Two Econometric Approaches for Spatial Fisheries Management

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Abstract: This paper analyzes spatial patterns of exploitation in the California sea urchin fishery using two different econometric approaches: a Poisson/SUR model of monthly observations and a micro-level Nested Logit model of individual harvester daily decisions. Each model is used to simulate the spatial distribution of fishing effort. The models are compared using goodness of fit measures and implications for management are discussed.

Keywords: spatial, fishery, nested logit, SUR, Poisson

I. INTRODUCTION*

In recent years, spatial policies such as rotating spatial closures and permanent marine reserves have gained support amongst commercial fishery managers around the world. A spatial closure policy would shut down part of a commercial fishing ground either temporarily or permanently as a means to regenerate a fish stock or provide stock security. Unfortunately, standard economic models of fishing behavior do not incorporate space; typical bioeconomic models, in fact, consider resources to be homogenous across space. In contrast, ecologists argue that fishery management should consider a resource's spatial particularities such as density-dependent reproduction. Many recent ecological studies adopt metapopulation models.[1] In these models, marine resources are depicted as discrete and heterogenous patches of biomass that are linked through highly unpredictable oceanographic processes including upwelling, currents, wind, and advection. Economists, as such, must model the spatial behavior of harvesters to understand how real economic agents would respond to spatial closures. The essential empirical question is: how do biological, economic, and oceanographic factors determine the spatial distribution of fishing effort? This paper models the spatial distribution of fishing trips in the California sea urchin industry using two different empirical approaches: one based on aggregate monthly data and the other based on individual harvester decision-making. The results of the two approaches are compared using forecast evaluation methods, and the relative merits of each approach are discussed.

Although several recent works have addressed spatial fisheries issues from a bioeconomic perspective and have highlighted the importance of space in fisheries management, little is known about how fishing effort will respond to a real spatial policy. Sanchirico (1998) and Sanchirico and Wilen (1999) show how the traditional critiques of an open access institutional setting continue to be valid when the resource is spatially heterogeneous. In their case, rents appear as spatial arbitrage opportunities that arise due to the spatial character of biological dynamics and are dissipated due to open access. Holland and Brazee (1996) analyze conditions under which marine reserves are likely to succeed as a regulatory policy. Though the authors provide an interesting discussion of biological and economic issues, the results of the analysis are driven by an assumption that total fishery effort is fixed. Moreover, the model only incorporates spatial heterogeneity as a difference between reserve and non-reserve areas. In my analysis, effort changes are not assumed but instead are outputs of the empirical model. Hannesson (1998) also analyzes marine reserves and compares pure open access and private ownership institutional settings. Rents are generated by the marine reserve as fish disperse outside the reserve. But, when there is open access outside the reserve, these rents are dissipated as in the standard case. Sanchirico and Wilen (2000) incorporate more biological sophistication in their study of marine reserves and suggest specific biological characteristics that would likely lead to successful implementation of marine reserves. Specifically, when patches are biologically linked (i.e. there is dispersal between patches), it is possible that reserve creation under open access can both increase aggregate harvests and aggregate biomass. Though the existing papers on spatial management clarify the importance of space and the ways that space can affect traditional management, they are all theoretical and do not address the institutional details of any particular policy setting. My paper builds empirical models that capture the institutional character of California's red sea urchin fishery, which is neither pure open access nor pure private ownership.

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* 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.

[1] See, for instance, Botsford, Louis W., James F. Quinn, Stephen R. Wing, and John G. Brittnacher (1993), Quinn, James F., Stephen R. Wing, and Louis W. Botsford (1993), and Morgan, Lance E., Stephen R. Wing, Louis W. Botsford, Carolyn Lundquist, and Jennifer M. Diehl (1999).

The first approach is an econometric model of aggregate participation and harvest shares across space. It is a behavioral model at the industry level. A Poisson regression is used to estimate aggregate participation (measured in trips) as a function of open season days, weather conditions, mean revenues, and variance of revenues. The Seemingly Unrelated Regression (SUR) model of location-specific shares posits that fishery spatial dynamics are a function of revenue differentials across space. Predicted shares in each location, or patch, are multiplied by aggregate participation to arrive at spatially explicit predictions of fishing effort.

The second approach is a micro-level behavioral model that treats individual harvester decisions as discrete choices among non-participation and participation in different spatial locations. These choices are functions of weather, mean revenues, variance of revenues, and travel costs. A random utility model (RUM) provides the motivation for a Nested Logit specification. Predictions from the Nested Logit regression are aggregated across days and divers to arrive at monthly industry participation and location shares.

The two models are compared using goodness of fit measures from the aggregate model and from the discrete choice aggregated predictions. In-sample, the Poisson/SUR model predicts spatially explicit participation somewhat better than the discrete choice model, but out-of-sample the discrete choice model actually performs better. Although both approaches could be used to simulate spatial closures, each model has its advantages and disadvantages. The Poisson/SUR model is easy to estimate, is suitable for analysis of season closures, and provides some insight on spatial closures. Nevertheless, the discrete choice model is more appropriate for analysis of spatial closures because it has a natural structure for eliminating one of the location choices, and it can also be used to analyze season closures.

