A Spatial Model of Dolphin Avoidance in the Eastern Tropical Pacific Ocean

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Working Paper Number 25

January 2006

COLLEGE OF WILLIAM AND MARY
DEPARTMENT OF ECONOMICS
WORKING PAPER # 25
January 2006

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Abstract

This paper examines the impact of dolphin-safe eco-labeling and how it fundamentally altered the spatial distribution of fishing effort and fishermen's willingness to pay to avoid dolphins. To do this, a dynamic discrete choice econometric model is applied to the Eastern Tropical Pacific tuna fishery. This econometric approach combines a dynamic programming component with the static discrete site choice model. This estimator couples the current period projected profits associated with fishing a specific site with the value of all future location choices on the cruise, assuming choices are made optimally. The key feature of this model is that it recovers behavioral parameters and solves the dynamic programming problem recursively. The dynamic site choice model reveals a markedly higher impact on producers as compared to the commonly used static model following the labeling regime. Further, in all but a few cases the common practice in dynamic choice models of setting discount factors equal to one is rejected.

JEL Codes: C35, Q20, Q58

Keywords: location choice, dynamic random utility modeling, dolphin-safe eco-labeling.

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I. Introduction

Eco-labeling has been touted as a way for consumer preferences for environmentally benign products to be transmitted in markets. The label, as the argument goes, provides information to consumers who may then pay a price premium for the labeled products. Producers view demand for the eco-labeled products as quality differentiated and defined by the producer's production method. With a high enough price premium for the "green" good, producers may alter production practices to meet labeling certification requirements. Sedjo and Swallow [34] and Basu et al. [2] have examined the welfare implications of labeled products in a general equilibrium setting.[1] Their findings regarding when a labeling program is likely to send positive signals to producers shows that the cost of choosing the green method of production is a significant determinant, along with consumer preferences. While many studies have examined the demand side of eco-labeling (Gudmundson and Wessels [11]; Bjorner et al. [4]; O'brien and Teisl [26]; and Nimon and Beghin [25]) including the dolphin-safe labeling program (Teisl et al. [42]), little attention has been devoted to the impacts on producers from labeling programs. This paper examines the impact of dolphin-safe tuna labeling on fishermen's production practices and spatial choices in the Eastern Tropical Pacific Ocean (ETP hereafter).

To examine this question, a model of fishing that links fishermen's spatial choices during a cruise is developed. This model is premised on the assumption that fishermen choose an optimal cruise trajectory and do not make spatial decisions myopically. Since the dolphin-safe standard of the early 1990s required fishermen to avoid dolphins for the entire cruise, we believe that this model of fishing can better describe behavior than the commonly employed static site choice model. In contrast to the restrictive static model which only considers the current period rewards from choosing a site, our model allows fishermen to base their site choice decisions on current fishing conditions and what they believe will happen in the future. Our model, therefore, allows fishermen to spatially hedge by choosing areas that are situated near other attractive fishing sites while avoiding dolphin bycatch.

Although it is well accepted by neo-classical economists that agents behave dynamically when faced with inter-temporal discrete choices, the econometric modeling of this behavior has not been as prevalent as static discrete choice modeling. In natural resource economics, the use of dynamic discrete choice modeling is complicated by the dimensions of the choice set, the

[1] Basu et al. [2] examine the general implications for guaranteed child labor free products. However, their theoretical findings yield insight for eco-labels.

endogenous evolution of an agent's information, and the length of the time horizon studied. Researchers have been successful in the application of dynamic econometric techniques to problems having small choice sets because these models are tractable when the number of choice alternatives is small. For problems having a large numbers of choices, the dynamic implications of site choice are commonly ignored and agents are assumed to behave myopically. This is because the dynamic methods traditionally used become intractable when the choice set expands.

To tackle problems where dynamic choices are being made *and* where there exist many choice alternatives and a large state space, we offer a computationally tractable middle ground estimator. In order to approximate dynamic behavior, our model assumes that the state space is known to the agent prior to taking their actions, thereby eliminating the stochastic evolution of the state space. While this assumption may seem restrictive, it is likely suitable for a large number of problems where the cost (to the agent) of obtaining and updating information for a large number of alternatives is high, yet the agent is adopting a decision rule that approximates dynamically optimal behavior. This model therefore assumes that fishermen base their site characteristic expectations during a cruise on previously observed conditions. Hicks and Schnier [14] have investigated the suitability of this dynamic model for a wide range of fishery types using simulation methods. A key finding in their work is that when potential distances traveled are large relative to the value of catch and/or the resource is heterogeneously distributed the dynamic estimator is preferred to the static random utility model (RUM). In this paper, we argue that the ETP tuna fishery, because of its spatially dynamic characteristics, lends itself to the dynamic random utility model (DRUM) proposed by Hicks and Schnier [14].

Since its first use in the fishery economics literature by Bockstael and Opaluch [5] to investigate the supply response decision of fishermen in New England fisheries, the multinomial logit model has been the standard method employed to estimate RUMs in fisheries. It has been utilized to investigate location choice in both the pink shrimp fishery (Eales and Wilen [10]) and in the New England groundfish fishery (Holland and Sutinen [15], [16]).[2] Extending this model to a nested-logit framework, other researchers have utilized static RUMs to investigate sea turtle conservation areas (Curtis and Hicks [8]), marine protected areas (Smith and Wilen [40], [41]) and essential fish habitat conservation areas (Hicks et. al. [13]). Furthermore, these studies have spanned a diverse range of fisheries, from the sedentary sea urchin along the coast of Northern California (Smith [38]; Smith and Wilen [40], [41]), to highly migratory species in the Pacific

[2] For a more in-depth discussion of the use of discrete choice models is fisheries see Smith [37].

Ocean (Curtis and Hicks [8]) as well as the Atlantic Ocean (Mistiaen and Strand [23]). One common denominator shared by all of these papers is that they do not explicitly account for the inter-temporal aspects of commercial fishing site choice; they lack a rigorous dynamic discrete choice framework.[3]

The application of dynamic discrete choice models in the natural resource economics literature has been limited by the curse of dimensionality. However, these models have been successfully used to solve the optimal stopping rule in forest rotation policy (Provencher [27]), recreational angling in the Great Lakes (Provencher and Bishop [28]) and search behavior in the Northern California sea urchin fishery (Smith and Provencher [39]). In addition, these models have been used in agricultural economics to study the dairy cow replacement decision (Miranda and Schnitkey [20]). The foundation for these models is the full-solution method developed by John Rust [29], which was initially used to analyze bus engine replacement decisions and has subsequently been used to investigate an individual's retirement decisions (Rust and Phelan [31]).[4]

The aforementioned studies have utilized the dynamic discrete choice framework because the static assumptions made in the RUM are too restrictive given the purpose of their research. They have also awakened other researchers to consider the dynamic nature of decision environments, as a realistic depiction of many observable choices possesses a dynamic component. This has stimulated an area of research to develop middle ground estimators which are computationally tractable, yet capture the essence of complex dynamic programming models. Although dynamic programming models elegantly allow for the stochastic evolution of the state space within the discrete choice model, they become intractable as the choice set increases. The limitations of these models will presumably be reduced as computer processor speeds and memory capacity increase. However, with large choice set problems they will still exist and a middle ground estimator will be required to approximate dynamic behavior.

In the fisheries literature several middle ground estimators have been investigated. These estimators essentially append a proxy for the agent's future rewards from choosing a site to the

[3] Curtis and Hicks [8] approximate dynamic behavior by estimating the income stream from the duration of the cruise given a particular site selection. However, the method used is *ad hoc* and does not formally estimate the dynamic model.
[4] There are two conventional methods used to estimate stochastic dynamic programming models; they are full solution methods proposed by Rust [29] and the non-full solution methods developed by Keane and Wolpin [19]. The model utilized here parallels the full solution method developed by Rust.

static model without resorting to stochastic dynamic programming methods. Expanding the multinomial logit model of site selection in fisheries, Curtis and Hicks [8] incorporate the expected future value and variance of wealth to investigate sea turtle closures off the coast of Hawaii. They construct the expected future value of wealth in a given site by extrapolating the current site specific returns forward in time utilizing a spatially weighted return function. They used these variables of location specific future returns to capture quasi-dynamic behavior. In a similar effort to expand the static RUM to incorporate dynamic information, Baerenklau and Provencher [1] recently proposed appending the RUM to include two individual specific constants to represent the expected utility of taking two alternative actions, the decision to take a fishing trip or not. In addition they employed a random effects framework for both options to help control for agent heterogeneity. Both of these models attempt to use static models to approximate dynamic behavior. However, neither directly estimates behavioral parameters which influence the current period rewards as well as the value of future optimal behavior. Rather, each study utilizes an additive utility framework with the dynamic component separately identified. The model we propose estimates behavioral parameters that influence *both* the contemporaneous component of expected utility as well as the value of future optimal spatial behavior simultaneously.

The model developed herein is limited by the fact that we assume all information is deterministic and known to the agent prior to making their site choice decision in any period. If this assumption is relaxed, we would be forced to estimate the model via stochastic dynamic programming or utilizing a random grid search algorithm (Rust [30]), which would be intractable given the dimensions of the state space used in this research. However, it is important to note that the information assumed to be possessed by agents in our dynamic model is the same as both the conventional static models discussed earlier and the approximations of dynamic behavior proposed by Curtis and Hicks [8] and Bearenklau and Provencher [1]. Therefore the data requirements are very similar to the conventional models used in the discrete choice literature.

In the following section we outline the DRUM and the requirements relative to the static model. Section three provides a brief discussion of the ETP tuna fishery and the time period over which our study is conducted. It also elaborates on the significance of the dolphin-safe tuna labeling initiatives in the late 1980’s and early 1990’s. The fourth section summarizes our results and the final section discusses the importance of modeling dynamic behavior and the potential future applications of the DRUM developed.

II. Dynamic Random Utility Modeling (DRUM)

The DRUM estimator we propose degenerates to the static RUM whenever the discount factor is equal to zero, whether by assumption or as revealed by agent behavior. Therefore, we will briefly discuss the RUM and then expand it to reflect the addition of dynamic decision making. Assuming that there exist N alternatives (ie. feasible fishing locations), the indirect utility function for location j in time period t is denoted,

$$\bar{v}_{jt} = R(x_{jt};\beta) + \varepsilon_{jt} \tag{1}$$

where, x_{jt} is a vector of location specific characteristics which may vary over time and space and β is a parameter vector of preferences.[5] Within the fisheries literature x_{jt} often contains location specific information on expected revenues, expected climatic conditions and the distance traveled from one site to another, to cite a few. The agent knows $\bar{v}_{jt}$ with certainty, whereas the researcher only observes $R(x_{jt};\beta)$. Therefore, it is assumed that research does not observe the random error component ε_{jt}. Agents are assumed to select alternative j whenever the following is true,

$$\bar{v}_{jt} \geq \bar{v}_{kt}, \forall j \in N, \forall k \in N. \tag{2}$$

Therefore, the agent's unconditional expected utility at each time period t is,

$$R_t = \max\{R(x_{1t};\beta) + \varepsilon_{1t}, R(x_{2t};\beta) + \varepsilon_{2t}, R(x_{3t};\beta) + \varepsilon_{3t}, ..., R(x_{Nt};\beta) + \varepsilon_{Nt}\}. \tag{3}$$

Assuming that the random error component, ε_{jt} , is independently and identically distributed with an extreme value distribution, the probability that an agent selects alternative j in time period t can be expressed as,

[5] The indirect utility function may also possess variables which are assumed to only vary across time such as vessel specific characteristics, e.g. the number of crew members on board, but since our empirical application does not include this information we have elected to not incorporate this information in the indirect utility function.

$$\Pr(j) = \frac{\exp(R(x_{jt};\beta))}{\sum_{i=1}^{N}\exp(R(x_{it};\beta))}. \tag{4}$$

In a complete dynamic model the state space x_{jt} is assumed to be path dependent and evolve stochastically across time. This assumption has substantially reduced the adoption of dynamic discrete choice models due to the computational difficulties required to obtain parameter estimates. In the DRUM all of the observations in x_{jt} are assumed to be deterministic except for the distance traveled from one location to another. Therefore, the choice made in time period t effectively defines the distance traveled, and hence the travel costs that must be expended to reach each of the N alternatives at time $t+1$. When the distance traveled between sites and/or the costs of traveling are high, the importance of a current period choice on future payoffs is magnified. The choice alternatives in our study are sets made while on a fishing trip. Therefore, our application of the DRUM estimates intra-cruise dynamic behavior; however it could be extended to other types of dynamic behavior as well.

