A Dynamic Model of Intra-Annual Species Selection in Fisheries

Kurt E. Schnier[ϕ]
Georgia State University
Department of Economics

Robert L. Hicks
The College of William and Mary
Department of Economics

Charles Adams
University of Florida
Department of Food and Resource Economics

Sherry Larkin
University of Florida
Department of Food and Resource Economics

(*Preliminary and Incomplete Draft: Do Not Cite Without Permission from the Authors*)

Abstract:

Within a year fishermen must manage a portfolio of fishery participation decisions. Fishermen often switch their primary target species within a year according to their seasonal expected abundance, regulatory policies and gear utilized. Utilizing fish ticket data on commercial fishermen operating in the Key West region of Southern Florida during 1994-1998 we directly investigate fishermen's annual decisions on when to switch across four primary target species as well as their decision to not fish in a given month. To model this decision we utilize a dynamic discrete choice model which empirically links their contemporaneous fishery selection decision with their expected future optimal behavior for the duration of the year. Furthermore, we use the empirical results to conduct policy simulations which determine how fishermen will switch among different fisheries. Results are compared to a static behavioral model and the policy impacts of ignoring dynamic decision making are discussed. In general, our results illustrate that ignoring dynamic behavior generates a substantially different profile of policy responses, which may have a profound impact on management policy.

[ϕ] Corresponding Author: Andrew Young School of Policy Studies, 14 Marietta Street NW, Suite 436 email : kschnier@gsu.edu ; Phone : (404)413-0159; Fax: (404)413-0248.

Introduction

A sizeable literature has illustrated that fisheries management is complicated by the multi-species nature of fisheries as well as trophic relationships (Pauly et al. 1998; U.S. Commission on Ocean Policy 2004). This literature has illustrated that it is necessary to develop management institutions that properly address the ecological interactions present within fisheries (Arnason 1998, 2000; Hanna 1998). The primary theme within this literature is that it is necessary to simultaneously determine the optimal harvesting rules for all species present within the fishery incorporating its role in the broader ecological structure, thereby altering the traditional paradigm of single species management which has been argued to be an over simplification of fisheries management (Walters et al. 1997). However, in order to achieve this goal it is also necessary to incorporate the observed behavior of fishermen within this broader ecological structure to develop effective management measures. This research addresses this issue by developing a dynamic model of species selection (targeting decisions) and empirically investigates the switching behavior of fishermen across different species within an ecosystem. Knowledge of this structural behavior can be used to facilitate management and simulate the impacts of alternative fishery policies.

The push towards managing fishery resources as a complete integrated unit has recently fallen under the title of ecosystem-based fisheries management (Marasco et al. 2007; Pauly et al. 2002). One of the initial ecosystem-based fisheries management instruments was the proposal of generating large scale marine protected areas as a precautionary approach (Lauck et al. 1998).[1] In this environment it has been well illustrated that the behavioral response of fishermen to a marine protected area is extremely important to the success of the policy (Sanchirico and Wilen 2001; Smith and Wilen 2003). However, the previous focus has been on the spatial behavior of fishermen and how they move from one location to another in response to the rent differentials present within the metapopulation (Sanchirico and Wilen 1999; Smith and Wilen 2003). This research illustrates the importance of behavior when temporal rent differentials exist across species, generating complex dynamic switching between different species within the ecosystem.

Few papers have directly addressed the question of species selection and switching behavior in fisheries. The first researchers to explore this issue were Bockstael and Opaluch (1983) in their seminal paper on effort supply response in New England fisheries and the role of uncertainty in fishery specific returns. Since that time most of the empirical research has focused on using the random utility framework (McFadden 1973) to investigate the spatial behavior of fishermen within a single fishery (Curtis and

[1] Recently, the resource economics literature has proposed the adoption of portfolio theory to manage our marine resources in order to derive efficient ecosystem based fishery management instruments (Baldursson and Magnusson 1997; Edwards et al. 2004; Sanchirico et al. 2007). However, these management instruments focus on deriving optimal harvesting levels and do not explicitly incorporate the behavioral responses of fishermen.

