Spatial Search and Fishing Location Choice: Methodological Challenges of Empirical Modeling

Martin D. Smith

Recent work in ecology emphasized the spatial patchiness of marine resources. Fish and shellfish populations often occur in clumps or discrete patches of habitat with different population levels and dynamics in each patch. Patches are linked through a set of complex biological and oceanographic factors. This new view has given rise to spatial marine management proposals, including permanent marine reserves and rotating spatial closures. Reserve proposals are particularly popular among ecologists because closed areas can presumably augment the biomass in areas that were overharvested due to stochastic shocks or poor management practices. Little is known, however, about how individual harvesters would respond to spatial management. Economists can contribute substantially to debates about spatial policies by building models that explain spatial behavior of commercial fishers.[1]

Beliefs about profitability of different locations are the most important determinants of location choice for commercial fishing, but they are unobservable. Differences in profitability are driven, in part, by the spatial heterogeneity of the resource. In many fisheries, individual harvesters make discrete location choices across space on a daily basis. This paper addresses the connections that bridge fishers' observed data, the beliefs that the fishers formulate, and the resulting location choice behavior. The crux of the modeling problem is that we, as analysts, observe individual discrete choices and we observe the location-specific catch and revenue histories of individuals (information or data), and yet we do not really know how individuals process their data into beliefs. In these circumstances, is it possible to make inferences simultaneously about behavioral responsiveness and information processing? Can we use behavioral models to test hypotheses about search behavior? Is it possible to determine both how harvesters share information and how this sharing affects behavior? To address these questions, this paper looks at three aspects of information processing: the choice between structural and reduced-form models, information decay, and complexities of spatial search and information sharing.

The Choice between Structural and Reduced-form Models

Typical location choice models begin with a random-utility model (RUM) based on the expected utility hypothesis. Indexing individuals by i, fishing locations for j, and time (choice occasions) by t, utility for an individual is defined as

$$U_{ijt} = v_{ijt} + \varepsilon_{ijt} = f(\mathbf{X}_{ijt}; \boldsymbol{\theta}) + \varepsilon_{ijt} \tag{1}$$

where $\boldsymbol{\theta}$ is a parameter vector and $\mathbf{X}_{ijt}$ contains moments of a wealth distribution that varies across individual, site, and time. This is essentially where Bockstael and Opaluch began in their article that launched discrete choice modeling of commercial fisheries.[2] To

Martin D. Smith is PhD candidate in Agricultural and Resource Economics at the University of California, Davis.

The author thanks Jim Wilen for his helpful comments and encouragement throughout the project. This research was partially funded by a grant from the National Sea Grant College Program, NOAA, U.S. Department of Commerce, under Grant No. NA66R G0477, Project No. R/F-169.

This paper was presented in a principal paper session at the AAEA annual meeting (Tampa, FL, August 2000). Papers in these sessions are not subjected to the Journal's standard refereeing process.

[1] What is needed is a model that predicts spatial responses to policies that have never been implemented. So, a pure time-series approach would suffer from a spatial Lucas critique. Though a complete structural model of the bioeconomic system is unnecessary, for policy analysis we do need a spatially explicit behavioral model that predicts responses to changes in observables.

[2] Other authors who applied discrete choice techniques to commercial fishery supply include Eales, Eales and Wilen, Campbell, Dupont, Ward, and Sutinen, Evans, Smith, and Wilen, and Holland and Sutinen.

Amer. J. Agr. Econ. 82(5) (Number 5, 2000): 1198–1206
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study choices among different commercial fishing activities, these authors assumed a logarithmic utility function on wealth and expressed indirect utility as a function of mean returns and variance of returns.

