Behavioral Modeling and Fisheries Management

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Abstract Because of the extreme uncertainty in fisheries biology, efforts to determine a stock-recruitment relationship have not been entirely successful. In the face of this uncertainty, this paper argues for a change in focus for fisheries economics from bioeconomic optimization toward goals which are more modest and more easily achievable. In particular, a satisficing approach to management is advocated, whereby efforts are made to reallocate some porportion of effort from overutilized to underutilized fisheries, with no attempt to determine the optimum. In order to achieve such a solution efficiently, managers must accurately predict the response of fishermen to public policy. This paper reports on a study which develops a discrete choice model to predict fishermen's supply response. Fishermen are shown to respond to economic incentives of expected returns and variability of returns, but only after these incentives surpass a substantial threshold.

The Argument for Behavioral Modeling

Uncertainty permeates the fishery management problem. This paper attempts to deal with the complexities arising from a num-

Marine Resource Economics, Volume 1, Number 1
0738–1360/84/010105–00$02.00/0

ber of distinctly different sources of uncertainty in the management context. The research attempts to explain fishermen's behavior by capturing the uncertainty faced by fishermen with regard to prices and landings. Additionally, the framework employed explicitly recognizes the uncertainty of fisheries managers regarding fishermen's reactions to regulation. In particular, fishermen facing the same decision environment are not necessarily predicted to make identical choices. Instead, probability distributions over choices are predicted. Of most importance, however, this paper represents a reaction to the seemingly insurmountable uncertainty policy makers and researchers face concerning the dynamics of fish populations.

For some time fishery scientists have attempted to measure fish stocks and to model their growth and recruitment, but without overwhelming success. Their difficulties are not attributable to any lack of effort or ingenuity but rather arise from the fact that there is far more noise in the system than there is signal. Scientists have, for example, been unable to estimate reliable stock-recruitment functions. Yet the calculation of "optimal harvest levels," as prescribed by the Fishery Conservation and Management Act (FCMA), requires in theory the construction of bioeconomic models reflecting the underlying biological and economic relationships. In practice, these models have been dominated by noise and have yielded good predictions only by chance. Predictions have proven to be very sensitive to the probability distributions chosen as well as to environmental parameters which are typically unobservable, unmeasurable, or at the very least, unpredictable.

There is no question that bioeconomic models are analytically useful for yielding insight into the nature of the fisheries problem and for characterizing the optimal solution. However, it is difficult to place much confidence in the numerical results from the application of these models, a fact which is particularly troublesome from a management point of view.

The basic premise of this paper is that optimal harvesting defined by dynamic bioeconomic criteria is not now an operationally useful goal, nor is it likely to be in the near future. We argue here for a fundamentally different approach, narrower in scope and less rigorously defensible, yet more likely to succeed as the basis for pragmatic fisheries management.

We argue that, in the face of overwhelming uncertainty about fisheries dynamics, an appropriate goal for fisheries management is the achievement of an acceptable range of target levels of effort. This "satisficing" approach would require only the determination of approximate biological, social, and economic minimum requirements in defining the acceptable range.

The task of determining what is acceptable and choosing among the set of policies which will yield results within the acceptable range is admittedly subjective. However, these are decisions for which political processes are well suited. On the other hand, political processes are not well suited for determining which policies are capable of satisfying the target goals. This determination requires input from biologists and economists, but not to the extent or level of accuracy demanded by bioeconomic analysis.

The "satisficing" approach to management has the effect of changing the focus of research endeavors. Once we face the fact that policy makers cannot have complete control over fishing effort, predictions of fishermen's response to the economic and biological environment and to management policies become essential. When behavioral response is incorrectly understood, regulatory policies can have unexpected and adverse effects, potentially missing the target range altogether.

In a sense we are arguing for a change in research focus from the behavior of fish to the behavior of fishermen. Unfortunately, little explicit modeling and estimation of behavioral relationships has been accomplished to date. Yet the fisherman's decision as to effort level is perhaps the most important type of behavior to be understood.

