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Location Choice Behavior of Gulf of Mexico Shrimpers under Dynamic Economic Conditions

Tao Ran, Walter R. Keithly, and Richard F. Kazmierczak

This study uses a mixed logit model to analyze monetary and nonmonetary factors that influence location choice behavior of the U.S. Gulf of Mexico shrimpers. Shrimpers' responses to economic conditions are compared and contrasted for two periods related to changing economic conditions in the industry. Results show that even though shrimpers are generally revenue driven in choosing a fishing site, their past experience also plays an important role. Further, changes in economic conditions appear to exhibit an influence on the risk attitudes of some shrimpers.

Key Words: location choice, loyalty, mixed Logit, risk averse, shrimp fishery

JEL Classifications: Q2, L2

Location choice is one of the most important short-run decisions confronting commercial fishermen. Fishermen's site selection behavior is influenced by an array of considerations including monetary (e.g., initial wealth, expected revenue, and costs) and nonmonetary (e.g., uncertainties and past experiences) factors (Anderson, 1982; Bockstael and Opaluch, 1983; Breffle and Morey, 2000; Dupont, 1993; Holland and Sutinen, 2000; Mistiaen and Strand, 2000; Smith, 2005; Smith

and Wilen, 2005). While those factors are expected to influence shrimpers' location choice behavior, the magnitude of the impact associated with any specific factor is likely to vary in association with macro-economic conditions in that fishery.

The purpose of this paper is to develop, based on discrete choice theory, an analysis of shrimpers' location choice behavior and changes therein under deteriorating economic conditions. To do so, a mixed logit model is used in the analysis. Compared with the previous literature which considers only the heterogeneous preferences of fishers (such as Mistiaen and Strand, 2000), or only the effect of past experience (such as Holland and Sutinen, 2000), this study considers both aspects. While Smith (2005) incorporated true state dependence into a mixed logit model with emphasis on the modeling aspect, this study includes a more complete suite of factors to help explain location choice behavior by the Gulf of Mexico shrimp fleet. Further, to examine the dynamics of shrimpers' responses to economic changes, two time periods

Tao Ran is postdoctoral researcher, Department of Agricultural Economics and Agribusiness, Louisiana State University, Baton Rouge, LA. Walter R. Keithly is associate professor, Department of Agricultural Economics and Agribusiness, Louisiana State University, Baton Rouge, LA. Richard F. Kazmierczak is professor at the Center for Natural Resource Economics and Policy, Louisiana State University, Baton Rouge, LA.

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are considered. The earlier period, which covers the 5 years ending in 1999, corresponds to a relatively stable economic environment in the fishery. The later period, extending from 2000 through 2004, is associated with rapidly deteriorating economic conditions in the fishery. Differences in various parameter estimates between the two periods are examined, and the economic implications of the differences are discussed. The development and empirical testing of this model helps in assessing and forecasting shrimpers' spatial behavior, and has the potential to lead to more effective management of the Gulf of Mexico shrimp fishery.

To accomplish these objectives, the paper proceeds as follows. A brief description of the Gulf of Mexico shrimp harvesting sector is first presented, followed by a review of the pertinent literature and an illustration of the conceptual model. Attention is then turned to the discussion of the data sources and explanatory variables used in the analysis. Following the presentation of relevant results, policy implications from the model are briefly considered.

The Industry

The shrimp industry is the largest income generator among the Gulf of Mexico commercial fisheries. In general terms, the shrimp harvesting fleet is comprised of an inshore component and an offshore component. The inshore component consists of several thousand "smaller" boats and vessels (i.e., generally less than 60 feet in length) with limited mobility, and thus many consistently fish only a very limited geographical area. The offshore component is primarily comprised of larger vessels, generally in excess of 60 feet, that are considerably more mobile than the inshore fleet. This added mobility allows the offshore fleet to follow the migration patterns of shrimp (i.e., from nearshore to offshore waters) as well as traverse large areas of the Gulf if warranted by economic conditions or regulation.

Unlike the biological structure of most fisheries, the Gulf shrimp stock is generally considered to be an annual crop and not subject to recruitment overfishing. Given that, management activities by the Gulf of Mexico Fishery Management Council have primarily focused on

increasing the size and revenues from the fishery at harvest and reducing the incidental take of finfish and turtles. With respect to the first objective, the Council initiated a 45-day closure in 1981 to "protect small brown shrimp emigrating from bay nursery areas," a phenomenon which occurs during the mid-May through mid-July period and covers all state and federal waters off the Texas coast.

Although still the largest income generator among the Gulf of Mexico commercial fisheries, the shrimp harvesting sector has, since the turn of the decade, faced increasing financial stress. For example, annual dockside revenue fell about 40% from \$582 million in 2000 to \$367 million in 2004. This decline in revenue is largely due to a sharp increase in imports, which led to dockside price declining from \$2.27 per pound in 2000 to \$1.43 per pound in 2004 (Keithly and Poudel, 2008). In conjunction, the price of diesel, which constitutes the largest variable cost component of the offshore fleet, increased approximately 30%. The decreasing output price and increasing input costs have created a classic "cost-price squeeze" on harvesters.

To remain viable in the middle of this "cost-price squeeze," the industry has been forced to adapt to the changing economic climate. At the macro level, much of the adaption is reflected in a reduction in fleet size and in the number of days fished. At the micro level, much of the adaption relates to changes in fishing practices, including that of the site selection behavior. This study utilizes a random utility model to understand the factors that influence shrimpers' location choice behavior, as well as the change in the impacts of those factors.

Literature Review

Bockstael and Opaluch (1983) laid the groundwork for behavioral modeling of fishers using a random utility model with two key factors—economic returns and uncertainties. Later studies further contributed to the literature by either expanding the nonmonetary attributes to include uncertainties (e.g., Smith and Wilen, 2005) and past experiences (e.g., Holland and Sutinen, 2000), or by utilizing more sophisticated models to capture the heterogeneity in fishers' risk preferences

(e.g., Eggert and Tveteras, 2004; Mistiaen and Strand, 2000).

