Econometric modeling of fisheries with complex life histories: Avoiding biological management failures

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Abstract

Economics of the fishery has focused on the wastefulness of common pool resource exploitation. Pure open access fisheries dissipate economic rents and degrade biological stocks. Biologically managed fisheries also dissipate rents but are thought to hold biological stocks at desired levels. We develop and estimate an empirical bioeconomic model of the Gulf of Mexico gag fishery that questions the presumptive success of biological management. Unlike previous bioeconomic life history studies, we provide a way to circumvent calibration problems by embedding our estimation routine directly in the dynamic bioeconomic model. We nest a standard biological management model that accounts for complex life history characteristics of the gag. Biological intuition suggests that a spawning season closure will reduce fishing pressure and increase stocks, and simulations of the biological management model confirm this finding. However, simulations of the empirical bioeconomic model suggest that these intended outcomes of the spawning closure do not materialize. The behavioral response to the closure appears to be so pronounced that it offsets the restriction in allowable fishing days. Our results indicate that failure to account for fishing behavior may play an important role in fishery management failures.
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1. Introduction

There is little doubt that the state of world fisheries is cause for concern [9,25,36,48]. Fisheries economists have focused on understanding the causal explanations and economic implications of overexploitation. Simply put, the cause is open access, the result is economic waste through the dissipation of rents, and the solution is some type of property right that aligns the incentives of the harvest sector with the objectives of optimal

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management. A long line of theoretical and empirical economic research demonstrates that a lack of property rights squanders resource rent and degrades biological stocks relative to their optimal level [4,7,21,40,46,51].

However, most fisheries are not characterized by pure open access; instead they are regulated in ways that target the biological health of the resource through restrictions on inputs, outputs, or access to the resource. These regulations tend to leave the underlying open access incentive structure intact, and consequently economists find that there are numerous pathways through which competitive forces dissipate rents in managed fisheries [26].[1] In this context, fishing behavior is tied to rent dissipation but not to biological overexploitation. This assumption sits in sharp contrast to both the pure open access and pure private ownership cases in which there is a direct link between fishing behavior and the biological health of the resource; behavior of the harvest sector directly determines the biological state of the system. For regulated fisheries, however, managers are assumed to protect the biological health of the resource. Managers determine what is biologically safe and target these safe levels with a suite of policy instruments including total allowable catch, entry restrictions, input controls on vessels and fishing gear, size limits, seasonal closures, and area closures. Fishing behavior then matters only to the extent that it affects how different management systems generate economic rent.

We argue that the separation between fishing behavior and biological outcomes in managed fisheries is unrealistic and misleading. What is biologically safe cannot meaningfully be determined without accounting for the behavioral responses of the fishing fleet. After all, if biological management is successful in preserving the biological health of the resource, why is there so much bad news about the state of our marine resources?[2]

The presumptive ability of biological management to maintain stocks has stood in the economics literature arguably because questioning it takes economists outside their realm of expertise. To refute biological success, it is necessary to construct an empirically based bioeconomic model that nests a standard management model. The standard management model in fisheries biology is a life history (or cohort) model that tracks the number of fish at each age and/or life stage. These models inform biological management that aims to protect organisms at different life stages by accounting for age-dependent growth, survival, and fecundity as well as reproductive styles. Examples include minimum size limits that intend to protect immature fish and provide them an opportunity to reproduce; seasonal closures that intend to protect fish during spawning or simply reduce overall fishing mortality; and area closures that intend to increase biomass either by allowing some fish to grow larger or through larval sink–source dynamics. Biological intuition typically guides the choice of fishery policy instruments without regard for potential reactions of the harvest sector.[3]

In spite of the prominent role of life history modeling in fisheries ecology, there is a dearth of empirical bioeconomic literature that quantifies the effects of different fisheries management alternatives. Conceptual models that account for life history and aging are well-known in renewable resource economics [12], but there are few empirical studies. One example is Deacon's econometric model of the production parameters of a life history model for abalone [18]. However, his model does not endogenize behavior of the harvest sector. In most fisheries science, both prospective policy analysis and retrospective policy evaluation ignore the ways in

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[1]Depending on the management regime, this process unfolds along intensive or extensive margins. The classic intensive case is capital stuffing in restricted access fisheries [20,34]. Under limited entry, fishery participants compete rents away by increasing inputs like quantity of gear, engine horsepower, and vessel size. Managers, in turn, shorten seasons, and vessels subsequently compete in a race to fish. Rent dissipation can also occur through short-run behavioral responses such as excess search or crowding in fishing grounds [52]. A similar race unfolds along extensive margins when there is regulated open access [24]. The manager sets a total allowable catch, vessels enter to capture rents, and the manager must respond by shortening the season. In an empirical bioeconomic model of the Pacific halibut fishery, Homans and Wilen find that season closures without entry restrictions exacerbate overcapitalization relative to open access. The economic wastefulness of the regulated open access fishery exceeds that of the pure open access fishery [24].

[2]We know that most global wild fish catches fall within 200-mile Exclusive Economic Zones. So, in principle, most fisheries can be managed to generate rents and to avoid degrading fish stocks to unhealthy levels. But even in the United States, we see 31% of fish stocks below levels that would achieve long-term potential yield [32].

[3]Although fisheries scientists and managers have long considered life history characteristics in modeling [6], recent studies have reinforced the importance of life history features in managed populations. For many fish species, larger individuals tend to produce more offspring than smaller ones [28]. Egg production generally is proportional to fish volume, which in turn is roughly proportional to length cubed [35]. In economic terms, there are increasing reproductive returns to organism size [41]. Individual offspring of older fish can also be more viable than those of younger fish [5], while some fish are more vulnerable to environmental perturbations at different life stages [22]. Moreover, through size selection and size limits, fishing pressure can influence the evolutionary path of species by selecting genotypes with slower or faster growth rates [16].

which economic incentives affect the behavior of the harvest sector.[4] Studies that both endogenize fishing behavior—i.e. that allow fishing effort to respond to economic incentives—and account for complex life histories are only beginning to emerge in the literature [29,39,42,43]. These previous studies are plagued by the need to calibrate the behavioral model to the bioeconomic simulation after completing the econometric estimation. In this paper, we propose a solution to the calibration problem by embedding the econometrics directly in the life history simulation.

We conduct the first empirical analysis of how behavioral responses of a fishing fleet might undermine the biological targets of management. To that end, we develop an empirical bioeconomic model of Gulf of Mexico gag (*Mycteroperca microlepis*), a commercially harvested grouper species, to examine the 1-month (February 15–March 15) spawning closure. The standard management model that incorporates fishing mortality exogenously suggests that such closures increase biomass and reduce fishing pressure.

