Identification of resource extraction technologies when the resource stock is unobservable

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Keywords
Latent stock abundance, omitted variable bias, multi-output technology

Disciplines
Aquaculture and Fisheries | Behavioral Economics | Econometrics
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JEL Classification: C13, Q22
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Introduction

The management of fisheries resources requires knowledge of the growth potential of the fish stock and the benefits and costs of extracting the resource (Clark, 1974). Empirical measurement of two of these components, stock growth potential and extraction costs, is complicated by the unobservability of the *in situ* fish stock, and by endogenous, stock-dependent production decisions of fishermen. Fishermen have better information about stock abundance 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 impacts empirical measurement of fishing technologies, with serious implications for management (Ekerhovd and Gordon, 2013; Zhang and Smith, 2011; Weninger, 2019). 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 to the Gulf of Mexico commercial reef fish fishery is presented to illustrate the approach and quantify the magnitude of the omitted variable problem.

The size of the fish stock, measured as numbers of fish or total biomass, is assumed to be a key determinant of the productivity of factor inputs, e.g., labor, fuel, nets and other gear, bait, and capital, in fisheries (Gordon, 1954; Schaefer, 1954; Smith, 1968). True stock abundance is however unobservable; at best the researcher has access to an estimate of abundance generated from a stock assessment model. While true stock conditions, i.e., abundance and species’ composition at spatial-temporal scales at which harvesting operations take place, are unknown to the researcher, fishermen can amass extensive knowledge of stock conditions and may directly observe the productivity of their gear as it is set and retrieved from the water. This production setting introduces a crucial empirical challenge: potential bias that derives from endogenous factor input choices and species’ targeting decisions that vary with stock abundance that is observed, at least partially, by fisherman but unknown to the researcher.

Empirical measurement is further complicated in multi-species fisheries, where public factors of production such as nets, hooks and bait simultaneously intercept multiple species of fish, even as different combinations of these inputs are used to target preferred species mixes. The technology we measure in this paper exhibits 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 (Turner, 1995; Singh and Weninger, 2009) wherein fishermen are able to influence the mix of species that are intercepted by their gear.

Our model of trip level fishing behavior and estimation strategy overcomes these empirical challenges. We break the trip-level production problem into two stages. In a first planning stage, fishermen configure their vessel operation: they choose the mix of fuel, crew labor, gear, food, and other supplies for the trip. They also select net mesh sizes, hook and bait types, etc., and the at-sea loca-

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1. In addition to wildlife populations, oil, natural gas, and mineral reserves are similarly difficult to measure to a degree of accuracy necessary for precise empirical investigation.

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), and Singh and Weninger (2017).
tion at which harvesting operations will commence. We assume these endogenous choices are made with the goal of maximizing the expected profit for the trip, conditional on available (exogenous) information on input prices, the prices of landed fish, other constraining factors such as regulations, capital constraints and, importantly, expectations of stock conditions that will be encountered at sea. A nonlinear instrumental variables estimation is used to correct for the endogeneity in production decisions made at the planning stage.

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 actual stock conditions encountered on a fishing trip will, in all likelihood, deviate from fishermen’s expectations. In the second at-sea operations state of our model, fishermen observe the productivity of their gear as it is set and retrieved from the water. In other words, they obtain a signal about the true stock abundance as harvest operations proceed. Our model explicitly allows fishermen to make at-sea adjustments in response to unanticipated stock abundance. For example, if the abundance is higher than expected and the productivity of gear exceeds planning stage expectations, more gear may be applied, e.g., the length of the trip may be extended relative to pre-trip plans. The opposite adjustment might occur if stock abundance/gear productivity falls below expectations. We exploit methods used in the stock assessment literature to construct a proxy for the at-sea productivity signal that is observed by the fishermen on each trip.

Our estimations exploit the timing of productions decisions, available information, and natural variability in the fish stock to obtain consistency in estimation. We collected trip-level cost and catch data from the US Gulf of Mexico commercial reef fish fishery; 75,564 observations in all for the 2005-14 fishing seasons. Gulf of Mexico reef fish fishermen target five major species, and harvest roughly 90 minor reef fish species, across a spatially and temporally heterogeneous fishing ground. Our application shows how estimations that ignore the omitted variable bias can significantly miss-measure the structural properties of a fishing technology. Estimates of species-specific marginal harvesting costs obtained under a naive estimation, i.e., where latent stock effects and endogenous harvesting and targeting are ignored, are between 41.3% - 87.7% larger than our model estimates. The extent to which bias of this magnitude has misdirected management policy in the reef fish fishery is beyond the scope of our paper but a worthy topic of investigation.

Our paper is the first to link harvest costs to a latent, multiple-species fish stock that is heterogeneous across space and time. It is also the first to estimate a weak output disposability or costly targeting harvest technology. These contributions open new avenues for evaluating the bioeconomic effects of fisheries management policies and regulations. We demonstrate this possibility by simulating, with our fitted cost function, the effects of a quota regulation on costs and wasteful discarding in the reef fish fishery.

The rest of the paper is organized as follows. The next section reviews existing models of fish harvesting technologies, emphasizing the empirical challenges that arise particularly in applications with spatially and temporally varying stock abundance. Section 1 outlines features of commercial fishing data generating processes that guide our cost function specification and estimations. Section 2 presents the model. Section 3 describes our data and section 4 presents estimation results and simulations. Section 5 summarizes the main findings and discusses some extensions.
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 (G-S) 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 fact a composite (index) of factors of production such as capital, crew labor, fuel, nets, hooks and bait used to harvest fish.\(^3\) Dual models of harvesting 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 in multiple species fisheries. 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 (1987b, 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. We next demonstrate the omitted variable bias problem in empirical measurement of fishing technologies. We also review methods that have been proposed to control for stock abundance effects in empirical analyses.

