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Spatial Models in Fisheries Economics (Nancy Bockstael, University of Maryland, presiding)

Location Choice of Commercial Fishermen with Heterogeneous Risk Preferences

Johan A. Mistiaen and Ivar E. Strand

The decision of where to fish is central to most commercial fishing activity. Fishermen targeting the same species typically have dramatically different net returns depending on their location choice. For regulators, closure of fishing grounds is currently among the most widely implemented regulations. Originally this intervention was premised on the need to protect both exploitable and spawning stocks or to separate contentious participants such as recreational and commercial fishermen. More recently, area closures were extended to protect marine mammals, threatened noncommercial fish species and even entire marine habitats. The critical dimension of fishing behavior and area closures is space, the subject of this session.

A key element in the analysis of fishing behavior and the impact of marine closures is uncertainty. Consider the following example. Suppose that an area is to be closed and that the random profits associated with the proposed area closure are characterized by low expected profits with a relatively low variance. If one considers only the loss of expected profits as the industry's loss from the closure, the welfare consequences of the closure are understated if fishermen are risk averse and overstated if fishermen are risk lovers.

The work of Bockstael and Opaluch on fisheries supply response was the first to incorporate uncertainty and risk preference into the behavioral motivations of fishermen. The discrete choice model used by Bockstael and Opaluch has since become the framework of choice for fisheries economists dealing with spatial aspects of commercial fishing activities. In general, studies find that in the short run fishers are responsive to economic incentives (Eales and Wilen). However, long-run adjustments of fixed and quasi-fixed factors appear to be more sluggish (Bockstael and Opaluch, and Dupont). More recently, Holland and Sutinen showed that both past information and recent information are important in location and fishery choice.

Thus far, several researchers have utilized a model based on a logarithmic utility function specification.[1] Because this functional form imposes risk aversion, the only legitimate test of behavior is whether the data are consistent with the logistic utility function. This is not made clear in the literature. For instance, Dupont uses a logistic utility function and subsequently claims to show that some fishermen are risk averse and some are risk loving. The logistic utility specification does not permit these assessments of behavior. A flexible functional utility specification is necessary to test this particular behavioral attribute.

In this paper, we develop and we test a conceptual short-run model of fishermen seeking to maximize their expected utility via discrete location choices and we use a utility function specification that enables us to test for risk preferences. However, perhaps more important than allowing for risk-loving and risk-averting behavior, a general model of discrete location choices under uncertainty should also allow risk preferences to vary among fishermen. Bockstael and Opaluch used a multinomial logit approach

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[1] It is unclear what utility function the Holland and Sutinen model uses.

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and introduced heterogeneity in the degree of risk aversion by allowing preferences to be based on initial wealth level. However, data on wealth are typically unavailable to researchers and, to the best of our knowledge, hitherto no fishing location choice study has allowed for heterogeneous risk preferences. To introduce risk-preference heterogeneity in the absence of initial wealth data, we propose to use the random-parameters logit (RPL) specification and to use an estimation approach developed by Train.[2] This method permits risk preferences to vary across the population and incorporates both risk-loving and risk-averting behavior. In the context of discrete choice under uncertainty, our research is more of a test rather than an endorsement of a particular approach. It is preferable to utilize individual data (such as initial wealth levels) on which the risk preferences could depend but when these data are not available, our approach may offer a reasonable alternative.

The paper presents a conceptual model of location choice for short-run fishing behavior, examines the potential for heterogeneous risk preferences within that model, and applies the model to the coastal East Coast and Gulf longline fleet.

The Conceptual Model

Supply response decisions by firms are primarily modeled assuming marginal behavior and perfect information. However, to analyze the behavior of commercial fishermen, especially in the short run, this framework is often inappropriate. In the short run, arguably the most important decision for many fishermen is a discrete choice about where to fish, and this choice must be made under stock-induced uncertainty. We postulate that the location choice is made on the basis of expected utility comparisons. The fishermen's problem is to select the location that will yield the highest expected utility.

