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Incorporating Information and Expectations in Fishermen's Spatial Decisions

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Abstract *Applied economic analyses conducted on fishermen's spatial decisions have primarily used random utility models of location choice. A common characteristic of these studies is that they typically assume that fishermen have current information on catch rates at all fishing sites in the fishery, which implies a high degree of information sharing among fishermen while at sea. Using data from the Hawaii longline fishery, this paper tests this hypothesis, analyzing whether varying assumptions on information available to fishermen for basing spatial choices affects predictions regarding those decisions.*

Key words Spatial behavior, fisheries.

JEL Classification Code Q22.

Introduction

With the increasing use of area closure policies to regulate fisheries, understanding how commercial fishermen choose their fishing grounds has never been more important to fishery managers. Random utility models are well suited for handling discrete problems, such as choice of fishing grounds, and a small but vibrant literature is emerging (Bockstael and Opaluch 1983; Eales and Wilen 1986; Dupont 1993; Holland and Sutinen 1999, 2000; Curtis and Hicks 2000; Mistiaen and Strand 2000; Smith 2001). In constructing random utility models of commercial fishing location choices, researchers have a series of modeling decisions that precede model estimation. These decisions concern the time period over which the decisions are made, the level of aggregation of fishing locations, and the nature of the preference function. The time period may be for an individual set per fishing trip, for the trip itself, or for a fishing season. One finds examples of various time periods. The original paper by Bockstael and Opaluch (1983) modeled the choice of what fishery to pursue, which might be considered a medium-run decision. Mistiaen and Strand (2000) model the short-run decision of choice location of a fishing trip, while Eales and Wilen (1986) model the location of the first set, a very short-run decision. One of the objects of choice in a fisheries location model is the geographic area. These can be defined quite large, as in the case of Mistiaen and Strand, who aggregate longline

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fishing in the Gulf and south Atlantic into eight areas. The smaller the area, the less the aggregation bias and the greater the ability to model realistic policy measures. Yet the smaller the site, the less likely the spatial resolution of the data will provide much information about the site.

The definition of the preference function is arguably more difficult in commercial fishing than in other applications. To see why, consider the initial applications of these models to transportation choices, typically involving commuters. In these cases, knowledge of the costs and other characteristics of alternatives is common across commuters. Further, once the characteristics of different alternatives are known, commuters have little need to update their information about characteristics of choices. In the many applications of random utility models to recreational fisheries, the chief characteristics of a choice are travel cost and fishing success, typically measured as a catch rate. When the model is estimated on a cross-sectional data set, the problem of updating is limited to calculating different catch rates for different seasons. As in the commuter applications, recreational anglers have no need to update their expectations *within* a trip. In commercial fishing, the characteristics of the sites are not known, which has led researchers to specify the preference function as the expected utility of wealth or the expected utility of profits. Below, we argue for expected profits. In addition, in those fisheries in which fishermen make multi-day trips, the researcher must consider whether fishermen are able to update their expectations of returns and, if so, identify a plausible mechanism for updating this information. In any case, the correct specification and use of the model depend on a clear understanding of the behavior of the particular fishery.

Because of the uncertainty associated with fishing returns and the potential importance of updating expectations while at sea, the degree to which fishermen share information becomes relevant. Little attention has been paid to the role of information sharing in random utility models of location choice. Indeed, it is commonly assumed that fishermen have information on returns at their current site choice, as well as all other sites in the fishery, presumably through information sharing among fishermen. Yet there is no reason for fishermen to share information so freely with one another and, in fact, the evidence from the anthropology literature indicates that there is a considerable secrecy and deceit in some fisheries (Anderson 1972, 1979, 1980; Gatewood 1984; Orbach 1977; Palmer 1990). In addition, the evidence of information sharing among fishermen suggests that broad-based pooling of information does not occur, but instead is limited to small circles of fishermen who have familial or long-standing relationships. Wilson and Acheson (1980) provide further insights into the role of information sharing among fishermen, suggesting that the value of information varies across fisheries, with greater secrecy and deceit associated with more sedentary species. This is the case since the knowledge one obtains on aggregations of sedentary species lasts longer and is more valuable than is the case for migratory species.