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

\(^4\)Alternative dual models of harvesting technologies are reviewed in Jensen (2002).
1.2 Omitted stock abundance and bias in estimation

For simplicity we discuss the omitted variable problem in the context of a more general, single-species G-S model. The arguments are easily extended to the multiple-species case. We consider a Cobb-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 \( s \) denotes the location and \( t \) the date at which fishing takes place.

The 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 sufficiently 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; \( \alpha \) and \( \delta \) are the parameters of interest.

The fisherman’s problem for any trip time and location is to also choose effort \( E \) to maximize 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 (we relax this assumption below). The skipper’s problem is then,

\[
\pi(p, w|X_{st}) = \max_E \{pqE^{\alpha}X_{st}^{\delta} - wE\}, \text{ for given } s \text{ and } t,
\]

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

Identification of the model parameters in the primal framework requires data on harvest, effort, prices, and the spatial-temporal stock abundance. Stock abundance however is unknown to the researcher. A model-generated estimate of the total abundance in the entire fishery may be available; stock estimates that are delineated at the spatial-temporal scale of an individual fishing trip are uncommon.

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 parameter \( \alpha \) could be obtained but 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 unobserved stock abundance. In either case, failing to control for stock abundance introduces
omitted variable bias in the estimation (Ekerhovd and Gordon, 2013).

Several approaches have been proposed to address the problem of omitted stock abundance in the analysis of fisheries production data. The two-equation model of Gordon (1954) and Schaefer (1954) has been used extensively in stock assessment modeling (see Zhang and Smith (2011) for a review). A recent adaptation of this approach by Zhang and Smith (2011) uses panel data to estimate latent stock abundance and the Cobb-Douglas harvest-effort elasticity parameter, $\alpha$ from the generalized Cob-Douglas model. Estimation of the harvest-stock elasticity is not possible because absolute abundance is not identified in the G-S two-equation model. The authors form a multiple species harvest 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 $\alpha$, 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 stock conditions, and (3) within-period variation in effort that is sufficient to identify the harvest-effort elasticity parameter. Below we will argue that conditions (1)-(3) do not characterize 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, stock abundance estimates are produced with models that are populated from indirect data sources, and are rarely if ever available at fine spatial-temporal scale. If true stock abundance is heterogeneous across space and time, inserting a seasonal/regional average estimate will not address the omitted variable problem, since at any spatial location or date fishermen will be harvest at an abundance level 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 changing abundance over time (see Maunder and Punt (2004); SEDAR (Southeast Data and Review) (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.

Virtual population analysis (VPA) is commonly used to estimate stock abundance. The approach tracks the number and age of fish that are removed from the fishery over time. Observable (but invariably estimated) 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 method’s name implies, a estimate of a virtual rather than actual fish population obtains. It is the latter, we claim, on which fishermen base their endogenous production decisions. VPA-based stock estimates therefore does not appear to be a promising approach for addressing the problem of omitted variable bias in fisheries analysis.

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5Consistent 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 $\alpha$. 
We contend that the problem of unobserved and/or omitted fish stock abundance impacts all previous estimations of fishing technologies. To address the 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 in 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 structure, e.g., coral reefs, bottom substrate, and water depth, currents, which is heterogeneous across space. 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 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 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

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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 Abbott et al. (2015); Branch and Hilborn (2008); Singh and Weninger (2017) for empirical evidence.
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.

**Regulations:** A central goal of fisheries management is to ensure 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.

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.  

Input controls were replaced with individual fishing quotas (IFQs) in 2007 for red snapper and in 2010 for grouper and tilefish species. Under the IFQ regulation, fishermen hold shares of an aggregate annual quota for individual species or species groups. Quota shares translate to annual 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.

Note that trip level landings constraints were dropped under the IFQ regulation. Under IFQs, fishermen face a quota user cost but otherwise free to organize aspects of production at the level of an individual trip.

**Space and time:** It is worth emphasizing that space and time are continuous objects and we treat them as such in our model. Collecting fishing trips into bins of arbitrary calendar length, e.g., weeks, months, or years, does not match the decision environment in a trip-level analysis. Barring constraints from spatial or temporal closure regulations, the date and location for a trip is endogenous and continuous. Dividing continuous space into discrete units or patches is restrictive and potentially misleading (Berman, 2006). Discritization across space requires delineation of boundaries between patches or subregions, with an implicit assumption that a distinct subregion shares common stock abundance and/or stock effects. It is unclear how such boundaries would be determined in practice, e.g., subregions that follow political considerations are unlikely to coincide with heterogeneous ecological mosaic of a fishing ground.

Finally, we do not model the decision of where and when trips are taken in this paper. Our estimates of trip costs are therefore conditional on predetermined \((s, t)\) choices.

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.

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8Closures were staggered throughout each year to avoid supply gluts and low dockside prices.
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 particular species mix. We define \( t \) as the trip start 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 operations stage, hereafter referred to as the planning and operations stages, respectively. We assume the optimizing agent, the vessel skipper, makes planning stage decisions and at-sea adjustments with the goal of maximizing trip expected profits given available information on prices, regulations, and stock conditions, and the constraints imposed by the technology.

Planning stage choices include the mix of factor inputs (labor, fuel, gear, bait, food and other supplies) to be used on the trip and selection of the coarse location and date of the trip. We do not model the choice of \((s, t)\) but rather focus on optimizing behavior, given the decision to take a trip is made. Importantly, randomness of the fish stock imply that planning decisions be based on expectations of abundance that will be encountered on the trip, as summarized by \( F(X|s, t) \).

It should be emphasized that planning stage decisions endogenously determine the expected trip harvest and cost only. The realized harvest and cost are also impacted by the realization of the random stock, \( X_{st} \).

The harvest operations stage begins when the vessel departs port and ends when the vessel returns. Once on the water, adjustments to factor inputs and targeting actions are assumed to be limited. For example, the mix of crew, fuel, gear is fixed, and hook types and bait cannot be changed once the vessel leaves port. Moreover, a change in the coarse trip location is unlikely given the fixed quantity of fuel onboard.