Because this paper attempts to provide a roadmap for fisheries managers as well as simulate spatially explicit effort for the California sea urchin fishery, the data requirements are discussed in section II. Section III outlines the Poisson/SUR model. The next section discusses estimation and results of the Poisson/SUR model. Section V outlines the Nested Logit model. Section VI presents results from the discrete choice analysis. Section VII compares the model using mean squared error, mean absolute error, and simple correlations. Finally, section VIII discusses the usefulness of each empirical approach for simulating spatially explicit policies and concludes.

II. DATA

The fishery data, collected by the California Department of Fish and Game, include 257,000 observations on California urchin dives over the period 1988-1997. The estimation uses only data through 1996, reserving the 1997 data for out-of-sample validation.[2] Each observation combines geographically specific log book information about dive duration, depth, number of divers, and pounds caught with landings ticket information about price, quantity sold, landing site, and diver license. Boat code and date are fields common to both data sets and allow one to link the information.

The analysis in this paper focuses on Northern California. This section of the fishery is divided into eleven geographically distinct harvest zones that roughly correspond to proposed spatial management zones. All zones are contiguous along the coast except zone 0, which is the Farallon Islands northwest of San Francisco. Figure 1 shows the spatial distribution of effort in north-central California. Though there are six total ports in Northern California at which divers land urchin, the four ports depicted in Figure 1 account for more than 90% of Northern California catch.

The fishery data is combined with geographically specific weather data from the National Buoy Data Center. These data contain hourly observations on variables that affect diving conditions including wave height, wave period, and wind speed. The hourly observations are aggregated into daily observations and linked to the urchin databases. For the SUR/Poisson model, the fishery data are aggregated into monthly observations, summing across all individuals on all days in each month. Note that there are some months in which the entire fishery was closed, so there are no observations for these months. There are other months in which the fishery was open but not all of the patches had participation. For the discrete choice model, the data are left disaggregated such that there are daily observations on each urchin diver. Since the data only include days on which divers actually participated, a complete set of choice occasions is constructed based on the season closure regulations and active divers. The information from the original data set is added to the set of all choice occasions to create the final augmented data set.

Although the empirical specifications below are particular to the urchin dive fishery, similar analyses could be done on other fisheries with only slight modifications. The essential data requirements are covered if boat log books record catch, effort (fishing time), and location, and

[2] The data set is currently being updated to include 1998 through 1999.

landings tickets can be matched to boats and record prices. The fishery manager can determine what outside data, such as weather, are relevant to the analysis.

III. POISSON/SUR MODEL

The Poisson/SUR model uses monthly data to describe participation and spatial dynamics. The idea is to treat participation and location choices separately because the participation effects would otherwise swamp the spatial dynamics in the fairly short panels that are available.[3] This bifurcation also allows the analyst more flexibility in how to simulate spatial closures and the ability to simulate season closures.

A Poisson regression estimates how a dependent variable (y_t), which takes on only integer values, responds to a parameter (λ_t) using a Poisson probability density.[4] The parameter λ_t, in turn, is a function of independent variables ($\mathbf{x_t}$) and parameters (β). The likelihood function is:

$$\Pr(y = y_t) = \frac{e^{\lambda_t} \lambda_t^{\,y_t}}{y_t!} \qquad (1)$$

I assume that the independent variables map into the Poisson parameter as follows:

$$\ln(\lambda_t) = \beta' x_t \qquad (2)$$

In the participation regression, y is a count of fishing trips in month t (TRIPS), and **x** includes open season days (DAYS), weather conditions (WV15, WV30, and WV50), mean revenues (ER), and variance of revenues (VR). ER and VR are computed using the averages of all observations in the month across all patches. The weather variables are wave heights measured in number of days in the month on which average wave height exceeds 1.5 meters, 3.0 meters, and 5.0 meters respectively. Together they create a spline function in order to capture nonlinear participation responses to weather. *Ex ante*, we expect the coefficients for DAYS and ER to be positive and the coefficients for WV15, WV30, and WV50 to be negative. More fishing opportunities and greater revenue potential generate more fishing effort. Adverse weather conditions deter fishing effort. If urchin divers are risk averse, then the coefficient on VR would be negative.

The Seemingly Unrelated Regression (SUR) component of the model captures spatial dynamics through a system of share equations.[5] It operates like a demand system. All of the patch shares sum to one in each period. Share in patch i (s_i) is a constant (α_i) plus a linear combination of net revenue differentials between patch i and other pathes, denoted as j ($\gamma_{i,j}\Delta NR_{i,,j} = \gamma_{i,j}[NRi - NR_j]$). Assuming an additive error (ε_i) and M total patches, the system is:

$$s_i = \alpha_i + \sum_{\forall j \neq i} \gamma_{i,j} \Delta NR_{i,j} + \varepsilon_i \quad ,i = 1,\ldots,M \qquad (3)$$

When there are no revenue differentials, the share identity implies:

$$\sum_{i=1}^{M} \alpha_i = 1 \qquad (4)$$

If we interpret the responses to net revenues as effort flows, as in Wilen and Sanchirico (1999), the γ parameters are symmetric:

$$\gamma_{i,j} = \gamma_{j,i}\,, \quad i = 1, \ldots, M, \quad j = 1, \ldots, M, \quad \text{and } i \neq j\,. \qquad (5)$$

As in a demand system, the fact that the shares sum to one combined with parameter restrictions lead to a singular covariance matrix. In this case, the singularity arises from the restriction on the alphas and the symmetry restriction combined with the fact that $\Delta NR_{i,,j} = -\Delta NR_{j,,i}$. Thus, one equation must be dropped from the estimation. The parameters from the dropped equation can then be recovered from the restrictions in the system.

