Title
Structural behavioral models for rights-based fisheries

Authors
Reimer, Matthew N
Abbott, Joshua K
Haynie, Alan C

Publication Date
2022-05-01

DOI
10.1016/j.reseneeco.2022.101294

Highlights

Structural Behavioral Models for Rights-Based Fisheries[⋆]

Matthew N. Reimer, Joshua K. Abbott, Alan C. Haynie

- We develop a model of spatiotemporal fishing behavior in catch-share fisheries.
- We extend RUM models of fishing behavior to include a lease market for quota.
- We demonstrate the importance of our approach for predicting out-of-sample policies.
- We show ecosystem-based policies can distort price signals in rights-based fisheries.

Structural Behavioral Models for Rights-Based Fisheries

Matthew N. Reimer*

Department of Agricultural & Resource Economics, University of California, Davis, One Shields Ave, Davis, CA 95616 USA

Joshua K. Abbott

School of Sustainability and Center for Environmental Economics and Sustainability Policy, Arizona State University, P.O. Box 875502, Tempe, AZ 85287 USA

Alan C. Haynie

Resource Ecology and Fisheries Management Division, Alaska Fisheries Science Center, National Marine Fisheries Service, NOAA, 7600 Sand Point Way NE, Bldg. 4, Seattle, WA 98115 USA

Abstract

Rights-based management is prevalent in many fisheries, yet conventional spatiotemporal models of fishing behavior do not reflect such institutional settings. We adapt random utility maximization (RUM) models of spatiotemporal fishing behavior to capture the general equilibrium dynamics of catch-share fisheries by incorporating endogenously determined equilibrium quota prices. We demonstrate how a structural estimation strategy is capable of recovering policy-invariant behavioral parameters and predicting out-of-sample counterfactual policies. We illustrate the utility of our structural modeling approach by evaluating the efficacy of "ecosystem-based" policies, such as spatial closures, in a catch-share-managed fishery. Simulation results reveal that such policies have the potential to distort price signals in the quota market and prevent quota prices from coordinating fishing behavior in an

⋆We thank several individuals for helpful comments, including Corbett Grainger, Ling Huang, Linda Nøstbakken, Kathleen Segerson, and Brett Watson; seminar participants at Arizona State University, University of Alaska Anchorage, University of Connecticut, and the Norwegian School of Economics; and session participants at the IIFET 2018, NAAFE 2019, AERE 2019, and ASSA 2020 meetings. Funding for this research was provided by the North Pacific Research Board (NPRB-1607). The scientific results and conclusions, as well as any views or opinions expressed herein, are those of the authors and do not necessarily reflect those of the authors' affiliate or funding organizations. We declare no conflicts of interest and that we have no relevant or material financial interests that relate to the research in this paper.

*Corresponding author

Email addresses: `mnreimer@ucdavis.edu` (Matthew N. Reimer), `Joshua.K.Abbott@asu.edu` (Joshua K. Abbott), `Alan.Haynie@noaa.gov` (Alan C. Haynie)

efficient manner. Ecosystem-based policies may thus fall short of their intended objectives when introduced into rights-based managed fisheries. Importantly, we demonstrate that such conclusions cannot easily be drawn from behavioral models that omit or approximate the general equilibrium dynamics of rights-based fisheries.
Keywords: structural econometrics, rights-based management, discrete choice models, fisheries, RUM model

---

1. Introduction

Economists are often called upon to inform policy makers of the potential consequences of proposed environmental and natural resource regulations. For economists to offer reliable advice, their models must adequately capture individual decision-making processes, contextual variables, and institutional settings to provide externally valid predictions across the range of policy scenarios of interest to decision-makers (Lucas, 1976; Heckman, 2010). If the range of these counterfactuals deviates markedly from in-sample conditions, then purely empirical, reduced-form descriptions of behavior will likely be unsatisfactory. Instead, structural models that explicitly model individuals' decision-making process in terms of objective-seeking (e.g., profit or utility-maximizing) behavior under the salient economic, environmental, and institutional constraints are needed (Wolpin, 2007; Keane, 2010).

In this paper, we demonstrate how a structural approach for estimating commercial-fishing behavior under rights-based management institutions can provide out-of-sample predictions of counterfactual policies that differ substantially from commonly used alternatives. Despite the prevalence of rights-based management in today's developed-world fisheries, most empirical models of commercial fishing behavior—those intended to inform management decision making—do not explicitly reflect the incentives and constraints underlying rights-based institutions. Instead, they reflect the implicit theoretical assumptions of regulated open or limited access fisheries. As such, even if these models are calibrated on behavior under rights-based management, they do not capture the theoretical *mechanisms* by which incentives under rights-based management affect fishers' behavior. The result, as we demonstrate, is that the predictions of these models could be highly misleading.

To address this deficiency, we show how random utility maximization (RUM) models of spatiotemporal fishing behavior (e.g., Eales and Wilen, 1986; Holland and Sutinen, 2000; Smith, 2005; Haynie et al., 2009; Abbott and Wilen, 2011), which are the dominant form of management models used to predict the consequences of proposed fishery policies, such as spatial regulations (Smith and Wilen, 2003; Berman, 2006; Haynie and Layton, 2010; Hicks and Schnier, 2010), can be extended to incorporate the general equilibrium dynamics of catch share fisheries. Conventional RUM models of fishing behavior do not consider the implications of individualized (and often transferable) quotas of catch entitlements within a season, which create a shadow value reflecting the opportunity cost of quota. We demonstrate how the dynamic and general equilibrium elements of fisheries with tradable short-term rights of annual catch entitlements can be captured through the introduction of a lease-market for quota, which we model as a pure exchange economy. Fishers are assumed to be forward-looking within the fishing 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 problem reduces to a period-by-period static maximization problem given a set of equilibrium quota prices. Critically, expectations are updated in each period, leading to a new set of equilibrium quota prices to reflect the changing relative scarcity of quota in a stochastic production environment.

We demonstrate the utility of our estimation strategy—which we dub the rational expectations RUM (RERUM)—for both parameter estimation and out-of-sample prediction through numerical simulations and Monte Carlo analyses. We first show how our estimation approach can be used for *ex ante* policy evaluation in rights-based fisheries by evaluating the efficacy of hypothetical bycatch reduction policies, such as bycatch "hot-spot" area closures or reductions in bycatch quotas. Our numerical simulations reveal the importance of quota-lease prices for signalling bycatch scarcity and for incentivizing cost-effective bycatch reductions. Indeed, we show that "ecosystem-based" policies such as hot-spot area closures, which attempt to address the spatiotemporal footprint of fishing effort, can fail to send correct scarcity signals, and in turn, may fall short of their intended objectives.

We then examine whether the conventional RUM approach, which either omits or approximates quota-lease prices, is capable of producing insightful *ex ante* policy evaluations for rights-based fisheries. We show that the omitted nature of quota-lease prices in the conventional RUM approach leads to a form of omitted variable bias (or, alternatively, non-classical measurement error). These biases could jeopardize the estimation of shadow values or welfare estimates (e.g., Abbott and Wilen, 2011; Haynie et al., 2009; Hicks and Schnier, 2006). Moreover, we find that as counterfactual policy changes lie increasingly out-of-sample, as measured by the degree to which lease prices are responsive to the counterfactual policy, the conventional RUM approach performs worse for *ex ante* evaluations. Conversely, for counterfactuals that have only a marginal influence on quota-lease prices, reduced-form approaches that approximate the equilibrium lease prices can be sufficient for *ex ante* evaluations.

We demonstrate that substitution of high-resolution lease prices as data into the conventional RUM model eliminates estimation bias of behavioral parameters. Unfortunately, thin markets combined with confidentiality concerns rarely allow for such an approach (Holland et al., 2014). Imputing annual average prices—which are more commonly available—offers only a partial mitigation of the bias, since it fails to capture dynamic adjustments of behavior within the fishing season. Furthermore, even if high-resolution lease prices are available, prediction for out-of-sample policy scenarios requires the imputation of counterfactual lease prices that are consistent with the stochastic production environment *and* the changes in market, ecological, or policy conditions embodied in the scenario. Our estimation approach imputes quota-lease prices via a market simulator at the core of the estimation procedure, whereby a fixed-point problem is solved to determine state-contingent equilibrium lease prices in every period. Thus, the RERUM estimator does not rely on the availability of high-resolution lease-price data and can produce counterfactual lease prices for out-of-sample prediction that are consistent with the structure of fishers' dynamic decision problems and observed fisher behavior.

Finally, while our demonstration is tailored specifically to the production process and institutions of modern-day fisheries, our work has broader relevance for other industrial and institutional settings—particularly for industries characterized by stochastic production processes and managed under quotas (or quantity controls) with transferable property rights. For example, cap-and-trade systems for controlling greenhouse gas emissions are typically comprised of firms that make dynamic production decisions under uncertainty of future abatement costs while balancing emissions and permits over a fixed regulatory horizon (Rubin, 1996; Kling and Rubin, 1997; Fell, 2016; Kollenberg and Taschini, 2016). As in our setting, binding quota allocations create shadow values that reflect the opportunity cost of such constraints, and these shadow values are harmonized through the coordinating mechanism of the quota market. Any proposed policy that influences these shadow values will thus be reflected in the equilibrium quota prices. Thus, quota prices are not policy invariant, and therefore, models of endogenous quota prices are generally required for counterfactual policy evaluations.