We do allow one particular modification to pre-trip plans during the at-sea operations phase. As gear is set and retrieved the skipper and crew observe its productivity and thus learn about realized stock abundance. Fishing thus provides a signal about the productivity of applying factor inputs on the trip. It is reasonable to expect the skipper will make adjustments 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 thus reducing inputs allocated relative to 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. True stock abundance, \( X_{st} \), is unknowable.

**Assumption 2 (Costly targeting).** Fishermen choose the mix of factor inputs (fuel, labor, gear, food, bait and other supplies) and targeting actions at the pre-trip planning stage, conditional on exogenous or predetermined information \( \Omega = \{p, w, R, k, F(X|s, t)\} \), where \( p \) and \( w \) are vectors
of species-specific 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 signal \( \chi \) of the realized stock abundance \( X_{st} \) and correspondingly the realized productivity of factor inputs during the operations stage. Operations stage adjustments to pre-trip plans are limited to increasing or decreasing input and harvest scale; no adjustments to the 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):

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

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 \( S_i(h) = \sum_j h_j \) 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 are in fact zero.

The targeting component of costs, \( A \), 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 net returns at the dock (Singh and Weninger, 2009).

Singh and Weninger (2009) assume 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. 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 \( h \) (Smith, 1968; Clark, 1974). The form for \( \delta(X_{st}) \), and its identification is addressed below.

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9Prices may vary across space and time. We exclude \((s, t)\) subscripts to simplify notation.
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) implicitly treats vessel capital as a fixed input. Thus, (2) is interpreted as a short run cost function.\(^\text{10}\) We assume that factor input prices are exogenous.

The regression error term \( u \) is assumed to have zero mean and finite variance, and to satisfy the following assumptions:

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

Two challenges must be overcome to obtain consistent estimates of the cost function parameters. The first arises from the endogenous targeting actions chosen during planning. The second from potential adjustments in the harvest scale in response to the at-sea signal of the trip’s productivity, \( \chi \). 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 utilize assumptions (1)-(3) 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 nuisance parameters associated with these approximations with the Greek symbol, \( \theta \).

**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, \( \chi_n \), for each trip in our data. Catch and effort stock assessment maintains the assumption that at small spatial scale, the catch of fish, typically measured as the number of 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 must be emphasized that for use in stock assessment, **effort** is defined as the units of gear, such as nets or baited hooks that are deployed to the water only. Units of gear deployed should not be confused with the total quantity of fuel, labor, capital, gear, bait and supplies that are allocated on a trip. In our empirical application, we follow GOM stock assessment scientists (SEDAR (Southeast Data and Review), 2014) and use the number of hooks times the hours hooks are soaked in the construction of reef fish catch-effort indices. This definition of effort is used for the remainder of the paper.

Stock assessment proceeds by specifying a catch per unit of effort (CPUE) equation, \( h/E = qX \). To address the multispecies nature of the catch in our data, let \( \bar{h}_n = h_n'\omega \) and \( \bar{X}_n = X_n'\omega \) denote, respectively, linear aggregates across species of trip \( n \) harvest and abundance. In data on 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 harvest and transport more fish per trip and operate in more severe weather conditions and more distant locations from port.
catch, harvest is typically measured in pounds of each specific species, so we set \( \omega_i = \frac{1}{\text{wgt}_i} \), where \( \text{wgt}_i \) 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.\(^{11}\) Recall that all planning decisions are made conditional on the information set \( \Omega_n \), 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 \( \overline{h}_n / E_n = q(\Omega_n)X_n \).

We next decompose \( X_n \) into the product of a deterministic component, denoted \( \mu(s,t) \), and a deviation \( \chi_n \). 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:

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

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 \( (\Omega_n, s, t) \), and \( \theta_J \) is a conformable parameter vector. Generalized cross validation can be used to determine \( J \) (Li and Racine, 2007).

Making this final substitution obtains our CPUE estimating equation:

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

The unknown parameters \( (\alpha_f, \theta_J) \) can be estimated with ordinary least squares. An estimate of \( \chi_n \) is then obtained as:

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

\(^{11}\)Maunder and Punt (2004) and Maunder et al. (2006), acknowledge 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 \( \chi_n \) and therefore we follow this level of generality.
where we are relying on the approximation in (4) to be good enough (i.e. \( J \) to be large enough) to render \( \epsilon_n \) 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. The implication is that the catch-and-effort model cannot be used for stock assessment if catchability varies with 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 shock; 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 operations stage information received on trip \( n \). 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 clarified above. Equation (5) controls for the non-\((s, t)\) elements of \( \Omega_n \), 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 \( \beta_w \) is an factor price-cost elasticity parameter vector.\(^{12}\) Taking logarithms in equation (2) and making substitutions obtains:

\[
\ln C(y_n) = \ln (A_n) + \delta(X_n) + \beta_0 + \beta'_h h_n + \beta'_w \ln(w_n) + \beta_k \ln(k_n) + u_n. \tag{7}
\]

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 species mix on harvest costs operates through the no-targeting-cost share vector \( \varphi(X_n) \in \Phi_n \). (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 \( \delta(s, t) \) into a deterministic component, \( \bar{\delta}(s, t) = E[\delta(st)] \), and a component that is unanticipated. The\(^ {12}\)The log-log form allows the property of linear homogeneity in factor input prices to be imposed through the restriction \( \sum_j \beta_{w,j} = 1 \).
unanticipated component is naturally specified as $\chi_n$, which was estimated by $\hat{\chi}_n$ in the previous step.