Actual implementation of the SUR share system for the sea urchin fishery presents challenges. First, there are eleven patches in the Northern Californian fishery, based on possible spatial management zones. With symmetry imposed, there are sixty-five parameters to estimate (121 parameters without symmetry) in addition to parameters of the covariance matrix. Even with the rich data set available on California sea urchins, monthly aggregation leaves just ninety-two observations for each patch. My proposed solution is to use the contiguous patch revenue differentials only. Thus, each share equation has two γ parameters, one for the patch to the north and one for the patch to the south. A second difficulty is that the model requires observations on net revenues, but only gross

[3] Clearly, the level of time aggregation drives the panel length. Though daily information exists in the data set (and is used in the discrete choice model), one month is chosen so that the analysis is not plagued by missing observations on independent variables, numerous zeros in aggregate participation, and a predominance of zeros in patch participation shares.

[4] For further discussion of Poisson regression, see Cameron and Trivedi (1998).

[5] Seemingly Unrelated Regression (SUR) is a technique that models a system of individual regression equations to allow for contemporaneous correlation in the individual regression error terms. If there is a shock that affects all equations similarly but that is not controlled for in the explanatory variables, SUR is a more efficient method for dealing with the shock than estimating a series of individual regression equations. See Greene (1993) or Judge, Hill, Griffiths, Lütkepohl, and Lee (1988) for good discussion of the technique.

revenues (R_i) are observed and can be used. The empirical specification is thus:

$$s_i = \alpha_i + \gamma_{i,North} \Delta R_{i,North} + \gamma_{i,South} \Delta R_{i,South} + \varepsilon_i$$

where

$$\sum_{i=1}^{M} \alpha_i = 1 \qquad (6)$$

$$\left.\begin{aligned} \gamma_{i,North} &= \gamma_{j,South} \quad \text{if } i = j-1 \\ \gamma_{i,South} &= \gamma_{j,North} \quad \text{if } i = j+1 \end{aligned}\right\} i = 1,\ldots,M$$

This system is parsimonious enough to estimate but also maintains spatial interconnectedness; not all patches are directly linked but all are linked together through other patches.[6] Use of gross revenues can be justified if they are perfectly correlated with net revenues across space or if decisions are made based on gross revenues. In many fisheries, crews are paid on the share system such that crew members receive a share of the boat's total revenue. Thus agent behavior often is driven by gross revenues. The assumption is also plausible because many spatial aspects of costs are approximately constant across time. For instance, transportation costs from patch i to patch j are roughly constant throughout the data because the distances (and hence time costs) are fixed and fuel prices do not vary much.

IV. POISSON/SUR ESTIMATION AND RESULTS

Table 1 reports the Poisson regression results. All coefficients are statistically significant and have the signs anticipated *ex ante*. It appears that urchin divers in aggregate are also risk averse.[7] The magnitude pattern of the weather coefficients suggests that participation is concave in bad weather. This result can be interpreted as another manifestation of diver risk aversion; as conditions worsen (i.e. risk increases), the probability of taking a trip (i.e. willingness to accept the gamble) decreases at an increasing rate. Table 1 also includes results from a linear regression of log of trips on logs of the same independent variables. The adjusted R^2 in the linear model indicates that these variables explain much of the variation in aggregate participation. Though the linear model gives qualitatively similar results to the Poisson model, the Poisson has much lower standard errors.[8]

Table 2 reports results of the spatial dynamics model. Estimation was performed using Iterated Seemingly Unrelated Regression. As mentioned above, one equation was dropped for purposes of identification. Here, the Patch 10 equation was dropped, and as a result, there is no standard error reported for the Patch 10 constant parameter. Since the **X** variables are constants and revenue differences, we expect the coefficients all to be positive. Indeed all of the intercept terms and most of the slope terms are positive. The negative slope coefficients are not statistically significant, but all intercept terms and all but one positive slope coefficient are significant. The low system weighted R^2, however, suggests that the model does not explain much variation in patch shares across time.

One possible future extension for the SUR model is to impose a spatial autocorrelation pattern in the covariance matrix. Since the patches are arranged along a line (rather than in two-dimensional space), the simplest form would be a first-order autoregressive matrix. As such, the covariance matrix Σ of the SUR estimation would be a function of only a single variance parameter, σ, and a single correlation term, ρ.

IV. DISCRETE CHOICE MODEL

Urchin divers make a series of discrete decisions about fishing effort and location. On each open season day, each diver chooses whether or not to participate based on prevailing weather conditions, expected prices, expected resource abundance, individual diver traits, and processor contractual arrangements with of the Tokyo wholesale market. Among the individual traits are diver skill, attitudes towards risk, outside opportunities, and values of leisure time. Divers who have chosen to participate then choose diving locations based on expectations about spatially varying resource abundance and travel costs. Thus, on any given open season day there are two decision nodes or nests.