Bockstael and Opaluch (1983) argued that, due to economic or noneconomic inertia, movement from one fishery to another in response to higher expected returns might not occur as rapidly as expected. One possible cause of the inertia was the negative response by some proportion of fishermen to increasing variation in returns (i.e., they were risk averse). Another explanation, as illustrated in Eales and Wilen (1986) and Holland and Sutinen (2000), is that "old habits die hard." Analysis by Eales and Wilen (1986) pointed out that fishers tend to exhibit repeated behavior in the choice of fishing location. Focusing on the New England trawl fishery, Holland and Sutinen (2000) examined reasons for participation in a given fishery and the fishing location choice. Through ethnographic interviews and the explicit use of spatial components in a random utility, nested-logit model, the authors were able to conclude that both historical and more recent information (particularly information based on personal experience) were important determinants in location and fishery choice. While the method provided a significant contribution to location choice behavior modeling, their use of simple dummy variables to proxy experience and their use of nested logit without considering the heterogeneous preferences of fishers suggest potential modeling refinements.

With increased computational ability facilitating the estimation of random parameter logit models, the assumption of homogeneous risk preferences for fishers has been relaxed in more recent research. Mistiaen and Strand (2000) pointed out that because initial wealth was often unknown to the researchers, the heterogeneity of risk preferences could be incorporated into the random-parameter specification in the logit model. In doing so, the authors concluded that most fishermen in the East Coast and Gulf swordfish and/or tuna longline fleets were risk-averse, with about 5% of the trips exhibiting risk-seeking behavior. Eggert and Tveteras (2004) analyzed gear choice, and their results indicated that a conditional logit model that ignores substantial heterogeneity in the fleet might produce misleading results. Breffle and Morey (2000) pointed out that randomizing parameters

improves model fit and significantly affects welfare estimates.

While those studies incorporated the heterogeneity of fishers' risk attitudes by using a mixed logit model, they tended to ignore the effect of past experience. Smith (2005), in his study of the sea urchin fishery in California, illustrated that the exclusion of true state dependence (or the true impact of past experience) might exaggerate the significance of the random preference parameters, which are the indicators of preference heterogeneity. Using a linear combination of previous periods' state dependence level and a geometrically decaying summation of all previous decisions associated with that location to represent state dependence, Smith's mixed logit model included two other explanatory variables: expected revenue and distance. Various groups of models were compared, which show the significance of including state dependence variables in the model.

The importance of the distinction between true state dependence and heterogeneity in modeling was initially considered by Heckman (1981) in an analysis of labor supply. Using examples, he clarified that heterogeneity captured by unobservable variations correlated over time could be mistakenly considered as true state dependence (i.e., the genuine effect of past experience) if the model was improperly specified. This concept and method have been widely applied in marketing studies, such as Keane (1997) and Seetharaman (2004), in the analysis of consumer brand loyalty. In fishers' location choice literature, only Holland and Sutinen (2000) and Smith (2005) have considered the effect of past experiences. Holland and Sutinen (2000), as noted, simply used discrete variables for past experience. Adopting a more sophisticated method from the marketing literature, Smith (2005) put more emphasis on the modeling rather than the economic implications of the results. This paper follows Smith (2005) in modeling the true state dependence/loyalty/site fidelity variable. Further, our model incorporates other monetary and non-monetary factors such as financial risk factor, vessel characteristics, and regulatory measures. Doing so allows for a more comprehensive understanding of the factors influencing location choice of shrimpers.

Conceptual Model

To incorporate a more complete set of variables, the conceptual utility function is assumed to be influenced by two primary attribute categories. The first category includes monetary attributes, such as expected revenue, financial risk indicator, and costs. The second category includes non-monetary attributes, such as loyalty and regulatory measures, hypothesized to influence location choice (Wilén, 2002). The general model is given as:

$$(1) \quad EU_{ijt} = E\bar{U}(\beta, X_{it}, Y_{jt}, Z_{ijt}) + \varepsilon_{ijt}$$

where β is the parameter vector; X_{it} includes individual-specific and time-specific characteristics such as vessel length, seasonality, and regulation-based (i.e., Texas Closure) dummy variables; Z_{ijt} includes individual and alternative-specific characteristics such as loyalty (true state dependence variable), expected revenue, and its variation coefficient; and Y_{jt} includes alternative-specific and time-varying characteristics such as costs. As is the case with most other location choice studies, initial wealth information on Gulf of Mexico shrimp fishermen is not available. Accounting for the heterogeneity in risk attitudes using a random parameter logit, however, provides a reasonable alternative (Mistiaen and Strand, 2000). The flexible form of the mixed logit (random parameter logit) model also allows for non Independence of Irrelevant Alternatives error patterns, correlation among observations, and preference variation among the fishermen. Further, as suggested by Revelt and Train (1998), mixed logit models yield efficient estimation of parameters when repeated choices are made by the individuals being modeled, which is the case in this study.