To simplify, assume that indirect utility is a linear function of mean profits and variance of profits as

$$(2) \qquad v_{ijt} = \alpha E[W_0 + R_{ijt} - C_{ijt}] + \beta \mathrm{Var}[W_0 + R_{ijt} - C_{ijt}]$$

where R_{ijt} and C_{ijt} are, respectively, revenues and costs for individual i in location j at time t, and W_0 denotes an individual's wealth outside the fishery. In most instances, costs are known deterministic functions for the resource harvester. Suppose that costs are a linear function of distance from an individual's port to the site (d_{ij}) and a parameter γ_{it}, which reflects changing fuel prices and individual harvester opportunity costs of time. Equation (2) thus reduces to

$$(3) \qquad v_{ijt} = \alpha W_0 + \alpha E[R_{ijt}] - \alpha \gamma_{it} d_{ij} + \beta \mathrm{Var}[R_{ijt}].$$

Assuming that γ does not vary across individuals or time and recognizing that αW_0 simply rescales indirect utility (i.e., it neither varies across choice nor varies across time for an individual), the RUM can be expressed as

$$(4) \quad U_{ijt} = \alpha E[R_{ijt}] + \beta \mathrm{Var}[R_{ijt}] + \gamma^* d_{ij} + \varepsilon_{ijt}$$

where $\gamma^* = -\alpha\gamma$. The simplest way to estimate this model of location choice is to assume ε_{ijt} are identically and independently distributed (i.i.d.) type I extreme value and apply McFadden's (1974) conditional logit.

Since the original Bockstael and Opaluch formulation, developments in the discrete choice literature enabled analysts to consider more sophisticated models.[3] Although these new models add interesting dimensions to the behavioral modeling problem, some unresolved issues still remain about the original problem. In particular, what data go into the expected revenue and variance of revenue terms? These terms are belief variables, reflecting individual agents' views about expected payoffs of different fishing activities. As analysts, we place ourselves inside the minds of the decision makers and we make assumptions about these beliefs; but in truth, we do not know precisely what these beliefs are and how they are formed. Thus, the most critical variables that drive choice are unobservable in spite of the fact that we observe individuals' information.

There are two ways to deal with the unobservability problem: (1) structural modeling of the bioeconomics and (2) reduced-form approaches. The idea of a structural model is to embed system dynamics into the expected revenue and variance computations and then to derive an econometric specification that is a function only of observables. A reduced-form method, as in many time-series problems, seeks to forecast revenue belief variables without modeling the structural forces that change them from one period to the next.

A structural model of fishing revenues must link prices, catch, and the evolution of biomass in each fishing location. Suppose that price (p) and hours per fishing trip (h) are constant, and suppose further that catch is proportional to fishing effort times biomass as in the standard Schaefer model. Thus, revenues are

$$(5) \qquad R_{ijt} = pqhX_{jt}$$

where X_{jt} is unobservable biomass in location j at time t, q is a catchability coefficient. Now suppose that biomass evolves according to the simplest possible process, or

$$(6) \qquad X_{jt} = \delta X_{jt-1} - \sum_{i=1}^{n} H_{ijt}$$

where δ is a combined growth, survival, and recruitment parameter, H_{ijt} is individual i's harvest at the site, and there are n harvesters. By recursive substitution of (6) into itself, we obtain

$$(7) \qquad X_{jt} = \delta^t X_{j0} - \sum_{k=0}^{t} \delta^k \left(\sum_{i=1}^{n} H_{ijt-k} \right).$$

Even with such simplifying assumptions, to estimate the model one must assume that δ^k is close to zero because initial biomass is unobserved, or one must do an infinite recursion and truncate it in some ad hoc way.[4]

[3] For instance, simulation-based estimation allows one to model formally mean-variance preference heterogeneity across different industry participants. McFadden (1989), Pakes and Pollard, and McFadden and Train are important papers that develop simulation-based discrete choice econometric techniques.

[4] A more pressing problem with this particular structure, however, is that biomass tends toward zero in the steady state without harvesting if $\delta < 1$, and biomass explodes in the long run if $\delta > 1$.

