Structural Behavioral Models for Rights-Based Fisheries

Matthew Reimer[a], Joshua K. Abbott[b], Alan Haynie[c]

[a]*Institute of Social and Economic Research, University of Alaska Anchorage*
[b]*School of Sustainability, Arizona State University*
[c]*Alaska Fisheries Science Center, National Marine Fisheries Service, NOAA*

Abstract

Rights-based management is prevalent in today's developed-world fisheries, yet spatiotemporal models of fishing behavior do not reflect such institutional settings. We develop a model of spatiotemporal fishing behavior that incorporates the dynamic and general equilibrium elements of catch-share fisheries. We propose an estimation strategy that is able to recover structural behavioral parameters through a nested fixed-point maximum likelihood procedure. We illustrate our modeling approach through a Monte Carlo analysis and demonstrate its importance for predicting out-of-sample counterfactual policies.

Keywords: structural econometrics, rights-based fisheries, discrete choice models

1. Introduction

The governance of many nation states' fisheries has been transformed in recent decades—from the "tragedies" of open access and input regulation to a range of governance structures based upon individual or collective extractive rights. By one estimate, approximately 20% of global catch comes from fisheries managed under individual transferable quotas (Costello and Ovando, 2019)—a number that only partially accounts for the full spectrum of rights-based management approaches, including fishing cooperatives (Deacon, 2012) or TURFs (Wilen et al., 2012). Rights-based management (RBM) is particularly common in the Global North where it is facilitated by strong scientific input and adequate governance. RBM, in combination with scientifically-based quotas and sound enforcement, has played a prominent role in reversing overfishing and improving economic efficiency in many fisheries (Worm et al., 2009; Grafton et al., 2006; Hilborn et al., 2005).

Despite these successes, RBM has not reduced the role of fisheries managers to merely conducting stock assessments and setting seasonal quotas. Catch shares, especially individual quotas, may leave significant in-season externalities unaddressed (Boyce, 1992; Costello and Deacon, 2007), forcing managers to deploy additional management measures to address concerns such as growth overfishing or in-season rent dissipation. Furthermore, many of the concerns of ecosystem-based management—e.g., protection of spawning stocks or vulnerable life stages, reducing external impacts on unfished stocks or species of conservation concern, and habitat protection—are outside the scope of most RBM systems (Holland, 2018).

As a result of these concerns, managers use a wide range of tools, including input restrictions, protected areas, time-area closures, and dynamic ocean management (Maxwell et al., 2015), *in addition to* RBM systems. Economists have informed managers of the potential consequences of these actions by developing positive bioeconomic models (e.g., Smith and Wilen, 2003; Hutniczak, 2015; Lee et al., 2017; Holland, 2011; Huang and Smith, 2014) that predict how changes to policy design may change catch, effort, profits, employment, or ecological impacts. For economists to offer reliable advice, their models must adequately capture the economic decision-making process and contextual variables to provide externally valid predictions across the range of policy/economic/ecological scenarios of interest to managers (Lucas, 1976; Wolpin, 2007; Keane, 2010). If the range of counterfactuals deviates markedly from in-sample conditions, then purely empirical, reduced-form descriptions of fisher behavior will likely be unsatisfactory. Instead, structural models that explicitly model fishers' *decision-making process* in terms of objective-seeking (e.g., profit or utility-maximizing) behavior under economic, ecological and management constraints are needed (Reimer et al., 2017a,b).

The continued adoption of RBM presents a significant challenge to fisheries policy modeling in that the overwhelming majority of empirical models used to inform in-season management measures fail to consider the implications of individualized (and often transferable) catch rights within a season. Catch share fisheries define individualized (or sometimes cooperative-based) quota constraints, which create a shadow value reflecting the opportunity cost of the quota. Within-season trading of seasonal quota harmonizes these shadow values through the coordinating mechanism of a shared lease market. Experience has demonstrated that in-season behavior is often drastically altered by catch shares. This is particularly likely in terms of the allocation of fishing "effort" in both space and time (Reimer et al., 2014; Abbott et al., 2015; Birkenbach et al., 2017; Miller and Deacon, 2017). Fishers may spread their effort temporally and reallocate where they fish to enhance revenues or reduce costs. More complex patterns may emerge in multispecies catch-share fisheries as vessels utilize space and time to maximize the profit associated with their quota portfolios. However, the current range of economic simulation models in fisheries have been specified and calibrated under preceding conditions of regulated open or limited access. As such, these models do not capture the theoretical *mechanisms* by which incentives under RBM affect fishers' in-season behavior, with the result that their predictions could be highly misleading.

There is a rich economic literature on the modeling of the spatiotemporal behavior of fishers (e.g., Eales and Wilen, 1986; Holland and Sutinen, 2000; Smith, 2005; Haynie et al., 2009; Hicks and Schnier, 2010; Abbott and Wilen, 2011). The dominant modeling approach in these papers is the static random utility maximization (RUM) model, which assumes that individual fishers choose from a set of discrete fishing sites in order to maximize their expected utility, where the expected utility of selecting a fishing site is modeled (among other factors) as a function of expected revenue and the distance from a fisher's current location. Observed fishing location choices are then used to estimate the RUM model, which can then be used to predict the effects of regulations on the amount and spatial distribution of fishing effort, harvest, revenues, and welfare.

The static RUM approach has been useful for examining the spatiotemporal behavior of fishermen in fisheries with insecure rights to seasonal catch. However, we argue that it is generally inadequate for estimation and prediction in RBM fisheries. The reason lies in the fact that seasonal individualized quotas define a set of evolving, state-contingent shadow prices for quota usage throughout the season. Dynamic profit maximization requires that these opportunity costs of quota should be subtracted from the ex-vessel price of harvest. Instead, they are lacking altogether in the estimation and prediction of static RUM models. The omitted nature of lease prices has several important implications. The absence of lease prices from expected revenues in the RUM leads to a form of omitted variable bias (or, alternatively, non-classical measurement error)—shrinking the coefficient on expected revenues towards zero and creating indeterminate biases for the coefficients of other included variables. These biases could jeopardize the estimation of shadow values (e.g., Abbott and Wilen, 2011; Haynie et al., 2009) or welfare estimates. In principle, estimation bias could be eliminated by including high-frequency lease-price data in the model; however, thin markets combined with confidentiality concerns rarely allow this.

To address these shortcomings, we develop an estimation approach for RUM models under RBM institutions that provides consistent estimates of structural model parameters while also satisfying the need to impute lease prices for out-of-sample scenarios. Our model of spatiotemporal fishing behavior incorporates the dynamic and general equilibrium elements of fisheries with tradable short-term rights of annual catch entitlements. The key innovation of our approach is the introduction of an annual lease-market for quota, which we model as a pure exchange economy with a rational expectations equilibrium. Fishers are assumed to be forward-looking within the season and form expectations over future quota usage when considering contemporaneous quota supply and demand decisions. Under the assumption of rational expectations, each fisher's stochastic dynamic programming (SDP) problem reduces to a period-by-period static maximization problem given a set of equilibrium quota prices. The intuition for this result is straightforward—all necessary information regarding quota scarcity is embedded in the equilibrium quota price.

We propose and demonstrate an estimation strategy — dubbed the rational-expectations RUM (RERUM) — that is able to recover structural behavioral parameters, even if quota-market prices are unobserved. The introduction of the quota-lease market drastically simplifies the process of recovering structural parameters because we do not have to solve a SDP problem through recursive methods. Instead, we solve a fixed-point problem to determine the equilibrium lease prices in every period, which does not suffer from the curse of dimensionality because the dimensions of the problem increase linearly, as opposed to exponentially, with the number of quota-constrained species. Thus, we are able to solve the behavioral model exactly and recover the structural parameters through a nested fixed-point (NFXP) maximum likelihood procedure (Rust, 1987). We conduct numerical simulations to demonstrate how our model can be used for *ex ante* evaluation of fishery policies, such as spatial closures or TAC reductions. We illustrate this point through a Monte Carlo analysis and investigate data-generating environments for which our approach matters most for out-of-sample predictions.

Our simulation results show the utility of the RERUM model for both parameter estimation and out-of-sample prediction. In terms of estimation, we find that substitution of high-resolution lease prices as data into the static RUM is able to mimic the performance of the RERUM. However, imputing annual average prices—which are much more commonly available— offers only a partial mitigation of the bias, since it fails to capture dynamic adjustments of behavior within the season. Furthermore, even if high-resolution lease price are available to consistently estimate the RUM model, prediction for out-of-sample scenarios requires the imputation of counterfactual lease prices that are consistent with the stochastic production environment *and* the alterations to market, ecological, or policy conditions embodied in the scenario. The market simulator at the core of the RERUM model provides this link in a way that is both consistent with the structure of fishers' dynamic decision problem and computationally feasible.

The course of the paper is as follows. Sections 2 and 3 present the structural behavioral model and the estimation strategy of the RERUM estimator. Section 4 simulates the structural model with known parameter values, but under different biological scenarios, to show the utility of the RERUM model for out-of-sample prediction under realistic policy changes, such as quota reductions and spatial closures. Section 5 provides Monte Carlo simulation evidence of the estimation performance of the RERUM model in comparison to reduced-form alternatives. It also shows the predictive utility of the RERUM model in comparison to these alternatives. Section 6 concludes the paper.

2. Conceptual Approach

Our objective is to build a model of within-season fishing behavior that generates externally valid *ex ante* predictions of fishery policies in a multispecies catch-share fishery. This prospective model must be *structural* or *mechanistic*, in the sense that it identifies policy-invariant parameters that can be safely transported into "out-of-sample" environments, facilitating the job of *ex ante* prediction (Heckman and Vytlacil, 2007; Heckman, 2010).

Structural models achieve this flexibility through explicitly modeling the hypothesized decision process of agents in response to their decision context, usually through a constrained optimization approach. This differs from estimating a reduced-form decision rule in that the latter runs the risk of fragility since underlying ecological, economic, or policy state variables may be subsumed into the estimated reduced form parameters (Fenichel et al., 2013).

Our model must satisfy several criteria. First, it must capture the primary within-season mechanisms fishermen use to shape economic returns and catch compositions. While some aspects of input usage (e.g., bait or crew staffing) may be somewhat variable within a season, the primary short-run mechanisms influencing vessel output are where and when to fish (Abbott et al., 2015; Reimer et al., 2017b; Scheld and Walden, 2018). Therefore, the spatial and temporal scale must be sufficiently disaggregated to capture important variation that fishermen use to meet their economic objectives and to inform managers of relevant impacts (e.g., catch of target and non-target species or impacts to sensitive habitat). Second, the model must be both dynamic and stochastic. Dynamic models consider that fishermen allocate their portfolio to maximize seasonal returns so that current fishing decisions depend on expectations of fishery conditions later in the season. Stochasticity implies that planning will not be perfect—catch, and hence quota balances, will not exactly match expectations. Third, the model must easily accommodate realistic changes to management policies—such as catch limits and time/area closures. Finally, estimation and simulation of the model must be achievable from available data with reasonable technology and computing time.

Our modeling approach is not the first to include dynamic and stochastic elements of spatiotemporal fishing behavior. Indeed, fishing location choice models have been extended previously to include elements of dynamic planning within the trip (Curtis and Hicks, 2000; Curtis and McConnell, 2004; Hicks and Schnier, 2006, 2008). These studies expand the myopic utility maximization assumption to consider the logistical problem of the optimal trajectory of fishing locations given that the current location choice affects the cost of access to other locations later in the trip. Optimal intra-trip location selection is therefore cast as a dynamic programming problem, with estimation of model parameters coinciding with the solution (Hicks and Schnier, 2006, 2008) or approximation (Curtis and Hicks, 2000; Curtis and McConnell, 2004) of the dynamic programming problem. Such models, however, do not capture the overriding dynamic concern that we would expect to emerge under catch shares—the management of a portfolio of quotas over the course of an entire season, where the state variables that provide the information set for fishermens decisions (i.e., expected catch, quota balances) evolve in a partially stochastic manner. A handful of papers have tackled seasonal fishing supply decisions dynamically (Provencher and Bishop, 1997; Smith and Provencher, 2003; Huang and Smith, 2014). However, the stochastic evolution of the state variables coupled with the need to solve a fisher's seasonal optimization repeatedly in the estimation process through stochastic dynamic programming (SDP) has resulted in the imposition of very strong assumptions on the models to maintain computational tractability. This has usually taken the form of severely limiting the number of spatial locations available to fishermen and curtailing the horizon of decision making in order to reduce the "curse of dimensionality." Indeed, while notable advances have been made in reducing these computational burdens, the dimensionality of most applied dynamic discrete choice models remains quite small (Aguirregabiria and Mira, 2010). As we explain below, the coordinating mechanism of the quota lease market allows us to specify production decisions over a realistic spatial and temporal scale and number of state variables (species), thereby satisfying the aforementioned criteria for a useful predictive model.