Hicks 2000; Eales and Wilen 1986; Hicks et al. 2004; Holland and Sutinen 2000; Smith and Wilen 2003), as well as risk preferences (Dupont 1993; Mistiaen and Strand 2000) instead of targeting decisions. This discrete choice literature essentially removes one layer of the decision process by conditioning a fisherman's spatial choices on the fishery selected. There have been a few publications that have directly investigated the species selection question (Eggert and Tvetras 2004; Perusso et al. 2005; Pascoe 2007), but none of these utilize a dynamic discrete choice framework such as adopted in this research effort.

Eggert and Tvetras (2004) estimate a two-stage model of revenue generation and gear switching within the Swedish West Coast demersal trawl fleet to investigate heterogeneous risk preferences and a vessel's decision to participate in either the shrimp, lobster or cod fisheries. One of their central discoveries was that fishermen possessed a strong state dependence in their gear selection activity, which is consistent with recent research on state dependence in fishermen spatial behavior (Smith 2005). Given the importance of state dependence in species selection, the structural model we develop will incorporate this important facet of the decision process.

Perruso et al. (2005) use a portfolio theory approach to multi-species targeting. This method treats species targeting decisions as percentages of aggregate rents and cannot be used to predict how fishermen will switch between fisheries when the economic fundamentals change, as is the case in the discrete choice model developed by Eggert and Tvetras (2004). However, it does elegantly derive species portfolio frontiers which minimize the variance in revenues subject to expected trip wealth (Perruso et al. 2005).

Pascoe et al. (2007) use a multispecies output distance production function (an approach that has been adopted in a number of different applications, namely: Felthoven et al. 2007; Morrison Paul and Nehring 2005; Orea et al. 2005) to investigate the ability of fishermen in the North Sea to substitute one species for another by altering their fishing behavior. Given that altering targets is conveyed through substitution patterns in the joint production function they do not explicitly investigate targeting decisions. Therefore, their analysis is restricted to species that are simultaneously captured using similar technology. Using the Morishma elasticity of substitution measures, they illustrate that fishermen possess a limited degree of target substitution in their production processes, which they attribute to differences in management regimes and capital inputs within the fishery (Pascoe et al. 2007).

The empirical model we use investigates targeting decisions using a structural dynamic discrete choice model that links contemporaneous fishery rents with the expected value of future optimal behavior conditional on one's current choice. These models have been effectively used in the natural resource economics literature to investigate the optimal stopping rule in forest rotation (Provencher 1995), recreational angling (Provencher and Bishop 1997), search behavior in the Northern California sea urchin fishery (Smith and Provencher 2003) and the dairy cow replacement decision (Miranda and Schnitkey

1995). These models, as well as that developed in the upcoming section, stem from the full solution method developed by Rust (1987) to estimate structural models of dynamic behavior which have been used in the marketing (Gönul and Shi 1998; Gönul 1999), health economics (Gilleskie 1998), and the labor economics literature (Rust and Phelan 1997; Arcidiacono 2004). However, these models have not been utilized in the spatial choice modeling literature due to the exceptionally large state space, which subjects the modeler to the "curse of dimensionality" (Bellman 1957).[2]

In the following section we outline the dynamic discrete choice model used to investigate the targeting decisions of fishermen. Section three provides a brief description of the fishery studied as well as the data utilized in the analysis. Section four summarizes the empirical results from the alternative structural models estimated. Section five conducts a series of ex-post policy simulations to illustrate the benefits of using a structural dynamic discrete choice model of targeting decisions. The final section discusses potential future applications of the model, including the importance of using these models to inform policy makers of the behavioral changes of fishermen that impact other fisheries.