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Although the state equation in (6) lacks realism, the problem quickly becomes intractable when one includes a more suitable population state equation. With a nonlinear state equation for biomass, recursive substitution would lead to an extremely complicated nonlinear function of past harvests.[5] Another fundamental problem with structural bioeconomic modeling as a basis for behavioral modeling is that it assumes that individual harvesters know aggregate time and location-specific harvest. As analysts, we see this information *ex post*, but harvesters may not have access to it when they make their daily location choices. Structural bioeconomic modeling thus may be a useful means to estimate biological parameters and aggregate industry responses to trends in the fish stock but does not seem promising to study individual harvester decision making.

Reduced-form approaches, in contrast, avoid some tractability problems by treating revenue as stochastic and by ignoring bioeconomic processes that produce its deterministic components. Since expected revenues are composed of price and catch expectations, it would be naive to abandon structure where it can be incorporated easily. Price is known in some fisheries before location decisions are made, in which case the stochasticity is completely contained in the harvest variable such that[6]

$$E[R_{ijt}] = p_t E[H_{ijt}] \tag{8}$$

and

$$\mathrm{Var}[R_{ijt}] = (p_t)^2\,\mathrm{Var}[H_{ijt}].$$

Still other fisheries operate to produce both price and catch uncertainty on a continuous basis.[7] Hence, it might be sensible to assume that a single random-revenue variable contains all of the randomness.

Specification of a reduced-form model implicitly assumes a hypothesis about how agents transform data into beliefs about means and variances. Imagine the following laboratory experiment. There are two urns, each with an unknown number of balls that have different numbers printed on them. An individual subject draws T balls from each urn (say with replacement), but she is neither told how many total balls are in each container nor told anything about the distribution of ball numbers. Then, the experimenter tells the subject that she will be allowed to select a ball from one of the urns and will receive the amount shown on the ball in cash. The subject then selects one of the urns and receives her payoff. Now, if we run this experiment for n subjects, how could we build a behavioral model of choice? At the end, the experimenter has each individual's data and knows each individual's choice. How can we test hypotheses about the processes by which the individuals make their selections? If we believe the expected utility hypothesis discussed above, we might first calculate the sample mean and the sample variance of each individual's draws, then we might plug these into a RUM, and we might estimate a logit or a probit regression. Denoting individual draws from urn j as R_{ijt}, $i = 1, \ldots, n$, $j = 1, 2$, and $t = 1, \ldots, T$, the data for the discrete choice model would be

$$E[R_{ijt}] = \overline{R}_{ij} = \frac{1}{T}\sum_{t=1}^{T} R_{ijt} \tag{9}$$

and

$$\begin{aligned}\mathrm{Var}[R_{ijt}] &= s_{ij}^2 \\ &= \frac{1}{(T-1)}\sum_{t=1}^{T}(R_{ijt} - E[R_{ijt}])^2.\end{aligned}$$

The experimenter and each subject have the same information, and all of the information relevant for choice is contained in each subject's sequence of draws. What matters for choice, however, are individuals' beliefs about the parameters of the stochastic process and uncertainty about the parameters.

For example, suppose we alter the experiment and we allow a different number of draws from each urn, T_j. An individual with identical sample means and variances for the two urns might be expected to choose the urn with more draws simply because she has more certainty about its distribution. Thus, the relevant variance that should be included in the discrete choice accounts for the sampling error as

$$\mathrm{Var}[R_{ijt+1}] = s_{ij}^2\left(1 + \frac{1}{T_j}\right). \tag{10}$$

[5] For example, after just two periods of recursion with the Schaefer model, the expression for biomass is an eighth-order polynomial that contains cross-product terms of unobservable lagged biomass and lagged harvest. Stochastic biological shocks compound the problem further by introducing cross-product terms of unobservable shocks, unobservable biomass, and lagged harvest.

[6] For example, in most Alaskan salmon fishing, trips are made after a contract has been signed in which the processor guarantees a certain price.