Our specification of $\delta(s, t)$ follows from the assumptions for the CPUE model. Under the assumption that catchability is $(s, t)$—invariant, the deterministic component $\delta(s, t)$ can be specified as a function of the constructed abundance index, $\hat{\mu}(s, t)$. If $q \perp (s, t)$ cannot be justified, $\delta(s, t)$ remains latent. We consider two additional possibilities for our estimation. We can specify $\delta(s, t)$ 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 $\delta(s, t) = \delta$, 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 $\delta(s, t)$ to a polynomial of $(s, t)$ or to a constant will allow us to identify absolute abundance effects on costs. 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 but rather approximate $A^*$ as: $A^*(\Omega_n) = \sum_{j=1}^J \theta_j b_j(\Omega_n) + a_n$, where $b_j(\Omega_n)$ are known functions of the components of $\Omega_n$, $\theta_j$ is a vector of parameters, and $a_n$ is an approximation error. Generalized 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 $A^* + \delta(s, t)$ 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,

$$\ln C(y_n) = B^J(\Omega_n, s, t)\theta + \delta_n \hat{\chi}_n + \beta_0 + \beta_h h_n + \beta_w \ln(w_n) + \beta_k \ln(k_n) + u_n. \tag{8}$$

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

Including the series approximation for $A^* + \delta(s, t)$ and the control for the at-sea productivity shock $\delta_n \hat{\chi}_n$ 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 $(\beta_h)$ is obtained through the exogenous, natural variation in unobserved stock conditions. Identification of input price and capital effect parameters, $\beta_w$, and $\beta_k$ respectively, follows from our assumptions that input prices are exogenous and available capital predetermined.

In light of the difficulties anticipated in further identifying the targeting cost term, one may choose to end the analysis here. The term $\beta_0 + \ln(A^*) + \delta(s, t)$ can be treated as the model constant or estimated in reduced form as a function of arguments $\Omega_n, s, t$. In the former case, the model summarizes harvest costs evaluated at sample average targeting costs. The latter approach would
map \( \Omega_n, s, t \) 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 \( \Theta = (\gamma, \beta_0, \delta(s, t), \varphi_1(X_n), \ldots, \varphi_I(X_n)) \).

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

\[
\varphi_i(X_n) = \frac{\exp\left(\mathcal{P}_i(s, t|\theta_i)\right)}{\sum_i \exp\left(\mathcal{P}_i(s, t|\theta_i)\right)}, \quad i = 1, \ldots, I. \tag{9}
\]

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 \( n \),

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

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 \( \Theta \). 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,

\[
\mathbb{E}(Z'_n f(\Theta, S(h_n))) = 0,
\]

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

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

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

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

\[
Q(\Theta, S(h)) = \frac{1}{N} F(\Theta, S(h))' Z\Sigma^{-1} Z' F(\Theta, S(h)). \tag{12}
\]
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:\(^{13}\)

\[
\mathbb{E}\left(f(\Theta, s(h_n))^2\right) = \sigma_f,
\]

where \( \sigma_f \) 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 non-linear GMM estimator.

3 Data

Our empirical application features the Gulf of Mexico (GOM) commercial reef fish fishery during 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 vessel operators. A survey of annual capital and fixed operating expenses conducted by the Southeast Fisheries Science Center supplements the logbook data.

Trip level costs are the sum of fuel expenses, crew labor expenses, measured as the opportunity cost of hours worked outside the fishery (described below), bait, food and other miscellaneous expenses, and capital costs that are calculated as described in appendix 7.

\(^{13}\)Serial correlation in the model error term cannot be separated from latent and potentially temporally correlated stock effects. We therefore rule out serial correlation in the model error.
The full 2005-14 log book data contain 75,564 trips taken in the eastern GOM region. We focus our analysis on the most common gear types, bandit, handline, trolling and bottom longline 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 harvest, hooks, and soak time; 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 than 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 all 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 6.

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,

14 We drop 3,532 trips that landed primarily shark species (75% or more of total trip landings), and 202 trips with incomplete vessel and gear deployment data.
and dolphin species) and all remaining reef fish species. Quantities in output groups that consist of multiple species are formed as linear aggregates.

**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).\(^{15}\)

The regulations in place at the date that each trip occurred are obtained from the Southeast Fisheries Science Center (see table 8 of appendix 6 for details).

Our measure of space corresponds to the coarse management subregions shown 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 subregional 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 \(t\).\(^{16}\)

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 longer term trend effects.

Instrument variables available in our data include species-specific landings prices, the price of fuel, the labor wage rate, a measure of vessel capital (vessel length in feet), and the regulations including species-specific closures (used during the pre-IFQ regime), and annual quotas. Endogenous targeting under the quota regulation is expected to vary with the virtual fish prices, the landings price less the quota lease rate (Singh and Weninger, 2009; Squires and Kirkley, 1996). We do not observe equilibrium quota lease prices in our data. We construct a proxy measure of quota scarcity and lease prices by calculating the ratio of unfished to total quota by species at commencement date for each trip. A complete list and description of instruments are presented in table 8 of appendix 6.

Chebychev transformations (Miranda and Fackler, 2004) of our \((s, t)\) measures are used in the all polynomial approximations. Analysis and regressions are carried out using Gauss 18 software.

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\(^{15}\)As in many commercial fisheries a common form of labor remuneration in the GOM reef fish fishery pays crew members with shares of the trip revenue, or shares of revenue less some component of variable trip costs. Pricing crew labor at its opportunity cost avoids further removal of observations with missing crew share information.

\(^{16}\)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 regional and depth spatial dimensions used here. This extension is reserved for future work.
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.

**CPUE model results**

Effort is calculated as the number of hooks times the hours the gear is soaked on each trip (SEDAR (Southeast Data and Review), 2014). Our weighting vector, used to construct $\bar{h}_n = \sum_i h_{n,i} wgt_i$ is the average fish weight estimated from an observer database that is maintained by the NMFS.\(^{17}\)

We estimate equation (5) with the sum of log catchability and $\log \mu(s, t)$ 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 15.01% of the variability in the abundance index is orthogonal to $\Omega_n$, 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 ‘$\hat{\cdot}$’ 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

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\(^{17}\)Observer 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.
the results for illustrative purposes. We calculate the index $\hat{\mu}_n$ by centering all non-$(s, t)$ elements of $\Omega_n$ at their sample mean values. Appendix 6 reports results, including plots of $\hat{\mu}_n$ against space and time. The range of $\hat{\mu}_n$ 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 $\gamma$ 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 microfishing locations to target individual reef fish species may be more difficult with longline gear.