Using our empirical bioeconomic model, we find that fishing pressure increases or decreases only slightly for the years in which the one-month spawning closure was in effect. This finding is a net effect after econometrically controlling for time-varying factors that could also influence fishing effort—such as price, biomass, economic opportunities in other fisheries and outside of fishing, seasonality, weather conditions, and other policy changes. Though we do not directly test the causal mechanism, the closure appears to induce a behavioral response in the fleet that offsets the reduction in fishing days. Thus, management models based on biological controls can be misleading if they disregard harvest sector behavior.

The biological components of the model are parameterized using published studies in fisheries ecology and official federal government stock assessments. The economic model includes both production and behavioral parameters. The rationale is that individual firms act independently to make fishing effort decisions and only indirectly control their catches [1]. The economic parameters are econometrically estimated in a multi-stage iterative procedure, and bioeconomic outcomes result from aggregating across individual vessels as the state dynamics unfold over time.

2. Empirical setting

Gag is a long-lived, slow-growing grouper. Adults have high site fidelity and aggregate to spawn from January through April, with peak spawning occurring in February and March [13]. Year class strength is likely determined during the pelagic larval stage, before gag recruit to seagrass beds inshore. They move offshore as a cohort during their first year, and are distributed along the continental shelf more or less by size with increasing depth [23].

Gag are protogynous hermaphrodites, which means that fish first mature as female and transition to male later in life. Fishing pressure, because it tends to select for larger fish, may select for males. The limited historic data on gag sex ratios support management concerns. Between the 1970s and the 1990s, the percentage of male gag declined from 17% to 2% in the Gulf of Mexico [14].

Gag is one of 62 species in the Gulf of Mexico reef-fish complex. The complex, which is managed partly as species aggregates and partly on a single species basis, includes ten other grouper species and ten snapper species. Annual commercial value of gag landings in the Gulf ranged from $3.3 million to $8.4 million over the period 1994–2003 (NOAA Office of Science and Technology, www.st.nmfs.gov/st1/). Reef-fish fisheries are conducted with a wide range of gears including hook and line, bottom long line, and traps (although this gear is being phased out). Most gag are caught in reef habitat along the continental shelf edge with hook and line (i.e. handlines, electric bandit reels, buoy gear, conventional rod and reel).

Commercial fishing for all reef fish requires a reef-fish permit. The number of permits ($N = 1079$) is restricted through a limited entry program,[5] although it is unclear whether the total permit number is set low

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[4]Quantifying the effects of past policies can be approached econometrically with non-structural treatment effects or with an explicit model of the population dynamics. Previous work on the Gulf of Mexico reef-fish fishery analyzed the fishery impacts of two marine reserves using a treatment effects approach with area-specific constants and trends to proxy for some of the biological structure [45]. However, simulating the effects of future policy changes (or current policies on future outcomes) requires an explicit model of the state equations.

[5]Official management documents do not refer to a "limited entry program," but there has been a moratorium on issuing new reef-fish permits since 1992.

enough to effectively restrict overall effort. Twenty-five percent of the permits land 75% of the reef fish over the period 1993–2002 [45].

For the empirical analysis, we construct a relational database from several sources. National Oceanic and Atmospheric Administration (NOAA) Fisheries fishing logbooks report individual commercial gag fishing trip decisions and the total catch of gag.[6] State of Florida landings tickets report prices of each fish species.[7] For gaps in the price time series, we use NOAA's online commercial fishery statistics, NOAA Office of Science and Technology (www.st.nmfs.gov/st1/). We build a time series of wave heights using NOAA's National Data Buoy Center (www.ndbc.noaa.gov) and online records of policy decisions of the Gulf of Mexico Fishery Management Council (GMFMC). We develop the time series of policy changes for the reef-fish complex based on Waters [49,50], Rueter [37], and personal experience of one of the authors (Coleman) on the GMFMC. The complete data set spans 1994–2003.

Multiple federal regulations directly affect the commercial gag fishery in the Gulf of Mexico. The GMFMC developed a reef-fish fishery management plan in the 1980s and set a 51 million pound maximum sustainable yield for the entire complex. In 1990, the council set a gag minimum size limit of 20 in (50.8 cm) total length and a total commercial grouper quota of 11 million pounds, of which 9.2 million was allocated to shallow-water groupers. The council also set depth restrictions on buoy lines and bottom long lines, and set a biological goal that the spawning stock biomass per recruit would be 20% of that which would occur with no fishing by the year 2000. In 1991, the shallow water grouper quota increased to 9.9 million lb. In 2004, the commercial shallow-water quota was reduced to 8.8 million lb (gutted weight) with 5.3 million pounds allocated to red grouper. A closure would result when either the shallow-water or red grouper quota was reached. The shallow-water grouper fishery closed in November 2004 when the red grouper quota was reached.

Regulations set exclusively for red snapper—a valuable target species for many vessels that also fish for grouper—indirectly affect the gag fishery. During our sample period, snapper seasons open and close at various times throughout the calendar year, largely depending on quotas.[8] There is also a two-tier red snapper endorsement, a Class I permit allowing a 2000 pound trip limit for high-end red snapper fishermen, and a Class II permit limiting it to 200 pounds. All other reef-fish permits allow the recreational bag limit. These permit layers and season closures indirectly affect the gag fishery and generate time-varying opportunity costs of fishing for gag or other reef-fish species.

Beyond the time-varying indirect effects of snapper regulations, several grouper regulations changed during our sample period. GMFMC formed two no-take marine reserves in 1999 that went into effect in June 2000.[9] Coincident with forming reserves, GMFMC also increased the size limit for gag from 20 to 24 in (61 cm). The following year (2001), a 1-month seasonal closure was implemented during the peak spawning period for gag (February 15–March 15), which prohibited landing shallow-water groupers. The expectation was that the closure would reduce landings by 9%, assuming no effort shifting.

3. An empirical bioeconomic life history model

We develop and estimate an empirical bioeconomic life history model for the Gulf of Mexico gag fishery by building on a biological model of the fishery that treats fishing mortality exogenously [23]. The biological portion of our model contains 181 state variables that represent a total of four life stages: recruits (1 state, age 0), immature females (60 states), mature females (60 states), and males (60 states). Age 0 fish enter the model as recruits, and those that survive until age 6 months become immature females. As fish grow and age, they become mature females; some portion of the female population become males. Reproduction is a function of the number of eggs produced, which is a function of the number of mature females in each size class, and

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[6]We thank John Poffenberger of National Marine Fisheries Service for providing access to reef-fish logbook data.

[7]We thank Joe O'Hop of the Florida Fish and Wildlife Conservation Commission for providing access to landings tickets.