Dynamic Fishery Selection Model

Defining the Fishing Objective

In each time period, fishermen decide among one of *N-1* targeting alternatives or an alternative occupation (work or leisure). Consider a model of *C* fishermen deciding among these *N* alternatives to select in a given month, *m*, within the year. Each fisherman's objective function in a given month is to maximize

$$E\left[\sum_{\tau=m}^{M}\delta^{\tau-m}\sum_{n=1}^{N}R_n(\tau)d_n(\tau)\mid S(\tau)\right] \tag{1}$$

where $0<\delta<1$ is the fisherman's monthly discount factor, $E[\bullet]$ is the expectation operator, $S(\tau)$ is the observed state space at month $\boldsymbol{\tau}$, $R_n(\tau)$ is the monthly expected return from choosing alternative *n* in month $\boldsymbol{\tau}$, and $d_n(\tau)$ is a binary variable indicating whether or not the alternative *n* is selected in month $\boldsymbol{\tau}$.

In order to maximize their objective function, each fisherman must select a sequence of binary choice variables $\{d_n(\tau)\}_{n\in N}$ for $\tau=1,2,....,M$, with each choice maximizing the sum of

[2] The presence of the "curse of dimensionality" has stimulated a vein of research focused on developing middle ground empirical models which possess key features of a more complete structural model (Baerenklau and Provencher 2005; Curtis and Hicks 2000; Hicks and Schnier 2006, 2007) as well simulation and interpolation methods which may be used to mitigate, but not eliminate, the curse of dimensionality (Keane and Wolpin 1994).

contemporaneous returns from the alternative plus the discounted value of their expected future optimal behavior conditional in their current choice. The maximum expected value of the sequence of binary choice variables in month τ is equal to

$$V(S(\tau),\tau) = \max_{\{d_n(\tau)\}_{n\in N}} E\left[\sum_{\tau=m}^{M} \delta^{\tau-m} \sum_{n=1}^{N} R_n(\tau) d_n(\tau) \mid S(\tau)\right] = \max_{n\in N}\left\{V_n(S(\tau),\tau)\right\}. \tag{2}$$

where $V_n(S(\tau),\tau)$ represents the fisherman's value function at time period τ conditional on the state space $S(\tau)$ for alternative *n*. The alternative specific value functions, $V_n(S(\tau),\tau)$, follow the Bellman equation (Bellman 1957) and are defined as

$$V_n(S(\tau),\tau) = \begin{cases} R_n(\tau) + \delta E\left[V(S(\tau+1),\tau+1) \mid S(\tau), d_n(\tau) = 1\right] \text{for} \tau = 1,\ldots,M-1 \\ R_n(M) \text{ for } \tau = M \end{cases} \tag{3}$$

The dynamics of the fisherman's objective function is generated through the evolution of the state space $S(\tau)$, which often depends on the history of discrete choices made in the time periods prior to $\tau, d(h) = \{d_n(\tau-1), d_n(\tau-2),\ldots,d_n(1)\}$, where $d_n(1)$ is the fisherman's first choice. In our application the binary decision $d_n(\tau)$ satisfies the following maximization

$$\max_{n\in N}\{V_n(S(\tau),\tau)\} = \max\left[V_1(S(\tau),\tau), V_2(S(\tau),\tau),\ldots,V_5(S(\tau),\tau) \mid S(\tau-1), d(h)\right], \tag{4}$$

which must be solved for each of the *n* alternatives made in period τ and each $V_n(S(\tau),\tau)$ satisfying equation (3).

To investigate each captain's decision on when to switch, we define five alternatives that they must select from each month to maximize the objective function expressed in equation (4). These alternatives are to target grouper and/or snapper ($d_1(\tau)$), king mackerel ($d_2(\tau)$), stone crab ($d_3(\tau)$), spiny lobster ($d_4(\tau)$), or to choose alternative employment or leisure activities ($d_5(\tau)$). Given the discrete nature of each fishery participation decision, we impose the following constraint: $\sum_{n=1}^{5} d_n(\tau) = 1$. As such, the returns from fishing for each of the respective fisheries, $R_n(\tau)$ are defined as

$$R_1(\tau) = \left(\gamma_1 exrev_1(\tau) + \alpha_1 \left(\sum_{t=\tau-4}^{\tau} d_1(t) \right) + \theta_1 \left(d_3(\tau-1) + d_4(\tau-1) \right) + \varepsilon_1(\tau) \right) I_1(\tau) \tag{5}$$