The targeting parameter is specified as $\gamma = \exp(\tilde{\gamma} + \tilde{\gamma}^{LL}D_{n,LL}^{LL})$ where $D_{n,LL}^{LL}$ is set equal to 1 if trip $n$ fishes with longline gear, and zero otherwise. Parameters $(\tilde{\gamma}, \tilde{\gamma}^{LL})$ are estimated. The 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 $\ln(A^*) + \delta(s, t)$ (equation (8)) that includes all components of $\Omega_n$ 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.

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,
<table>
<thead>
<tr>
<th>Variable</th>
<th>Parm.</th>
<th>Est.</th>
<th>Std. Err.</th>
<th>p-val.</th>
<th>90% c.i.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red. snap.</td>
<td>(\beta_{h1})</td>
<td>0.047</td>
<td>0.012</td>
<td>&lt;0.001</td>
<td>0.027, 0.074</td>
</tr>
<tr>
<td>Verm. snap.</td>
<td>(\beta_{h2})</td>
<td>0.206</td>
<td>0.020</td>
<td>&lt;0.001</td>
<td>0.170, 0.246</td>
</tr>
<tr>
<td>Red grp.</td>
<td>(\beta_{h3})</td>
<td>0.421</td>
<td>0.027</td>
<td>&lt;0.001</td>
<td>0.366, 0.477</td>
</tr>
<tr>
<td>Gag grp.</td>
<td>(\beta_{h4})</td>
<td>0.204</td>
<td>0.057</td>
<td>&lt;0.001</td>
<td>0.102, 0.328</td>
</tr>
<tr>
<td>O.S.W. grp.</td>
<td>(\beta_{h5})</td>
<td>1.080</td>
<td>0.164</td>
<td>&lt;0.001</td>
<td>0.782, 1.431</td>
</tr>
<tr>
<td>D.W. grp.</td>
<td>(\beta_{h6})</td>
<td>0.311</td>
<td>0.064</td>
<td>&lt;0.001</td>
<td>0.214, 0.471</td>
</tr>
<tr>
<td>Tilefish</td>
<td>(\beta_{h7})</td>
<td>0.202</td>
<td>0.183</td>
<td>0.272</td>
<td>-0.161, 0.683</td>
</tr>
<tr>
<td>Oth. Spec.</td>
<td>(\beta_{h8})</td>
<td>0.188</td>
<td>0.016</td>
<td>&lt;0.001</td>
<td>0.156, 0.217</td>
</tr>
<tr>
<td>Red. grp. (LL)</td>
<td>(\beta_{h9}^{LL})</td>
<td>0.042</td>
<td>0.007</td>
<td>&lt;0.001</td>
<td>0.029, 0.058</td>
</tr>
<tr>
<td>Oth. sp. (LL)</td>
<td>(\beta_{h9}^{LL})</td>
<td>0.054</td>
<td>0.008</td>
<td>&lt;0.001</td>
<td>0.040, 0.072</td>
</tr>
<tr>
<td>ln((w_{f}))</td>
<td>(\beta_{f})</td>
<td>0.298</td>
<td>0.078</td>
<td>&lt;0.001</td>
<td>0.135, 0.444</td>
</tr>
<tr>
<td>ln((w_{l}))</td>
<td>(\beta_{l})</td>
<td>0.546</td>
<td>0.273</td>
<td>0.046</td>
<td>0.052, 1.121</td>
</tr>
<tr>
<td>ln(vessel len.)</td>
<td>(\beta_{k})</td>
<td>1.171</td>
<td>0.104</td>
<td>&lt;0.001</td>
<td>0.979, 1.381</td>
</tr>
<tr>
<td>(\chi_n)</td>
<td>(\beta_{\chi})</td>
<td>-0.056</td>
<td>0.009</td>
<td>&lt;0.001</td>
<td>-0.075, -0.039</td>
</tr>
</tbody>
</table>

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.

\[
\beta_0 + \delta(s, t) + \ln(A^*) + u_n = \ln C_n - \hat{\beta}_h h_n - G(w_n, k_n, \hat{\beta}).
\]  

A maintained hypothesis of our model is that individual species targeting in response to economic incentives and regulations is an important component of the reef fish 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 \(\Omega_n\). 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. The results find that gear types are significantly correlated with the step 1 residual. The model R-squared is 61.6%. 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 \(\Omega_n\) 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 unfished quota at the date of the trip, \(Q_1\) for red snapper, and \(Q_3\) for red grouper, 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); the findings offer evidence in support of our characterization of the costly species’ targeting we