[7] In the sea urchin fisheries in both California and Maine, prices are determined in part by quality, which is not measured until the buyer has processed the urchin and evaluated roe content.

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If harvesters really make mean-variance trade-offs, ignoring sampling error may overstate the individual's risk aversion and may neglect the value of information. There is always variation in observed *ex post* revenues due to the stochastic nature of revenues, but with known parameters, there is no value to having more information. From a harvester's perspective, it may not matter whether the variance comes from the sampling error or from the intrinsic stochastic component of the revenue process.

In the real world, harvesters make repeated decisions and observe new information before each decision in the sequence. To extend the laboratory analogy further, suppose the subject chooses an urn again after observing the outcome of the choice round, i.e., after seeing the number on the ball that was drawn. Suppose these decisions are repeated so that the agent continues to collect information as the experiment proceeds. Then, mean and variance beliefs on each day would be updated based on the previous draw.[8]

The model described above leaves unanswered the question of what a harvester might do with no information, i.e., no past observations, on the revenue distribution in some patches. In the laboratory analogy, under what circumstances would one ever choose an urn from which she has never sampled? The only explanation for such a choice, barring explanations based on irrational behavior, would be that the agent has some prior belief about the urn before sampling from it. As such, a Bayesian approach can be a useful tool to model the information of harvesters. With this story, harvesters have priors on different locations, make choices about where to go, collect information in the process, update their priors to form a posterior distribution, and repeat the decision on the next choice occasion. In the Bayesian lingo, the beliefs about location-specific revenues would be means and variances of the posterior predictive distributions, i.e., the means and variances of a forecast draw from the posterior.

Mangel and Clark, Mangel, and Swierzbinski apply an analytical Bayesian framework to information updating in ocean fisheries. They model catch as a Poisson process with uncertainty about the parameter λ modeled with a gamma distribution (with parameters a and b). Harvesters have a prior distribution on λ, fish in a location, collect data on λ, and form a posterior using Bayes rule. Denoting catch as C, the following describes the probabilistic framework:

$$\text{(11)} \quad \text{Prob}(C) = \frac{1}{C!}\lambda^C, \qquad C = 0, 1, \ldots,$$

and

$$\text{Prob}(\lambda) = \frac{a^b}{\Gamma(a)}\lambda^{a-1}e^{-b\lambda}, \qquad \lambda > 0.$$

Since gamma is a conjugate prior for a Poisson, the posterior distribution for catch given the catch histories $(C_t, t = 1, \ldots, T)$ is distributed gamma$(a + \sum_{t=1}^{T} C_t, b + T)$. Moreover, one can decompose the variance into variance of the underlying stochastic process on catch and variance attributed to uncertainty about the parameters. This approach can be extended easily to model individual sites with different Poisson distributions.

A major drawback of this analytical model is that it is a single parameter model that imposes equal mean and variance of the data-generating process.[9] A realistic empirical model requires at least a two-parameter distribution on revenues: one parameter for scale and the other for location. Added realism, however, comes at a cost. One must commit to a two-parameter probability distribution on continuous and positive data. Given that distributions on revenues may also be skewed, it would help to choose a distribution that has this flexibility as well.[10] Two suitable distributions are gamma and log-normal. Both are potentially skewed distributions on strictly positive and continuous data, but neither distribution has convenient

[8] With a linear model, this would simply be equivalent to Kalman filtering. Without autocorrelation, this is equivalent to recomputing the ordinary least squares estimator after each observation for each urn.

[9] Another drawback is the difficulty of choosing a prior distribution. This is often a criticism of Bayesian approaches that comes from the frequentist camp. What is different about this setting is that choice of a prior is one step removed from the behavioral model. Bayesians typically evaluate the sensitivity of their results to the choice of a prior, but it becomes a considerably more difficult task when the results are essentially data that enter into another statistical model. Nevertheless, one can ameliorate this problem to some extent by choosing a diffuse prior.