$$R_2(\tau) = \left(\gamma_1 exrev_2(\tau) + \alpha_2 \left(\sum_{t=\tau-4}^{\tau} d_2(t) \right) + \theta_2 \left(d_3(\tau-1) + d_4(\tau-1) \right) + \varepsilon_2(\tau) \right) I_2(\tau) \tag{6}$$

$$R_3(\tau) = \left(\gamma_1 exrev_3(\tau) + \alpha_3 \left(\sum_{t=\tau-4}^{\tau} d_3(t) \right) + \theta_3 \left(d_1(\tau-1) + d_2(\tau-1) \right) + \varepsilon_3(\tau) \right) I_3(\tau) \tag{7}$$

$$R_4(\tau) = \left(\gamma_1 exrev_4(\tau) + \alpha_4 \left(\sum_{t=\tau-4}^{\tau} d_4(t) \right) + \theta_4 \left(d_1(\tau-1) + d_2(\tau-1) \right) + \varepsilon_4(\tau) \right) I_4(\tau) \tag{8}$$

$$R_5(\tau) = \lambda_1 + \alpha_5 \left(\sum_{t=\tau-4}^{\tau} d_5(t) \right) + \varepsilon_5(\tau), \tag{9}$$

where $I_j(\tau)$ is a season indicator variable that takes a value of one if fishery j is open in time period τ. The expected revenues for each fishery, $exrev_n$, captures the propensity for captains to target a given species within a month based upon the revenues they will derive from the fishery; the methods used to model revenue expectations are discussed in the following sub-section. The state dependence terms, $\sum_{t=\tau-4}^{\tau} d_n(t)$, capture the number of times that the fisherman has fished for a given species within the past four months in order to investigate state dependence in their decisions within the year. The interpretation of these coefficients is similar to the sluggish response variables proposed by Smith (1969) to explain fishermen entry and exit decisions and the state dependence observed by Eggert and Tvetras (2004). The θ coefficients determine how the costs of switching fishing between different types of fishing gear impacts targeting decisions. These coefficients are necessary since targeting stone crab or spiny lobster (j = 3 or 4) requires the use of traps but fishermen targeting either snapper/grouper or king mackerel (j = 1 or 2) use gillnets or hook and line gear.[3] Therefore, the $(d_3(\tau-1) + d_4(\tau-1))$ and $(d_1(\tau-1) + d_2(\tau-1))$ variables serve as proxies for the costs of gear switching between the fisheries. Finally, the constant in the returns from the fifth alternative, λ_1, represents the opportunity cost of participating in either of the four primary fisheries and the coefficient on the state dependence term captures the propensity to not fish if a fisherman has not been fishing over the past four months.

[3] The traps used for stone crabs and spiny lobsters are not interchangeable, however, it is assumed that switching from one type of trap to another is relatively easy since it does not require a substantial reconfiguring of the vessel's capital inputs whereas switching between traps and gillnets does.

Combined, all of the fishery specific information comprises the state space, $S(\tau)$, observed by each fisherman in time period τ. $S(\tau)$ is defined as

$$S(\tau) = \left\{ exrev_1,..,exrev_4, d_1(\tau-1), d_2(\tau-1), d_3(\tau-1), d_4(\tau-1), \sum_{t=\tau-4}^{\tau} d_1(t),.., \sum_{t=\tau-4}^{\tau} d_5(t) \right\}, \tag{10}$$

which determines the alternative specific return functions, $R_n(\tau)$. The additive random variables $\varepsilon_n(\tau)$ affect the contemporaneous returns from each of the N alternatives in time period τ and is known to the fisherman, but unknown to the researcher. Assumptions regarding the distribution of the error structure will be discussed in more detail in the *Model Estimation* sub-section.

Modeling Expected Revenues

To model the formation of expected revenues in each of the fisheries we use three alternative specifications. The first specification for revenue expectations is expressed as

$$E\left[exrev_n(m)\right] = \rho_1 exrev_n(m-1) + \rho_2 exrev_n(m-2) + \upsilon_m . \tag{11}$$

This specification assumes that current revenues are a function of the revenues obtained in the previous two months as well as a random error component $\upsilon_m \sim N(0, \sigma_m^2)$, where the variance is a parameter to be estimated within the model.