---

18 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.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coeff.</th>
<th>Std. Err.</th>
<th>t-stat</th>
<th>p-val.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.532</td>
<td>0.053</td>
<td>9.955</td>
<td>0.000</td>
</tr>
<tr>
<td>HL gear</td>
<td>-0.317</td>
<td>0.049</td>
<td>-6.535</td>
<td>0.000</td>
</tr>
<tr>
<td>TR gear</td>
<td>-0.729</td>
<td>0.083</td>
<td>-8.743</td>
<td>0.000</td>
</tr>
<tr>
<td>LL gear</td>
<td>1.058</td>
<td>0.051</td>
<td>20.570</td>
<td>0.000</td>
</tr>
<tr>
<td>$S_{h1}$</td>
<td>-0.050</td>
<td>0.123</td>
<td>-0.409</td>
<td>0.341</td>
</tr>
<tr>
<td>$S_{h3}$</td>
<td>-0.145</td>
<td>0.074</td>
<td>-1.960</td>
<td>0.025</td>
</tr>
<tr>
<td>$S_{h8}$</td>
<td>-0.600</td>
<td>0.093</td>
<td>-6.483</td>
<td>0.000</td>
</tr>
<tr>
<td>$S_{h1} \cdot S_{h3}$</td>
<td>-0.016</td>
<td>0.344</td>
<td>-0.047</td>
<td>0.481</td>
</tr>
<tr>
<td>$S_{h3} \cdot S_{h8}$</td>
<td>0.673</td>
<td>0.565</td>
<td>1.191</td>
<td>0.117</td>
</tr>
<tr>
<td>$S_{h1} \cdot s$</td>
<td>1.312</td>
<td>0.383</td>
<td>3.428</td>
<td>0.000</td>
</tr>
<tr>
<td>$S_{h1} \cdot t$</td>
<td>0.108</td>
<td>0.110</td>
<td>0.981</td>
<td>0.163</td>
</tr>
<tr>
<td>$S_{h3} \cdot s$</td>
<td>0.260</td>
<td>0.126</td>
<td>2.060</td>
<td>0.020</td>
</tr>
<tr>
<td>$S_{h3} \cdot t$</td>
<td>-0.015</td>
<td>0.065</td>
<td>-0.235</td>
<td>0.407</td>
</tr>
</tbody>
</table>

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 errors 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.

**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.

Step 2 estimation is carried out under three specifications for the stock level effect; (1) $\delta_n$ constant and thus subsumed into the model constant $\beta_0$, (2) $\delta_n$ proportional to $\hat{\mu}_n$ obtained from the CPUE model, and (3) $\delta_n$ set to a polynomial of space and time. The expression in 10 makes clear that identification of $\varphi_i$’s is not guaranteed if we are forced to also estimate $\delta_n$ as a polynomial of space and time. In the third specification, identification of the $\varphi_i$’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 $\delta_n$ is identified from the CPUE model, i.e., if 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
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.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Est. 90% c.i.</th>
<th>Est. 90% c.i.</th>
<th>Est. 90% c.i.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_n = 0$</td>
<td>-0.022 [-2.877, 2.762]</td>
<td>0.043 [-2.890, 2.520]</td>
<td>-0.025 [-3.013, 2.620]</td>
</tr>
<tr>
<td>$\delta_n = \beta_0 \mu_n$</td>
<td>-0.453 [-0.616, -0.320]</td>
<td>-0.419 [-0.591, -0.314]</td>
<td>-0.407 [-0.542, -0.308]</td>
</tr>
<tr>
<td>$\delta_n = P(s, t</td>
<td>\theta)$</td>
<td>-1.080 [-1.412, -0.758]</td>
<td>-1.030 [-1.392, -0.778]</td>
</tr>
<tr>
<td>$\beta_{HL}$</td>
<td>0.519 [-1.947, 1.536]</td>
<td>0.720 [-1.720, 1.567]</td>
<td>1.001 [0.176, 1.627]</td>
</tr>
<tr>
<td>$\gamma_{VL}$</td>
<td>1.488 [0.300, 3.210]</td>
<td>1.385 [0.187, 3.546]</td>
<td>1.189 [0.022, 2.979]</td>
</tr>
<tr>
<td>$\gamma_{LL}$</td>
<td>3.159 [0.060, 5.450]</td>
<td>2.374 [0.038, 4.354]</td>
<td>1.022 [0.022, 5.494]</td>
</tr>
<tr>
<td>$\beta_{ef}$</td>
<td>- -</td>
<td>-0.027 [-0.067, 0.015]</td>
<td>- -</td>
</tr>
<tr>
<td>$\beta_s$</td>
<td>- -</td>
<td>- -</td>
<td>0.010 [-0.082, 0.180]</td>
</tr>
<tr>
<td>$\beta_t$</td>
<td>- -</td>
<td>- -</td>
<td>0.106 [-0.030, 0.237]</td>
</tr>
<tr>
<td>$\beta_{st}$</td>
<td>- -</td>
<td>- -</td>
<td>0.199 [-0.180, 0.323]</td>
</tr>
</tbody>
</table>

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 $\gamma$ 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 differences will be reflected in the point estimate of $\gamma$ 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.

| Species | $\delta_n = 0$ | $\delta_n = \beta \mu_n$ | $\delta_n = P(s, t|\theta)$ |
|---------|----------------|--------------------------|-----------------------------|
|         | Ave. | Std. | Ave. | Std. | Ave. | Std. |
| $\varphi_1$ | 0.232 | 0.316 | 0.185 | 0.285 | 0.195 | 0.295 |
| $\varphi_2$ | 0.007 | 0.007 | 0.005 | 0.009 | 0.008 | 0.014 |
| $\varphi_3$ | 0.102 | 0.173 | 0.125 | 0.228 | 0.073 | 0.132 |
| $\varphi_4$ | 0.038 | 0.076 | 0.030 | 0.066 | 0.038 | 0.109 |
| $\varphi_8$ | 0.582 | 0.254 | 0.609 | 0.271 | 0.662 | 0.272 |
| $\hat{A}$ | 1.580 | 0.510 | 1.551 | 0.417 | 1.420 | 0.312 |
| $C_1$ | 0.151 | 0.195 | 0.150 | 0.193 | 0.150 | 0.178 |
| $C_2$ | 0.664 | 0.847 | 0.658 | 0.838 | 0.657 | 0.774 |
| $C_3$ | 1.357 | 1.727 | 1.344 | 1.710 | 1.341 | 1.579 |
| $C_4$ | 0.655 | 0.836 | 0.649 | 0.827 | 0.648 | 0.764 |
| $C_8$ | 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 $\varphi_i$ and marginal costs (species are: 1-red snapper; 2-vermilion snapper; 3-red grouper; 4-gag grouper; 8-other species).

Further investigation reveals that 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. Sample mean estimates of $\varphi_1$ (red snapper) vary around 20% from 18.5% to 23.2%. Sample mean values for $\hat{A}$ 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.

Hereafter we report results for the case where $\delta_n = P(s, t|\theta)$.

