $\overline{\delta}(s,t)$ to a polynomial of (s,t) or to a constant will allow us to identify absolute stock abundance. It is therefore important that our results be interpreted as measures of the harvesting technology in the neighborhood of the absolute stock levels present during our data period.

By assumption 2, endogenous targeting actions are chosen optimally during pre-trip planning and their effect on costs enter through term A_n. The solution to the pre-trip planning problem can be expressed as $A^*(\Omega_n)$. We do not derive a closed form for A^* but rather use a series function approximation of the form: $A^*(\Omega_n) = \sum_{j=1}^{J} \theta_j b_j(\Omega_n) + a_n$, where $b_j(\Omega_n)$ are known functions of the components of Ω_n, θ_j is a vector of parameters, and a_n is an approximation error. Cross validation tests determine J such that $a_n \approx 0$ and $\sum_{j=1}^{J} \theta_j b_j(\Omega_n) + a_n \approx B^J(\Omega_n)'\theta$.

To make clear that we are using the polynomial to approximate $A^* + \overline{\delta}(s,t)$ we write it as $B^J(\Omega_n, s, t)'\theta$ (as opposed to $B^J(\Omega_n)'\theta$).

Making substitutions in equation (7) obtains,

$$ln\, C(y_n) = \underbrace{B^J(\Omega_n, s, t)'\theta}_{\approx ln(A^*) + \overline{\delta}(s,t)} + \delta_\chi \hat{\chi}_n + \beta_0 + \beta_h' h_n + \beta_w' ln(w_n) + \beta_k ln(k_n) + u_n. \tag{8}$$

The constant term β_0 in the above is not identified and $\beta_0 + B^J(\Omega_n, s, t)'\theta$ are treated as a single polynomial approximation. Equation (8) can be estimated with ordinary least squares.

Including the series approximation for $A^* + \overline{\delta}(s,t)$ and the control for the at-sea productivity shock $\delta_\chi \hat{\chi}_n$ in the equation (7) regression, *annihilates* the component of trip cost that is attributable to endogenous pre-trip planning and at-sea scale adjustment. Identification of the parameter vector

(β_h) is obtained through the exogenous, natural variation in unobserved stock conditions. Identification of input price and capital effect parameters, β_w, and β_k respectively, follows from our assumptions that input prices are exogenous and available capital predetermined.

In light of the difficulties that are anticipated in further identifying the targeting cost term, one may choose to end the analysis here. The term $\beta_0 + ln(A^*) + \overline{\delta}(s,t)$ can be treated as the model constant or estimated in reduced form as a function of arguments Ω_n, s, t. In the former case, the model summarizes harvest costs evaluated at sample average targeting costs. The latter approach would map Ω_n, s, t to the targeting cost residual. A third alternative, which we explore next, is to impose additional structure to the model and estimate the remaining model parameters.

Cost function estimation: Step 2

Denote the remaining model parameters as $\Theta = (\gamma, \beta_0, \overline{\delta}(s,t), \varphi_1(X_n), \ldots, \varphi_I(X_n))$.

A functional form for $\varphi_i(X_n)$ is required. We specify $\varphi_i(X_n)$ as:

$$\varphi_i(X_n) = \varphi_i(s,t|\theta) = \frac{\exp\Big(\mathcal{P}_i(s,t|\theta_i)\Big)}{\sum_i \exp\Big(\mathcal{P}_i(s,t|\theta_i)\Big)}, \quad i = 1, \ldots, I. \tag{9}$$

In the above $\mathcal{P}_i(s,t|\theta_i) = \sum_{j=1}^{J_i} \theta_{ij} b_j(s,t)$, where $b_j(s,t)$ are known basis functions of (s,t). The set of basis coefficients is $\theta = (\theta_1, \ldots, \theta_I)$ where $\theta_i = (\theta_{i1}, \ldots, \theta_{iJ_i})$, with J_i denoting the polynomial order for species i. The specification in (9) insures that, for all (s,t), $\varphi_i(.) \in [0,1]$ for all i, and $\sum_i \varphi_i(.) = 1$ as required.

Inserting (9) into (2), taking logarithms and rearranging obtains the nonlinear elementary zero function for trip observation n,

$$f(\Theta, S(h_n)) = ln\, C_n = ln\left(\left[1 + \frac{\gamma}{2}\sum_i \Big(S_i(h) - \varphi_i(s,t)\Big)^2\right]\right) + \beta_0 + \overline{\delta}(s,t) + \hat{B}_n + u_n, \tag{10}$$

where $\hat{B}_n = \hat{\beta}_h h_n + G(w_n, k_n|\hat{\beta})$.

A non-linear generalized method of moments (GMM) estimator is used to estimate Θ. The moment condition is,

$$\mathbb{E}(f(\Theta, S(h_n)|\Omega_n) = 0, \tag{11}$$

which for the n'th trip is written as,

$$\mathbb{E}(Z_n' f(\Theta, S(h_n))) = \mathbf{0},$$

where Z_n is a vector of instrumental variables. The full sample $n = 1, \ldots, N$ moment conditions is,

$$\mathbb{E}(Z' F(\Theta, \mathbf{S}(h))) = \mathbf{0},$$

where Z is an $N \times \kappa$ matrix of instruments and $F(\Theta, \mathbf{S}(h))$ is the N-vector of elementary zero functions.

The nonlinear GMM instrumental variable estimator is obtained by minimizing the criterion function,

$$Q(\Theta, \mathbf{S}(h)) = \frac{1}{N} F(\Theta, \mathbf{S}(h))' Z \hat{\Sigma}^{-1} Z' F(\Theta, \mathbf{S}(h)). \tag{12}$$

Feasible estimation proceeds by first minimizing the criterion function (12) with $\hat{\Sigma}$ set equal to an identity matrix. This estimation obtains consistent but inefficient parameter estimates. We allow for heteroskedasticity at the level of individual vessel operation:

$$\mathbb{E}\Big(f(\Theta, s(h_n))^2\Big) = \sigma_f,$$

where σ_f denotes operation f-specific variance. This matrix $\hat{\Sigma}$ is then estimated as,

$$\hat{\Sigma} = Z' \hat{\Psi} Z,$$

where $\hat{\Psi}$ is a diagonal matrix with typical element $\hat{\sigma}_f$.

The criterion function in equation (12) is minimized a second time to obtain the efficient nonlinear GMM estimator.

3 Data

Our empirical application studies the Gulf of Mexico (GOM) commercial reef fish fishery from 2005-14. The GOM reef fish fishery is a complex of bottom-dwelling species consisting of red, black, yellowedge, gag, warsaw and other species of groupers, amberjacks, triggerfish, porgies, tilefish, as well as red, vermilion and other snapper species. Vertical hook and line and longline are the main gear types used. The US portion of the fishery extends from the US border with Mexico in the western Gulf to the Florida Keys. Figure 1 delineates management subregions of the fishery within the eastern GOM; our analysis will focus on management subregions 1-11. In 2014, the eastern GOM commercial fleet generated \$46.771 m. in revenue on 13.762 m. pounds landed across all reef fish species.

Trip-level data 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 factors. All vessels holding commercial reef fish permits complete the catch and effort portion of the log book form. Beginning in 2005, expense and payment data collection began for a stratified sample of permitted reef fish vessel operators. A survey of annual capital and fixed operating expenses conducted by the Southeast Fisheries Science Center supplements the logbook data.

The full 2005-14 log book data contain 75,564 trips taken in the eastern GOM region.[14] We focus our analysis on the most common gear types, bandit, handline, trolling and bottom longline

[14]We drop 3,532 trips that landed primarily shark species (75% or more of total trip landings), and 202 trips with

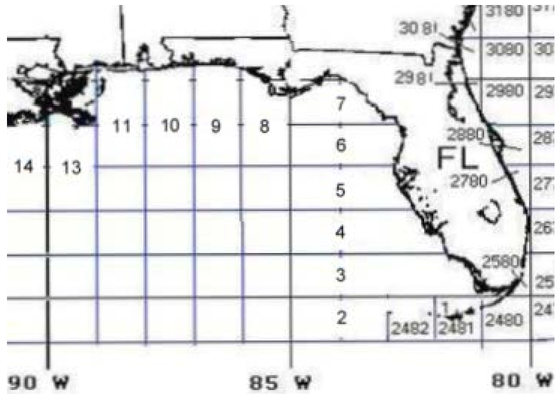

Figure 1: Eastern Gulf of Mexico Regional Designations

gear, which account for 98% of all trips taken, 93.00% of total landed pounds, and 96.81% of revenues during the 2005-14 data period.

Note that estimation of CPUE index model and residual $\hat{\chi}_n$ requires data on harvests and effort; trip expense information is not required. Of the 75,564 total eastern trip observations, 12,125 (16.0 %) recorded both discard and trip expense information. Trip observations with missing fuel expenses were dropped leaving 10,107 complete observations. We drop vessel operations that record fewer that 5 trips during the 2005-14 data period to ensure all skippers in the sample have some reef fish experience.