[8]As an example, in 2003, the number of snapper open days by month (January through December) was (0, 10, 10, 10, 10, 10, 7, 7, 0, 10, 10, 7).

[9]The Madison Swanson and Steamboat Lumps reserves are 115 and 104 square nautical miles, respectively. The rationale for the reserves was to address the skewed gag sex ratio. The reserves were authorized for 4 years initially and recently were reauthorized for an additional 6 years.

fertilization success, which is a function of the percentage of males. The large state space is required to incorporate the nonlinearity of egg production, fertilization success, and stage transitions as well as the effect of an in-sample size limit policy change.

At first glance, the biological model appears highly parameterized. However, the basic structure of the model is standard in fisheries biology and thus serves as the relevant benchmark for understanding biological management. Moreover, the ways in which most parameters enter the model allow fisheries scientists to measure them with fishery-independent data. This simplification allows us to use the information content of fishing data to resolve key production and behavioral parameters. The model description below provides details on growth, stage transitions and survival, reproduction, and determinants of fishing mortality. It follows the published study on gag population dynamics [23] for the biological processes but modifies the treatment of fishing mortality.

There are 60 age classes, each representing 0.5 years, and the time step for harvest is monthly.[10] Let a index age class (in years). Gag grow according to a von Bertalannfy growth function (as in [39,42]) such that the length of a fish (L) in millimeters at age a is

$$L(a) = L_\infty[1 - e^{\beta(\alpha+a)}], \tag{1}$$

where L_∞ is the terminal length, and $\alpha > 0$ and $\beta < 0$ are parameters. Allometric parameters (η and υ) convert length to weight (w) in grams:

$$w(a) = \eta L(a)^\upsilon. \tag{2}$$

We model natural mortality (m) and recruitment on an annual basis, fish growth on a semi-annual basis, and fishing mortality (f) on a monthly basis.[11] Let τ index time (in years), and t index time (in months). For each age class, there is a state variable that tracks the number of immature females ($IF_a(\tau,t)$), mature females ($MF_a(\tau,t)$), and males ($M_a(\tau,t)$) in the class. The additional state variable is the number of new recruits ($R(\tau)$) in each year, which is a function of the number of mature females and the percentage of male gag in the previous year. Recruits that survive to age 1 enter into the simulation as immature females. Fish experience stage-specific natural mortality in addition to fishing mortality, which we assume is not stage-specific. Transition probabilities across life stages (γ) are assumed exogenous but age-dependent [23].[12] Thus, the following equations describe the transitions from immature to mature female and from mature female to male:

$$\gamma^{\text{mat}}(a) = 1/[1 + e^{\rho_{\text{mat}}+\varsigma_{\text{mat}}a}] \tag{3}$$

and

$$\gamma^{\text{male}}(a) = [1 - e^{\rho_{\text{male}}(a-\zeta_{\text{male}})}] \times I(a > \zeta_{\text{male}}), \tag{4}$$

where I is the indicator function. The state equations for the number of fish in each life stage (on an annual basis) are then

$$IF_a(\tau) = [1 - \gamma^{\text{mat}}(a)][e^{-(m_{IF}+\sum_{t=1}^{12} f(\tau,t))}]IF_a(\tau-1) + e^{-m_1}R(\tau-1), \tag{5}$$

$$MF_a(\tau) = \gamma^{\text{mat}}(a)[e^{-(m_{MF}+\sum_{t=1}^{12} f(\tau,t))}]IF_a(\tau-1) + [1 - \gamma^{\text{male}}(a)][e^{-(m_{MF}+\sum_{t=1}^{12} f(\tau,t))}]MF_a(\tau-1) \tag{6}$$

and

$$M_a(\tau) = \gamma^{\text{male}}(a)[e^{-(m_{\text{male}}+\sum_{t=1}^{12} f(\tau,t))}]MF_a(\tau-1) + [e^{-(m_{\text{male}}+\sum_{t=1}^{12} f(\tau,t))}]M_a(\tau-1)$$
$$\text{for } a = 0.5, 1, 1.5, \dots, 30. \tag{7}$$

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[10]Heppell et al. [23] use 30 age classes. We double this number for empirical reasons. With just 30 age classes, the actual size limit change that took place in 2000 is within the same class due to the steep slope of the von Bertalannfy growth function at the corresponding age. Moving to 60 classes allows the different size limits to correspond to different cutoff classes.

[11]Our estimate of natural mortality also implicitly captures mortality due to recreational fishing. We lack sufficient temporal resolution of recreational data to model recreational fishing explicitly.

[12]The exogeneity assumption allows us to identify the role played by economic behavior.

These state equations capture the net changes in the number of fish of each age class due to entry and survivorship. Because these fish are sequential hermaphrodites, a fish can only enter the state from the previous state (e.g. recruit to immature female). Fish either exit a state via: (1) transition to the next state (e.g. immature female to mature female), (2) death from natural mortality, or (3) death from fishing mortality. Thus for a given period, e^{-m} is the fraction of fish surviving natural mortality, and e^{-f} is the fraction surviving fishing mortality.

We apply the same fishing mortality across life stages and age classes for two reasons. First, the fishery data do not allow us to identify separate fishing mortality rates; logbooks do not report catch by age or size. Second, all age classes are subject to fishing mortality, in spite of the size limit, due to the physiological consequences of barrotrauma. Fishing gear cannot avoid catching some undersized fish, and when caught in deep water, gag swim bladders are unable to decompress fast enough. Undersized fish die before they can be thrown back.

Recruitment is a function of egg production (G), the fertilization rate (ψ), and larval survival (φ). These, in turn, are functions of the number of mature females in each age class, the percentage of male fish (p^{male}), and decreasing returns to larval settlement as the carrying capacity of seagrass beds is approached. Egg production for an individual at age a is

$$G(a) = \Gamma a^{\delta}. \tag{8}$$

Thus, our model controls for the increasing returns to fish size in the production of eggs [35,41] but does not explicitly account for the egg viability effect of older fish [5]. To capture the possibility of sperm limitation, the fertilization rate asymptotes to a maximum rate as the percentage of males increases:

$$\psi(\tau) = f^{\text{max}}(1 - e^{\lambda p^{\text{male}}(\tau)}), \tag{9}$$

where

$$p^{\text{male}}(\tau) = \sum_{a=0.5}^{30} M_a(\tau) \Bigg/ \left[\sum_{a=0.5}^{30} M_a(\tau) + \sum_{a=0.5}^{30} MF_a(\tau) + \sum_{a=0.5}^{30} IF_a(\tau) \right].$$

We assume deterministic recruitment with a maximum level of K:

$$R(\tau) = \max\left\{ \left[\sum_{a=0.5}^{30} MF_a(\tau)G(a) \right] \psi(\tau)\varphi, K \right\}. \tag{10}$$

The biological parameter values that we use in the bioeconomic simulation are available in an online appendix that can be accessed at http://www.aere.org/journal/index.html, along with the sources in the fisheries management and ecology literature [15,23,31,38].