In the DRUM estimated in this paper the endogenous evolution of the state space is defined by the evolution of the distance traveled from one site to another but it could be expanded to include experience at sites, cumulative catch during the cruise, or a state dependent mechanism for updating expectations (Smith [38]). However, for simplification we focus only the evolution of the state space implied by the distance traveled from one site to another within a fishing cruise. This simplification allows us to extend dynamic discrete choice modeling to situations having numerous choice alternatives and long time horizons. The DRUM broadens the RUM by allowing the agent to consider the impact of current period choice on all future choices. In the DRUM, the agent's objective function in time period t is to maximize,

$$E\left[\sum_{\tau=t}^{T}\delta^{\tau-1}\sum_{k=1}^{N}v_{kt}d_k(\tau)\,|\,S(\tau)\right]. \tag{5}$$

E[.] represents the agent's expectation operator, δ is the discount factor, $d_k(\tau)$ is a binary control variable indicating whether site k is chosen in time period τ, $S(\tau)$ is the current state variables observed by the agent in time period τ which consists of all the x_{jt}*'s* in time period τ and v_{kt} is as defined earlier. To maximize this objective function each agent must select a sequence of binary control variables, $d_k(t)$ for $t=0,\ldots,T$ indicating which site is selected in each time period.

In the absence of forward looking behavior equation (5) degenerates to equation (3) as the future optimal rewards given an agent's current state is fully discounted. However, if future optimal rewards are not fully discounted the agent's maximum discounted expected utility is,

$$V_k(S(t),t) = \max_{\{d_k(t)\}_{k\in N}} E\left[\sum_{\tau=t}^{T} \delta^{\tau-1} \sum_{k=1}^{N} v_{kt} d_k(\tau) \mid S(\tau)\right] = \max_{k\in N} \{V_k(S(t),t)\} \tag{6}$$

where, $V_k(S(t),t)$ is the alternative specific value function of choosing the k^{th} site in time period t. The value function, $V_k(S(t),t)$ depends on the state space $S(t)$ observed in time period t and follows the Bellman equation (Bellman [3]),

$$V_k(S(t),t) = \begin{Bmatrix} \bar{v}_k + \delta E[V(S(t+1),t+1) \mid S(t), d_k(t)=1] \ldots for \ldots t \le T-1 \\ \bar{v}_k \ldots for \ldots t = T \end{Bmatrix}. \tag{7}$$

Given the definition of $\bar{v}_{jt}$ defined in equation (1), the value function can be rewritten as,

$$V_k(S(t),t) = \begin{Bmatrix} R(x_{kt};\beta) + \varepsilon_{kt} + \delta E[V(S(t+1),t+1) \mid S(t), d_k(t)=1] \quad for\ t \le T-1 \\ R(x_{kt};\beta) + \varepsilon_{kt} \ldots for \ldots t = T \end{Bmatrix}. \tag{8}$$

Given this formulation, the agent selects the optimal trajectory of discrete choices which maximizes their contemporaneous expected utility as well as the expected discounted returns from a fishing trip (cruise) of length T. In the DRUM application to the ETP tuna fishery we assume that T is known prior to leaving port; however this assumption can be relaxed by altering the value function expressed in equation (8). The expected discounted reward function, $\delta E[.]$, complicates the estimation procedure as it must be solved using backwards recursion and estimating the value function involves a multi-dimensional integral over the vector of random elements, $\{\varepsilon\}$. Rust's conditional independence assumption simplifies the latter complication, which assumes that the errors are distributed multi-variate extreme value, are conditional on the observable state variables, and are serially independent (Rust [29]). This simplification allows the expected discounted reward function $\delta E[.]$, to be depicted as an additively separable value function which may be solved recursively and depicted as follows,

$$\delta E[V(S(t+1),t+1) \mid S(t), d_k(t)=1] = \delta\left(\gamma + \ln\left[\sum_{k\in N} \exp(\bar{v}_k(\bar{S}(t+1),t+1)\right]\right), \tag{9}$$

where, γ is Euler's constant and

$$\bar{v}_k(\bar{S}(t+1),t+1) = R(x_{jt+1};\beta) + \delta E[V(S(t+2),t+2) \mid S(t+1), d_k(t+1)=1] \tag{10}$$

is the expected conditional value function in time period $t+1$ for each of the k alternatives. Using the conditional independence assumption the alternative specific reward function in time period t, $V_j(S(t),t)$, can be expressed as,

$$V_j(S(t),t) = R(x_{jt};\beta) + \varepsilon_{jt} + \delta\left(\gamma + \ln\left[\sum_{k\in N} \exp(\bar{v}_k(\bar{S}(t+1),t+1)\right]\right) \tag{11}$$

where all parameters are as defined earlier. The addition of the third term in equation (11) defines the difference between the RUM and DRUM. The parameter vector, β, must not only determine the contemporaneous indirect utility of selecting location j, it must also fit the additively separable expected value of future optimal behavior from the current time period forward to time period T. This is easily seen focusing on $V_j(S(T-1),T-1)$ where equation (11) becomes,

$$V_j(S(T-1),T-1) = \max\left\{R(x_{jT-1};\beta) + \varepsilon_{jT-1} + \delta\left(\gamma + \ln\left[\sum_{k\in S} \exp(R(x_{kT};\beta)\right]\right)\right\}. \tag{12}$$

Further recursions of the value function compounds the nesting of the parameter vector, β, and the discount factor, δ, within the value function. Given the assumed properties of the DRUM, the probability that an agent selects option j in time period t can be represented as,

$$\Pr(d_j(t)=1 \mid x;\beta) = \frac{\exp\left(R(x_{jt};\beta) + \delta\left(\gamma + \ln\left[\sum_{k\in N} \exp(\bar{v}_k(\bar{S}(t+1),t+1)\right]\right)\right)}{\sum_{k\in N} \exp\left(R(x_{jt};\beta) + \delta\left(\gamma + \ln\left[\sum_{k\in N} \exp(\bar{v}_k(\bar{S}(t+1),t+1)\right]\right)\right)} \tag{13}$$

which can be estimated using a multinomial logit likelihood function following the backward recursion formulation of $V_j(S(t),t)$. The similarities of the RUM and DRUM are readily evident when we assumes that $\delta = 0$ because equation (13) degenerates to equation (4), thus depicting the "middle ground" properties of the DRUM estimator.

Estimation of equation (13) is accomplished using limited information maximum likelihood (LIML) techniques.[6] Given starting parameters for β a gradient-based search algorithm is used to obtain parameter estimates that maximize the likelihood function. Rust pointed out that the discount factor is often highly collinear with the parameter estimates (Rust [29]). Therefore, obtaining estimates for the discount factor δ requires a separate search over the feasible parameter space to obtain estimates which maximize the likelihood function. Alternatively, one can assume a discount factor with the understanding that the parameter estimates obtained are contingent on the assumed discount factor. To obtain estimates of δ within this paper we utilize the former method as we discovered that the parameter estimates of β vary substantially depending on the assumptions made regarding δ. The method used to conduct the search for the optimal discount factor, δ^*, is discussed following the description of the data. In addition, we compare the parameter estimates for the optimal discount factor with those obtained when we assume that discount factor is zero (static RUM) and one, where one is often chosen in the literature when the time horizons are short (Rust [29]; Provencher [27]; Provencher and Bishop [28]; Bearenklau and Provencher [1]; Rust and Phelan [31]).

One practical concern in implementing the DRUM is the proper characterization of the site-specific reward function using observable data and whether the characterization is dynamically consistent. To appreciate the importance of this consideration, note that an important independent variable in site choice models of commercial fishing, the expected site-specific revenue, is sometimes calculated based on a 10 day or 30 day moving average of site-specific revenues. Studies employ moving averages of recent activity because it approximates the information on the most recent fleet activity that is likely to influence site choice. Using this data in the dynamic model in equation (13) may yield an endogeneity problem. For instance, if one is using 10 day moving average revenues at each site as a site selection predictor on the first day of the cruise and the cruise is expected to last 20 days, using this information within the value

[6] The maximum likelihood routine was maximized using the GAUSS Constrained Maximum Likelihood (CML) procedure.

function would be dynamically inconsistent. This is because future site selections (in periods 2, 3, .., 11) would be incorporating information from the site choice in time period one even though the site choice has not yet been made. To rectify this we use non-overlapping data for the time length of the cruise T^C, where T^C is a calendar measure of time, used in the Bellman equation.[7] Lagging site specific revenues by at least the calendar length of the cruise will ensure that the information used to calculate the Bellman equation does not include information about actions which have not yet been made.[8]

Following estimation of equation (13) the parameter estimates obtained from the DRUM have a similar, albeit mathematically different, interpretation as those obtained from the static RUM in equation (4). Haab and McConnell (2002) have shown that for a Δq_t change in site quality in the static RUM, the willingness to pay (WTP) for this change in site quality at *all* sites can be written as,

$$WTP_t(\Delta q_t) = \frac{\Delta q_t \beta_q^s}{\beta_{REV}^S} \tag{14}$$

where, β_q^S is the marginal utility for site characteristic q and β_{REV}^S is the marginal utility of revenues (the superscript S indicates the parameter estimates are from the static RUM). A similar expression can be obtained for the DRUM (denoted by the superscript D), where the WTP in each time period between the current time period, t, and the final time period, T, for a Δq_t change at all sites is,

$$WTP_\tau(\Delta q_\tau) = \frac{\Delta q_\tau \beta_q^D}{\beta_{REV}^D} \quad \forall \tau = t,...,T \tag{15}$$

[7] A distinction is made between the T used in equations (6) through (13) and T^C because in our application T does not need to correspond with an explicit calendar time step but to an interval step in the agent's choice set. Whereas, T^C references the time horizon over which the data used to estimate dynamic behavior is defined.