Summarizing, the CPUE model uses 17,257 observations on eastern region trips with complete catch and effort data and for vessels that took 5 or more trips during 2005-14. The cost function estimation utilizes a subset of this data for which trip expense information is available; 9,941 observations on 358 unique vessel operations. Descriptive statistics for the full data, and the samples used in the analysis are reported in appendix 7.

Outputs:

Practical considerations require aggregation across some reef fish species. We form eight harvested outputs based on regulations and the importance of individual reef fish species in landings and revenue. Outputs 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 (8) an all 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 species are formed by simple linear aggregation.

incomplete vessel and gear deployment data.

Supplemental information:

We observe the crew size and days at sea for each trip. We calculate trip labor opportunity cost as the total captain and crew hours at sea times the quarterly state- and quarter-specific average hourly wage rate for agriculture and fishery workers (wage information is obtained from the US Department of Labor).

The regulations in place at the date that each trip occurred are obtained from the Southeast Fisheries Science Center (see table 8 of appendix 7 for details).

Our measure of space corresponds to the coarse management regions in figure 1): regions 1, and 2 from the Florida Keys, north and west to region 11 in the Mississippi delta. The depth of fishing is considered among the set of actions that commercial fishermen choose to influence the mix of species they harvest. We use depth of fishing in our CPUE estimation, which is intended to retrieve the at-sea signal of unanticipated abundance. The cost function specification uses the regional spatial location measure only. The trip cost $C(h, w|X_{st}, k)$ can thus be interpreted as the cost of harvesting h in the coarse location s at date t.[15]

Two measures of time are used in our analysis. We construct a within-season measure of time that is set to the day of the year that trip n begins. This time measure takes values from 1-365 (except in a leap year), and captures any effects that exhibit within season variation. Our second measure of time is the cumulative day since January 1, 2005, which takes values from 1-3,652 for our data. This measure is intended to capture effects exhibiting longer term trends.

The elements of Ω available for analysis include species-specific landings prices, the price of fuel, the labor wage rate, vessel capital, and a host of regulations used in the GOM reef fish fishery during 2005-14. A list of elements of Ω with variable descriptions is provided in table 8 of appendix 7. Our measure of trip-level capital cost is described in appendix 8.

Chebychev transformations (Miranda and Fackler, 2002) of our (s, t) measures are used in the all polynomial approximations.

Analysis and regressions are carried out using Gauss 18 software.

4 Results

In each calendar year the Southeast Fisheries Science Center (SEFSC) selects sample vessels that are asked to complete the discard and economic components of the logbook reporting form. These vessels are sampled for a full calendar year. Standard errors of all cost function parameters are obtained with a bootstrap re-sampling algorithm that mirrors this stratified sampling procedure.

We randomly draw, with replacement, 1,000 bootstrap re-samples from the sample of vessels that completed discard and trip expense information during a calendar year. The number of vessels selected per year is chosen to match the number vessels sampled by the SEFSC. We repeat the two-step cost function estimation for each bootstrapped sample. The estimates of $\hat{\chi}_n$ and $\hat{\mu}_n$ obtained from the CPUE regression are included as a component of the trip n data from which the bootstrap re-samples are derived, thus making our analysis conditional on these.

[15] For safety and regulatory purposes, commercial fishing vessel often utilize vessel-monitoring technology that record exact latitudes and longitudes throughout the course of each fishing trip. Latitude and longitude data, if available, could replace the region-depth spatial dimensions used here. This extension is reserved for future work.

CPUE model results

Effort is calculated as the number of hooks times the hours the gear is soaked on each trip (SEDAR, 2014). Our weighting vector, used to construct $\overline{h}_n = \sum_i \frac{h_{n,i}}{wgt_i}$ is the average fish weight estimated from an observer database that is maintained by the NMFS.[16]

We estimate equation (5) with the sum of log catchability and $\log \mu(s,t)$ is approximated as a polynomial of (1) location, (2) fishing depth, (3) within-season trip date and (4) the cumulative trip date (beginning at January 1, 2005). All available economic and regulatory instruments, e.g., landings prices, fuel and labor prices, fishery closures, seasonal total allowable catch, were included. We further include indicator variables for the trolling and longline gear types. A generalized cross validation test (Li and Racine, 2007) finds that polynomial orders in the range of 4-6 for our spatial measure and long-term temporal measure are appropriate for the approximation of $\ln q(\Omega_n) + \ln \mu(s,t)$.

The CPUE model R-squared statistic is 84.99 suggesting that about 15% of the variability in the abundance index is orthogonal to Ω_n, space, and time. This finding is consistent with assumption 3, i.e., that reef fish fishermen obtain an operations-stage signal about trip productivity that very likely differs from pre-trip expectations. The extent to which this signal affects the harvested output on the trip is investigated below.

Hereafter a '$\hat{}$' will be used to denote the fitted values for various model components. We calculate $\hat{\chi}_n$ following equation (6) of section 2. This estimate is winsorized at the 5'th and 95'th percentile values for the purpose of moderating the effects of prediction error in subsequent regressions. After winsorization, the range of $\hat{\chi}_n$ is from 23.19% to 260.97% of the sample mean value, which suggests considerable randomness in unanticipated productivity.

If we are willing to assume that q is independent of (s,t), $\mu(s,t)$ can be identified from the CPUE regression model. While we question whether this is a reasonable assumption, we provide the results for illustrative purposes. We calculate the index $\widehat{\mu}_n$ by centering all non - (s,t) elements of Ω_n at their sample mean values. Appendix 7 reports results, including plots of $\widehat{\mu}_n$ against space and time. The range of $\widehat{\mu}_n$ is from 22.31% to 258.17% of the sample mean value, which we interpret as evidence that reef fish fishermen fish in conditions of widely varying anticipated stock abundance.

Cost function results

We estimate a more general specification than shown in equation (2). We allow the intercept terms and targeting cost parameter γ to vary by gear type, which appears influential in terms of per-trip harvest amounts, e.g., longline gear trips harvest an average of 6,442.82 pounds compared to the 1,643.74 pounds for non-longline gears. Longline fishing involves setting a main line across a transect that can be miles in length. Vertical line gear, as its name suggests, lowers baited hooks at precise locations. These differences likely imply different targeting costs, e.g., adjusting micro-fishing locations to target individual reef fish species may be more difficult with longline gear.

The targeting parameter is specified as $\gamma = exp(\tilde{\gamma} + \tilde{\gamma}^{LL} D_n^{LL})$ where D_n^{LL} is set equal to 1 if trip n fishes with longline gear, and zero otherwise. Parameters $(\tilde{\gamma}, \tilde{\gamma}^{LL})$ are estimated. The

[16]The data contain 1,342 observations on fish species, length and weight, region and date of fishing. Species, region, date, and length-specific average fish weights were used. Length-specific averages were used with minimum length regulations to differentiate the weight of landed fish that was discarded due to minimum length regulations.

transformation insures the targeting cost parameter is non-negative.

Cost function estimation: Step 1

Step 1 of the estimation specifies a series function approximation of $ln(A^*) + \overline{\delta}(s,t)$ (equation (8)) that includes all components of Ω_n and our space and time measures. A polynomial of order 4 for space, and 3 for trip date were used along with cross effects terms.

Table 1 reports parameter estimates, bootstrap standard errors, asymptotic normal p-values for a two-sided test of the null hypothesis that the estimated parameter is equal to zero, and 90% confidence intervals (c.i.) obtained directly as the 5'th and 95'th percentile values of the sorted bootstrapped estimates.

Variable	Parm.	Est.	Std. Err.	p-val.	90% c.i.
Red. snap.	β_{h1}	0.047	0.012	<0.001	0.027, 0.074
Verm. snap.	β_{h2}	0.206	0.020	<0.001	0.170, 0.246
Red grp.	β_{h3}	0.421	0.027	<0.001	0.366, 0.477
Gag grp.	β_{h4}	0.204	0.057	<0.001	0.102, 0.328
O.S.W. grp.	β_{h5}	1.080	0.164	<0.001	0.782, 1.431
D.W. grp.	β_{h6}	0.311	0.064	<0.001	0.214, 0.471
Tilefish	β_{h7}	0.202	0.183	0.272	-0.161, 0.683
Oth. Spec.	β_{h8}	0.188	0.016	<0.001	0.156, 0.217
Red. grp. (LL)	β_{h3}^{LL}	0.042	0.007	<0.001	0.029, 0.058
Oth. sp. (LL)	$\beta_{h.}^{LL}$	0.054	0.008	<0.001	0.040, 0.072
ln(w_f)	β_f	0.298	0.078	<0.001	0.135, 0.444
ln(w_l)	β_l	0.546	0.273	0.046	0.052, 1.121
ln(vessel len.)	β_k	1.171	0.104	<0.001	0.979, 1.381
$\hat{\chi}_n$	β_χ	-0.056	0.009	<0.001	-0.075, -0.039

Table 1: Estimation Results I: Table reports, parameter estimates, bootstrap standard errors, p-values for a two-sided test of the null hypothesis that the parameter is equal to zero, and 90% confidence intervals.