Typically economists have viewed fishing effort as an aggregate variable which responds to any nonzero level of profits within a fishery. The aggregation is of critical proportions. Not only do we aggregate over fishermen, but also over types of decisions which affect total industry effort levels. Both of these forms of aggregation present potential sources of bias which need to be considered when dealing with predictions at the aggregate level. In order to avoid these potential sources of bias, the aggregate decision function should be based on the actual behavior of the fisherman at the microeconomic level.

Aggregating over fishermen leads to bias if parameters of the micro level decision functions vary or if the industry composition changes over time. For example, if an increasing proportion of the industry is adopting some new technology or new size vessel, parameters of the aggregate decision function will be changing over time. If these parameters are estimated using aggregated past information, the estimated parameter values will lag behind the true parameters and will lead to biased parameter estimates. Employing micro level modeling, however, allows estimation of parameters which vary over vessel class or technology. These estimates, combined with information about the proportion of the industry characterized by that technology, will yield good predictions.

Aggregation over those types of decisions which affect industry effort levels is potentially even more serious. There are at least three such decisions: (1) Fishermen already within some fishery can change their "intensity" of fishing; (2) the distribution of effort among fisheries can be changed by fishermen switching among fisheries; and (3) effort can change through entry or exit from fishing altogether. These three decisions are fundamentally different choices which occur within different time frames and which depend upon different factors. Hence aggregating these into a single effort function is inappropriate. Choosing the number of days fished is a short-run decision which depends, in part, upon the absolute level of returns within that particular fishery. Switching among fisheries, on the other hand, will likely depend more on relative levels of profitability of the alternative fisheries than upon the absolute level of profits. To the extent that switching fisheries requires changing gear or port or learning new skills, the decision is likely to be an intermediate-run decision and will require some threshold of potential gain in order to induce response. Finally, entering or leaving fishing altogether is a long-run decision which will depend on both the absolute level of profits and the relative profitability of the alternatives. Because this decision represents a substantial change in life-style as well as a large investment, one would expect that economic incentives would need to surpass a substantial threshold before entry or exit were induced.

Predicting response of effort to economic incentives and to policies which affect these incentives requires accurate modeling of fishermen's behavior at the micro level. Such modeling allows the separate treatment of different types of decisions as well as accurate predictions when industry structure and composition change. What follows is a brief description of an example of this type of empirical work. A more detailed discussion is contained in Bockstael and Opaluch (1983).

A Behavioral Model of Allocation of Fishing Effort Under Uncertainty

The problem is considered from a management point of view, attempting to predict switching behavior in response to a changing economic, biological, and regulatory environment. Uncertainty occurs at two levels: Fishermen are uncertain concerning returns from the various alternatives, and the management agency is uncertain of the response of fishermen to returns.

Uncertainty at the fisherman level is modeled employing the usual assumption of expected utility maximization. Fishermen derive utility from wealth, which is affected by the returns from fishing. Fishermen are assumed to incorporate information on past returns from the various fisheries in forming expectations on future returns. The more profitable a fishery appears, the more likely it is that an individual will choose that alternative.

However, one would not expect an individual to switch immediately to the most profitable fishery. Because of imperfect malleability, switching fisheries imposes a variety of costs on the fisherman. Some of these costs are monetary costs of converting gear or changing port. Other costs are nonmonetary, such as the costs of acquiring expertise in a different type of fishery or on different fishing grounds or the psychic costs of departing from family tradition or simply overcoming inertia. In any case, one would expect substantial resistance to changing fisheries, and potential returns from switching would thus need to surpass some threshold before an individual would be induced to switch. From the manager's point of view, uncertainty arises because individuals facing the same environment are observed to make different decisions. Some of the variation may be attributed to observable differences in characteristics, such as differences in the age or socioeconomic background of the fisherman or differences in the size or construction of his vessel. There will always be, however, unobservable characteristics which vary among individuals and which lead to different behavior.