A Random Utility Model provides a useful motivation and framework for discrete daily participation and diving location decisions. Index individuals by i, diving locations by j, and days by t. Diver i's utility from diving in harvest zone j on day t is:

$$\begin{aligned} U_{ijt} &= v_{ijt} + \varepsilon_{ijt} \\ &= f(\mathbf{X}_{it}, \mathbf{Z}_{i1t}, \mathbf{Z}_{i2t}, \ldots, \mathbf{Z}_{iMt}; \theta) + \varepsilon_{ijt} \end{aligned} \qquad (7)$$

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[6] For the border patches (Farallon Islands and Patch 10), only one revenue differential parameter is estimated.

[7] The Poisson model was estimated using both SAS GENMOD and GAUSS MAXLIK. The procedures produced identical estimates of the parameters and standard errors. To achieve convergence, ER and VR were re-scaled so that they measure so that they are computed with hundreds of dollars rather than dollars.

[8] A negative-binomial model was also estimated and produced qualitatively similar results.

where **X** includes diver-specific and time-specific characteristics that are constant across choices, **Z** denotes choice-specific characteristics such as travel costs and resource abundance, θ is a parameter vector, and ε_{ijt} is a mean-zero random component that is unobservable by the analyst. Given M possible diving locations, the Random Utility Model posits that a diver chooses location 1 if the utility of choice 1 is higher than that of the (M-1) other location choices as well as the choice of not to dive. For example:
Pr[i chooses 1 at t] = $\Pr[U_{i1t} > U_{i2t}, U_{i1t} > U_{i3t}, ..., U_{i1t} > U_{iMt}, U_{i1t} > U_{i\,not\,t}]$.

There are numerous discrete choice formulations that capture the essence of spatial decision-making and are consistent with the above Random Utility Model. Many similar analyses that model participation and location choices have appeared in the literature on recreation demand.[9] The general approaches fall into the following categories: multinomial (and conditional) logit, discrete choice dynamic programming, random parameters logit, mulitnomial probit, and Nested Logit. The basic multinomial (and conditional) logit is easy to estimate but inappropriate for spatial policy simulation because it imposes Independence of Irrelevant Alternatives (IIA); the relative choice probabilities are unchanged by a change in the choice set. A spatial closure analysis with a model that imposes IIA would, in essence, assume the answer to the policy question. Discrete choice dynamic programming is attractive to the analyst because it is an empirical model that is consistent with intertemporal optimizing behavior of individual agents and it avoids IIA. In the context of most commercial fisheries, however, it is unnecessary. The open access aspect of most fisheries truncates the time horizon from the individual fisher's point of view. Moreover, it is computationally burdensome. The random parameters logit and multinomial probit models can allow for heterogeneity of individual responses to independent variables and do not suffer from IIA problem, but they are also computationally cumbersome. The method used in this paper is Nested Logit. Nested Logit does not impose IIA, is easy to estimate, and allows for different variances at different decision nodes. So, Nested Logit is a structural model of the interdependent decisions of whether to go and where to go but is also quite flexible.[10] Moreover, in contrast to discrete choice dynamic programming, random parameters logit, and multinomial probit, the Nested Logit model is simple to use for policy simulation because it neither requires calculation of an individual agent's entire optimal path nor integration over individual heterogeneity that is manifested in random parameters.

McFadden (1978) showed that if ε_{ijt} is independently and identically distributed Generalized Extreme Value, maximization of random utility gives rise to the Nested Logit model.[11] If we assume further that indirect utility is linear in **X** and in **Z**, the following probabilistic model characterizes individual choices:

$$\Pr(\text{Go to } j) = \frac{\exp\{z_{jt}'\gamma + x_t'\beta + (1-\sigma)I\}}{\sum_{k=0}^{10}[\exp\{z_{kt}'\gamma\} + \exp\{z_{kt}'\gamma + x_t'\beta + (1-\sigma)I\}]} \quad (8)$$

$$\begin{aligned}\Pr(\text{Do not go}) &= 1 - \sum_{k=0}^{10}\Pr(\text{Go to k}) \\ &= \frac{1}{1+\exp\{x_t'\beta + (1-\sigma)I\}}\end{aligned} \quad (9)$$

where $I = \ln(\sum_{k=0}^{10}\exp\{z_{kt}'\gamma\})$ (10)

The i subscripts for individuals are suppressed because the form of the model is the same for each individual in the data set; only some **X** characteristics vary across individuals. β denotes the parameter vector for characteristics that vary across individuals and/or choice occasions but not across choices. The parameter vector for characteristics that vary across choices is γ. The coefficient on the Nested Logit inclusive value is $(1 - \sigma)$. For identification, I have normalized the indirect utility not diving to zero. Nevertheless, it is important to keep in mind that the indirect utility of not diving captures the value of leisure, work opportunities outside the fishery, and the value of not being exposed to unsafe diving conditions.

For empirical analysis, **X** includes wave period (WP), wind speed (WS), wave height (WH), and day-of-week dummies (SUN, …, SAT). *Ex ante*, there are strong expectations about parameter signs; we expect weather variables to have negative coefficients. If the data were available, **X** would also include variables to control for individual diver heterogeneity such as demographic indicators. For each location, **Z** contains patch-specific constants (D0, ..., D10), patch-specific expected revenues (ER), patch-specific variance of revenues (VR), travel distance from the diver's home port (DISTANCE), and a

[9] See, for instance, Morey, Shaw, and Rowe (1991), Morey, Rowe, and Watson (1993), McConnell, Strand, and Blake-Hedges (1995), Morey and Waldman (1998), and Font (1999).

[10] For more discussion of Nested Logit and discrete choice models in general, see Maddala (1983).