The signs on all parameters are as one would expect. The fuel price-cost elasticity estimate indicates that a 1% increase in the price of fuel leads to a 0.298% (90% c.i., [0.135, 0.444]) increase in cost. A 1% increase in the crew wage increases trip costs by 0.546% with 90% c.i., [0.052, 1.121] and a 1% increase in the length of the vessel increases trip costs by 1.171% with 90% c.i., [0.979, 1.381].

The coefficient on our measure of unanticipated stock abundance and its 90% confidence interval are both negative. This result affirms that trip-level abundance shocks are an important feature of the GOM commercial reef fish data generating process and a source of potential omitted variable bias. We have hypothesized that harvest scale may be positively correlated with unanticipated abundance. The simple correlation in our data between $\hat{\chi}_n$ and cumulative trip-level harvest is 0.131 with 95% bootstrap confidence interval, [0.112, 0.150]. We investigate the effects of omitted variable further below using the full set of model parameter estimates.

Before we proceed to step 2 of our estimation we conduct a preliminary search for evidence of targeting behavior in our data. According to equation (10), the remaining unexplained variation in our data can be written as,

$$\beta_0 + \overline{\delta}(s,t) + ln(A^*) + u_n = ln\ C_n - \hat{\beta}_h' h_n - G(w_n, k_n|\hat{\beta}). \quad (13)$$

A maintained hypothesis of our model is that targeting by GOM commercial reef fish fishermen in response to economic incentives and regulations is an important component of the data generating process. If so, we can see from (13) that the economic and regulatory variables must retain some ability to explain the residuals from the step 1 estimation. To test this claim, we present result from reduced form regressions of the step 1 residuals (the right hand side of equation (13)) first on (i) trip harvest shares and (ii) on elements of Ω_n.

Variable	Coeff.	Std. Err.	t-stat	p-val.
Constant	0.532	0.053	9.955	0.000
HL gear	-0.317	0.049	-6.535	0.000
TR gear	-0.729	0.083	-8.743	0.000
LL gear	1.058	0.051	20.570	0.000
S_{h1}	-0.050	0.123	-0.409	0.341
S_{h3}	-0.145	0.074	-1.960	0.025
S_{h8}	-0.600	0.093	-6.483	0.000
$S_{h1} \cdot S_{h3}$	-0.016	0.344	-0.047	0.481
$S_{h1} \cdot S_{h8}$	0.673	0.565	1.191	0.117
$S_{h3} \cdot S_{h8}$	1.312	0.383	3.428	0.000
$S_{h1} \cdot s$	-0.426	0.141	-3.030	0.001
$S_{h1} \cdot t$	0.108	0.110	0.981	0.163
$S_{h3} \cdot s$	0.260	0.126	2.060	0.020
$S_{h3} \cdot t$	-0.015	0.065	-0.235	0.407

Table 2: Targeting Residual Results I: Table reports parameter estimates, standard errors, p-values for a two-sided test of the null hypothesis that the parameter is equal to zero, and 90% confidence intervals. Standard error are obtained with a robust covariance estimator (Greene, 2017). Species numbers are: 1 - red snapper, 3 - red grouper, 8 - other species. HL denotes handline gear, TR denotes trolling gear, and LL denotes longline gear.

Table 2 reports results from a linear regression of the step 1 residual on select harvest shares, interacted with other species harvest shares, and interacted with our measures of space and time.[17] The results find that gear types are significantly correlated with the step 1 residual. The model R-squared is 61.6% and an F-test that the effects of the regressors is zero is rejected at conventional levels.

Table 3 reports results from a linear regression of the step 1 residual on the elements of Ω_n directly. Again many of the variables are significant at conventional levels. The model R-squared statistic is 0.543 and thus over half of the variation in the step 1 residual can be explained (an F-test that the model has no explanatory power is rejected at conventional levels of significance). We see that the step 1 residual varies strongly with gear type, fishery openings for red snapper and red grouper, the scarcity of the aggregate quota for these species as measured by variables Q_1, and Q_3, respectively, sales prices for some species, and space.

The results in tables 2 and 3 do not of course prove the existence of targeting, they are a necessary condition for targeting to be present. Nor do they validate the function form for A in (2).

[17] Harvest shares sum to unity and thus all cannot be included as regressors. The results are qualitatively similar when alternate species' harvest shares are used.

Variable	Coeff.	Std. Err.	t-stat	p-val.
Constant	0.478	0.196	2.441	0.007
HL gear	-0.454	0.056	-8.072	0.000
TR gear	-1.147	0.057	-20.053	0.000
LL gear	1.118	0.055	20.382	0.000
Q_1	0.353	0.121	2.922	0.002
Q_3	-0.364	0.109	-3.338	0.000
Q_4	0.001	0.086	0.013	0.495
h_1 open	-0.188	0.116	-1.614	0.053
h_3 open	0.263	0.104	2.519	0.006
Red snap. TAC	-0.002	0.022	-0.091	0.464
Red Grp. TAC	-0.042	0.036	-1.158	0.123
Gag Grp. TAC	0.005	0.009	0.501	0.308
Class 2 permit	-0.034	0.068	-0.496	0.310
Class 3 permit	0.029	0.082	0.354	0.362
p_1	0.053	0.028	1.902	0.029
p_2	-0.010	0.021	-0.477	0.317
p_3	-0.061	0.028	-2.194	0.014
p_8	-0.001	0.016	-0.068	0.473
s	0.118	0.044	2.662	0.004
t	0.094	0.082	1.146	0.126
$s \cdot t$	-0.051	0.061	-0.845	0.199

Table 3: Targeting Residual Results II: Table reports, parameter estimates, standard errors, p-values for a two-sided test of the null hypothesis that the parameter is equal to zero, and 90% confidence intervals. Standard error estimates are obtained with a robust covariance estimator (Greene, 2017). HL denotes handline gear, TR denotes trolling gear, and LL denotes longline gear. Species indices are: 1 - red snapper, 2 - vermilion snapper, 3 - red grouper, 4 - gag grouper, 8 - other species. s denotes space and t denote date since January, 2005.

They do however offer evidence in support of our characterization of the costly species' targeting we maintain is important in our data.

Cost function estimation: Step 2

The step 2 estimation specifies first order polynomials of space and time for species-specific no-target-cost share vectors ($\varphi_i(s,t|\theta)$). A within-season temporal measure is included for gag grouper to accommodate winter aggregation patterns for this species.

The step 2 estimation is carried out under three specifications for the stock level effect; (1) $\overline{\delta}_n$ constant and thus subsumed into the model constant β_0, (2) $\overline{\delta}_n$ proportional to $\hat{\mu}_n$ obtained from the CPUE model, and (3) $\overline{\delta}_n$ set to a polynomial of space and time. The expression in 10 makes clear that identification of φ_i's is not guaranteed if we are forced to also estimate $\overline{\delta}_n$ as a polynomial of space and time. In the third specification, identification of the φ_i's and stock level effects obtains through the specific functional forms that we specify. The only circumstance under which we can identify all remaining parameters is in the case where $\overline{\delta}_n$ is identified from the CPUE model, i.e., if the assumption $q \perp (s,t)$ is maintained. We reiterate that each of these specifications face identification challenges.

The number of instruments employed is 23; we estimate 17 free parameters, so the model is over-identified. The Hansen-Sargan over-identification test statistic is never exceeds 0.011 and we therefore fail to reject the null hypothesis that our identification restrictions are valid.

The structural properties of the harvest technology vary with spatial-temporal stock conditions, through the estimated $\varphi_i(s,t)$ terms, the stock level effect if present, gear type, factor prices, vessel length, and the trip harvest vector. We calculate economic effects of interest at each data point and report averages across the full sample. Below we demonstrate key properties of the model by summarizing their implications for targeting behavior and, through a simulation, potential implications of regulations on fishing outcomes.

