LOCATION CHOICE BEHAVIOR MODELING OF SHRIMP FISHERMEN IN THE GULF OF MEXICO

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ABSTRACT

The shrimp fishery accounts for more than one-half of the total revenues generated by commercial fishing activities in the U.S. Gulf of Mexico. Due to its historical open access nature the harvesting sector has historically been overcapitalized (from an economic perspective) resulting in a suboptimal generation of rents. Various management measures have been considered/implemented in an effort to reduce shrimp trawling externalities. The studies upon which many of these measures were based, however, have failed to account for the behavioral reaction of the shrimp fishermen to the policy. As a result, enacted regulations may not have achieved the anticipated goal(s) and proposed management measures are likely not to meet expectations. Based on sound discrete choice theory, the purpose of this paper is to develop an analysis of shrimpers_ spatial behavior under uncertainty and to provide an ex post empirical economic analysis of this behavior. Location choice decision is modeled in an effort to examine short-run behavior of the shrimp fleet in response to economic and non-economic factors of relevance including (a) proposed regulation, (b) seasonality, (c) past siting choice experience, (d) risk attitudes, (e) vessel mobility, (f) profit, and (g) crowding effects. The development and empirical testing of this model will be used to assess and forecast spatial activities of fishermen for more effective management of the Gulf of Mexico shrimp fishery.

Keywords: mixed logit, TX closure, risk attitudes, expected revenue, loyalty, crowding externality

INTRODUCTION

Fishermen's location choice is one of the more important short-run decisions made for each trip. Smith and Wilen (2003) show that the incorporation of spatial behavior has strong effects on the prediction of the outcomes of management tools even in the case when the policy analyzed is not spatial in nature (minimum size limits was given as an example). There has been increasing agreement among marine ecologists, biologists and fishery managers in recent years that conventional measures to protect fish stocks, such as season lengths and gear restrictions, have generally not reached the desired management goal and that new management approaches are warranted. It is also becoming clear that new policies need to be spatially explicit, reflecting the patchiness of real systems, the heterogeneity of productivity and other life-cycle factors over space, and the kinds and character of mechanisms that link various elements of metapopulations. (Walters, 1998, 2000).

The purpose of this paper is to develop, based on simple discrete choice theory, an analysis of shrimpers' spatial behavior and to provide an *ex post* empirical economic analysis of this behavior. A flexible random utility model, mixed logit model is used to capture the influence of the above mentioned factors in shrimp fishermen's location choice behavior. The model is used to incorporate the heterogeneity of the fishermen's risk attitudes into the model, and to avoid the restrictive IIA assumption in the more common conditional logit approach. Also, the development and empirical testing of this model can be used to assess and forecast spatial management for more effective management of the Gulf of Mexico shrimp fishery.

LITERATURE REVIEW

Bockstael and Opaluch (1983) are the first to extend the fisheries economic literature in the direction of behavior modeling. A discrete choice model of supply response is developed under uncertainty and is applied to fishery choice problems of New England fishing firms. The aspect of intermediate-run choice of fishery in which the fisherman employs his capital stock is the focus of the paper. Based on random utility theory, their model incorporates “two key factors”: “inertia” and uncertainty. They conclude that fishermen respond to changes in expected profit in a “sluggish” manner. Also, the results are contradictory to the belief at that time that fishermen were risk lovers. Holland and Sutinen (2000) examine both the participation in certain fishery and location choice in New England trawl fisheries by adding a spatial component to the random utility, nested-logit specification. To account for the past experience’s influence on the choice behavior, they include dummy variables of whether the same area was chosen during the previous ten days and whether the same area was chosen during similar time last year. Average revenues for the previous ten days and average revenues for the same ten-day period in the previous year are also considered. To explain the fishermen’s attitude towards uncertainty, the variations of the revenues are also incorporated in the model. The authors conclude that both past information and recent information are important in location and fishery choice. Also, “in a fishery with complex seasonal patterns of fish movement, catchability and value, individual’s historical fishing patterns are major determinants of how effort is distributed in the future.” However, their method for calculating past experience by simply using dummy variables can be considered naive. In addition, the fishermen are found to be risk-loving, which is contradictory to the conclusion made in previous analyses of fishing behavior.