For each fisherman, the choice depends on the distribution of random profits associated with each fishing location and on the risk preferences. The latter are not necessarily identical over fishermen and therefore a general model of fishing location choice should allow for heterogeneous risk preferences. Bockstael and Opaluch used a multinomial logit approach and allowed preferences to be based on wealth. However, this information is rarely available to researchers, including us. Therefore, we propose to use an alternative specification and to use an estimation approach developed by Train referred to as the Random Parameters Logit (RPL) framework. The RPL generalizes the standard logit model by allowing the coefficients associated with observed variables to vary randomly over individuals rather than being fixed for everyone. With this generalization, the discrete choice model does not exhibit the restricted substitution patterns underlying the independence of irrelevant alternatives (IIA) assumption.[3]

We now proceed to formalize the conceptual model. On a choice occasion (for us the beginning of a trip fishing trip), the nth fisherman is assumed to have the following conditional expected utility function associated with the ith alternative at time t,

$$(1) \quad EU_{\text{nit}} = E\overline{U}(\boldsymbol{\beta}_n, \mathbf{x}_{\text{nit}}) + \varepsilon_{\text{nit}}$$

where $\mathbf{x}_{\text{nit}}$ is the vector of factors that influence the fisherman's decisions and that are known to the researcher, the vector $\boldsymbol{\beta}_n$ is a vector of coefficients that is unobserved for each n and varies randomly over fishermen representing each fisherman's preferences, and the function $E\overline{U}$ is the fisherman's expected utility function known to the researcher. The error term ε_{ni} arises because of factors unknown to the researcher and is assumed to be identically and independently distributed (i.i.d.) extreme value, independent of $\mathbf{x}_{\text{nit}}$ and $\boldsymbol{\beta}_n$. At each time t, each fisherman chooses the ith alternative if it maximizes expected utility. Hence, the nth fisherman's unconditional expected utility per trip location choice at time t is given by

$$(2) \quad V_{nt} = \max_{i=1,\ldots,I} \{E\overline{U}_{\text{nit}} + \varepsilon_{\text{nit}}, \ldots, E\overline{U}_{\text{nit}} + \varepsilon_{\text{nit}}\}.$$

Fishermen are postulated to compare the expected utility of all possible alternatives and to choose the one associated with maximum expected utility. If the researchers knew

[2] Train points out that RPL models are also referred to as "mixed logit," "random-coefficients logit," and "error-components logit."

[3] In a standard logit model, the IIA assumption implies that a change in the attributes of one fishing location will induce proportional changes in the probabilities associated with all other alternative locations.

the fishermen's individual tastes, for instance if we knew the value of $\boldsymbol{\beta}_n = \boldsymbol{\beta}$, then the probability that the nth individual chooses the ith alternative in time t is computed as

$$(3) \quad I_{\text{nit}} = \frac{\exp\{E\bar{U}(\boldsymbol{\beta}, \mathbf{x}_{\text{nit}})\}}{\sum_{i=1}^{n} \exp\{E\bar{U}(\boldsymbol{\beta}, \mathbf{x}_{\text{nit}})\}}.$$

However, we do not know individual preferences and therefore we hypothesize that these vary across the population with density denoted as $f(\boldsymbol{\beta}|\boldsymbol{\theta}^*)$, where $\boldsymbol{\theta}^*$ are the parameters of this distribution (e.g., the mean and standard deviation of preferences in the fishermen population).

Therefore, the actual probability that the nth individual chooses the ith alternative is given by the integral of equation (3) over all possible values of $\boldsymbol{\theta}^*$ weighted by the density $f(\boldsymbol{\beta}|\boldsymbol{\theta}^*)$,

$$(4) \quad Q_{\text{nit}}(\boldsymbol{\theta}^*) = \int L_{\text{nit}}(\boldsymbol{\beta}) f(\boldsymbol{\beta}|\boldsymbol{\theta}^*)\, d\boldsymbol{\beta}.$$

