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Modeling trip choice behavior of the longline fishers in Hawaii

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Abstract

Fishers' trip choice behavior in Hawaii's longline fishery was analyzed by applying a utility theoretic mixed model (a combination of the conditional and multinomial logit (unordered) models) which accounts for both choice- and individual-specific attributes. The results indicate that fishers demonstrated utility maximizing and risk-averse behavior. They exhibited 'inertia' in switching to alternate trip choices. The stock level of major species, vessel age and size also significantly influenced fisher's trip choice behavior. There was a high proportion of concord between the actual choice and model's in-sample prediction of choices. Trip choice behavior was also simulated under different fleet structure and stock conditions.
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1. Introduction

Economic theory predicts that fishers will redistribute fishing effort across fisheries or fishing locations when expected economic return differs across them (Gordon, 1954). Predicting the distribution of fishing effort becomes much more complex in a multispecies fishery where profit expectations differ across fisheries, fishing locations, and fishers. Changes in biological, economic or regulatory conditions that change the profitability of one fishery or fishing location will result in redistribution of fishing effort between alternative fisheries or fishing locations (Holland and Sutinen, 1999). Fishers may also consider any belief, tradition, preferences, and risk factors in their trip choices. Identification of the sources of expansion and contraction of fishing effort would be important in predicting fishery choice behavior of fishers under the realistic assumption that management cannot completely control fishing effort. Fisher's behavioral response is crucial for a rational fishery management (Bockstael and Opaluch, 1983). An understanding of the behavioral response of fishers on their trip choice decisions will be, therefore, of paramount importance in Hawaii's longline fishery from a fishery policy and management perspective. Studies on behavioral aspects of fishers are emerging and the discrete choice model used by Bockstael and Opaluch on output supply response has since become the framework of choice for fishery economists on studies related to fishery and fishing location choices (Mistianen and Strand, 2000).

Fishery choice is defined as the choice of a major target species or a group of species that could be harvested by a single gear type (Opaluch and Bockstael, 1984). Fishery choice in the present study specifically

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means the longline fisher's choice of a trip type as reflected in their choice of major targeted species. Other fishing gears such as troll and handline or fisheries like bottomfish and lobster fisheries were not considered, as switching between them rarely occurs. In fact, not in any situation are fishers able to make frequent gear changes or major vessel outfitting to harvest fish of different dwelling and foraging habits, as this may involve substantial cost in retro-fitting a fishing vessel. However, the use of the same basic equipment for all target species in the longline gear or fishery allows fishers to switch between major target species even on a trip-to-trip basis without the need for major outfitting of vessels. Based on major targeted species or group of species, three trip choices are prevalent in Hawaii's pelagic longline fishery: swordfish, tuna, and mixed trips. During swordfish and tuna trips, the primary targeted species are swordfish (*Xiphias gladius*) and bigeye tuna (*Thunnus obesus*), respectively. However, fishers target both in mixed trips. These choices are discrete as they are planned a priori and hence carried out accordingly with suitable strategies and inputs for the trip. The choices are influenced by various factors, such as the amount and variability of expected return from a particular trip type; belief, tradition, habit and preferences; seasonal abundance and demand for fish; knowledge of fish habitats and their movements; shared information among fishers; availability of target specific equipments in the vessel; and skills and knowledge about technologies to target a particular species or group of species. It was observed that some fishers switched between trips while others adhered to the same type of trip for a long period. For a fishery manager it is important to know which fishery fishers prefer to be in, and what triggers them to choose one type of trip over another. The information would be useful for fishery policies, planning, and management.

In this paper, an analysis of trip choice behavior of Hawaii's longline fishers is presented in a utility theoretic framework using trip-level information over the period 1991–1998. McFadden's choice model or *mixed* model was applied in analyzing the trip choice behavior. Whether fishers were behaving rationally by choosing a trip that yields higher expected revenue among the alternative trips was examined. Also examined were their risk behavior and resistance to change from one trip type to another, and how fish stock abundance, vessel age and size affect the type of trip chosen. Further, how redistribution of fishing effort to different trip types occurs under different stock levels and fleet structures was also examined. In the following sections, a brief description of Hawaii's longline fishery is presented, followed by a conceptual/empirical model specification, discussion of results, and concluding remarks.

2. Longline fishery and trip choices in Hawaii

Hawaii's commercial fishing industry consists primarily of multispecies pelagic fisheries. The fishery is generally confined in the mid-North Pacific Ocean in the range of 40°N to the equator and 145°W–175°E (Pooley, 1993). Although Japanese immigrants introduced longline fishing technology to Hawaii in the early 20th century, a large number of modern capital-intensive longline vessels entered Hawaiian waters from mainland US during the late 1980s. The number of active longline vessels almost quadrupled from 37 in 1987 to 141 vessels in 1991. This number then leveled off at about 120 vessels from 1992 through 1994, declined slightly to 103 in 1996, and increased to 125 in 2000 (Ito and Machado, 2001). However, these numbers are still below the issued 164 number of "limited entry" permits. Currently the longline fleet includes several older wooden longliners, a few fiberglass vessels, and many newer steel longliners that were previously engaged in the fishery off the US mainland (WPRFMC, 1995).

In a relatively short time span, the longline fishery has also grown to be the largest and most prominent commercial fishery in Hawaii. The structure of the fishery has witnessed dramatic changes in almost every aspect, including marketing strategies, gear selection, species composition, and fishing destination. Many vessels have upgraded to high-tech monofilament line and adopted a multitude of modern and efficient technologies, such as acoustic Doppler current profilers, chronoscopic fish finders, satellite navigation systems, communications, color video echo sounders (Dollar, 1992; WPRFMC, 1995). In 1998, the longline fishery alone accounted for 85% of the commercial catch that totaled nearly 29 million pounds (13.18 million metric tonnes) with an ex-vessel value of about US$ 47 million (Ito and Machado, 1999). Bigeye tuna has been a major target species of the

Hawaii longline fishery since the 1950s. Swordfish was a minor species until the 1990s (Curran et al., 1996; Dollar, 1992). Other commercially important pelagic bycatch are yellowfin tuna (*T. albacares*), albacore (*T. alalunga*), and marlins (Blue marlin *Makaira mazara*, Striped marlin *Tetrapturus audax*, and Black marlin *M. indica*), etc. Until June 2000, there was no limit to the total allowable catch of each commercially important species. But, swordfish harvest by longliners was banned due to the concern over marine turtle interaction with longline swordfish fishing till September 2003. This study, therefore, analyzes fishers' trip choice behavior during the period when there was no swordfish harvest ban.