[10] Location-specific revenue histograms in the California red sea urchin fishery show long right tails.

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conjugate priors for both location and scale parameters.[11]

Although the specification problem becomes more difficult without conjugate priors, Markov chain Monte Carlo simulation allows us to entertain the possibility of numerous distributions. The best known of these techniques is the Gibbs sampler.[12] For each location, individual, and choice occasion, the analyst would run a separate simulation to generate the belief variables for the behavioral model. This procedure is becoming more possible with advances in computational power, but application of the Gibbs sampler to a fishery with daily data, multiple sites, and numerous individuals or boats is still a daunting task.

Information Decay

Any systematic examination of how information affects location choices must consider information decay. The previous section discussed choice models when the revenue distribution is fixed. Unfortunately for the analyst of fisheries data, repeated draws on location-specific revenues are not coming from the same distribution. We would expect, in fact, that the underlying probability density is changing over time, since market conditions, population distributions, and policy settings change over time. The abundance in each patch should vary differentially as harvesting, growth, natural mortality, and recruitment occur. In addition, in many fisheries prices vary as world markets and exchange rates change, as substitute prices and incomes change, and as quality of landed product changes. In the California sea urchin fishery, for example, quality varies intraseasonally due to spawning cycles and varies interseasonally due to the changing abundance of food supplies.[13] Thus, information about abundance, quality, price, and hence revenues decays over time. It is not surprising that the Bayesian updating analytical literature on search in fisheries ignored this problem.

Although the information decay process may not be known precisely, past information presumably carries some signal about future conditions. How do we think individuals transform past observations on revenues into beliefs about future revenues? A return to the experiment with urns and balls will help to clarify the problem. Suppose that after each subject collects samples, the experimenter pours more balls into each urn. The balls that were already in the urn are still there, but an unknown quantity of new balls with an unknown distribution has been added. Then the subject is asked to choose between the urns. How does she weight the information that she collected given that the distributions of balls in the urns have changed? Suppose that after making a choice, the experimenter again pours more balls into each urn, and the subject is asked to choose again. Now what information does the subject use to decide? Clearly, the old information has decayed more than the new information, but is the old information worthless? Whereas without information decay observations are weighted equally, here one must choose to truncate the sample period or to apply weights that decline with age.

If one truncates the sample period, one chooses a τ such that observations prior to $(t - \tau)$ are not considered in revenue-density estimation. However, there are no clear guidelines on how to choose τ, and once a τ is chosen, the revenue moment estimates, i.e., belief variables, enter into the behavioral model as if they were data. So, identifying the optimal truncation length is a difficult statistical problem because the different models are nonnested. Another problem is that some patches have too few observations to estimate the revenue parameters in most real world situations. For instance, at sites with minimal fishing effort, there may be long stretches of time in which no one chooses to

[11] Log-normal is conjugate with itself if the scale parameter is fixed and known but not if it is unknown. Unfortunately, there is no reason to make such a strong assumption about the variance of revenues in the case of spatial search in fisheries. See Kaufman for further discussion of the log-normal distribution in Bayesian analysis.

[12] The idea is to derive a full conditional distribution for each parameter, i.e., a distribution that combines the prior and the data assuming that the other parameter is known. Then, one can simulate a sequence of draws from these conditionals that eventually converges to the joint distribution. Convergence to the joint distribution may require many draws, and even if the joint distribution is achieved quickly, the analyst would need to use many draws in the simulation to limit simulation noise. Draws from the joint distribution can then be used to calculate means and variances. One added complication is that there is a burn-in phase of unknown length, which is a period of nonstationarity at the beginning of a sample. So, every time one applies the Gibbs sampler, it is necessary to identify the burn-in phase and to discard the records in this period. For more discussion of the Gibbs sampler, see Gelman et al.