The objective of this study is to investigate empirically how fishermen's expectations of returns are formulated by considering alternative hypotheses on what information the fishermen use to choose their fishing grounds. To conduct this analysis for the Hawaii longline fishery, we estimate random utility models for location and target choice, which involves a gear configuration choice that determines the target species. In the case of longlining, where vessels make trips that last for many days, there are numerous site choices made for each trip. Each site choice carries with it access to additional sites and eventually the necessity to return to port to sell the harvest and prevent deterioration of the fish. Consequently, the site choice may be considered a type of dynamic programming problem, where the location of the site is the state. We do not solve the dynamic programming problem, but we devise a method that accounts for the forward-looking behavior of longliners. This type of site choice is a great deal more complicated than the single choice models of Bockstael and Opaluch (1983) and Eales and Wilen (1986), incorporating evolving information and changing choice sets.

To investigate the degree of information sharing among longliners, we compare three plausible methods of calculating the economic returns to sets. The first model estimated assumes that while at sea, fishermen can update their expectations daily on returns to all location and target choices. The second model assumes that the fishermen's site choices are based strictly upon the expectations they form at port, and are not updated after each set. The third model assumes that the fishermen can only update their expectations on returns to their current location but that there is no information sharing with fishermen at neighboring sites. By varying expected returns based on the information the fisherman is believed to have access to or use, the analysis provides insights into the extent of at-sea information sharing among fishermen. A more accurate portrayal of the fishermen's expectations process improves effort allocation predictions and provides more accurate assessments of the economic impacts of an area closure.

Results showed that the third model, in which only the expectations of returns at the current fishing site were updated daily, performed statistically the best. However, all of the models predicted well (over 85% of choices were predicted correctly for all models) and, somewhat surprisingly, the model in which decisions are based strictly upon information available prior to debarking from port predicted better than the model that assumed universal information sharing among fishermen. This suggests that information sharing at sea among longliners in Hawaii may be limited and, further, that at-sea decisions may be more determined by *ex-ante* expectations (and decisions) made from port than previously realized. The ability to predict at-sea behavior based upon information available prior to the start of the trip is potentially quite useful to fishery management, particularly in those fisheries with in-season quota monitoring.

Effort Allocation in the Hawaii Longline Fishery

In Hawaii, the longline fisherman can influence catch and catch composition through his choice of production technology, henceforth referred to as targeting strategy, and through his location choice. Longliners pursue different targeting strategies by varying input usage and fishing practices (see table 1). For example, vessels targeting tuna set their gear in the morning and haul in the evening, typically setting 20–25 miles of mainline with about 1,300 hooks. Vessels targeting swordfish set 35–45 miles of mainline, with about 870 hooks and light sticks (fluorescent glow sticks) attached and fish at night. Differences in set times are due to differences in foraging habits of the species; hook usage differs because the highest-value tuna are found in the deeper waters, and the more hooks on a line, the deeper the set of the line. A mixed targeting strategy identifies vessels targeting both tuna and swordfish. A swordfish set can be distinguished from a mixed set by the high light sticks-to-hooks ratio on the swordfish set relative to that on sets in which the longliner has a mixed targeting strategy. Finally, targeting behavior varies across space. For example, 94% of the sets in which tuna is targeted occur in the most southern fishing grounds (south of 23°N) of the fishery, but less than 1% occur in the most northern fishing grounds (north of 33°N).