The National Marine Fishery Services' (NMFS) Honolulu Laboratory also classifies longline fishing trips into one of the three trip categories—swordfish trip, tuna trip, and mixed trip, based on in-person interviews, fishing destination, input use, time of set, catch composition, and species targeted (Curtis, 1999). However, each fishing trip choice is basically a priori choice of a fisher, as each trip strategy involves a different production technology, such as timing of laying out of sets, depth and number of hooks and light sticks, and type of hooks or baits to be used. Such input decisions are made prior to a trip is actually taken. In 98% of trips during 1991–98, it was observed that fishers selected only one type of set throughout a trip. It is evident from the logbook records that, on average, tuna sets use more hooks per set compared to swordfish and mixed sets, i.e., 1441 hooks per set in tuna sets versus 815 and 876 in swordfish and mixed sets, respectively. The timing and configuration of a set used in the mixed trip is similar to that used in the swordfish trip except that the mixed set uses fewer light sticks and slightly more hooks, enabling the mixed set to target both bigeye tuna and swordfish. Therefore, swordfish sets use about 485 light sticks per set compared to 225 in mixed sets. Further, the mixed trip does not involve altering a set or switching sets designed to target bigeye tuna or swordfish during a trip. The length of the main line in a tuna set is about 20–25 miles, compared to 35–45 miles in swordfish and mixed sets. The tuna set is laid out in the morning and hauled in the evening, while swordfish and mixed sets are laid out in the evening and hauled in the morning (Curtis, 1999). Thus, the operational strategies vary with the targeted species without involving any major outfitting of the vessel or gear. Most fishers adhered to a particular trip choice for most of the time. However, some switched target species on a seasonal or quarterly basis and in some instances on a trip-to-trip basis. On a sequential quarter-to-quarter basis the longline fishers switched from one trip type to another in 17% of the 2855 quarterly averaged trip observations during 1991–1998 (Table 1). The most frequent switching took place by the mixed trippers, followed by swordfish trippers. Therefore, it is imperative to understand the factors why some fishers switched trips and others did not.

3. Conceptual framework

Following McFadden (1973), a random utility model is used to analyze a fisher's fishery or trip choice behavior. Chronological development of

Table 1
Switching trip choices by the longline fishers in Hawaii during 1991–1998

Trip switching: From	To	Number of switches between trips	Proportion of: Total trips (%)	Own trip type (%)
Tuna trip ($n = 1184$)	Mixed trip	39	1.37	3.29
	Swordfish trip	58	2.03	4.90
Swordfish trip ($n = 741$)	Tuna trip	46	1.61	6.21
	Mixed trip	99	3.47	13.36
Mixed trip ($n = 930$)	Tuna trip	93	3.26	10.00
	Swordfish trip	152	5.32	16.34
Total quarterly averaged trips ($n = 2855$)		487	17.06	

Source: Data compiled from the logbook records, Honolulu Laboratory.

different forms of economic decision models can be found in McFadden (2001), but the details of different choice models can also be found in Maddala (1983), Train (1993), Long (1997), Poweres and Xie (2000), and Greene (2000). A random utility model arises when one assumes that, although the decision maker's utility function is deterministic for that person, it contains some components which are unobservable to the econometric investigator and are treated by the investigator as random variables. The unobservable could be the characteristics of the decision-maker or attributes of the choices. The concept, therefore, combines two ideas that have a long history in economics—the idea of a variation in tastes between individuals in a population and the idea of unobserved variables in the econometric model (Hanemann, 1984).

In the random utility maximization hypothesis, a decision maker i can be described as facing a choice between a finite and exhaustive set of mutually exclusive J alternatives. He chooses an alternative j in J if and only if $U_{ij} > U_{il}$ for $l \neq j$. Preferences are described by a well-behaved utility function whose arguments include a vector of exogenous constraints on current decision-making. For a given individual i, the probability that a choice j within the choice set C will be made can be expressed as

$$P_c^i(j) = P\left[U_j^i = \max_{l \in C} U_l^i\right] \quad \forall j, l \in C, \ j \neq l$$

where U_j^i is the maximum utility attainable for an individual i if he chooses a decision j from C, $[j = 1, \ldots, J]$. Typically, the linear utility function is specified as the function of observable variables that are assumed to impact the relative utility of alternative choices. Specifically, the random utility function can be decomposed into a systematic (deterministic) term (V) and a stochastic component (ϵ) as follows (Greene, 2000):

$$\begin{aligned} U_{ij} &= V_{ij} + \varepsilon_{ij} = \theta' Z_{ij}(X_{ij,} W_i) + \varepsilon_{ij} \\ &= X_{ij}\beta + W_i\alpha_j + \varepsilon_{ij} \end{aligned}$$

where $\boldsymbol{\theta}$, $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}_j$ are vectors of coefficients providing information on the marginal utilities with respect to the relevant characteristics. U_{ij} is interpreted as the indirect utility function. The deterministic component V_{ij} can be thought of as the expected utility the individual can obtain and the random component ϵ_{ij} represents unobservable factors, measurement errors, and unobservable variations in preferences and/or random individual behavior (Fry et al., 1993). The error term is assumed to be uncorrelated across choices, and this assumption leads to the independence of the irrelevant alternative property in the choice model, i.e., outcome categories can be plausibly assumed to be distinct in the eyes of each decision-maker. Utility depends on characteristics specific to the choices as well as to the individual-specific (or vessel specific in trip choice analysis here). X_{ij} are the attributes of the choices for which the values of variables vary across choices and possibly across the individuals as well. W_i contains the characteristics of the individual or factors whose values are invariant to a choice one makes. The unobserved component of the utility is assumed, through extreme value distribution, to have a zero mean; the observed part of the utility, V_{ij}, is the expected or average utility (Train, 1993). The expected utility is a reasonable objective for choice problems in the face of uncertainty (Varian, 1993). The statistical model is driven by the probability that choice j is made, which is

$$P_{ij} = P(V_{ij} - V_{il} > \varepsilon_{il} - \varepsilon_{ij}) \quad \forall l \neq j$$

Since ϵ_{ij} and ϵ_{il} are random variables, the difference between them is also a random variable. Let Y_i be a random variable that indicates the choice made. If (and only if) the J disturbances are independent and identically distributed with Weibull distribution as $F(\varepsilon_{ij}) = \exp(-\mathrm{e}^{-\varepsilon_{ij}})$, then the probability that the decision-maker will choose alternative j is given as (Greene, 2000):

$$P(Y_i = j|X_{ij}, W_i) = \frac{\mathrm{e}^{V_{ij}}}{\sum_{j=1}^{J}\mathrm{e}^{V_{ij}}} = \frac{\mathrm{e}^{\beta' X_{ij}}\,\mathrm{e}^{\alpha'_j W_i}}{\sum_{j=1}^{J}\mathrm{e}^{\beta' X_{ij}}\,\mathrm{e}^{\alpha'_j W_i}}$$