[8] Should the researcher find that site selection is highly dependent on behavior in the recent past and that the assumption fisherman calculate the optimal cruise trajectory prior to leaving port is overly restrictive, the model in equation (13) can be estimated using non-lagged data provided agents update the Bellman each period conditional on the new information available to them at that time. Since the value function is updated each period, this substantially increases the number of times that the Bellman equation must be evaluated for each candidate parameter vector during estimation. For fisheries with only a few time steps this is feasible, but for fisheries with exceptionally long cruise lengths this significantly reduces the convergence speed of the LIML estimates of β and the search for δ*. In addition, if the researcher allows for continuous updating of the Bellman then the dynamic consistency concerns must be considered.

The proof of equation (15) is contained in the appendix.[9] Although the WTP measures expressed in equations (14) and (15) are identical, they will yield different estimates whenever the parameter estimates obtained from the RUM and DRUM differ. This will be the focus of our empirical application as we discovered substantial differences in the WTP's resulting from the informational assumptions implied under both models. The following section discusses the dataset used in our empirical application, the ETP tuna fishery, as well as the precise specification of the econometric model and data requirements.

III. Data Description and Model Specification

Large purse seiners have been catching tuna in the ETP since the early nineteen-sixties.[10] These vessels, typically some 220 feet in length, deploy seines that are as long as one mile and reach a depth of 600 feet deep in the water column.[11] Purse seiners in the ETP have caught tuna using one of three predominant methods. In the first method (referred to as a log set), floating debris is targeted since it is known to attract tuna. Purse seiners spot the debris, encircle it with their nets, and capture tuna. Schools of tuna, once spotted, are also targeted (this method is referred to as school sets). Schools often move quickly, and encirclement usually requires small speedboats to herd tuna. By far the most predominant method of capturing tuna in the ETP involves dolphins (referred to as 'dolphin sets'). In the ETP, tuna are often found near dolphins. Compared to school and log sets, purse seiners can more easily spot dolphins than tuna or logs, since dolphins surface often for air. The search for tuna typically involves crew with binoculars, speedboats, and helicopters that are launched off of the purse seiner. The degree of searching effort does differ across fishing methods, with log and school sets typically requiring more search activity. Using some combination of these three methods of fishing, vessels typically set their gear in the water an average of 44 times during a cruise.[12]

From the fisherman's perspective, the ease of spotting dolphins coupled with the very strong

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[9] It is evident from the proof, that equation (15) holds for any quality change and WTP stream, so long as Δq and WTP are experienced in the same period(s) in the future.

[10] In what follows, we summarize facts presented in two important documents describing tuna fishing in the Eastern Tropical Pacific Ocean: National Research Council [9] and U.S. International Trade Commission [43].

[11] A 'set' refers to putting the seine in the water. A 'cruise' is comprised of a series of 'sets' made before returning to port.

[12] This average is over the years 1979 through 1992 for the U.S. monitored fleet in the ETP.

association of large and valuable tuna with dolphins led to dolphin fishing being the most dominant method of fishing in the fishery (Joseph [18]). Unfortunately, the process of encircling dolphins with the seine often leads to dolphin mortality. While mitigation efforts by the U.S. vessels in the industry drastically reduced dolphin mortality during the nineteen-seventies and eightees, fleet-wide kills by U.S. vessels routinely exceeded yearly totals set forth by the U.S. Secretary of Commerce as directed under the U.S. Marine Mammal Protection Act.[13] Also, the U.S. fleet was required to employ observers who recorded various data on the cruise including location, amount of catch, sea conditions, the type of set, and dolphin mortality. At the same time that the U.S. vessels were being required to use mitigation efforts to reduce dolphin kills, foreign vessels in the fishery were fishing on dolphins and were responsible for a significant level of dolphin mortality.[14] In 1987, the famous Labudde video was aired on numerous national news outlets showing the sometimes brutal treatment of dolphins by the ETP purse seine fleet. Shortly thereafter, the Secretary of Commerce embargoed all foreign tuna that was caught without using the U.S. prescribed mitigation efforts.[15]

The embargo was eventually lifted because a General Agreement on Tariffs and Trade panel ruled that products could not be discriminated against based on production practices and methods, thereby setting the stage for dolphin-safe labeling in the United States. Although import restrictions were off the table, it was possible to label products differently depending on how it was produced. Tuna from cruises that consisted exclusively of school or log sets could be labeled "dolphin-safe", while tuna associated with a cruise that at any time fished on dolphins could not. U.S. canneries began labeling dolphin-safe tuna in April of 1990 and soon thereafter, the Dolphin Protection Consumer Information Act placed government credibility behind the label.

Our study uses data collected by the National Marine Fisheries Service as part of the U.S. observer program of purse seine fishing in the ETP.[16] For the time period considered in this study, all large purse seine cruises required the presence of observers. Consequently, the data completely characterizes U.S. flagged tuna purse seiners fishing in the ETP. Figure 1 shows the

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[13] However, the U.S. fishery was closed only in 1986 due to too much dolphin mortality. In other years, the quota was exceeded, yet the fishery was not closed.
[14] Mitigation efforts included installing a Medina Panel on the seine (to submerge some parts of the seine during a process known as backing down), using swimmers to lift dolphins over the seine, and avoiding fishing during nighttime and heavy seas).
[15] Brower [6] provides an excellent summary of the Labudde video and a sense of the public uproar surrounding the issue.
[16] The observer program of tuna purse seiners in the ETP is currently administered by the Inter-American Tropical Tuna Commision.

spatial extent of the fishery for each of the three set types in the ETP fishery. Notice the extremely large spatial extent of the fishery. Vessels during the period 1979-1992, on average, travel 14,000 miles and switch areas (the grids in Figure 1) 7.7 times during a cruise. Additionally, significant changes in location (of at least 1000 and 2000 miles) occur, on average 2.87 and 2.00 times per cruise, respectively. The choice of location is the single most important decision made during a cruise. Figure 1 also demonstrates the concentration of log and school sets predominantly near coastlines, while dolphin sets occur throughout the geographic range of the fishery.

To be certified as dolphin-safe, fishermen had to fish on log and school sets for the entire cruise. The dolphin-safe definition greatly reduced the geographic range of the fishery (see Figures 2 and 3 for the dolphin-safe and non dolphin-safe cruises made after the institution of the label). The label effectively eliminates entire areas of the ocean to fishing by requiring fishermen to target schools and logs for an entire cruise. While in a probabilistic sense it might be possible to fish anywhere in the ocean and happen upon a log or school, this is undoubtedly more costly to do in some areas than in others.

Figure 4 illustrates the trend in set type selection within the ETP tuna fishery from 1979 through 1992. The effect of pre and post dolphin-safe tuna labeling are readily evident in the trend of dolphin set utilization during this time period. In the early 80's dolphin sets were the most prevalent set choice and by the mid 80's this method dominated the fishing practices within the ETP tuna fleet.[17] Around the late 80's, presumably around the time period of consumer awareness, dolphin sets began to rapidly decrease. By the time dolphin-safe tuna labeling was enacted, 1990, dolphin sets had dropped precipitously. Although, dolphin sets appear to rebound in 1992 this is anomalous because it is based on a very small number of observations and occurs during a time period when many of the vessels in the U.S. monitored ETP tuna fleet shifted their homeport designation and were no longer recorded in our data set. When considering the impacts to producers from the labeling policy, there is certainly a dynamic component across sets since the dolphin-safe criteria applies to an entire cruise.

In addition to the shift in set types over the time period 1979 through 1992, there also occurred a shift in the spatial distribution of the fleet within the ETP. Figures 5 and 6 illustrate the set type choice by site for the time periods 1988-89 and 1990-92 respectively. In the years 1988 and 1989

[17] This trend was exacerbated by the El-Nino events in the ETP at that time.

a majority of the fleet activity took place in sites 17 through 25, located in the open ocean southwest of Mexico. This shifted in 1990 through 1992 where a majority of the fleet activity took place in sites 34 through 40, off the coast of Panama. This shift in the spatial distribution could to some degree be explained by a shift in the spatial distribution of tuna, but this is something which we can not measure in our data set. However the locations selected in 1990 through 1992 were also those regions in which school sets and log sets were the predominate technology choice in the years 1988 and 1989. In 1988 and 1989 73.7%, 80.8% and 100% of the set choices made in sites 37, 38 and 39 respectively where either log sets or school sets. These same three sites possessed the largest number of sets over the time period 1990 through 1992. Therefore, the predominant utilization of these fishing methods within these sites suggests that vessels selected these sites to facilitate their compliance with tuna safe labeling, not as a result of a shifting spatial distribution within the tuna population.

Model Specification

There are three econometric models that we estimate utilizing two alternative data assumptions. The first econometric model utilizes data from 1980 and 1981. This data set was selected because it represents a time period prior to the full-blown tuna-dolphin controversy and labeling. Parameter estimates obtained utilizing this data set represent the baseline parameters for the ETP tuna fishery. The econometric model is,[18]

$$\begin{aligned} R_{jt}(x_{jt};\beta) = \beta_1 Dist_{jt|k} + \beta_2 ExpRev_{jt} + \beta_3 Search_{jt} + \beta_4 SearchDum_{jt} + \\ \beta_5 DolphKill_{jt} + \beta_6 LogSet_{jt} + \beta_7 DolphSet_{jt} \end{aligned} \quad \forall j \in S. \qquad (16)$$

$Dist_{jt|k}$ represents the expected distance traveled to site *j* from site *k* (a vessel's current location), $ExpRev_{jt}$ is the expected revenues from visiting site *j*, $Search_{jt}$ is the expected amount of search time (expressed in hours) they will incur if they visit site *j* before they encounter tuna, $SearchDum_{jt}$ is a dummy variable indicating whether or not the site was previously visited, $DolphKill_{jt}$ is the expected number of dolphins they will kill if they visit site *j*, $DolphSet_{jt}$ is the percentage of sets in site *j* that were dolphin sets and $LogSet_{jt}$ is the percentage of sets in site *j* that were log sets. All variables except for $Dist_{jt|k}$ and $ExpRev_{jt}$ were based on yearly averages from the previous year of fishing activity. $Dist_{jt|k}$ represents the number of kilometers (expressed in

[18] Recall that in the DRUM, the utility from choosing a site, consists of the contemporaneous reward function ($R(x_{jt};\beta)$) and the value function for all future optimal behavior.

1000 kilometers) necessary to travel from their current grid location to all other grid locations. All distances are calculated using grid centerpoints. $ExpRev_{jt}$ (expressed in \$1000s) changes depending on which of the two different data assumptions are utilized in the estimation.

The first specification, model 16.1, uses the 30 day moving average lagged one year, expressed as $ExpRev_{year-1}$, for $ExpRev_{jt}$. The second specification, model 16.2, uses the 30 day moving average lagged 90 days, expressed as $ExpRev_{t-90days}$, for $ExpRev_{jt}$. These two models both assume that the Bellman equation is not updated each period, therefore the cruise trajectory is determined prior to leaving port. The results from these regressions are illustrated in Table 1.