In addition, unless we only observe only one trip per fishermen, for maximum likelihood estimation we have to compute the probability associated with each sample fisherman's sequence of choices. Again, if we knew $\boldsymbol{\beta}_n$, then the probability of a fisherman's choices for multiple trips would be the product of logit formulas,

$$(5) \quad S_n(\boldsymbol{\theta}^*) = \prod_t L_{ni(n,t)t}(\boldsymbol{\beta})$$

where $i(n, t)$ denotes the location chosen by the nth fisherman in time t. However, since preferences are unknown, the actual probability is computed as the integral of this product,

$$(6) \quad P_n(\boldsymbol{\theta}^*) = \int S_n(\boldsymbol{\beta}) f(\boldsymbol{\beta}|\boldsymbol{\theta}^*)\, d\boldsymbol{\beta}.$$

Thus, the goal of the researcher is to estimate the parameters that characterize the distribution of preferences, i.e., $\boldsymbol{\theta}^*$. Exact maximum likelihood estimation is not possible because the integral in equation (6) cannot be evaluated analytically. Consequently, we have to resort to approximating the probability via simulation and instead maximize a simulated log-likelihood function (Hajivassiliou, Train). For given values of the parameters in (6), we take random draws of $\boldsymbol{\theta}^*$ from its distribution and we approximate $P_n(\boldsymbol{\theta})$. The choice of distribution for (6) is made by the researcher and has modeling implications. We address these issues in the application section of the paper and detailed further discussions regarding the estimation procedures are provided in McFadden and Train and Revelt and Train. However, before turning to this application, we first address functional representation of the expected utility function.

To apply the conceptual model, we must specify a specific functional form for the expected utility function. In our choice of functional form, we want a testable hypothesis yet we want our choice set to be constrained by neoclassical theory. Ideally, expected utility would be a function of both initial wealth and a random return determined by location choice (Anderson, Dillon, and Hardaker). The initial level of wealth can vary among individuals and determines their position along the expected utility curve. This is the approach used by Bockstael and Opaluch to introduce some heterogeneity among fishermen. Under this specification a logit model allows for heterogeneity in initial wealth levels (i.e., different initial positions along the same expected utility curve) but imposes homogeneous risk preferences (i.e., the trade-offs for all fishermen are evaluated along the same expected utility curve). However, our data preclude us from calculating initial wealth levels and we have only random returns on which to explain behavior. Fortunately, by using the RPL approach we can still introduce heterogeneity in risk preferences despite these data availability constraints (i.e., instead of distinguishing between positions on *the* expected utility curve, we estimate not one but a random distribution of curves).

In our application, we postulate that the utility function can be represented by a quadratic form, i.e., $U = b_1 x + b_2 x^2$, where x represents random net returns. Consequently, for the nth fisherman the expected utility associated with the ith site at time t is given as

$$\begin{aligned}(7) \quad E\bar{U}_{\text{nit}} &= U[E(\boldsymbol{\beta}_{n1}\mathbf{x}_{\text{nit}})] + \boldsymbol{\beta}_{n2} M_2(\mathbf{x}_{\text{nit}}) \\ &= \boldsymbol{\beta}_{n1} E(\mathbf{x}_{\text{nit}}) + \boldsymbol{\beta}_{n2}[E(\mathbf{x}_{\text{nit}})^2] \\ &\quad + \boldsymbol{\beta}_{n2} V(\mathbf{x}_{\text{nit}})\end{aligned}$$

where M_2 is the second moment of $\mathbf{x}_{\text{nit}}$ and β_{n1} and β_{n2} are parameters of the utility function and $V(\mathbf{x}_{\text{nit}})$ is the variance of $\mathbf{x}_{\text{nit}}$. The parameter β_{n2} is assumed to follow a random distribution that is estimated through simulation estimation methods. While the quadratic utility function may impose nonmonotonicity in income, we do not anticipate that this will pose any problems in the range of our data. Moreover, while other functional forms such as the logistic may have some desirable properties, the quadratic formulation does allow us to test whether fishermen are risk loving, averse, or neutral.[4] However, one is advised not to use the estimated parameters for decisions that have values for the alternatives that lie beyond the range of the data.