The probability function of mixed logit is based on the probability for a conditional logit model, which can be expressed as

$$(2) \quad P_{ijt} = \frac{\exp[E\bar{U}(\beta, X_{it}, Y_{jt}, Z_{ijt})]}{\sum_{j=1}^J \exp[E\bar{U}(\beta, X_{it}, Y_{jt}, Z_{ijt})]}$$

If the parameter vector β is not fixed, then the conditional probability can be obtained by integrating over the density of β . The result of this integration is called mixed logit probability, which has the form

$$(3) \quad L_{ijt} = \int P_{ijt}(\beta) f(\beta) d\beta$$

where P_{ijt} is the conditional logit probability and $f(\beta)$ is the density function of β . In practice, the density $f(\beta)$ is usually characterized by some set of parameters, which are themselves estimated. If we define the parameter vector that describes the density of β as θ^* , the probability function takes the form:

$$(4) \quad L_{ijt} = \int P_{ijt}(\beta) f(\beta | \theta^*) d\beta$$

A couple of distributions can be specified to estimate the parameters of β . The normal distribution is assumed for most variables considered in this study due to its popularity and simplicity. Theory suggests, however, that certain variables included in the analysis (e.g., cost and expected revenues) exhibit either a nonpositive or nonnegative parameter. We therefore assume a lognormal distribution with respect to these variables. Due to the integrals in the probability function, simulated maximum likelihood is used for estimation, which is discussed in detail in Train (2003).

Data Considerations

The data used in the location choice model is a combination of the Vessel Operating Unit File (VOUF) and the Shrimp Landings File (SLF), both of which are collected and maintained by the National Marine Fisheries Service. Information in the VOUF, which is collected on an annual basis, includes vessel and gear characteristics. The SLF has detailed information on individual shrimp trips. Of particular interest to the current study, the SLF has per trip geographical information covering the spatial distribution of landings and effort. The geographical information has three major components—a harvesting location (subarea) defined on a statistical grid of longitude and latitude, a harvesting depth based on the fathom zone where harvesting is reported, and a record that identifies the port where the harvest was landed. The combination of subarea and fathom zone yields a total of 210 statistical areas¹ (Figure 1).

¹ These 210 statistical areas are based on 21 sub-areas and 10 fathom zones (defined in the data set as intervals of water depth in five fathom increments from the U.S. shoreline out to 50 fathoms).

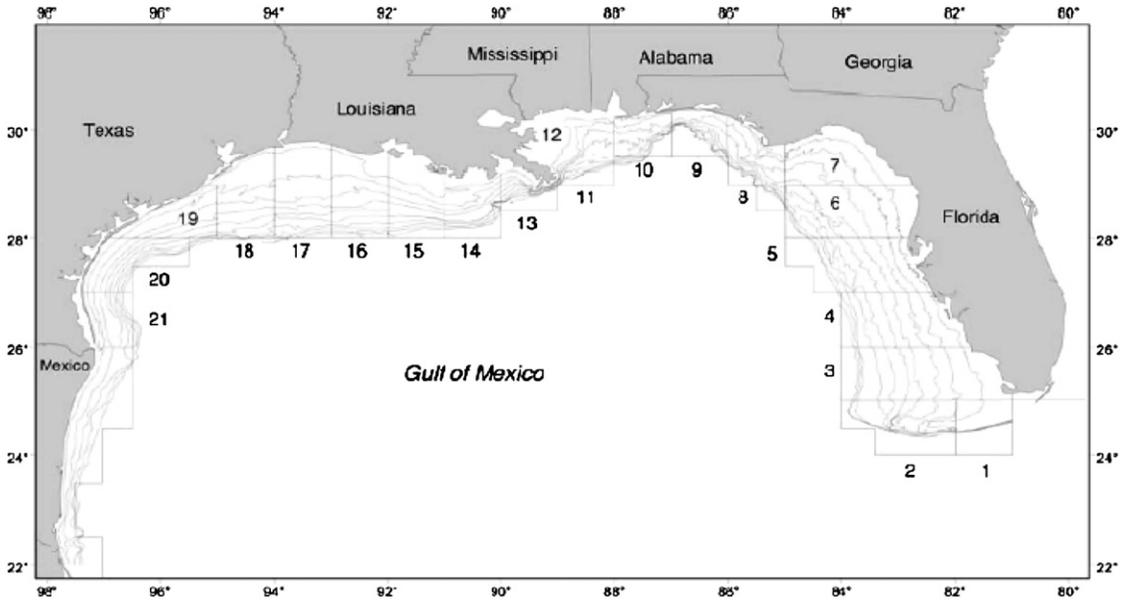


Figure 1. Relationship of Longitude/Latitude Statistical Grids with Fathom Zones in the U.S. Gulf of Mexico (Source: Nance et al., 2006)

Preliminary examination of the data suggests that vessels home ported in Texas fished primarily in statistical subareas 14–21, while vessels home ported in Louisiana, Mississippi, and Alabama (LAM) primarily fished in statistical subarea 10–18.² These observed differences led us to treat each of these groups (i.e., the Texas vessels and the LAM vessels) independently in the location choice modeling analysis.³ For either Texas or LAM areas, not all potential statistical areas (80 for Texas area and 90 for LAM area) defined by subarea and fathom zone receive an adequate number of visits. To ensure that any given spatial location has enough observations for analysis, the statistical areas were aggregated into newly defined grids. Meanwhile, we kept the geographic expanse of each grid at a minimum to be useful for management purposes. In addition, trips to some infrequently visited subareas that lay at the outer spatial edges of harvesting activity are deleted from the data (approximately 5–7% of all trips).

This process yielded 20 aggregated grids for the LAM-based vessels (Figure 2) and 25 aggregated grids for the Texas-based vessels (Figure 3). As noted, two 5-year periods (1995–1999 and 2000–2004) were chosen to capture fishermen’s location choice behavior and changes therein. The first 5-year period can be characterized as one of relative financial stability while the second 5-year period can be characterized as one of rapidly deteriorating economic conditions. Only larger vessels were included in the analysis (vessel length ≥ 60 feet, which accounts for roughly 70% of the fleet in our dataset) because smaller boats do not have enough mobility to visit various locations.

Variable Considerations

Based upon theory and relevant research on location choice modeling, the econometric model is specified as the following:

$$\begin{aligned}
 EU_{ijt} = & \beta_0 + \beta_1 \cdot wer + \beta_2 \cdot vcof + \beta_3 \cdot dist \\
 & + \beta_4 \cdot vel + \beta_5 \cdot loy + \beta_6 \cdot season1 \\
 & + \beta_7 \cdot season2 + \beta_8 \cdot txcl + \epsilon_{ijt}
 \end{aligned}
 \tag{5}$$

² Vessels home ported in Florida exhibited little mobility and are not included in the analysis.