	$\overline{\delta}_n = 0$		$\overline{\delta}_n = \beta_\mu \hat{\mu}_n$		$\overline{\delta}_n = \mathcal{P}_i(s,t\|\theta)$	
Parameter	Est.	90% c.i.	Est.	90% c.i.	Est.	90% c.i.
β_0	-0.022	[-2.877, 2.762]	0.043	[-2.890, 2.520]	-0.025	[-3.013, 2.620]
β_{HL}	-0.453	[-0.616, -0.320]	-0.419	[-0.591, -0.314]	-0.407	[-0.542, -0.308]
β_{TR}	-1.080	[-1.412, -0.758]	-1.030	[-1.392, -0.778]	-1.017	[-1.346, -0.809]
β_{LL}	0.519	[-1.947, 1.536]	0.720	[-1.720, 1.567]	1.001	[0.176, 1.627]
γ_{VL}	1.488	[0.300,3.210]	1.385	[0.187,3.546]	1.189	[0.379,2.979]
γ_{LL}	3.159	[0.060,54.500]	2.374	[0.038, 40.354]	1.022	[0.022,5.494]
β_μ	-	-	-0.027	[-0.067,0.015]	-	-
β_s	-	-	-	-	0.010	[-0.082, 0.180]
β_t	-	-	-	-	0.106	[-0.030, 0.237]
β_{st}	-	-	-	-	0.019	[-0.180, 0.232]

Table 4: Estimation Results II: Table reports, model constant and targeting cost parameters estimates with 90% (bootstrap) confidence intervals. Gear types are: VL - denotes vertical line gear; HL - denotes hand line gear; TR - denotes trolling gear; LL - denotes longline gear.

Table 4 reports point estimates and 90% bootstrap confidence intervals for our step 2 estimations. The targeting cost parameters for all gear types other than longline, and intercepts terms for four separate gear types and under the three specifications for the stock level effects are reported.

Observe first that the estimated parameters are quite stable across the different specifications. Confidence intervals for γ are large, particularly for the non-vertical-line gear types. This result further highlights the identification challenges in our estimations of targeting effects, although there may be other confounding factors. One consideration is that targeting *ability* may vary across vessel operations, e.g., skipper experience/skill likely plays a role in the process of targeting individual reef fish species. These difference will be reflected in the point estimate of γ and other parameters under our bootstrap procedure which samples unique vessel operations. An investigation of potential heterogeneity in targeting skill is a topic for future work.

Further investigation reveals similar predictions of key model elements emerge across the three specifications for stock level effects. Table 5 reports fitted values of the no-targeting-cost vector (key species only), the targeting cost term A, and the marginal cost of harvesting individual reef fish species. Sample means and standard deviations for select reef fish species are reported.

The results are similar across the three stock-level effect specifications. For example, sample mean estimates of $\varphi_1(\cdot)$ (red snapper) vary around 20% from 18.5 % 23.2 %. Sample mean values for $\hat{A}_n$ vary from a low of 1.420 when stock level effects are approximated with a polynomial to 1.580 when they are assumed constant. Differences in fitted marginal costs for key reef fish species show little variation across the three specifications.

Results reported below assume the polynomial specification for stock level effects, $\overline{\delta}_n = \mathcal{P}_i(s,t|\theta)$.

	$\bar{\delta}_n = 0$		$\bar{\delta}_n = \beta_\mu \hat{\mu}_n$		$\bar{\delta}_n = \mathcal{P}_i(s,t\|\theta)$	
	Ave.	Std.	Ave.	Std.	Ave.	Std.
$\varphi_1(\cdot)$	0.232	0.316	0.185	0.285	0.195	0.295
$\varphi_2(\cdot)$	0.007	0.007	0.005	0.009	0.008	0.014
$\varphi_3(\cdot)$	0.102	0.173	0.125	0.228	0.073	0.132
$\varphi_4(\cdot)$	0.038	0.076	0.030	0.066	0.038	0.109
$\varphi_8(\cdot)$	0.582	0.254	0.609	0.271	0.662	0.272
$\hat{A}(\cdot)$	1.580	0.510	1.551	0.417	1.420	0.312
$C_1(\cdot)$	0.151	0.195	0.150	0.193	0.150	0.178
$C_2(\cdot)$	0.664	0.847	0.658	0.838	0.657	0.774
$C_3(\cdot)$	1.357	1.727	1.344	1.710	1.341	1.579
$C_4(\cdot)$	0.655	0.836	0.649	0.827	0.648	0.764
$C_8(\cdot)$	0.604	0.771	0.599	0.763	0.597	0.705

Table 5: Estimation Results III: Table reports the sample average and the standard deviation for major species estimates of φ_i and marginal costs (species are: 1-red snapper; 2- vermilion snapper; 3 - red grouper; 4-gag grouper; 8-other species).

Targeting Costs

Figure 2 plots fitted values for $\hat{\varphi}_i$ (select species) across space and time holding the seasonal time index at its mid-summer value. The space (s) axes extends from the Florida Keys to the Mississippi delta (figure 1). The temporal (t) axes is denoted as the number of years following January, 2005. We report results for red and vermilion snapper, and red and gag grouper. Results for remaining species appear in appendix 7.

From panel (a) of figure 2 we see that the red snapper estimate of $\hat{\varphi}_i$ varies widely from 0 in the south to values near unity in the northern region of the fishery. The estimate increased during the data period in the north. The vermilion snapper estimate of $\hat{\varphi}_i$ hovers near zero and shows less variation across space and time. The fitted value suggests species-specific marginal costs that are almost everywhere positive. Recall that vermilion snapper is a relatively unregulated species, which presumably suggests its stock is of healthy size. Reef fish fishermen may therefore have little incentive to avoid this species, consistent with the finding that $\hat{\varphi}_i$ is small.

The red grouper estimate of $\hat{\varphi}_i$ peaks in the northern region at about 40% of trip catch and shows decline over time. The gag grouper estimate increases in southern regions of the fishery to a peak of roughly 60% of trip harvest. A small upward trend is indicated.

It is reasonable to interpret our estimates of $\hat{\varphi}_i$'s as proxies for higher-relative abundance of species i fish. In this case, the patterns in figure 2 are generally consistent with known reef fish ecology, e.g., red snapper is a northern gulf species while gag grouper tend to favor southern waters (SEDAR, 2014). In lieu of species-specific and spatially and temporally delineated estimates of abundance, further investigation of the link between our $\hat{\varphi}_i$ estimates and reef fish ecology is not possible.

Targeting behavior

Insights into the targeting behavior of GOM reef fish fishermen obtain through direct examination of harvest shares and our $\hat{\varphi}_i$ estimates. We calculate the difference $S_i(h) - \hat{\varphi}_i$ for each trip observation

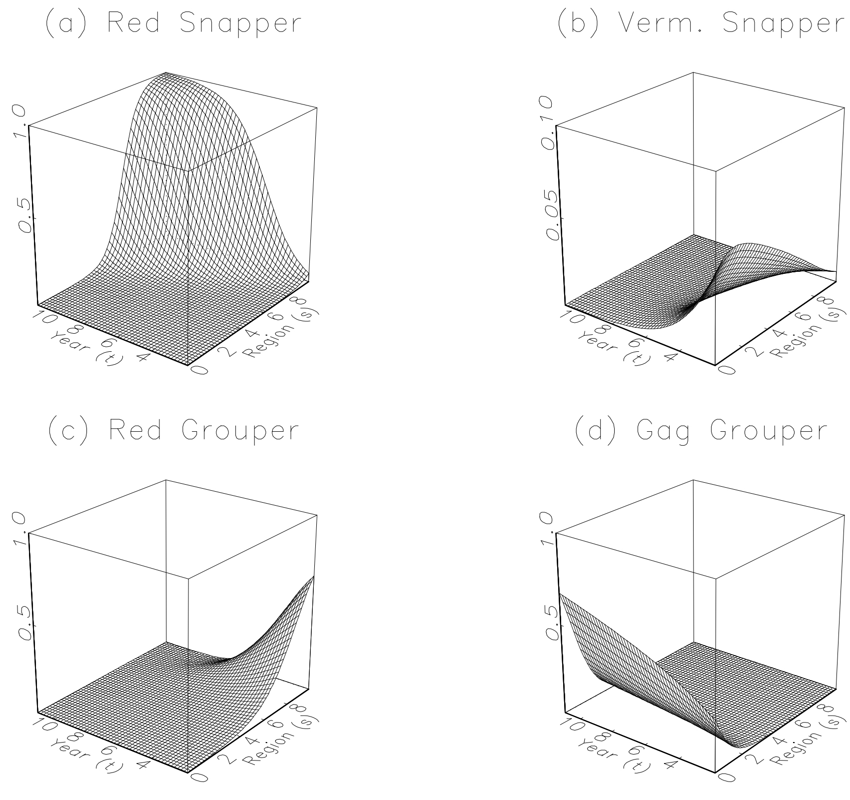

Figure 2: Fitted $\varphi_i(s, t|\theta)$'s.

and for each species. A positive (negative) value suggested that costly actions were taken to increase (reduce) the harvest of species i in trip catch, i.e., $S_i(h) - \hat{\varphi}_i$ is thus a measure of targeting intensity for species i and we hereafter refer to it as such.

	p_i	$S_i(h)$	$S_i(h) - \hat{\varphi}_i$	$\hat{C}_i(\cdot)$	$p_i - \hat{C}_i(\cdot)$
Red. snap.	4.070	0.154	-0.040	0.150	3.742
Verm. snap.	2.942	0.136	0.127	0.657	2.227
Red grp.	3.298	0.222	0.149	1.341	1.985
Gag grp.	4.470	0.048	0.010	0.648	3.837
O.S.W. grp.	4.305	0.020	0.000	3.440	0.984
D.W. grp.	3.639	0.019	0.016	0.990	2.205
Tilefish	2.100	0.011	0.009	0.641	1.153
Oth. sp.	1.972	0.391	-0.271	0.597	1.179

Table 6: Targeting Descriptive Statistics. Table reports sample average values o the landings price, harvest share, targeting intensity $S_i(h) - \hat{\varphi}_i$, marginal cost, and marginal profit.