The second econometric model captures the behavioral changes resulting from the consumer's awareness and concern for dolphin-safe fishing practices and the advent of dolphin-safe tuna labeling. Utilizing data from 1988 through 1992 we estimate the following model,

$$\begin{aligned} R_{jt}(x_{jt};\beta) = {} & \beta_1 Dist_{jt|k} + \beta_2 ExpRev_{jt} + \beta_3 Search_{jt} + \beta_4 SearchDum_{jt} + \\ & \beta_5 DolphKill_{jt} + \beta_6 LogSet_{jt} + \beta_7 DolphSet_{jt} \qquad \forall j \in S \,. \quad (17) \\ & + \beta_8 Dum90 * DolphKill_{jt} + \beta_9 Dum90 * LogSet_{jt} + \beta_{10} Dum90 * DolphSet_{jt} \end{aligned}$$

Equation (17) incorporates the same variables used in equation (16) with the addition of *Dum90* which indicates whether or not the time period is after 1990. April of 1990 was the point of inception for dolphin-safe tuna labeling in the ETP tuna fishery and *Dum90* is interacted with $DolphKill_{jt}$, $LogSet_{jt}$ and $DolphSet_{jt}$ to estimate structural changes in the site choice model resulting from this change in marketing practices.[19] Estimation of equation (17) was conducted in the same manner as equation (16) with two separate models estimates, models 17.1 and 17.2, each possessing informational assumptions identical to models 16.1 and 16.2 respectively. The results from these regressions are illustrated in Table 2.

The third econometric model differentiates producers during the period 1990-1992 who engaged in dolphin-safe cruises and those that did not. Model (17), does allow for variation following the beginning of the labeling program, but does not fully exploit the spatial differences between those obeying dolphin-safe practices and those which do not. More importantly, the model does not

[19] We include all tuna caught in 1990 using dolphin-safe methods as dolphin-safe since the labeled product, rolled out by the canneries in April of 1990 required fishermen to engage in dolphin-safe cruises for a period prior to April of 1990.

allow choice parameters to differ across the probability of encountering dolphin sets versus log and school sets. Consequently, the estimator is likely straight-jacketing the representative cruise following 1990 to be a mixture of dolphin-safe and unsafe fishing practices. To alleviate this restriction we focus our attention on behavior during the period 1990-1992 and we allow the set type variables to differ according to dolphin-safe behavior while on the cruise.[20] We estimate the following model,

$$
\begin{aligned}
R_{jt}(x_{jt};\beta) = {} & \beta_1 Dist_{jt|k} + \beta_2 Exp\,\mathrm{Re}\,v_{jt} + \beta_3 Search_{jt} + \beta_4 SearchDum_{jt} + \\
& \beta_5 DolphKill_{jt} + \beta_6 LogSet_{jt} * (1 - DolpSafe) + \beta_7 DolphSet_{jt} * (1 - DolpSafe) + \\
& \beta_7 * LogSet_{jt} * DolpSafe + \beta_{10} DolphSet_{jt} * DolpSafe \\
\forall j \in S\,. & \qquad (18)
\end{aligned}
$$

The variable *DolphSafe* is a binary variable equal to 1 if the entire cruise met the dolphin-safe criteria and 0 otherwise.

Estimating the models discussed above proceeded in four steps. First, the static RUM was estimated with the resulting parameter estimates indicated in the first column of each models results within Tables 1, 2 and 3. Secondly, we conducted a search from zero to one using steps of 0.1 to obtain our first approximation of the discount factor using the DRUM estimator, denoted $\delta^{Initial}$. After obtaining this estimate we conducted a search for the discount factor over the interval [$\delta^{Initial}$*-0.1,* $\delta^{Initial}$*+0.1*] using steps of 0.02. This generated our second estimate of the discount factor, denoted δ^{Second}. Finally, we conducted a search over the interval [δ^{Second}*-0.02,* δ^{Second}*+0.02*] using steps of 0.0025 to obtain our final estimate of the "optimal" discount factor, δ^*.[21] To select the "optimal" discount factor we used the log-likelihood value obtained from each iteration of the search algorithm to determine the best fit for the data. Parameter estimates reported in Tables 1, 2 and 3 for the two respective models are illustrated assuming that the discount factor is equal to one, the second column for each model, and equal to the "optimal" discount factor we obtained via our search algorithm, the third column for each model.[22]

[20] The choice of whether or not to abide by dolphin-safe fishing practices may be an endogenous decision made by captains after departing from port. By construction, model 18 assumes that this decision is made prior to leaving port; we believe this is a reasonable way to proceed given that our data does not reflect the intentions of fishermen regarding dolphin sets.

[21] This procedure required estimating the log-likelihood for the DRUM 39 times to obtain the final estimates. The marginal for error in the "optimal" discount factor is ±0.0025.

[22] For models 18.1 and 18.2 the "optimal" discount factor obtained via our search algorithm was one. Therefore, we only express results when the discount factor is zero (RUM) and one.

The Impact of the Dolphin-Safe Labeling Program

Using the results in equations (14) and (15), we can examine fishermen's WTP for a 10% increase in the probability of encountering log sets with a corresponding decrease in encountering dolphin sets at all sites in the ETP.[23,24] This WTP, given model (16) can be written as,

$$WTP = .1 \times 1000 \times \left(\frac{\beta_6 - \beta_7}{\beta_2} \right) \tag{19}$$

For model (17) this relationship can be expressed as,

$$WTP = .1 \times 1000 \times \left(\frac{\beta_6 + \beta_9 Dum90 - \beta_7 - \beta_{10} Dum90}{\beta_2} \right) \tag{20}$$

Notice that this expression is allowed to differ according to whether fishing occurred prior to the institution of the labeling program (*Dum90*=0) or after (*Dum90*=1).

Focusing attention solely on fishing activity after the institution of the labeling program, we can use model 18 to express the willingness to pay for more log sets for cruises not meeting the dolphin-safe criteria as

$$WTP = .1 \times 1000 \times \left(\frac{\beta_6 - \beta_7}{\beta_2} \right) \tag{21}$$

and for dolphin-safe cruises as,

$$WTP = .1 \times 1000 \times \left(\frac{\beta_9 - \beta_{10}}{\beta_2} \right). \tag{22}$$

[23] Since the probability of encountering each settype must sum to one, a 10% increasing in log sets must come at a price of decreasing dolphin sets by 10%, holding the number of school sets constant.
[24] One can derive similar expressions for how fishermen value dolphin kills. However, since the dolphin-safe criteria is based on whether dolphin-sets are targeted and **not** whether dolphins were killed while fishing, it is of secondary importance for measuring the impact of dolphin-safe labeling.

Comparing the results obtained from estimating equation (16) with those obtained from equations (17) and (18), we can investigate three different behavioral changes in fishermen operating in the ETP tuna fishery. Differences in parameter estimates for β_1 through β_7 capture the change in behavior resulting from a time period of little concern for dolphin-safe tuna fishing practices to a time period where concerns were mounting. Comparing the full parameter estimates β_1 through β_{10}, netting the effect of dolphin-safe tuna labeling, will capture the complete effect of dolphin-safe tuna labeling. Focusing solely on the parameter estimates obtained from equation (17) we can investigate the marginal changes surrounding the dolphin-safe tuna labeling practice. The parameter estimates from equation (18) allow us to investigate asymmetric willingness to pay measures for those abiding by dolphin-safe tuna labeling practices and those not. This allows us to quantify the spillover production costs resulting from dolphin-safe labeling. In addition to these behavioral comparisons, we can also focus on the informational assumptions implied by the two alternative models. The results are discussed in the following section.

IV. Results and Discussion

An examination of the estimates from models 16-18 reveal similar patterns with regard to the parameters on distances traveled, search time, and expected revenues. All things equal, fishermen are more likely to choose sites nearby, and also favor sites with a history of lower search times and higher revenues. While the signs of these parameters are the same across all models including the static RUM and DRUM, the magnitudes differ substantially. In particular, the static model assigns a higher relative weight to both search time and current period revenues than the dynamic model. Since, the dynamic model allows both current and future expected search and revenues to influence a current site choice, the model places less weight on the current period. Collectively, the current period and future values of search and revenues has an impact that spans beyond a single choice occasion in the DRUM.

This study focuses on the impact of the dolphin-safe designation. While an examination of the data in Figure 4 shows an increase in dolphin sets during the nineteen-eighties, this does not necessary imply that this method yielded the most economic returns per a set. It only implies that dolphin sets were the most commonly method used to capture tuna. The two reasons for the prevalence of dolphin sets are 1) they occur with great frequency throughout the range of the ETP fishery and 2) dolphin sets are easier to initially locate than either log or school sets. As referred to earlier, school sets are costly and often require the use of aircraft. On the other hand, log sets are less costly because they do not require spotter planes or the costly removal of dolphins from the seine. Therefore, although we see a large number of dolphin sets within the fishery, fishermen may still possess a positive willingness to pay for log sets because of the costs they avoid utilizing this method. This may be true for those vessels obeying and not obeying the dolphin-safe labeling requirements. Additionally, it is common for vessels to repeatedly target floating logs once located. Therefore, in a dynamic sense locating a log set is very valuable to fishermen. However, since the number of potential log sets depends on an exogenous environmental factor, the presence of debris in the open ocean, the desire to utilize this set type may not be a true choice variable in the vessel's optimization. What we may observe is vessels fishing in areas possessing a higher concentration of log sets in the past in order to lower their production costs. This will be investigated further in the econometric results.

Estimates of the fleet's WTP to avoid areas associated with large numbers of dolphin kills are contained in Table 4 and the WTP for increasing the probability of encountering log sets (at a corresponding decrease in dolphin sets) is presented in Table 5. During the years 1980 and 1981 both models, the RUM and DRUM, indicate that vessels were WTP more to fish in sites which possessed a higher number of dolphin kills.[25] This propensity, at a time when the tuna-dolphin issue was not at the forefront of national debate, is linked to the strong association of tuna and dolphins. Although all of the statistically significant WTP measures for the models are positive during this time period, the magnitudes of these measures are different across the models. In general the RUM estimates are below those obtained by the DRUM.[26] The magnitude of these differences results from the static versus dynamic information assumptions made in both models. In the static RUM, the marginal propensity to visit a site which possesses a larger number of dolphin kills is made only incorporating the impact that it will have on the current rewards. The decision to visit a given site does not incorporate the implications of visiting that site on future expected returns. In the DRUM the decision to visit a site with a higher number of dolphin kills is made based on whether or not it will also place them in a region where dolphins are expected to be in the future, thereby increasing the relative importance of visiting an area with a higher number of dolphin kills.

[25] Results in Table 4 are expressed as a one unit increase in the expected number of dolphin kills within a given site.
[26] In model 16.1 the RUM estimates of WTP are similar to those obtained via the DRUM. However, given that the coefficient on $ExpRev_{year-1}$ is not highly significant in the RUM, this estimate of WTP is not reliable.

In 1988 and 1989, around the time of dolphin-safe fishing concerns but prior to the institution of the dolphin-safe label, the WTP measures for visiting sites possessing a higher number of dolphin kills had reversed. In all the models estimated the WTP was negative, indicating that vessels in the ETP tuna fleet were WTP a substantial amount of money to avoid dolphins. Comparing the magnitude of these WTP measures across the RUM and DRUM results indicates that they are larger for the RUM. This is the opposite of what we found over the years 1980 and 1981 when the DRUM was greater than the RUM. However since the differences across the models are marginal, usually within a hundred dollars of each other, they have a similar marginal effect in both models.