Probabilities are estimated for each individual as a group (each individual facing all probable choices). When the data consist of only choice-specific attributes and whose values vary across alternatives, the appropriate model is the *conditional logit*. One estimates a single parameter for the effect of the variable. When data consist of only individual-specific information and the value of a variable does not differ across outcomes, the appropriate model is the *multinomial (unordered) logit*. On the other hand, when data consists of choice- and individual-specific attributes, an interesting possibility is combining the conditional and multinomial logit (unordered) model in a single model, referred to as a mixed model and estimated by modifying the conditional logit model. The mixed model could avoid specification error, if any, due to the omission of relevant variables. To incorporate individual-specific covariates in the conditional logit model, a set of dummy variables corresponding to each of the J alternatives is created and each individual-specific covariate is multiplied by this set of dummies (Long and Freese, 2001; Poweres and Xie, 2000; Hoffman and Duncan, 1988). To identify the model, one would have to normalize one of the alternative and set the α for that alternative to zero. Following this approach, the logit in the mixed model is expressed as (Poweres and Xie, 2000):

$$\log\left(\frac{P_{ij}}{P_{il}}\right) = W_i'(\alpha_j - \alpha_i) + (X_{ij} - X_{il})'\beta$$

The model can be evaluated using one of the following goodness of fit tests as in Judge et al. (1985): (i) a comparison of the actual share in the sample for each alternative with the predicted share allows an evaluation of different model specifications; (ii) Lagrange multiplier (log likelihood chi-square test) where all coefficients in a model are equal to zero under the null hypothesis implying all alternatives are equally likely; and (iii) The likelihood ratio index and pseudo ρ^2 is expressed as, $\rho^2 = 1 - L(\hat{\beta})/L(\hat{\beta}^{\mathrm{H}})$, where $L(\hat{\beta})$ is the log likelihood of the unconstrained model and $L(\hat{\beta}^{\mathrm{H}})$ is the log likelihood of the model under the null hypothesis. The model is a perfect predictor when $\rho^2 = 1$.

4. Empirical procedures

4.1. Previous studies and current approaches

There are only limited studies in fishery economics literature on modeling commercial fishers' fishery choice behavior. Many of these studies followed an initial application of discrete choice model by Bockstael and Opaluch (1983) in studying fisher's fishery choice behavior in New England's ports. Larson et al. (1999) analyzed fishers' choice behavior in the Bering sea/Aleutian islands trawl ground fisheries in Alaska. Eggert and Tveteras (2001) modeled commercial fishers' gear selection behavior in the Swedish demersal fishery. Several other studies are related to fishing location choices, such as the studies by Eales and Wilen (1986), Mistianen and Strand (2000) and Smith (2000); and still others are related to fishing location/fishery choice, as those by Holland and Sutinen (2000) in the New England trawl fishery and by Curtis and Hicks (2000) in Hawaii's longline fishery. The choice of functional forms also varied in these studies. For example, Bockstael and Opaluch (1983) suggest that the choice of utility function is necessarily arbitrary, and they use a logarithmic utility function. The function is restrictive as it assumes monotonicity in wealth and implied risk aversion. Mistianen and Strand (2000) use a quadratic utility function where utility function is non-monotonic in wealth in certain ranges, and the unlikely preference structure of increasing absolute risk aversion. Eggert and Tveteras (2001) and Larson et al. (1999) use the linear utility function in the mean-standard deviation framework in the fishing gear choice study. The model used by Holland and Sutinen (2000), Mistianen and Strand (2000), and Eggert and Tveteras (2001) allows fishers to reveal heterogeneity in preferences by relaxing the wealth and cost data requirement, as both of these kinds of information are costly to gather and not consistently available from all fishers.

Our approach to a behavioral analysis of fishers' fishery choice differs from previous works in several aspects. We extend the modeling approach applied in the literature to accommodate fishers' trip choice behavior in the pelagic fishery environment using trip-level pooled cross-sectional and time-series data for the period 1991–1998. A longer time series data would enhance our understanding of the patterned behavior of fishers. Earlier studies use choice-specific variables in modeling fishers' fishery choice behavior. In this study, in addition to using choice-specific variables, the model includes individual-specific variables (i.e., fisher- or vessel-specific) together with biological variables like stock indices, as it would be interesting to identify fishers' behavior in relation to the seasonal/biological variation of major targeted stocks. Application of the mixed model in trip choice analysis is not found in the fishery economics literature, and the application of this model is also rarely found in other social science literature. This is because the datasets typically analyzed by economists do not contain mixtures of choice- and individual-specific attributes, as such data would be far too costly to gather for most purposes (Greene, 2000; Judge et al., 1985). Trip choice simulation under different stock and fleet structure conditions may also provide some insights to fishery managers about the degree to which fishing effort is redistributed among fisheries.

4.2. Empirical model

Fisher's trip choice behavior under uncertainty was empirically modeled by specifying the mixed model. It assumed the expected utility maximization hypothesis in a linear mean-standard deviation framework where fishers' risk attitudes are independent of initial wealth level. The Just–Pope production function that meets the requirement of the linear mean-standard deviation utility function is specified (Appendix A), as in Eggert and Tveteras (2001). The basic assumption in using the mean-standard deviation utility function is that it can accommodate fishers' expectation formation on trip revenues. It allows heterogeneous risk preferences between fishers.

It is assumed that fishers consider both the expected relative revenue and its variability for the given choice in their trip choice decision. The expected revenue per unit effort and its variability are choice-specific attributes. Fishers' beliefs, traditions, habits, and skills, may also affect trip choice decisions. Other factors that may affect fishers' trip choices are individual- or vessel-specific and biological variables, such as vessel age, vessel size, and stock indices to reflect seasonal variations in stock conditions. The inclusion of these attributes in the mixed model is done through their interactions with the trip choice dummies. Interacting individual-specific variables with the choice dummies allow the coefficients to vary across the choices instead of the characteristics. The deterministic component of the indirect utility function or the expected utility function of the mixed model is empirically specified as

$$\begin{aligned} V_{ijq} = {} & \beta_1 \times \mathrm{EREVNTD}_{ijq} + \beta_2 \times \mathrm{ESDREVNTD}_{ijq} \\ & + \delta_1 \times \mathrm{PVTRP}_{iq} + \alpha_{1j} \times \mathrm{SW} \times \mathrm{AGE}_{iq} + \alpha_{2j} \\ & \times \mathrm{TN} \times \mathrm{AGE}_{iq} + \alpha_{3j} \times \mathrm{SW} \times \mathrm{MED}_i + \alpha_{4j} \\ & \times \mathrm{TN} \times \mathrm{MED}_i + \alpha_{5j} \times \mathrm{SW} \times \mathrm{LRG}_i + \alpha_{6j} \\ & \times \mathrm{TN} \times \mathrm{LRG}_i + \alpha_{7j} \times \mathrm{SW} \times \mathrm{STKNDX}_{sq} \\ & + \alpha_{8j} \times \mathrm{TN} \times \mathrm{STKNDX}_{sq} \end{aligned}$$

The dependent response variable V_{ijq}, represents the three trip choices: swordfish trip, mixed trip, and tuna trip as indexed by j for the ith vessel or fisher in qth quarter of a year. The vectors $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$ and, $\boldsymbol{\delta}$ are coefficients to be estimated in the mixed model. A value of one (1) is assigned to the dependent variable if a trip of a particular type was actually chosen, and zero (0) otherwise. Stata SE 7.0 econometric software was used in model estimation (Stata, 2001).