The second revenue expectation model invokes the informational assumptions latent in the dynamic random utility model (DRUM) developed by Hicks and Schnier (2006, 2008). In this model, revenues are assumed to be known prior to the decision period for all relevant time periods in the future based on historical information. Given that the time horizon used in the study is 12 months the DRUM assumes the following functional form for the revenue expectations

$$E\left[exrev_n(m)\right] = exrev_n(m-12) \ . \tag{12}$$

The limitation of this model is that it is not possible to forecast revenues in an effort to determine how fishermen form their revenue expectations. Furthermore, should the time period exceed 12 months, the modeling assumptions underlying the DRUM are rendered untenable, precluding its use as a rational empirical model. However, as has been illustrated in the literature, it does generate a tractable empirical model of dynamic behavior because all information is known prior to the decision period and the

stochasticity present in equation (11) is removed (Hicks and Schnier 2006, 2008). This makes the model amenable to problems having a large numbers of choice alternatives such as this one.

The final specification investigated in this analysis is the naïve revenue expectation model, which assumes that $\rho_1 = 1$ and $\rho_2 = \sigma_m^2 = 0$ in equation (11). In essence, the naïve expectation model assumes that fishermen believe that the currently observed revenues will remain the same for the duration of their decision horizon. This type of revenue expectation is expressed as

$$E\left[exrev_n(m)\right] = exrev_n(m-1). \tag{13}$$

The primary difference between the naïve expectation model and the DRUM expectation model is that seasonality is easily accounted for in the DRUM because expected revenues are expressed as yearly lags of the revenue expectations derived in a given month for each fishery. However, it is worth noting that neither model allows for the stochastic evolution of the state space or the direct estimation of parameters in the fisherman's revenue expectation function; only equation (11) allows for both of these features.

Model Estimation

Conditional on the parameter vector $\Omega = (\gamma_1, \lambda_1, \alpha_n, \vartheta_j, \rho_1, \rho_2, \sigma_m^2)$ as well as the error vector $\{\varepsilon_n(\tau)\}_{\forall\tau}$ being known, the dynamic programming model can tractably be solved using the backward recursion of the monthly value functions $V_n(S(\tau),\tau)$ (Bellman 1957). However, given that neither of these components of information is known *a priori*, both must be dealt with in order to estimate the multi-species fishery switching model. Putting aside the issue of estimating $V_n(S(\tau),\tau)$ for now, we follow Rust's (1987) conditional independence assumption and assume that the monthly errors are independent Gumbel-distributed random variables (Ben-Akiva and Lerman 1985) with scale parameter σ. Invoking this allows us to write $\delta E[V(S(\tau+1),\tau+1) \mid S(\tau), d_n(\tau)]$ expressed in equation (3) as[4]

$$\delta E[V(S(\tau+1),\tau+1) \mid S(\tau), d_n(\tau)] = \delta\left\{\zeta + \ln\left[\sum_{n=1}^{N} \exp(V_n(S(\tau+1),\tau+1)\right]\right\} \tag{14}$$

where ζ is Euler's constant.

[4] Following common practice, parameters are recovered assuming $\sigma = 1$. In the empirical results to follow we also assume the discount factor $\delta = 0.995$.

As discussed in Keane and Wolpin (1994) and Rust (1987), the conditional independence makes three important assumptions: (1) the return functions $R_n(\tau)$ are additively separable from the unobservables $\varepsilon_n(\tau)$, (2) the unobservables are serially independent, and (3) the unobservables are distributed multivariate extreme value. Given these assumptions the choice probabilities, $\Pr(d_n(\tau)=1 \mid S(\tau))$ can be conveniently expressed as a multinomial logit model,

$$\Pr(d_n(\tau)=1 \mid S(\tau)) = \exp\{V_n(S(\tau),\tau)\} \Big/ \sum_{j=1}^{N} \exp\{V_j(S(\tau),\tau)\},$$