The WTP estimates for visiting sites possessing a higher number of dolphin kills during the time period 1990 through 1992 is not consistent and, in many cases, are not statistically significant from those obtained over the years 1988 and 1989. It is important to recall that whether a vessel attains dolphin-safe status is not tied to dolphin mortality, but rather whether dolphins were intentionally targeted for the cruise. For those vessels remaining in the fishery after the label who choose to target dolphins, there is really no reason to avoid areas with high dolphin kills, since the fleet-wide quota set during a time when dozens of vessels were in the fishery simply was no longer binding. For dolphin-safe cruises, high mortality areas signal likely concentrations of tuna and since these vessels are not conducting dolphin sets, it is seen as a positive attribute. By 1992, most of the U.S. vessels remaining in the ETP fleet were not conducting dolphin-safe cruises and were exporting their product to Italy (U.S. International Trade Commission [43]). This explains why in Figure 3 there was an increase in dolphin sets within the dataset.

These results may also be attributed to the fact that although vessels tried to avoid dolphins during this time period, they were not further impacted by the dolphin-safe tuna labeling practices because they were already taking actions to mitigate the adverse effect they had on dolphins by not directly targeting them via dolphin sets. This would manifest itself in a higher WTP for increasing the number of log sets within the econometric results. To investigate this phenomenon further, it is necessary that we separate out the “labeled” vessels, those who obey dolphin-safe practices, and “unlabeled” vessels, those who conduct dolphin sets. The econometric estimates from models 18.1 and 18.2 can be used to determine whether or not these segments possessed asymmetric WTP measures for visiting sites with a higher concentration of log sets.

The primary signal for the impact of the dolphin-safe designation will be whether fishermen, in an attempt to comply with the label, choose areas where the probability of encountering the safe methods of fishing- log and/or school sets- are prevalent. There are two benefits to conducting log sets over dolphin sets and school sets, (i) they may be conducted at a lower cost than either set type because they require less vessel fuel usage and they do not require the use of spotter planes, (ii) a log set may be continual fished, once they have been found. The first advantage of log sets would be captured by both the RUM and DRUM parameter estimates as they both incorporate current period rewards. However, the second benefit will not be completely captured by the RUM because it does not allow for the dynamic component to influence site selection and a vessel's WTP to visit sites which possess a larger number of log sets.

Given this reasoning, one would expect that vessels in the ETP tuna fishery possess a positive WTP for increasing log sets and that the DRUM estimates of this WTP will exceed those obtained using the static RUM. Table 5 expresses a vessel's WTP for a 10% increase in log sets in all sites for each of the three econometric models estimated. The WTP measures for increasing the probability of log sets within the ETP tuna fishery are generally consistent with our expectations. The primary exception occurs in model 16 when we utilize the $ExpRev_{year-1}$ variable. Otherwise the DRUM estimates exceed the RUM estimates of WTP. The most consistent estimates of WTP across the three models result from the DRUM, whereas the RUM estimates of WTP possess a broader range of values. In addition, the WTP measures are predominately lower when using the $ExpRev_{t-90days}$ variable compared to the $ExpRev_{year-1}$ variable.

The most striking results occur within Model 18, where the "labeled" and "unlabeled" cruises are separated out. Both the RUM and DRUM estimates of WTP for log sets are greater for the "labeled" vessels then the "unlabeled" vessels. However, the RUM estimates for "unlabeled" vessels indicate a negative WTP for log sets, whereas the DRUM estimates are positive yet lower than "labeled" vessels. These differences between the RUM and DRUM are most likely driven by the informational assumptions of both models. The RUM estimates do not account for the opportunistic value of log sets, the ability to repeatedly fish a log set, whereas the DRUM model does. Therefore, the RUM assigns more weight to the school and dolphin sets than the DRUM. This said, the DRUM results indicate that "labeled" vessels value log sets over 2.64 and 2.34 times as much as "unlabeled" vessels using the $ExpRev_{year-1}$ and $ExpRev_{t-90days}$ variables respectively. This strongly supports the hypothesis that dolphin-safe tuna labeling altered the spatial behavior of vessels within the ETP fleet and generated two distinct classes of vessels.

These results show that fishermen are willing to pay a great deal to expand potential fishing areas of the ocean beyond the “safe areas” depicted in Figure 3. This willingness to pay probably reflects a desire to hedge against natural shocks (e.g. weather patterns) by having a larger spatial choice set from which one can likely conduct safe cruises.

V. Conclusion

This paper proposes a middle-ground estimator that strikes a balance between utilizing rigorous dynamic optimization algorithms and the simplicity of static models. Applying this method to the ETP tuna fishery, we illustrate that static models yield substantially different parameter estimates and WTP measures than if we assume that fishermen are forward looking. These differences are due to the dynamic nature of the DRUM estimator, which looks not only at the contemporaneous expected utility of fishing in a given site, but the expected future optimal behavior given the current choice alternative. The most pronounced effect of this assumption is the difference in the fleets WTP to increase log sets surrounding the implementation of dolphin-safe labeling practices. The static RUM substantially underestimates the benefit of fishing in an area which possesses a larger number of log sets because it does not capture the dynamic factors which make a log set area more favorable. Log set regions are primarily near other log set regions; this increases the impact they have on future optimal behavior. In addition, log sets can be repeatedly fished. These factors are not captured by the RUM estimates.

In addition to the illustrated differences between the RUM and DRUM estimations of WTP, we have shown that the tuna-dolphin issue and later the enactment of dolphin-safe tuna labeling did alter the spatial and production behavior of fishermen within the ETP tuna fishery. This manifested itself in a shift from being WTP to visit sites which possessed more dolphin kills in the early 1980s, invariably yielding the explosion of dolphin sets in the fishery through the mid 1980s, to being WTP to avoid dolphin in the late 1980s and early 1990s. This also generated a shift in the fleets WTP for increasing the amount of log sets within the tuna fishery during this time period. However, these WTP measures are much larger in the DRUM due to the assumptions made regarding dynamic behavior and there relevance to log set utilization. Combined these results suggest that the dolphin-safe tuna labeling did have a substantial short-run effect on the tuna fleet. This evidence, coupled with the exodus of many ETP seiners to the Western Tropical Pacific, provides evidence that the costs of meeting the dolphin-safe requirements were not fully compensated by consumer willingness to pay.

Although the DRUM estimated has been applied to the ETP tuna fishery, it can be utilized in a number of alternative environments. It may be used in recreational demand modeling, and other applications were dynamic behavior is believed to be present but the dimensions of the choice set preclude the use of alternative dynamic optimization algorithms, such as stochastic dynamic programming. In addition, this model can feasible be used to investigate heterogeneous behavior in dynamic models via the synthesis of the DRUM with either random coefficient models, which have already been utilized in the multi-nomial logit framework (McFadden and Train [22]; Smith [38]), or latent class regression models, such as finite mixtures models, which have been recently used in the recreational demand literature (Scarpa and Thiene [33]; Morey et. al [24]). These are all fruitful extensions, especially given the segmentation results generated in model 18, that we intend to investigate in future research.

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Tables and Figures:

Table 1: Regression Results – ETP 1980-81.

Coefficient	Static Model 16.1	Dynamic Model 16.1	Dynamic Model 16.1 (δ^*)	Static Model 16.2	Dynamic Model 16.2	Dynamic Model 16.2 (δ^*)
Distance	-4.2609	-4.3634	-4.2975	-4.2559	-4.3721	-4.2899
	(-91.43)	(-90.32)	(-91.83)	(-91.35)	(-90.36)	(-92.00)
$ExpRev_{year-1}$	0.0025	0.0018	0.0020	-------	-------	-------
	(1.59)	(7.13)	(3.71)	-------	-------	-------
$ExpRev_{t-90days}$	-------	-------	-------	0.0071	0.0001	0.0023
	-------	-------	-------	(4.55)	(0.168)	(3.17)
ExpRev	-------	-------	-------	-------	-------	-------
	-------	-------	-------	-------	-------	-------
Search	-0.2080	-0.0319	-0.0739	-0.2071	-0.0349	-0.0833
	(-9.97)	(-3.06)	(-6.03)	(-8.99)	(-3.30)	(-6.50)
SearchDum	-0.5328	-0.1503	-0.2239	-0.5299	-0.1550	-0.2395
	(-9.22)	(-7.03)	(-8.54)	(-9.08)	(-7.00)	(-8.61)
DolphKill	0.0036	0.0026	0.0026	0.0037	0.0027	0.0028
	(0.88)	(3.38)	(1.85)	(0.91)	(3.46)	(1.81)
LogSet	1.4412	0.3094	0.4414	1.4169	0.3045	0.4757
	(13.50)	(10.82)	(11.78)	(13.26)	(10.36)	(11.66)
DolphSet	0.5960	0.1381	0.1659	0.5889	0.1401	0.1850
	(6.37)	(6.65)	(5.37)	(6.32)	(6.69)	(5.50)
δ	0	1	0.9050	0	1	0.8725
# of Obs.	3999	3999	3999	3999	3999	3999
Mean Log-Likelihood	**-1.42349**	**-1.41118**	**-1.40521**	**-1.42135**	**-1.41425**	**-1.40556**

Table 2: Regression Results – ETP 1988-92.

Coefficient	Static Model 17.1	Dynamic Model 17.1	Dynamic Model 17.1 (δ^*)	Static Model 17.2	Dynamic Model 17.2	Dynamic Model 17.2 (δ^*)
Distance	-4.3026	-4.3323	-4.3166	-4.2902	-4.3217	-4.2917
	(-140.11)	(-140.65)	(-141.08)	(-139.55)	(-139.99)	(-140.58)
$ExpRev_{year-1}$	0.0043	0.0018	0.0019	-------	-------	-------
	(4.66)	(7.43)	(6.80)	-------	-------	-------
$ExpRev_{t-90days}$	-------	-------	-------	0.0087	0.0025	0.0036
	-------	-------	-------	(7.59)	(7.91)	(8.68)
ExpRev	-------	-------	-------	-------	-------	-------
	-------	-------	-------	-------	-------	-------
Search	-0.0720	-0.0199	-0.0260	-0.0714	-0.0165	-0.0287
	(-5.25)	(-3.96)	(-4.55)	(-5.26)	(-3.24)	(-4.47)
SearchDum	-0.3826	-0.1124	-0.1299	-0.3618	-0.1031	-0.1356
	(-8.76)	(-7.19)	(-7.79)	(-8.27)	(-6.38)	(-7.47)
DolphKill	-0.0101	-0.0027	-0.0033	-0.0100	-0.0027	-0.0039
	(-3.14)	(-1.84)	(-2.07)	(-3.07)	(-1.85)	(-2.23)
LogSet	0.8332	0.3319	0.3592	0.8229	0.3433	0.3984
	(5.46)	(9.60)	(9.11)	(5.35)	(10.18)	(8.49)
DolphSet	0.8163	0.1384	0.1565	0.8007	0.1282	0.1793
	(8.70)	(6.51)	(6.49)	(8.55)	(6.02)	(6.31)
*DolphKill*D90*	0.0068	0.0044	0.0047	0.0055	0.0044	0.0047
	(0.88)	(2.07)	(1.95)	(0.49)	(1.97)	(1.62)
*LogSet*D90*	-0.6786	-0.0258	-0.0326	-0.6647	-0.0948	-0.0738
	(-3.48)	(-0.62)	(-0.68)	(-3.40)	(-3.61)	(-1.24)
*DolphSet*D90*	-0.6940	-0.1050	-0.1286	-0.6999	-0.0281	-0.1617
	(-5.50)	(-3.97)	(-4.30)	(-5.55)	(-0.69)	(-4.56)
δ	0	1	0.9700	0	1	0.9275
# of Obs.	9319	9319	9319	9319	9319	9319
Mean Log-Likelihood	**-1.44576**	**-1.44122**	**-1.44063**	**-1.44392**	**-1.44082**	**-1.43919**