The course of this paper is as follows. Section 2 discusses the relevant literature and the institutional background of rights-based management of commercial fisheries. Sections 3 and 4 present the structural behavioral model and the estimation strategy of the RERUM estimator. Section 5 demonstrates the utility of the RERUM model for predicting realistic policy changes, such as quota reductions and spatial closures. Section 6 provides Monte Carlo simulation evidence of the estimation performance and predictive utility of alternative RUM model specifications and Section 7 concludes the paper.

2. Background and Related Literature

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 is particularly common in the Global North where it is facilitated by strong scientific input and adequate governance. Rights-based management, 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, rights-based management has not reduced the role of fisheries managers to merely conducting stock assessments and setting seasonal quotas. Rights-based management, especially individual output 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 rights-based managed 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* rights-based managed systems. Economists have informed managers of the potential consequences of these actions by developing positive bioeconomic models (e.g., Smith and Wilen, 2003; Holland, 2011; Huang and Smith, 2014; Hutniczak, 2015) that predict how changes to policy design may change catch, effort, profits, employment, or ecological impacts. However, the continued adoption of rights-based management 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, and the shadow values that arise from such constraints are coordinated through within-season quota trading in 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 (Birkenbach et al., 2020). However, models of commercial fisheries often do not capture the behavioral mechanisms that arise under rights-based managed institutions, with the result that their predictions could be highly misleading (Reimer et al., 2017b).

Our econometric estimation approach is not the first to include dynamic or stochastic elements of within-season fishing behavior. Models of within-trip behavior have been extended to consider the logistical problem of the optimal trajectory of fishing decisions within a trip. Optimal within-trip behavior 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; Abe and Anderson, 2020) 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 fisher' decisions (i.e., expected catch, quota balances) evolve in a partially stochastic manner.

A handful of papers have tackled seasonal fishing behavior dynamically (Provencher and Bishop, 1997; Huang and Smith, 2014; Birkenbach et al., 2020). 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 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 fishers 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).

3. A Model of a Catch Share Fishery

Our objective is to build a model of within-season fishing behavior that generates externally valid *ex ante* predictions of fishery policies in a 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 a greater 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 fishers 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., 2017a; Scheld and Walden, 2018). Second, the model must be both dynamic and stochastic. Dynamic models consider that fishers 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.

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 quota lease-market, for which we make two simplifying assumptions. First, we assume that fishers must have enough quota at the end of the fishing season to cover their cumulative catch. Accordingly, the market for leasing quota clears at the end of the season, and fishers' expectations regarding end-of-season quota demand and supply form the basis for within-season quota prices. Second, we assume the market for quota is competitive. That is, fishers' treat their expectations of quota-lease prices 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.

3.1. *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 incurs costs or receives revenues from buying or selling quota in the leasing market according to their cumulative quota usage. 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 excess demand for quota. 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: $z_{i,t} = (x_{i,t}, \varepsilon_{i,t})$. The subvector $\varepsilon_{i,t}$ is private information known only by agent i at the time of decision, and is assumed to be exogenous. The subvector $x_{i,t}$ is an endogenous and stochastic state variable representing 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 $\xi_{i,t}$ 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. We denote $x_t = \sum_{\forall i} x_{i,t}$ as the vector of fleet-wide cumulative catch at the beginning of period t for all species, which we assume to be common knowledge to all fishers.

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

[1] Note that the time index t should also be a component of the state vector, but we omit it here for the sake of keeping notation as simple as possible.

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

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]

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 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: $E(y_{i,t}|a_{i,t}, x_{i,t}, \varepsilon_{i,t}) = E(y_{i,t}|a_{i,t})$. 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 $x_{i,t}$, 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 conditional logit model (Rust, 1987).[3]

[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 Appendix B for details).

[3]We choose to follow the well-known assumptions of the "Rust model" because, as will soon become apparent, the likelihood function for the unknown structural parameters of the RERUM bears considerable resemblance to the likelihood function arising from static discrete choice methods, thereby facilitating the comparison of our approach to conventional models. In general, many of these assumptions can be relaxed; however, in doing so, the form of the likelihood function changes, as does the solution and estimation

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.[4]

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 dynamic programming conditional logit model, combined with the additional assumption that fishers are risk-neutral, imply that fisher i's optimal decision rule in each period is dramatically simplified. The expected quota-lease price w in period t acts as a shadow price of quota, which is harmonized across fishers given the transferability of quota.[5] Conditional on expected lease prices w, the solution of Eq. (3) takes on a simple, static form:[6]

methods. We refer the reader to Aguirregabiria and Mira (2010) for an excellent summary of solution and estimation methods for dynamic discrete choice models as assumptions deviate from the Rust model.

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

[5]The assumption of risk neutrality has the practical implication that revenue enters utility linearly and is additively separable from the rest of utility.

[6]See Appendix C for a formal derivation.

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

Notably, 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 current private information $\varepsilon_{i,t}$ and the expected quota-lease price w, 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.[7] 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.

3.2. Rational Expectations Equilibrium Quota Prices

Eq. (4) presents a fisher's optimal decision rule for a given expected quota-lease price w. Fishers determine their current and future optimal location choices given perceived quota prices w as specified by the policy function $\alpha(z_{i,t}|w)$ in equation (4). In this sense, quota prices determine fisher behavior. At the same time, given fishers' decision rules $\alpha(z_{i,t}|w)$, the 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 is the equilibrium price that clears a seasonal competitive market for quota leasing, which is assumed to be frictionless and without transaction costs. Let $\bar{\Omega} = \sum_{\forall i} \Omega_i$ denote the vector of fleet-wide quota endowments for all species. Then the seasonal excess demand for quota for species s can be written as $e_s = x_{s,T+1} - \bar{\Omega}_s$. 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, forward-looking fishers form expectations over excess demand given a perceived w and the state of the world in period t:

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

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

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.[8] 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:

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

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

$$
\begin{aligned}
E\left(e_s|w,x_t\right) &= 0 \quad \text{for} \quad w_s > 0 \\
E\left(e_s|w,x_t\right) &\leq 0 \quad \text{for} \quad w_s = 0.
\end{aligned} \tag{6}
$$

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 state-contingent—i.e., they are 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:

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

[8] 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 have assumed here, this has a negligible influence on our results; it is, however, trivial to relax this assumption at the cost of model presentation.

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

We emphasize here that the state-contingent equilibrium prices $\tilde{w}(x_t)$ reflect the scarcity of quota that exists in time t given expectations regarding optimal future behavior and harvesting conditions. Thus, while the equilibrium quota prices are determined by a market-clearing condition at the end of the season, $\tilde{w}(x_t)$ are the equilibrium prices that emerge in period t as quota is exchanged. We further note that since equilibrium quota prices are determined by common knowledge of *aggregate* cumulative catch x_t, and not knowledge of individual catch $x_{i,t}$, it is not necessary to track within-season quota exchanges.

4. Estimation

Thus far, we have characterized equilibrium fishing behavior for a known set of behavioral parameters. In this section, we present an empirical strategy for estimating 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 3. 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 $x_{i,t}$ of the state vector $z_{i,t} = (x_{i,t}, \varepsilon_{i,t})$. 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:[9]

[9] 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.

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

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:

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

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 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 $f\left(a_{i,t}|x_t, \hat{\theta}_0\right)$. 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.[10]

5. The RERUM Estimator: A Demonstration

In this section, we demonstrate how the RERUM can be used for predicting counterfactual fishery policies. Specifically, 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 the structural model described in Section 3 with known parameter values to evaluate 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.

5.1. The data-generating process

The data generating process (dgp) 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 in equation (1) for location a is specified as:

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

where $Dist(a)$ represents the distance from port to location a. A fisher's optimal location choice is determined by equation (7), which takes on the specification

$$\alpha(z_{i,t}) = \underset{a \in A}{\text{argmax}} \left\{ \theta_{Rev}(p - \tilde{w}(x_t))' E(y_{i,t}|a) + \theta_{Dist} Dist(a) + \varepsilon_{i,t}\left(a\right) \right\},$$

where the rational-expectations quota prices $\tilde{w}(x_t)$ are determined by equation (6).[11]

We model fisher i's catch of species $s \in \{1, 2\}$ in period t and location a as $y_{s,i,t} = Y(a, \xi_{s,i,t}) = q_{s,i} \exp\left\{\xi_{s,i,t}(a)\right\}$, where $q_{s,i} \in (0, 1)$ denotes fisher i's catchability coefficient

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

[11]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. 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 its quota.

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 $E(y_{s,i,t}|a) = q_{s,i} \exp\{\mu_s(a) + \sigma^2/2\}$.[12] 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 $\xi_{s,i,t}(a)$.[13]

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 fishers must travel further away from port to avoid bycatch.

5.2. Bycatch quota reductions and hot-spot closures: Simulation results

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.[14] Harvest and utility shocks (ξ and ε) are drawn from their respective probability distributions, and state variables are endogenously updated in each time period. The remaining data-generating parameter values are known and remain fixed across all policy simulations (presented in column 1 of Table 1).