Mistiaen and Strand (2000) point out that ideally the expected utility should be a function of both initial wealth and random returns. Since initial wealth data is not easy to obtain, however, a random parameter logit approach can be used to estimate a random distribution of the expected utility curves instead of distinguishing between positions on the utility curve. Their conclusion is that most fishermen in the U.S. East Coast and Gulf longline fleet are risk-averse, with about 5% of the trips taken considered as risk-loving behavior. Further, due to the quadratic form of the utility function, the functional curves are presented as concave in both cases of multinomial logit estimation and random parameters logit estimation. Nevertheless, the quadratic utility function may impose nonmonotonicity in income and may not be proper in out-of-range forecasting. Smith (2005) distinguishes the difference between state dependence and preference heterogeneity in fishers’ location choice behavior for sea urchin divers in California. He points out that the exclusion of state dependence may exaggerate the significance of random preference parameters which are the indicators of preference heterogeneity. Results developed by Smith indicate that exclusion of preference heterogeneity does not substantially alter findings but that the omission of state dependence from the model can significantly influence results.

ECONOMETRIC MODEL

Mixed logit is a flexible function form which allows for non IIA error pattern, correlation among observations, and preference variation among the fishermen. In fact, McFadden and Train (2000) show that any random utility model can be approximated by a mixed logit model with an appropriate choice of variables and mixing function. Furthermore, as Revelt and Train (1998) demonstrate, when repeated choices are made by the individuals, as the case with the dataset in this study, the mixed logit model allows efficient estimations.

The probability function for conditional logit can be given as:

$$P_{ijt} = \frac{\exp[E\overline{U}(\theta, X_{it}, Z_{ijt})]}{\sum_{j=1}^{J} \exp[E\overline{U}(\theta, X_{it}, Z_{ijt})]} \qquad \text{(Eq. 1)}$$

If the parameter vector θ is not fixed, integration over the density of θ is required to obtain the unconditional probability. The integration is called mixed logit probability, which has a form of

$$L_{ijt} = \int P_{ijt}(\theta) f(\theta \mid \beta^*) d\theta \qquad \text{(Eq. 2)}$$

where P_{ijt} is the conditional logit probability and $f(\theta)$ is the density function of θ, and β^* is the parameters describing the density such as mean and variance in normal distribution.
Due to the integrals in the probability function, the Log likelihood function associated with the mixed logit model cannot be solved explicitly. Simulation methods for estimation are discussed in Train (2003).

DATA DESCRIPTION

The data used in the current analysis include the Coast Guard Vessel Operating Unit File and the Shrimp Analyst File (collected and maintained by the Southeast Fishery Science Center in Miami). Two periods of time (1995-1999 and 2000-2004) have been chosen to compare and contrast the change in fishermen's location choice behavior. Among them, only large vessels (vessel length >= 60) who appeared at least once each of five years are of interest since their movement is more relevant and their choice decisions are more consistent. For year 1995-1999, 6,410 vessels were in the industry and 2,172 appeared at least once in each of the five years. Out of this total, 1,276 were large vessels making 91,464 trips with 482,934 observations. From the 4,613 vessels who fished in during the period 2000-2004, 1,998 of them fished at least once each year during the five years, and 1,352 were large vessels. Those large vessels made 79,193 trips with 429,780 observations from 2000 to 2004.