³ Subareas 14, 15, 16, 17, and 18 in Figure 1 are visited by both Texas and LAM vessels, which are independently treated.

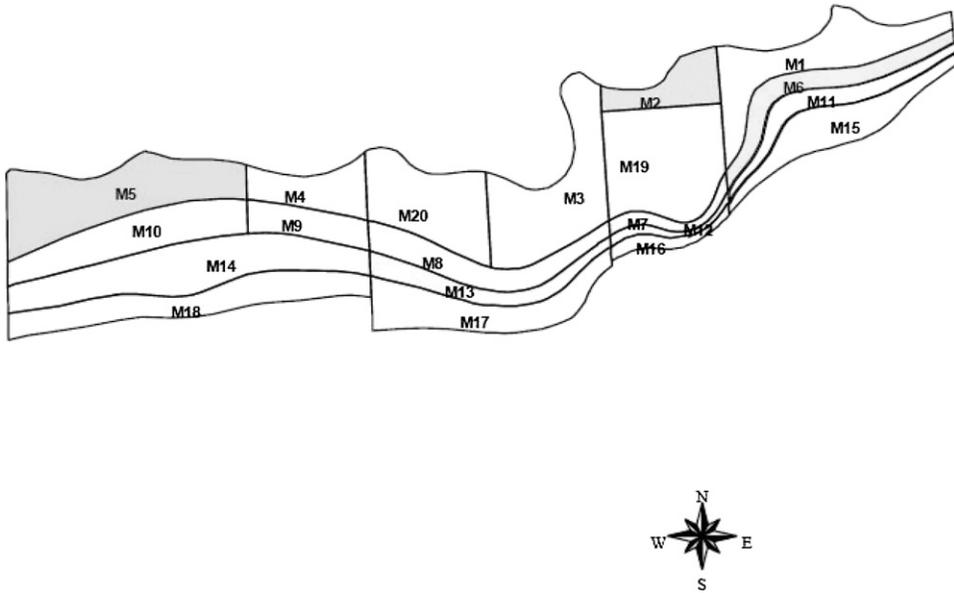


Figure 2. Grids in LAM Area

A brief discussion of the explanatory variables considered in this study is given in Table 1.⁴

The monetary variables included in this model are expected revenue (*wer*), the coefficient of variation in expected revenue (*vcof*), and distance (*dist*) as a proxy for cost. Generally, a “site” is considered attractive to a shrimper if the expected utility of visiting that site exceeds that of visiting other sites. One monetary factor that influences the expected utility is the revenue that one expects from fishing at the site. Based on the assumption that shrimpers share information about past catch experience at alternative sites (through either formal financial ties among vessels that provide incentives for information sharing or through family/social arrangements), the weighted average fleet revenue during the previous 10 days was used as a proxy for the expected revenue of a particular vessel trip to a given site.⁵

While the motivation associated with visiting any given site is hypothesized to increase in relation to the expected revenues, the uncertainty caused by the fluctuations in expected revenue

might be of concern to the fishers. Thus, the coefficient of variation of expected revenue, calculated based on the same assumptions employed in the calculation of expected revenue, was included in the analysis as a measure of uncertainty.

Cost is another monetary factor expected to influence location choice. Since an estimate for trip cost in relation to distance traveled was not available, we used the distance traveled to a fishing site weighted by the monthly diesel price index as a proxy for cost, where distance was determined using a GIS (Geographic Information System) routine that calculates the straight-line distance from a vessel’s departure port to the centroid of each fishing location grid.

With respect to nonmonetary factors, vessel length (*vel*), loyalty (*loy*), seasonal discrete variables, and a discrete variable used to “capture” the influence of the Texas Closure (*txcl*) are included in the analysis. Since vessel length is positively related to vessel’s mobility, the probability of visiting more distant sites should increase with respect to vessel length. As shown to be the case in other fisheries (e.g., Holland and Sutinen, 2000; Smith, 2005), shrimpers also likely develop site fidelity, and this site fidelity influences site selection behavior. In this study, we adopt the loyalty variable commonly used in the marketing literature (or, the state dependence

⁴ In the model to be analyzed, interaction terms such as the interaction between intercepts and vessel length are created to avoid inverting singular matrix in estimation.

⁵ Five days and 20 days are also considered. All yield similar results.