[13] Abundance of kelp, in particular, affects quality and overall abundance of California sea urchin. Kelp abundance, in turn, depends on urchin populations, occeanographic conditions, and sometimes human activities.

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fish there, and the chosen truncation length could lead to a paucity of data. Alternatively, one could choose a bigger τ and have more data available, but then it would be harder to justify equal weights for the sample observations.[14]

Imposing information decay has the advantage of there always being enough data to estimate belief variables because observations are never discarded from the sample as time passes.[15] The disadvantage is that old information always has some impact on the current revenue assessment. Nevertheless, old information receives less weight than new information. One way to impose this structure is to assign geometrically declining weights. Consistent with an adaptive expectations model of revenues, this is precisely what Bockstael and Opaluch do for expected revenues. Two drawbacks are the difficulty of estimating the weighting parameter and the ultimate need to truncate the lag for estimation.

An alternative information-decay approach is to treat the problem as a regression of revenue on a constant with a heteroskedastic error. The form of the heteroskedasticity is imposed to reflect decaying information on revenues in a patch. For instance, the variance of an observation might grow proportionally to the number of periods that observation is distant from the present. The model can be estimated using generalized least squares (GLS) with more weight placed on recent observations. One virtue is that periods with no data do not prohibit one from performing estimation. The expectation of revenues is simply the current estimate for the mean. The variance is a bit more complicated, incorporating variance from the error and variance of the estimated mean. Nevertheless, it follows from the approach in equation (10), substituting the sum of the weights for T_j and using the GLS s^2.

Another method of dealing with the evolution of a stochastic process is to apply time-series techniques.[16] Implicitly, these models assume that the underlying revenue distribution is fixed but that recent observations provide more information on shocks to the system than old information. Thus, they are no more consistent with what we know about the bioeconomics than other methods discussed so far, though they may be useful for prediction. Unfortunately, time-series data rarely exist on a daily basis without gaps; in most cases gaps appear in the data due to limited fishing activity in some locations.

No matter what belief variable specifications are chosen, the analyst is faced with formulating a statistical model that is, at best, an approximation of a nonstationary stochastic process that changes on a very small time scale. Methods for incorporating information decay or for truncating the data set are both imperfect attempts to match a tractable time scale to the actual time scale of the revenue generation process. With the exception of the Bayesian methods, the approaches discussed so far either do not make explicit distributional assumptions or do not assume normality; they are all variants on a least squares estimator. However, revenues are likely better characterized by some other distribution. These problems are confounded by repeating seasonal patterns. Wilson refers to the different information types as coarse-grained and fine-grained. The former captures seasonal information that is often common knowledge in the fishery, while the latter is idiosyncratic knowledge that is potentially proprietary in nature. This separation poses further problems for information-decay modeling, calling into question geometrically declining weights and simple truncations.[17]

The problem of unobserved and possibly changing quality of a location is also extremely important in the recreation

[14] Adopting a truncation approach, Holland and Sutinen use ten-day average lagged revenues and average revenues from the previous year of the industry to proxy for expected revenues. They circumvent the missing data problem by including dummy variables for choice occasions on which there were no trips in the sample period used to construct the proxy. Interestingly, they include the coefficient of variation to reflect risk preferences and to conclude that the positive sign suggests risk-loving behavior. Equally plausible is skewness-loving behavior. If the true data generating process (dgp) is gamma, for instance, the coefficient of variation is equal to two times the skewness coefficient.

[15] The exception, of course, is for the beginning of a data set when there are fewer than two observations.

[16] Though motivated by the Bayesian framework, Eales and Eales and Wilen regress catch on lagged catch (catch from the previous day) to obtain a model for expected catch, which they combine with price to form an expected profit measure included in the discrete choice location choice model. Implicitly this model assumes constant steady-state catch with short-run shocks that die off geometrically. Dupont applies ARIMA models to forecast prices that are then combined with a profit maximization model to generate expected profits for the discrete choice location model. In her analysis, the fish stock is treated as known and nonstochastic. While it may be true that prices vary according to some stationary stochastic process, the forces that affect abundance of a resource are likely nonstationary and possibly chaotic.