Modeling Locational Choices in the Longline Fishery

Constructing the Choice Alternative

To estimate a model of locational choice, we could simply define fishing areas on a sufficiently small scale that longliners can switch sites on a daily basis, and let the vessels engage in whatever targeting activity they found most attractive when they make their location decisions. A model with more choices would provide more information, both for understanding the fishery and for matters of policy. But careful analysis of the distribution of trips (table 1) suggests there are roughly three regions of the northern Pacific that serve as distinct fishing areas:

1. The northern most area, from north of 33°N, where most of the fishing is for swordfish;

2. The middle area, where the sets are for tuna, swordfish, or a mixed targeting strategy [23°N – 33°N];

3. The southern area, from 12°N to 23°N, where vessels tend to target tuna.

These areas or regions, also called fisheries, will be the three largest areas of vessel choice, denoted f in the models below. The areas do not determine completely what vessels target, however. For example, although targeting tuna is the dominant practice in the tuna region, vessels also target swordfish or employ a mixed targeting strategy in this region. Hence, even when vessels have chosen the region, they can still choose the species to target, denoted c. We model the three target species and the three regions as eight choices: swordfish, tuna, and mixed target in each of the three regions, dropping tuna targeting in the swordfish fishery as a choice since this activity does not occur. Each region-target combination (except tuna in the swordfish region) is considered a separate alternative, so that we have eight region-species alternatives, $fc = 1,\ldots,8$, where $fc = 1$ is for the swordfish region; swordfish target,

Table 1
Hawaii Longline Set and Trip Characteristics in 1998 by Target Choice

Choice Characteristics	Swordfish	Mixed	Tuna
Average number of hooks per set	867	868	1,359
Average number of light sticks per set	581	310	131
Average fuel usage per trip (gallons)	9,656	6,780	2,085
Average set time	7:00 p.m.	6:00 p.m.	8:00 a.m.
Average trip length (days)	26.2	16.8	14.8
Average number of fishing sets	14.3	11	10.1
Distance to initial site from port	778.7	510.4	223
Number of sites fished per trip	3.8	3.2	2.7
Percentage of sets in tuna fishery (12°N – 24°N)	6	14	94
Percentage of sets in mixed fishery (24°N – 33°N)	69	75	6
Percentage of sets in swordfish fishery (33°N – 45°N)	25	11	~
Trip revenue from bigeye tuna catch	$7,613	$10,861	$25,963
Trip revenue from yellowfin tuna catch	$809	$2,090	$5,925
Trip revenue from swordfish catch	$22,807	$16,869	$339
Catch deterioration	$402	$3,014	$5,642

fc = 2, is for swordfish region; mixed target, *fc* = 3, is for mixed region; swordfish target, *fc* = 4, is for mixed region; mixed target, *fc* = 5, is for mixed region, tuna target, *etc*. In this construction of the model, target species and regions are not chosen independently. The vessel chooses a region-target species as one choice.

When the vessel has chosen one of the eight region-species alternatives, the vessel then must choose the site within this alternative in which to make a set. This is the site choice, denoted *s*. Site definitions range from 2° x 3° (120 miles by 180 miles) to 3.5° x 3° (210 miles by 180 miles), which is a sufficiently small scale that does not preclude vessels from switching sites on a daily basis. We develop the location model as a nested logit model in which the angler chooses the region-fishery, denoted *fc*, and given this choice, then selects the site.[1] The number of sites defined ranges from 46 *sites* in the tuna region; 40 *sites* in the mixed region; and 51 *sites* in the swordfish region. The choices are made for each day of the trip, denoted *t*. The site choice set, conditional on fishing region-target species, is denoted M^{fc}.

To formulate a model of the location where vessels choose to fish, and the sites where their sets are taken, we need assumptions about what motivates the skipper or owner to be molded into a preference function. A clear sense of the objective function is essential to capturing the behavior correctly, as well as an essential guide to welfare measurement. There is no doubt that skippers want profits as high as possible, other things equal. But since Bockstael and Opaluch, it has been customary to assume that the skipper cares about the dispersion of profits as well as the mean. Hence, it has been the accepted practice to model the choice of location in an expected utility framework, so that the variance matters as well as the mean of profits (see Mistiaen and Strand 2000; Curtis and Hicks 2000). There are several reasons to doubt that risk aversion is an important determinant of choice of the set level. The difference among expected profit levels is relatively small at the set level. As Rabin (2000) has shown, the implication of risk aversion for small differences in income is a utility function that is quite extreme for large changes. Further, Eggert and Martinsson (2002) have survey evidence that risk aversion is not an important influence for choice among locations. While this issue needs to be investigated further, we assume that skippers make set choices to maximize expected profit and that they are risk neutral.