There are two economic components of the model. The first describes the production function, while the second describes the determinants of fishing effort. For the latter, we develop models for both endogenous and exogenous fishing mortality in order to compare our empirical bioeconomic model with the standard approach in fisheries science. In both cases, fishing mortality is decomposed into fishing effort (E), which we measure as number of fishing trip days that catch gag, and a catchability parameter that varies based on whether gag are aggregating to spawn (q):

$$f(\tau, t) = q_t E(\tau, t). \tag{11}$$

Because fishing mortality unfolds on a monthly basis and natural mortality is assumed to be annual, we can separate out fishing mortality in the Beverton–Holt catch function. Catch (C) is then

$$C(\tau, t) = (1 - e^{-qE(\tau,t)}) \sum_{a=0.5}^{30} w(a)[M_a(\tau, t) + IF_a(\tau, t) + MF_a(\tau, t)] \times I(L(a) > L^{\text{lim}}(\tau, t)), \tag{12}$$

where the indicator function is used to exclude biomass of fish that are below the size limit. Since e^{-f} is the fraction of fish surviving fishing mortality in a given period, $(1 - e^{-f})$ represents the fraction of fish that are caught. The summed terms in (12) constitute legal fishable biomass. In our setting, the size limit changes in sample, so L^{lim} is a function of time. Note that in the state equations, we still apply fishing mortality to

survival in all age classes due to barrotrauma, but these fish cannot be landed and do not show up in the landings data. In the econometric estimation below, we use data on catch and fishing trips for gag combined with the life history model in (1)–(12) to estimate the catchability parameters q_t as well as a size distribution of initial abundance. We take the initial distribution of immature females, mature females, and males directly from [23], which estimates these proportions from fishery-independent observations in [31].

To estimate the behavioral model, we decompose fishing effort to reflect individual choices. Following Smith and Wilen [42,43], number of fishing trips is the product of boats (b), choice occasions per boat (o), and the probability of fishing during the month (π):

$$E(\tau, t) = b(\tau, t)o(\tau, t)\pi(\tau, t). \tag{13}$$

The limited entry program controls the number of boats, and seasonal closures (in conjunction with minor variation in calendar days within each month) control the number of choice occasions. In the ECON model, the probability of fishing is a function of fishing conditions, whereas in the NOECON model, this probability is assumed constant over time. In essence, the NOECON model assumes that the responsiveness of fishing behavior to prices, biomass, and weather conditions simply adds noise. Responses to regulation are mechanistic such that reductions in fishing pressure are proportional to reductions in the fishing season.

Following Smith and Wilen [44], we use a linear random utility model to characterize individual trip decisions, but here we aggregate to the monthly level prior to estimation. In general, using a discrete choice model ensures that trip predictions in- and out-of-sample will be strictly non-negative. As above, the number of trips taken in a month is E, the vector of behavioral parameters as $\boldsymbol{\theta}$, and the vector of influences on the trip decision as $\mathbf{X}$, which includes price of gag, fishable biomass, regulatory changes, weather, prices of other reef-fish species, catch-per-unit-efforts (CPUEs) of other reef-fish species, and seasonal effects. Assuming Type I Extreme Value errors as in McFadden [30], and also assuming that these errors are independent across individuals and time, the individual likelihood contribution in a month is

$$\text{Lik}(\tau, t) = \left(\frac{e^{\mathbf{X}'(\tau,t)\boldsymbol{\theta}}}{1 + e^{\mathbf{X}'(\tau,t)\boldsymbol{\theta}}} \right)^{E(\tau,t)} \left(\frac{1}{1 + e^{\mathbf{X}'(\tau,t)\boldsymbol{\theta}}} \right)^{[b(\tau,t)o(\tau,t) - E(\tau,t)]}. \tag{14}$$

In order to explore the effects of management, we need to estimate the production parameters (two q's and the shape of the initial abundance distribution) and the behavioral parameters ($\boldsymbol{\theta}$) in (14).

4. Estimation and results

4.1. Econometric analysis

To avoid the calibration problem that plagues other empirical bioeconomic life history models [29,42], we embed the econometric estimation within the dynamic simulation model. We then iterate through each component of the bioeconomic model until all parameters converge to a solution. In so doing, behavior is allowed to respond directly to states of the system in the econometrics, so there is no need to match simulated bioeconomic states to regressors used in the behavioral model.

We start with a simulation of the life history model conditional on actual trips taken and guesses for the shape of the initial abundance distribution and catchability coefficients (the parameters that map fishing trips and fishable biomass into catch). We assume that initial abundance across age classes is distributed exponentially with a decay parameter that needs to be estimated. We then allocate individuals in each age class to the life stages based on probabilities estimated in [23]. We input actual trips taken into the bioeconomic simulation model and, conditional on catchability and initial abundance, use the model to generate predicted catch. Thus, to start our estimation routine running, we are using actual trips as a proxy for predicted trips. We use nonlinear least squares to minimize the squared difference between actual and predicted catch. This provides an update to our initial guess for the production parameters.

Conditional on our current production parameter vector and actual trips taken, we simulate the life history model again to produce time-specific biomass estimates. Biomass then becomes a covariate in the fishing participation regression. Conditional on these biomass estimates, which are conditional on the current production parameter estimates, we estimate the behavioral model using maximum likelihood. We use the

Table 1
Production parameters (nonlinear least squares; dependent variable—actual gag catch)

Coefficient	Parameter estimate	Standard error	t Stat	P-value
$\ln(q_{spawning})$	−11.8365	1.3514	−8.7587	0.000
$\ln(q_{not\ spawning})$	−11.8959	1.3653	−8.713	0.000
Shape of initial abundance	−0.2621	0.1352	−1.9386	0.053
n	120			
Transformed $q_{spawning}$	7.23558E−06			
Transformed $q_{not\ spawning}$	6.8183E−06			
% Difference	6%			

Note: Catchability coefficients are estimated in logs to manage the numerical optimization by avoiding negative catches in the simulation model.

resulting parameter vector to endogenize trips taken in the life history simulation. This then feeds back into the production parameter estimation, the production routine generates new estimates of biomass, and these feed back into the behavioral routine. We stack the production and behavioral parameter vectors and use relative Euclidean distance between two consecutive iterations as a convergence criterion. We stop iterating when the distance is less than 0.0001.[13]

Table 1 reports the results for the production parameters, which are statistically significant and bioeconomically plausible.[14] Note that there are two catchability coefficients. The first one corresponds to the spawning season (January through April), and the other represents that rest of the year. Biologically, we know that gag aggregate to spawn, and this is precisely what the data tell us. The first catchability coefficient is larger than the second such that conditional on the same amount of effort, one can catch more gag during the spawning season. However, the difference is not statistically significant. The premise of the seasonal closure is to protect gag during spawning when they are more vulnerable to harvest. Though the catchability coefficients are not statistically different, we use both of them in the simulation model to be conservative; higher catchability in the spawning season allows more biomass to be conserved with a seasonal closure.