Table 3: Regression Results – ETP 1990-1992

Coefficient	Static Model 18.1	Dynamic Model 18.1	Static Model 18.2	Dynamic Model 18.2
Distance	-3.8472	-4.0365	-3.8370	-4.0336
	(-93.77)	(-94.83)	(-93.46)	(-94.10)
$ExpRev_{year-1}$	0.0095	0.0032	-------	-------
	(6.97)	(8.05)	-------	-------
$ExpRev_{t-90days}$	-------	-------	0.0088	0.0047
	-------	-------	(5.78)	(9.88)
ExpRev	-------	-------	-------	-------
	-------	-------	-------	-------
Search	-0.0854	-0.0653	-0.0841	-0.0605
	(-4.24)	(-5.99)	(-4.30)	(-5.69)
SearchDum	-0.4122	-0.1690	-0.4060	-0.1534
	(-6.72)	(-7.30)	(-6.61)	(-6.62)
DolphKill	-0.0030	0.0021	-0.0053	0.0023
	(-0.44)	(1.58)	(-0.74)	(1.64)
LogSet(1-DumSafe)*	0.2423	0.6436	0.2152	0.7108
	(1.48)	(15.53)	(1.30)	(16.58)
*DolphSet**(1-DumSafe)*	1.2576	0.3305	1.2676	0.3393
	(11.49)	(11.80)	(11.49)	(11.83)
*LogSet*DumSafe*	0.8308	0.6509	0.9416	0.6715
	(4.68)	(19.72)	(5.36)	(19.50)
*DolphSet*DumSafe*	-0.5771	-0.1783	-0.6164	-0.2075
	(-2.85)	(-3.71)	(-3.02)	(-4.32)
δ	0	1	0	1
# of Obs.	4454	4454	4454	4454
Mean Log-Likelihood	**-1.60245**	**-1.52979**	**-1.60417**	**-1.52776**

The optimal discount factor found by the LIML grid search was δ=1.

Table 4: Willingness to Pay for Dolphin

(- indicates a willingness to pay to avoid dolphin kills)

Model Assumption		1980-1981	1988-1989	1990-1992
16.1-RUM		1,440.00**	----------	----------
16.1-DRUM		1,444.44	----------	----------
16.1-DRUM *(δ^*)*		1,300.00	----------	----------
16.2-RUM		521.13	----------	----------
16.2-DRUM		27,000.00**	----------	----------
16.2-DRUM *(δ^*)*		1,217.39	----------	----------
17.1-RUM		----------	-2,348.84	-767.44*
17.1-DRUM		----------	-1,500.00	944.44
17.1-DRUM *(δ^*)*		----------	-1,736.84	736.84
17.2-RUM		----------	-1,149.43	-517.24*
17.2-DRUM		----------	-1,080.00	680.00
17.2-DRUM *(δ^*)*		----------	-1,083.33	222.22*

[*] indicates that coefficient on *DolphKill*D90* was insignificant.

**indicates that the coefficient on expected revenues is not statistically significant; therefore the WTP estimates are not statistically significant.

Table 5: Willingness to Pay for a 10% increase in Log Sets

(The negative of these numbers indicates the WTP for a 10% increase in dolphin sets).

Revenue Estimate	Model Estimated		Log Set 1980-81 Model 16	Log Set 1988-89 Model 17	Log Set 1990-92 Model 17	Log Set (Dirty Cruise) 1990-1992 Model 18	Log Set (Clean Cruise) 1990-1992 Model 18
	RUM		**33,808.00**	**393.02**	**751.16**	**-10,687.37**	**14,820.00**
$ExpRev_{year-1}$	**DRUM (δ=1)**		**9,516.17**	**10,750.00**	**15,150.00**	**9,784.38**	**25,912.50**
	DRUM (δ^*)		**13,775.00**	**10,668.42**	**15,531.58**	**9,784.38***	**25,912.50***
	RUM		**11,661.97**	**255.17**	**659.77**	**-11,959.10**	**17,704.54**
$ExpRev_{t-90days}$	**DRUM**		**164,400.00****	**8,604.00**	**5,936.00**	**7,904.26**	**18,702.13**
	DRUM (δ^*)		**12,204.35**	**6,086.11**	**8,402.78**	**7.904.26***	**18,702.13***

*Recall $\delta^*=1$.

**indicates that the WTP estimate is not statistically significant.

Figure 1. Total Vessel activity by set type in the ETP fishery (1979-1992)

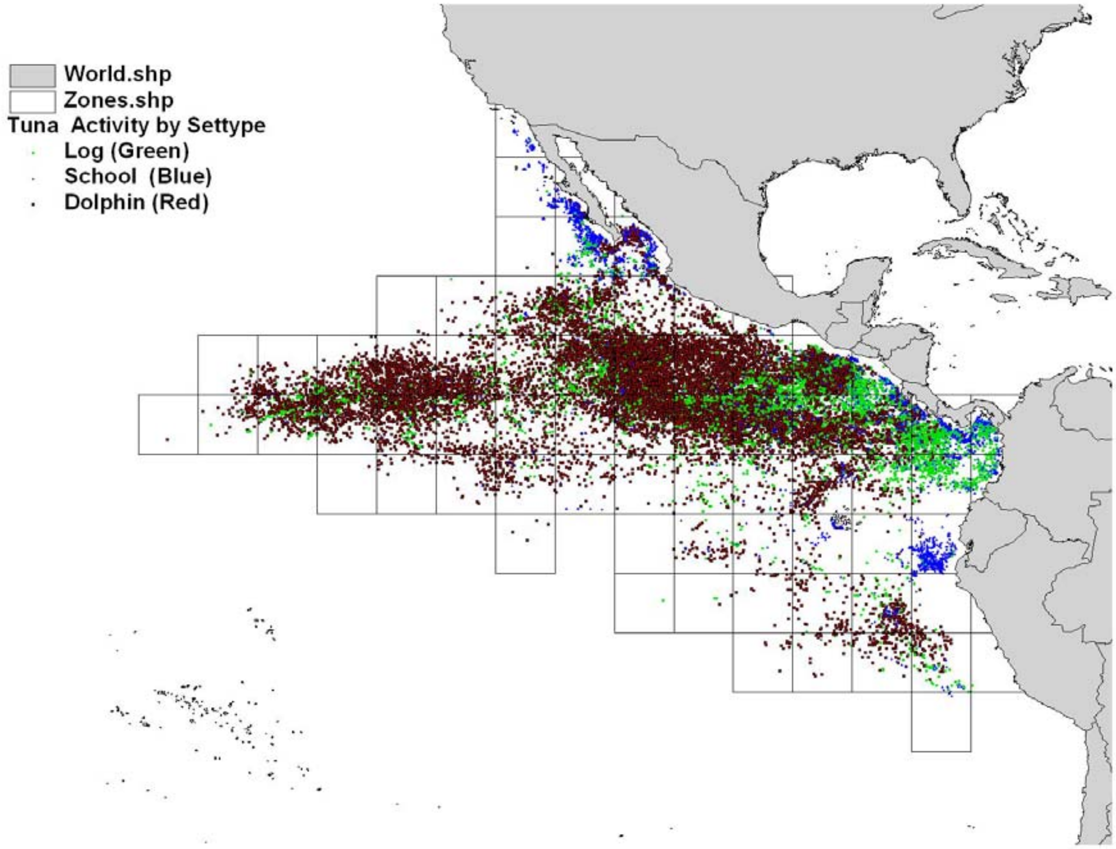


Figure 2. Vessel Activity in ETP targeting dolphins (1979-1992)

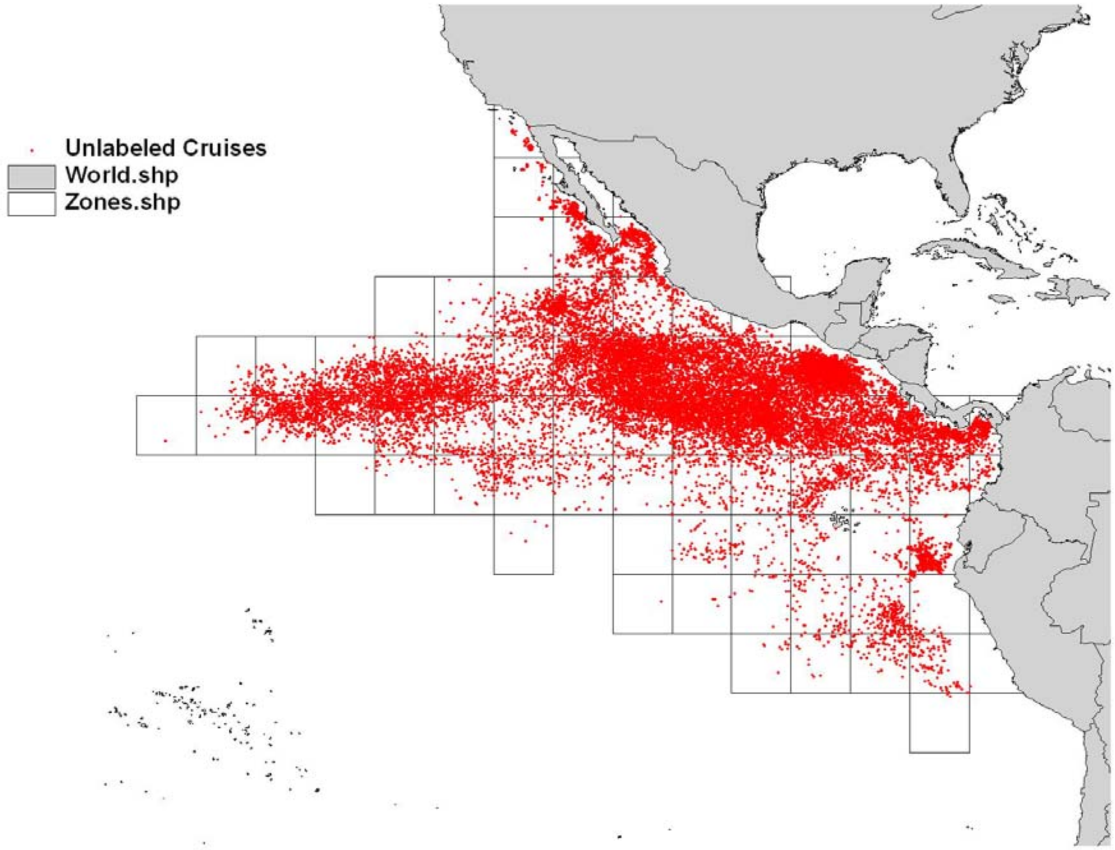


Figure 3. Dolphin-safe Vessel Activity in the ETP (1979-1992)