The Structure of the Preference Function

If this were a single choice of one set, then the nested model would be straightforward to estimate. The skipper would choose the site and fishery/catch target with the highest expected profits. But the problem is more complicated, because each site choice determines the alternatives that are available for the next choice. A vessel that has incurred the large expense of fishing distant sites in the swordfish fishery on day *t* is not likely to choose a site near to port in the tuna fishery on day *t* + 1 because he has yet to earn back his sunk cost in fuel. This is essentially a dynamic programming problem. We adopt the approach taken in Curtis (1999) and Curtis and Hicks (2000), which does not solve the complete dynamic programming problem but looks ahead at the alternatives available from each site. We assume that the fisherman's objective is to maximize the expected value of the sum of profits from the finite stream of daily fishing sets made during the course of a trip. The periodic

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[1] This is similar to Holland and Sutinen's (2000) model of the New England trawl fishery in which fishermen first choose a fishery and fishing region (*e.g.*, groundfish on Georges Bank) and then area choice within the larger region.

flow of profits consists of revenues less costs less the value of catch deterioration. Deterioration of catch plays a dynamic role that varies among species. Tuna deteriorate more quickly than swordfish, and the larger the previous harvests, the greater the loss from deterioration. Accordingly, in each period, t, the daily profits the jth fisherman expects to receive from site choice, s, conditional on having chosen fishing region-target species, fc, is defined as:

$$E(\Pi_{js,\,fc|t}|\Omega_t) = E\Big\{\Big[REV_{s,\,fc|t} - \mathbf{w}_j\mathbf{x}_{js,\,fc|t} - \alpha_s\boldsymbol{\gamma}Y_{jt-1}\Big]\Big|\Omega_t\Big\},\ s \in M^{fc}, \qquad (1)$$

where $REV_{s,fc|t}$ represent revenues in period t at site s conditional on having chosen fishery target fc; $\mathbf{w}_j$ and $\mathbf{x}_{js,fc|t}$ represent the vector of input prices and variable input usage for $k = 1,\ldots,n$ inputs, *e.g.*, fuel, bait, labor, and light sticks, of the jth fisherman using region-target strategy fc at site s; $\alpha_s\boldsymbol{\gamma}\mathbf{Y}_{jt-1}$ represents the value of catch deterioration; Ω_t is the fisherman's information set at time t; M^{fc} denotes the choice set of sites given fc is chosen. Note that profits are to be computed from available data, not estimated.

Catch deterioration is a common feature in fresh-product fisheries and helps to explain patterns of location choices through its impact on the production horizon. For example, vessels that target both swordfish and tuna during the course of a trip typically first target swordfish in the north and then switch to tuna as they return to port since swordfish has a long shelf life, and tuna is highly perishable. For each additional day at sea, the total loss in value of the jth fisherman's catch from all m species at time t from deterioration equals γY_{jt-1}, where $\boldsymbol{\gamma} = (\gamma_1,\ldots\gamma_m)$ and $\mathbf{Y} = (Y_1,\ldots Y_m)$, where $\gamma_m \geq 0$ equals the daily rate at which the accumulated value of catch of the mth species, denoted Y_m, loses value. The deterioration of value associated with accessing a more distant fishing site equals $\alpha_s\boldsymbol{\gamma}\mathbf{Y}_{jt-1} \geq 0$, where α_s equals the travel days required to access site s.