For the behavioral model, we define a gag trip as a vessel landing at least 25% gag (we explore sensitivity to this assumption in the next section). The regressors in the model include price of gag, biomass (based on simulations from the life history model), open days in the snapper fishery, a dummy to capture implementation timing of the marine reserves and size limit change, the 90th percentile of wave height (to capture dangerous fishing days), two dummies to capture the shallow-water grouper fishery closure (one for months during the spawning season and one for months during the rest of the year), CPUE and price for other groupers, red snapper, and other reef fish (together with gag this forms a complete partition of all 62 reef-fish species), unemployment, and monthly dummies to account for the spawning aggregation effect from January through April. The monthly dummies also capture unobservable sources of seasonality not contained in other regressors. Some of the spawning aggregation effect is contained directly in the biomass regressor because the timing of the bioeconomic simulation allows new fish to recruit into the fishery in January. Thus, we do not have firm *a priori* expectations about the relative magnitudes of monthly dummies.

Behavioral results appear in Table 2. Because gag are concentrated in the northeastern Gulf, we assume that the number of boats exploiting gag is a subset of the total permit holders (500 in our model) and explore sensitivity to this assumption in the next section. All coefficients have their expected signs. Gulf of Mexico vessels fish more intensively for gag when the price is high or the biomass is high. At the same time, bad weather can reduce fishing effort, and opportunities outside of fishing (using unemployment as a proxy) can reduce effort. Opportunities in other fisheries could increase or reduce effort depending on whether they are substitutes or complements in production. The positive coefficients on both seasonal closure dummies indicate

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[13]A reviewer correctly pointed out that statistical inference about our parameter estimates is conditional on biological parameters from sources in ecology being true.

[14]Both raw catchability estimates are significant at the 1% level, while the initial abundance shape is only significant at the 10% level.

Table 2

Behavioral parameters (binary logit—maximum likelihood; dependent variable—take a gag fishing trip ('yes' or 'no'))

Coefficient	Parameter estimate	Standard error	Z stat	P-value	Elasticity at means
Constant	−9.1384	0.183	−49.91	0.000	
Price	0.4706	0.041	11.45	0.000	1.071
Snapper days open	0.0034	0.001	3.78	0.000	0.021
Size limit/marine reserve	0.3515	0.024	14.71	0.000	
Wave height (90th %)	−0.0181	0.002	−9.53	0.000	−0.045
Grouper closure (spawning months)	0.2895	0.020	14.62	0.000	
Grouper closure (all months)	0.4449	0.023	19.69	0.000	
Other grouper CPUE	0.3101	0.541	0.57	0.566	0.015
Red snapper CPUE	−0.25	0.146	−1.72	0.086	−0.013
Other reef CPUE	0.1199	0.521	0.23	0.818	0.003
Price other grouper	0.0542	0.030	1.82	0.068	0.104
Price red snapper	0.019	0.006	3.02	0.003	0.034
Price other reef	0.159	0.025	6.46	0.000	0.189
Unemployment	0.0844	0.010	8.88	0.000	0.479
Fishable biomass (total > size limit)	0.3184	0.008	38.83	0.000	3.929
Dummy—January	−0.4778	0.029	−16.48	0.000	
Dummy—February	−0.2546	0.029	−8.90	0.000	
Dummy—March	−0.2895	0.030	−9.75	0.000	
Dummy—April	−0.3183	0.025	−12.53	0.000	
Dummy—May	−0.03	0.020	−1.48	0.139	
Dummy—June	−0.2243	0.024	−9.46	0.000	
Dummy—July	−0.5055	0.023	−22.47	0.000	
Dummy—August	−0.7416	0.024	−31.42	0.000	
Dummy—September	−0.8198	0.022	−36.76	0.000	
Dummy—October	−0.3983	0.021	−18.79	0.000	
Dummy—November	−0.2105	0.019	−11.08	0.000	
Dummy—December	0 —Restricted for Identification—				

that after the closure was implemented, gag fishermen appeared to respond by fishing more in the remainder of the year.

The effects of other reef-fish fisheries on gag fishing appear mixed. Red snapper days and price are positive and significant, while red snapper CPUE is negative and significant (at the 10% level). This is plausible in light of how the three-tiered access to red snapper could induce behavioral heterogeneity that is lumped together in our model. Prices and CPUEs for other groupers and other reef fish are positive, but not all coefficients are significant. Beyond the usual multicollinearity issues, these results suggest that further research that explicitly models behavioral heterogeneity in the reef-fish complex is warranted.

Effort response to price and biomass are both elastic, but response to all other covariates is inelastic. The effort/biomass elasticity suggests that short-run behavioral responses may be offset by long-run adjustment to lower (or higher) stocks. That is, short-run behavior has bioeconomic consequences that cannot be predicted without simulating the state dynamics. This result reinforces the need for an explicit model of the population dynamics if one wishes to answer policy questions prospectively [45]. In the simulations below, we label models based on the behavioral parameters in Table 2 as ECON. We also estimate the model with a constant only, which we refer to as the NOECON model to denote the standard management model with exogenous fishing mortality. For the NOECON model, $\hat{\pi}(\tau, t) = e^{\hat{\theta}}/1 + e^{\hat{\theta}}$, and $\hat{\theta} = -3.0915$ (0.0037) with the standard error in parentheses.

It appears that the increases in fishing effort before and after the effective dates of the seasonal closure are sufficiently large as to completely offset the predicted benefits. Recall that the spawning season for gag spans January through April, roughly 120 days. The closure cuts out 29 days during peak spawning. Evaluating all other variables at the means, the probability of fishing during the remaining open season days increases by 101%. The presence of some intertemporal effort substitution in response to the closure is not surprising because at the margin some effort can be redistributed with little cost. However, the finding of a net increase in

effort is surprising. Though our model does not directly test that the closure caused the increase, by controlling for other plausible causes, it points to the closure as a potential causal factor.