Results from the policy simulations are presented in Figure 2, where we've simulated

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

[13] 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.

[14] 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.

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 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 since 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. The structural model can yield counterfactual policy 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. The 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.

6. Evaluating Alternative RUM models: A Monte Carlo Analysis

The previous section established that the RERUM estimator has the potential to produce meaningful insights for policies specific to rights-based managed fisheries. We now consider whether alternative, commonly-used RUM models of spatiotemporal fishing behavior are capable of producing similar insights for rights-based fishery policies. Specifically, we evaluate the in- and out-of-sample predictive performance of conventional RUM model specifications through a Monte Carlo analysis, assuming the data generating process is as described in Section 5. We investigate several different biological and regulatory scenarios to determine the conditions under which alternative RUM models may provide adequate predictions of fishing behavior under rights-based management. To judge each estimator's in-sample predictive performance across different data-generating and sampling environments, we also draw randomly from the data-generating parameter space (e.g., θ, μ, σ) and the sampling parameter space (e.g., T, N, S). To evaluate out-of-sample prediction performance, we simulate the same counterfactual bycatch-reduction policies as in Section 5, using estimated parameters from the alternative RUM estimators.[15]

We emphasize that our intent in this section is not to investigate whether the RERUM estimator is superior to the alternative RUM models, since the RERUM is a consistent estimator of the true parameters by construction. Rather, our intent is to illustrate the potential promise and peril of using conventional RUM models for policy evaluation in rights-based managed fisheries, and in doing so, highlight when (and how) capturing the general equilibrium dynamics of rights-based fisheries matters. For completeness, we also include Monte Carlo results for the RERUM estimator. For a more detailed consideration of practical issues for estimating the RERUM model, we refer the reader to Appendix F.

6.1. Alternative RUM model specifications

We consider the following alternative RUM model specifications, described in further detail below, which differ in their treatment of the shadow cost of quota in the specification of a fisher's optimal location choice:

Static RUM (SRUM):

$$\alpha_{i,t} = \underset{a \in A}{\operatorname{argmax}} \left\{ \theta_{Rev} p' E(y_{i,t}|a) + \theta_{Dist} Dist(a) + \varepsilon_{i,t}(a) \right\};$$

Quota-Price RUM (QPRUM):

$$\begin{aligned} \alpha_{i,t} &= \underset{a \in A}{\operatorname{argmax}} \left\{ \theta_{Rev} \left(p - w_t\right)' E(y_{i,t}|a_{i,t}) + \theta_{Dist} Dist(a_{i,t}) + \varepsilon_{i,t}(a) \right\}, \\ \text{where} \quad w_t &= \text{observed quota-lease prices;} \end{aligned}$$

Approximate Rational Expectations RUM (ARUM):

$$\begin{aligned} \alpha_{i,t} &= \underset{a \in A}{\operatorname{argmax}} \left\{ \theta_{Rev} \left(p - \hat{w}_t\right)' E(y_{i,t}|a_{i,t}) + \theta_{Dist} Dist(a_{i,t}) + \varepsilon_{i,t}(a) \right\}, \\ \text{where} \quad \hat{w}_{s,t} &= \gamma_{0,s} + \gamma_{1,s}' z_t + z_t' \gamma_{2,s} z_t, \quad z_t' = \left[x_{1,t}, x_{2,t}, t\right], s = 1, 2, \end{aligned}$$

[15] 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. Code for reproducing Monte Carlo results can be found at https://github.com/mnreimer/RERUM.git

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 a static RUM approach that does not account for the forward-looking thinking of fishers, and thus, estimates a policy function that does not deduct 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 (QPRUM) 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 policy function. We consider two versions of this approach, one which uses the period-specific quota-lease prices w_t (QPRUM1, the best-case scenario) and another which uses the seasonal average quota price $\bar{w}$ (QPRUM2, 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.[16] 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 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 (Holland et al., 2014); thus, we omit $\gamma_{0,s}$ from the

[16]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 its superior predictive performance.

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.

6.2. Estimation and in-sample performance

For each of 200 independent Monte Carlo draws, we estimate the parameters of the RERUM and the alternative RUM models, and calculate parameter bias and the root-mean-squared-error (RMSE) of predicted location-choice probabilities, relative to the true model (described in Section 5). Column 2 of Table 1 provides the range of parameter values for the random parameter space that we sample from (uniformly).

As expected, both the RERUM and QPRUM1 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 estimation process (Figure 3). The QPRUM2 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.[17]

Altogether, despite having trouble using variation in observed state variables to identify θ_{Rev}, the ARUM model offers an improvement over the SRUM model for in-sample predictions according to the RMSE of choice probabilities. By contrast, the QPRUM2 estimator

[17] This symmetry is exhibited in our Monte Carlo sample (with random error) since we allow for the spatial overlap of species to be randomly determined when drawing from the data-generating parameter space.

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.

6.3. Out-of-sample Performance

For both forms of policy counterfactuals considered in Section 5.2, 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 policy-function specification (i.e., SRUM, QPRUM, ARUM, or RERUM). 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 QPRUM 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 QPRUM models use the observed quota prices from the estimation sample, essentially considering them exogenous to the counterfactual policies under consideration. For each counterfactual policy, we generate 200 independent draws from the dgp. Process error is introduced through harvest and utility shocks (ξ and ε), which are drawn from their respective probability distributions. Sampling error is introduced by drawing utility parameters from simulated sampling distributions, which are generated by estimating the parameters of the RERUM and the alternative models using 500 independent draws from the dgp under the baseline policy. More details concerning the process for generating out-of-sample simulations is contained in Appendix E.

In general, the alternative RUM 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 4).[18] In both scenarios, the alternative RUM models tend to overestimate the cost of reducing the bycatch TAC. The

[18] Given the similarity in the out-of-sample predictions for the QPRUM1 and QPRUM2 models, we only present the results for QPRUM1.

SRUM and QPRUM 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 QPRUM 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 alternative RUM models tend to do better predicting changes in expected utility from the hot-spot closures. The performance of the SRUM and QPRUM 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 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.

7. Conclusion

We demonstrate how commonly-used models of spatiotemporal fishing behavior can be adapted to incorporate 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 estimation strategy is able to consistently recover structural behavioral parameters, even when quota-lease prices are unobserved. We demonstrate the use of our approach 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 important insights. First, quota markets that convey price signals that fully reflect the scarcity of managed species are essential for coordinating fishing behavior to achieve managers' objectives in an efficient manner. The introduction of additional constraints on production decisions, including ecosystem-based policies such as spatial closures, to rights-based management systems has the potential to distort these price signals. Such interactions between price- and non-price-based policies may be counterproductive and yield outcomes that fall well short of intended objectives, while imposing unnecessarily high costs on the fleet. Insights from this interaction between ecosystem- and rights-based policies are generally not available from conventional models of spatiotemporal fishing behavior. Explicitly modelling the general equilibrium dynamics of rights-based fisheries, as we do here, allows researchers to better understand potential feedbacks between ecosystem- and rights-based policies, and evaluate whether rights-based policies are capable of achieving ecosystem-based management objectives (Miller and Deacon, 2017).

Second, 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.

Third, 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 5, even seemingly "marginal" policy changes can result in large quota-price changes. 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.

Our intent in this paper has been to demonstrate the fundamental role of quota-lease (or shadow) prices as a coordinating mechanism for general equilibrium dynamics in right-based fisheries, and how conventional empirical models can be adapted to include them in a theoretically consistent manner. In doing so, we have made a number of simplifying assumptions for pedagogical purposes. For example, the computation of our equilibrium quota-lease prices relies on the assumptions that fishers are rational and risk-neutral, and that the quota-lease market is competitive, frictionless, and without transaction costs. As with any model, real-world applications must assess and adapt these assumptions according to the empirical setting at hand. Empirical investigations of quota-lease prices demonstrate that some quota markets may be competitive (e.g., Newell et al., 2007; Jin et al., 2019); however, evidence of price dispersion (e.g., Newell et al., 2005; Ropicki and Larkin, 2015) and reliance on barter transactions (Holland, 2013) in some quota markets suggests that quota markets may not be operating efficiently. Moreover, previous work has demonstrated that fishers may be risk-averse (e.g., Dupont, 1993; Mistiaen and Strand, 2000) and may not be rational (Holland, 2008). However, we argue that the ultimate test of any structural model is not how realistic its assumptions are; rather, its ability to capture policy-invariant parameters and its predictive performance in policy-relevant out-of-sample contexts is what matters most (Heckman, 2010; Low and Meghir, 2017). Fortunately, there exist well-established model validation techniques that are readily applicable to a variety of structural estimation settings (e.g., Keane and Wolpin, 2007). We believe the RERUM estimator, as presented here, provides a useful framework for future model development as assumptions are relaxed and/or adapted to fit real-world rights-based-management contexts.