After observing the frequency of the vessels who visited different areas from their homeports, it is found that most trips that departed from Florida had as their destinations subareas 1-8. For the trips that departed from the Texas area, most had as their destinations subareas 14-21. For those departed from Alabama, Louisiana, and Mississippi, their fishing sites were mainly in subareas 10-18. Because of this, the whole dataset is divided into three big areas: FL area, TX area, and LAM area. For each area, statistical grids are defined according to the subarea and fathom zone of the fishing sites. The grids are decided so that each statistical area will have enough observations for the analysis. Among the three areas, Florida is the one that has the fewest trips, and most of the trips from FL visited one site only. Specifically, 412 vessels of interest made 14,043 trips in year 1995-1999. In year 2000-2004, only 336 vessels of interest made 10,312 trips. In TX area, 971 vessels of interest made 41,757 trips in the first five years; and the numbers are 964 vessels with 32,433 trips in the second five years. For LAM area, 689 vessels of interest made 33,664 trips in year 1995-1999, and 722 vessels made 32,076 trips in year 2000-2004. There are six grids in FL area for the vessels, that is, there are six alternatives in the choice set in FL area. In the case of TX area there are 16 grids, and for LAM area there are 18 grids. The areas and their grids are defined as in the following figures:

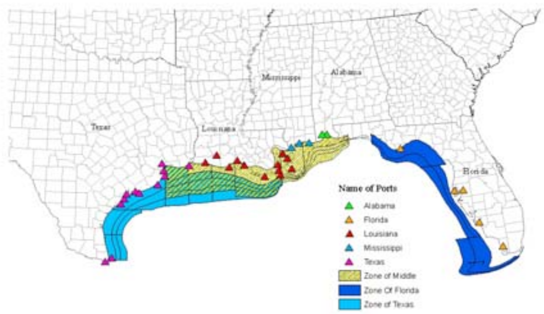

Figure 1. Gulf ofMexico area

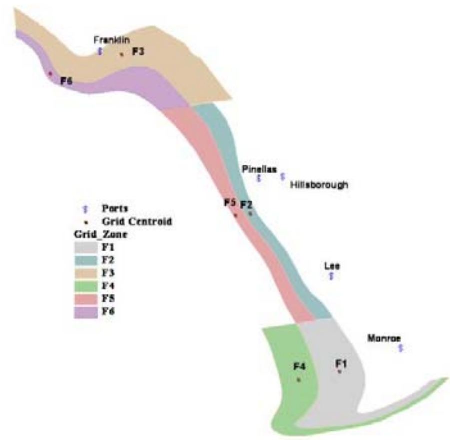

Figure 2. Florida area with six grids

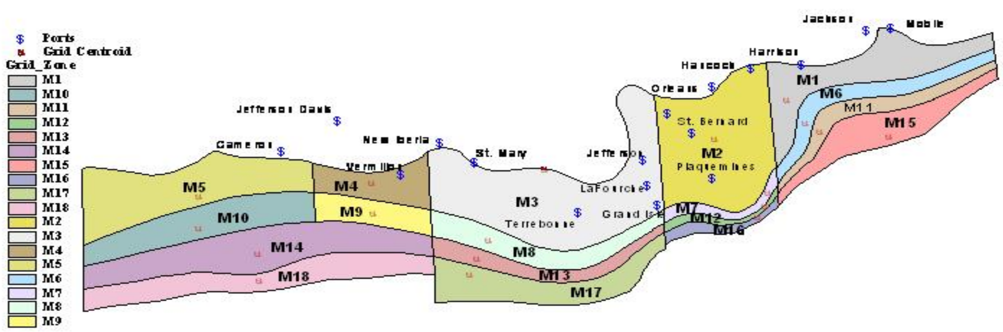

Figure 3. LAM area with 18 grids

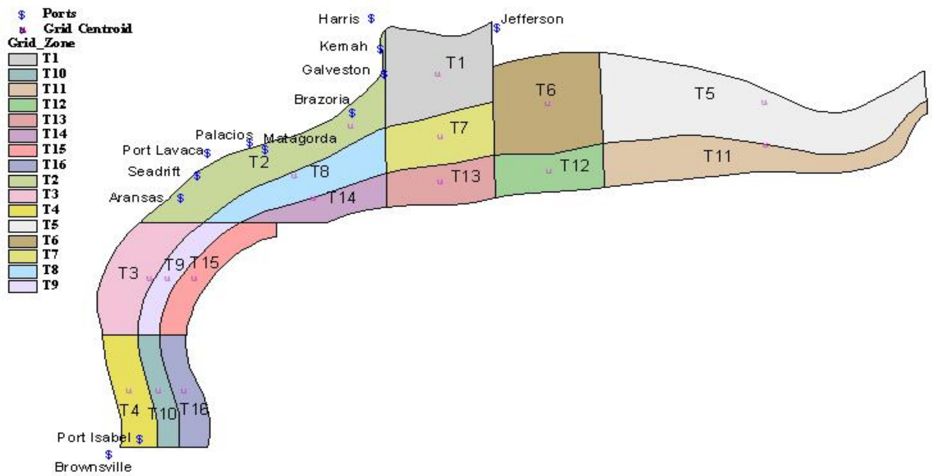

Figure 4. TX area with 16 grids

VARIABLE DESCRIPTION

The dependent variable for the three areas is grid choice. The explanatory variables selected are TX closure, loyalty, vessel length, seasons, expected revenue, variation of expected revenue, distance, crowding externality, and the squared term of crowding externality. For all the three areas, seasons are defined to measure different seasonality effects. In FL area, two seasons are defined: season1 (November-June), and season2 (July-October). In LAM area, three seasons are defined: season1 (December-April), season2 (May-June), and season3 (July-November). In TX area, three seasons are defined: season1 (January-May), season2 (June-September), and season3 (October-December).