2.1. A model of a catch-share multispecies fishery

Structural models face a trade-off between realism and computational tractability, requiring that modeling decisions preserve realism where it is fundamental to the nature of agents' decision problem and predicted outcomes while sacrificing it elsewhere. In our case, the most fundamental decision concerns the modeling of the seasonal quota lease-market, which we assume to be competitive and to clear at the end of the season. That is, fishers are assumed to form expectations over quota lease-prices and treat them as given, even though prices are endogenously determined by the aggregate behavior of all fishers. Given the incentives embodied in these expected prices, fishers carry out individually optimal "on-the-water" plans by allocating their effort over a discrete number of fishing sites and time periods. We close the model under the assumption of rational expectations so that equilibrium quota prices are consistent with fishers' beliefs.

2.1.1. A fisher's dynamic programming problem

Consider agent (i.e., the fisher) i, who has preferences defined over a sequence of states of the world $z_{i,t}$ from period $t = 1$ until period $t = T + 1$. In periods $t \leq T$, agents choose a fishing location $a \in A = \{0, 1, ..., J\}$, where $a = 0$ represents the option of not fishing. In the final period $t = T + 1$, the agent buys or sells quota in the leasing market according to their accumulated quota usage. Within-season decisions are driven by agents' expectations of the end-of-season quota lease-market. In any given time period, fishers must account for the opportunity cost of using quota—whether it is best to use quota today for the profits it generates or preserve it for sale in the competitive quota market. The problem is stochastic because fishers do not know exactly what they (or others) will catch at each location and time period, and thus, they form expectations over fleet-wide catch realizations and the resulting end-of-season quota lease prices. We assume that the number of fishers is large enough that any single fisher perceives their effect on aggregate harvest and the quota lease price as negligible. Therefore, fishers' expectations of quota prices are formed exogenously to their own decisions.

We make a number of simplifying assumptions for the sake of tractability. First, the state of the world at period t for agent i is assumed to consist of two components: $z_{i,t} = (x_t, \varepsilon_{i,t})$. The subvector $\varepsilon_{i,t}$ is private information known only by agent i at the time of decision. The subvector $x_t = (x_{1,t}, ..., x_{N,t})$ contains state variables that are common knowledge to all N agents at the time of decision. For our application, $x_{i,t}$ represents an agent's S-dimensional vector of cumulative catch prior to making a decision in period t: $x_{i,t} = f_x(x_{i,t-1}) = \sum_{k=1}^{t-1} y_{i,k} = x_{i,t-1} + y_{i,t-1}$, where $y_{i,t} = Y(a_{i,t}, \xi_{i,t})$ represents fisher i's S-dimensional vector of catch in period t.[1] The term $\xi_{i,t}$

[1]In practice, the time index t and time-invariant individual characteristics can also be components of the state vector $x_{i,t}$, but we omit them here for the sake of simplicity.

represents the stochastic component of catch, which we assume to be serially uncorrelated and unknown to any fisher at the time a decision is made in period t.

Second, we assume that an agent's contemporaneous utility function for location $a_{i,t}$ is additively separable in the observable and unobservable components:

$$U\left(a_{i,t}, z_{i,t}\right) = \begin{cases} u\left(a_{i,t}, p' y_{i,t}\right) + \varepsilon_{i,t}\left(a_{i,t}\right) & \text{if } t \in \{1, ..., T\} \\ u\left(0, w'\left(\omega_i - x_{i,T+1}\right)\right) & \text{if } t = T+1, \end{cases} \tag{1}$$

where ω_i denotes a vector of quota endowments possessed by fisher i at the beginning of the season, w denotes a vector of quota-lease prices, and p denotes a vector of ex-vessel prices. An agent's utility in the final period $T+1$ is evaluated at port $(a = 0)$ with revenue equal to the value of their remaining endowment of quota.[2] For simplicity, we further assume that fishers are risk-neutral so that revenue enters utility linearly and is additively separable from the rest of utility.

Third, we assume that the unobserved state variables $\varepsilon_{i,t}$ are independently and identically distributed (iid) across agents, time, and locations, and have an extreme-value type 1 distribution that is common knowledge across fishers.

Fourth, we assume that catch y is independent of the unobserved state variables ε and the observed endogenous state variables x, conditional on

[2]It can be shown that the indirect utility function in period $T+1$ follows from an agent choosing consumption and an amount of quota to maximize utility, subject to a budget constraint (see section Appendix B for details).

the location choice a. This assumption implies that the stochastic component of catch ξ is conditionally independent of past, present, and future values of ε and x, so that: $E(y_{i,t} \mid a_{i,t}, x_{i,t}, \varepsilon_{i,t}) = E(y_{i,t} \mid a_{i,t})$. Practically speaking, this assumption has several implications. First, a fisher's private information about a location choice does not affect catch (or expectations of catch) once the fisher's choice has been made—i.e., private information only influences catch by influencing a fisher's choice. Second, cumulative catch, as reflected in x_t, does not influence the distribution of contemporaneous catch—i.e., within-season spatiotemporal stock dynamics are exogenous to fishing behavior. Finally, this assumption also implies that the next-period cumulative catch $x_{j,t+1}$ of any fisher j is independent of fisher i's current period unobserved state variable $\varepsilon_{i,t}$, conditional on the values of the decision $a_{i,t}$ and state variable $x_{i,t}$. Together, these assumptions define what is often referred to as the dynamic programming (DP) conditional logit model (Rust, 1987).

In periods $t \leq T$, an agent observes the vector of state variables $z_{i,t}$ and chooses an action $a_{i,t} \in A$ to maximize expected utility

$$E\left(\sum_{j=0}^{T+1-t} U\left(a_{i,t+j}, z_{i,t+j}\right) \,\middle|\, a_{i,t}, z_{i,t}\right). \tag{2}$$

The decision at period t affects the evolution of future values of the state variables $x_{i,t}$, but the agent faces uncertainty about these future values due to the unknown nature of future catch. The agent forms beliefs about future states, which are objective beliefs in the sense that they are the true transition probabilities of the state variables. By Bellman's principle of optimality, the value function during the fishing periods $t \leq T$ can be obtained using the recursive expression:

$$V\left(z_{i,t}\right)=\max_{a\in A}\left\{U\left(a,z_{i,t}\right)+E_z\left(V\left(z_{i,t+1}\right)\,\middle|\,a,z_{i,t}\right)\right\},\tag{3}$$

where E_z denotes the expectations operator with respect to the state vector z.[3]

Unfortunately, there is typically no analytical form for the expected value function, and computationally expensive numerical and recursive methods are often needed to solve the Bellman equation instead. The restrictions these methods place on the dimensionality of the state space have often limited the empirical relevance of dynamic programming models of fisher behavior. Thankfully, the assumptions underlying the DP conditional logit model imply that fisher i's optimal decision rule in each period is dramatically simplified if fishers possess a vector of "shadow prices" reflecting the expected marginal value of additional quota for each species in the fishery given current quota usage, w_t. Given transferability of quota across fishers in a fluid within-season market, these shadow prices are harmonized across fishers and equivalent to the expected end-of-season lease prices. Conditional on these lease prices, the solution of Eq. (3) takes on a simple, static form:[4]

$$\alpha(z_{i,t}\mid w_t)=\underset{a\in A}{\operatorname{argmax}}\left\{u\left(a,(p-w_t)'\,E\left(y_{i,t}\,\middle|\,a\right)\right)+\varepsilon_{i,t}\left(a\right)\right\}.\tag{4}$$

The policy function has a simple analytical form that does not depend on the endogenous state variable $x_{i,t}$. Rather, it depends only on the fisher's

[3]Note that we do not include a discount factor.

[4]See Appendix C for a formal derivation.

current private information $\varepsilon_{i,t}$ and the expected quota-lease price w_t, both of which are exogenous. Intuitively, the quota-lease price embeds all relevant information regarding expected future quota scarcity needed to inform the present-day decision.[5] Functionally, this means that, given a perceived quota-lease price, the location-choice problem in equation (2) reduces to a tractable period-by-period static maximization problem that does not require recursively solving the Bellman equation.

2.1.2. Rational Expectations Equilibrium Quota Prices

Eq. (4) presents a fisher's optimal decision rule for a given quota-lease price at a point in time w_t. Fishers determine their optimal location choices over the course of the season given perceived quota prices w_t as specified by the policy function $\alpha(z_{i,t} \mid w_t)$ in equation (4). In this sense, quota prices determine fisher behavior. At the same time, given fishers' decision rules $\alpha(z_{i,t} \mid w_t)$, the end-of-season quota market determines expected quota prices in each period so that aggregate fisher behavior determines the equilibrium quota prices. Rational expectations states that the market-clearing quota prices implied by fisher behavior are the same as the quota prices on which fishers' decisions are based. That is, the market-clearing equilibrium quota prices are consistent with fishers' quota-price expectations.

The expected quota-price vector w_t is determined by a competitive market equilibrium in the final period $T + 1$. Let $X_t = \sum_{\forall i} x_{i,t}$ denote the vector of fleet-wide cumulative catch at the beginning of period t for all species and let

[5] The policy function in equation (4) takes on a similar form to the utility function used by Miller and Deacon (2017).

$\Omega = \sum_{\forall i} \omega_i$ denote the vector of fleet-wide quota endowments for all species. Then the end-of-season excess demand for quota for species s can be written as $e_s = X_{s,T+1} - \Omega_s$. In any given period $t \leq T$, a fisher does not know with certainty what the demand for quota will be at the end of the season; thus, fishers form expectations over end-of-season excess demand given a perceived w_t and the state of the world in period t:

$$\begin{aligned} E\left(e_s \mid w, x_t\right) &= E\left(X_{s,T+1} \mid w_t, x_t\right) - \Omega_s \\ &= \left[\sum_{k=t}^{T} \sum_{\forall i} \sum_{\forall a \in A} f\left(a \mid w_t\right) E\left(y_{i,s,k} \mid a\right)\right] + X_{s,t} - \Omega_s, \end{aligned} \tag{5}$$

where $f(\cdot)$ denotes the probability mass function for the discrete location-choice variable a and the bracketed term represents the expected catch for all fishers in the remaining periods.[6] Given the assumption that fishers know the distribution of private information for all agents, $f(\cdot)$ can be derived by integrating the policy function (4) over the unobserved state variable:

$$f\left(a \mid w\right) = \int I[\alpha\left(z \mid w\right) = a] g(\varepsilon) d\varepsilon,$$

where $I[\cdot]$ is an indicator function and $g(\cdot)$ is the probability density function of ε. The expected equilibrium quota-lease prices in period t can then be

[6] For simplicity, we have implicitly assumed that a fisher forms their expectation of excess demand before they observe their private information ε. For a large number of fishers, as we've assumed here, this has a negligible influence on our results; it is, however, trivial to relax this assumption at the cost of model presentation.

defined as those that satisfy the following market-clearing conditions:

$$\begin{aligned} E\left(e_s \mid w_t, x_t\right) = 0 \quad \text{for} \quad w_{s,t} > 0 \\ E\left(e_s \mid w_t, x_t\right) \leq 0 \quad \text{for} \quad w_{s,t} = 0. \end{aligned} \tag{6}$$

That is, in equilibrium, prices will adjust so that positive prices achieve zero expected excess quota demand for scarce species, while prices fall to zero for species in excess supply (i.e., "free goods"). The equilibrium quota prices that solve the market-clearing conditions in the system of equations (6) are thus a function of the observed (and common knowledge) state of the world in period t. We denote the equilibrium quota-lease price vector as $\tilde{w}(x_t)$.