In summary, the layering of spatial closures and a host of other policies on top of rights-based management 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 rights-based management 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

Abbott, J.K., Haynie, A.C., Reimer, M.N., 2015. Hidden flexibility: Institutions, incentives, and the margins of selectivity in fishing. Land Economics 91, 169–195. URL: https://doi.org/10.3368/le.91.1.169, doi:10.3368/le.91.1.169.

Abbott, J.K., Wilen, J.E., 2011. Dissecting the Tragedy: A Spatial Model of Behavior in the Commons. Journal of Environmental Economics and Management 62, 386–401. URL: https://doi.org/10.1016/j.jeem.2011.07.001.

Abe, K., Anderson, C.M., 2020. A Dynamic Model of Endogenous Fishing Duration. Journal of the Association of Environmental and Resource Economists .

Aguirregabiria, V., Mira, P., 2010. Dynamic discrete choice structural models: A survey. Journal of Econometrics 156, 38–67. URL: https://doi.org/10.1016/j.jeconom.2009.09.007.

Berman, M.D., 2006. Modeling Spatial Choice in Ocean Fisheries. Marine Resource Economics 21, 375. URL: https://doi.org/10.1086/mre.21.4.42629522.

Birkenbach, A.M., Cojocaru, A.L., Asche, F., Guttormsen, A.G., Smith, M.D., 2020. Seasonal Harvest Patterns in Multispecies Fisheries. Environmental and Resource Economics 75, 631–655. URL: https://doi.org/10.1007/s10640-020-00402-7.

Birkenbach, A.M., Kaczan, D.J., Smith, M.D., 2017. Catch Shares Slow the Race to Fish. Nature 544, 223–226. URL: https://doi.org/10.1038/nature21728.

Boyce, J.R., 1992. Individual Transferable Quotas and Production Externalities In a Fishery. Natural Resource Modeling 6, 385–408. URL: https://doi.org/10.1111/j.1939-7445.1992.tb00286.x.

Costello, C., Deacon, R.T., 2007. The Efficiency Gains from Fully Delineating Rights in an ITQ Fishery. Marine Resource Economics 22, 347–361. URL: https://doi.org/10.1086/mre.22.4.42629566.

Costello, C., Ovando, D., 2019. Status, Institutions, and Prospects for Global Capture Fisheries. Annual Review of Environment and Resources 44, 177–200. URL: https://doi.org/10.1146/annurev-environ-101718-033310.

Curtis, R.E., Hicks, R.L., 2000. The Cost of Sea Turtle Preservation: The Case of Hawaii's Pelagic Longliners. American Journal of Agricultural Economics 82, 1191–1197. URL: https://doi.org/10.1111/0002-9092.00119.

Curtis, R.E., McConnell, K.E., 2004. Incorporating Information And Expectations In Fisherman's Spatial Decisions. Marine Resource Economics 19, 131–143. URL: https://doi.org/10.1086/mre.19.1.42629422.

Deacon, R.T., 2012. Fishery Management by Harvester Cooperatives. Review of Environmental Economics and Policy 6, 258–277. URL: https://doi.org/10.1093/reep/res008.

Dupont, D.P., 1993. Price Uncertainty, Expectations Formation and Fishers' Location Choices. Marine Resource Economics 8. URL: https://doi.org/10.1086/mre.8.3.42629067.

Eales, J., Wilen, J.E., 1986. An Examination of Fishing Location Choice in the Pink Shrimp Fishery. Marine Resource Economics 2, 331–351. URL: https://doi.org/10.1086/mre.2.4.42628909.

Fell, H., 2016. Comparing policies to confront permit over-allocation. Journal of Environmental Economics and Management 80, 53–68. URL: https://doi.org/10.1016/j.jeem.2016.01.001.

Fenichel, E.P., Abbott, J.K., Huang, B., 2013. Modelling angler behaviour as a part of the management system: synthesizing a multi-disciplinary literature. Fish and Fisheries 14, 137–157. URL: https://doi.org/10.1111/j.1467-2979.2012.00456.x.

Grafton, R.Q., Arnason, R., Bjørndal, T., Campbell, D., Campbell, H.F., Clark, C.W., Connor, R., Dupont, D.P., Hannesson, R., Hilborn, R., Kirkley, J.E., Kompas, T., Lane, D.E., Munro, G.R., Pascoe, S., Squires, D., Steinshamn, S.I., Turris, B.R., Weninger, Q., 2006. Incentive-based approaches to sustainable fisheries. Canadian Journal of Fisheries and Aquatic Sciences 63, 699–710. URL: https://doi.org/10.1139/f05-247.

Haynie, A.C., Hicks, R.L., Schnier, K.E., 2009. Common Property, Information, and Cooperation: Commercial Fishing in the Bering Sea. Ecological Economics 69, 406–413. URL: https://doi.org/10.1016/j.ecolecon.2009.08.027.

Haynie, A.C., Layton, D.F., 2010. An Expected Profit Model for Monetizing Fishing Location Choices. Journal of Environmental Economics and Management 59, 165–176. URL: https://doi.org/10.1016/j.jeem.2009.11.001.

Heckman, J.J., 2010. Building Bridges Between Structural and Program Evaluation Approaches to Evaluating Policy. Journal of Economic Literature 48, 356–398. URL: http://doi.org/10.1257/jel.48.2.356.

Heckman, J.J., Vytlacil, E.J., 2007. Econometric Evaluation of Social Programs, Part I: Causal Models, Structural Models and Econometric Policy Evaluation, in: Heckman, J., Leamer, E. (Eds.), Handbook of Econometrics. Elsevier, New York. volume 6B. chapter 70, pp. 4779–4874. URL: https://doi.org/10.1016/S1573-4412(07)06070-9.

Hicks, R.L., Schnier, K.E., 2006. Dynamic Random Utility Modeling: A Monte Carlo Analysis. American Journal of Agricultural Economics 88, 816. URL: https://doi.org/10.1111/j.1467-8276.2006.00900.x.

Hicks, R.L., Schnier, K.E., 2008. Eco-Labeling and Dolphin Avoidance: a Dynamic Model of Tuna Fishing in the Eastern Tropical Pacific. Journal of Environmental Economics and Management 56, 103–116. URL: https://doi.org/10.1016/j.jeem.2008.01.001.

Hicks, R.L., Schnier, K.E., 2010. Spatial Regulations and Endogenous Consideration Sets in Fisheries. Resource and Energy Economics 32, 117–134. URL: https://doi.org/10.1016/j.reseneeco.2009.11.008.

Hilborn, R., Orensanz, J.M.L., Parma, A.M., 2005. Institutions, incentives and the future of fisheries. Philosophical transactions of the Royal Society of London. Series B, Biological sciences 360, 47–57. URL: http://doi.org/10.1098/rstb.2004.1569.

Holland, D., Thunberg, E., Agar, J., Crosson, S., Demarest, C., Kasperski, S., Perruso, L., Steiner, E., Stephen, J., Strelcheck, A., Travis, M., 2014. U.S. Catch Share Markets: A Review of Characteristics and Data Availability. Technical Report. U.S. Department of Commerce, National Marine Fisheries Service.

Holland, D.S., 2008. Are Fishermen Rational? A Fishing Expedition. Marine Resource Economics 23, 325–344. URL: https://doi.org/10.1086/mre.23.3.42629621.

Holland, D.S., 2011. Optimal Intra-annual Exploitation of the Maine Lobster Fishery. Land Economics 87, 699–711. URL: http://doi.org/10.3368/le.87.4.699.

Holland, D.S., 2013. Making Cents out of Barter Data from the British Columbia Groundfish ITQ Market. Marine Resource Economics 28, 311–330. URL: https://doi.org/10.5950/0738-1360-28.4.311.

Holland, D.S., 2018. Collective Rights–Based Fishery Management: A Path to Ecosystem-Based Fishery Management. Annual Review of Resource Economics 10, 469–485. URL: https://doi.org/10.1146/annurev-resource-100517-023110.

Holland, D.S., Sutinen, J.G., 2000. Location Choice in New England Trawl Fisheries: Old Habits Die Hard. Land Economics 76, 133–149. URL: https://doi.org/10.2307/3147262.

Huang, L., Smith, M.D., 2014. The dynamic efficiency costs of common-pool resource exploitation. The American Economic Review 104, 4071–4103. URL: http://doi.org/10.1257/aer.104.12.4071.

Hutniczak, B., 2015. Modeling heterogeneous fleet in an ecosystem based management context. Ecological Economics 120, 203–214. URL: https://doi.org/10.1016/j.ecolecon.2015.10.023, doi:10.1016/J.ECOLECON.2015.10.023.

Jin, D., Lee, M.Y., Thunberg, E., 2019. An empirical analysis of individual fishing quota market trading. Marine Resource Economics 34, 39–57. URL: https://doi.org/10.1086/701971, doi:10.1086/701971.

Keane, M.P., 2010. Structural vs. Atheoretic Approaches to Econometrics. Journal of Econometrics 156, 3–20. URL: https://doi.org/10.1016/j.jeconom.2009.09.003.

Keane, M.P., Wolpin, K.I., 2007. Exploring the Usefulness of a Nonrandom Holdout Sample for Model Validation: Welfare Effects on Female Behavior. International Economic Review 48, 1351–1378. URL: http://doi.wiley.com/10.1111/j.1468-2354.2007.00465.x, doi:10.1111/j.1468-2354.2007.00465.x.