4.3. Variables

The variables used in the mixed model are defined in Table 2. The explanatory variables in the indirect utility function are quarterly averaged trip-level expected revenue per unit effort ($\mathrm{EREVNTD}_{ijq}$), standard deviation of trip revenue per unit effort ($\mathrm{ESDREVNTD}_{ijq}$), a dummy for the previous trip as 'inertia' to change

Table 2
Variable definitions

Variables	Definition
$\mathrm{EREVNTD}_{ijq}$	Expected revenue per unit of composite effort of the ith fisher in jth trip in qth quarter (in US\$ per net tonne day)[a]
$\mathrm{ESDREVNTD}_{ijq}$	Standard deviation of $\mathrm{EREVNTD}_{ijq}$ (in US\$ per net tonne day)
PVTRP_{iq}	Inertia dummy equal to 1 if current quarter's trip type is same as in previous quarter, or 0 otherwise
AGE_{iq}	Vessel age in years when the time trip was taken
MED_i	Vessel size dummy equal to 1 if it is of medium size (56–74 ft), or 0 otherwise
LRG_i	Vessel size dummy equal to 1 if it is of large size (>74 and up to 100 ft), or 0 otherwise
STKNDX_{sq}	Fish stock index for the species swordfish, bigeye tuna, and yellowfin. The base case scenario is 1.0 for the first quarter of 1992
SW	Trip dummy equal to 1 if the chosen trip is swordfish trip, 0 otherwise
TN	Trip dummy equal to 1 if the chosen trip is tuna trip, 0 otherwise

[a] Composite effort is a product of trip length and vessel net tonnage.

trip ($PVTRP_{iq}$), vessel age (AGE_{iq}), vessel size (MED_i and LRG_i), and quarterly stock index ($STKNDX_{sq}$) of the *s*th species. An 'inertia' variable was included as there may be economic and non-economic factors that may prevent fishers from switching from one type of trip to another. Sources of 'inertia' could be monetary costs associated with the conversion of the vessel for an alternate choice, and non-economic costs like psychic costs associated with switching fisheries due to family tradition, preferences, fishery-specific knowledge and skills, etc. (Bockstael and Opaluch, 1983). The 'inertia' variable $PVTRP_{iq}$ takes the value of 1 if the current trip choice for a fisher is the same as his trip choice in the immediate previous trip and 0 otherwise.

The trip-level expected revenue and its standard deviation were estimated by using the Just–Pope production function following the procedure in Eggert and Tveteras (2001), as detailed out in Appendix A. Stochastic revenue functions with fixed effects were specified to estimate the trip-level expected revenue and its standard deviations. Therefore, the trip-level expected (predicted) revenue ($EREV_{ijt}$) and its standard deviation ($ESDREV_{ijt}$) were normalized by the corresponding trip's composite effort to derive the expected revenue per net tonne day ($EREVNTD_{ijt}$) and its standard deviation ($ESDREVNTD_{ijt}$) for the *t*th trip. Trip-level observations of these variables were then aggregated and averaged for each fisher and by trip type during a quarter to generate quarterly averaged trip-level variables, i.e., expected revenue per net tonne day ($EREVNTD_{ijq}$) and its standard deviation ($ESDREVNTD_{ijq}$). Thus, multiple trips of the same trip type by a fisher during a quarter were averaged for the quarter is considered as one type of trip observation. If a fisher had also different trip choice during the same quarter, those observations were similarly aggregated/averaged and considered as a separate trip choice observation. These variables served as explanatory variables for the utility function in the empirical model and have choice-specific attributes as they vary with the outcomes and individual. The variables thus normalized also capture the relative return to capital investment and labor in fishing, making choice analysis feasible even in the absence of cost information.

To make the mixed model operational, one has to assign expected values for the explanatory variables in the non-chosen alternatives as well assuming that those alternatives were also available to the fishers. For the chosen alternative, $EREVNTD_{ijq}$ and $ESDREVNTD_{ijq}$ take the values as estimated by using the Just–Pope production function, but takes proxy values if the alternative was a non-chosen one.[1] The proxy values were estimated by taking the means of the expected values of these variables for the vessels of similar size and trip type for the given quarter of a year, an approach similar to that taken by Bockstael and Opaluch (1983).

The other explanatory variables that are interacted with the trip choice dummies (SW, TN, and MX, for swordfish, tuna, and mixed trips, respectively) comprise vessel age (AGE_{iq}) which is expressed in years at the time the trip decision was made, vessel size (MED_i and LRG_i), and quarterly stock indices ($STKNDX_{sq}$) for the *s*th fish species in the *q*th quarter of a year. Vessel sizes are dummy variables with large and medium vessels taking a value of 1 if they belong to one of those categories. To avoid the dummy variable trap, the small (<56 ft) vessel dummy was omitted in the estimation.

Stock indices were included since trip choice also depends on fishers' expectation about the seasonal changes in fish abundances. Tuna and billfish are migratory, and stocks are known to fluctuate on a seasonal and annual basis (Campbell and McIlgorm, 1995). Seasonal fluctuation of different pelagic species in Hawaii is also noted in Boggs and Ito (1993), Curran et al. (1996), and Ito and Machado

[1] The data structure to estimate the mixed model is different from other regressions. The data was constructed as in Hoffman and Duncan (1988). Each longline fisher generally faces three choice situations, but he chooses only one per period. For the chosen one, the choice-specific attributes (X) take the expected values. However, proxy expected values have to be assigned for the non-chosen choices assuming that a fisher had the option to choose from other alternatives as well. This ramifies the number of observations by the multiple of total available choices. The differences in the values for each choice determine the probabilities of various choices for the fisher in that particular trip. Let us see how an attribute that is invariant across alternatives can be introduced to create a mixed model. Let D_2 and D_3 be the dummy variables for choices 2 and 3, respectively. Interacting the individual-specific (W) variable with D_2 and D_3, we have D_2W and D_3W variables. Just as in the multinomial logit estimation, they give the effect of variable X relative to an omitted category, i.e., choice 1. Estimation of this mixed model would yield three coefficients—one each for X, D_2W, and D_3W.

(1997). The species considered in the model were swordfish, bigeye tuna, and yellowfin tuna. Catch per unit of effort (CPUE) by species is the only available proxy information on stock abundance for this study. Clark (1990) has also pointed out that the ratio of catch divided by effort is almost always taken as at least a rough indication of the current stock level of the fish population. The CPUE measure of the number of fish per 1000 hooks was used as a basis for the measure of stock abundance.