The impact of the choice of the current set on the future profits can be modeled by calculating the stream of profits. The expected value of the stream of profits from choosing s,fc in period t is defined as:

$$V(s,\ fc;\Omega_t) = E(\Pi_{js,\,fc|t}|\Omega_t) + \frac{1}{R^{fc}}\sum\nolimits_{\tau=t+1}^{T}\sum\nolimits_{r\in M^{fc}} E(\Pi_{jr,\,fc|\tau}|\Omega_\tau), \qquad (2)$$
$$r, s \in M^{fc} = (1,\ldots,R_{fc}),\ fc = M,$$

where the first term on the right-hand side (RHS) is (1), the expected profits to be added to total trip profits from the next fishing set. The second term on the RHS equals the sum of expected profits to be added to total trip profits for fishing sets $t = 2,\ldots,T$ and is calculated for each set as the average of all site profits for each region/target choice. The value of T, the number of days available for sets, is given by the number of sets the vessel actually makes.

Expressions (1) and (2) identify the need for estimates of current and future expected returns as well as the potential importance of information in formulating these estimates. Previous studies have assumed that fishermen have current information on returns at all fishing sites in a fishery; *i.e.*, perfect information sharing among all fishermen in the fishery. This paper tests this assumption by employing alternative approaches to modeling fishing returns.

Forecasting Expected Returns To Choices

To forecast daily returns to fishing sites, an autoregressive moving average model (ARMA) is used to reveal the data generating process, relating average returns to site s in period t ($REV_{s,t}$) to lagged values of these returns ($REV_{s,t-1},\ldots,REV_{s,t-\rho}$) and to current and past disturbances ($\varepsilon_{s,t-1},\ldots,\varepsilon_{s,t-\rho}$) at site s. ARMA models have also been used by Dupont (1993) for similar purposes. The general specification of the ARMA used is:

$$REV_{s,\,fc|t} = \sum_{p=1}^{T} \delta_{fc|t-p} REV_{s,t-p} + \sum_{p=1}^{T} \upsilon_{fc,t-p} \varepsilon_{t-p},$$

where $\delta_{fc,p}$ and $\upsilon_{fc,p}$ are parameters to be estimated and other variables are defined above.

To implement the ARMA for this analysis, a separate model was developed for each fishing region due to differences in the physical characteristics of each fishery. For example, in the northern waters of the swordfish fishery, the isotherm is much higher than in the temperate waters of the mixed and tuna fisheries.[2] This may, for example, affect nutrient upwellings and, more generally, species' foraging patterns, as species that are usually found over a wider range of depths are essentially compressed into a much narrower band of the water column. In contrast, the stratification of stocks permitted by the low depth of the isotherm in the tuna fishery requires longliners to use a lineshooter to target deep-water species such as bigeye tuna.

Prior to estimation, a 5% random sample was selected from the daily observations of each series to be used as an out-of-sample benchmark against which forecasting performance could be measured. The within-sample data for each forecasting model was then evaluated pairwise against alternative specifications using a general to specific model building process. Evaluation criteria consisted of the Schwarz Box Criteria, Akaike Information Criteria, and visual inspection of the autocorrelation function.

Results from testing the ARMA structure are presented in table 2. Briefly, all models revealed a first-order moving average structure, with results from both the mixed and tuna fisheries yielding an ARMA (3,1) specification, and results from the swordfish fishery yielding an ARMA (2,1) specification. Fishermen's expectations of returns to a site in future periods were forecast for sites in each fishery using the step-ahead approach.

The Empirical Model

The intertemporal model shown in equation (2) fits naturally into the nested logit framework because both impose additive separability on the utility function. The intuition of this approach is that each fisherman, facing a finite set of fishing choices on each choice occasion, chooses a fishing site from each fishery/target alternative based upon current expected profits and incorporates this information into their choice of fishery/target, which is made based upon the long-run stream of profits associated with each of these alternatives.

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[2] The isotherm refers to the depth at which the temperature is too low to support life or, in this case, pelagic species.

Table 2
Site Revenue Forecasting Model Results

Variable	Tuna	Mixed	Swordfish
δ_1	0.704	0.58618	0.435
	(9.61)*	(8.54)	(11.28)
δ_2	0.174	0.289	0.385
	(5.73)	(4.00)	(3.30)
δ_3	0.095	0.062	
	(1.90)	(2.85)	
υ_{t-1}	0.252	0.22	0.21
AIC	6,958.5	8,519.0	9,481.9
SBC	6,973.2	8,538.2	9,496.2

* Estimated parameters/standard errors in parentheses.