Kling, C., Rubin, J., 1997. Bankable permits for the control of environmental pollution. Journal of Public Economics 64, 101–115. URL: https://doi.org/10.1016/S0047-2727(96)01600-3.

Kollenberg, S., Taschini, L., 2016. Emissions trading systems with cap adjustments. Journal of Environmental Economics and Management 80, 20–36. URL: https://doi.org/10.1016/j.jeem.2016.09.003.

Low, H., Meghir, C., 2017. The Use of Structural Models in Econometrics. Journal of Economic Perspectives 31, 33–58. URL: http://pubs.aeaweb.org/doi/10.1257/jep.31.2.33, doi:10.1257/jep.31.2.33.

Lucas, R.E., 1976. Econometric Policy Evaluation: A Critique, in: Brunner, K., Meltzer, A.H. (Eds.), The Phillips Curve and Labor Markets, Carnegie-Rochester Conference Series on Public Policy. North Holland, Amsterdam, pp. 19–46. URL: https://doi.org/10.1016/S0167-2231(76)80003-6.

Maxwell, S.M., Hazen, E.L., Lewison, R.L., Dunn, D.C., Bailey, H., Bograd, S.J., Briscoe, D.K., Fossette, S., Hobday, A.J., Bennett, M., Benson, S., Caldwell, M.R., Costa, D.P., Dewar, H., Eguchi, T., Hazen, L., Kohin, S., Sippel, T., Crowder, L.B., 2015. Dynamic ocean management: Defining and conceptualizing real-time management of the ocean. Marine Policy 58, 42–50. URL: https://doi.org/10.1016/j.marpol.2015.03.014.

Miller, S.J., Deacon, R.T., 2017. Protecting Marine Ecosystems: Regulation Versus Market Incentives. Marine Resource Economics 32, 83–107. URL: https://doi.org/10.1086/689214.

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

Mistiaen, J.A., Strand, I.E., 2000. Location Choice of Commercial Fishermen with Heterogeneous Risk Preferences. American Journal of Agricultural Economics 82, 1184. URL: https://www.jstor.org/stable/1244248.

Newell, R.G., Papps, K.L., Sanchirico, J.N., 2007. Asset Pricing in Created Markets. American Journal of Agricultural Economics 89, 259–272. URL: https://www.jstor.org/stable/4492809, doi:10.1111/j.1467-8276.2007.01018.x.

Newell, R.G., Sanchirico, J.N., Kerr, S., 2005. Fishing quota markets. Journal of Environmental Economics and Management 49, 437–462. URL: https://doi.org/10.1016/j.jeem.2004.06.005, doi:10.1016/j.jeem.2004.06.005.

Provencher, B., Bishop, R.C., 1997. An Estimable Dynamic Model of Recreation Behavior with an Application to Great Lakes Angling. Journal of Environmental Economics and Management 33, 107–127. URL: http://doi.org/10.1006/jeem.1996.0978.

Reimer, M.N., Abbott, J.K., Haynie, A.C., 2017a. Empirical Models of Fisheries Production: Conflating Technology with Incentives? Marine Resource Economics 32, 169–190. URL: https://doi.org/10.1086/690677.

Reimer, M.N., Abbott, J.K., Wilen, J.E., 2014. Unraveling the multiple margins of rent generation from individual transferable quotas. Land Economics 90, 538–559. URL: https://doi.org/10.3368/le.90.3.538.

Reimer, M.N., Abbott, J.K., Wilen, J.E., 2017b. Fisheries Production: Management Institutions, Spatial Choice, and the Quest for Policy Invariance. Marine Resource Economics 32, 143–168. URL: https://doi.org/10.1086/690678.

Ropicki, A.J., Larkin, S.L., 2015. Social Network Analysis of Price Dispersion in Fishing Quota Lease Markets. Marine Resource Economics 29, 157–176. URL: https://doi.org/10.1086/676852, doi:10.1086/676852.

Rubin, J.D., 1996. A model of intertemporal emission trading, banking, and borrowing. Journal of Environmental Economics and Management 31, 269–286. URL: https://doi.org/10.1006/jeem.1996.0044.

Rust, J., 1987. Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher. Econometrica 55, 999. URL: http://doi.org/10.2307/1911259.

Scheld, A.M., Walden, J., 2018. An Analysis of Fishing Selectivity for Northeast US Multispecies Bottom Trawlers. Marine Resource Economics 33, 331–350. URL: https://doi.org/10.1086/699712.

Smith, M.D., 2005. State Dependence and Heterogeneity in Fishing Location Choice. Journal of Environmental Economics and Management 50, 319–340. URL: https://doi.org/10.1016/j.jeem.2005.04.001.

Smith, M.D., Wilen, J.E., 2003. Economic impacts of marine reserves: the importance of spatial behavior. Journal of Environmental Economics and Management 46, 183–206. URL: https://www.sciencedirect.com/science/article/abs/pii/S009506960300024X, doi:10.1016/S0095-0696(03)00024-X.

Wilen, J.E., Cancino, J., Uchida, H., 2012. The Economics of Territorial Use Rights Fisheries, or TURFs. Review of Environmental Economics and Policy 6, 237–257. URL: https://doi.org/10.1093/reep/res012.

Wolpin, K.I., 2007. Ex ante policy evaluation, structural estimation, and model selection. American Economic Review 97, 48–52. URL: https://doi.org/10.1257/aer.97.2.48.

Worm, B., Hilborn, R., Baum, J.K., Branch, T.A., Collie, J.S., Costello, C., Fogarty, M.J., Fulton, E.A., Hutchings, J.A., Jennings, S., Jensen, O.P., Lotze, H.K., Mace, P.M., McClanahan, T.R., Minto, C., Palumbi, S.R., Parma, A.M., Ricard, D., Rosenberg, A.A., Watson, R., Zeller, D., 2009. Rebuilding global fisheries. Science (New York, N.Y.) 325, 578–85. URL: http://doi.org/10.1126/science.1173146.

Tables

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

[a] Denotes the parameter values (species-specific, where applicable) for the data generating process with known (and fixed) parameter values.

[b] Denotes the range of parameter values for the data generating process with a random parameter space. Parameter values are drawn randomly from a uniform distribution.

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

Figures

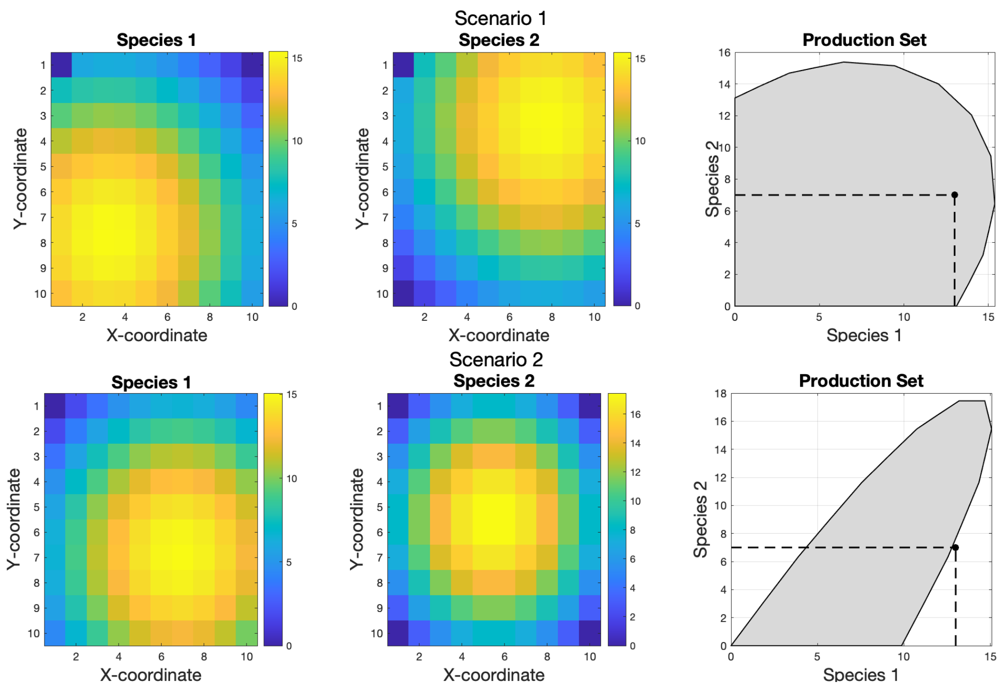

Figure 1: Spatial distribution of expected catch for species 1 (left) and 2 (center) with port located in the upper left-hand corner in cell [1,1]; expected global production set (right) with the total allowable catch (black dot and dashed lines).