The stock variable is expressed in terms of an index. The components going into the stock index that measures relative stock abundance are assumed exogenous. The circulatory or collinear problem with individual's trip revenue is not serious because the indices thus generated are aggregate estimates for the entire fleet. Species-specific stock indices for each quarter were constructed from each individual fisher's trip-level CPUE for each species. The entire trip observations were used for this purpose. Then this trip-level CPUE was later aggregated and averaged quarterly over all fishers and trip types for each species or group of species considered in the analysis. The estimated species-specific quarterly CPUE was indexed by taking the CPUE measure for the first quarter of 1992 as a reference. A value greater (or smaller) than 1 implies a better (or worse) stock situation for the quarter relative to the first quarter of 1992. The quarterly stock indices were created in such a way that all fishers face the same fleet level stock index for a given quarter of a year no matter what type of trip choice one makes, as trip-level CPUE is not introduced in the model. The quarterly stock indices capture both seasonal and annual stock variations, as well as migratory patterns, recruitment, and other environmental aspects affecting CPUE. The indices thus created also exhibit quarter-to-quarter variation reflecting seasonal differences in species abundances. The variations may be attributed to seasonal migratory and other behavioral patterns of species under consideration.

There are few variables of interests, such as data on fishing experiences, information on if fishers followed lunar calendar in planning swordfish trip, information on the customary practice of observing what other fishers have landed in large amounts, and information on communication between peers about the location where a large school of desired species was encountered were not included in the model due to data unavailability or difficult to collect.

4.4. Data

The US National Marine Fisheries Service's (NMFS) Honolulu Laboratory longline logbook and the State of Hawaii's Division of Aquatic Resources (HDAR, 1990–1998) commercial catch records are the key sources of data involved in this study. The NMFS logbook data provide information on fishing effort (such as trip length, number of sets, number of hooks, number of light sticks, etc.), trip type, ocean conditions like sea temperature, wave height, and number of fish caught by species. The HDAR data provide information on total pounds and number of fish caught, and revenue by species. Additional vessel-specific information (such as tonnage, size, age, etc.) was obtained from the data maintained by the US Coast Guard.

The HDAR data are maintained at the trip-level, while NMFS logbook data are at the set level. Therefore, the initial task involved the transformation of the logbook data from set level to trip-level. Then, the data from the two sources were merged using some key identifying variables, such as vessel permit number/name, hauling and reporting dates, species and the number of fish reported. For the period from 1991 to 1998, the trip-level longline observations in the NMFS logbook and HDAR datasets totaled 10,597 and 8618, respectively, of which 6666 were matched. The matched dataset represented about 77% of the total catch. The mean statistics between the matched and unmatched data were also similar. The data for the trip choice analysis included 95% or 158 out of the 167 vessels operating during the same period.

Because of the seasonal nature of trip choices, the trip-level information for each fisher is averaged quarterly, i.e., information generated by a vessel taking multiple trips for a type of trip during a quarter of a year was aggregated and averaged to generate quarterly averaged trip-level information, and considered as one unit of observation. Thus, the final dataset consisted of 2855 quarterly averaged trip-level observations during 1991–1998. This dataset increases to 8565 observations for the mixed model estimation because of the three trip choices. All of these observations were used in the analysis.

Table 3
Quarterly statistics for a longline vessel by trip choices during 1991–98

Variables	Unit	Tuna trip ($n = 1184$)	Mixed trip ($n = 930$)	Swordfish trip ($n = 741$)
Total revenue	US$ per quarter	78292 (57908)	78532 (57151)	97206 (71526)
Revenue	US$ per trip	28199 (15228)	36270 (24508)	59643 (34351)
Revenue/composite effort	US$ per trip day per net tonne	64.74 (58.13)	55.67 (44.44)	58.44 (49.62)
Trip length	Days per trip	11.53 (3.45)	11.98 (5.94)	17.98 (8.05)
Number of trips	No. per quarter	2.70 (1.34)	2.33 (1.30)	1.59 (0.73)
Hooks	No. per trip	13985 (6200)	7879 (3603)	10478 (4556)
Sets	No. per trip	9.59 (2.70)	9.09 (3.93)	12.80 (4.93)
Vessel capacity	Net tonnage	53.87 (25.67)	68.01 (25.85)	76.92 (28.88)
	Length (ft)	62.28 (11.15)	72.47 (9.37)	75.07 (9.45)
Vessel age	Years	18.99 (14.37)	8.06 (6.44)	8.49 (5.49)
Total catch sold	Pounds per quarter	34973	28727	33124
Swordfish	Pounds per trip	704	6458	16616
Bigeye tuna	Pounds per trip	5381	2643	1856
Yellowfin tuna	Pounds per trip	1464	1580	1001
No. of fish caught	No. per quarter	640	394	385
No. of fish caught	No. per trip	228	179	239
Expected values				
Expected revenue/effort	US$ per trip day per net tonne	60.12 (54.83)	54.77 (41.18)	57.96 (44.19)
Expected standard deviation of revenue/effort	US$ per trip day per net tonne	18.30 (27.25)	16.93 (13.93)	14.92 (14.60)

Values in parentheses are standard deviations.

5. Results and discussion

Quarterly statistics of some characteristics in the longline fishery by trip type are reported in Table 3. There are differences in some important characteristics between the types of trips, e.g., swordfish trips had the largest quarterly total revenue and revenue per trip, followed by mixed trips and tuna trips. However, the relative revenue in terms of revenue per unit effort was higher for the tuna trip as compared to swordfish and mixed trips. The quarterly total catch by weight was higher with tuna and swordfish trips than in mixed trips. Further, fishers made more frequent tuna trips during a quarter than other types of trips, and smaller and older vessels were more associated with taking tuna trips than other types of trips.

Many coefficients in the mixed model were statistically significant (Table 4). A statistic analogous to R^2, i.e., the pseudo ρ^2 of value 0.496 explains a substantial proportion of variation in fishers' trip choice behavior. The log likelihood chi-square is also large and significant.

The coefficient $\mathrm{EREVNTD}_{ijq}$, β_1, indicates how the logs of the probability ratio of two alternatives are affected by a change in expected revenue per unit effort. For example, if the expected revenue per unit effort increased by US$ 1 for a given trip choice, the likelihood of that choice increased by 0.26% (or 2.57% for every US$ 10 increase in expected revenue per effort). This indicates that the higher the expected revenue per effort in a given trip alternative, the higher the likelihood of that trip being chosen because of the higher utility associated with that choice, ceteris paribus. The negative coefficient on the risk variable $\mathrm{ESDREVNTD}_{ijq}$, β_2, reflects that fishers exhibited risk aversion, and implies that they preferred alternatives with less variation in expected revenue per unit effort, ceteris paribus. For example, when the expected standard deviation of the expected revenue per effort increased by US$ 1, the odds of taking that trip decreased by 0.92% (or 4.60% for every US$ 5 increase in the standard deviation of expected revenue per effort) holding the values for the other alternatives constant. The results, therefore, indicate that fishers responded positively to increases in expected revenues per effort, and exhibited the utility-maximizing behavior by choosing a trip type that yielded the best return. They also showed a risk-averse attitude by choosing a trip alternative