Under the assumption of rational expectations, fishers' beliefs are consistent with the market-clearing conditions in (6). Thus, to close the rational expectations model, we substitute the equilibrium quota prices $\tilde{w}(x_t)$ into a fisher's optimal decision rule:

$$\alpha(z_{i,t}) = \underset{a \in A}{\operatorname{argmax}} \left\{ u\left(a, (p - \tilde{w}(x_t))' E\left(y_{i,t} \,\middle|\, a\right)\right) + \varepsilon_{i,t}(a) \right\}, \tag{7}$$

Eq. (7) serves as the basis for our rational-expectations RUM (or RERUM) model.

3. Estimation

We wish to estimate a vector of structural parameters in the utility function θ utilizing panel data for N individuals who behave according to the decision model described in Section 2. For every observation (i, t) in this panel dataset, we observe the individual's action $a_{i,t}$, the payoff variable $y_{i,t}$, and the subvector x_t of the state vector $z_{i,t} = (x_t, \varepsilon_{i,t})$. Because the subvector

$\varepsilon_{i,t}$ is observed by the agent but not by the researcher, $\varepsilon_{i,t}$ is a source of variation in the decisions of agents conditional on the variables observed by the researcher. It is the model's econometric error, which is given a structural interpretation as an unobserved state variable.

Assuming that the data are a random sample over individuals, the log-likelihood function is $\sum_i^N l_i(\theta)$, where $l_i(\theta)$ is the contribution to the log-likelihood function of i's individual history:[7]

$$\begin{aligned} l_i(\theta) &= \log \Pr \left\{ a_{i,t} : t = 1, ..., T \;\middle|\; y_{i,t}, x_t, \theta \right\} \\ &= \log \Pr \left\{ a_{i,t} = \alpha(x_{i,t}, \varepsilon_{i,t}, \theta) : t = 1, ..., T \;\middle|\; y_{i,t}, x_t, \theta \right\} \\ &= \sum_{t=1}^{T} \log f \left(a_{i,t} \mid x_t, \theta \right). \end{aligned} \tag{8}$$

Closed-form expressions for $f(\cdot)$ follow from the iid extreme value type 1 distribution we've assumed for $\varepsilon_{i,t}$, which produces the conventional logit probabilities:

$$f \left(a \mid x_t, \theta \right) = \frac{e^{u\left(a,(p-w(x_t))' E(y \mid a)\right)}}{\sum_{\forall k} e^{u\left(k,(p-w(x_t))' E(y \mid k)\right)}}. \tag{9}$$

This expression is predicated on knowledge of the quota price rules $w(x_t)$. Therefore, we need to either observe the state-contingent quota prices or

[7]Note that we are estimating the structural parameters θ taking the harvest variable $y_{i,t}$ and state variable x_t as given. Thus, we are taking a partial MLE approach here. In theory, it is possible to jointly estimate the structural parameters of both the harvesting and utility functions in a full MLE approach; however, for the sake of simplicity, we leave that for future research.

come up with a strategy for determining the implied quota prices within the estimation process. In the former case, observed quota prices can simply be inserted into the choice probabilities in equation (9) and maximum likelihood estimation can proceed as usual. However, in many cases, these lease prices are not observed due to limitations on data disclosure or because only average prices are reported, as opposed to state-contingent prices. Given this missing data problem, we propose solving for the rational expectations equilibrium prices for each trial value of θ.

The nested fixed-point algorithm (NFXP) pioneered by Rust (1987) is a search method for obtaining maximum likelihood estimates of the structural parameters, which combines an "outer" algorithm that searches for the root of the likelihood equations with an "inner" algorithm that solves for the fixed-point of the rational expectations equilibrium for each trial value of the structural parameters. Specifically, consider an arbitrary value of θ, say $\hat{\theta}_0$. Conditional on $\hat{\theta}_0$, the inner algorithm solves for the w_t that solves the fixed-point problem in equation (6) given optimal fisher behavior described in equation (5). This produces an equilibrium vector of quota prices $\tilde{w}(x_t)$ for each observation in our data, which can be substituted into equation (9) to form the choice probabilities $f\left(a_{i,t} \mid x_t, \hat{\theta}_0\right)$. Next, the outer algorithm uses the gradient of the log-likelihood function with the choice probabilities in equation (9) to start a new iteration with a new structural parameter $\hat{\theta}_1$. This process continues until either $\hat{\theta}$ or the log-likelihood converges based on a pre-specified convergence tolerance.[8]

[8]For more details on the the NFXP algorithm, see Appendix D.

4. Numerical Policy Simulations

We utilize simulated data to demonstrate how our modeling approach can be used for evaluating fishery policies, such as spatial closures and quota reductions, within a multispecies catch-share fishery. We consider a fishery in which fishers receive individual quotas for two species that are jointly harvested, but only one of these species (Species 1) has an ex-vessel value to a fisher—i.e., Species 2 can be considered a bycatch species. We simulate two forms of hypothetical policies designed to reduce bycatch: (1) reductions to the quota for the bycatch species, and (2) bycatch hot-spot area closures.

4.1. The data-generating process

The data generating process (dgp) loosely follows that of Reimer et al. (2017a) and is purposefully simple to facilitate our understanding of the model predictions. We assume fishers begin each period in port and choose from a $n \times n$ grid of fishing locations. The observable component of a fisher's contemporaneous expected utility function is:

$$E\left(u_{i,t}\right) = \theta_{Rev} p' E(y_{i,t} \mid a_{i,t}) + \theta_{Dist} Dist(a_{i,t}), \tag{10}$$

where $Dist(a)$ represents the distance from port to location a. We model fisher i's catch of species $s \in \{1, 2\}$ in period t as $y_{s,i,t} = Y(a_{i,t}, \xi_{s,i,t}) = q_{s,i} \exp\{\xi_{s,i,t}(a_{i,t})\}$, where $q_{s,i} \in (0, 1)$ denotes fisher i's catchability coefficient and $\xi_{s,i,t}(a)$ is a normally distributed random variable with location-specific mean parameters $\mu_s(a)$ and a common variance σ^2. Catch is thus a log-normal distributed random variable with mean $E(y_{s,i,t} \mid a) = q_{s,i} \exp\{\mu_s(a) +$

$\sigma^2/2\}$.[9] For simplicity, $\mu_s(a)$ and σ^2 (and thus expected catch) are assumed to remain constant over all individuals and time periods; however, realized catch varies across all individuals and time periods due to the individual- and time-specific nature of the idiosyncratic shock $\xi_{s,i,t}(a)$.[10] A fisher's optimal location choice is determined by equation (7) and the rational-expectations quota prices are determined by equation (6). In general, quota prices are sensitive to the data-generating parameters, as depicted in Figure A.1, and have comparative statics that are consistent with theory: quota prices increase with ex-vessel prices, quota scarcity, and the marginal utility of revenue.[11]

We consider two different biological scenarios with different spatial distributions for each species, producing the global production sets depicted in Figure 1. In the first scenario, the two species have minimal spatial overlap, and thus, fishers are able to substitute between species relatively easily. In contrast, fishers are more constrained by the bycatch species in the second scenario as there is greater spatial overlap between species and

[9] The mean parameters $\mu_s(a)$ vary over the grid according to distinct two-dimensional normal density functions for both species.

[10] This example does not incorporate stock depletion or other spatial/temporal variability in expected catch over the course of the season. We do so to focus attention on the dynamics generated by the opportunity cost of quota. It is a relatively straightforward extension of our approach to include these extensions, so long as fishers consider stock depletion and other non-stationarities to be an exogenous process in their planning behavior.

[11] Note that the latter is only true for the target species. Quota prices decrease with the marginal utility of revenue if a species' net price (ex-vessel price minus quota lease price) is negative. In this case, fishers will try to avoid catching this species, decreasing demand for it's quota.

fishers must travel further away from port to avoid bycatch. The remaining data-generating parameter values for the policy simulations are presented in column 2 of Table 1.

We reduce the bycatch quota and the area open to fishing, respectively, by increments of 5% to a minimum of 25% of their baseline levels. For the area closures, we emulate a hot-spot closure policy by closing areas to fishing that experience the highest amount of bycatch in the baseline simulations.[12] Harvest and utility shocks (ξ and ε) are drawn from their respective probability distributions, and state variables are endogenously updated in each time period.

Results from the policy simulations are presented in Figure 2, where we've simulated 200 counterfactual seasons under each policy. Under the baseline policies, the quota for the bycatch species ($s = 2$) is binding in both biological scenarios, resulting in a positive quota-lease price in all simulated seasons. In scenario 1, the lease price for the target species ($s = 1$) is consistently positive as well, pointing toward the dominance of interior solutions in the quota market. In contrast, the target species almost always has a non-positive lease price in scenario 2, where the bycatch species consistently acts as a choke species, preventing the full harvest of the target species quota. This difference largely stems from the higher spatial overlap between the target and bycatch species in scenario 2, making bycatch avoidance so costly that it is not possible to fully utilize the target species quota.

The effect of the bycatch reduction policies differs across both biological

[12]For example, if 75% of a 100-location grid is closed to fishing, we close the 75 cells that have the highest amount of bycatch from a baseline simulation with no spatial closures.

scenarios and policy types. Not surprisingly, the quota reductions are effective at achieving desired bycatch reductions: bycatch falls at a 1:1 ratio with the bycatch quota as the quota remains binding over all reductions. The lost utility from achieving a given level of bycatch reduction is considerably higher in scenario 2 because of the higher cost of bycatch avoidance. In scenario 2, the primary cost of bycatch reduction is foregone catch of the target species, as the bycatch quota continues to bind before the target-species quota is harvested. By contrast, the primary cost in scenario 1 is traveling greater distances to avoid bycatch: there is minimal foregone target species catch in scenario 1 and the target species quota price declines very slowly on average while the price of bycatch quota rises steadily with increased scarcity.

Hot-spot closures, on the other hand, have virtually no impact on bycatch in either scenario over the examined range of closures. In fact, hot-spot closures have the effect of pushing fishers into areas with higher bycatch-to-target species ratios. Since fishers are already avoiding bycatch under the baseline policy, bycatch is being generated in areas with relatively low bycatch-to-target species ratios; hot-spot closures therefore push fishers out of relatively cleaner areas, thereby increasing bycatch per unit of target species catch.

The key difference between the two bycatch-reduction policies is reflected in the quota-lease prices: quota reductions signal scarcity to fishers through increased quota-lease prices, and fishers have the incentive to reduce bycatch in the most cost-effective manner given their information about catch rates. Hot-spot closures, on the other hand, do not signal bycatch scarcity over a wide spectrum of policy severity when bycatch quota is already sufficiently scarce under the baseline scenario to command a positive price. Instead, for fisheries where bycatch species does not consistently act as a choke species (scenario 1), the closures decrease the value of the target species quota price by pushing fishers into increasingly sub-optimal fishing locations. In fact, quota prices for the bycatch species are only responsive to the closures in scenario 1 once the target-species quota can no longer be harvested before the bycatch quota binds.

Altogether, these policy simulations demonstrate the utility of modeling the spatiotemporal production decisions of harvesters under the dynamically evolving constraints imposed by the seasonal quota market. We have demonstrated how this structural approach can yield out-of-sample predictions of fisher welfare, catch rates, and lease price behavior for changes in both rights-based management parameters (i.e., quota allocations) and "ecosystem based" policies targeting the spatiotemporal footprint of fishing effort. Our simulation results also highlight the role that lease prices play in relaying signals of quota scarcity, and how policies that fail to influence the relative scarcity of quota in the desired direction as reflected in these relative prices are likely to fall short of their intended objectives.