Data Description

We estimate our model of location choices on a trip basis using 1996 data of fishermen that participated in the North Atlantic highly migratory species (HMS) fishery. This is a multispecies fishery and our sample includes fishermen that harvested swordfish and/or tunas. Data were obtained on a total of 2599 trips taken by 265 vessels (that range in size from 7 gross registered tons to 199 gross registered tons) to any of eight possible fishing locations in the coastal waters of the Eastern Atlantic, the Gulf, and the Caribbean. We define the sites as follows (the corresponding fishing areas are delineated in figure 1): offshore New England-Mid-Atlantic (area 1), nearshore New England-Mid-Atlantic (area 2), South Atlantic without Florida (area 3), East Coast of Florida without Florida Straits (area 4), Florida Straits[5] (area 5), Eastern Gulf of Mexico (area 6), Western Gulf of Mexico (area 7), and the Caribbean Sea (area 8).

The vast majority of trips were taken in the Gulf of Mexico and along the East Coast of the United States. While there are trips ranging to the Grand Banks in the North Atlantic and to waters off of South America, they are the exceptional trip taken by relatively large vessels. The predominance of the activity is much nearer to shore. The more distant "trips," however, require more days at sea and represent greater effort (more sets) than the ones closer to shore.

At the same time, the distribution of the trips' port of debarkation reveals that the fleet is concentrated in the Gulf and South Atlantic where the primary fishing grounds can be easily accessed. The vast majority of vessels and trips in 1996 are concentrated in the Gulf of Mexico and along the South Atlantic. Vessels in these ports are generally smaller vessels and are likely to operate closer to their home port. Thus, the exotic episodes of the distance water fleets, so vividly captured in books like the *Perfect Storm* and the *Hungry Ocean*, may not be reflective of the activity that the bulk of the fleet experiences.

Using these data, the notation x_i in the conceptual model is defined as expected net revenues at the ith fishing location and landing port. The development of expected net revenues is a tedious, time-consuming process that requires generating not only expected net revenues for a vessel's actual site-port chosen but also generating the net revenues for the site-port that could possibly be chosen. We developed estimates for expected revenues by considering price as a deterministic variable and harvest as a stochastic variable. The product of the two is a random variable with an expected value across trips and location choices. The expected value and variance of revenues were computed for each month for each of the fishing location and landing port combinations. There were months during which no one fished in an area and these site-port combinations were eliminated as a choice for all vessels.

It was also necessary to develop costs from a vessel's home port to each of the feasible alternative fishing locations. This was accomplished in three stages: the estimation of a vessel's fuel consumption per mile, the estimation of a vessel's cost per mile, and the estimation of the distance traveled to go from a home port to every feasible site-port combination. Fuel consumption per mile was estimated based on a vessel's reported fishing activity and by linking this information with the purchased gasoline information from an independent economic survey. We chose to match the average fuel purchased per trip of a vessel with the same vessel's average miles traveled per trip and to compute the value of fuel per mile per trip for each vessel. We regressed this implied fuel consumption based on the vessel's length,

$$\underset{}{\text{Log(fuel/mile)}} = \underset{(-10.16)}{-1.57} + \underset{(13.09)}{0.33^{*}}\text{(vessel length)}$$

$$\bar{R}^2 = 0.61 \text{ Obs.} = 107$$

[4] While extent to which monotonicity in income is violated is an empirical matter, we do recognize that the quadratic form imposes a priori decreasing absolute risk aversion.

[5] This area is specifically chosen because it is an area that was considered for closure.