For this study, it is assumed that fishermen share information about past experience in catches, so the weighted average fleet revenue during the past 10 days is used as the proxy for the expected revenue of a particular vessel for a particular trip. To generate an estimate of the average fleet revenue, days fished for each trip has to be standardized. A detailed discussion of the estimation of standardized effort is in Griffin, Shah, and Nance (1997) and Griffin (2006).Variation of the expected revenue as a measurement of uncertainty in the expected revenue is calculated by dividing the variance by the expected revenue. If the parameter estimated from the model is positive for the coefficient of variation of expected revenue, the fishermen are risk-loving. On the other hand, if the parameter is negative, they are risk averse.

An area would generally be considered to be popular when the fish or shrimp is abundant. However, when too many vessels visit the same area, the area may become less desirable due to crowding externalities. If this occurs, fishermen may tend to avoid going to a given site even though abundance is high. The crowding externality is captured by including a variable representing days fished per unit area in the model.

As per the Texas Closure regulation, imposed by the Gulf of Mexico Fishery Management Council in the early 1980s, state and federal waters off the Texas coast are closed to shrimp fishing from approximately mid-May to mid-July each year. To incorporate this closure in the model, a dummy variable indicating whether it is Texas Closure time is created.

It has been widely recognized that people's current choice behavior is to some extent influenced by their past choice decisions. To take this into account, the method proposed by Guadagni and Little (1983) is used in the analysis. The variable loyalty used by them to measure true state dependence is an exponentially weighted average of the past purchase history of the individual. Specifically, the model has the structure of

$$LOY_j^i(t) = \lambda LOY_j^i(t-1) + (1-\lambda) y_j^i(t-1) \quad \text{(Eq. 3)}$$

where $LOY_j^i(t)$ is loyalty of individual i to alternative j on choice occasion t, $y_j^i(t)$ is a dummy variable indicating whether individual i chose alternative j on choice occasion t or not, and λ is a smoothing parameter which takes the value between zero and one.

Vessel length is the only individual-specific variable included in the model. It is used as a proxy for the vessel's mobility, since it is observed that vessels with longer length tend to move around more often. Distance is a proxy for the cost of the trip since the direct estimation of trip cost is complicated. It is calculated by GIS using the distance from the homeport to the centroid of each grid. Distance is then weighted by the monthly diesel price index in the Gulf of Mexico in the relevant years. The weights are designed in a way to accommodate the fact that diesel price change causes change in costs as well.