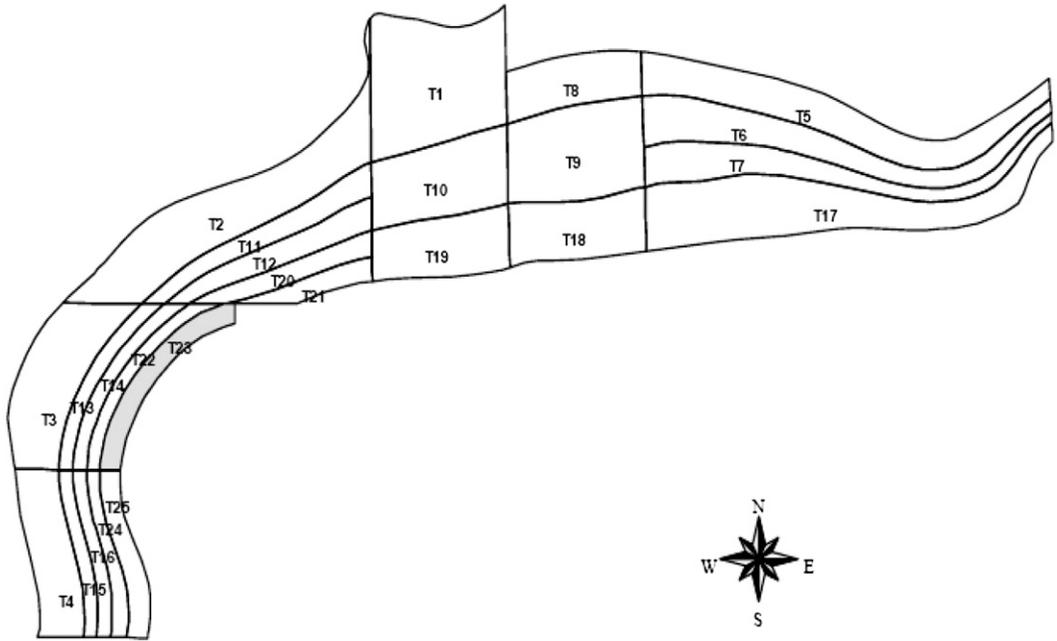


Figure 3. Grids in TX Area

variable employed in various economic studies) to examine the influence of site fidelity on location choice. Similar to Smith (2005), this study employs the method proposed by Guadagni and Little (1983) in conjunction with the smoothing parameter estimation as proposed by Fader, Lattin, and Little (1992) to estimate loyalty. Finally, various discrete variables are used to “capture” seasonal influences and the influence of the Texas Closure on site selection behavior. For both the LAM model and the Texas model, we have specified three seasons, which tend to correspond with the seasonal migration patterns of the shrimp stocks in the respective areas.⁶ The Texas Closure, as previously mentioned, results in an approximate 45-day closure of all state and federal waters off the coast of Texas, thereby reducing the probability of some sites being visited during the closure period. A discrete variable, equal to one during the closure and zero otherwise, was created to account for this.

⁶ The three seasons are defined as: season1 (December–April for LAM vessels and January–May for Texas vessels), season2 (May–June for LAM vessels and June–September for Texas vessels), and season3 (July–November for LAM vessels and October–December for Texas vessels).

Results and Interpretation

Recall that the random parameters in the mixed logit model were assumed to be normally distributed, except for the parameters for distance and expected revenue, which were assumed to have lognormal distribution. Theory suggests that the estimated parameter associated with the expected revenue variable is positive while that for distance as proxy for cost is negative (a negative sign is added to the distance variable before the analysis to ensure the correct result). In order to obtain the mean, median, and standard deviation of the lognormally distributed random parameter, certain transformations have to be conducted after the analysis. Specifically, if parameter β is assumed as lognormally distributed, the direct estimation results will provide mean b and standard deviation s for $\ln(\beta)$. The median, mean, and standard deviation of β are $\exp(b)$, $\exp[b+(s^2/2)]$, and $\exp[b+(s^2/2)] * \sqrt{\exp(s^2) - 1}$, respectively.⁷ In addition, a likelihood ratio test, proposed by Malhotra (1987),

⁷ A negative sign was added to the transformed mean and median for distance random parameter for corrected interpretation (Train, 1998).

Table 1. Description of Variables Included in the Analysis

Category	Variable Name	Description
Monetary factors	Expected revenue (<i>wer</i>)	Weighted average fleet revenue during the past 10 days
	Coefficient of variation of expected revenue (<i>vcof</i>)	A measurement of uncertainty in the expected revenue for each grid
	Distance (<i>dist</i>)	Proxy for cost
Nonmonetary factors	Vessel length (<i>vel</i>)	Proxy for vessels' mobility
	Loyalty (<i>loy</i>)	Measurement of shrimpers' past experience in visiting sites
	Season1	Discrete variables for season 1
	Season2	Discrete variables for season 2
	Season3	Discrete variables for season 3
	TX closure (<i>txcl</i>)	Discrete variable indicating closure in federal waters to shrimping off the Texas coast

was conducted to test for homogeneity of parameter estimates of the two periods for each area (Table 2). The hypothesis that the parameters for the first 5-year period (1995–1999) and those for the second 5-year period (2000–2004) are the same for all the two areas was rejected. This indicates a difference in shrimpers' behavior between the two periods of time. One may be concerned that the difference in parameter estimates between the two periods is the results of different scale parameters in the two periods (since the scale parameter is confounded with other parameters in a Logit model). To examine whether this concern is warranted, we followed Swait and Louviere (1993) and Louviere, Hensher, and Swait (2000) to test for differences in scale parameters. Based on the artificially constructed nested Logit model as in Louviere, Hensher, and Swait (2000), we were able to estimate the magnitude of the scale parameters for both periods. For TX area, the scale parameter estimate for 1995–1999 is 23.08, with a standard error of 2.84; while the scale parameter estimate for 2000–2004 is 22.34, with a standard error of 2.76. Therefore, the ratio of the two scale parameter estimates is 1.03. For LAM area, the ratio of the two scale parameter estimates is 1.13. The ratio being close to one indicates that the scale parameter estimate for the first period is not considerably different from the scale parameter in the second period for either area. In addition, distribution graphs of the scale parameters show

that the confidence interval of the scale parameter estimator for 1995–1999 period overlaps to a large extent the confidence interval of the scale parameter estimator for 2000–2004 period, which is another implication that the true scale parameters might be the same for the two periods. Therefore, it appears as though the difference in the parameter estimates between the two periods is not due to the change in scale parameters.

The choice behavior estimation results⁸ for the two time periods of interest are presented in Table 3 (LAM model) and Table 4 (Texas model).⁹ Most of the estimated parameters, as indicated, exhibit the expected signs. In general, larger vessels prefer fishing at greater depths. Among LAM-based shrimpers, for instance, an increasing vessel size was related to a preference for deeper-water sites (e.g., grids 16, 17, 18) in the earlier period (1995–1999). In 2000–2004, however, increasing vessel length was related to a preference

⁸ We use Proc MDC in SAS to do the analysis by specifying the mixed logit option. For the generation of random number for simulation, Halton sequence is specified with 11 being the starting point. The number of draws is 100, which is an appropriate choice according to Hensher and Greene (2003). The numerical algorithm for estimation is the dual quasi-Newton method. The results are not sensitive to the starting values.