Table 4
Parameter estimates from the mixed model on trip choice behavior

Variables	Coefficients	S.E.	Z	Odds ratio
EREVNTD (β_1)	0.0026*	0.0014	1.75	1.0026
ESDREVNTD (β_2)	−0.0092***	0.0035	−3.60	0.9908
PVTRP (δ_1)	2.4001***	0.0681	35.23	11.0242
SW × AGE (α_1)	−0.0325***	0.0118	−2.76	0.9680
TN × AGE (α_2)	0.0237***	0.0085	2.79	1.0239
SW × MED (α_3)	0.3821	0.2620	1.46	1.4653
TN × MED (α_4)	−0.2054	0.2258	−0.91	0.8143
SW × LRG (α_5)	0.2753	0.2641	1.04	1.3169
TN × LRG (α_6)	−0.8358***	0.2477	−3.37	0.4335
SW × SWNDX (α_{7s})	1.1925***	0.2027	5.88	3.2953
SW × BENDX (α_{7b})	−0.3355**	0.1639	−2.05	0.7149
SW × YFNDX (α_{7y})	−0.3099***	0.0952	−3.25	0.7335
TN × SWNDX (α_{8s})	−0.7281***	0.2014	−3.61	0.4828
TN × BENDX (α_{8b})	0.3634**	0.1509	2.41	1.4383
TN × YFNDX (α_{8y})	0.2235**	0.0908	2.46	1.2504

$N = 7746$; LR $\chi^2(15) = 2801.58$; pseudo $\rho^2 = 0.4957$; $P > \chi^2 = 0.0000$; log likelihood $= -1424.98$.

* Statistical significance at 10% level.

** Statistical significance at 5% level.

*** Statistical significance at 1% level.

that had less variability in expected revenue, ceteris paribus.

Longline fishers also exhibited a strong ‘inertia’ in switching between the type of trips. The value of the coefficient of the ‘inertia’ variable PVTRP_{iq} gives a measure of threshold. The estimated coefficient for this threshold variable, δ_1, was positive and statistically significant, showing a substantial ‘inertia’ to switch from one trip alternative to another. The likelihood of taking the same type of trip as in the previous trip by a fisher was as high as 11.02 times. This indicates a resistance to change which could also be partly due to belief, tradition, habit, and skill. Switching to an alternative trip may also require the fisher to be compensated substantially such that the payoff from the alternative choice exceeds the reserve (threshold) value specific to each fisher. Thus, a very large increase in the relative revenue may be necessary for a fisher to switch to an alternative trip choice. The above results are qualitatively comparable to those by Bockstael and Opaluch (1983).

The variables whose values do not vary across choices were interacted with the choice dummies. Coefficients on these variables interacted with tuna (TN) and swordfish (SW) trip dummies are interpreted relative to the mixed trip (i.e., the reference choice category), ceteris paribus. Interaction of the stock indices with the swordfish trip dummy indicates that a fisher is more likely to take swordfish trip relative to a mixed trip when the swordfish stock level increases. A unit (or 100%) increase in the quarterly swordfish stock level increases the odds of choosing the swordfish trip relative to the mixed trip by 3.29 times. However, a unit increase in bigeye tuna and yellowfin stock level would decrease the odds of choosing the swordfish trip by a factor of 0.72 and 0.73, respectively. Similarly, the likelihood of choosing the tuna trip is higher with an increase of bigeye tuna and yellowfin tuna indices, but decreases with an increase in the swordfish stock level. Relative to a mixed trip, a unit increase in the swordfish stock level would decrease the odds of taking a tuna trip by a factor of 0.48, and the odds would increase by a factor of 1.43 and 1.25 for an increase in bigeye and yellowfin tuna stock levels, respectively. Thus, the stock levels of the major species influenced fishers’ trip choices. A similar comparison between the tuna and the swordfish trips is possible by re-estimating the mixed model with one of these trips as the reference category.

Vessel size has an insignificant effect on the choice between taking a swordfish trip or a mixed trip. It appears that those vessels taking swordfish and mixed trips are of similar size, and most of them are medium to large. However, large vessels are less likely to take tuna trips relative to mixed trips, but most medium-size vessels also appeared to be taking tuna trips. The odds of taking a tuna trip relative to a mixed trip decrease by a factor of 0.43 for a large vessel. Finally, the age of the vessel did have a significant effect on the type of trip taken. For example, for each year increase in the age of a vessel, the odds of taking a tuna trip relative to a mixed trip increases by a factor of 1.02, and the odds of taking a swordfish trip relative to a mixed trip decreases by a factor of 0.96.

Goodness-of-fit is also measured by the relative correspondence between the actual trip choice and their