which can be represented as

$$\Pr(d_n(\tau)=1 \mid S(\tau)) = \frac{\exp\{R_n(S(\tau);\Omega)+\delta E[V(S(\tau+1),\tau+1) \mid S(\tau), d_n(\tau)=1]\}}{\sum_{j=1}^{N}\exp\{R_j(S(\tau);\Omega)+\delta E[V(S(\tau+1),\tau+1) \mid S(\tau), d_n(\tau)=1]\}}$$

$$= \frac{\exp\left\{R_n(S(\tau);\Omega)+\delta\left\{\zeta+\ln\left[\sum_{j=1}^{N}\exp\left(V_j(S(\tau+1),\tau+1)\right)\right]\right\}\right\}}{\sum_{j=1}^{N}\exp\left\{R_j(S(\tau);\Omega)+\delta\left\{\zeta+\ln\left[\sum_{j=1}^{N}\exp\left(V_j(S(\tau+1),\tau+1)\right)\right]\right\}\right\}} . \quad (15)$$

Consistent estimation of the $\Pr(d_n(\tau)=1 \mid S(\tau))$ requires that $V_n(S(\tau),\tau)$ be calculated for all elements of the state space and approximation leads to inconsistent estimates of Ω as well as finite sample bias (Keane and Wolpin 1994).

To estimate our model we utilize a nested optimization algorithm to obtain estimates of Ω. Conditional on Ω, the value function, $V_n(S(m),m)$, is recursively solved from the final time step *M* to the current time step in which the fishery decision is made. Following the estimation of the value functions, equation (13) is directly estimated to update our estimates of Ω and the process is continued until convergence is achieved.[5] Alternatively we could formulate the decision problem as a infinite horizon problem and either estimate the fixed point alternative specific value functions in the spirit of Rust (1987), use polynomial approximations of the fixed point value functions (Miranda and Schnitkey

[5] To estimate the variance of the revenue expectation parameter, σ_m^2, a series of random normal error draws were taken from the *N*(0,1) distribution prior to the beginning of the estimation procedure and then used to estimate the variance directly. Alternatively, we could have used a more conventional stochastic dynamic programming method but these methods were rendered computationally intractable so we elected to employ this simplification. The authors intend to investigate the sensitivity of this modeling simplification in their upcoming research efforts.

1995; Provencher and Bishop 1997; Smith and Provencher 2003) or use a convergence criterion for the value function using alternative terminal period assumptions (Gönül 1999), but given that we are concerned with annual fishery selection decisions we have elected to set $M = 12$.

Fishery and Data Description

Data for this empirical analysis come from the commercial trip tickets of fishermen operating in southern Florida during the years 1995-1998 obtained from the Florida Marine Research Institute, with daily fish tickets aggregated up to the monthly level.[6] During this time period the fisheries in southern Florida were managed on a species-by-species basis with the primary targets being stone crab, spiny lobster, king mackerel, snappers and groupers (Hutchinson 2003). However, most of the fishermen who participate in these fisheries harvest more than one of the primary species during a given year (Shivlani and Milon 2000 as cited in Hutchinson 2003). Therefore, there exists a substantial degree of species and gear switching within a given year.

During the time period studied, only stone crab and spiny lobsters were season constrained. Fishing for stone crab was open from October 15th through May 15th and the season for spiny lobster was open from August 6th through March 31st. Given that the interval of time utilized in our empirical model is a month we assume that if the fishery is open for any period of that month it is a potential monthly choice. Alternatively, we could model the fishermen's decision using weekly intervals, but this would substantially increase the computational difficulty of the model. In the empirical model, if a season was closed for the entire month it was removed from the choice set, as indicated in equations (5) through (8), thereby reducing the number of alternatives present.