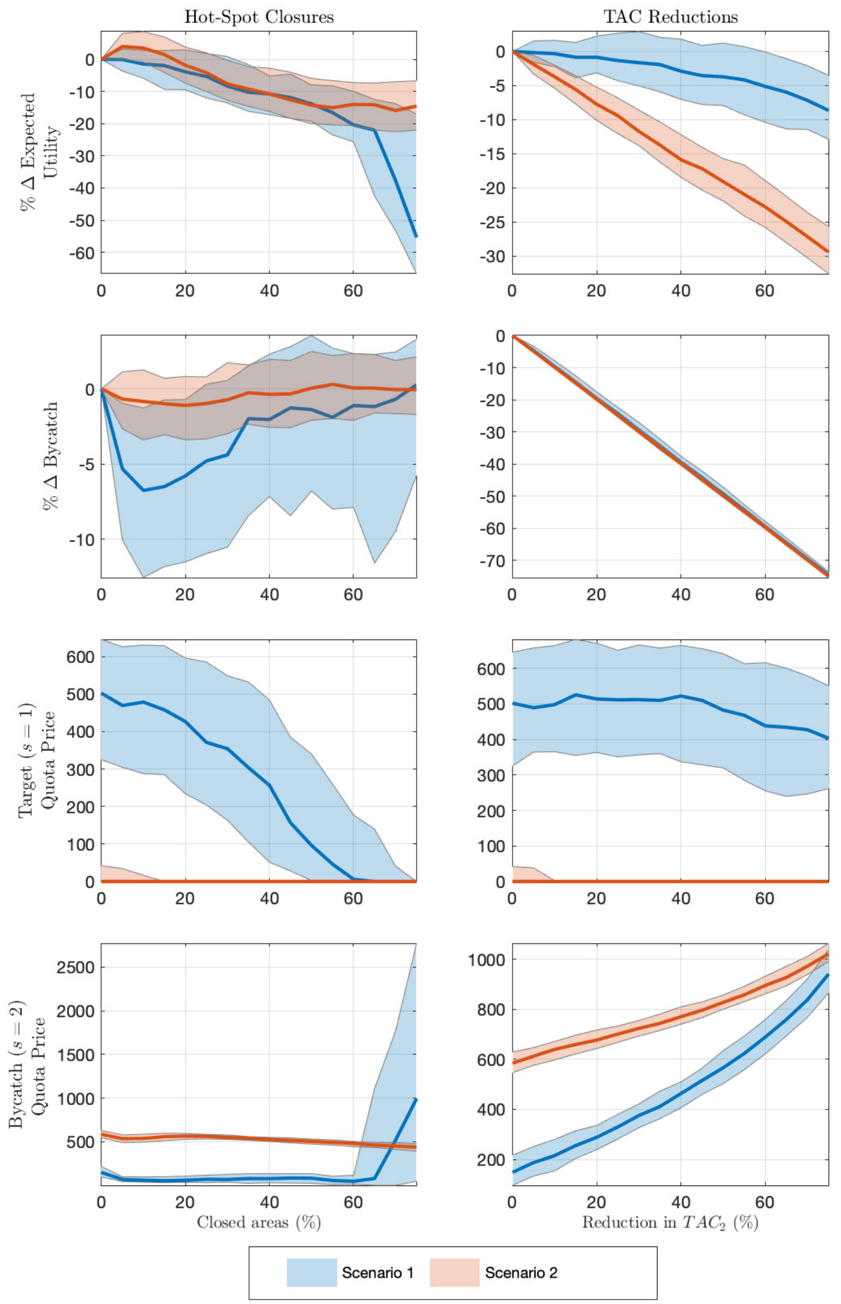

Figure 2: Numerical simulation outcomes—bycatch hot-spot closures (left column) and bycatch TAC reductions (right column) for two biological scenarios (blue and red). The median (solid line) and 25th-75th percentile range (shaded area) are presented using 200 draws from the data-generating process.

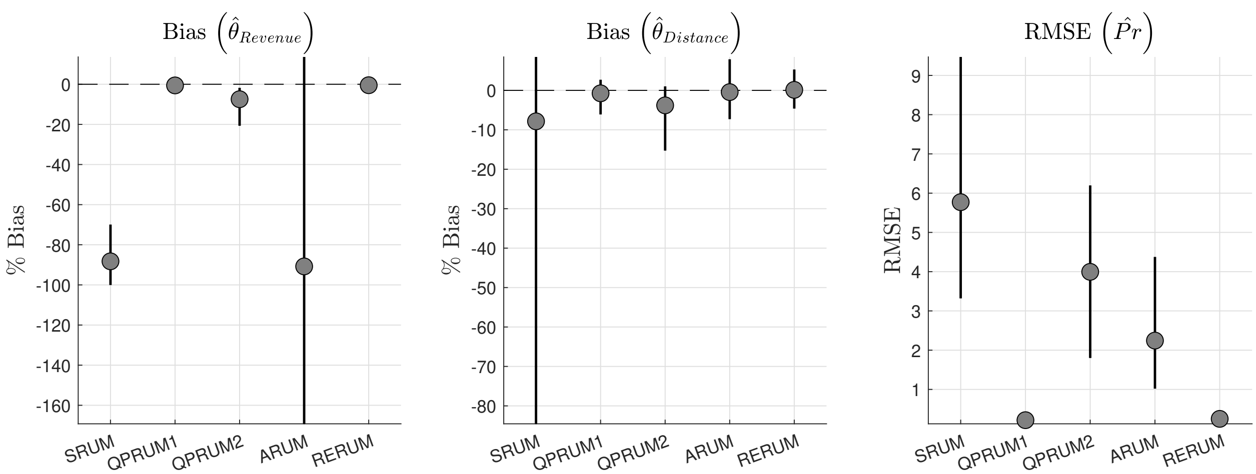

Figure 3: Parameter estimation and in-sample predictive performance—percent bias in utility parameter estimates (left and center columns); root-mean-square error (RMSE) between estimated and population choice probabilities (right column). Markers denote median values and error bars denote the 25th and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

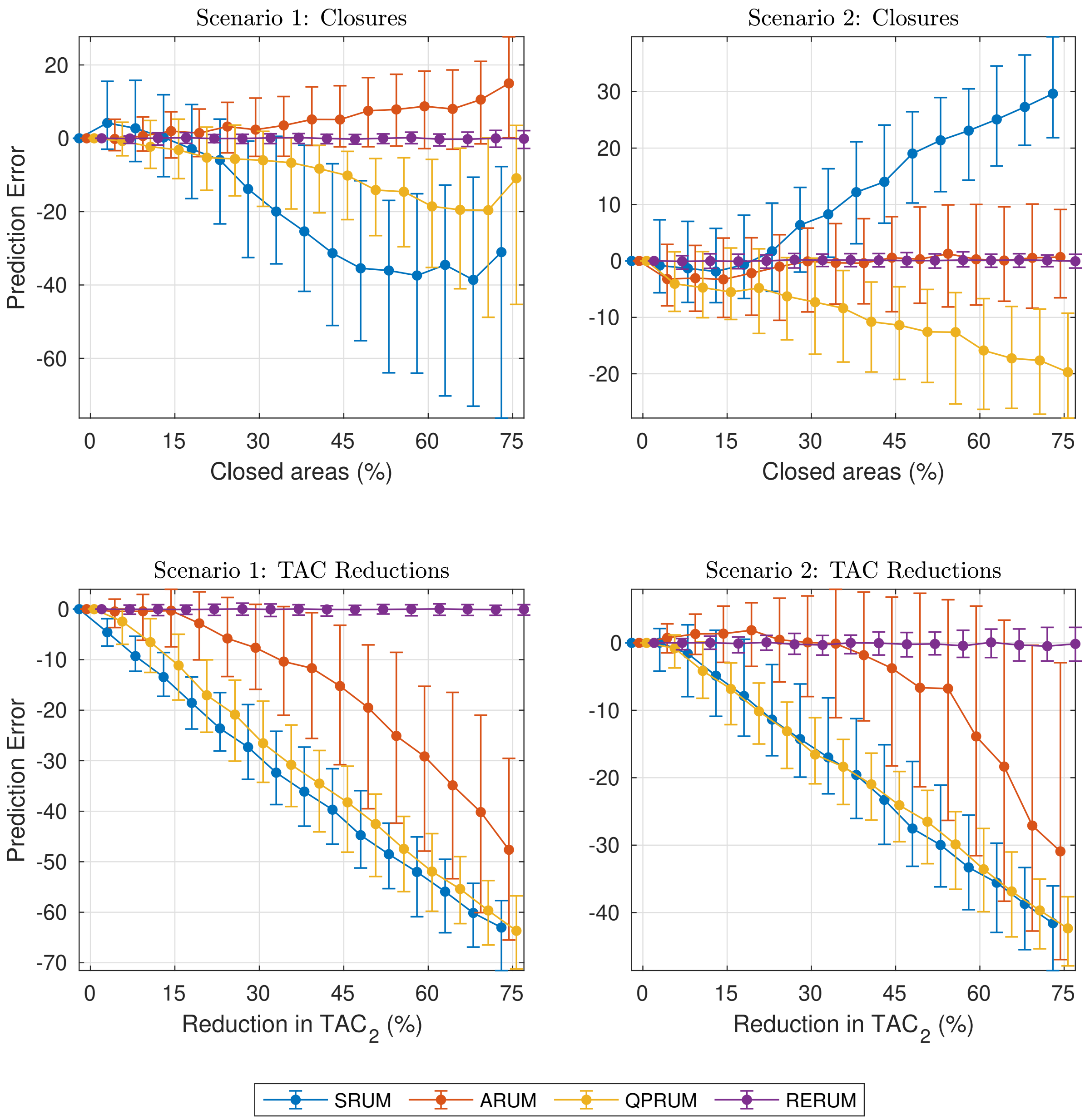

Figure 4: Out-of-sample prediction errors: percentage change in expected utility. Top: bycatch hot-spot closures. Bottom: bycatch total allowable catch (TAC) reductions. Markers denote median values and error bars denote the 25th and 75th percentiles. QP-SRUM model uses period-specific quota-prices from estimation sample. Distributions generated from 200 draws from the data generating process and sampling distributions of utility parameter estimates.