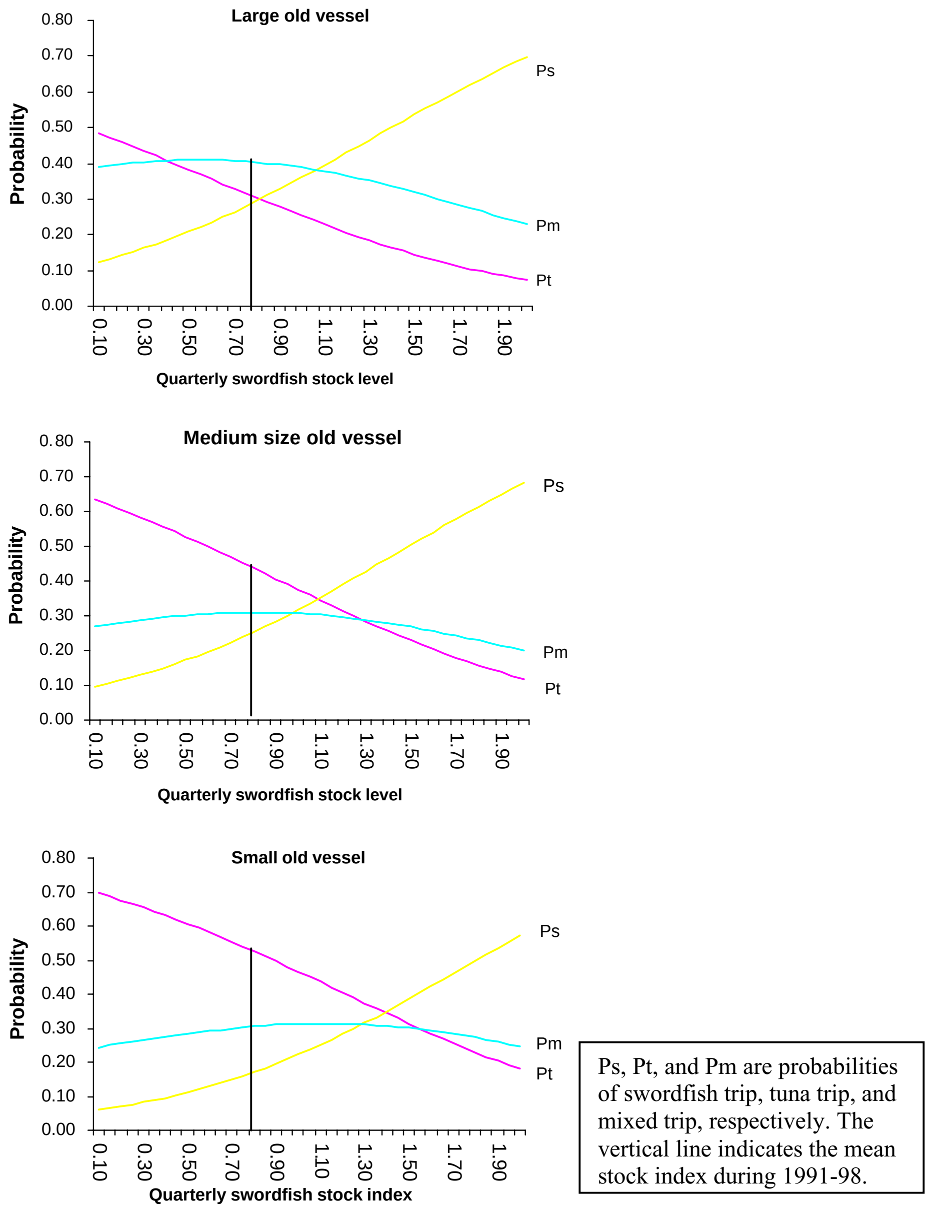

Fig. 1. Trip choice probabilities by vessel size for a 20-year-old vessel at different swordfish stock levels.

Table 5
Proportion of trip choices explained using mixed model estimates

Trip choices	Number of observations		
	Actual total[a]	Number of matched observations between actual and explained choice ($P \geq 0.50$)	Proportion predicted correctly
Swordfish	741 (26%)	515	69
Mixed	930 (33%)	670	70
Tuna	1184 (41%)	1028	87
Total	2855	2213	77

[a] Values in parentheses are trip proportions.

in-sample predicted choice. Using the estimated model coefficients, probabilities of different trip choices were predicted for each fisher for each trip in the sample. They were then compared with the actual trip choice of the fisher for that trip. There was an overall 77% match between the actual trip choice and the model prediction for the choice (with $P \geq 0.50$), i.e., the probability of selecting the actual trip choice is greater than one-half for 2213 of the 2855 observations (Table 5). The model's in-sample explanatory power is also reasonably good for each trip choice: swordfish (69%), mixed trip (70%), and tuna trip (87%).

Finally, effort redistribution by the longline fishers in terms of probabilities of different trip choices based on a change in an underlying factor were simulated by using the model coefficients. The simulation was carried out under different stock conditions (swordfish and bigeye tuna), vessel sizes, and vessel ages, holding the values of other variables constant. Only the result from swordfish stock simulation for a 20-year-old vessel is discussed here for an illustration. For an old vessel, a gradual increase in the swordfish stock index consistently increases the probability of taking a swordfish trip, but decreases the probability of taking a tuna trip for all sizes of vessels (Fig. 1). However, the probability of taking mixed trips rises for an increase in the swordfish stock index from a lower level up to a certain level, but declines as the swordfish abundance keeps rising. Medium- and small-size vessels bear increasing pressure for choosing tuna trips relative to the large vessels whenever there is a substantial decline in the swordfish stock level in the fishery.

Some of the simulation results may be useful in understanding fishers' behavior after the recent swordfish harvest ban. For example, the available swordfish stock level virtually dropped to zero after the swordfish harvest ban was imposed on the longliners. In the simulation exercise, fishers' probability of taking a swordfish trip dropped sharply due to a drop in the swordfish stock level. Many longline vessels engaged in harvesting swordfish subsequently left Hawaii right after the swordfish harvest ban, as the virtual swordfish level dropped precipitously. The impact of it was more pronounced in large- and medium-size vessels. This is just a simple illustration of how the model estimates can be used in predicting effort redistribution.

6. Concluding remarks

In this paper, fishers' trip choice behavior in Hawaii's longline fishery is studied by specifying a utility theoretic mixed model (a combination of the *conditional* and *multinomial logit* (unordered) models). The model accounts for both choice- and individual-specific attributes. The empirical results from this model suggest some important aspects of fishers' trip choice behavior. Fishers exhibited utility-maximizing behavior by choosing the trip type with a higher expected relative revenue, and they showed risk-averse attitude by choosing a trip alternative with less varying expected relative revenue, ceteris paribus. In other words, they exhibited positive marginal utility in expected relative revenues and negative marginal utility in the variability of the relative revenue. Their risk-averse behavior is in contrast to the widely held belief that fishers should be risk lovers because of the risk and uncertainties involved in marine fisheries (Bockstael and Opaluch, 1983; Dupont, 1993; Eggert and Tveteras, 2001).

Longline fishers also revealed substantial "inertia" in switching trips, as switching trips to the next best alternative requires return to exceed a “threshold” or “reserve” value. They showed a strong bias toward choosing the same trip choice over time, as was found in similar earlier studies. It is because fishers would require a significant variability in expected relative revenue before making the effort to switch to an alternative trip. Fishers’ high propensity to remain in the same fishery or take the same trip choice in the future and to resist frequent trip switching could also be due to their experiences in a particular trip/target or due to traditional beliefs and habits.

The stock levels of major species had a significant effect on fishers’ trip choices. For example, fishers were more likely to choose a swordfish trip relative to a mixed or tuna trip whenever the swordfish stock level increased, ceteris paribus. Similarly, fishers were inclined to choose a tuna trip relative to a mixed trip when there was an increase in bigeye tuna and yellowfin tuna stock levels.

Vessel-specific attributes like vessel age and size had also a significant effect on trip choices. The fishers with older and smaller vessels were more inclined to choose tuna trips rather than mixed trips. The predictive performance of the model was also reasonably good as there was a high degree of match between the actual choice and the model’s prediction of choice at a probability greater than 0.5. Finally, the probabilities of choosing different trip choices were simulated using the parameter estimates. Such simulation was carried out under different stock conditions and fleet structures.

The choice model used in this paper, which also accounts for heterogeneity between fishers, can be useful in fishery management and policy evaluation purposes. The models may be used to explain the redistribution of fishing effort under different situations. The results revealed that relative revenue did matter in fishers’ trip choices. Therefore, any fishery policies that affect the relative return or the variability of return will have a direct implication on the redistribution of fishing effort among different fisheries (Bockstael and Opaluch, 1983). By using simulation results on trip choices and by identifying the sources of ‘inertia’, it may be possible to reallocate fishing effort from over-utilized resources to under-utilized resources by various regulatory mechanisms, such as subsidy and tax incentives, and educational programs aimed at ultimate resource appropriators, as suggested by Bockstael and Opaluch (1983).

The model can be used in predicting the distribution of effort as was done in the simulation exercises. It can also help fishery managers and policy makers to understand the different impacts that a variable under consideration may have on different sectors of the fleet. Suitable policies may then be devised to accommodate changes in the distribution of effort, primarily for equity and political reasons also suggested by Holland and Sutinen (1999).