4.2. Policy simulations

Using the parameters estimated above, we have a fully dynamic bioeconomic simulation that is empirically based and does not need to be calibrated. Fig. 1 shows that predicted monthly fishing trips and catch from the bioeconomic model closely track time series of actual catch and trips. This result is surprising because no lagged endogenous variables were included as regressors in the econometrics. Though our model misses some of the peaks and troughs and a pure time series model could potentially improve upon this, we generally pick up the long-run patterns of catch and trips as well as the seasonal patterns. Most importantly, we have an empirical model that can be used for both *ex ante* and *ex post* policy analysis. We next use the empirical bioeconomic model to quantify the in- and out-of-sample effects of existing policies on catch, trips, biomass, and sex ratio. We then compare policy effects to those that result from model runs based on constant fishing effort assumptions.

We trace out the fully bioeconomic predictions of fishing effort for our 10-year sample period and 15 years out of sample. For the price path out of sample, we repeat the predicted prices from the last in-sample year. For wave heights, we repeat the in-sample wave heights for the entire 10-year period (1.5 times). This assumption does not seem likely to matter much given the low elasticity of effort with regard to waves in Table 2.

The four cases (depicted in a figure available in the online appendix) include the actual season closure and eliminating the season closure for both the NOECON and ECON models. The NOECON trajectories show minor fluctuations throughout the simulation that simply represent differences in the number of days in each month. With the closure, it shows a substantial dip relative to the model with no closure, but with no
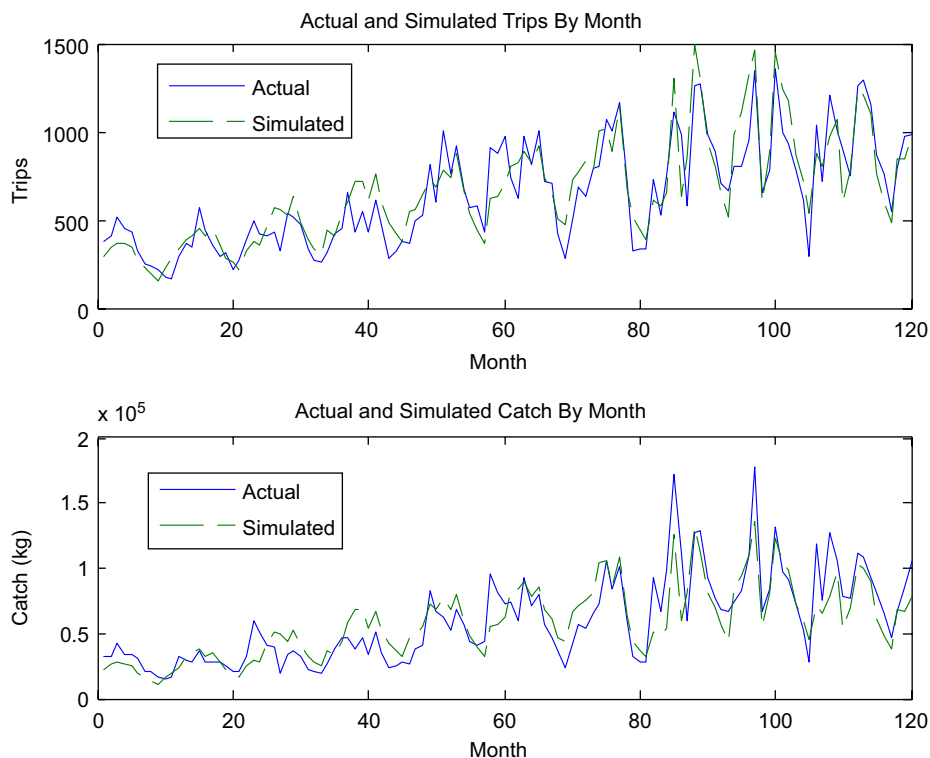

Fig. 1. Performance of the empirical bioeconomic model, 1994–2003. Gag trips include all trips for which landings are at least 25% gag by weight.

compensating response. The ECON models depict more complicated dynamics. In addition to variation in days per month, these dynamics reflect price movements, abundance changes, weather conditions, the spawning aggregation effect, and policy changes. While the ECON model shows intensified fishing effort during the spawning season both with and without a seasonal closure, the model with the closure shows it in a qualitatively different manner. Trips are lower in the two calendar months that contain the closure (February and March)—although not as much lower as in the NOECON model—and trips are higher in the other months of the spawning season (January and April).

Table 3 presents summaries of 25-year bioeconomic simulations based on point estimates of the production and behavioral parameters. The first 10 years are in sample. The top section of the table examines the grouper spawning closure with the fully bioeconomic ECON model, while the bottom section represents the policy experiment with the NOECON model. In the ECON model, average biomass and—of considerable contemporary importance for fisheries sustainability—the number of older fish are both lower with the closure. Total catch and trips increase, but CPUE declines. Of particular concern for the gag fishery is that the adult sex ratio decreases. In the NOECON model, all of these results reverse. Based on this observation, it is tempting to conclude that the closure is effective in increasing biomass, protecting older fish, and improving the sex ratio. Though some catch is lost, the CPUE increases, so the average profitability of a fishing trip increases. Not only does our bioeconomic model indicate negative consequences of the season closure, but it shows that the exact same model that does not account for economic behavior reaches the opposite conclusion. In other words, changes that are attributed to the closure in the standard management models all have the wrong signs.

To compare ECON and NOECON directly, the last column of Table 3 is the percentage of the predicted policy impact in the ECON model, where the predicted effect is the change in the NOECON model. By comparing the percentages for average biomass and ending biomass, there appears to be a dynamic attenuation effect of the policy. In ECON, effort substitution leads to increased total effort from the closure and lower biomass in the short run. In the long run, lower biomass leads to lower effort, *ceteris paribus*. Thus, the ending biomass effect (−133%) is smaller in magnitude than the average biomass effect (−193%).