To form the expectation of profits at a location choice, we calculate the profits that would be computed there, updated by information about the number of boats at the site and whether the fishermen fished at the site previously on the current trip. This permits the vessel skipper to update information in a small way. The impact of the location choice on the returns for the remainder of the fishing trip is given by the term Π*STREAM*, which is a measure of the profits that would be available in future sets contiguous to the site. Dropping the subscript on time, the empirical model is:

$$\hat{V} = \beta_1 SRPROFIT_{s,fc} + \beta_2 BOAT_{s,fc} + \beta_3 SETPREV_{s,fc} + \Pi STREAM_{fc} + \varepsilon_{s,fc}, \tag{4}$$

where $\Pi STREAM_{fc}$ is calculated as:

$$\Pi\, STREAM_{fc} = \frac{1}{R^{fc}} \sum_{\tau=t+1}^{T} \sum_{r\in M^{fc}} \Pi_{r,fc|\tau}. \tag{5}$$

The role of the ΠSTREAM variable is to influence the choice of region-target species. It captures the effects of relocating from one region to another. Note that $\Pi STREAM_{fc}$ is an average of profits at the available sites in the region-target species, *fc*. *BOAT* equals the number of boats at a site; *SETPREV* is a dummy variable that equals one if the fisherman has fished at the site in the previous set, zero else; $\varepsilon_{s,fc}$ is the unobservable component of utility, which is assumed to be randomly distributed and drawn from a generalized extreme value (GEV) distribution; and *SRPROFIT* equals $\Pi_{s,fc}$, as defined in equation (1). The GEV distribution implies that choices are correlated among daily site choices within a fishery, but long-run benefits are not correlated.

BOAT and *SETPREV* are included in the model as part of the information set. *BOAT* may be indicative of the potential for information sharing at a site, with increased numbers of vessels reflecting an increased likelihood that more information sharing cliques are represented at the site. *SETPREV*, which has previously been used in location choice models to capture habit formation effects that may result in inertia, is included here to capture potential differences in information available to fishermen at a fishing site he has recently fished. There is considerable anecdotal evidence of inertia in site choice. This may occur for reasons of uncertainty about revenues or because of the costs of relocating. In a more fundamental sense, the inertia may mean that the vessel owners or captains have learned about productive fishing sites.

Based on equation (4) and the assumed error structure, the probability of choosing site *s* conditional on having chosen fishery/catch target, *fc*, can be expressed:

$$P_{s,fc} = \frac{\exp\left[E\hat{\Pi}_{s,fc}/\rho\right]}{\sum_{r=1}^{M^{fc}} \exp\left[E\hat{\Pi}_{r,fc}/\rho\right]}, \tag{6}$$

where $E\hat{\Pi}_{s,fc} = \beta_1 SRPROFIT_{s,fc} + \beta_2 BOAT_{s,fc} + \beta_3 SETPREV_{s,fc}$. Estimation of equation (6) provides estimates of the vector of coefficients β/ρ, where ρ provides a measure of substitutability of sites within fishery/target choices. These estimates are used to construct the inclusive value (*INCVAL*), a measure that captures information from the short-run site decision and incorporates it in the long-run fishery/target choice and is defined as:

$$INCVAL_{fc} = \log \sum_{r=1}^{M^{fc}} \exp E(\hat{\Pi}_{r,fc}/\rho).$$

The probability of choosing site *s* conditional on having chosen fishery/target *fc* is:

$$P_{fc} = \frac{\exp(E\hat{\Pi}_{fc})}{\sum_{gd=1}^{M^{gd}} \exp(E\hat{\Pi}_{gd})}, \tag{7}$$

where $E\hat{\Pi}_{fc} = \phi_1 \Pi STREAM_{fc} + \rho INCVAL_{fc.}$ Estimation of ρ from equation (7) enables the β coefficients to be identified.