The model could be a useful additional assessment tool to evaluate fishers’ behavioral responses to the recent swordfish harvest ban for Hawaii’s longline fishery. Other forms of choice behavior may have evolved after the ban which we have not been able to account for due to the unavailability of data at the time of this study, but it may be an interesting future research that can enhance the knowledge about the dynamics of fishers’ choice behavior. Other forms of choice behavior, for example, could be taking tuna trips in Hawaii in certain time of a year, but taking swordfish or mixed trips at other times with a different port of landing elsewhere. Further, it will be interesting to observe an eco-system-based trip choice behavior in future after the recent lift of swordfish ban in September 2003 where the court ruling allows longline fishers to harvest swordfish, but also constrain them as any encounters of endangered sea turtle can lead to a legal prosecution. A periodic updating of this and similar models using regularly collected data can be useful for fishery policy and management purposes.

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Appendix A. Estimation of expected revenue and risk variables

It is presumed that fishers take account of expected revenue and revenue risk when they make fishery choices. In fisheries the primary source of revenue risk at trip level is production risk rather price risk. Production risk is modeled by applying the framework outlined by Just and Pope (1978) as $y = g(\mathbf{x}) + u = g(\mathbf{x}) + \sqrt{h(\mathbf{x})}\varepsilon$, where y is output, $\mathbf{x}$ is a vector of k inputs, $g(\cdot)$ is the mean function (non-stochastic part), $h(\cdot)$ is the variance function (stochastic or risk part), and ϵ is the exogenous production shock. This production function is flexible enough to accommodate both increasing and decreasing output risk in inputs and does not impose a priori restrictions on the risk effects of inputs (Eggert and Tveteras, 2001).

In expected utility models, producers choose the input vector $\mathbf{x}$ that maximizes their expected utility based on the observed (or expected) output and input prices $(p, \mathbf{w})$ and a priori knowledge of the structure of the risk in a production technology. Thus, the expected utility can be written as $\mathrm{EU} = g(E(\pi), \mathrm{Var}(\pi))$, where $E\pi(\cdot)$ and $\mathrm{Var}\,\pi(\cdot)$ are mean profit and the variance of profit, respectively. The function $g(\cdot)$ represents the fisher's subjective trade-off between mean profit (output) and variance of profit (output). Utility increases with profit, i.e., $\mathrm{d}U/\mathrm{d}E\pi(\cdot) > 0$ but utility decreases, does not change, or increases depending on whether the producer is risk-averse, risk-neutral or risk-lover, respectively. Under the Just–Pope production technology, the expected utility maximization problem $\max_x \mathrm{EU}(\pi(\mathbf{x}))$ is equivalent to the mean-standard deviation maximization problem $\max_x V(\mu, \sigma)$, where $\mu = E\pi = pf(\mathbf{x}) - \mathbf{w}'\mathbf{x}$, and $\sigma = ph(\mathbf{x})\sigma_\varepsilon$. There is a positive linear relationship between the moments of output (y) and the moments of profit (π) under Just–Pope production risk, with the mean and variance of profit given by $E\pi = pg(\mathbf{x}) - \mathbf{w}'\mathbf{x} = pEy - \mathbf{w}'\mathbf{x}$, and $\mathrm{Var}\,\pi = p^2 \times \mathrm{Var}\,y$. In case of risk affinity, fishers regard the variability in actual landings as something good (Eggert and Tveteras, 2001).

Lacking vessel-specific trip-wise cost information, we use the moments of revenues per unit effort instead profit in trip choice analysis, similar approach to those by Holland and Sutinen (1999), Smith (2000), and Eggert and Tveteras (2001). This is plausible assuming that the costs associated with vessel operation are highly correlated with the vessel capacity and trip-days, and revenues are correlated with profits. A linear quadratic form is specified for the fixed effect mean revenue function $g(\mathbf{x})$ as

$$E(Y_{it}) = \mathrm{REV}_{it} = \alpha_1\,\mathrm{HOOKS}_{it} + \alpha_2\,\mathrm{HOOKSQ}_{it} + \sum_{M=2,12} \alpha_m D_m + \sum_{i=1,158} \alpha_i V_i + u_{it},$$

where $E(Y_{it})$ is the revenue in US$ by the ith vessel in the tth trip, HOOKS_{it} is number of hooks used by the ith vessel in tth trip, HOOKSQ_{it} is hooks squared, D_m is the dummy variable for the month m, V_i is the dummy variable for each vessel, and u_{it} = error term. One of the months is dropped to avoid the dummy variable trap. Ordinary least square (OLS) procedure was employed in estimating the Just–Pope production function (mean revenue function) using the data from individual fishing trips of all 158 longline vessels during 1991–1998 by trip type. The fitted mean revenue function generated the trip-level expected revenues. The parameters of the variance function $h(\cdot)$ were estimated in the second stage to generate the risk variable. The variance function $\mathrm{Var}(u) = h(\cdot)$used is a special case of Harvey (1976) variance function specification $\mathrm{Var}(u) = h(z) = \exp(z\delta)$, where $\mathbf{z}$'s are inputs in level or transformation of input levels, e.g., logarithms of inputs and second-order terms.[2] The variance function was specified as

$$\mathrm{Var}(u_{it}) = \exp\left(\delta_1\,\mathrm{HOOKS}_{it} + \delta_1\,\mathrm{HOOKSQ}_{it} + \sum_{M=2,12} \delta_m D_m + \sum_{i=1,158} \delta_i V_i\right).$$

[2] The first element of z, z_0, is taken as unity. This implies that $\mathrm{Var}(\epsilon) = \exp(\delta_0)$. The estimating equation to obtain the parameters of the variance function is: $\ln(\hat{u}^2) = z\delta$, where $\hat{u} = Y - x\hat{\alpha}$, and $\hat{\alpha}$ are the estimated parameters from the first stage.

Thus, the log of the squared difference between predicted values and actual values from the mean revenue function was then regressed on the same set of variables used in the mean revenue function, and the coefficients were used to generate predicted variances, i.e., the risk variable. The expected (predicted) revenue and its standard deviation from the Just–Pope production function, i.e. $E(Y_{it}) = \boldsymbol{x}\hat{\alpha}$ and S.D. $= \sqrt{\exp(z\hat{\delta})}$, respectively, were normalized by the composite effort (i.e. a product of the trip length and net tonne) of the corresponding vessel and trip, thus generating the two variables, expected revenue per net tonne day (EREVNTD$_{it}$) and its standard deviation (ESDREVNTD$_{it}$), respectively. The trip-level observations for these variables were later aggregated and averaged quarterly for each fisher and by trip type for the quarter of a year. For different trip types, the adjusted R^2 of the mean revenue functions ranged from 0.45 to 0.53, but from 0.85 to 0.90 in the revenue risk functions. The estimated functions produced significant and correct a priori sign for the variables HOOKS and HOOKSQ. The parameter estimates from the Just–Pope production function (mean revenue function) and revenue risk functions can be made available upon request to the authors.

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