While the presence of a derby fishing effect is not surprising in and of itself, only an empirically based bioeconomic model can measure both in-sample effects and long-run bioeconomic consequences. Moreover, a model that tracks size classes is essential because it allows us to parse the intensification due to three effects:

Table 3
Bioeconomic policy simulation using point estimates (comparing 1-month spawning closure to no closure)

	No closure	Grouper spawning closure	Change	Qualitative change	% of predicted policy gain
Modeling economic behavior					
Avg. biomass (millions kg)	12.532	11.883	−0.649	−	−193
Avg. # big fish (>10 years)	86,262	79,893	−6369	−	−204
Total catch (millions kg)	14.978	15.848	0.87	+	−151
Total trip days	170,160	190,120	19,960	+	−170
Weighted catch per unit effort	88.025	83.358	−4.668	−	−233
Ending percentage of males	0.0689	0.0645	−0.004	−	−220
Ending biomass (millions kg)	11.992	11.015	−0.977	−	−133
No economic behavior					
Avg. biomass (millions kg)	11.665	12.001	0.336	+	
Avg. # big fish (>10 years)	77,509	80,627	3118	+	
Total catch (millions kg)	16.066	15.491	−0.575	−	
Total trip days	198,410	186,680	−11,730	−	
Weighted catch per unit effort	80.973	82.980	2.007	+	
Ending percentage of males	0.0660	0.0680	0.002	+	
Ending biomass (millions kg)	10.585	11.318	0.733	+	

Note: The simulation includes 25 years total with ten years in sample. The baseline predicted gain from the policy is what the standard management model predicts, i.e. the model with no economic behavior. Thus, the percentage of predicted policy gain is an index of the effectiveness of the policy relative to what it intends. It is the change in the ECON model divided by the change in the NOECON model.

the closure, the spawning aggregations in the early months of the year, and the arrival of a new cohort of fish that exceed the size limit. A model without size classes would necessarily lump these effects together.

Ultimately, what is striking about these results is that the intensity of fishing effort in the years with the spawning season closure is enough to more than offset the modeled biological benefits of the closure. The increase in fishing trips that may have resulted from the closure exceeds the number of trips expected without the closure, with the effect of decreasing biomass. In spite of the fact that effort supply is elastic with respect to biomass, this short-run biomass reduction does not induce enough effort attrition to make up for the lost biomass. Thus, the long-run average biomass is lower with the seasonal closure than without it.

The results in Table 3 may be surprising to many economists as well as biologists, but they are consistent with the emerging conceptual literature on fishing micro-behavior [2,3]. Nevertheless, we do not explicitly test an explanation. Because we use a reduced-form model of fishing behavior, the closure dummies could reflect a variety of influences including un-modeled dynamics, income targeting, capital market inefficiencies (due to the non-transferability of permits), or other market frictions. We leave an explanation for our result as a subject for further research and focus in this paper on exploring the robustness of this critical finding.

4.3. Policy sensitivity analysis

There are obviously many parameters in our bioeconomic model that could affect predicted outcomes. Because the focus of this paper is on the effect of fisherman behavior, we first explore the sensitivity of our conclusions to our behavioral parameter estimates. To that end, we run the bioeconomic simulation with 5000 draws from the empirical distribution of the logit parameters. For each simulation of the ECON model, we take a Cholesky factorization of the covariance matrix, which is positive definite by construction, and multiply it by a vector of independent standard normal errors and add the resulting vector to the point estimates in Table 2. We take the resulting draw and simulate the bioeconomic model with and without the closure. We follow the same procedure for the NOECON model.

Histograms for biomass and number of big fish (over 10 years of age) are available in an online appendix. In all 5000 cases, the pair-wise qualitative predictions of the ECON model are the same as those reported in Table 3. The closure reduces biomass, the number of older fish, and the adult sex ratio, and it increases catch and effort. Also as in Table 3, in all 5000 cases for the NOECON model, the qualitative outcomes are reversed. Even ignoring pair-wise comparisons, the histograms in do not overlap.

Two other important dimensions for sensitivity analysis are the definition of the dependent variable (gag trips) and the assumed number of boats that target gag. We run our model for three different definitions of trips ($>0\%$ gag, at least 25% gag, and at least 50% gag) and five different numbers of boats (100, 250, 500, 750, and 1079),[15] leaving us with 15 separate sets of results. In all models, gag price, gag biomass, the size limit/marine reserve dummy, and the spawning closure dummy are positive and significant. Wave height is always negative and significant. Monthly dummies are jointly significant in all cases. Table 4 summarizes the sensitivity of our main finding, that the apparent behavioral responses of the fleet offset the seasonal closure. We report the percentage of policy impact in each of the 15 cases. Clearly, the offset effect is always present; in no cases does the percentage of policy impact come close to 100% (the maximum is 21%). Only in a handful of cases is the effect even positive; in most, the behavioral response appears to more than offset the seasonal closure.

5. Discussion

Fisheries provide a unique opportunity for pushing the empirical modeling frontier in resource economics because there are many rich data sets resulting from federally mandated logbook programs and state trip ticket programs, and there is considerable policy variation to analyze. At the same time, these problems are some of the more difficult econometric ones that we face because renewable resource systems often involve

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[15]Choosing a targeting threshold will always be problematic in a multispecies fishery. We present all of the results without identifying one model run as best. We focus our attention above on the run in the middle of both ranges for our sensitivity analysis. What is important here is that all runs nest the implicit assumption in management models that behavior does not matter.

Table 4
Bioeconomic sensitivity—% of predicted policy gain realized in the ECON model

	Average biomass (%)	Average big fish (%)	Total catch (%)	Total trip days (%)	Weighted CPUE (%)	Ending % males (%)	Ending biomass (%)
Dependent variable >0% gag with boats =							
100	−8	−8	−8	−36	−89	−11	−9
250	21	21	14	2	−21	21	13
500	14	14	9	−5	−32	14	8
750	7	7	4	−13	−47	7	4
1079	3	3	1	−19	−57	0	1
Dependent variable >25% gag with boats =							
100	−193	−204	−153	−174	−238	−225	−137
250	−180	−191	−141	−161	−220	−200	−125
500	−193	−204	−151	−170	−233	−220	−133
750	−201	−213	−158	−178	−243	−224	−139
1079	−198	−209	−151	−176	−239	−224	−136
Dependent variable >50% gag with boats =							
100	−205	−215	−158	−156	−178	−228	−141
250	−211	−221	−162	−160	−182	−233	−145
500	−226	−236	−174	−171	−195	−250	−156
750	−243	−255	−189	−188	−217	−272	−170
1079	−255	−268	−200	−198	−228	−289	−181

nonlinearities, non-convexities, dynamics, and spatial considerations. To make the problem more challenging, in fisheries we do not even directly observe the state variable (the fish stock). The latency of fish stocks requires an explicit model of biological processes. Here we present a model of the population dynamics that captures many of the features that concern regulators and fishery biologists.

Virtually every fish species in the world has life history features or a reproductive style that will inform biological management. Analyzing the California sea urchin fishery, accounting for economic behavior can qualitatively change the predicted consequences of biological management tools, including size limits and marine reserves [42,43,53]. Without accounting for economic behavior in management models, the policy prescriptions of these models are suspect. In some cases, policies may fail miserably and lead to perverse outcomes. Our empirical case suggests that a perverse outcome is possible, but unlike previous studies, we actually rely on in-sample policy variation to arrive at this result.