5. Monte Carlo Analysis

We now evaluate the ability of the RERUM estimator to recover structural behavioral parameters through a Monte Carlo analysis. It is important to note that the RERUM estimator is an unbiased estimator of the true parameters by construction, so long as the NFXP maximum likelihood algorithm converges to it's global maximum. Thus, the Monte Carlo results for the RERUM estimator are useful for ensuring that the NFXP algorithm works appropriately and for investigating the properties of the estimator (e.g., precision and identification) under realistic data settings.

We also evaluate the in- and out-of-sample performance of common static RUM models with the true model to investigate the biological and regulatory conditions under which these reduced-form models may provide adequate in- and out-of-sample predictions of fishing behavior within a catch-share program. We consider the following reduced-form utility specifications, which differ in their treatment of the shadow cost of quota:

Static RUM (SRUM):

$$E\left(u_{i,t}\right) = \theta_{Rev} p' E(y_{i,t} \mid a_{i,t}) + \theta_{Dist} Dist(a_{i,t});$$

Quota-Price Static RUM (QP-SRUM):

$$\begin{aligned} E\left(u_{i,t}\right) &= \theta_{Rev}\left(p - w_t\right)' E(y_{i,t} \mid a_{i,t}) + \theta_{Dist} Dist(a_{i,t}), \\ \text{where} \qquad w_{s,t} &= \text{observed quota-lease prices;} \end{aligned}$$

Approximate Rational Expectations RUM (ARUM):

$$\begin{aligned} E\left(u_{i,t}\right) &= \theta_{Rev}\left(p - \hat{w}_t\right)' E(y_{i,t} \mid a_{i,t}) + \theta_{Dist} Dist(a_{i,t}), \\ \text{where} \qquad \hat{w}_{s,t} &= \gamma_{0,s} + \gamma_{1,s}' z_t + z_t' \gamma_{2,s} z_t, \quad z_t' = \left[X_{1,t}, X_{2,t}, t\right], s = 1, 2, \end{aligned}$$

and $X_{s,t}$ denotes the proportion of remaining fleet-wide quota for species s in period t. The parameters $\theta = [\theta_{Rev}, \theta_{Dist}]$ are the structural preference parameters of interest and are estimated alongside the vector $[\gamma_{0,s}, \gamma_{1,s}]$ and symmetric matrix $\gamma_{2,s}$.

The first specification (SRUM) is the static RUM approach that estimates contemporaneous utility without deducting the shadow cost of quota from expected revenues. So long as the TAC has a non-zero probability of binding for at least one species, the SRUM model will underestimate the expected revenue coefficient θ_{Rev}. Moreover, to the extent that a location's distance from port is correlated with the expected catch of a species with binding quota, the estimate of the distance coefficient θ_{Dist} will also be biased (upwards or downwards, depending on the direction of the correlation).

The second specification (QP-SRUM) represents the approach one would take to address the bias of the SRUM model if quota-lease prices were observed—that is, include the observed prices w_t directly into the contemporaneous utility function. We consider two versions of this approach, one which uses the period-specific quota-lease prices w_t (QP-SRUM1, the best-case scenario) and another which uses the seasonal average quota price $\bar{w}$ (QP-SRUM2, a more likely scenario).

The third specification (ARUM) attempts to address the bias of the SRUM model without the luxury of having quota-lease prices. Specifically, the ARUM model introduces a reduced-form quadratic approximation of quota-lease prices by interacting expected catch with observed state variables meant to reflect the scarcity of quota, including the proportion of remaining quota $X_{s,t}$ and time period t.[13] Similar approaches have been followed previously, for example, to estimate the implicit cost of fleet-wide bycatch quotas (Abbott and Wilen, 2011) and to estimate the extent of cooperation in a common-pool fishery (Haynie et al., 2009). The ARUM model approximates

[13] We also considered fleet-wide cumulative catch as a state variable, but the proportion of remaining quota was selected for the ARUM model due to it's superior predictive performance.

the shadow value of quota using both species' cumulative catch information. Note that without temporal variation in the ex-vessel price p, it is not possible to identify the constant $\gamma_{0,s}$ in the ARUM model. In practice, it is rare to observe within-season variation in prices; thus, we omit $\gamma_{0,s}$ from the ARUM specification, and note that only the differences in quota prices w across the state space are identified, as opposed to the absolute level of quota prices. As we discuss below, this has implications for identifying the structural parameter θ_{Rev}, but has no implications for prediction.

5.1. Estimation and in-sample performance

We generate 200 independent draws from the same dgp used for the numerical policy simulations in Section 4. To investigate each estimator's performance across different data-generating and sampling environments, we simultaneously draw randomly from the data-generating parameter space (e.g., θ, μ, σ) and the sampling parameter space (e.g., T, N, S). For each Monte Carlo draw, we estimate the parameters of the RERUM and the alternative models, and calculate parameter bias and the root-mean-squared-error (RMSE) of predicted location-choice probabilities.[14] Column 1 of Table 1 provides the range of parameter values we consider.

As expected, both the RERUM and QP-SRUM1 estimators are able to recover the structural parameters θ due to explicitly accounting for the evolving shadow-cost of quota (either imputed or observed, respectively) in the

[14]Monte Carlo simulations were conducted using Matlab (Version 2019a) with parallel computing (18 workers) running on an Amazon EC2 instance (c4.8xlarge) with an Intel Xeon E5-2666 v3 processor (2.9 GHz) and 60 GiB of memory.

estimation process (Figure 3). The QP-SRUM2 estimator, which accounts for only the seasonal average quota price, also provides a relatively unbiased estimator θ_{Rev}. In contrast, the SRUM specification underestimates θ_{Rev}, as predicted for situations in which the shadow cost of quota is strictly positive. The ARUM specification does not improve the estimation performance of θ_{Rev} over the SRUM because it is unable to identify the absolute level of the quota prices (γ_0) due to the time-invariant nature of prices p. Instead, γ_0 is subsumed into the estimate of θ_{Rev}, resulting in a underestimation of θ_{Rev}. Moreover, including an approximation of the shadow cost of quota creates challenges for precision, as reflected in the wide distributions of $\hat{\theta}_{Rev}$ for the ARUM specification. All five models have relatively good estimation performance for θ_{Dist}, which is expected when the distance from port to areas with high expected catch is symmetric across species.[15] Altogether, despite having trouble using variation in observed state variables to identify θ_{Rev}, the ARUM models do offer an improvement over the SRUM model for in-sample predictions according to the RMSE of choice probabilities. By contrast, the QP-SRUM2 estimator does not provide much improvement over the SRUM estimator for in-sample predictions because, despite incorporating quota price information into the estimation process, it does not account for the within-season evolution of the quota shadow costs.

In Figure 4, we investigate whether there are any particular areas of the data-generating and sampling parameter space in which the RERUM esti-

[15]This symmetry is exhibited, on average, in our Monte Carlo sample since we allow for the spatial overlap of species to be randomly determined when drawing from the data-generating parameter space.

mator performance is worse at recovering estimates of θ_{Rev}. The median bias of θ_{Rev} for the RERUM estimator is unsurprisingly zero across the parameters space; however, heterogeneity in the spread between the 10th and 90th percentiles indicates that there are some areas of the parameter space in which the sampling distribution of the RERUM estimator is more diffuse. Most notably, the RERUM estimator tends to perform better when there are a larger number of species S and a larger level of harvest variance σ^2. With more species, there is potential for greater spatiotemporal variation in "net revenue"—i.e., $(p - \tilde{w}_t)' E(y_{i,t})$—that can be used to identify θ_{Rev}, especially if quota prices vary asynchronously over time across species.[16] A similar argument can be made regarding σ^2: with low σ^2, quota prices tend to be relatively stable over time, providing less spatiotemporal variation for identifying θ_{Rev}. In general, Monte Carlo draws that have small S and/or small σ^2 tend to have a flatter log-likelihood function, resulting in less precise estimates.

We also consider practical issues regarding estimation of the RERUM model. To investigate the potential for convergence issues of the NFXP algorithm, we estimate the RERUM parameter vector multiple times for each Monte Carlo draw starting from different initial values.[17] While the algo-

[16] As an example, in the extreme case with $S = 1$, the relative fishing payoffs over space do not change over time because the quota price affects all locations the same, regardless of how much the quota price changes over time. With more species, the relative payoffs do change over time, so long as the quota prices for each species do not vary synchronously over time.

[17] Specifically, for each Monte Carlo draw, we estimate the RERUM model starting from nine different initial guesses arranged in a grid centered on the true data-generating

rithm displays occasional convergence issues, the RERUM estimator behaves reasonably well, with approximately 90% of the Monte Carlo draws appearing to converge to a global maximum.[18] Convergence issues generally occur under the same conditions that produce a flat log-likelihood function—i.e., when the number of species (S) or the variance of the stochastic harvesting component (σ^2) are small. Measures of estimation time demonstrate that while the computational burden of the RERUM estimator increases with the number of observations per year ($N \times T$) and the number of species (S), it does so at a rate that is more-or-less linear in S and slightly convex in $N \times T$ (Figure A.3).[19] Altogether, the computational costs of the RERUM estimator do not appear to be prohibitively burdensome within the range of sample sizes and numbers of quotas/species encountered by practitioners on a regular basis.

5.2. Out-of-sample Performance

To evaluate out-of-sample prediction performance, we simulate the same counterfactual bycatch-reduction policies as in Section 4 and narrow our

---

parameter values. The parameter vector(s) associated with the largest log-likelihood value is the RERUM estimate.

[18]The proportion of estimates that converged to the same maximum log-likelihood value is presented in Figure A.2

[19]In theory, the computational burden of the RERUM estimator (above that for a static RUM) is a function of the number of rational-expectations equilibrium quota prices that need to be computed. Let $time(T, N, J)$ represent the time it takes to solve for a single quota price, which is increasing linearly in the number of individuals (N), time periods (T), and locations (J) (see equation 5). Then the computation time devoted to solving for quota prices is equal to $time(T, N, J) \times T \times S \times Yrs$.

focus on the two biological scenarios depicted in Figure 1. For each biological scenario, we generate 200 independent draws from the dgp under the baseline policy, and for each draw, we estimate the parameters of the RERUM and the alternative models. For both forms of policy counterfactuals, we simulate an entire fishing season with stochastic harvest and state variables that are endogenously updated in each time period. Fishers make location choices according to their utility-function specification (i.e., SRUM, QP-SRUM, ARUM, or RERUM) and their corresponding parameter estimates. For both the ARUM and RERUM models, the quota-lease price is updated in each period using each model's respective quota-price rule. For example, the ARUM model inserts the observed state variables into the quadratic quota-price approximation function, while the RERUM model updates the quota-lease price using the observed state variables and solving for the rational-expectations equilibrium quota prices in equation (6). In contrast, the SRUM and QP-SRUM models are static, and do not update each period to reflect the evolving shadow cost of quota. The SRUM model uses no quota prices while the QP-SRUM models use the observed quota prices from the estimation sample, essentially considering them exogenous to the counterfactual policies under consideration. For each simulation, harvest and utility shocks (ξ and ε) are drawn from their respective probability distributions, while utility parameter estimates $\hat{\theta}$ and quota-price parameter estimates $\hat{\gamma}$ (where applicable) are drawn from their simulated sampling distributions; thus, the distribution of simulation results reflect both process error and sampling error.

In general, the reduced-form models perform well in predicting changes in expected utility for small changes from the baseline policy, but get progressively worse as counterfactual policies move farther away from the baseline (Figure 5).[20] In both scenarios, the reduced-form models tend to overestimate the cost of reducing the bycatch TAC. The SRUM and QP-SRUM models have no method of accounting for increased shadow prices from TAC reductions; thus, fishers are predicted to fish business-as-usual until the season ends from a binding TAC. As a result, predicted changes in expected utility under the SRUM and QP-SRUM models are proportional to bycatch TAC reductions. The ARUM model does account for changes in bycatch quota scarcity through the approximated quota-lease prices, and in turn, fishers are predicted to fish in different locations with less expected bycatch. As a result, early-season endings from hitting the bycatch TAC are avoided and predicted changes in expected utility are relatively close to the truth, at least for small reductions in the TAC.