ESTIMATIONS AND RESULTS

The results for the mixed logit estimation of the location choice for the two periods of analysis (i.e., 1995-99 and 2000-04) for TX area are presented in Table 1 (FL and LAM areas, in general, have similar results but are not listed here due to space limitation). A conditional logit was run first and tested for IIA assumption, which failed to hold. Also, a likelihood ratio test as mentioned in Malhotra (1987) for homogeneous parameters of the two periods for each area is conducted. We reject the hypothesis that the parameters for the first five years (1995-1999) and those for the second five years (2000-2004) are the same for all the three areas. Therefore, dividing the dataset at year 2000 is appealing from a statistical viewpoint.

Table I: Parameter Estimates--- TX Area

	1995-1999				2000-2004		
Parameter	Estimate	Standard Error	*Pr > |t|*		Estimate	Standard Error	Pr > |t|
Grid 1	-1.7359	0.8520	*0.0416*		-2.7258	0.7946	0.0006
Grid 2	-3.3950	0.7179	*<.0001*		-8.4580	0.9158	<.0001
Grid 3	-0.1928	1.1312	*0.8646*		0.3700	1.8444	0.841
Grid 4	1.4602	1.1523	*0.2051*		1.3401	1.7848	0.4528
Grid 5	-1.1132	0.9314	*0.232*		-3.1980	0.8321	0.0001
Grid 6	-0.0640	0.8231	*0.938*		-0.2523	0.7746	0.7447
Grid 7	-1.0424	0.8158	*0.2014*		-1.1725	0.7896	0.1375
Grid 8	-0.0863	0.6569	*0.8955*		-2.4538	0.6607	0.0002
Grid 9	1.5177	0.5681	*0.0076*		2.2451	0.5947	0.0002
Grid 10	0.6824	0.4778	*0.1532*		1.1168	0.4728	0.0182

Grid 11	3.1717	1.0417	*0.0023*		4.4658	0.9534	<.0001
Grid 12	-0.4755	0.8511	*0.5764*		3.8639	0.8190	<.0001
Grid 13	0.7993	0.9165	*0.3831*		4.6304	0.8351	<.0001
Grid 14	1.2606	0.6404	*0.049*		-0.2466	0.6378	0.699
Grid 15	1.0948	0.5271	*0.0378*		1.6445	0.5132	0.0014
Loyalty (mean)	3.7651	0.0354	*<.0001*		3.8415	0.0403	<.0001
Loyalty (s.d.)	0.0033	0.8123	*0.9968*		0.0485	0.9299	0.9584
Season 1 grid 1	0.0854	0.1743	*0.624*		0.6248	0.1882	0.0009
Season 1 grid 2	0.0317	0.1306	*0.8082*		2.3327	0.2250	<.0001
Season 1 grid 3	1.2454	0.1800	*<.0001*		2.6448	0.3913	<.0001
Season 1 grid 4	1.1457	0.1310	<.0001		0.3613	0.2689	0.1791
Season 1 grid 5	1.8087	0.2041	<.0001		3.3734	0.2136	<.0001
Season 1 grid 6	0.2477	0.1858	0.1826		1.0167	0.1875	<.0001
Season 1 grid 7	-0.4964	0.1773	0.0051		-0.1804	0.2120	0.3948
Season 1 grid 8	0.3001	0.1101	0.0064		0.2987	0.1258	0.0176
Season 1 grid 9	-0.0052	0.0888	0.9532		0.0310	0.1082	0.7747
Season 1 grid 10	0.0336	0.0630	0.5936		0.4117	0.0845	<.0001
Season 1 grid 11	1.7982	0.1798	<.0001		2.1547	0.1814	<.0001
Season 1 grid 12	0.2792	0.1488	0.0607		0.5459	0.1520	0.0003
Season 1 grid 13	-0.1177	0.1448	0.4164		-0.0726	0.1469	0.6213
Season 1 grid 14	-0.0643	0.0904	0.4771		-0.7611	0.1124	<.0001
Season 1 grid 15	-0.1145	0.0714	0.1086		-0.0055	0.0856	0.9492
Season 2 grid 1	-1.5639	0.1416	<.0001		-1.2540	0.1656	<.0001
Season 2 grid 2	-1.7196	0.1222	<.0001		-1.0585	0.2775	0.0001
Season 2 grid 3	1.1350	0.1837	<.0001		1.1502	0.4113	0.0052
Season 2 grid 4	1.1457	0.1379	<.0001		0.2328	0.2344	0.3207
Season 2 grid 5	-0.4034	0.1945	0.0381		0.4539	0.2030	0.0253
Season 2 grid 6	-1.1186	0.1442	<.0001		-1.6147	0.1661	<.0001
Season 2 grid 7	-0.2598	0.1266	0.0402		-0.3425	0.1523	0.0245
Season 2 grid 8	-0.1614	0.0959	0.0923		-0.7003	0.1079	<.0001
Season 2 grid 9	0.8375	0.0765	<.0001		0.1158	0.0860	0.1784
Season 2 grid 10	1.1827	0.0588	<.0001		0.9234	0.0656	<.0001
Season 2 grid 11	-1.8422	0.2087	<.0001		-2.6104	0.2219	<.0001
Season 2 grid 12	-1.8792	0.1689	<.0001		-2.2717	0.1729	<.0001
Season 2 grid 13	-1.6794	0.1604	<.0001		-1.4297	0.1389	<.0001
Season 2 grid 14	-0.8644	0.0993	<.0001		-0.8457	0.0989	<.0001
Season 2 grid 15	-0.5203	0.0779	<.0001		-0.3726	0.0759	<.0001
TX closure grid 1	-3.9738	0.2411	<.0001		-0.4860	0.2121	0.0219
TX closure grid 2	-6.1570	0.3873	<.0001		-1.2545	0.3805	0.001
TX closure grid 3	-9.2584	0.4198	<.0001		-4.0878	0.7924	<.0001
TX closure grid 4	-12.8827	0.7644	<.0001		-3.3988	0.4389	<.0001
TX closure grid 5	3.5839	0.1895	<.0001		2.7230	0.2024	<.0001
TX closure grid 6	0.5367	0.1626	0.001		1.2145	0.1984	<.0001
TX closure grid 7	-4.3519	0.2467	<.0001		-0.4769	0.2083	0.0221
TX closure grid 8	-6.3332	0.2012	<.0001		-0.9293	0.1968	<.0001