Table 6 reports sample average values for fish prices, harvest shares, targeting intensity, marginal cost (derived in appendix 7), and marginal profit, by species. The implications for targeting behavior are understood in the context of the regulations that were in place in the GOM reef fish fishery during our 2005-14 data period.

Consider red snapper. The sample average value for $S_i(h) - \hat{\varphi}_i$ is -0.040 suggesting that reef fish fishermen on average only slightly avoid this species. The sample average masks the extent of the avoidance behavior across space and time and in response to regulations. The sample average value of the targeting intensity measure in the northern region where red snapper is most prevalent is -0.069. During 2010-14, the sample average value falls to -0.116. Recall that red snapper was regulated with closures and a landings endorsement permit program during 2005-06, and with IFQs thereafter. The initial (free) allocation of red snapper IFQ went to fishermen based on historical landings history, i.e., vessels that held endorsement permits during the controlled access regime received the bulk of the red snapper quota. We compare values of targeting intensity by vessels that did not hold endorsement permits with those that did. Among the former class of vessels, the average value for targeting intensity (in the northern region of the fishery) is -0.163. The average targeting intensity for fishermen with endorsement permits is 0.035.

Similar patterns of costly targeting arise during grouper closures. Average targeting intensity values are as follows: for red grouper the average targeting intensity is 0.014 during closures and 0.154 when landings are permitted; for gag grouper the average targeting intensity is -0.200 during closures and 0.017 during openings; for O.S.W grouper species the sample average is -0.050 during closures and 0.000 during openings; the D.W. grouper average value is -0.000 during closures and 0.020 during openings; and for tilefish, the average value is 0.001 during closures and 0.011 during openings.

The sample average value of targeting intensity measure for the Other species output group is -0.271. This species group is also relatively unregulated. It includes some species that fetch low prices at the dock and some for which markets are underdeveloped or nonexistent. The average price for the All Other species group is \$1.97 per pound, considerably lower than for the other harvested outputs. Average marginal profit estimates also indicate a low margin compared to most of the other species. In this context, the finding that on average GOM reef fish fishermen take costly actions to avoid the Other species output group is not surprising.

Quota regulation and at-sea discarding

This section demonstrates the value of our model as a prescriptive management tool. We simulate fitted trip costs and marginal costs on a representative vertical line gear fishing trip that harvests roughly 2,367 total pounds of reef fish (the 75'th percentile value recorded in our data). We assume the representative trip is taken in the northern region of the Florida panhandle during the latter part of the data period, around 2013-14. This spatial-temporal combination is chosen to demonstrate the role of stock conditions on fitted costs and the incentive to discard fish at sea under a quota regulation. Specifically, the fitted value of φ_i for red snapper at this (s, t) combination is 0.380 (fitted $varphi_i(\cdot)$'s for remaining species are less than 0.015 with the exception of the Other species group which is 0.604).

Panel (a) in figure 3 plots the value of the fitted targeting costs term, $\hat{A}_n$ as total pounds of red snapper per trip range between from 200 to 1,800 pounds, i.e., the red snapper harvest share varies from less than 1% to more than 75% of trip catch. Panel (b) plots fitted red snapper marginal cost

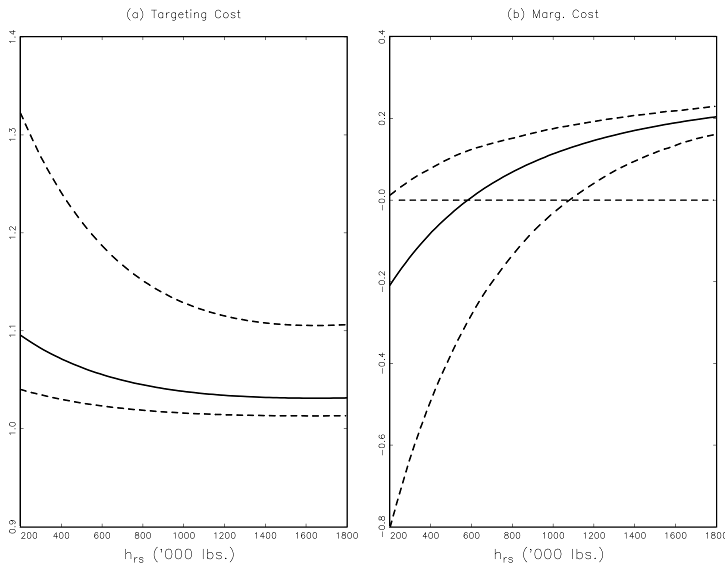

Figure 3: Targeting cost simulation.

for the same range of red snapper harvests. Both panels report 90% confidence intervals calculated from our bootstrap estimates.

Panel (a) shows the value of $\hat{A}_n$ in the range $[1.077, 1.153]$, implying that roughly 7.7% - 15.3% of trip costs can be attributed to costly targeting actions. Note that if such actions were not taken the harvest mix would match $\hat{\varphi}_n$. This would result in a lower trip cost but not necessarily higher trip profit. The reason is that the assumed harvest mix reflects the average targeting behavior observed in our data (see table 6) with higher harvest shares for high price species such as red and gag grouper and lower harvest share for low priced species such as the All Other species category.

Panel (a) shows that $\hat{A}_n$ declines as red snapper harvest increases from 200 to roughly 600 pounds and then increase thereafter. Avoiding red snapper in northern regions of the fishery during later data periods is costly. In other words, since $\hat{\varphi}_{in}$ = 0.38, choosing $S_i(h_n) = 0$ for red snapper implies higher costs.

The implication of keeping targeting costs in check is illustrated further in panel (b) of figure 3. We see that the estimate of red snapper marginal cost is negative for harvest quantities in the range of 0-600 pounds (holding other species harvests fixed). The conditions on the simulated trip are such that the fishermen faces an incentive to discard red snapper at sea when the red snapper quota is particularly scarce. The lesson for fishery managers is that tight limits on landings of individual species, while allowing other species to be legally landed, creates incentives to discard fish at sea (Singh and Weninger, 2009).

Omitted variable bias

Our final results will quantify the omitted variable bias that impact our estimations if the proposed steps to correct for unobserved abundance and endogenous harvest decisions are not taken. We do not observe stock abundance, which precludes a simple comparison of regression results with and without its inclusion in a regression model. Moreover, we have introduced a nonlinear functional form for trip-level costs that incorporates endogenous production decisions at multiple stages. Our demonstration of omitted variable bias thus focuses on the estimates of economic effects of interest which are the focus on applied production analysis and relevant for management purposes. We focus on estimates of reef fish marginal harvesting costs.

We estimate, using ordinary least squares, a log-linear model of trip costs as a function of the trip harvest vector, factor input prices, a measure of capital, and a polynomial of (s, t) to control for all effects, including latent abundance, that vary with space and time. The fitted parameters from this model are used to calculate species-specific marginal costs. The omitted relevant variables in this strawman model is the unobserved stock abundance. Omitted variable bias if present in the strawman model will impact the least squares estimates of the parameters associated with trip harvest. The bias is given by $\delta_X \frac{cov(h,X)}{var(h)}$, where δ_X is the stock effect on harvest costs. Our results confirm that unanticipated abundance negatively affects costs. Further evidence, although weaker, indicates that anticipated abundance may also negatively affect costs. The covariance between harvest and unanticipated abundance is positive. This suggests the strawman model will overestimate the parameter associated with trip harvest and thus overestimate true marginal costs.

We confirm this expected bias. Sample marginal costs estimates calculated from the strawman model are substantially above those reported in table 6 (for all species except the Other species output). Averaging the difference between the two model predictions finds that the strawman model overestimates marginal costs by 87.653% for red snapper, by 36.594% for vermilion snapper, by 41.298% for red grouper, and by 54.342% for gag grouper. The strawman model underestimates marginal costs obtained by our model by 10.240% for Other species. The finding that the direction of the omitted variable bias is reversed, and smaller for this output category may reflect an absence of endogenous targeting effects for the Other species grouping, although this intuition is unconfirmed.