⁹ Due to space limitations, parameter estimates for vessel length related to each grid, the Texas Closure, seasonal control variables, and intercepts are not presented. They are available upon request.

Table 2. Likelihood Ratio Test Results for Homogeneous Parameters

Area	Likelihood Value			Chi-Squared Test	p-Value
	Full Model	1995–1999	2000–2004		
LAM	–91961	–45658	–43066	6474	0
TX	–138846	–80336	–58234	551.94	5.45E-54

for relatively shallow-water sites (e.g., grids 10, 12, and 13). This suggests that larger vessels were trying shallower alternative fishing locations in the later time period vis-à-vis the earlier time period. This change in behavior may be the result of increasing fuel costs in the later period and the relatively high cost of trawling in deeper waters (in general, it is often believed that the fuel expended in trawling increases in relation to depth).

The effects of expected revenue are similar for both time periods and both areas. Even though the parameters are assumed to be random, the standard deviations of the random parameters are not significant. Exponential transformations are made on the parameters to obtain the final effects due to the lognormal distribution assumption imposed on the parameters. The results indicate that if the expected revenue of a grid goes up by \$1,000, the odds of choosing that grid increase by 0.3% to 8%, *ceteris paribus*.

While expected revenues are found to influence location choice, the influence associated with this factor is generally found to be dampened by the financial risk concerns associated with moving from one site to another. Texas-based shrimpers are found to be uniformly risk

averse in both periods of analysis, as indicated by the statistical significance of the parameter estimate associated with coefficient of variation in expected revenue (Table 4). Similarly, LAM-based shrimpers were found to be risk averse during the second 5-year period of analysis (2000–2004) when deteriorating profitability in the industry was the norm. Interestingly, however, the statistical insignificance of the parameter estimate associated with variation in expected revenue during the 1995–1999 period implies risk neutrality among LAM fishermen during a period when the industry can be characterized by relative economic stability. This indicates that LAM shrimpers, although revenue- (and perhaps profit-) driven in the late 1990s, paid little attention to the financial uncertainties in their harvesting activities. By 2000–2004, however, significant attention was being given to financial uncertainties and these uncertainties influenced location choice behavior. Specifically, in the second period harvesters displayed caution in choosing sites based solely on expected revenues, and were much more interested in assuring that those harvesting opportunities persisted over time before shifting effort to a new location. One might hypothesize that the change in the attitude to financial risks by

Table 3. Parameter Estimates—LAM Area

Parameter	1995–1999		2000–2004	
	Estimate	p-Value	Estimate	p-Value
Loyalty (mean)	4.3944	<0.0001	4.7449	<0.0001
Loyalty (SD)	1.3186	<0.0001	1.4097	<0.0001
Expected revenue (mean)	0.0785	<0.0001	0.004	0.0973
Expected revenue (SD)	0.000	0.7472	0.000	0.9998
Variation of Expected revenue (mean)	–0.0106	0.7719	–0.0357	<0.0001
Variation of Expected revenue (SD)	0.008482	0.9928	0.000367	0.9986
Distance (mean)	–3.0858	<0.0001	–1.8257	<0.0001
Distance (SD)	1.5462	<0.0001	1.2697	<0.0001

Note: Since the parameters of expected revenue and distance are assumed as log normally distributed, their means and standard deviations are calculated by transformation mentioned in Train (1998).

Table 4. Parameter Estimates—TX Area

Parameter	1995–1999		2000–2004	
	Estimate	<i>p</i> -Value	Estimate	<i>p</i> -Value
Loyalty (mean)	3.9439	<0.0001	4.2263	<0.0001
Loyalty (SD)	0.000313	0.9997	0.000629	0.9995
Expected revenue (mean)	0.0099	<0.0001	0.0038	0.0003
Expected revenue (SD)	0.000	0.9957	0.000	0.9999
Variation of Expected revenue (mean)	–0.2929	<0.0001	–0.1268	<0.0001
Variation of Expected revenue (SD)	0.00032	0.9994	0.000918	0.9953
Distance (mean)	–5.2946	<0.0001	–5.1027	<0.0001
Distance (SD)	4.4971	<0.0001	4.427	<0.0001

Note: Since the parameters of expected revenue and distance are assumed as lognormally distributed, their means and standard deviations are calculated by transformation mentioned in Train (1998).

LAM-based shrimpers is related to deteriorating economic conditions in the fishery during the later period of analysis. If a fisher's expected income per trip declined sharply during 2000–2004 relative to 1995–1999, the ability to absorb losses on any given trip with gains from a subsequent trip also declined. Thus, with an increased inability to absorb losses from a given trip came a concomitant unwillingness to accept additional risk even if the additional risk might be related to higher expected revenues.

Yet to be explained, however, is the uniform risk aversion by Texas-based shrimpers compared with LAM shrimpers. One possible explanation for the estimated difference in risk attitudes between the LAM shrimp fleet and the Texas shrimp fleet during the initial period of analysis when economic conditions in the shrimp fishery were relatively stable is that, while not documented, there is general agreement that the Texas fleet is more full-time in nature than its LAM counterpart. This difference may result in different risk attitudes between fishers in these two areas during the period of relative economic stability. An alternative explanation is that the majority of the Texas shrimpers are of Anglo and Hispanic origin while the LAM fleet has a significant Vietnamese component. Therefore, the change in risk attitudes might have to do with social characteristics of the individuals comprising the two fleets.