TX closure grid 9	-8.4649	0.2491	<.0001		-3.5083	0.2370	<.0001
TX closure grid 10	-10.2882	0.3072	<.0001		-4.3993	0.2735	<.0001
TX closure grid 11	2.1732	0.2344	<.0001		1.9597	0.2623	<.0001
TX closure grid 12	-4.9370	0.5363	<.0001		-2.7841	0.3342	<.0001
TX closure grid 13	-6.8270	0.2351	<.0001		-2.7085	0.2190	<.0001
TX closure grid 14	-9.3216	0.3063	<.0001		-4.1260	0.2595	<.0001
TX closure grid 15	-11.0111	0.3376	<.0001		-5.1315	0.2916	<.0001
Vessel length grid 1	0.0730	0.0123	<.0001		0.0774	0.0111	<.0001
Vessel length grid 2	0.0891	0.0104	<.0001		0.1228	0.0128	<.0001
Vessel length grid 3	0.0005	0.0167	0.9765		-0.0392	0.0274	0.1525
Vessel length grid 4	-0.0548	0.0174	0.0017		-0.0637	0.0265	0.0161
Vessel length grid 5	0.0735	0.0131	<.0001		0.0905	0.0111	<.0001
Vessel length grid 6	0.0613	0.0118	<.0001		0.0579	0.0107	<.0001
Vessel length grid 7	0.0637	0.0118	<.0001		0.0546	0.0111	<.0001
Vessel length grid 8	0.0434	0.0097	<.0001		0.0791	0.0095	<.0001
Vessel length grid 9	0.0002	0.0085	0.9854		-0.0130	0.0087	0.1375
Vessel length grid 10	-0.0234	0.0072	0.0011		-0.0307	0.0070	<.0001
Vessel length grid 11	0.0231	0.0148	0.1177		0.0032	0.0132	0.8061
Vessel length grid 12	0.0691	0.0122	<.0001		0.0038	0.0116	0.7407
Vessel length grid 13	0.0393	0.0134	0.0032		-0.0162	0.0120	0.175
Vessel length grid 14	0.0320	0.0094	0.0007		0.0498	0.0092	<.0001
Vessel length grid 15	0.0188	0.0078	0.0163		0.0033	0.0075	0.6572
Expected revenue (mean)	0.0187	0.0036	<.0001		0.0185	0.0067	0.0053
Expected revenue (s.d.)	-0.0083	0.0103	0.4203		-0.0039	0.1061	0.9707
Variation of ER (mean)	-0.0432	0.0246	0.0795		-0.0600	0.0109	<.0001
Variation of ER (s.d.)	0.0035	0.4129	0.9932		0.1286	0.0266	<.0001
Distance (mean)	-0.0222	0.0003	<.0001		-0.0162	0.0003	<.0001
Distance (s.d.)	0.0118	0.0003	<.0001		0.0092	0.0003	<.0001
Crowdedness (mean)	0.0350	0.0014	<.0001		0.0013	0.0004	0.0011
Crowdedness (s.d.)	-0.0152	0.0023	<.0001		0.0001	0.0026	0.9718
Crowdedness squared (mean)	-0.0002	0.0000	<.0001		4.1E-07	8.26E-07	0.6228
Crowdedness squared (s.d.)	0.0001	0.0000	0.0004		1.3E-06	4.41E-06	0.9768