5 Conclusion

This paper introduces a structural model of a dual (cost function) multiple-species harvesting technology. The setting is one where stock abundance and harvesting productivity varies across space and time in ways that are unobserved by the researcher but potentially quite well-understood by producers. We devise an estimation strategy which, under reasonable assumptions for fisheries data generating processes, obtains consistent estimates of key structural properties of the harvest technology. Our estimations exploit the information available to fishermen when production decisions are made and some unique features of the technology, e.g., limited ability to adjust or reorganize a production plan while at sea. We further exploit catch and effort stock assessment methods to help identify latent abundance and control for its effect on our measurement of the underlying technology. We show how naive estimations that ignore the impact of latent abundance suffer omitted variable bias that can result in substantial miss-measurement of the technology. An application of the model to the Gulf of Mexico commercial reef fish fishery demonstrates its strengths as well as its remaining limitations.

Our structural model of a costly targeting technology is particularly well-suited for conducting *ex ante* analysis of alternate regulations in fisheries, e.g., species-specific quotas, spatial closure regulations, taxes on factor inputs and on harvested outputs, among others. A simulation is presented to demonstrate this feature. We identify quota regulations for which GOM reef fish fishermen face incentives to discard red snapper at sea, due to costly targeting that would be required to avoid the species. This outcome is predicted under the weak output disposability property implicit in our cost functional form, and the identification of no-target-cost vectors across space and time. More broadly, our model can be used to predict the spatial-temporal distribution of harvests, discards, and resource rent, among other outcomes of interest to fishery managers and stakeholders, under alternative regulations, market condition, etc.

Multiple-species stock abundance is a latent variable in our model. The no-target-cost share vectors that we estimate link species-specific abundance to space and time, which to our knowledge has not been previously attempted. We are unable to identify absolute stock abundance. As a consequence, our approach does not generate an estimate of the cost-stock elasticity parameter, which is pivotal for setting harvest and stock abundance targets that maximize fishery rent (Clark 1990). Our next research steps will seek to fill this void. Research that improves the use of catch and effort data for assessing multiple species stock abundance may also prove useful in this effort.

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7 Appendix

Marginal costs

The functional form for variable costs (equation (2)) is:

$$c(h,w|X,k) = \underbrace{\Big[1 + \frac{\gamma}{2}\sum_i (s_i(h) - \varphi_i(x))^2\Big]}_{A} \underbrace{exp\Big(\beta_0 + \beta_h h + \beta_X X\Big)G(w,k)}_{B}.$$

The marginal harvesting cost for species i fish is,

$$\frac{\partial c(\cdot)}{\partial h_i} = \left[B\frac{\partial A}{\partial h_i} + A\frac{\partial B}{\partial h_i}\right], \quad \text{for } i = 1, \ldots, I.$$

Carrying out the derivations obtains:

$$\begin{aligned}
\frac{\partial A}{\partial h_i} &= \frac{\gamma}{H}\left[(s_i - \varphi_i)(1 - s_i) - \sum_{j \neq i}(s_j - \varphi_j)s_j\right] \\
&= \frac{\gamma}{H}\left[(s_i - \varphi_i) - \sum_{j=1}^{I} s_j^2 + \sum_{j=1}^{I}\varphi_j s_j\right] \\
\frac{\partial B}{\partial h_i} &= \beta_{h_i} B,
\end{aligned}$$

where $H = \sum_i h_i$. Function arguments are dropped to ease notation.
The matrix of second derivatives is derived as

$$\begin{aligned}
\frac{\partial^2 c(\cdot)}{\partial h_i \partial h_j} &= \frac{\partial}{\partial h_j}\left\{B\frac{\partial A}{\partial h_i} + A\frac{\partial B}{\partial h_i}\right\} \\
&= B\frac{\partial^2 A}{\partial h_i \partial h_j} + \frac{\partial B}{\partial h_j}\frac{\partial A}{\partial h_i} + \frac{\partial A}{\partial h_j}\frac{\partial B}{\partial h_i} + A\frac{\partial^2 B}{\partial h_i \partial h_j}.
\end{aligned}$$

The terms A, B, $\partial A/\partial h_i$ and $\partial B/\partial h_i$, are presented above. Terms to be evaluated include,

$\partial^2 A/\partial h_i \partial h_j$ and $\partial^2 B/\partial h_i \partial h_j$. Carrying out the derivations for the case of $j = i$ obtains:

$$\begin{aligned}
\frac{\partial^2 A}{\partial h_i^2} &= \frac{\partial}{\partial h_i}\left\{\frac{\gamma}{H}\left[(s_i - \varphi_i) - \sum_{j=1}^{I} s_j^2 + \sum_{j=1}^{I} \varphi_j s_j\right]\right\} \\
&= -\frac{\gamma}{H^2}\left[(s_i - \varphi_i) - \sum_{j=1}^{I} s_j^2 + \sum_{j=1}^{I} \varphi_j s_j\right] \\
&\quad + \frac{\gamma}{H}\left[\frac{H - h_i}{H^2} - 2s_i \frac{H - h_i}{H^2} - 2\sum_{k \neq i} s_k \left(\frac{-h_k}{H^2}\right) + \varphi_i \frac{H - h_i}{H^2} + \sum_{k \neq i} \varphi_k \left(\frac{-h_k}{H^2}\right)\right] \\
&= \frac{\gamma}{H^2}\left[1 - 4s_i - 2\varphi_i + 3\sum_k s_k^2 - 2\sum_k \varphi_k s_k\right]. \\
\frac{\partial^2 B}{\partial h_i^2} &= \beta_{h_i}^2 B.
\end{aligned}$$

When $j \neq i$ we find:

$$\begin{aligned}
\frac{\partial^2 A}{\partial h_i \partial h_j} &= -\frac{\gamma}{H^2}\left[(s_i - \varphi_i) - \sum_k (s_k - \varphi_k) s_k\right] \\
&\quad + \frac{\gamma}{H}\left[\frac{-h_i}{H} - 2s_j \frac{H - h_j}{H} - 2\sum_{k \neq j} s_k \left(\frac{-h_k}{H}\right) + \varphi_j \frac{H - h_j}{H} + \sum_{k \neq j} \varphi_k \left(\frac{-h_k}{H}\right)\right] \\
&= \frac{\gamma}{H^2}\left(-2\left(s_i + s_j\right) + (\varphi_i + \varphi_j) + 3\sum_k s_k^2 - 2\sum_k \varphi_k s_k\right). \\
\frac{\partial^2 B}{\partial h_i \partial h_j} &= \beta_{h_i} \beta_{h_j} B.
\end{aligned}$$

Data descriptive statistics

Table 7 reports data descriptive statistics for 358 unique vessels and 9,941 trips with complete cost data. The average trip spends just over 4 days at sea and carries a crew of 2.46 including the vessel skipper. Average harvest per trip is just over 2,000 pounds. Average trip revenue is just under \$6,000. The sample average net revenue is \$3,812.9 per trip, which implies, on average, \$1.87 of profit (also resource rent) per landed pound.

The average captain and crew labor expense share is 0.58. The Fuel and “Other” expense shares are 0.20 and 0.19, respectively. The sample average capital cost share is small at 0.03.

Red grouper, coastal pelagic species, red snapper, and vermilion snapper account for the bulk (73%) of average trip revenue (lower portion of table 7). The average gag grouper revenue share is

	Mean	Std.	5'th %	50'th %	95'th %
Days at sea	4.10	3.30	1.00	3.00	11.00
Crew size	2.46	1.08	1.00	2.00	4.00
Harvest (lbs.)	2,042.58	2,384.53	77.17	1,253.00	7,023.72
Revenue	5,897.30	7,511.92	191.59	3,155.98	21,296.48
Labor exp.	1,866.49	1,776.54	235.18	1,411.07	5,343.86
Fuel exp.	563.46	553.46	70.72	408.72	1,558.31
Oth. exp.	762.71	1,005.72	16.32	408.59	2,650.18
Capital exp.	116.85	157.00	14.66	75.09	343.16
Var. Cost	3,309.52	3,217.06	414.66	2,513.84	9,540.33
			Cost shares		
	Mean	Std.	5'th %	50'th %	95'th %
Labor	0.58	0.12	0.37	0.58	0.76
Fuel	0.20	0.09	0.08	0.18	0.39
Other	0.19	0.11	0.03	0.18	0.38
Capital	0.03	0.01	0.02	0.03	0.06
			Revenue shares		
Red group.	0.23	0.34	0.00	0.01	0.97
Coast. Pelag.	0.20	0.39	0.00	0.00	1.00
Red snap.	0.15	0.27	0.00	0.00	0.87
Verm. snap.	0.15	0.27	0.00	0.00	0.81
Gag group.	0.06	0.14	0.00	0.00	0.32
O.S.W. group.	0.03	0.08	0.00	0.00	0.12
D. W. group.	0.02	0.11	0.00	0.00	0.05
Tilefish	0.01	0.07	0.00	0.00	0.00
All oth. sp.	0.16	0.30	0.00	0.02	1.00

Table 7: **Trip Characteristics, Cost and Revenue Descriptive Statistics.** N = 9,941. Values are reported in \$2014.