In addition to the risk averse attitude exhibited by the majority of shrimpers, loyalty was also found to significantly contribute to sluggish response in fishing site switching behavior. The

positive and statistically significant estimate for loyalty is an indication of habit persistence, inertia related to exploration of other locations, or unfamiliarity combined with risk aversion. Further, the statistical significance of the standard deviation of the random parameter for loyalty in LAM models implies that there was variation in loyalty among shrimpers in LAM, which was not found in the Texas model results. Again, this might be due to the fact that Texas vessel owners were more full time in nature and more consistent in behavior, or it could be that there was some social economic difference between Texas-based shrimpers and LAM-based shrimpers that was not observable to the researchers. The finding of “old habits die hard” is consistent with Holland and Sutinen (2000) and Smith (2005), but the time element introduced by the smoothing parameter λ (the estimates for λ is about 0.79 for the models in this study) implies that most recent shrimping experience plays a more important role than that found in previous studies of location choice behavior. Smith (2005), for example, estimated a value for λ of approximately 0.5, with the implication of a slower decaying process of information about past experiences among sea urchin fishermen than among shrimp fishermen. The observed differences among these two studies may reflect, at least in part, the highly migratory nature of shrimp, where any given shrimp fisher is unable to remain at any given site for an extended period if he wishes to remain profitable on each trip. Hence, loyalty to any given site may decay relatively rapidly. The effect associated with this migration was likely

Table 5. Semi-Elasticity for LAM Area (season 2, non TX closure time)

Grid	Year 1995–1999				Year 2000–2004			
	Loyalty	Expected Revenue	Variation of Expected Revenue	Distance	Loyalty	Expected Revenue	Variation of Expected Revenue	Distance
1	0.0006	0.0007	0.0000	-0.0208	0.0137	0.0002	-0.0030	-0.1042
2	0.0026	0.0038	0.0000	-0.0691	0.0390	0.0009	-0.0094	-0.2409
3	0.0337	0.0209	0.0000	-0.3794	0.0310	0.0003	-0.0043	-0.1108
4	0.0170	0.0065	0.0000	-0.1179	0.0034	0.0000	-0.0005	-0.0276
5	0.0015	0.0009	0.0000	-0.0373	0.0006	0.0000	-0.0002	-0.0159
6	0.0017	0.0024	0.0000	-0.0432	0.0021	0.0001	-0.0010	-0.0490
7	0.0163	0.0155	0.0000	-0.2701	0.0028	0.0001	-0.0022	-0.0498
8	0.0142	0.0114	0.0000	-0.1937	0.0023	0.0001	-0.0018	-0.0403
9	0.0056	0.0063	0.0000	-0.1503	0.0000	0.0000	-0.0001	-0.0023
10	0.0002	0.0002	0.0000	-0.0084	0.0000	0.0000	0.0000	-0.0009
11	0.0017	0.0029	0.0000	-0.0406	0.0016	0.0001	-0.0006	-0.0364
12	0.0013	0.0034	0.0000	-0.0642	0.0004	0.0000	-0.0006	-0.0148
13	0.0022	0.0043	0.0000	-0.0743	0.0005	0.0000	-0.0008	-0.0231
14	0.0002	0.0005	0.0000	-0.0189	0.0000	0.0000	0.0000	-0.0021
15	0.0004	0.0011	0.0000	-0.0181	0.0018	0.0001	-0.0010	-0.0494
16	0.0018	0.0045	0.0000	-0.0659	0.0128	0.0002	-0.0032	-0.1325
17	0.0034	0.0043	0.0000	-0.0700	0.0478	0.0004	-0.0066	-0.3497
18	0.0001	0.0004	0.0000	-0.0119	0.0014	0.0000	-0.0007	-0.0503
19	0.2017	0.0406	0.0000	-0.7648	0.2565	0.0006	-0.0144	-0.3190
20	0.0117	0.0144	0.0000	-0.2447	0.0226	0.0002	-0.0032	-0.1205

exacerbated by local stock depletions. Within a given season, for instance, the concentration of shrimp in a given area quickly attracts vessels to that area. When more shrimpers “cluster” at a given location and deplete the local population, the fleet moves to an alternative site. Given the annual nature of the shrimp crop, this migration and localized depletion likely occurs in a time-frame much shorter than that associated with sea urchin, thus helping to explain why more recent experience plays a larger role in the shrimp fishery than some other fisheries.

The heterogeneity of shrimpers’ preferences is more obvious on the cost side. For both LAM and Texas shrimpers, the lognormally distributed random parameter for distance has a significant standard deviation in both periods. This implies that there was considerable variation among shrimpers with respect to the influence of cost on site selection; perhaps partially due to the manner in which the distance variable is constructed.

The analysis also suggests that, in general, the impact of the Texas closure was much larger

on the Texas-based fleet than on the LAM-based fleet. This finding is expected given the fact that all sites in the offshore Texas waters are closed to shrimping during the Texas Closure. According to Figure 3, the only open area for Texas-based vessels during this time was nearby Louisiana waters (grids 5, 6, 7, 17, and small part of grids 8, 9, and 18 in Figure 3). For LAM-based vessels, however, the majority of the grids are open during Texas Closure (exceptions are a few grids on the left which share boundaries between Texas and Louisiana).

Calculated semi-elasticities for the second season,¹⁰ based on the mean value of each random parameter as well as the means of all continuous variables, are presented in Tables 5 and 6. These semi-elasticities were calculated at various values associated with the categorical variables and under the assumption that the Texas Closure

¹⁰Recall that the second season covers May–June for LAM vessels and June–September for Texas vessels. The second season usually has a very high amount of fishing activity.