[11] In the simpler model in which the ε's are independently and identically distributed Type I Extreme Value, utility maximization gives rise to the familiar conditional logit model (McFadden, 1974).

variable that interacts DISTANCE with number of divers on the boat (DIS*DIV).[12] The strong *ex ante* sign expectations are positive for ER and negative for DISTANCE. Furthermore, we expect VR to have a negative coefficient if divers are risk averse.

The number of weather variables included in the discrete choice analysis is different the number in the Poisson/SUR model. The Poisson model includes only a spline function of wave height. The wave period and wind speed variables are dropped because the aggregated weather variables are highly correlated. This correlation is expected, since it is a result of seasonal variation in weather patterns. In the discrete choice model, weather variables are on a daily basis and include more idiosyncratic patterns. For instance, there are some days with big waves and slow wind yet other days with big waves and high wind. As such, effects of different weather characteristics can be resolved in the discrete choice model but not in the Poisson regression of aggregate participation.

VI. DISCRETE CHOICE ESTIMATION

Table 3 reports results from Nested Logit analysis on the 27,822 observations.[13] Except the interactive coefficient on divers and distance (DIS*DIV), all coefficients are statistically significant at the 10% level and most are highly significant. Although the coefficients of Nested Logit are not the marginal effects (because the model is nonlinear), the coefficient signs are interpretable as in a linear model. The negative coefficients on weather variables (WP, WS, and WV) all indicate that the probability of diving decreases when weather conditions are unfavorable. Wave period and height measure wave power, which increases the safety risk of diving, and wind speed is a general indicator of harsh weather.

The day-of-week dummies demonstrate the importance of urchin roe market institutions. The pattern of the effects is what is relevant as well as the coefficients being significantly different from each other. Most California urchin roe processors are closed on Sundays, so there is less diving activity on weekends. Urchin landings on late Thursday or early Friday may be shipped to Japan Friday night and arrive in Japan Sunday. Since the Tokyo wholesale market is closed on Sundays, this decreases fishing effort at the end of each week. Thus, diver participation is greatest in mid-week.

Patch-specific variables are also important explanatory variables. The positive sign on ER suggests that divers are more likely to choose a location that has higher payoffs, while the negative coefficient on VR suggests that divers are less likely to choose a patch that has a high variance in payoffs. These coefficients summarize the effects of biological and economic factors. The abundance of urchin affects the quantity, which in turn affects revenues. Roe quality and market conditions drive prices, which again affect revenues. The negative sign on DISTANCE suggests that travel costs deter divers from venturing far from their ports. Finally, a positive sign on DIS*DIV would have an interesting spatial economies of scale interpretation. It would suggest that when there are multiple divers on a boat, the fixed costs of travel are spread over multiple individuals, which partly offsets the DISTANCE variable.[14] However, the coefficient estimated here is negative and not statistically significant.

An important aspect of Nested Logit is the way that the nests of the model are linked. The probability of not participating is a function of the patch-specific variables and not just the weather and day-of-week dummies. So, the signs on patch-specific variables also can be interpreted as increasing (for positive signs) or decreasing (for negative signs) the probability of participating. For example, higher ER in a patch not only increases the probability of choosing that patch over other patches but also increases the probability of choosing to participate at all. The coefficient on the inclusive value, however, mitigates some of this affect. The coefficient is less than one, so a change in a **Z** variable has a smaller impact on the denominator of (9) than it would if the σ were = 0.

[12] For the discrete choice model, expected revenues and variance of revenues were calculated by estimating gamma distributions for each patch. A gamma density was chosen because revenues are always positive and appear to have a skewed distribution. In each period, the previous six months of observations within a patch were used to estimate parameters of a gamma density, and the resulting parameters were used to calculate ER and VR. For further discussion, see Smith (2000).

[13] These observations constitute a random sample of thirty divers followed across the entire data set. The data was sampled because the number of observations would otherwise be enormous and would require considerably more computing power and time given the highly nonlinear nature of Nested Logit. Ways of estimating the model using all of the data, a larger sample, and/or multiple samples are currently being investigated. The results in Table 3 were estimated using GAUSS MAXLIK.

[14] A different justification, however, can be made for the interactive variable having the opposite sign. Divers on multi-diver boats drive to a different port to reduce travel costs, since we expect that travel by boat is more costly and time-consuming than travel by car.

The model fits well overall, as the high pseudo-R^2 value of .24 indicates. Several tests were performed to evaluate the specification. First, the Nested Logit model was tested against a model that restricts the inclusive value coefficient (1-σ) to 1. The test statistic, distributed N(0,1) with one degree of freedom, was 12.181. Clearly, we reject this restriction in favor of the model in Table 3. The model was also tested against one in which the choice-specific constants are restricted to 0. The test statistic, distributed χ^2 with nine degrees of freedom, was 938.1. Again we reject the restrictions in favor of the model in Table 3.