**Targeting Costs**

Figure 2 plots fitted values for $\varphi_i$ (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
Figure 2: Fitted $\varphi_i(s, t|\theta)$’s.

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 6.

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 declines 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 \( \hat{\phi}_i \) 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 \( \hat{\phi}_i \) estimates. We calculate the difference \( S_i(h) - \hat{\phi}_i \) for each trip observation 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., \( S_i(h) - \hat{\phi}_i \) is thus a measure of targeting intensity for species \( i \) and we hereafter refer to it as such.

<table>
<thead>
<tr>
<th>Species</th>
<th>( p_i )</th>
<th>( S_i(h) )</th>
<th>( S_i(h) - \hat{\phi}_i )</th>
<th>( C_i(\cdot) )</th>
<th>( p_i - C_i(\cdot) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red. snap.</td>
<td>4.070</td>
<td>0.154</td>
<td>-0.040</td>
<td>0.150</td>
<td>3.742</td>
</tr>
<tr>
<td>Verm. snap.</td>
<td>2.942</td>
<td>0.136</td>
<td>0.127</td>
<td>0.657</td>
<td>2.227</td>
</tr>
<tr>
<td>Red grp.</td>
<td>3.298</td>
<td>0.222</td>
<td>0.149</td>
<td>1.341</td>
<td>1.985</td>
</tr>
<tr>
<td>Gag grp.</td>
<td>4.470</td>
<td>0.048</td>
<td>0.016</td>
<td>0.990</td>
<td>2.205</td>
</tr>
<tr>
<td>O.S.W. grp.</td>
<td>4.305</td>
<td>0.020</td>
<td>0.000</td>
<td>3.440</td>
<td>0.984</td>
</tr>
<tr>
<td>D.W. grp.</td>
<td>3.639</td>
<td>0.019</td>
<td>0.016</td>
<td>0.990</td>
<td>2.205</td>
</tr>
<tr>
<td>Tilefish</td>
<td>2.100</td>
<td>0.011</td>
<td>0.009</td>
<td>0.641</td>
<td>1.153</td>
</tr>
<tr>
<td>Oth. sp.</td>
<td>1.972</td>
<td>0.391</td>
<td>-0.271</td>
<td>0.597</td>
<td>1.179</td>
</tr>
</tbody>
</table>

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

Table 6 reports sample average values for fish prices, harvest shares, targeting intensity, marginal cost (derived in appendix 6), 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 \( S_i(h) - \hat{\phi}_i \) 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 groupers 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 $\varphi_i$ 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 cost 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 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 would impact estimation if the proposed steps to correct for unobserved abundance and endogenous harvest decisions were 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 of 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 variable 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 \(\delta_X \frac{\text{cov}(h, X)}{\text{var}(h)}\), where \(\delta_X\) 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 strawman model harvest effect parameters and thus overestimate true marginal costs.

We confirm this expected bias. Sample marginal cost 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 87.65% for red snapper, by 36.59% for vermilion snapper, by 41.29% for red grouper, and by 54.34% for gag grouper. The strawman model underestimates the Other species marginal costs obtained by our model by 10.24%. The finding that the direction of the omitted variable bias is reversed, and is smaller for this output category may reflect an absence of endogenous targeting effects for the Other species grouping, although this intuition cannot be confirmed.

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 thus 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 identify pre-trip targeting and at-sea adjustments in response to latent stock 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. An application of the model to the Gulf of Mexico commercial reef fish fishery demonstrates its strengths of the model and its remaining limitations.

Our structural model of a costly targeting technology is well-suited for conducting ex ante analysis of alternate regulations in fisheries, e.g., species-specific quotas, spatial closures, 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 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 harvest shares 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 however 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, 1974). 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.
References


6 Appendix

Marginal costs

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

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

The marginal harvesting cost for species \( i \) fish is,

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

Carrying out the derivations obtains:

\[ \frac{\partial A}{\partial h_i} = \frac{\gamma}{H} \left[ (s_i - \varphi_i)(1 - s_i) - \sum_{j \neq i} (s_j - \varphi_j)s_j \right] \]

\[ = \frac{\gamma}{H} \left[ (s_i - \varphi_i) - \sum_{j=1}^I s_j^2 + \sum_{j=1}^I \varphi_j s_j \right] \]

\[ \frac{\partial B}{\partial h_i} = \beta_h B, \]

where \( H = \sum_i h_i \). Function arguments are dropped to ease notation.

The matrix of second derivatives is derived as

\[ \frac{\partial^2 c(\cdot)}{\partial h_i \partial h_j} = \frac{\partial}{\partial h_j} \left\{ B \frac{\partial A}{\partial h_i} + A \frac{\partial B}{\partial h_i} \right\} \]

\[ = B \frac{\partial^2 A}{\partial h_i \partial h_j} + \frac{\partial B}{\partial h_j} \frac{\partial A}{\partial h_i} + \frac{\partial A}{\partial h_j} \frac{\partial B}{\partial h_i} + A \frac{\partial^2 B}{\partial h_i \partial h_j}. \]

The terms \( A, B, \frac{\partial A}{\partial h_i} \) and \( \frac{\partial B}{\partial h_i} \), 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:

\[
\frac{\partial^2 A}{\partial h_i^2} = \frac{\partial}{\partial h_i} \left\{ \frac{\gamma}{H} \left[ (s_i - \varphi_i) - \sum_{j=1}^I s_j^2 + \sum_{j=1}^I \varphi_j s_j \right] \right\}
\]

\[
= -\frac{\gamma}{H^2} \left[ (s_i - \varphi_i) - \sum_{j=1}^I s_j^2 + \sum_{j=1}^I \varphi_j s_j \right] + \frac{\gamma}{H} \left[ \frac{H - h_i}{H^2} - 2s_i \frac{H - h_i}{H^2} - 2 \sum_{k \neq i}^I s_k \left( \frac{-h_k}{H^2} \right) + \varphi_i \frac{H - h_i}{H^2} + \sum_{k \neq i}^I \varphi_k \left( \frac{-h_k}{H^2} \right) \right]
\]

\[
= \frac{\gamma}{H^2} \left[ 1 - 4s_i - 2\varphi_i + 3 \sum_k^I s_k^2 - 2 \sum_k^I \varphi_k s_k \right].
\]

\[
\frac{\partial^2 B}{\partial h_i^2} = \beta_{h_i}^2 B.
\]