Our paper is also the first empirical bioeconomic life history model that endogenizes fishing mortality without the need to calibrate the simulation model. The econometric estimation is embedded in the dynamic bioeconomic model. Previous studies have used backward-looking catch averages to estimate discrete fishing behavior and then calibrate a bioeconomic simulation based on the empirical results. This approach is consistent with the discrete choice fisheries literature that uses econometric results for policy analysis that is not explicitly bioeconomic [8,17,19]. Our model not only offers a solution to the bioeconomic calibration problem but also finds that by including fishable biomass directly, effort response appears more elastic than previous studies that rely on some form of backward-looking averages. Though our coupled modeling approach has some advantages, large-scale adoption of our model in fisheries management will require further research on its econometric properties.

It is tempting to conclude that the seasonal closure caused an increase in fishing effort, but our analysis is only suggestive of this connection. We do not model the mechanism through which the closure would cause a net increase in effort; instead, we include the closure as a dummy variable after controlling for a rich set of other factors that influence fishing behavior. As such, our tale for Gulf managers is a cautionary one. It is not likely that a seasonal closure will lead to a proportional reduction in fishing effort as typically assumed, and it is possible that a large portion or all of the closure will be offset. Priorities for future research include determining **why** effort appeared to increase in response to the closure and whether the case of gag is exceptional or commonplace.

While seasonal closures appear to backfire biologically in our case, there is also a literature that suggests that they increase safety risks to fishermen. Conditional on other factors, fishermen avoid bad weather [44]. Season closures could thus affect marginal decisions about avoiding bad weather. In a survey of Gulf of Mexico commercial reef-fish captains, 80% of respondents either agreed or strongly agreed with the statement "Seasonal closures force fishermen to fish in bad weather."[16] Moreover, the recent National Research Council report on individual fishing quotas cites safety concerns as one of the main justifications for rationalizing fisheries. With more flexibility to choose when to fish, fishermen can avoid dangerous conditions [34].

Managers arguably accept economically inefficient biological management tools like season closures, gear restrictions, and minimum size limits because they believe that these measures will achieve their biological goal and increase the value of catch, i.e. grow the total size of the pie [26].[17] The weakness of biological management is simply its inability to generate rents. Karpoff [27] dismisses the "biological bias" explanation for suboptimal regulations. He assumes that biological management can achieve its biological targets. He writes, "One weakness of the biological bias explanation of traditional regulatory controls is that it does not convincingly explain the proliferation of capital constraints. Season closures could be sufficient to assure a minimum level of fish escapement" (p. 183). With regard to season closures, gear restrictions, and minimum size limits, Johnson and Libecap [26] write, "We predict support from fishermen for these measures because they increase the value of the total catch by protecting juvenile shrimp and do not allocate individual effort" (p. 1018). Again, the presumption is that these measures are effective in achieving their biological goals.

The assumption of biological management success has at least partially enabled fisheries managers to resist individually transferable quotas and other economically motivated instruments. The old notion of biological bias that political economy rejected was a normative one that focused on setting non-economic goals. Here, we suggest a more positive notion that managers either misunderstand or are resistant to the bioeconomic system. By construction, behavior does not enter into fishery management models. If fishermen catch too many fish, the response is to tighten the controls. There is no urgency to fix the fundamental flaw in the management system, namely the lack of economic incentives. If we remove biological success from existing management, one is left to wonder what constituency supports biological overfishing and a failure to generate rents. Heterogeneous fishermen, fish processors, input suppliers, regulators, and consumers simply do not have a stake in management that biologically compromises the resource.[18] In this context, management resistance provides a plausible explanation for suboptimal controls to persist in the fishery. If everyone believes that the status quo maintains the biological pie, rationalization is a lower priority than in a world in which stakeholders believe that the biological pie is shrinking. Thus, without the ability of biological management to protect fish stocks, political economy stories about inefficient regulations unravel. We do not take issue with the notion that individual stakeholders contribute to the persistence of suboptimal regulations, but the relative importance of political economy and bioeconomic resistance is likely an empirical matter and will vary from fishery to fishery.

Biological failure also supports a ratchet effect that threatens long-run sustainability of fish stocks. By construction, management models assume that seasonal closures or other restrictions on fishing protect fish stocks. Empirically, when stocks decline, managers attribute failure to setting lenient management controls rather than to behavioral responses in the harvest sector. Managers react by changing the rules, which may then induce even greater behavioral response. Again, this will be an empirical question, though theoretically

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[16]Of the remaining respondents, 6% left the question blank, 3% were uncertain, and 11% disagreed or strongly disagreed. Raw survey response rate was 45.9% with an adjusted response rate of 46.7%.

[17]Johnson and Libecap [26] also argue that fishermen oppose rationalization policies like transferable quotas because they are potentially redistributive, and reaching agreement with a heterogeneous fleet is costly. Karpoff [27] takes this argument a step further by showing analytically that heterogeneous fishermen support suboptimal regulations specifically because they redistribute wealth. Capital constraints favor inefficient vessels, while season closures favor less capital-intensive vessels. Boyce [10] argues that the theoretical framework of heterogeneous fishermen fails to account for lack of support for transferable quotas. He suggests instead that the presence of input suppliers in the policy process can account for inefficient regulations. Finally, in an empirical study of participation in public meetings, Turner and Weninger [47] show that participants tend to reflect extreme views on regulations, and they suggest that this polarization could account for fishery management failures.

[18]We note the exception of Clark [11] in which the sole owner of a slow-growing fish stock with a high enough discount rate would maximize profits by liquidating the resource.

there is only so far that managers can tighten seasons without eliminating the economic viability of the fishery [24].

Grouper management after the end of our sample period (December 2003) is consistent with a ratchet effect. In 2004, commercial grouper quotas were reduced, and a fishery management plan amendment required closure of the entire shallow-water grouper fishery when either the red grouper or total shallow-water grouper quota is met. An emergency rule in 2005 established a 10,000 pound daily trip limit for the commercial shallow-water and deep-water groupers combined. The trip limit for all grouper was reduced to 7500 pounds in June 2005 when 50% of the red grouper quota was reached, and to 5500 pounds in August 2005. These limits were intended to "moderate the rate of harvest of the available quotas, reduce the adverse social and economic effects of derby fishing, enable more effective quota monitoring, and reduce the probability of overfishing" [33]. Although industry helped develop the trip limit rule, which is consistent with competition for inframarginal rents, the need for the rule at all reflects a failure of biological management to achieve its goals. If stakeholders that would otherwise support economically inefficient regulations are convinced that biological management compromises fish stocks, their opposition to rationalization may temper.

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