Data on Inputs, Sets, and Prices

Overall, 113 longline vessels completed 11,785 fishing sets on 1,101 trips in 1998. Logbook data contains detailed set-level information on the date, location, input use, and catch of each species on all longline trips. From this data, travel distances can be calculated and daily hook and light stick usage is obtained. Fish landings and price information are obtained from a random sample of sales at a fresh-fish auction in Honolulu at which fish are auctioned individually. Information on input costs and fuel and bait usage is from a cost-earnings survey of the Hawaii longline fleet that initially collected information on 1993 operations and updated in 1997.

Empirical Results

The empirical issue we address concerns information the fisherman uses to base expectations of returns to fishing alternatives. To provide insights into this issue, three models are estimated and compared. In the first model, referred to as the "Updating Model," it is assumed that fishermen are able to update their expectations on returns to site and fishery/target choices daily for the site at which they are currently fishing, as well as all neighboring sites. The fishermen's expectations of returns for other fishery/target choices are also updated daily in a like manner.

In the next model, referred to as the "No Updating Model," it is assumed that the fishermen's decisions are based upon the expectations they form at port. That is, if the fisherman left port on the first of the month, his expected returns on the eleventh are not based upon one-step-ahead forecasts made on the tenth using information from say the eighth through the tenth, as in the Updating Model. Instead, in the No Updating Model, expected returns on the eleventh are based upon 10-step ahead projections made on the first of the month. In No Updating, the only new 'information' the fisherman acquires from fishing is his location, the number of vessels at a site, and whether he has fished at a site previously. In the third model estimated, "Mixed Updating," it is assumed that the fisherman updates his expectations on returns to fishing sites he has recently or is currently fishing at but uses information acquired at port on returns to other alternatives. That is, it is assumed that there is no information sharing among fishermen operating at different locales.

Table 3 shows the site choice and fishery/target choice results for all models estimated including estimated coefficients and their *t*-statistics, the pseudo-R^2, and the percentage of correctly predicted choices for each model. With the exception of *SETPREV* in the Mixed Updating Model, all coefficients of the site choice nest are of the expected sign and are significantly different from zero, at least at the 5% level in all models. In particular, an increase in the expected profits at a site, *SRPROFIT*, has a positive effect on the probability of that site being chosen in all three models. *SETPREV* is insignificant in the Mixed Updating model, which assumes that fishermen only have current information on which to base their expectations of fishing returns at their current site. For all other sites, they must base their expectations on information gained while at port. This result may suggest that controlling for differences in information available to a vessel may better explain location persistence than simply attributing this behavior to inertia effects.

In the fishery/target choice nest, an increase in the expected profits (Π*STREAM*) has a positive effect on the probability of a fishery/target alternative being chosen in all models. In addition, the coefficient on the inclusive value (*INCVAL*) is within the theoretical bounds, (0,1), for all models. Note that the coefficient on *INCVAL*, which is indicative of the influence of the site choice decision on the long-run path, is

Table 3
Empirical Results of Nested Logit Models

	Updating	No Updating	Mixed Updating
SRPROFIT	0.00806	0.0064	0.00876
	(10.619)*	(8.987)	(9.347)
SETPREV	22.818	26.414	22.819
	(63.076)	(46.873)	(.037)
BOAT	0.04039	0.1029	0.04037
	(8.926)	(30.662)	(29.145)
Π*STREAM*	0.00349	0.00124	0.00447
	(10.860)	(1.992)	(11.012)
INCVAL	0.532	0.682	0.524
	(34.380)	(44.784)	(40.633)
Site Pseudo R^2	0.72	0.65	0.86
Fishery/Target Pseudo R^2	0.53	0.44	0.71
Percentage of Choice Occasions Correctly Predicted	86.6	91.1	94.7

* Estimated parameters with *t*-statistics in parentheses.

greatest for the No Updating Model. This difference may be due to the fact that the values of *INCVAL* are higher relative to Π*STREAM* in the No Updating Model, the latter of which are of relatively lower value in the No Updating Model than in the other models because of the substantially longer forecasting stream.