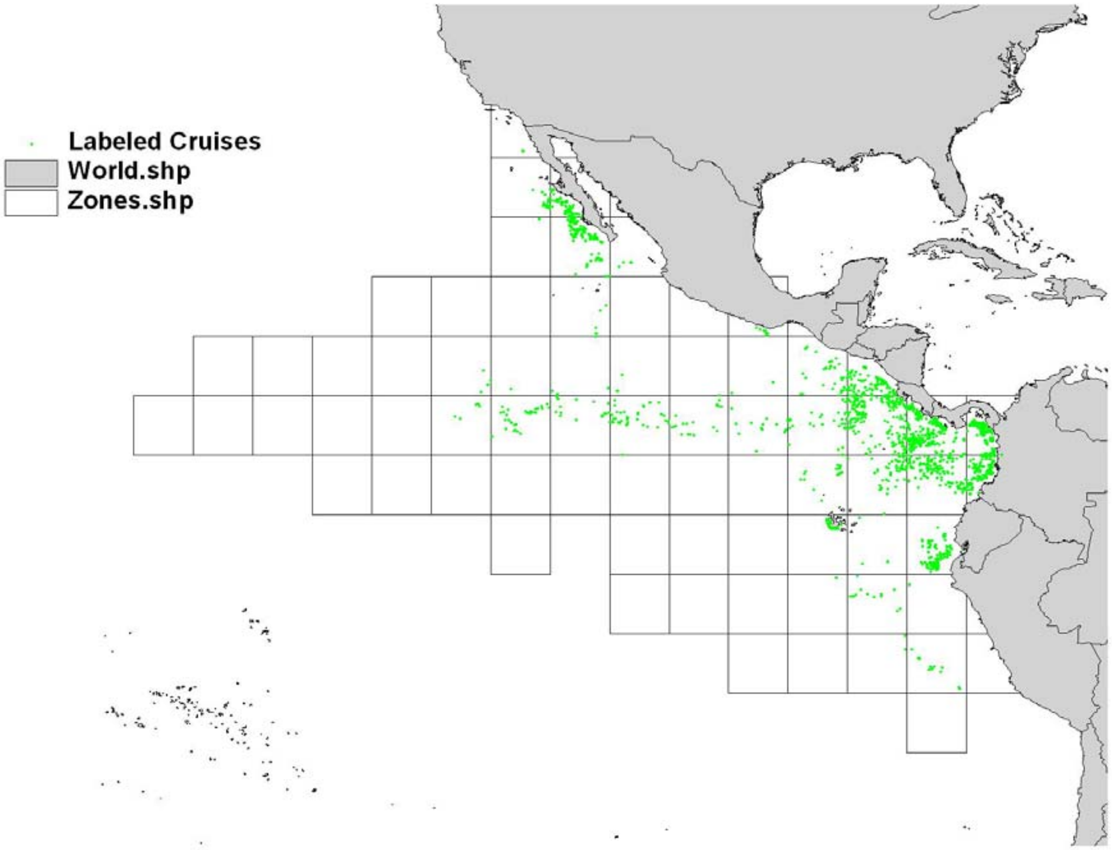
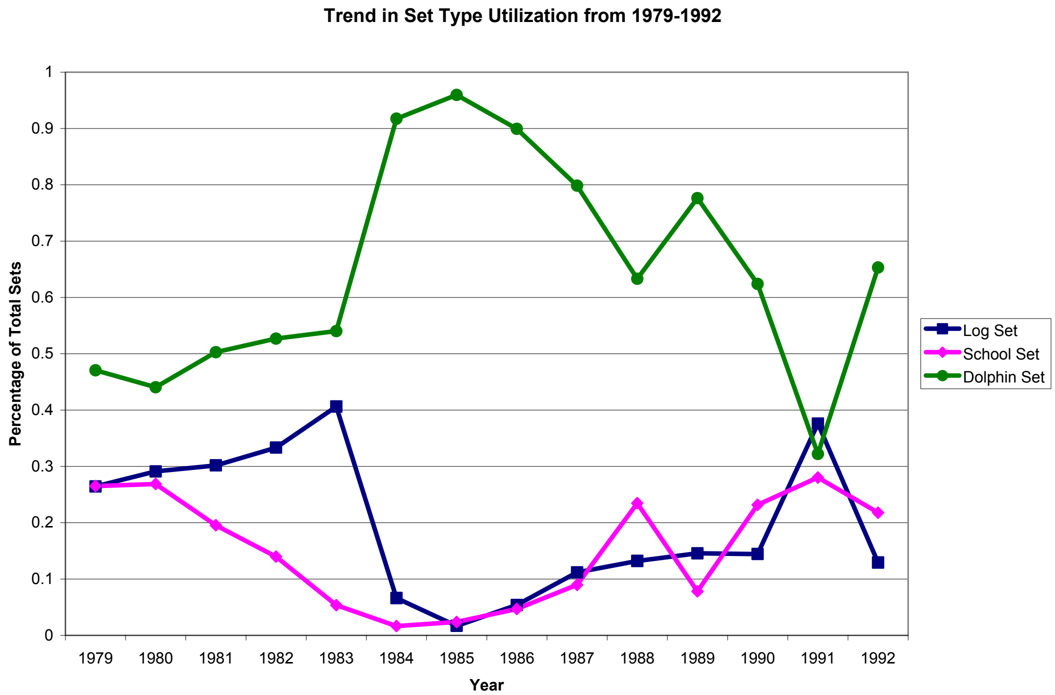
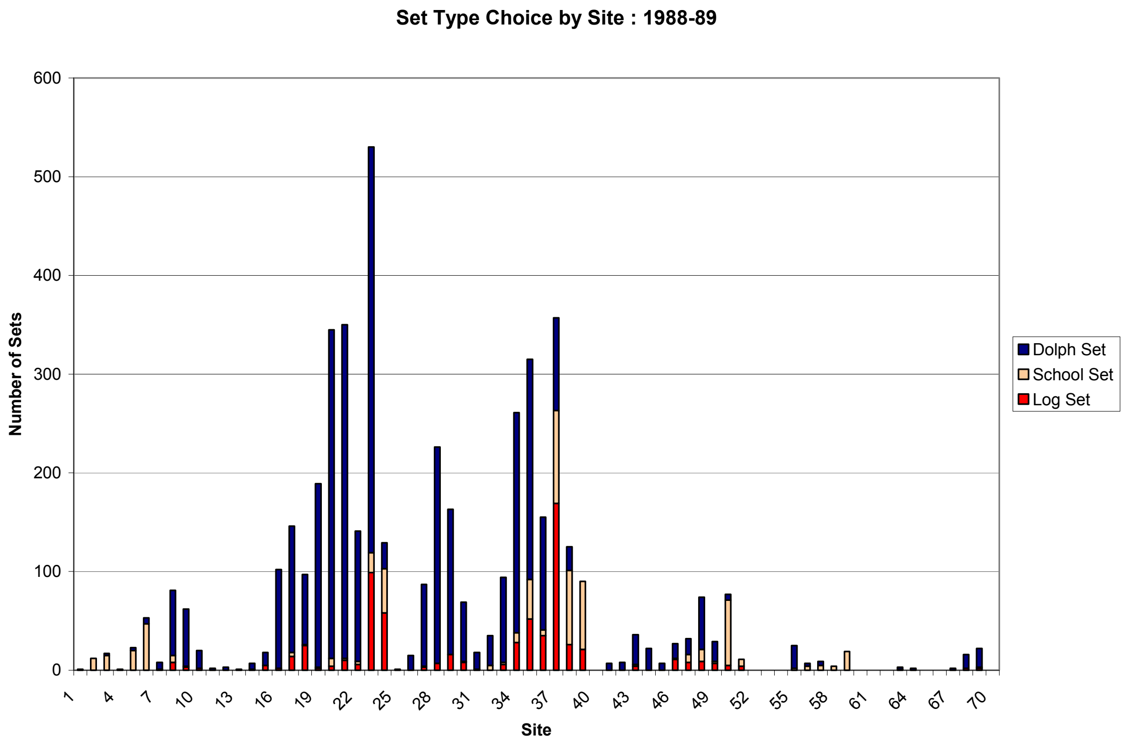


Figure 4:



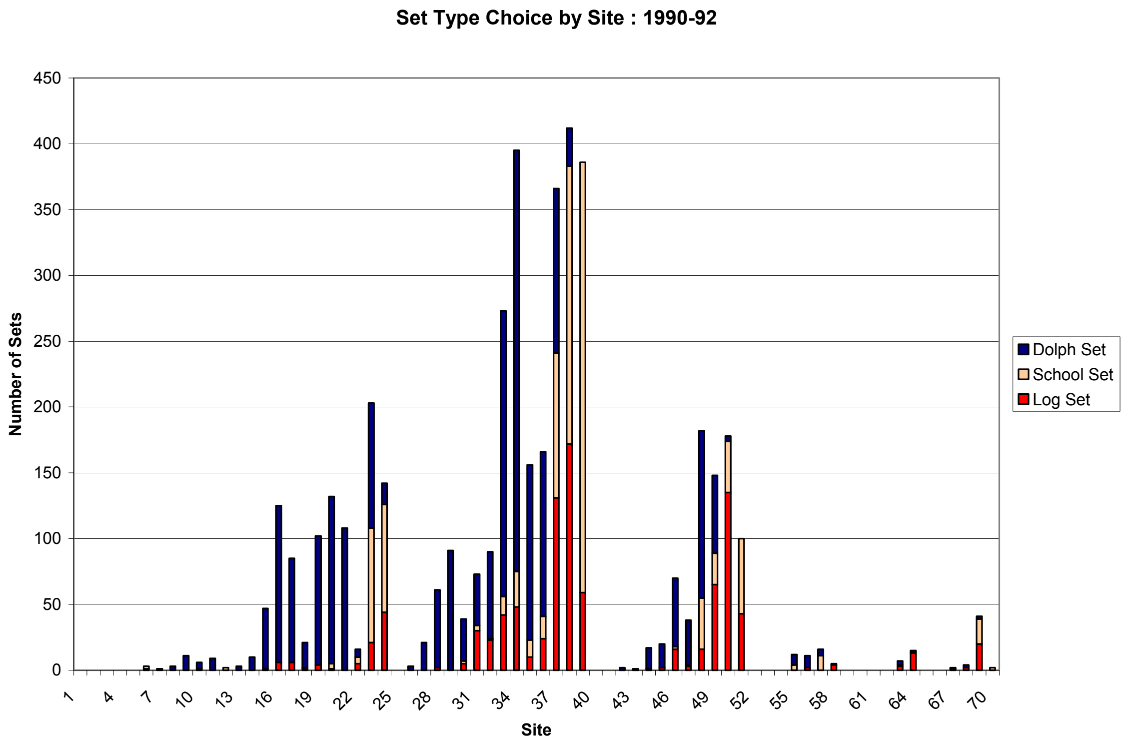
Trend in Set Type Utilization from 1979-1992
Percentage of Total Sets
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
Year
Log Set
School Set
Dolphin Set

Figure 5:



Set Type Choice by Site : 1988-89
Number of Sets
Site
600
500
400
300
200
100
0
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
46
49
52
55
58
61
64
67
70
Dolph Set
School Set
Log Set

Figure 6:



Set Type Choice by Site : 1990-92
Number of Sets
450
400
350
300
250
200
150
100
50
0
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
46
49
52
55
58
61
64
67
70
Site
Dolph Set
School Set
Log Set

Appendix:

In what follows, we prove the result given in equation (15). Following work by Hanemann [12], we can define the willingness to pay for an improvement in quality from the current period until T at all sites by the amount Δ_τ as the series of payments made *each period from the current period until period T* that equates the expected utility with and without the quality change at all sites (denote these payments as (WTP_τ)). Given the assumed form of the error structure and a starting point j, this can be written as

$$\begin{aligned}(A.1)\quad &\gamma + \ln\left(\sum_{k\in N^0}\exp\left(x_{kt}^j\beta^D + \beta_q^D\Delta_\tau - \beta_N^D WTP_\tau + \delta\left[\gamma + \ln\left[\sum_{k\in N^0}\exp(\overline{V}_k(\overline{S}^\Delta(t+1),t+1)\right]\right]\right)\right) \\ &-\left[\gamma + \ln\left(\sum_{k\in N^0}\exp\left(x_{kt}^j\beta^D + \delta\left[\gamma + \ln\left[\sum_{k\in N^0}\exp(\overline{V}_k(\overline{S}(t+1),t+1)\right]\right]\right)\right)\right] = 0\end{aligned}$$

where $S^\Delta = \{x_{kt+1}^j, Exp\mathrm{Re}v_{kt+1}^j - WTP_\tau, q_{kt+1}^j + \Delta_\tau\}$, γ is Euler's constant, and β_q^D and β_N^D are the coefficients on a site specific quality measure and the marginal utility of income, respectively. The latter expression for the state space under the policy change, S^Δ, makes explicit the notion that both Δ_τ and WTP_τ are experienced *each period* from the current period onward until the end of the time horizon, T.