6%; gag grouper is an important species not for its total revenue share but for the fact that the gag price is high and the species is regulated with its own relatively tight annual quota.

Economic	
Output prices	Logbook system records revenues and pounds by species landed on each reef fish trip. Spatial-temporal average prices are used on trips that do record positive landings of species i fish.
Input prices	Fuel pries are inferred from trip-level fuel expense/fuel quantity data. Crew labor wages are assumed equal to state- and quarter-specific mean hourly wage rates for agriculture and fishery workers. Data are obtained from US Department of Labor.
Regulatory	
Annual quotas	Annual total allowable catch (TAC) for red snapper, red grouper, gag grouper, shallow water grouper species, deep water groupers and tilefish are collected from the Southeast Fisheries Science Center.
Quota scarcity	We use the ratio of annual cumulative landings to date t over the annual TAC to reflect to the tightness of the species i quota market.
Red Snapper Endorsement	Historic landings records are used to identify vessels holding class 1 (2,000 lbs. per trip), class 2 (200 lbs. per trip) or no endorsement (zero landings permitted) red snapper endorsement permits. The red snapper endorsement regulation was in place during 2005-07.
Closure Regulations	Closures (species-specific landings restrictions) were used from 2005-07 for red snapper and from 2005-10 for grouper and tilefish species. We use species- and date-specific indicator variables to distinguish open and closed periods.
Space and time	
	The logbook system records the trip start date, management subregion (see figure 1) and depth at which the majority of each reef trip revenues were obtained. We collapse management subregions 1-2 to a single spatial zone to form 10 spatial subregions. We calculate two temporal measures: a within-year measures is set to the day of the year that each trip begins (range is 1-365; 1-366 on leap years). A long term temporal measures is set equal to the cumulative day since the January 1, 2005 (range 1-3,652).
Other	
Deep Water Horizon	Large regions of the eastern Gulf of Mexico (maximum of 88,522 square miles in June, 2010) were closed to commercial fishing. We calculate the ratio of total area closed to the maximum area closed.
Vessel capital	Data contain measures of vessel length and value, which are assumed predetermined in the short run.

Table 8: Instrumental Variables.

Sample:	1	2	3	4
N	75,564	17,568	12,125	9,941
Unique vess.	1,677	624	518	358
Days at sea	3.88	3.89	4.04	4.10
Crew size	2.34	2.38	2.44	2.46
Lbs./trip	1,470.27	1,621.23	1,776.77	1,866.54
Rev./trip	4,611.50	5,096.70	5,555.23	5,897.30
	Average revenue shares			
Red snap.	0.13	0.15	0.14	0.15
Verm. snap.	0.08	0.12	0.15	0.15
Red group.	0.28	0.24	0.24	0.24
Gag group.	0.10	0.07	0.06	0.06

Table 9: Descriptive statistics I: Table reports observations, number of unique vessels, and average values for days at sea, crew size, pounds landed and revenue per trip and revenues shares for four major reef fish species. Column 1 reports values for all eastern regions trips taken during 2005-15. Column 2-4 report sub-sample values. The sample in column 2 includes all trips that report discard information. Sample 3 includes all trips that report both discard and trip expense information. Sample 4 includes all trips with discard and expense information for the subset of vessels with a minimum of 5 trips during 2005-14. Values are reported in $2014.

Further results

Mean CPUE index: $\hat{\mu}(s, t)$

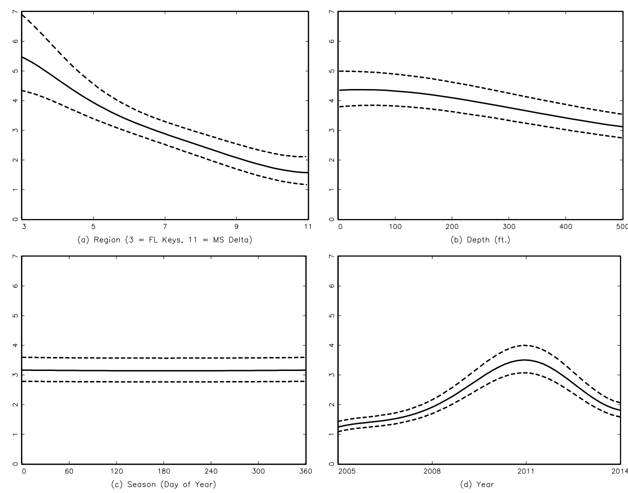

Figure 4: Panels report the fitted values for $\hat{\mu}(s, t)$ (solid lines) and 95 % confidence intervals (dashed values).

Figure 4 plots fitted values of the deterministic CPUE index $\hat{\mu}(s, t)$ across space and time. Panel (a) shows from left to right, the estimate in the Florida Keys and ending at the Mississippi delta, holding depth at 145 feet, the day of the year at mid-summer, and the calendar date at January 1, 2010, the midpoint of our data period. The index takes its lowest value in the Florida keys and increases gradually moving north and west to the Florida panhandle and the Mississippi delta. Panel (b) indicates that the CPUE index peaks at shallower depths and declines in deeper waters. Panel (c) indicates the fitted index exhibits virtually no within seasonal variation. In panel (d) shows the index increasing throughout the early years of our data, with a peak in 2011 and declining thereafter.

Trip level estimates: $\hat{\mu}_n$, $\hat{\chi}_n$

The left-hand panel in figure 5 reports estimates of the trip level CPUE index, $\hat{\mu}_n$. The right-hand panel in figure 5 reports estimates of the trip level productivity signal, $\hat{\chi}_n$. Both estimates are winsorized below the 5'th$\%$ and above the 95'$\%$ values.

The above table reports fitted values for $\varphi_i(s, t|\theta)$ estimates across space and time for shallow water groupers, deepwater groupers, tilefish and Other species.

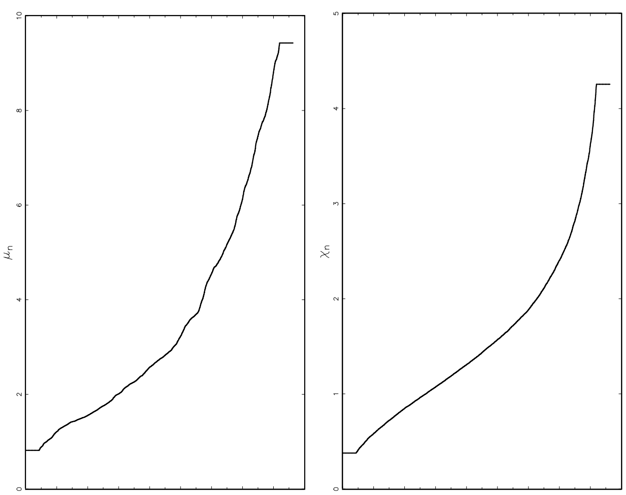

Figure 5: Left-hand panel reports sorted trip-level estimates of $\hat{\mu}_n$; right-hand panel reports sorted trip-level estimates of $\hat{\chi}_n$.

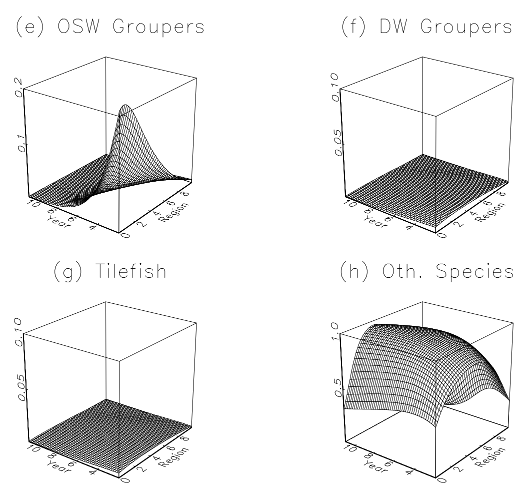

Figure 6: Fitted $\varphi_i(s, t|\theta)$'s.

8 Extended Appendix: capital services and costs

Vessel capital services and fixed costs

The fisheries economics literature often measures the capital input as a stock, e.g., the number of boats in a fleet or at the trip level, or with a measure of capital size such as the vessel length or its water displacement (e.g., Felthoven and Morrison Paul, 2004). However, a stock measure cannot reflect differences in the capital services that are provided on trips that vary in duration. For example capital services provided by a 50 foot boat on a 1 day trip are likely greater than the capital service provided by the same boat on a 10 day trip. A stock measure that is independent of trip duration therefore does not reflect difference in services provided or their costs.

Our empirical model interprets a fishing vessel as a composite bundle of attributes that provide a flow of productive services per unit time. We assume the capital services utilized on a given fishing trip are proportional to the trip's duration, which we measure as the days-at-sea for the trip. Larger vessels likely provide more services than smaller vessels, e.g., a larger boat is effectively a larger floating platform from which gear can be deployed, fish sorted, and preliminary processing (eviscerating, and icing and freezing the fish) conducted. Larger heavier boats are more costly (utilize more fuel) to move on the ocean. Larger vessel may also operate in more severe weather conditions, and are generally safer.