[17] Using a truncation approach, Holland and Sutinen also account for coarse- and fine-grained information by including separate terms in their regressions to summarize recent and previous year revenues.

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demand literature. Numerous authors confronted this problem in the context of studying angler location choice when expected catch is unknown, but solutions either assume a fixed distribution or use an ad hoc decay structure.[18] Recent work in recreation demand investigated preference heterogeneity over site quality without resolving the unobservable quality issue.[19] Such papers raise the question: do individual agents really have different preferences or do they simply have different beliefs about site quality?[20] To explore this issue, let us return to the harvest notation in equation (8) and let us suppose, for simplicity, that indirect utility is a linear function of expected revenue. Make the parameter α random to denote preference heterogeneity such that $\alpha = \bar{\alpha} + \eta_i$ and $\eta_i \sim N(0, \sigma_\eta^2)$. Suppose that the analyst includes the same expected revenue variable for all agents in the model, i.e., $R_{ijt} = R_{jt}$. Thus, utility is

$$U_{ijt} = (\bar{\alpha} + \eta_i)E[R_{jt}] + \varepsilon_{ijt}. \tag{12}$$

However, if agents are actually the same and have different information sets, one might falsely conclude that there is preference heterogeneity. Assume $E[R_{ijt}] = E[R_{jt}] + \zeta_{ij}$ and $\zeta_{ij} \sim N(0, \sigma_{\zeta j}^2)$. The true model would be

$$U_{ijt} = \alpha\big(E[R_{jt}] + \zeta_{ij}\big) + \varepsilon_{ijt}. \tag{13}$$

Though different models, the specification in (12) might pick up the variance in revenues as a random parameter.

Spatial Search and Information Sharing

This paper so far focused on choice modeling issues assuming that information is individual-specific and taken as given but not sought out by harvesters. The models thus ignore the possibility that fishers may make decisions to gather information purposefully, not just choose a location that is most profitable in the short run. This raises the issue of optimal search.[21] The appropriate analytical framework would be dynamic optimization. An immediate difficulty is that the search phase and the harvest phase are not distinct. The process of harvesting leads to more information, so the decision about where to go must weight the value of potential information with the value of potential harvest.[22] This, then, introduces the possibility that information is endogenous.

The problem may not actually be as severe in marine fisheries, since there are reasons that fishers might not undertake this intertemporal optimization. Harvesters might be myopic about gathering information because information is ephemeral. Thus, the opportunity cost of searching in unfamiliar areas rather than harvesting in well-known areas is high. In addition, the stylized race for fish still persists in many marine fisheries, so once an abundant place is found, harvesters cannot bank the information and continue searching. Instead, they must drop their search efforts and begin harvesting. Similarly, the incentives to share information are mixed. The ephemeral nature of information motivates harvesters to cooperate because individual fishers may not possess sufficient capacity to harvest an abundant area before it becomes unattractive.[23] Yet, the open access characteristic of many fisheries provides a disincentive to share information.

While conflicting forces make the payoff from information sharing ambiguous, identifying evidence of shared information from observed choices promises to be even more

[18] Several examples include Bockstael, McConnell, and Strand; Morey, Shaw, and Rowe; and Provencher and Bishop. McConnell, Strand, and Blake-Hedges provide a useful summary of different ad hoc approaches in the literature and argue in favor of modeling catch with a Poisson process, though implicitly they assume a fixed distribution. Following this method, Morey and Waldman emphasize the random nature of catch and argue that models using average observed catch in location choice regressions will suffer from an errors-in-variables problem.

[19] Train calculates fish stock as a weighted average of stream segments from the Montana River information system, assumes that the fish stock is known to anglers, and proceeds to estimate taste parameters that vary across individuals in the sample. Chen and Cosslett construct a salmon variable that is site and time specific and also allow for taste heterogeneity.