Appendix A. Supplementary Figures

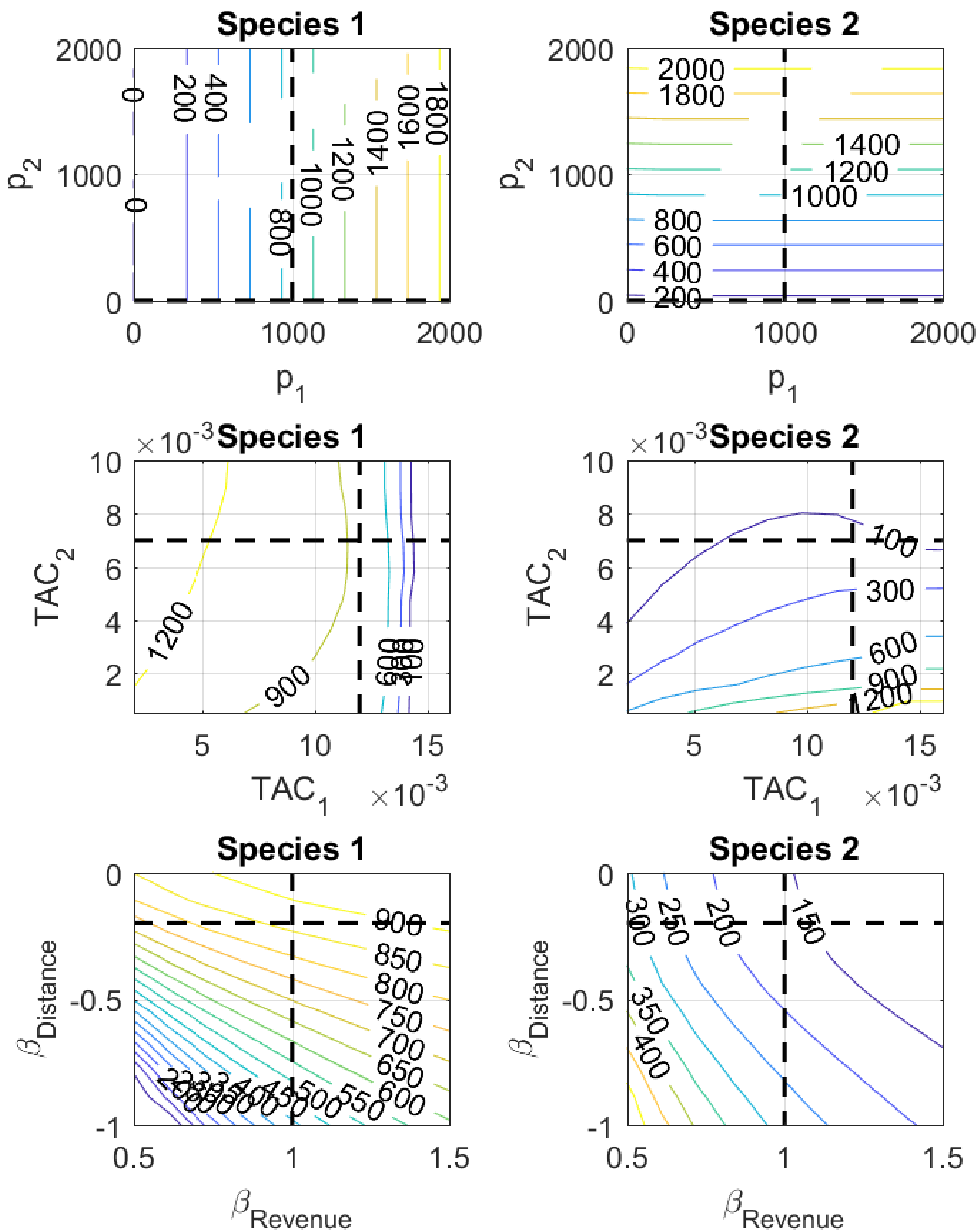

Figure A.1: Quota prices in period $t = 1$ as a function of ex-vessel prices (p_1 and p_2, row 1), total allowable catches (TAC_1 and TAC_2, row 2), and preference parameters (θ_{Rev} and θ_{Dist}, row 3). Dashed lines indicate the data-generating parameter values.

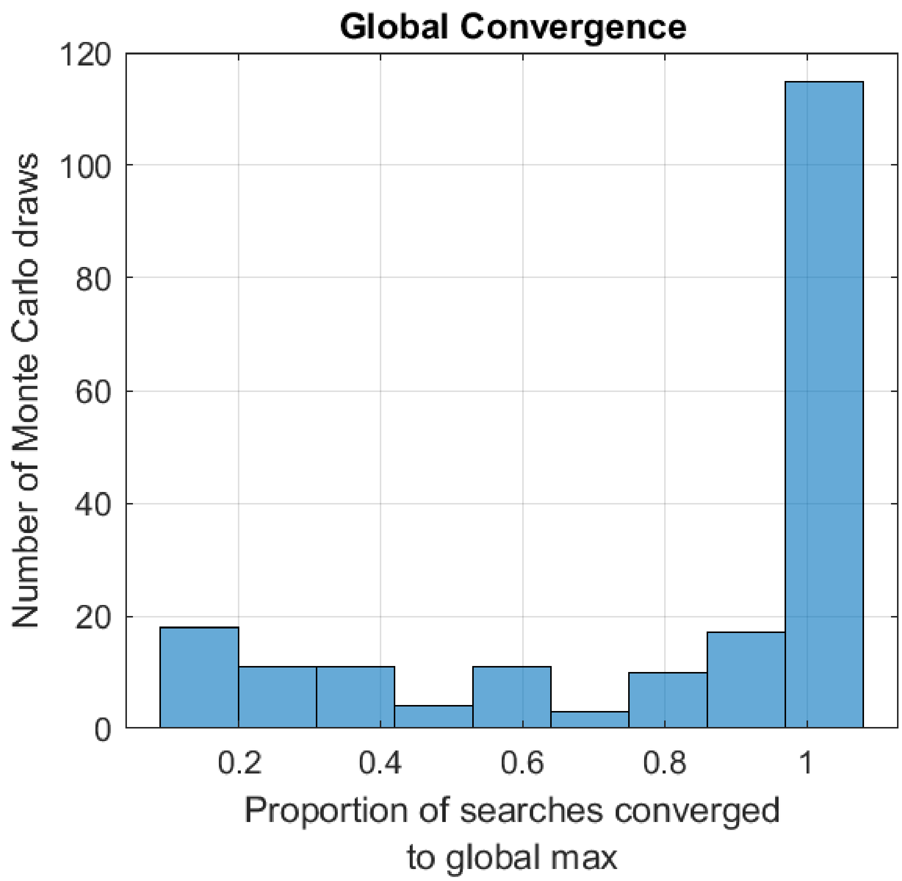

Figure A.2: Global convergence of the RERUM estimator—the proportion of maximum-likelihood searches, for each draw from the data generating process, that converged to the same maximum. Distribution generated by 200 independent draws from the data-generating process and 9 initial values for each draw.

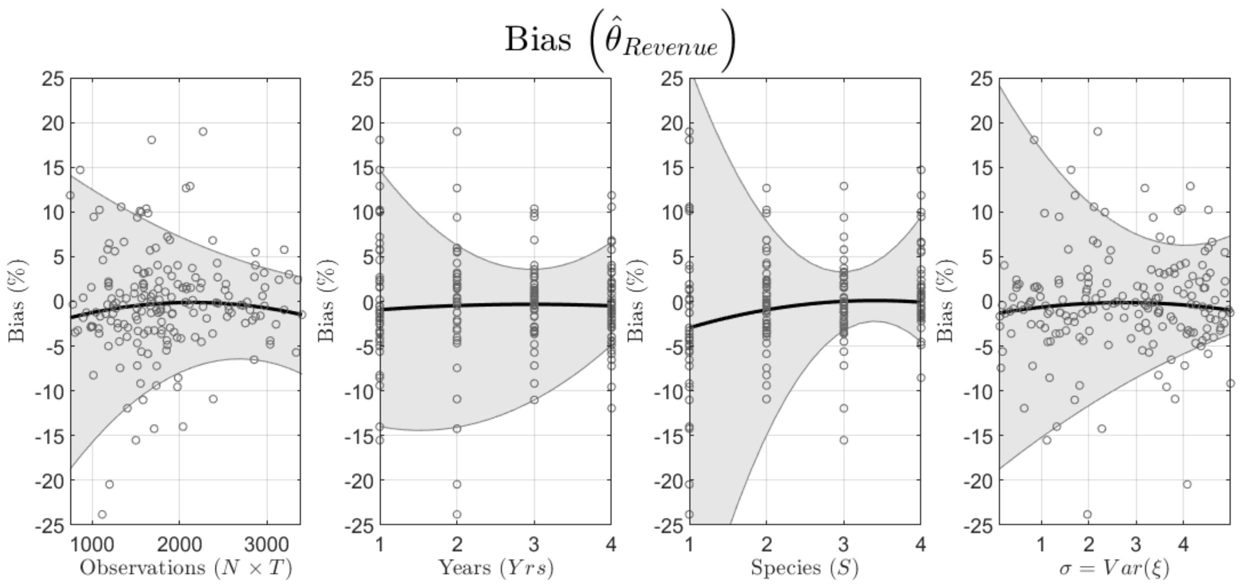

Figure A.3: RERUM parameter bias for θ_{Rev} across four parameter spaces: number of observations per year (far left), number of years (mid left), number of species (mid right), and the variance of the stochastic harvest component (far right). The lines denote quantile regression predictions for the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