VII. FORECASTING WITH THE POISSON/SUR AND NESTED LOGIT MODELS

The SUR/Poisson approach makes separate forecasts of the participation and the spatial dynamics, and multiplies them to obtain forecasts of monthly fishing trips for each patch. Participation simulation is quite simple. The Poisson specification implies that:

$$E[y_t \mid x_t] = Var[y_t \mid x_t] = \lambda_t = e^{\beta' x_t} \tag{11}$$

Predicted participation is simply a function of exogenous **X** variables and the parameter estimates, $\hat{\beta}$. From here, one can immediately forecast in-sample and out-of-sample. The in-sample period consists of ninety monthly observations from 1988 through 1996, deleting months during which the fishery was closed. The out-of-sample period is eleven observations during 1997, since the fishery was closed during July. The SUR model is used to predict mean shares for each month in each patch, both in-sample and out-of-sample. These predictions are simply linear functions of the data and parameter estimates. The predicted shares are multiplied by monthly trip predictions to obtain patch-specific monthly trip predictions.

There are at least two ways to generate predictions about participation and location choices using the discrete choice model. The easiest is simply to calculate the indirect utility of each choice (including the choice of not to dive) for each individual on each choice occasion. The prediction is then the choice with the highest indirect utility. This method ignores the probabilistic nature of a random utility framework but is the best if the analyst is truly interested in what a particular individual will do on a particular day. In this paper, however, the interest lies in what the group of divers will do as a whole over some interval of time. As such, a second, more useful way to generate predictions is to calculate the probabilities of each choice for each individual on each choice occasion. Then add up all of the probabilities over the relevant interval to arrive at the predictions. This method is used to generate the Nested Logit predictions, which are the actual and predicted number of diving trips at each location in-sample and out-of-sample.

Table 4 compares forecasts from the Poisson/SUR model and the Nested Logit model using mean squared error (MSE), mean absolute error (MAE), and correlation of actual and predicted values.[15] In-sample, each model performs better than the other for some patches. Nested Logit beats Poisson/SUR, for instance, on all three measures forecasting Patch 9, and Poisson/SUR out-performs Nested Logit in-sample for Patch 5. The average correlation of actuals and predicted values across all patches is slightly better for the Nested Logit in-sample than for the Poisson/SUR model. Nevertheless, the overall performance of Poission/SUR on both magnitude measures (MSE and MAE) is better than that of Nested Logit. Out-of-sample, it appears that Nested Logit performs better than Poisson/SUR. The system average of MSE and MAE are both lower for the Nested Logit model and the system average correlation is higher. Nonetheless, Poisson/SUR does perform better in Patch 2, Patch 4, and Patch 8.

VIII. DISCUSSION

Although superior out-of-sample performance is an argument for Nested Logit, it does not perform so well that one can be comfortable ruling out other models. Using MSE, MAE, and correlation, it is likely that a pure time series model would perform better than either of the models proposed in this paper. However, a pure time series model would be unable to simulate policies such as spatial closures and marine reserves because these policies have not been implemented in the sample period and thus would constitute a nonstationarity out-of-sample. In contrast, the models proposed in this paper fully structural and capable of simulating a variety of policy scenarios. Thus, an important criterion for empirical model selection is a model's applicability to the policy situation.

For use as a policy tool, each econometric approach has its advantages and its disadvantages. One straightforward use of the Poisson/SUR model is to simulate partial season closures. In this case, one could fix all of the regressors except open season days and reduce the number of open season days by the amount of the season closure. The Poisson/SUR model is also easier to estimate and easier to use as a simulation tool than the Nested Logit model. Moreover, Poisson/SUR does not require data on individual decision-makers but instead relies on a long panel of industry totals that are disaggregated only into spatial units. In contrast, the Nested Logit model is more consistent with individual

[15] Mean absolute percentage error (MAPE) was not used because many month/patch combinations have zero actual trips.

decision-making, requires fewer assumptions in simulations, and does not require a long time series.

Although the Poission/SUR model is structural, spatial policy simulation would require many assumptions. The assumptions begin with a need to simulate the effect of the policy on aggregate effort because there is no policy variability in the sample period. In other words, spatial closures have never been tried as a management tool in the urchin fishery (and likely have never been tried in other fisheries considering them). This means that there is no explicit independent variable on which to condition effort responses to closures. The analyst must simulate spatial closures through a plausible proxy for the policy variable. A sensible assumption might be to scale the open season days in the participation regression by the number of open patches. For instance, suppose that there are ten patches and thirty open season days in a month. Then one might simulate a single patch closure by reducing the season days by 30/10 = 3 days. To capture spatial dynamics, the analyst sets the closed patch shares to zero. Unfortunately, further assumptions are required about how the share of the closed patch redistributes amongst the remaining open patches. Setting closed patch revenues to zero will facilitate the redistribution, but there is no guarantee that remaining open patch shares will sum to one. Thus, some other assumption is required. Admittedly, this approach is *ad hoc*, but it is more structural than what has been done in some of the theoretical research on spatial closures, and it is motivated by the spatial adjustment model of Sanchirico and Wilen (1999).

Spatial policy simulation with Nested Logit, in contrast, is quite straightforward and uses a more compelling behavioral model. To simulate a patch closure, one sets the indirect utility of the closed patch to a very negative number and then proceeds to calculate the probabilities of all the choices.[16] In theory there is still a positive probability of going to the closed patch using this method, but in practice this probability is zero out to many decimal places. This method can be extended easily to model multiple patch closures by substituting very negative numbers into the corresponding indirect utilities and performing the same calculations above.