The reduced-form models tend to do better predicting changes in expected utility from the hot-spot closures. The performance of the SRUM and QP-SRUM models tend to be inferior to the ARUM model, although they are still capable of producing reasonable predictions for a small number of closures. Predictions from the ARUM model are quite good for the hot-spot closures, particularly for scenario 2; ARUM predictions are close to the true model, on average, even for large changes from the baseline. However, sampling error in the lease-price parameters leads to considerably more variation in the ARUM model's prediction error, demonstrating a potential drawback of

[20]Given the similarity in the out-of-sample predictions for the QP-SRUM1 and QP-SRUM2 models, we only present the results for QP-SRUM1.

using the reduced-form approach to approximate the quota-lease prices.

The out-of-sample predictions we consider here produce two important insights. First, despite being able to recover structural parameters reasonably well, static RUM models that incorporate observed quota-lease prices in the estimation process do not produce good out-of-sample predictions if quota-prices are not allowed to adjust to the market, ecological, or regulatory conditions of the counterfactual policy. This is true even for policies such as the bycatch hot-spot-closure policy for scenario 2, which does not induce large changes in quota prices, on average (Figure 2). The reason lies in the stochastic realizations of production, which are embodied in the observed quota prices but are not expected to be the same as those observed in the estimation sample. Thus, quota prices that do not update to reflect the prevailing state-of-the-world under counterfactual policies will not accurately predict behavior.

Second, RUM models that incorporate a state-contingent, reduced-form approximation of the quota-price, such as the ARUM, are capable of improving out-of-sample predictions over static RUM models. However, this improvement is limited to only certain situations. The reason largely lies in the quota-price responses to the policy change (Figure 2): as quota prices move further away from those observed in the estimation sample, predictions from the reduced-form models tend to move further away from the truth. For example, hot-spot closures in scenario 2 have almost no effect on quota prices. Accordingly, the ARUM model does very well at predicting out-of-sample in this case since the lease-price parameters of the ARUM are calibrated to replicate the in-sample behavior under economically equivalent scenarios. In contrast, TAC reductions in scenario 1 have the largest influence on quota prices, and in turn, predictions from the ARUM model are only acceptable for small changes in the TAC.

6. Conclusion

We develop a model of spatiotemporal fishing behavior that incorporates the dynamic and general equilibrium elements of catch-share fisheries. Our approach extends the traditional RUM framework for estimating fishing location choices by incorporating a within-season market for quota exchanges, which determines equilibrium quota-lease prices (or, equivalently, quota shadow costs) endogenously. Our proposed estimation strategy is able to recover structural behavioral parameters under reasonable sample sizes and specifications of the data generating process, even when quota-lease prices are unobserved. We demonstrate the use of our model for predicting behavioral responses to fishery policies, such as spatial closures and TAC reductions, within a catch-share fishery and illustrate the importance of allowing quota-prices to be endogenous for conducting out-of-sample policy evaluations.

Our study provides several insights. First, the inclusion of quota-prices, either observed or imputed, in the specification of RUM models is necessary to identify structural parameters. However, identifying the structural parameters of the RUM model is not sufficient for making accurate out-of-sample predictions of counterfactual policy changes. Rather, sufficiency lies in determining what quota prices would be under the counterfactual policy change. Thus, even if practitioners observe quota prices and use them to recover the structural behavioral parameters, a model of endogenous quota prices is necessary for counterfactual policy evaluations. In other words, quota prices themselves are not policy invariant.

Second, in the absence of a structural model for quota-lease prices, a reduced-form approximation of state-contingent quota-lease prices can perform well in evaluating out-of-sample policy changes, provided there is adequate quota-price variation in the sample, relative to the range of price variation induced by the counterfactual policy. Changes in quota prices reflect the realized magnitude of the effect of the policy on economic incentives, and therefore function as sufficient statistics for whether a particular policy/economic/biological regime is sufficiently "in sample" to be evaluated using a reduced-form model. The challenge is knowing *ahead of time* whether a policy change of interest will result in quota-prices that lie out-of-sample. As we demonstrate in Section 4, even seemingly "marginal" policy changes can result in large quota-price changes, and vice versa. Without knowing how quota prices will respond to a policy change, it is hard to determine *ex ante* whether a reduced-form approach will produce adequate policy evaluations.

In short, the layering of spatial closures and a host other policies on top of RBM systems creates unavoidable feedbacks to seasonal quota markets. These prices, or internal shadow prices for systems that disallow leasing, are *the* endogenous mechanisms by which RBM alters the responses of fishers to these scenarios. Our model has shown the crucial importance of drawing upon *structural models* of the quota-price determination process for prediction—whether or not these models are used to estimate fishers' underlying behavioral parameters. Failure to do so will fundamentally limit the ability of economists to answer crucial “what if” questions posed by fishery managers.

References

C. Costello, D. Ovando, Status, Institutions, and Prospects for Global Capture Fisheries, Annual Review of Environment and Resources 44 (2019) 177–200.

R. T. Deacon, Fishery Management by Harvester Cooperatives, Review of Environmental Economics and Policy 6 (2012) 258–277.

J. E. Wilen, J. Cancino, H. Uchida, The Economics of Territorial Use Rights Fisheries, or TURFs, Review of Environmental Economics and Policy 6 (2012) 237–257.

B. Worm, R. Hilborn, J. K. Baum, T. A. Branch, J. S. Collie, C. Costello, M. J. Fogarty, E. A. Fulton, J. A. Hutchings, S. Jennings, O. P. Jensen, H. K. Lotze, P. M. Mace, T. R. McClanahan, C. Minto, S. R. Palumbi, A. M. Parma, D. Ricard, A. A. Rosenberg, R. Watson, D. Zeller, Rebuilding global fisheries., Science (New York, N.Y.) 325 (2009) 578–85.

R. Q. Grafton, R. Arnason, T. Bjørndal, D. Campbell, H. F. Campbell, C. W. Clark, R. Connor, D. P. Dupont, R. Hannesson, R. Hilborn, J. E. Kirkley, T. Kompas, D. E. Lane, G. R. Munro, S. Pascoe, D. Squires, S. I. Steinshamn, B. R. Turris, Q. Weninger, Incentive-based approaches to sustainable fisheries, Canadian Journal of Fisheries and Aquatic Sciences 63 (2006) 699–710.

R. Hilborn, J. M. L. Orensanz, A. M. Parma, Institutions, incentives and the future of fisheries., Philosophical transactions of the Royal Society of London. Series B, Biological sciences 360 (2005) 47–57.

J. R. Boyce, Individual Transferable Quotas and Production Externalities In a Fishery, Natural Resource Modeling 6 (1992) 385–408.

C. Costello, R. T. Deacon, The Efficiency Gains from Fully Delineating Rights in an ITQ Fishery, Marine Resource Economics 22 (2007) 347–361.

D. S. Holland, Collective RightsBased Fishery Management: A Path to Ecosystem-Based Fishery Management, Annual Review of Resource Economics 10 (2018) 469–485.

S. M. Maxwell, E. L. Hazen, R. L. Lewison, D. C. Dunn, H. Bailey, S. J. Bograd, D. K. Briscoe, S. Fossette, A. J. Hobday, M. Bennett, S. Benson, M. R. Caldwell, D. P. Costa, H. Dewar, T. Eguchi, L. Hazen, S. Kohin, T. Sippel, L. B. Crowder, Dynamic ocean management: Defining and conceptualizing real-time management of the ocean, Marine Policy 58 (2015) 42–50.

M. D. Smith, J. E. Wilen, Economic impacts of marine reserves: the importance of spatial behavior, Journal of Environmental Economics and Management 46 (2003) 183–206.

B. Hutniczak, Modeling heterogeneous fleet in an ecosystem based management context, Ecological Economics 120 (2015) 203–214.

M.-Y. Lee, S. Steinback, K. Wallmo, Applying a Bioeconomic Model to Recreational Fisheries Management: Groundfish in the Northeast United States, Marine Resource Economics 32 (2017) 191–216.

D. S. Holland, Optimal Intra-annual Exploitation of the Maine Lobster Fishery, Land Economics 87 (2011) 699–711.

L. Huang, M. D. Smith, The dynamic efficiency costs of common-pool resource exploitation, The American Economic Review 104 (2014) 4071–4103.

R. E. Lucas, Econometric Policy Evaluation: A Critique, in: K. Brunner, A. H. Meltzer (Eds.), The Phillips Curve and Labor Markets, Carnegie-Rochester Conference Series on Public Policy, North Holland, Amsterdam, 1976, pp. 19–46.

K. I. Wolpin, Ex ante policy evaluation, structural estimation, and model selection, American Economic Review 97 (2007) 48–52.

M. P. Keane, Structural vs. Atheoretic Approaches to Econometrics, Journal of Econometrics 156 (2010) 3–20.

M. N. Reimer, J. K. Abbott, J. E. Wilen, Fisheries Production: Management Institutions, Spatial Choice, and the Quest for Policy Invariance, Marine Resource Economics 32 (2017a) 143–168.

M. N. Reimer, J. K. Abbott, A. C. Haynie, Empirical Models of Fisheries Production: Conflating Technology with Incentives?, Marine Resource Economics 32 (2017b) 169–190.

M. N. Reimer, J. K. Abbott, J. E. Wilen, Unraveling the multiple margins of rent generation from individual transferable quotas, Land Economics 90 (2014) 538–559.

J. K. Abbott, A. C. Haynie, M. N. Reimer, Hidden flexibility: Institutions, incentives, and the margins of selectivity in fishing, Land Economics 91 (2015) 169–195.

A. M. Birkenbach, D. J. Kaczan, M. D. Smith, Catch Shares Slow the Race to Fish, Nature (2017).

S. J. Miller, R. T. Deacon, Protecting Marine Ecosystems: Regulation Versus Market Incentives, Marine Resource Economics 32 (2017) 83–107.

J. Eales, J. E. Wilen, An Examination of Fishing Location Choice in the Pink Shrimp Fishery, Marine Resource Economics 2 (1986) 331–351.

D. S. Holland, J. G. Sutinen, Location Choice in New England Trawl Fisheries: Old Habits Die Hard, Land Economics 76 (2000) 133–149.

M. D. Smith, State Dependence and Heterogeneity in Fishing Location Choice, Journal of Environmental Economics and Management 50 (2005) 319–340.

A. C. Haynie, R. L. Hicks, K. E. Schnier, Common Property, Information, and Cooperation: Commercial Fishing in the Bering Sea, Ecological Economics 69 (2009) 406–413.

R. L. Hicks, K. E. Schnier, Spatial Regulations and Endogenous Consideration Sets in Fisheries, Resource and Energy Economics 32 (2010) 117–134.

J. K. Abbott, J. E. Wilen, Dissecting the Tragedy: A Spatial Model of Behavior in the Commons, Journal of Environmental Economics and Management 62 (2011) 386–401.

J. Rust, Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher, Econometrica 55 (1987) 999.

J. J. Heckman, E. J. Vytlacil, Econometric Evaluation of Social Programs, Part I: Causal Models, Structural Models and Econometric Policy Evaluation, in: J. Heckman, E. Leamer (Eds.), Handbook of Econometrics, volume 6B, Elsevier, New York, 2007, pp. 4779–4874.

J. J. Heckman, Building Bridges Between Structural and Program Evaluation Approaches to Evaluating Policy, Journal of Economic Literature 48 (2010) 356–398.

E. P. Fenichel, J. K. Abbott, B. Huang, Modelling angler behaviour as a part of the management system: synthesizing a multi-disciplinary literature, Fish and Fisheries 14 (2013) 137–157.

A. M. Scheld, J. Walden, An Analysis of Fishing Selectivity for Northeast US Multispecies Bottom Trawlers, Marine Resource Economics 33 (2018) 331–350.