Consider a two site, three period model that demonstrates how our model works and how the dynamics of location choice fundamentally alters the interpretation of model parameters. The derived result is easily extended to a choice set containing S sites and T time periods. Following the notation in the paper, denote $x_{k\tau}^m$ as the vector of site-specific explanatory variables for site k in time τ given a starting point of site m. Also, denote the vector β^D as the estimated parameters from the DRUM model. To see how a payment of WTP_τ defined by equations 15 and satisfies (A.1), consider the matrix of site-specific utilities for the DRUM model in Table (A.1).

Table(A.1). Matrix of Site-Specific Utilities for a Two site Three Period Model

Time Period	Starting Location	Location Choice	
		a	b
3	a	$x_{a3}^{a}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau}$ (A.2)	$x_{b3}^{a}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau}$ (A.3)
3	b	$x_{a3}^{b}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau}$ (A.4)	$x_{b3}^{b}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau}$ (A.5)
		a	b
2	a	$x_{a2}^{a}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau} + \delta\left(\gamma + \ln(e^{A.2} + e^{A.3})\right)$ (A.6)	$x_{b2}^{a}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP + \delta\left(\gamma + \ln(e^{A.4} + e^{A.5})\right)$ (A.7)
2	b	$x_{a2}^{b}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau} + \delta\left(\gamma + \ln(e^{A.2} + e^{A.3})\right)$ (A.8)	$x_{b2}^{b}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau} + \delta\left(\gamma + \ln(e^{A.4} + e^{A.5})\right)$ (A.9)
		A	B
1	a	$x_{a1}^{a}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau} + \delta\left(\gamma + \ln(e^{A.6} + e^{A.7})\right)$ (A.10)	$x_{b2}^{a}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau} + \delta\left(\gamma + \ln(e^{A.8} + e^{A.9})\right)$ (A.11)
1	b	$x_{a2}^{b}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau} + \delta\left(\gamma + \ln(e^{A.6} + e^{A.7})\right)$ (A.12)	$x_{b2}^{b}\beta^{D} + \beta_{q}^{D}\Delta_{\tau} - \beta_{N}^{D}WTP_{\tau} + \delta\left(\gamma + \ln(e^{A.8} + e^{A.9})\right)$ (A.13)

Simplify the last term in equation (A.6):

(A.14)
$$\begin{aligned}
\delta\left(\gamma+\ln(e^{A.2}+e^{A.3})\right) &= \delta\left(\gamma+\ln\left(e^{x_{a3}^{a}\beta^{D}+\beta_q^D\Delta_\tau-\beta_N^D WTP_\tau}+e^{x_{b3}^{a}\beta^{D}+\beta_q^D\Delta_\tau-\beta_N^D WTP_\tau}\right)\right)\\
&= \delta\left(\gamma+\ln\left(\left[e^{x_{a3}^{a}\beta^{D}}+e^{x_{b3}^{a}\beta^{D}}\right]e^{\beta_q^D\Delta_\tau-\beta_N^D WTP_\tau}\right)\right)\\
&= \delta\left(\gamma+\ln\left(e^{x_{a3}^{a}\beta^{D}}+e^{x_{b3}^{a}\beta^{D}}\right)+\ln\left(e^{\beta_q^D\Delta_\tau-\beta_N^D WTP_\tau}\right)\right)\\
&= \delta\gamma+\delta\ln\left(e^{x_{a3}^{a}\beta^{D}}+e^{x_{b3}^{a}\beta^{D}}\right)+\delta\left(\beta_q^D\Delta_\tau-\beta_N^D WTP_\tau\right)
\end{aligned}$$

Using similar logic, one can derive

(A.15)
$$\delta\left(\gamma+\ln(e^{A.4}+e^{A.5})\right)=\delta\gamma+\delta\ln\left(e^{x_{a3}^{b}\beta^{D}}+e^{x_{b3}^{b}\beta^{D}}\right)+\delta\left(\beta_q^D\Delta_\tau+\beta_N^D WTP_\tau\right).$$

Given the results found in (A.14) and (A.15), simplify equations (A.6) and (A.7):

$(A.6')$
$$x_{a2}^{a}\beta^{D}+\beta_q^D\Delta_\tau(1+\delta)-\beta_N^D WTP_\tau(1+\delta)+\delta\gamma+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)$$

$(A.7')$
$$x_{b2}^{a}\beta^{D}+\beta_q^D\Delta_\tau(1+\delta)-\beta_N^D WTP_\tau(1+\delta)+\delta\gamma+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right).$$

Finally, assume that the agent starts in area a in period 1, and simplify equation (A.10) using the two preceding results in equations (A.6') and (A.7'). First, begin with the last term in equation (A.10), which can be written:

(A.16)

$$\delta\left(\gamma+\ln\left(e^{A.6}+e^{A.7}\right)\right)=\delta\left(\gamma+\ln\left(e^{A.6'}+e^{A.7'}\right)\right)$$

$$=\delta\left(\gamma+\ln\left(e^{x_{a2}^{a}\beta^{D}+\beta_{q}^{D}\Delta_{\tau}(1+\delta)-\beta_{N}^{D}WTP_{\tau}(1+\delta)+\delta\gamma+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\beta_{q}^{D}\Delta_{\tau}(1+\delta)-\beta_{N}^{D}WTP_{\tau}(1+\delta)+\delta\gamma+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)\right)$$

$$=\delta\left(\gamma+\ln\left(\left[e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right]e^{\beta_{q}^{D}\Delta_{\tau}(1+\delta)-\beta_{N}^{D}WTP_{\tau}(1+\delta)+\delta\gamma}\right)\right)$$

$$=\delta\gamma+\delta\ln\left(e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)+\delta\ln\left(e^{\beta_{q}^{D}\Delta_{\tau}(1+\delta)-\beta_{N}^{D}WTP_{\tau}(1+\delta)+\delta\gamma}\right)$$

$$=\delta\gamma+\delta\ln\left(e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)+\delta\left(\beta_{q}^{D}\Delta_{\tau}(1+\delta)-\beta_{N}^{D}WTP_{\tau}(1+\delta)+\delta\gamma\right)$$

$$=\gamma(\delta+\delta^{2})+\delta\ln\left(e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)+\beta_{q}^{D}\Delta_{\tau}(\delta+\delta^{2})-\beta_{N}^{D}WTP_{\tau}(\delta+\delta^{2})$$

Finally, using the preceding result, we can derive a simplified version of the site-specific utility at a conditional on starting at a in period 1:

(A.17)

$$x_{a1}^{a}\beta^{D}+\beta_{q}^{D}\Delta(1+\delta+\delta^{2})-\beta_{N}^{D}WTP(1+\delta+\delta^{2})+\gamma(\delta+\delta^{2})+\delta\ln\left(e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)$$

Using the same technique yields a similar expression for equation (A.11), the expected utility of a choice of site b given a starting point of a

(A.18)

$$x_{b1}^{a}\beta^{D}+\beta_{q}^{D}\Delta_{\tau}(1+\delta+\delta^{2})-\beta_{N}^{D}WTP_{\tau}(1+\delta+\delta^{2})+\gamma(\delta+\delta^{2})+\delta\ln\left(e^{x_{a2}^{b}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{b}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)$$

.

Finally, using (A.18 and A.19) and substituting into (A.1), we show that the result given in equation (15) holds.

$$\gamma+\ln\left(e^{x_{a1}^{a}\beta^{D}+\beta_{q}^{D}\Delta_{\tau}(1+\delta+\delta^{2})+\beta_{N}^{D}WTP_{\tau}(1+\delta+\delta^{2})+\gamma(\delta+\delta^{2})+\delta\ln\left(e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)}+e^{x_{b1}^{a}\beta^{D}+\beta_{q}^{D}\Delta_{\tau}(1+\delta+\delta^{2})+\beta_{N}^{D}WTP_{\tau}(1+\delta+\delta^{2})+\gamma(\delta+\delta^{2})+\delta\ln\left(e^{x_{a2}^{b}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)}\right)-$$

$$\left(\gamma+\ln\left(e^{x_{a1}^{a}\beta^{D}+\gamma(\delta+\delta^{2})+\delta\ln\left(e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)}+e^{x_{b1}^{a}\beta^{D}+\gamma(\delta+\delta^{2})+\delta\ln\left(e^{x_{a2}^{b}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)}\right)\right)=0$$

Simplifying yields

$$\gamma+\gamma(\delta+\delta^{2})+\ln\left(e^{x_{a1}^{a}\beta^{D}+\delta\ln\left(e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)}+e^{x_{b1}^{a}\beta^{D}+\delta\ln\left(e^{x_{a2}^{b}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)}\right)+\beta_{q}^{D}\Delta_{\tau}(1+\delta+\delta^{2})-\beta_{N}^{D}WTP_{\tau}(1+\delta+\delta^{2})-$$

$$\left(\gamma+\gamma(\delta+\delta^{2})+\ln\left(e^{x_{a1}^{a}\beta^{D}+\delta\ln\left(e^{x_{a2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)}+e^{x_{b1}^{a}\beta^{D}+\delta\ln\left(e^{x_{a2}^{b}\beta^{D}+\ln\left(e^{x_{a3}^{a}\beta}+e^{x_{b3}^{a}\beta}\right)}+e^{x_{b2}^{a}\beta^{D}+\ln\left(e^{x_{a3}^{b}\beta}+e^{x_{b3}^{b}\beta}\right)}\right)}\right)\right)=0$$

All terms cancel except for $\beta_q^D \Delta_\tau (1+\delta+\delta^2) - \beta_N^D WTP_\tau (1+\delta+\delta^2) = 0$, which says that the discounted streams of marginal utility resulting from paying WTP_τ and enjoying Δ_τ must be equal for the expected utilities given in (A.1) to be equal. Rearranging yields the result demonstrated in equation (15), $WTP_\tau = \frac{\beta_q^D \Delta_\tau}{\beta_q^D}$. While this expression is similar to (14), the quantities WTP_τ and Δ_τ are experienced *every period* from the time of the current choice until period T. While the interpretation of parameters is similar to the static model, this derivation demonstrates that the interpretation must include the stream of improvements in quality and payments made by fishermen at each period forward during the cruise.