The Nested Logit model is more structural than the Poisson/SUR model. Independent variables map into diver utility, which in turn drives choices. Even though there is no spatial policy variation in the sample period, all of the factors that determine choice are identified by the model, allowing the analyst to simulate the spatial closure. Thus, the analyst does not need to identify an *ad hoc* proxy for the policy variable. The reason for this is that choice occasions in the sample for which a patch is highly unattractive to a diver (or divers) mimics a patch closure. As a patch becomes more unattractive, its indirect utility (relative to the indirect utilities of other choices) decreases. From the analyst's perspective, the corresponding probability of going to the unattractive patch is driven towards zero. Thus, the utility-theoretic basis of the Nested Logit model provides a motivation for the spatial closure simulation method suggested above.

As more fisheries managers around the world consider spatial closure policies, the need for spatially explicit and empirical bioeconomic models grows. Both models in this paper are capable of simulating spatial closures using only standard data collected by fishery managers augmented with publicly available weather data. The Poisson/SUR model performs better in-sample than the Nested Logit, but the Nested Logit does relatively better out-of-sample. Since there is no clear overall winner based on goodness of fit measures, model selection can proceed based on policy applicability and theoretical consistency. On these criteria, the Nested Logit is a superior choice; it has a utility-theoretic foundation and a natural structure for simulating spatial closures without the need for numerous *ad hoc* assumptions.

[16] The choice of the indirect utility for the patch closure only must be small enough to drive the probability close enough to zero. But, if one chooses a number that is more negative than necessary, it does not matter because the functional form of logit always exponentiates this number, which, in turn, zeroes out the effect.

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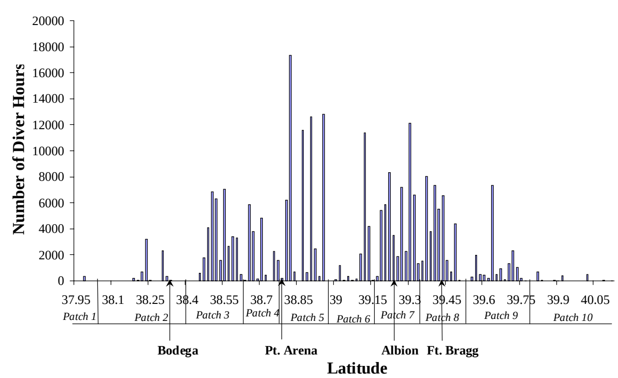

Figure 1: Urchin Diver Spatial Histogram

Table 1
Participation Regression Results

Poisson Regression

Variable	Coefficient	Standard Error	Z - statistic
CONSTANT	6.6354	0.0323	205.4303
DAYS	0.0141	0.0008	17.1750
WV15	-0.0152	0.0007	-22.1050
WV30	-0.0170	0.0009	-18.2810
WV50	-0.0449	0.0050	-8.9880
ER	0.0617	0.0040	15.5110
VR	-0.0020	0.0002	-8.7480
observations		92	
Log-likelihood		-4022.001	

Linear Regression

Variable	Coefficient	Standard Error	Z - statistic
CONSTANT	6.4470	0.3639	17.7200
DAYS	0.0144	0.0088	1.6400
WV15	-0.0130	0.0077	-1.6900
WV30	-0.0239	0.0089	-2.6800
WV50	-0.0395	0.0415	-0.9500
ER	0.0761	0.0395	1.9300
VR	-0.0023	0.0024	-0.9800
observations		92	
Adjusted R^2		0.39	

Table 4
Comparison of Forecasts

In-Sample (90 Observations)

	Mean Squared Error		Mean Absolute Error		Correlation	
	Poisson/SUR	**Nested Logit**	**Poisson/SUR**	**Nested Logit**	**Poisson/SUR**	**Nested Logit**
Farallon Islands	18,622.35	22,212.12	8.94	10.96	0.34	0.24
Patch 1	17,397.09	22,051.58	10.01	8.76	0.11	0.28
Patch 2	17,300.99	51,365.48	9.49	19.02	0.43	0.49
Patch 3	131,248.59	306,241.37	28.43	44.27	0.46	0.70
Patch 4	43,792.58	222,832.65	16.67	40.53	0.44	0.44
Patch 5	491,027.54	992,649.14	55.38	79.50	0.48	0.37
Patch 6	64,664.91	113,968.74	20.78	27.97	0.47	0.54
Patch 7	552,486.05	848,504.22	61.75	77.61	0.34	0.66
Patch 8	228,209.05	483,648.90	43.61	58.55	0.50	0.72
Patch 9	87,380.35	79,511.23	22.25	19.90	0.40	0.48
Patch 10	7,592.42	11,568.76	5.54	5.85	0.48	0.35
System Average	**150,883.81**	**286,777.65**	**25.71**	**35.72**	**0.41**	**0.48**

Out-of-Sample (11 Observations)

	Mean Squared Error		Mean Absolute Error		Correlation	
	Poisson/SUR	**Nested Logit**	**Poisson/SUR**	**Nested Logit**	**Poisson/SUR**	**Nested Logit**
Farallon Islands	609.77	458.53	7.23	5.41	0.16	-0.16
Patch 1	505.42	292.68	5.05	3.85	-0.52	-0.17
Patch 2	538.99	986.82	6.02	8.71	0.56	0.38
Patch 3	10,160.02	7,688.84	22.62	18.13	0.07	0.49
Patch 4	1,946.05	2,625.65	11.40	13.86	0.31	0.02
Patch 5	26,867.42	8,685.76	37.38	24.22	0.29	0.54
Patch 6	9,420.28	3,093.58	25.63	14.42	0.34	0.56
Patch 7	51,205.23	58,811.67	57.32	65.94	0.10	0.39
Patch 8	18,573.86	24,068.50	36.70	41.57	0.34	0.20
Patch 9	3,924.17	1,823.25	16.87	11.73	0.58	0.19
Patch 10	333.44	176.05	4.64	2.87	0.28	0.77
System Average	**11,280.42**	**9,882.85**	**20.99**	**19.16**	**0.23**	**0.29**