When \( j \neq i \) we find:

\[
\frac{\partial^2 A}{\partial h_i \partial h_j} = -\frac{\gamma}{H^2} \left[ (s_i - \varphi_i) - \sum_k (s_k - \varphi_k) s_k \right] + \frac{\gamma}{H} \left[ \frac{-h_i}{H} - 2s_j \frac{H - h_j}{H} - 2 \sum_{k \neq j}^I s_k \left( \frac{-h_k}{H} \right) + \varphi_j \frac{H - h_j}{H} + \sum_{k \neq j}^I \varphi_k \left( \frac{-h_k}{H} \right) \right]
\]

\[
= \frac{\gamma}{H^2} \left[ -2(s_i + s_j) + (\varphi_i + \varphi_j) + 3 \sum_k s_k^2 - 2 \sum_k \varphi_k s_k \right].
\]

\[
\frac{\partial^2 B}{\partial h_i \partial h_j} = \beta_{h_i} \beta_{h_j} B.
\]

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

(73%) of average trip revenue (lower portion of table 7). The average gag grouper revenue share is 6%; gag grouper is an important species not for its revenue share but for the fact that the gag price is high and the species is regulated with its own relatively small 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 prices 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 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.

### Further results

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

Figure 4 plots fitted values of the deterministic component of the 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 which is the midpoint of our data. 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 index exhibits little within seasonal variation. In panel (d) shows the index increasing throughout the early years of our data, with a peak in 2011. The index declines 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 sorted and winsorized below the 5'th% and above the 95'th% values.
<table>
<thead>
<tr>
<th>Sample:</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>75,564</td>
<td>17,568</td>
<td>12,125</td>
<td>9,941</td>
</tr>
<tr>
<td>Unique vessels</td>
<td>1,677</td>
<td>624</td>
<td>518</td>
<td>358</td>
</tr>
<tr>
<td>Days at sea</td>
<td>3.88</td>
<td>3.89</td>
<td>4.04</td>
<td>4.10</td>
</tr>
<tr>
<td>Crew size</td>
<td>2.34</td>
<td>2.38</td>
<td>2.44</td>
<td>2.46</td>
</tr>
<tr>
<td>Lbs./trip</td>
<td>1,470.27</td>
<td>1,621.23</td>
<td>1,776.77</td>
<td>1,866.54</td>
</tr>
<tr>
<td>Rev./trip</td>
<td>4,611.50</td>
<td>5,096.70</td>
<td>5,555.23</td>
<td>5,897.30</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Average revenue shares</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red snapper</td>
</tr>
<tr>
<td>Verm. snapper</td>
</tr>
<tr>
<td>Red grouper</td>
</tr>
<tr>
<td>Gag grouper</td>
</tr>
</tbody>
</table>

Table 9: Descriptive statistics I: Table reports observations, 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 2005-14. 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.

The above figure reports fitted $\varphi_1(s, t|\theta)$ estimates across space and time for shallow water groupers, deepwater groupers, tilefish and Other species.
Figure 4: Panels report the fitted values for $\hat{\mu}(s,t)$ (solid lines) and 95 \% confidence intervals (dashed values).
Figure 5: Left-hand panel reports sorted and winsorized estimates of $\hat{\mu}_n$; right-hand panel reports sorted and winsorized estimates of $\hat{\chi}_n$. 
Figure 6: Fitted $\varphi_1(s,t|\theta)$'s.
7 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.

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

Table 10: Vessel Characteristics.

<table>
<thead>
<tr>
<th></th>
<th>Parm. est.</th>
<th>Std. err.</th>
<th>t-stat.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-5.21</td>
<td>0.87</td>
<td>-5.99</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Length</td>
<td>1.84</td>
<td>0.30</td>
<td>6.18</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Engine HP</td>
<td>0.48</td>
<td>0.11</td>
<td>4.45</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Hold Cap.</td>
<td>0.10</td>
<td>0.07</td>
<td>1.35</td>
<td>0.18</td>
</tr>
<tr>
<td>Vessel Age</td>
<td>-0.23</td>
<td>0.08</td>
<td>-2.81</td>
<td>0.01</td>
</tr>
</tbody>
</table>

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 provided 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
\[
\hat{V}(len.) = \bar{z}_{len.}\hat{\beta},
\]
where \(\bar{z}_{len.}\) 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 \(\rho\) denotes the rate of interest on financial capital. The capital cost incurred on a single fishing trip \(j\) is then calculated as,
\[
\frac{D_j}{D(\kappa)}\rho\hat{V}(len.),
\]
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.

<table>
<thead>
<tr>
<th>Length Class</th>
<th>Annual Fixed Cost (by DAS)</th>
<th>Annual Days-at-Sea</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>150</td>
<td>200</td>
</tr>
<tr>
<td>25</td>
<td>36,942</td>
<td>40,323</td>
</tr>
<tr>
<td>35</td>
<td>56,311</td>
<td>59,692</td>
</tr>
<tr>
<td>45</td>
<td>70,778</td>
<td>74,159</td>
</tr>
<tr>
<td>55</td>
<td>82,330</td>
<td>85,711</td>
</tr>
<tr>
<td>65</td>
<td>91,947</td>
<td>95,327</td>
</tr>
</tbody>
</table>

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.\(^1\)

---

\(^1\)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.
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 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 $\frac{D_j}{D(\kappa)}$. Trip fixed costs for vessel length len. on trip $j$ is estimated as,

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

Appendix References