The utility of the ith individual for the jth alternative, U_{ij}, depends upon the random wealth which comes about by participating in that alternative and an unobservable or random component, ξ_{ij}. That is,

$$U_{ij} = [U_i\ (W_{oi} + R_{ij})] + \xi_{ij} \tag{1}$$

where W_{oi} is the initial wealth of individual i and R_{ij} is the ith individual's return from the jth fishery. A Taylor series expansion of this expression, suppressing subscripts, yields

$$U(W) = U(W_o + ER) + \sum_{k=1}^{\infty} \left\{ U^{(k)}\ (W_o + ER)\ \frac{(W - W_o - ER)^k}{k!} \right\} \tag{2}$$

where $U^{(k)}$ is the kth moment of R about its mean. In order to implement this approach, we need to assume a specific form for the utility function and a distribution for the random component.

While the choice of a form for the utility function is necessarily somewhat arbitrary, we would like it to be consistent with reasonable behavioral postulates. It is well known that the log function exhibits the best properties of the simple functional forms under uncertainty. This study will employ a second-order Taylor series approximation to the log utility function about the expected value for returns, which can be expressed as

$$E(U_{ij}) = \ell n\ (W_{oi} + ER_{ij}) - \frac{\text{VAR}\ (R_{ij})}{2(W_{oi} + ER_{ij})^2} + \xi_{ij} \tag{3}$$

Generalizing this formulation by estimating coefficients on these two terms yields

$$E(U_{ij}) = \theta_1 \, \ell n \, (W_{oi} + ER_{ij}) + \theta_2 \, \frac{\text{VAR}\,(R_{ij})}{2(W_{oi} + ER_{ij})^2} + \xi_{ij} \qquad (4)$$

Incorporating the threshold concept described above requires adding a term, T_{jk}, reflecting the threshold to the alternative which the fisherman is now engaged in. The variable T_{jk} is a dummy variable which equals one for $j = k$, zero otherwise. Thus, when considering the fishery in which the fisherman was previously engaged, a constant is added to the expected utility of wealth. This means that for an alternative fishery to be chosen, the economic incentive of expected utility of wealth must surpass the incentive from the present fishery by more than the threshold.

Since the threshold includes both monetary conversion costs and nonmonetary factors, it is not directly observable. The only observable measure of the threshold is the observed resistance to change. For this reason we estimate the threshold by employing a dummy-variable formulation which accounts for all sources of resistance—monetary and nonmonetary. The complete behavioral model to be estimated is now

$$E(U_{ij}) = \theta_1 \, \ell n \, (W_{oi} + ER_{ij}) + \theta_2 \, \frac{\text{VAR}\,(R_{ij})}{2(W_{oi} + ER_{ij})^2} + \theta_3 T_{jk} + \xi_{ij} \qquad (5)$$

where T_{jk} is the threshold dummy variable and the Θ's are estimated coefficients.

The final decision required to make the model operational involves the assumptions on the distribution of ξ_{ij}. Normality assumptions on the ξ_{ij} generate the probit model. If the ξ_{ij} are assumed to be distributed as Weibull random variables, the logit model results. We make the Weibull assumption, because probit is not computationally tractable for a problem with many alternatives.

Rather than predicting the actual alternative chosen by each individual, discrete models explicitly recognize the uncertain nature of the problem by predicting the *probability* of an individual choosing a given alternative. The probabilities can then be employed in a straightforward manner to predict the proportion of each group of fishermen, with the same measurable characteristics and facing the same decision environment, which will choose a given alternative. Again, a strength of this type of model is that all observably similar fishermen are not predicted to do the same thing.

The logit formulation leads to a model of the form

$$P_{ij} = \frac{\exp\left[\theta_1 \ \ell n \ (W_{oi} + ER_{ij}) + \theta_2 \ \dfrac{\text{VAR} \ (R_{ij})}{(W_{oi} + ER_{ij})^2} + \theta_3 T_{jk}\right]}{\sum\limits_{\ell} \exp\left[\theta_1 \ \ell n \ (W_{oi} + ER_{i\ell}) + \theta_2 \ \dfrac{\text{VAR} \ (R_{i\ell})}{(W_{oi} + ER_{i\ell})^2} + \theta_3 T_{\ell k}\right]} \tag{6}$$

where P_{ij} is the probability that individual i will choose alternative j. The parameters of θ_1, θ_2, and θ_3 are then estimated by maximizing the likelihood function

$$\max_{\theta_1, \theta_2, \theta_3} \ L = \prod_{i=1}^{n} P_{ic} \tag{7}$$

(where c is the alternative chosen by the ith individual), that is, by choosing the parameters which make the observed choices as likely as possible.