Table 3
Nested Logit Estimates

Not Location-Specific

Variable	Coefficient	Standard Error	Z - statistic
WP	-0.1432	0.0219	-6.53
WS	-0.0839	0.0123	-6.80
WH	-0.6486	0.0446	-14.53
SUN	1.7227	0.3176	5.42
MON	2.4629	0.3082	7.99
TUE	2.5718	0.3088	8.33
WED	2.4854	0.3082	8.07
THU	2.3735	0.3102	7.65
FRI	1.8478	0.3157	5.85
SAT	1.793	0.3149	5.69

Location-Specific

Variable	Coefficient	Standard Error	Z - statistic
DISTAN	-11.9829	0.7346	-16.31
DIS*DIV	-0.0583	0.2121	-0.28
ER	0.0459	0.0235	1.95
VR	-0.0318	0.018	-1.76
D0	1.6795	0.4495	3.74
D1	1.342	0.6104	2.20
D2	-3.8288	0.5052	-7.58
D3	-2.0986	0.4861	-4.32
D4	-2.0504	0.4491	-4.57
D5	-3.1385	0.4755	-6.60
D6	-4.0405	0.4841	-8.35
D7	-5.0215	0.5277	-9.52
D8	-6.8449	0.5825	-11.75
D9	-4.4365	0.5187	-8.55
D10	0	- restricted for identification -	
sigma	0.5972	0.049	12.181

Log-likelihood	-10293
Observations	27822
Pseudo R-square	0.23554

The Pseudo R-squared is based on the log-likelihood in a Conditional Logit Model with choice-specific constants.

Table 2
SUR Results for Spatial Dynamics

Parameter	Variable	Coefficient	Standard Error	t Statistic
α_0	Farallon Intercept	0.011515	0.002	4.65
α_1	Patch 1 Intercept	0.019126	0.003	7.37
α_2	Patch 2 Intercept	0.022343	0.003	8.04
α_3	Patch 3 Intercept	0.079158	0.005	14.74
α_4	Patch 4 Intercept	0.046607	0.004	11.26
α_5	Patch 5 Intercept	0.213346	0.014	14.89
α_6	Patch 6 Intercept	0.088105	0.006	14.49
α_7	Patch 7 Intercept	0.28932	0.013	23.06
α_8	Patch 8 Intercept	0.170614	0.010	17.00
α_9	Patch 9 Intercept	0.048293	0.005	8.83
α_{10}	Patch 10 Intercept	0.011573	Recovered from restrictions.	
$\gamma_{0,1}$	$\Delta R_{0,1}$	6.73E-06	0.0000016	4.31
$\gamma_{1,0}$	$\Delta R_{1,0}$	6.73E-06	0.0000016	4.31
$\gamma_{1,2}$	$\Delta R_{1,2}$	6.03E-07	0.0000019	0.32
$\gamma_{2,1}$	$\Delta R_{2,1}$	6.03E-07	0.0000019	0.32
$\gamma_{2,3}$	$\Delta R_{2,3}$	1.26E-05	0.0000032	3.92
$\gamma_{3,2}$	$\Delta R_{3,2}$	1.26E-05	0.0000032	3.92
$\gamma_{3,4}$	$\Delta R_{3,4}$	-8.25E-06	0.0000053	-1.57
$\gamma_{4,3}$	$\Delta R_{4,3}$	-8.25E-06	0.0000053	-1.57
$\gamma_{4,5}$	$\Delta R_{4,5}$	1.52E-05	0.0000084	1.81
$\gamma_{5,4}$	$\Delta R_{5,4}$	1.52E-05	0.0000084	1.81
$\gamma_{5,6}$	$\Delta R_{5,6}$	-8.53E-06	0.0000111	-0.77
$\gamma_{6,5}$	$\Delta R_{6,5}$	-8.53E-06	0.0000111	-0.77
$\gamma_{6,7}$	$\Delta R_{6,7}$	-2.02E-06	0.0000189	-0.11
$\gamma_{7,6}$	$\Delta R_{7,6}$	-2.02E-06	0.0000189	-0.11
$\gamma_{7,8}$	$\Delta R_{7,8}$	-1.90E-05	0.0000336	-0.57
$\gamma_{8,7}$	$\Delta R_{8,7}$	-1.90E-05	0.0000336	-0.57
$\gamma_{8,9}$	$\Delta R_{8,9}$	3.27E-05	0.0000166	1.97
$\gamma_{9,8}$	$\Delta R_{9,8}$	3.27E-05	0.0000166	1.97
$\gamma_{9,10}$	$\Delta R_{9,10}$	9.67E-06	0.0000020	4.82
$\gamma_{10,9}$	$\Delta R_{10,9}$	9.67E-06	0.0000020	4.82

System Weighted R^2	0.0752
Total Observations	990