Vessel values were obtained through a survey of vessel owners conducted in 2013 and in 2014. Owners were asked to report vessel characteristics including vessel length (measured in feet), engine horse power, hold capacity (measured by total pounds capacity), the age of the vessel, and the vessel's market sale price. Our data include 233 complete observations. Table 10 reports descriptive statistics. As is apparent in table 10, vessels in our sample vary in terms of size, power configuration, hold capacity, and age.

	Median	Mean	Std.	Min.	Max.
Length (feet)	36	37.61	9.71	18	69
Engine HP	315	377.34	217.10	76	1,320
Hold Cap. (pounds)	3,500	6,703.87	9,152.00	300	76,000
Vessel Age (yrs.)	30	27.84	11.97	1	69
Value ($'000 2014):	68.35	113.73	138.83	7.97	960.68

Table 10: **Vessel Characteristics.**

	Parm. est.	Std. err.	t-stat.	P-value
Constant	-5.21	0.87	-5.99	< 0.01
Length	1.84	0.30	6.18	< 0.01
Engine HP	0.48	0.11	4.45	< 0.01
Hold Cap.	0.10	0.07	1.35	0.18
Vessel Age	-0.23	0.08	-2.81	0.01

Table 11: **Capital Index Model.** N = 233. The model R^2 is 0.43.

Table 11 reports the results of an ordinary least squares regression of self-reported vessel values

($2014) on vessel length (feet), engine horse power, hold capacity (pounds storage) and the vessel age (years). The results suggest that length, engine power, and hold capacity are positively related to sale value, whereas age of the vessel is negatively related to value. The regression equation is specified in log-log form and, therefore, coefficients can be interpreted as the percentage change in vessel value from a 1% increase in the attribute. A 1% increase in length, about 3.5 feet, increases vessel value by 1.84%, roughly $2,092. Under our competitive capital market assumption, $2,092 can be interpreted roughly as the present discounted value of productive services provide by the additional 3.5 feet of vessel length (above the sample mean).

We next use our data to construct a measure of capital services provided by different vessels. For this purpose we make the additional assumption that length, which measures the size of the platform from which harvesting operations are conducted, is an appropriate proxy of the capital services provided on a typical fishing trip.

To obtain a *price* of capital services we regress vessel value on a cubic specification of vessel length. We then calculate $\hat{V}(len.) = z_{len.}\hat{\beta}$, where $z_{len.}$ is shorthand for the cubic function of vessel length and $\hat{\beta}$ is the fitted parameter vector. We truncate $\hat{V}(len.)$ at the 1 and 99 percentile fitted values to reduce the effects of extremes on later analysis.

The opportunity cost of employing a vessel of particular length for a full year can be estimated as $\rho\hat{V}(len.)$, where ρ denotes the rate of interest on financial capital. The capital cost incurred on a single fishing trip j is then calculated as,

$$\frac{D_j}{\bar{D}(\kappa)}\rho\hat{V}(len.),$$

where D_j denotes the days-at-sea for trip j and $\bar{D}(len.)$ is the *full utilization* days-at-sea for a vessel of length $len.$. We estimate $\bar{D}$ from our data.

Full utilization days-at-sea is a construct that reflects the fact that time at port between trips is required to offload the catch, replenish fuel and supplies and perhaps to rest the vessel skipper and crew. Time at port is a choice variable that is made by an optimizing agent. Our data indicate that individual trip lengths range from 1 and 12 days. Large vessels tend to take longer trips. Sample average trip length for vessels in the 25 foot length class is 1.41 days; average trip lengths for larger vessel classes are as follows: 35 ft. - 3.57 days; 45 ft. - 5.73 days; 55 ft. - 5.37 days; 65 ft. - 5.76 days.

Table 12 reports that vessels in the smallest length class (20-30 feet) spend fewer days at sea per year on average than do larger boats. The difference may be due to constraints imposed by weather, but may also reflect larger quota holdings by owners of larger vessels.

We set $\bar{D}(\kappa)$ equal to 170 days for vessels in the 25 foot length class. $\bar{D}(\kappa)$ is set at 230 for vessels in the 35 and 45 foot length class and at 250 days for vessels in the 55 and 65 foot length class.

Annual fixed costs

Information on annual fixed cost is obtained from the Southeast Fisheries Science Center. Our data include 775 complete observations on 752 distinct vessels that operated during the 2005-14 fishing seasons. Key components of annual operating costs include maintenance, repairs and upgrades to the vessel, office expenses, annual docking fees, expenses for lost or damaged gear, and vessel insurance.

A few comments on commercial fishing fixed costs are warranted. First, some repair and maintenance expenditures must be incurred regardless of how extensively a commercial fishing vessel is utilized during a calendar year. Vessel capital literally rusts (with or without use), oil and hydraulic seals become brittle and leak, marine weather causes metal, wood and other materials to deteriorate. The cost of replacing damaged gear on the other hand is sure to be positively related to its intensity of use. Preliminary data analysis finds that annual fixed cost are positively correlated with the number of days spent at sea during the year for which fixed costs are reported.

Annual fixed costs also vary with vessel size, e.g., docking fees are commonly levied per vessel length. A final consideration is that roughly half of the vessel-year observations in our sample report positive expenditures for insurance. Insurance may be required to qualify for capital loans but is generally not essential for conducting commercial harvesting operations. We include insurance expenses in our measure of fixed costs and therefore implicitly assume these expenditures reflect a real cost of obtaining financial capital required to purchase and operate a commercial fishing vessel.

We sum the various fixed cost components for each vessel-year observation, and convert the values to \$2014 using the GDP implicit price deflator. We then regress annual fixed costs on vessel length, the total days the vessel spent at sea during the year, and a linear trend term which is added to capture changes in the prices of fixed operating expenses over the 2005-14 data period (e.g., docking fees may change over time with increased demand for dock space). Fitted fixed costs are reported in table 12.

	Annual Fixed Cost (by DAS)				Annual Days-at-Sea		
Length Class	150	200	250	300	N	10%	90%
25	36,942	40,323	42,945	45,088	225	4	162
35	56,311	59,692	62,314	64,457	493	10	227
45	70,778	74,159	76,781	78,924	300	42	203
55	82,330	85,711	88,333	90,475	34	34	253
65	91,947	95,327	97,949	100,092	31	33	238

Table 12: **Annual Fixed Costs by Vessel Length and Days at Sea.** Values are reported in \$2014.

Table 12 reports fixed cost estimates for 5 vessel length classes. Each length class spans 10 feet and is centered on the values reported in the first column of the table.[18] Table 12 reports fitted annual fixed cost for varying utilization rates, which we measure as days the vessel spent at sea. The three right-hand columns in the table report the number of observations in each length class (with observations reporting 0 days-at-see dropped) along with 10'th and 90'th percentile values.

Fixed costs by definition do not vary with the level of production and the estimates in table 12 generally adhere to this principle. The exception is that fitted fixed costs increase modestly with days-at-sea. This relationship is explained by the inclusion of *lost and damage gear expenses* in the fixed cost category. Expenses due to lost or damaged gear likely increase with the amount the gear

[18]For example, the 25 foot length class includes vessels greater than 20 feet and less than or equal to 30 feet in length. Length classes reported in table 12 reflect the range of lengths in our sample; 10-69 feet. Average sample length is 37.51 feet. The 10% and 90% vessel lengths are 26 feet and 49 feet, respectively.

is used. Including lost and damaged gear as a variable cost expense in a trip-level analysis raises more problems, e.g., the gear loss would have to be distributed across multiple trips, or allocated to an individual trip. Neither of these approaches is palatable.

The three right-hand columns in table 12 report the number of vessels in each length class and the 10'th and 90'th percentile values for the reported total annual days-at-sea. The wide range in annual days-at-sea is explained by the regulatory history in the GOM commercial reef fish fishery and data collection method. A significant proportion of the licensed GOM commercial reef fish fleet are aptly described as part time or *weekend* fishermen. These vessels hold commercial licenses and were granted small quantities of tradable fishing quota in the transition to the red snapper and grouper-tilefish individual transferable quota programs. Part time vessels appear in our sample but are far less active boats and not representative of a full time commercial harvesting operation. Our analysis is modified to account for differences in seasonal activity level.

We assume that annual fixed costs (table 12) can be apportioned to the trip level through the factor $\frac{D_j}{\bar{D}(\kappa)}$. Trip fixed costs for vessel length $len.$ on trip j is estimated as,

$$fc_j(len.) = \frac{D_j}{\bar{D}(len.)} fc(len).$$

Appendix References

Felthoven, R. G. and Morrison Paul, C. J. Directions for productivity measurement in fisheries, *Marine Policy*, 28 (2004): 161–169.