R. E. Curtis, R. L. Hicks, The Cost of Sea Turtle Preservation: The Case of Hawaii's Pelagic Longliners, American Journal of Agricultural Economics 82 (2000) 1191–1197.

R. E. Curtis, K. E. McConnell, Incorporating Information And Expectations In Fisherman's Spatial Decisions, Marine Resource Economics 19 (2004) 131–143.

R. L. Hicks, K. E. Schnier, Dynamic Random Utility Modeling: A Monte Carlo Analysis, American Journal of Agricultural Economics 88 (2006) 816.

R. L. Hicks, K. E. Schnier, Eco-Labeling and Dolphin Avoidance: a Dynamic Model of Tuna Fishing in the Eastern Tropical Pacific, Journal of Environmental Economics and Management 56 (2008) 103–116.

B. Provencher, R. C. Bishop, An Estimable Dynamic Model of Recreation Behavior with an Application to Great Lakes Angling, Journal of Environmental Economics and Management 33 (1997) 107–127.

M. D. Smith, B. Provencher, Spatial Search in Commercial Fishing: A Discrete Choice Dynamic Programming Approach, 2003.

V. Aguirregabiria, P. Mira, Dynamic discrete choice structural models: A survey, Journal of Econometrics 156 (2010) 38–67.

M. Miranda, P. L. Fackler, Applied Computational Economics and Finance, The MIT Press, Cambridge, MA, 2002.

Tables

Parameter	Parameter Values		Description
	In-Sample[a]	Out-of-Sample[b]	
θ_{Rev}	[0.5,1.5]	1	True preference parameter for expected revenue
θ_{Dist}	[-0.5,-0.1]	-0.4	True preference parameter for distance
J	[36,144]	100	Number of locations
N	[10,40]	20	Number of individual fishers
T	[25,60]	50	Number of time periods in a year
S	[1,4]	2	Number of species
Yrs	[1,5]	1	Number of years
p	[500,1500]	(1000,0)	Ex-vessel price vector
q	$[0.15,5.8]\times10^{-3}$	10^{-3}	Catchability coefficient, $q = (J/100) \times (1/TN)$
σ^2	[0.1,5]	3	Variance of random harvest component (ξ)
TAC	$[0.8,1.5]\times10^{-3}$	$(13,7)\times10^{-3}$	Total allowable catch (proportion of abundance)

[a] Denotes the range of parameter values for the data generating process considered in the evaluation of in-sample performance.

[b] Denotes the parameter values (species-specific, where applicable) for the data generating process considered in the numerical policy simulations and the evaluation of out-of-sample performance.

Table 1: Parameter values and descriptions for the data generating process.

Figures

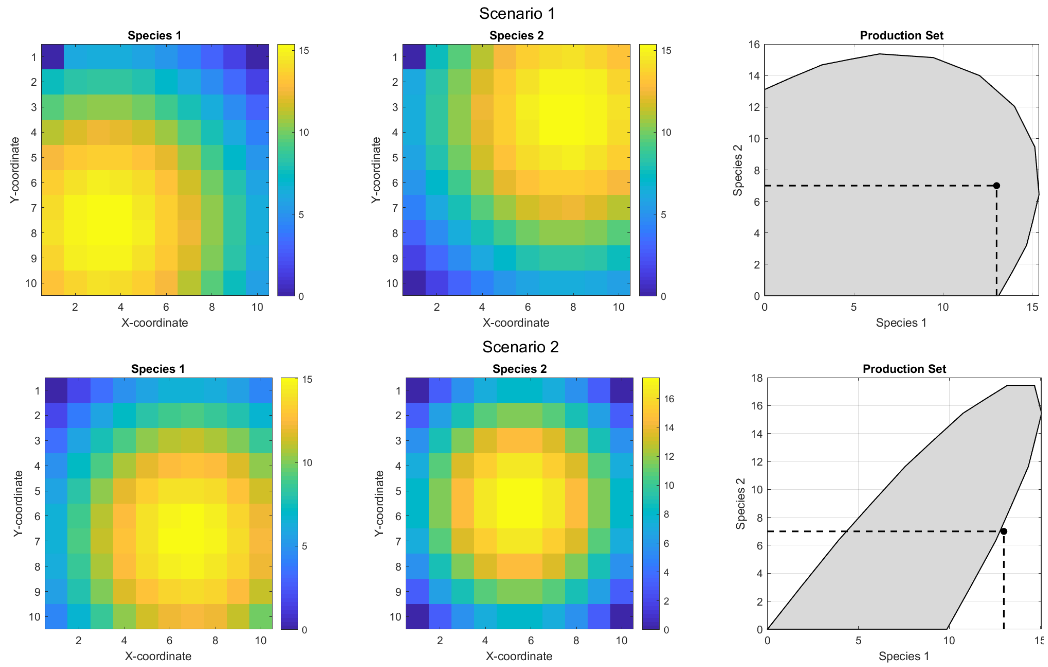

Figure 1: Spatial distribution of expected catch for species 1 (left) and 2 (center) with port located in the upper left-hand corner in cell [1,1]; expected global production set (right) with the total allowable catch (black dot and dashed lines).

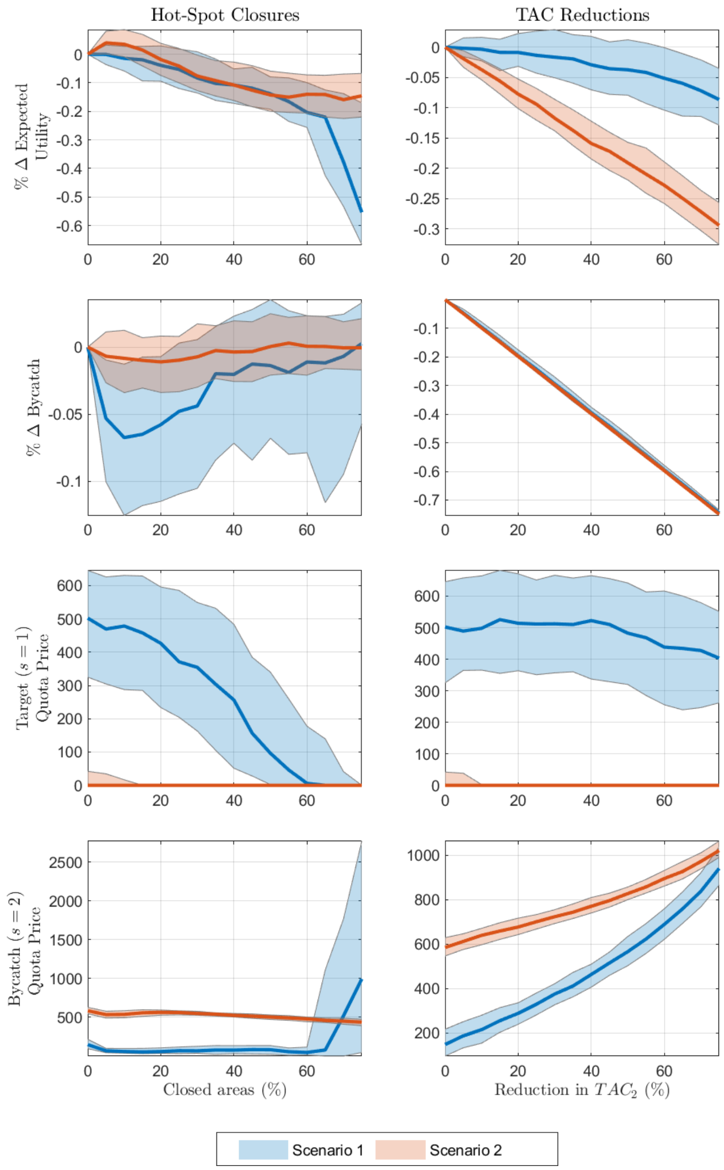

Figure 2: Numerical simulation outcomes—bycatch hot-spot closures (left column) and bycatch TAC reductions (right column) for two biological scenarios (blue and red). The median (solid line) and 25th-75th percentile range (shaded area) are presented using 200 draws from the data-generating process.

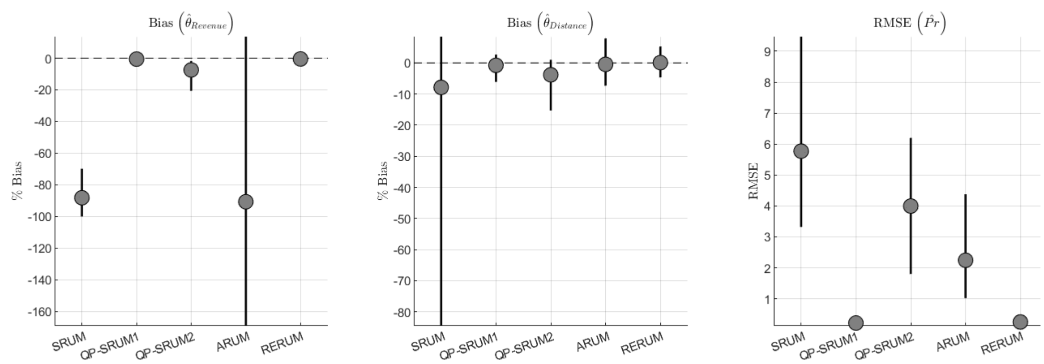

Figure 3: Parameter estimation and in-sample predictive performance—distance between estimated and population preference parameters (left and center columns); root-mean-square error (RMSE) between estimated and population choice probabilities (right column). Markers denote median values and error bars denote the 25th and 75th percentiles. Distributions generated from 200 draws from the data-generating process with random draws from the parameter space.

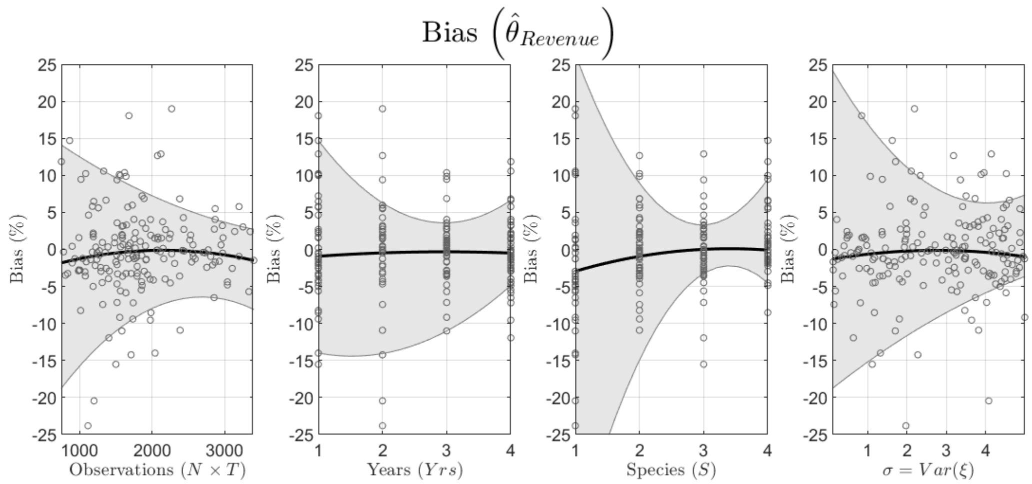

Figure 4: RERUM parameter bias for θ_{Rev} across four parameter spaces: number of observations per year (far left), number of years (mid left), number of species (mid right), and the variance of the stochastic harvest component (far right). The lines denote quantile regression predictions for the 10th, 50th, and 90th quantiles. Distributions generated from 200 draws from the data-generating process with random draws from the data-generating and sampling parameter space.