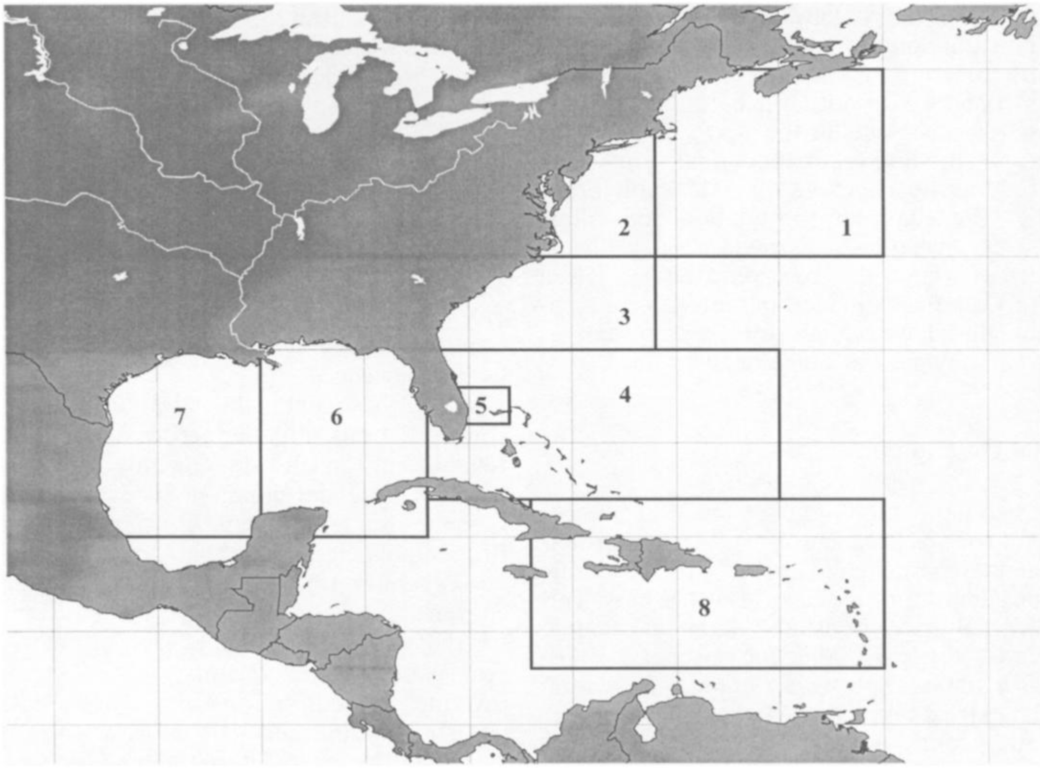

Figure 1. Fishing location areas for the Coastal Gulf and East Coast longline fleet

where the values in parentheses are t-values under the null hypothesis of no effect. Using this equation, we were able to compute the fuel consumption per mile for each vessel in the sample. The cost per mile for each vessel was determined by multiplying the fuel consumption per mile by a cost per gallon.

The next step was to compute distances from each vessel's initial home port to each alternative fishing ground-landing port. Centroids based on each vessel's sets were computed for each trip to obtain an "average" location fished per trip for each of the twelve fishing locations. These centroids were then averaged across all trips in a given fishing area to use as the point to which the vessels would travel to fish. Thus, the "travel" distance for each vessel was from the home port to a centroid of a fishing area and then to a landing port. Straight-line distances could not always be used because vessels had to avoid going aground on land areas, such as Florida. Thus, linear segments approximating travel routes were devised to avoid the land areas.

Empirical Application

We begin by estimating a standard McFadden multinomial logit (MNL) model that serves as a benchmark for the RPL model. The model follows equation (7) except that there are no random effect elements included. The two estimated coefficients, β_1 and β_2, are shown in the first row of table 1. They indicate a concave utility function with a turning point of about $3,000, which is greater than the maximum expected revenue for our sample.

The second model is the RPL in which we postulated the β_2 coefficient to be normally distributed.[6] It is presented as a way to determine how heterogeneous risk preferences are in our sample of fishermen. Moreover, in addition to allowing for different degrees of risk aversion, the model is also flexible enough to allow some fishermen in the population to positively respond to the variance

[6] We also estimate a model that permits β_1 to have a random component. The estimated standard error of this coefficient was small (less than 5% of the coefficient's value). We chose to set it to zero so as to focus our discussion.

Table 1. Estimated Coefficients of the Multinomial Logit and Random Parameter Logit Models

Model	Estimated Coefficients		
	β_1	β_2	
Multinomial logit (MNL)	0.2729 (0.0081)	−0.00004424 (0.0210)	
	β_1	$\theta_{(\text{mean of } \beta_2)}$	$\theta_{(\text{std. dev. of } \beta_2)}$
Random parameters logit (RPL)	0.2989 (0.0109)	−0.00005280 (0.0320)	0.2549 (0.0412)

Note: Standard errors given in parentheses.