Note: s.d. stands for standard deviation.

When we conduct a likelihood ratio test by considering the conditional logit model as a nested model in the mixed logit model, the hypothesis that the reduced model and the full model are of no difference is rejected for all the four models for LAM and TX area.

For TX area, the signs of non-random parameters are similar to those obtained from conditional logit, but the mixed logit model provides a significant improvement on the log likelihood value. The standard deviation of the parameter for loyalty is not significant for either model of two different time periods. This suggests that in terms of variety seeking, fishermen are uniformly highly risk-averse, with little interest in alternative site seeking due to the uncertainties that might be involved. For year 1995-1999, the standard deviations of the expected revenue and its variation are not significant, implying that the fishermen in TX area during this period of time are profit driven and risk-averse towards revenue uncertainty. In addition, their risk attitude does not vary significantly among themselves. During 2000-2004, however, a change in their attitude towards expected revenue is evident. Though still maximizing profit, some were found to be risk-averse, some risk-neutral and some even risk-loving. The mean of the variation of expected revenue is -0.06, with standard deviation of 0.13, which implies about 40% of the population is risk-loving during year 2000-2004. This is illustrated in Figure 5:

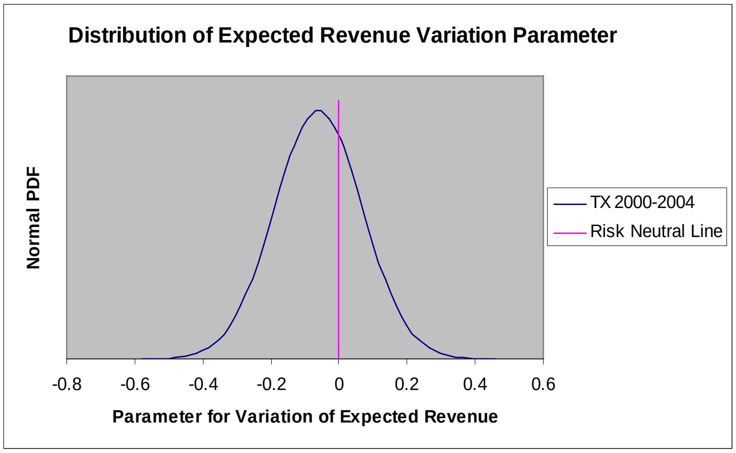

Figure 5. Distribution of the risk attitudes for TX shrimpers in year 2000-2004

As for crowdedness, the first period of time saw all significant estimates of crowdedness indicators and their standard deviation. The threshold of "crowdedness" calculated has mean of 97.22 and standard deviation 67.29, which implies that around 10% of the population has threshold of at least zero. Again this kind of negative feeling about crowdedness might take place right at the TX closure re-open time. Since the majority of the grids in TX area is closed during that time, with the exception of grid 5, 6, 11, and 12, the first day of re-open to some fishermen is like the shopping tide on black Friday and they might choose not go in spite of the chance of good catches. For year 2000-2004 however, since the square term of crowdedness and its variation are not significant, there is no threshold during this period of time. That is, the utility function is positively related to crowdedness indicator no matter how big the number is. This might be because fewer vessels are in the industry in general and about 10,000 less trips are taken in year 2000-2004 to TX area, such that fishermen never feel "crowded" at all at any point.

Smith (2005) mentions that potentially spurious preference heterogeneity might occur when state dependence is not modeled. This is also tested in this current dataset by deleting the variable loyalty from the model and observing the significance of the random parameters. The results show that there is not much spurious preference heterogeneity when the state dependence variable is ignored. Therefore, Smiths's conclusion does not hold in this case, probably due to different ways of calculating state dependence variable and/or different datasets that are used. The likelihood value decreases to a large extent without state dependence variable in the model though, which means the state dependence variable representing old habit or past experience of the fishermen has big explanatory power in the model.