Empirical Results and Conclusions

The model described above was applied to the choice among fishery alternatives faced by New England fishermen. The application is discussed in more detail by Bockstael and Opaluch (1983). The data consist of a cross-sectional sample of 657 fishermen landing fish in New England ports and include all vessels reported in the National Marine Fisheries Service land-

Table 1
Estimation Results

Variable	Coefficient	t-Statistic
$\ln [W_o + E(R)]$	1.341	(5.00)
$\dfrac{\frac{1}{2}\,\mathrm{VAR}\,(R)}{(W_o + ER)^2}$	-1.712	(2.64)
T	4.364	(46.98)
$\tilde{R}^2$	-0.99	
Test	Statistic	Degrees of freedom
$-2 \ln L_O/L_\theta$	93.29	3
$-2 \ln L_T/L_\theta$	39.20	2

L_O = value of likelihood at zero parameter values
L_θ = maximum values of likelihood with all three parameters estimated
L_T = maximum value of likelihood with only third parameter estimated

ings records except those less than 5 gross tons or those which were on the fishing grounds fewer than 100 days in either year.

Each vessel participated in an initial fishery in 1975 and a subsequent fishery choice in 1976. A fishery alternative was defined as a group of species which could be harvested by a single gear type in a given geographical location. Examples of fishery alternatives include scalloping from New Bedford and otter trawling from southern New England ports. Depending on the fisherman's vessel and initial situation, the number of alternatives varied between nine and twelve.

The coefficients were estimated using a maximum likelihood approach, as discussed above. The estimated values for the coefficients are given in Table 1. All coefficients are significant at the 95 percent level. A statistic $\tilde{R}^2$, analogous to the multiple regression R^2, indicates that the model explains a substantial portion of the variation in behavior.

These results can be used to compare different behavioral models. A naive model of behavior might assume that individuals choose randomly among fisheries with equal probability.

Such a model implies that we have no information with which to predict fishery choice and thus all coefficients in Equation 1 are zero. Alternatively, estimating a coefficient on the threshold leads to a simple inertia model which predicts that some given proportion of fishermen never switch fishery and that those fishermen who do switch choose among the alternatives without regard to economic incentives. Finally, estimating coefficients on all three variables leads to a model incorporating economic incentives as an important basis of choice. The likelihood ratio statistic

$$-2\ \ell n\ \frac{L_O}{L_\theta} = 93.29 \tag{8}$$

provides a means of testing the value of the economic model over the naive model and is significant at an extremely high level. A more meaningful test compares the economic model to the simple inertia model

$$-2\ \ell n\ \frac{L_T}{\ell_\theta} = 39.20 \tag{9}$$

and is again significant at greater than the 99 percent level. This leads to the conclusion that while the threshold is important, fishermen do indeed appear to respond to economic incentives.

Besides providing a means of predicting specific quantitative results (e.g., changes in participation rates in different fisheries resulting from changes in stocks, prices, etc.), the results suggest a number of interesting qualitative implications for policy. In considering the actual values of the coefficients, rather than just their statistical significance, it becomes clear that a large change in expected returns is necessary to make a substantial change in the probability of switching fisheries. Consequently, while fishermen are shown to respond to economic incentives, they exhibit a strong inclination toward remaining within the same fishery over time. Given this result, policies designed to reallocate effort from overutilized to underutilized species by differentially affecting returns will need to be rather extreme to have any significant effect. In fact, they are likely to be so extreme as to meet with political resistance. Consequently, alternative policies which directly influence inertia should perhaps be an important part of any policy designed to reallocate effort.

In order to determine which policies are likely to be effective, the important components for the threshold must be identified. If monetary conversion costs dominate, then subsidies for gear or port conversion or lump-sum payments may significantly reduce the threshold. If information asymmetries are important so that individuals who are not in some fishery at present have relatively little information about the fishery, then public information services may be effective. If fishing skills differ substantially among the fisheries of interest, then education and training programs may be useful. In any case, identifying the important components of the threshold is likely to be crucial for effective policy formation and thus represents an important area for future research.

Reference

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