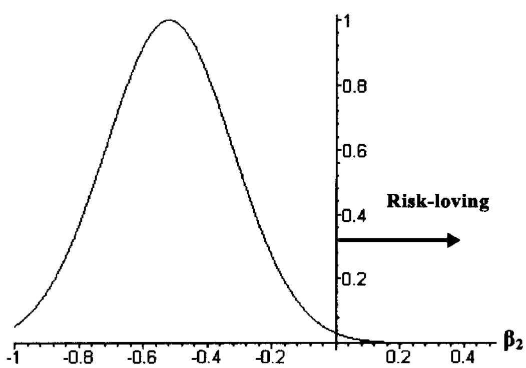

Figure 2. The estimated distribution of β_2

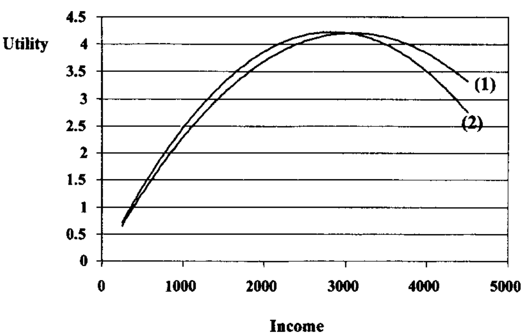

Figure 3. Estimated utility function for the homogeneous risk preferences (1) and for the heterogeneous risk preferences (2) model

in expected revenues and to therefore be risk lovers. The proportion of risk-averse fishermen will be determined by the estimated mean and standard deviation of the β_2.

The estimated parameters of the RPL are shown in the last row of table 1. All parameters, including the estimated standard deviation of β_2, are statistically significant at the 1% level of confidence. Thus, we fail to reject the hypothesis that risk preferences are heterogeneous in our sample of commercial fishermen. The distribution of β_2 implied by the parameters of the RPL model is shown in figure 2. Although we found no evidence of substantial risk-loving behavior, the distribution does show approximately 5% of the trips falling in this range.[7] The value of β_1 and the mean value of β_2 estimated from the RPL model differ from those in the MNL model by about 7.5 and 18.5%, respectively.

[7] Of course, given that the tails of a normal distribution tend to infinity, we must bear in mind that in principle some portion of the distribution associated with β_2 will always be negative.

The implied turning points in utility falls from about \$3,000 net revenue per trip (MNL model) to about \$2,750 per trip (RPL model). Both are greater than the largest expected return in our sample, leaving us with slightly more faith in our choice of the quadratic function. However, there is little difference in the estimated MNL utility function and the RPL utility function using the mean of β_2 (see figure 3). Recall, however, that the RPL has a family of distribution functions arising from the assumed randomness in β_2.

Although space restrictions in this paper prevent us from presenting an analysis of the welfare implications of the different specifications, our intuition suggests that welfare calculations may change substantially with the two specifications. For the closure of an area to fishing, for example, there may be some individuals who would be estimated as risk lovers in the RPL and who would require a premium above the normal compensation for closure of an area with low variation in expected returns. The nonlinearity in welfare estimates and Jensen's inequality would suggest differences between the MNL and RPL models.

Conclusions

In this paper, we presented an approach for incorporating heterogeneous risk preferences in situations where data are limiting. Specifically, we have shown how to use a quadratic utility function with an RPL model to estimate risk preferences that vary across the sample while also allowing for risk-averse as well as risk-loving behavior. The quadratic utility function, with all of its limitations, was used to permit risk-loving behavior in the sample. While we would prefer to have data on individual wealth, these measures are not always available and they are not always reliable. Moreover, our procedure could be applied as a test to determine whether greater effort in obtaining wealth information was necessary. In other words, if one observes no substantial variation in the risk-preference parameter (in our case, if the standard deviation of β_2 was not statistically significant), then incurring the costs of collecting data on wealth might not be fruitful.

Substantial exploration is still possible within this fundamental model. We have not used the panel data form of the RPL and while we have computed consistent estimates, they are not efficient. Incorporating correlation across error among trips of the same firm would improve our efficiency. Deriving welfare estimates under uncertain conditions is a challenge in itself but doing it within the structure of the RPL model offers even greater challenges. Finally, the potential for nonconvexity in individual utility is ever present. Much is yet to be learned about estimating heterogeneous risk preferences among fishermen and the policy implications thereof.

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