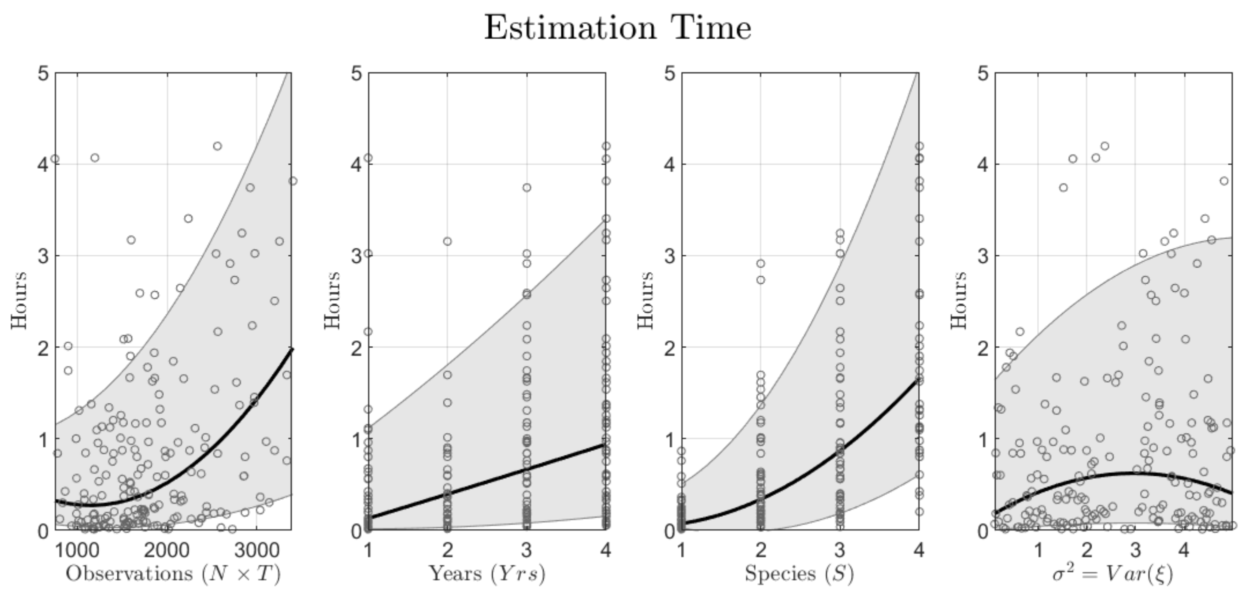

Figure A.4: RERUM estimation time across four parameter spaces: number of observations per year (far left), number of years (mid left), number of species (mid right), and the variance of the stochastic harvest component (far right). The lines denote quantile regression predictions for the 10th, 50th (dark lines), 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 agent's objective in period $T+1$ is to maximize utility with respect to consumption c, subject to a budget constraint:

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

where the consumption good is the numeraire good whose price is normalized to one, w denotes a vector of quota lease prices, $u(\cdot)$ is equivalent to the utility function in equation (1) evaluated at $a = 0$ (i.e., port), and m_i denotes agent i's exogenous component of income. The constraints act to restrict the agent from consuming more than their net income, while also ensuring that the owner has enough quota to cover their annual harvests. Assuming that $u'(c) > 0$ for $c > 0$ and that m_i is large enough to allow for positive consumption, 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

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

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 choice alternative.

Appendix C. Derivation of the Policy Function

Consider the Bellman equation in (3) given the state of the world $z_{i,t} = (x_{i,t}, \varepsilon_{i,t})$, where we substitute in the assumed utility function (1) and, since catch is not known *ex ante*, we replace it with the expected catch:[19]

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

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 used 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 remaining quota—is sunk and does not influence the contemporaneous location choice. Substituting the derivation of the next-period expected value function into the Bellman equation for the last fishing period T, we have:

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

[19] This substitution is justified on the basis that revenues are assumed to be enter linearly into utility (i.e., risk neutrality).

where we've used the fact that utility is linear in revenue and revenues are additively separable from non-revenue aspects in utility. The optimal location choice in period T is therefore defined as:

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

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

$$E_z\left(V\left(z_{i,T} \;\middle|a_{i,T-1}, z_{i,T-1}\right)\right) = E_{x,\varepsilon}\left(\max_{a_{i,T}\in A}\left\{u\left(a_{i,T}, (p-w)'E_y\left(y_{i,T}\middle|a_{i,T}\right)\right)\right.\right.$$
$$\left.\left.+\varepsilon_{i,T}\left(a_{i,T}\right)\right\} + v\left(w'\left(\Omega_i - x_{i,T}\right)\right)\middle|a_{i,T-1}, x_{i,T-1}, \varepsilon_{i,T-1}\right).$$

Let $\Lambda_{i,T} = \max_{a_{i,T}\in A}\left\{u\left(a_{i,T}, (p-w)'E_y\left(y_{i,T}\middle|a_{i,T}\right)\right) + \varepsilon_{i,T}\left(a_{i,T}\right)\right\}$ 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 $E_{x,\varepsilon}\left(\Lambda_{i,T}|a_{i,T-1}, x_{i,T-1}, \varepsilon_{i,T-1}\right) = E_\varepsilon\left(\Lambda_{i,T}\right)$ and simplify the next-period expected value function in the Bellman equation as:

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

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

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

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, the assumption that utility is linear in revenue (and therefore also additively separable in non-revenue components in utility), 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 $\tilde{w}(x_t|\theta)$ such that:[20]

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

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 $\tilde{w}(x_t|\theta)$, 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 $f(a_{i,t}|x_t, w_0)$.

[20] 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 $E(e_s|w_0, x_t)$ for each species $s \in \{1, ..., S\}$ using $X_{s,t}$ from step 1 and $f(a_{i,t}|x_t, w_0)$ 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 $\tilde{w}(x_t|\theta)$ 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 rational-expectations quota price $\tilde{w}(x_t|\theta)$ 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 $f\left(a_{i,t}|x_t, \hat{\theta}_0\right)$.
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).[21]
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.

Appendix E. Out-of-Sample Policy Simulations

The out-of-sample policy simulations presented in Section 6 are generated in the following way. We first generate sampling distributions for the structural parameter estimates $\hat{\theta}$ and $\hat{\gamma}$

[21] 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 $w(x_t|\theta)$ 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.

(where applicable) under the baseline policy scenarios using the data-generating parameter values reported in Column 1 of Table 1. The sampling distributions are created using 500 independent samples from the dgp, where draws differ due to harvest and utility shocks (ξ and ε). To simulate outcomes under the counterfactual policies, we use the following procedure:

1. For each counterfactual policy (including the baseline) and RUM model (including the RERUM model): draw parameter values from their respective simulated sampling distribution, draw harvest and utility shocks from the dgp, and simulate an entire fishing season.
2. Compare a model's simulated outcome against its baseline counterpart to generate a "relative impact". For example, for the SRUM model under the 5% TAC reduction policy, compare a fisher's expected utility $u(\alpha(z_{i,t}), p'E(y_{i,t}|\alpha(z_{i,t}))$ from draw 1 to the expected utility predicted by the SRUM model for draw 1 under the baseline policy.
3. Compare a model's relative impact against the relative impact from the true model to come up with the "impact prediction error."
4. Repeat Steps 1-3 200 times.

Note that for a given draw, the set of harvest and utility shocks are the same for each of the counterfactual policies and RUM models, so the only differences across policies and models are the policy and model parameters.

Appendix F. Performance of the RERUM Estimator

In Figure A.3, we investigate whether there are any particular areas of the data-generating and sampling parameter space in which the RERUM estimator 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.[22] 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.[23] While the algorithm 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.[24]. 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.4).[25] Altogether, the computational costs of the RERUM estimator do not appear to be prohibitively

[22] 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.

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

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

[25] 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 $time(T, N, J) \times T \times S \times Yrs$.

burdensome within the range of sample sizes and numbers of quotas/species encountered by practitioners on a regular basis.