CONCLUSIONS

This paper uses a mixed logit discrete choice model to analyze the various factors that influence shrimp fishermen's short-run location choice in the Gulf of Mexico. Consistent with that found by Holland and Sutinen (2000), results from this study suggest that fishermen's past experiences associated with visiting certain grids exhibit a significant impact on current site selection behavior. Besides old habits, expected revenues generally exhibit a important role in explaining their location choice behavior. The results show that fishermen, in general, are reluctant to seek alternative sites once they are use to the fishing area they go, even though their levels of reluctance are heterogeneous. In addition, the thresholds of "crowdedness" are in general different among fishermen. The results indicate that people might have the threshold at the point where the crowdedness indicator is zero. Probably those are fishermen who took the trips right at the TX closure re-open time and were expecting a lot of vessels to rush in once the area is re-open in mid-July. That is, they foresee the "heavy traffic" even though the indicator is zero.

In spite of the uncertain nature of the fishery industry, only a few studies examine the effects of risks on the decision choice behavior of the fishermen. Bocksteal and Opaluch (1983) is one of the earliest studies in this regard but bases their conclusions on the wealth level of the fishermen, which is hard to get in most cases in other fishery. Anderson (1982) looks at single location fishing decisions under uncertainty by fishers who are profit maximizers. Holland and Sutinen (2000) includes the variation of the expected revenue of the fishing trip into the model and concludes that the fishermen in their study are risk-loving. The same risk-loving conclusion is made by Dupont (1993) for the salmon fishermen when the model uses wealth level as explanatory variables. Dupont (1993) also break the sample into four different groups according to their vessel types and run the same model with wealth level included. The results show that different groups have different risk attitudes and it is concluded that heterogeneity in risk preferences does exist among fishermen. Nevertheless, the studies on heterogeneous risk preferences of the fishermen are even fewer. Mistiaen and Strand (2000) use random parameter analysis to accommodate the heterogeneity of risk preferences in their model and conclude that a small proportion of the fishermen are risk-lovers. A quadratic functional form is used for the variation though. Eggert and Tveteras (2004) are interested in the risk preferences heterogeneity in gear choices. Using a mixed logit model, this study is able to accommodate the risk in expected revenue by specifying the coefficient of variation for the expected revenues as random and normally distributed to reflect the heterogeneity of risk attitude. Even though most of the fishermen have uniform risk attitudes in LAM area, the fishermen in TX area exhibit heterogeneous risk preferences in year 2000-2004, with about 40% of them being risk-loving. In terms of goodness of fit, mixed logit improves over conditional logit by having considerably higher log likelihood value at the cost of adding a few more parameter estimators for models in TX and LAM area. There is not much improvement using mixed logit model for FL area data though.

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