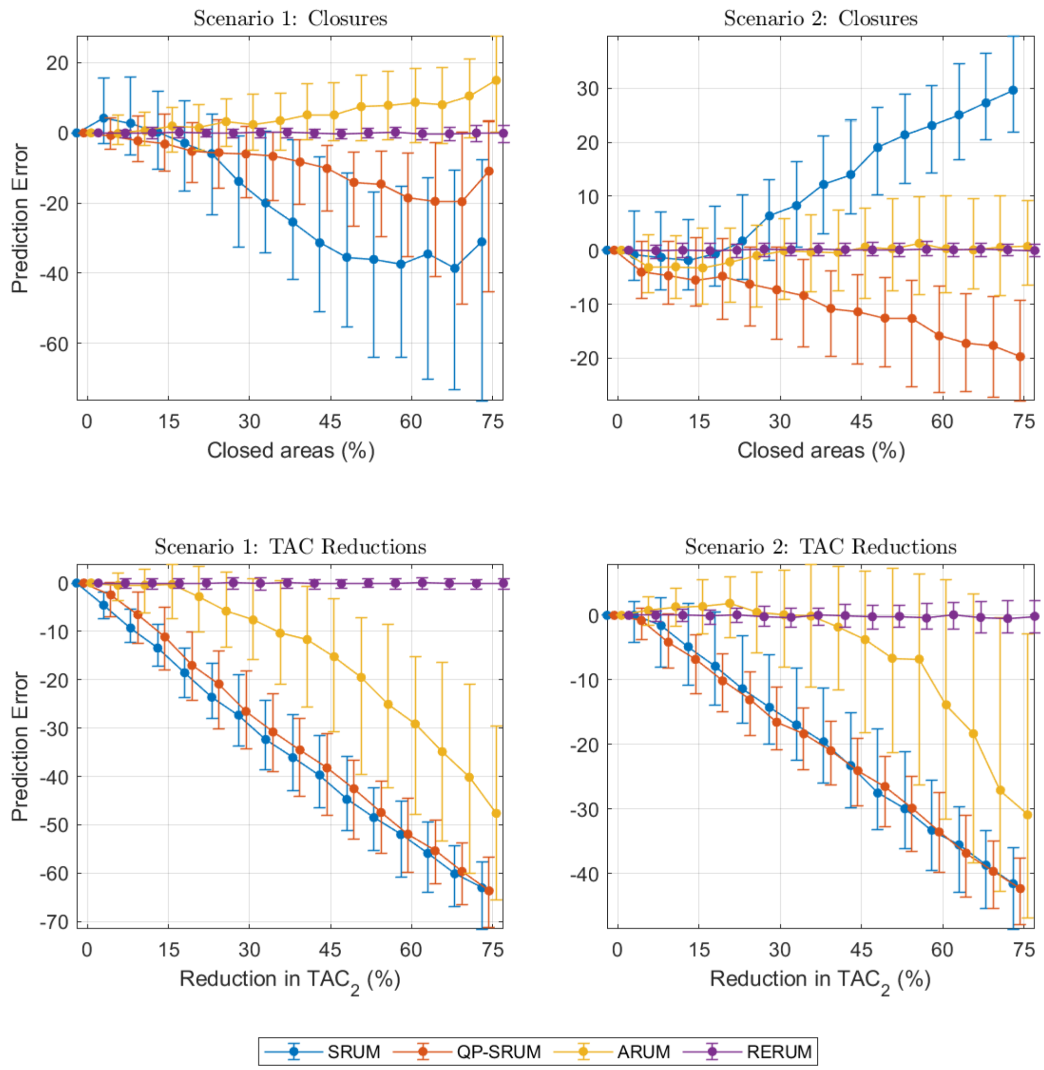

Figure 5: Out-of-sample prediction errors: percentage change in expected utility. Top: bycatch hot-spot closures. Bottom: bycatch TAC reductions. Markers denote median values and error bars denote the 25th and 75th percentiles. QP-SRUM model uses period-specific quota-prices from estimation sample. Distributions generated from 200 draws from the data generating process and sampling distributions of utility parameter estimates.

Appendix A. Supplementary Figures

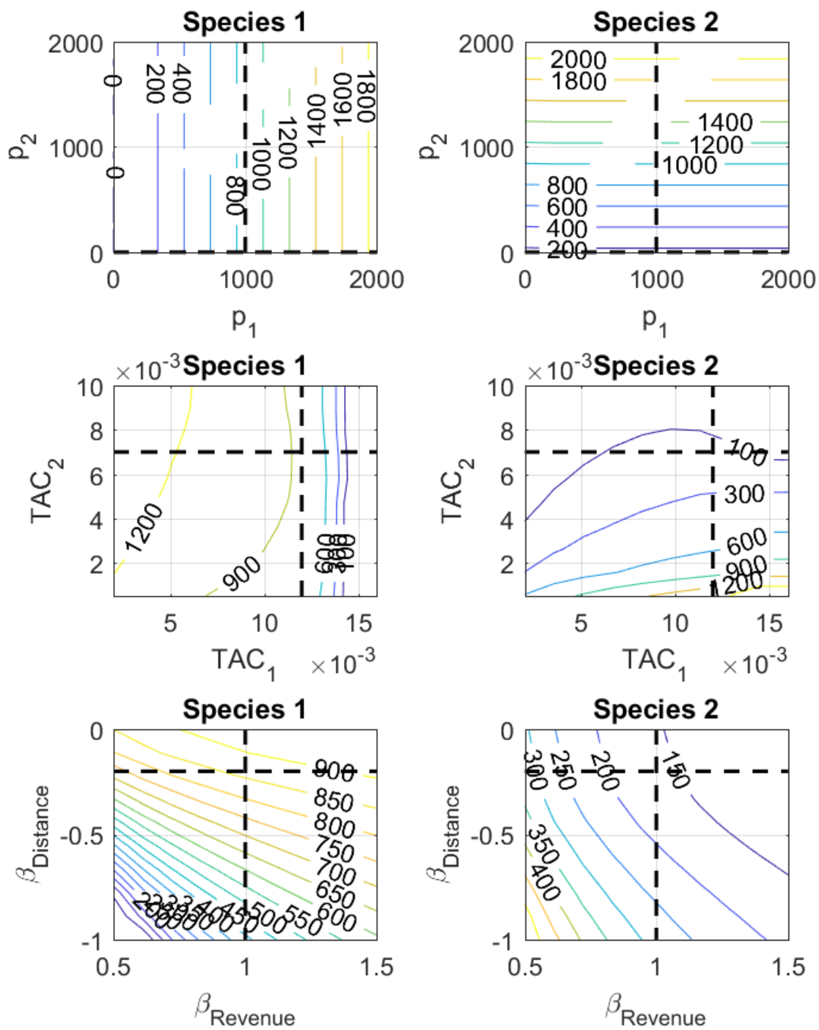

Figure A.1: Quota prices in period $t = 1$ as a function of ex-vessel prices (p_1 and p_2, row 1), total allowable catches (TAC_1 and TAC_2, row 2), and preference parameters (β_{Rev} and $\beta :_{Dist}$, row 3). Dashed lines indicate the data-generating parameter values.

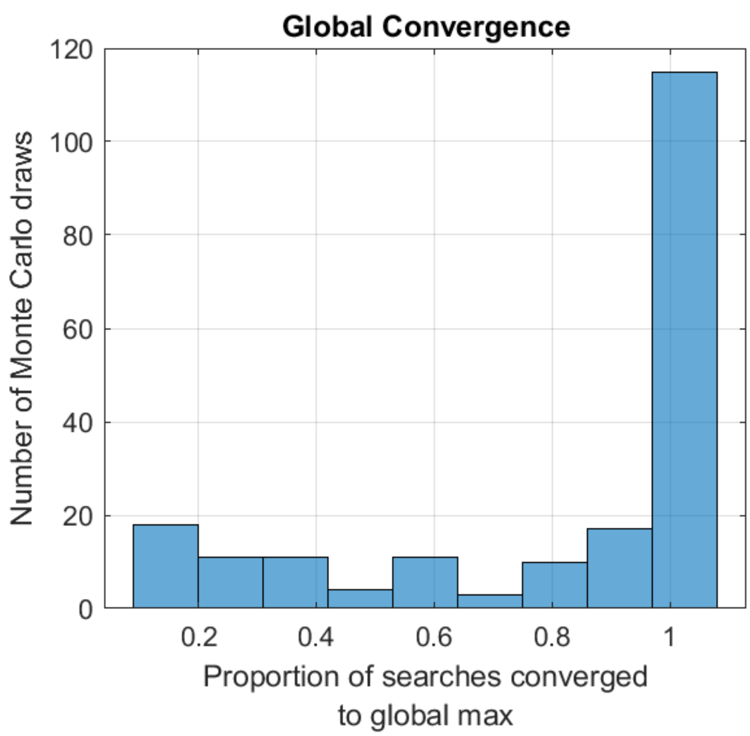

Figure A.2: Global convergence of the RERUM estimator—the proportion of maximum-likelihood searches that converged to the same maximum. Distribution generated by 200 independent draws from the data-generating process and 9 initial values for each draw.

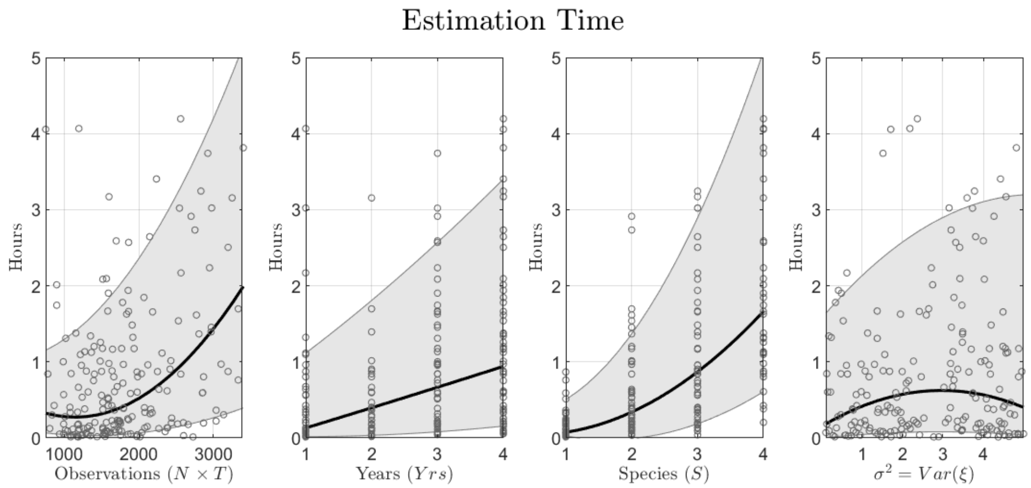

Figure A.3: RERUM estimation time across four parameter spaces: number of observations per year (far left), number of years (mid left), number of species (mid right), and the variance of the stochastic harvest component (far right). The lines denote quantile regression predictions for the 10th, 50th, and 90th quantiles. Distributions generated from 200 draws from the data-generating process with random draws from the data-generating and sampling parameter space.

Appendix B. Deriving the Last-Period Utility Function

The indirect utility function in period $T+1$ in equation (1) can be derived as follows. Each agent is endowed with an $S \times 1$ vector of quota ω_i, which can be used to fund harvests over the season or be leased in the competitive quota market. The agent buys a vector of quota q_i after observing their cumulative harvest $x_{i,T+1}$. The agents objective in period $T+1$ is to maximize utility with respect to consumption c, subject to a budget constraint:

$$\max_{c,q} u\left(0, c\right) \quad \text{subject to} \quad c \leq w'\left(\omega_i - q\right); \, q \geq x_{i,T+1},$$

where the consumption good is the numeraire good whose price is normalized to one, w denotes a vector of quota lease prices, and $u(\cdot)$ is equivalent to the utility function in equation (1) evaluated at $a = 0$ (i.e., port). The constraints act to restrict the agent from consuming more than the net income they receive from the purchase and sale of quota, while also ensuring that the owner has enough quota to cover their annual harvests. Assuming that $u'(c) > 0$ for $c > 0$, then the budget constraint will be binding, and the agent will choose quota such that $q_i^*(w) = x_{i,T+1}$. Thus, the agent's indirect utility function can be expressed as

$$V(z_{i,T+1}) = u\left(0, w'\left(\omega_i - x_{i,T+1}\right)\right),$$

which gives us the indirect utility function for period $T+1$ in equation (1). For supplemental derivations, it is useful to simplify this expression further as

$$\begin{aligned} V(z_{i,T+1}) &= u(0) + v\left(w'\left(\omega_i - x_{i,T+1}\right)\right) \\ &= v\left(w'\left(\omega_i - x_{i,T+1}\right)\right), \end{aligned} \tag{B.1}$$

where the first equality follows from the assumption that revenue is additively separable from the rest of utility and the second equality follows from using location $a = 0$ as the baseline alternative.