[20] This issue is similar to the question of state dependence or heterogeneity that has a long history in the labor literature and a growing interest in the marketing literature. There are numerous empirical labor supply studies that analyze state dependence and heterogeneity. A particularly useful exposition is Heckman, which discusses these issues conceptually. In the marketing literature, Erdem and Keane and Keane provide good examples.

[21] The classic text in statistics is DeGroot. Most works on search in economics deal with where to look first, e.g., Weitzman, how to formulate search rules, e.g., Morgan and Manning, or empirically when to terminate a search, e.g., Wolpin.

[22] For discussions of the way that optimal search (rather than random search) affects the observed data, see Mangel and Walters.

[23] For instance, sea urchins are most valuable just prior to spawning, and there is geographic spawning heterogeneity in California. An individual diver who locates ripe urchin may not be able to harvest it all before spawing takes place and might be willing to share the location with other divers in exchange for information about good locations in the future.

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difficult. Wilson recognizes these conflicting forces and discusses the ways that harvesters form networks and share information, but an empirical road map remains elusive. Returning one last time to the urn and ball experiment, imagine that there are 100 subjects, each of whom has drawn from the urns. Now, suppose that the experimenter allows the subjects to talk with one another and to discuss their draws. How might one track the flow of information and the way it affects individual beliefs? One possibility is to assume that all information is transmitted to everyone. That is, all data become public. Though arguably unrealistic, this is the most tractable way to approach the problem. A more challenging prospect is to observe which subjects communicate and then merge these subjects' data sets to calculate expected revenues.[24] There is some hope that we can isolate information networks with real world data. When individuals are licensed in a fishery rather than boats, the analyst can construct networks based on harvesters who have been on the same boat together. This is the case in California's sea urchin fishery. The assumption is that individuals on boats together are forthcoming with their private information.

Conclusions

Discrete choice modeling of fishing location tries to resolve simultaneously behavioral responses to information, what this information is, and the way that the information is gathered and processed. Without observing the process itself, the modeler really only sees choices and revenue (or catch) histories. We cannot separate how these histories are combined into measures of profitability and how these measures affect choice. This paper discussed two fundamentally different attempts to resolve questions about information. The author concludes that structural attempts are essentially intractable in every setting, and reduced-form methods are by nature ad hoc. Nevertheless, some hope lies in reduced-form methods. A conclusion of the first section is that even ad hoc approaches to information processing should account for sampling variance in addition to variance of the underlying stochastic process. Of the methods discussed, the Bayesian approach with a realistic probability model seems most compelling but is also the most difficult to implement. In contrast, it is much less clear how best to model the decay of information.

Though tractability problems and the unknown nature of information decay do not bode well for testing hypotheses about preference heterogeneity, risk aversion of harvesters, intertemporal search behavior, and information sharing, discrete choice models of fisher behavior are still valuable. These models may not resolve deep economic questions about optimizing behavior, but when ad hoc assumptions are chosen carefully, they should still provide insight. Moreover, models that predict well, especially if they do well out-of-sample, can be used for policy analysis. If methods used to calculate explanatory variables lead to covariates that are highly correlated with the true covariates, estimated parameters will scale the indirect utilities in a way that still generates reasonable predictions. This is precisely what is needed in simulating spatial management options: a model that matches the daily time scale and discrete spatial scale and that successfully translates observables into behavioral predictions.

The outlook, unfortunately, is more bleak for modeling the isomorphic recreation site choice problem. Here, it is essential to identify the connection between unobservable site quality and behavior because the ultimate aim is often to obtain estimates of welfare changes due to quality changes. However, without a reliable method that maps observable quality indicators into beliefs about site quality, welfare estimates derived from discrete choice behavioral models are problematic.

[24] See Eales and Eales and Wilen for other methods of identifying groups that share information.

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