Table 6. Semi-Elasticity for TX Area (season 2, non TX closure time)

Grid	Year 1995–1999				Year 2000–2004			
	Loyalty	Expected Revenue	Variation of Expected Revenue	Distance	Loyalty	Expected Revenue	Variation of Expected Revenue	Distance
1	0.0031	0.0004	-0.0025	-0.1301	0.0135	0.0002	-0.0077	-0.3448
2	0.0135	0.0018	-0.0171	-0.5546	0.0042	0.0001	-0.0155	-0.3341
3	0.0003	0.0002	-0.0013	-0.0552	0.0000	0.0000	-0.0004	-0.0087
4	0.0000	0.0000	0.0000	-0.0018	0.0000	0.0000	0.0000	-0.0001
5	0.0000	0.0000	-0.0001	-0.0069	0.0000	0.0000	-0.0001	-0.0088
6	0.0000	0.0000	-0.0001	-0.0067	0.0001	0.0000	-0.0002	-0.0128
7	0.0001	0.0000	-0.0001	-0.0145	0.0002	0.0000	-0.0004	-0.0320
8	0.0140	0.0006	-0.0036	-0.2518	0.0137	0.0001	-0.0056	-0.2866
9	0.0065	0.0008	-0.0096	-0.4502	0.0026	0.0000	-0.0086	-0.3146
10	0.0103	0.0019	-0.0144	-0.6328	0.0111	0.0003	-0.0234	-0.8951
11	0.0361	0.0040	-0.0308	-1.1275	0.0218	0.0003	-0.0256	-0.8334
12	0.0867	0.0074	-0.0400	-1.6457	0.1096	0.0011	-0.0479	-1.8294
13	0.0030	0.0009	-0.0051	-0.2131	0.0012	0.0000	-0.0021	-0.0784
14	0.0059	0.0015	-0.0077	-0.3063	0.0017	0.0001	-0.0027	-0.1046
15	0.0001	0.0000	-0.0001	-0.0067	0.0000	0.0000	0.0000	-0.0008
16	0.0003	0.0000	-0.0002	-0.0101	0.0001	0.0000	0.0000	-0.0018
17	0.0001	0.0000	-0.0001	-0.0153	0.0002	0.0000	-0.0004	-0.0252
18	0.0017	0.0009	-0.0041	-0.2584	0.0039	0.0002	-0.0054	-0.3928
19	0.0021	0.0018	-0.0081	-0.3840	0.0104	0.0004	-0.0223	-0.8809
20	0.0003	0.0001	-0.0010	-0.0314	0.0001	0.0000	-0.0002	-0.0053
21	0.0007	0.0001	-0.0008	-0.0313	0.0001	0.0000	-0.0001	-0.0044
22	0.0004	0.0001	-0.0007	-0.0292	0.0001	0.0000	-0.0001	-0.0057
23	0.0008	0.0002	-0.0007	-0.0344	0.0002	0.0000	-0.0001	-0.0066
24	0.0002	0.0001	-0.0003	-0.0154	0.0001	0.0000	-0.0001	-0.0043
25	0.0005	0.0001	-0.0003	-0.0170	0.0002	0.0000	-0.0001	-0.0048

was not in effect. While the assumption used to calculate these semi-elasticities may be somewhat naïve (e.g., using the mean values of all random parameters), using this method provides straightforward implications of the estimation results. For instance, the information in Table 5 demonstrates that the average LAM-based shrimper did not respond to the variation in expected revenue during the period of relative economic stability in the fishery (1995–1999), suggesting risk neutrality during that period. Under deteriorating economic conditions (2000–2004), however, a negative attitude toward financial risks was the norm. Further, an average shrimper appears to be more sensitive to costs than expected revenues, as the percentage change in probability due to increases in expected revenue is generally small compared with the percentage change in

probability due to increase in distance, a proxy for cost.

Conclusions

This study uses a mixed logit discrete choice model to analyze the monetary and nonmonetary factors that influence location choice behavior of Gulf of Mexico shrimpers. For purposes of analysis two groups of shrimpers—those homeporting in Texas and those homeporting in Louisiana, Mississippi, or Alabama—are treated separately as a means of examining the consistency of findings among participants operating out of different areas of the Gulf of Mexico. In addition, two 5-year periods (1995–1999 and 2000–2004) are selected to examine the behavior and intertemporal changes therein.

Consistent with other studies, our results indicate that expected revenues play an important role in site selection. Harvester behavior toward risk in the form of variations in expected revenues, however, was not consistent between the two groups considered in the analysis and was also not consistent between the two periods of analysis for one area. While LAM-based shrimpers exhibited risk-neutral behavior in the initial period of analysis (1995–1999), exhibited behavior changed to one of risk-aversion in the later period of analysis. This later period coincides with growing unfavorable economic conditions in the fishery and thus likely more caution being employed on any individual trip. In contrast, Texas based shrimpers exhibited risk averse in location choice in both periods of analysis.

Past experiences of shrimp harvesters at specific harvesting locations have a significant impact on the probability associated with their current period site choices. This result, which holds across both study areas (LAM and Texas) and time periods (1995–1999 and 2000–2004), is consistent with the results in other location choice studies (e.g., Holland and Sutinen, 2000). In essence, the behavioral inertia associated with changing fishing sites, perhaps due to lack of information or habit persistence, made harvesters reluctant to change fishing location from one trip to the next. In addition, the declining overall profit opportunities in the industry during 2000–2004, and thus the need to exercise more caution before switching fishing sites, might also play a role.

In summary, changing economic conditions appeared to have influenced the short-run decision making behavior among Gulf of Mexico shrimpers. Due to less favorable economic conditions in the industry since the turn of the decade, some shrimpers appear to have become more risk averse and/or more “habit driven” in choosing shrimping locations. In other words, they became more cautious in choosing new, potentially higher revenue generating sites; especially ones that they had not previously visited. Because of the exhibited inertia on the part of shrimpers in changing sites due to either site loyalty or risk aversion, the use of economic incentives as a means of influencing location-choice behavior would appear to be a significant

challenge, especially under unfavorable economic conditions.

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