Appendix C. Derivation of the Policy Function

Consider the Bellman equation in (3) given the state of the world $z_{i,t} = (x_{i,t}, \varepsilon_{i,t})$, which we reproduce here for convenience:

$$V(z_{i,t}) = \max_{a \in A} \left\{ u\left(a, p'E\left(y_{i,T} \mid a\right)\right) + \varepsilon_{i,t}(a) + E_z\left(V(z_{i,t+1}) \mid a, z_{i,t}\right) \right\}.$$

To see that the policy function takes the form presented in equation (4), note that the next-period expected value function in the last fishing period T can be written in the following way:

$$\begin{aligned} E_z\left(V\left(z_{i,T+1}\right) \,\middle|\, a_{i,T}, z_{i,T}\right) &= v\left(w'\left(\omega_i - E_x\left(x_{i,T+1} \,\middle|\, a_{i,T}, x_{i,T}\right)\right)\right) \\ &= v\left(w'\left(\omega_i - x_{i,T}\right)\right) - v\left(w' E_y\left(y_{i,T} \,\middle|\, a_{i,T}\right)\right). \end{aligned}$$

The first equality follows from substituting the indirect utility function in period $T+1$ (equation B.1) into the expectation of the last-period value function, while the second equality follows from the transition equation, $x_{i,T+1} = x_{i,T} + y_{i,T}$, and the linear nature of $v(\cdot)$. Notice that $v\left(w' E_y\left(y_{i,T} \,\middle|\, a_{i,T}\right)\right)$—i.e., the marginal effect of location choice on the value of remaining quota in the last period—is the only term that affects the optimal location choice in period T. In contrast, the term $v\left(w'\left(\omega_i - x_{i,T}\right)\right)$—i.e., the value of already used quota—is sunk and does not influence the contemporaneous location choice. Substituting the derivation of the next-period expect value function into the Bellman equation, we have:

$$
\begin{aligned}
V\left(z_{i,T}\right) &= \max_{a_{i,T}\in A}\Big\{u\left(a_{i,T}, p'E_y\left(y_{i,T} \mid a_{i,T}\right)\right) + \varepsilon_{i,T}\left(a_{i,T}\right) \\
&\qquad -v\left(w'E_y\left(y_{i,T} \mid a_{i,T}\right)\right) + v\left(w'\left(\omega_i - x_{i,T}\right)\right)\Big\} \\
&= \max_{a_{i,T}\in A}\Big\{u\left(a_{i,T}\right) + v\left(p'E_y\left(y_{i,T} \mid a_{i,T}\right)\right) + \varepsilon_{i,T}\left(a_{i,T}\right) \\
&\qquad -v\left(w'E_y\left(y_{i,T} \mid a_{i,T}\right)\right)\Big\} + v\left(w'\left(\omega_i - x_{i,T}\right)\right) \\
&= \max_{a_{i,T}\in A}\Big\{u\left(a_{i,T}\right) + v\left((p-w)'E_y\left(y_{i,T} \mid a_{i,T}\right)\right) \\
&\qquad +\varepsilon_{i,T}\left(a_{i,T}\right)\Big\} + v\left(w'\left(\omega_i - x_{i,T}\right)\right) \\
&= \max_{a_{i,T}\in A}\Big\{u\left(a_{i,T}, (p-w)'E_y\left(y_{i,T} \mid a_{i,T}\right)\right) + \varepsilon_{i,T}\left(a_{i,T}\right)\Big\} \\
&\qquad +v\left(w'\left(\omega_i - x_{i,T}\right)\right),
\end{aligned}
\tag{C.1}
$$

where we've used the fact that utility is linear in revenue. The optimal location choice in period T is therefore defined as:

$$
\alpha(\varepsilon_{i,T} \mid w) = \underset{a_{i,T}\in A}{\operatorname{argmax}}\Big\{u\left(a_{i,T}, (p-w)'\,E_y\left(y_{i,T} \mid a_{i,T}\right)\right) + \varepsilon_{i,T}\left(a_{i,T}\right)\Big\}.
$$

Moving to the second-last fishing period $T-1$, we can write the next-period expected value function in the Bellman equation as:

$$
\begin{aligned}
E_z\left(V\left(z_{i,T} \mid a_{i,T-1}, z_{i,T-1}\right)\right) = E_{x,\varepsilon}\Bigg(&\max_{a_{i,T}\in A}\Big\{u\left(a_{i,T}, (p-w)'E_y\left(y_{i,T} \mid a_{i,T}\right)\right) \\
&+\varepsilon_{i,T}\left(a_{i,T}\right)\Big\} + v\left(w'\left(\omega_i - x_{i,T}\right)\right) \Bigm| a_{i,T-1}, x_{i,T-1}, \varepsilon_{i,T-1}\Bigg).
\end{aligned}
$$

Let $\Lambda_{i,T} = \max\limits_{a_{i,T}\in A}\left\{u\left(a_{i,T}, (p-w)'E_y\left(y_{i,T} \mid a_{i,T}\right)\right) + \varepsilon_{i,T}\left(a_{i,T}\right)\right\}$ for notational simplicity. Because w is considered exogenous by fishers and y is conditionally independent of x, $\Lambda_{i,T}$ is not influenced by the location choice $a_{i,T-1}$. Thus, we can write $E_{x,\varepsilon}\left(\Lambda_{i,T} \mid a_{i,T-1}, x_{i,T-1}, \varepsilon_{i,T-1}\right) = E_{\varepsilon}\left(\Lambda_{i,T}\right)$ and simplify the next-period expected value function in the Bellman equation as:

$$
\begin{aligned}
&E_z\left(V\left(z_{i,T} \mid a_{i,T-1}, z_{i,T-1}\right)\right) \\
&\qquad = E_{x,\varepsilon}\left(\Lambda_{i,T} + v\left(w'\left(\omega_i - x_{i,T}\right)\right) \,\middle|\, a_{i,T-1}, x_{i,T-1}, \varepsilon_{i,T-1}\right) \\
&\qquad = E_{x,\varepsilon}\left(\Lambda_{i,T} + v\left(w'\left(\omega_i - x_{i,T-1} - y_{i,T-1}\right)\right) \,\middle|\, a_{i,T-1}, x_{i,T-1}, \varepsilon_{i,T-1}\right) \\
&\qquad = -v\left(w' E_y\left(y_{i,T-1} \,\middle|\, a_{i,T-1}\right)\right) + v\left(w'\left(\omega_i - x_{i,T-1}\right)\right) + E_{\varepsilon}\left(\Lambda_{i,T}\right).
\end{aligned}
$$

As in period T, the only component of next-period's value function that varies with a is its effect on the value of remaining quota in the final period: $v\left(w' E_y\left(y_{i,T-1} \,\middle|\, a_{i,T-1}\right)\right)$. Thus, the optimal decision rule in period $T-1$ is fully characterized by

$$
\begin{aligned}
&\alpha(\varepsilon_{i,T-1} \mid w) \\
&\qquad = \underset{a_{i,T-1} \in A}{\operatorname{argmax}} \left\{u\left(a_{i,T-1}, (p-w)' E_y\left(y_{i,T-1} \,\middle|\, a_{i,T-1}\right)\right) + \varepsilon_{i,T-1}\left(a_{i,T-1}\right)\right\}.
\end{aligned}
$$

Repeated substitution into earlier periods generalizes this result to any decision period t, giving us the optimal decision rule in equation (4). Ultimately, it is the conditional independence assumption for y and the assumption that fishers consider their effect on the quota price w to be negligible that allow us to reduce a fishers optimal decision rule to something tractable and easily solvable (conditional on w).

Appendix D. The Nested Fixed-Point (NFXP) algorithm

Appendix D.1. Inner algorithm: the fixed-point problem

A rational expectations equilibrium for the inner algorithm is a vector-valued function of quota prices $w(x_t|\theta)$ that solves the market clearing conditions in (6) subject to fishers making their optimal fishery choices according to equation (4) for a given vector of structural parameters θ. Our goal is to find $w(\theta)$ such that:[21]

$$F\left(w(\theta)\right) = \max\left\{E\left(e_s \mid w(\theta), x_t\right), -w(\theta)\right\} = 0 \quad \forall s \in \{1, ..., S\}, \tag{D.1}$$

where e_s is the end-of-season excess demand function for species s quota. Since we are solving for S quota lease prices that satisfy S equilibrium equations, the system of equations in (D.1) is just identified.

Appendix D.1.1. Algorithm

Consider an arbitrary initial vector of quota prices w_0. Then the rational equilibrium quota prices $w(x_t \mid \theta)$, conditional on a given vector of structural parameters θ, can be determined by the following algorithm:

1. For each time period t in the data, use the observed state variable x_t to calculate the cumulative fleet-wide catch for each species, $X_{s,t}$.
2. Calculate the choice probabilities $f_a(a_{i,t} \mid x_t, w_0)$.

[21] This is actually a complementarity problem, as opposed to a fixed-point problem. See page 44 in Miranda and Fackler (2002) for more details.

3. Calculate the expected end-of-season excess demand $E(e_s \mid w_0, x_t)$ for each species $s \in \{1, ..., S\}$ using $X_{s,t}$ from step 1 and $f_a(a_{i,t} \mid x_t, w_0)$ from step 2.
4. Given the expected excess-demand functions from step 3, compute the system of equations $F(w_0)$ in (D.1).
5. In general, $F(w_0)$ will not equal 0, as required by the equilibrium conditions in (D.1). Generate a new value of w, say w_1, using a Newton step (or some other method).
6. Repeat steps 2 to 5 until $F(w_k) = 0$.
7. Repeat steps 2 to 6 for all time periods t in the data.
8. Use the resulting equilibrium quota-price vector $w(x_t|\theta)$ to calculate the rational expectations choice probabilities (equation 9) and pass them to the outer algorithm.

Appendix D.2. Outer algorithm: maximum likelihood estimation

The goal of the outer algorithm is to find a value for the vector of parameters $\hat{\theta}$ that maximizes the log-likelihood function $\sum_{\forall i} l_i(\theta)$ while allowing the REE quota price $w(x_t \mid \theta)$ to be endogenous to the structural parameter vector θ. Consider an arbitrary value of θ, say $\hat{\theta}_0$. Then NFXP maximum likelihood parameter $\hat{\theta}$ is determined as follows:

1. Pass $\hat{\theta}_0$ to the inner algorithm, which will return the choice probabilities $\left\{f_a\left(a_{i,t} \mid x_t, \hat{\theta}_0\right)\right\}_{\forall i,t}$.
2. Use the choice probabilites in step 1 to evaluate the log-likelihood $l(\hat{\theta}_0) = \sum_{\forall i} l_i(\hat{\theta}_0)$ and it's gradient, where $l_i(\cdot)$ is given in equation

(8).[22]

3. Use the gradient from step 2 to obtain a new structural parameter vector, say $\hat{\theta}_1$.

4. Repeat steps 1 through 3 until either $\hat{\theta}_k$ or $l(\hat{\theta}_k)$ converges based on a pre-specified convergence tolerance.

[22]While the gradient of the log-likelihood function, conditional on w, has a closed-form expression under the DP conditional logit assumptions, the gradient of $w(x_t \mid \theta)$ does not; thus, the gradient of the log-likelihood function must be computed using numerical methods. This means that each time θ is 'perturbed' to obtain the numerical gradient, a new solution for the rational-expectations quota prices is required.