An additional test of the models is their predictive ability. The Updating Model predicts choices well, but the No Updating Model predicts marginally better. Mixed Updating has the highest explanatory power in terms of the R^2, as well as the highest percentage of accurately predicted choices.

Measuring the Welfare Effects of Area Closures

Although the expected signs of the coefficients estimated in a random utility are intuitive, the actual parameter estimates are not. To provide greater context to the model comparison of this analysis, we consider an area closure policy that NMFS recommended in 2000 to reduce longline interactions with sea turtles. This policy recommended closing the fishing grounds between 30°N to 44˚N between 137˚W and 173˚E throughout the year, and during April and May, closing the area between 23˚N and 44˚N as well as between 6˚N lat. and 16˚N lat. between 137˚W and 173˚E. The welfare measure we adopt is that proposed by Curtis and Hicks (2000), which reflects the amount a fisherman needs to be compensated at the start of a trip in order to equate his expected benefits from a trip after the closures with his pre-closure level of expected benefits. This payment is the amount of profits, denoted Π_w, that will make the fisherman indifferent between the alternatives before and after the closure:

$$\Pi^1(\Omega_t) + \Pi_w = \Pi^0(\Omega_t),$$

where

$$\Pi^1(\Omega_t) = \log\left(\sum_{fc=1}^{M}\left[\sum_{r=1}^{M^{fc1}} \exp(E\Pi_{s,fc|t}) + \frac{1}{R}\sum_{\tau=t+1}^{T}\sum_{r=1}^{M^{fc1}} (E\Pi_{r,fc|\tau})\right]^{1-\sigma}\right)$$

is expected maximum profits and Π^0 represents expected maximum profits before the closure. $\Pi^1(.)$ is calculated for those sites in each fishery, M^{fc1}, still open after the closure. The idea of expected maximum profits is that the researcher does not have full information about the profit function and so does not know the choices of the vessels. Taking the expected maximum profit accounts for the researcher's uncertainty. Even for vessels that don't visit the closed sites, the probability that they will visit influences the welfare measure. For firms that have higher probability of visiting the closed sites, the welfare loss will be higher.

Welfare estimates from each model are shown in table 4 for each targeting strategy. Overall, the models yielded similar results, with swordfish fishermen needing to be compensated the most for lost profits due to the closure ($11,200 to $16,000), and tuna fishermen needing to be compensated the least ($700–$900). The higher welfare losses for swordfishing stem, in part, from their longer trips and in part because the closure eliminated more sites in the swordfish region. Compensation to mixed-target fishermen for lost profits due to the closure ranged from $4,800 to $7,300. All compensation schemes under the Mixed Updating model were higher than those calculated under either the Updating or the No Updating models.

Table 4
Welfare Estimates from Turtle Closures

	Updating	No Updating	Mixed Updating
Swordfish	$14,378	$11,219	$16,040
Mixed	$6,522	$4,790	$7,256
Tuna	$735	$869	$880

Conclusions

Overall, the model that performed best was that in which expected returns at the current fishing site were based upon information that was updated daily, but expected returns at neighboring and more distant sites were based upon information available prior to debarking from port. This may suggest that while some information sharing among longliners may occur at sea, it may be limited. Alternatively, it may indicate that the longliners have little ability to respond to new information on more distant fishing sites once at sea or do not trust the information.

While the No Updating Model was not as statistically reliable as the Mixed Updating Model, it outperformed the traditional approach to measuring returns at a site; i.e., assuming the fishermen have current information on returns at all sites in a fishery and also had a respectable number of accurate predictions. The ability to predict at-sea behavior based upon information available prior to the start of the trip is potentially quite useful to fishery management. For example, in fisheries with in-season quota monitoring, it may be possible to more accurately predict when the quota has been reached. More generally, the results underscore the need for behavioral models in fishery economics that account for *ex-ante* decision making, such as ex-ante cost functions, which have been more widely applied in the agricultural economics literature but have yet to gain prominence in the fisheries economics literature despite the stochastic nature of fishery production.

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