Spiny lobster and stone crab for the commercial market are primarily harvested using traps, which accounted for 92% and 97% of the landings during the study period, respectively; however, due to regulations on trap design in each fishery the traps are not interchangeable (Hutchinson 2003). Prior to the time period studied, the general consensus among fishery managers was that these two species were being over-exploited due to excess capacity within the fishery (i.e., increasing trap numbers and declining average landings per trap). To mitigate this problem, managers began to consider controlling the number of traps allowed for fishing each species, in addition to the season length constraint. In 1993, the State of Florida implemented a trap reduction program for the spiny lobster fishery. Under this program, transferrable certificates were issued to fishermen based on historic landings and each certificate allows the fishermen to use a single trap (Hutchinson 2003). During the time period of this study, trap numbers were decreased by approximately 34%. Stone crabs are also managed using a similar trap certificate

[6] Data was also used from 1994, but only as a baseline for the use in the revenue expectations.

program but total trap numbers were not reduced during the modeling period since the program was not approved until 2000. From 1995 through late June 2002 there was, however, a moratorium on the issuance of permits to enter the stone crab fishery (Hutchinson 2003).

King mackerel, snappers and groupers are primarily harvested using gillnets or hook-and-line gear in south Florida (Hutchinson 2003). King mackerel is a pelagic species that is managed with seasonal quotas, in part due seasonal migrations that limit abundance throughout the year, using stock assessments from both the Gulf and South Atlantic regions (Hutchinson 2003). Snappers and groupers are both part of the reef fishery and consist of a large number of individual species that are targeted to different degrees. The most valuable snapper species landed in South Florida (i.e., Monroe and Collier Counties) in1998 were yellowtail and vermillion, which accounted for 43% and 25%, respectively, of the total snapper landings (Hutchinson 2003). The most valuable grouper species landed in South Florida in 1998 were red and gag, which accounted for 51% and 33%, respectively, of the grouper landings (Hutchinson 2003). For the purpose of our analysis we aggregate all snapper and grouper species into the same targeting designation because they comprise targeted reef fish species, which are readily distinguishable from pelagic species or those harvested with traps.

Commercial fishermen are required to sell their catch to licensed dealers who then record their landings information on a trip ticket, which is then submitted to the state. The fish tickets contain information on where the majority of their landings were caught, gear used, and the quantity and unit price of all species landed and sold to the dealer. To focus our analysis on a manageable number of fishermen and to control for potential spatial variation in the target species concentrations at different points along the Florida coast, we focus our analysis on those fishermen who reported fishing in the Key West region of Florida. To determine the species that were targeted each month, a targeting designation was constructed based on the greatest total revenues derived from each of the four primary species groups.[7] In addition, a fifth alternative was constructed to represent their decision not to fish in a given month. In total the dataset contains 768 observations consisting of a balanced panel of 48 monthly observations for 16 individual fishermen.

Table 1 summarizes the descriptive statistics for the data set of 768 observations. The mean monthly revenues within the stone crab and spiny lobster fisheries are greater than the other species targeted, however the standard deviation in the spiny lobster fishery illustrates that the mean revenues are the most variable among all the fisheries. The least variable mean revenues are associated with the snapper/grouper fishery, yet this fishery also possesses the lowest mean monthly revenues. Given these statistics, it is evident that there exists substantial opportunities to switch among the different fisheries

[7] For these select fishermen, black grouper was more valuable than gag and mutton and grey snappers were more valuable than vermillion.

when opportunities arise. To further illustrate these opportunities, Figure 1 shows the mean revenues derived from each fishery over the 48 months studied (1995-1998). The stability of returns within the snapper/grouper fishery is well illustrated, as is the strong seasonality in the stone crab and spiny lobster fisheries. This switching is further illustrated in Table 1 where the mean number of choices for all the alternatives is presented with the minimum and maximum values for any one fisherman within the data set. By and large fishermen elect to not fish around one third of the time, fish for snapper and grouper slightly less than one third of the time and then target spiny lobster, stone crab and king mackerel in decreasing order. This profile suggests that these fishermen are more opportunistic in their participation within the king mackerel, stone crab and spiny lobster fisheries and select to fish in these fisheries only when the opportunity costs of switching out of snapper/grouper are covered by their expected switching revenues. In the tails of the distribution of choices (min and max choices) fishermen within the data set fished for king mackerel at least once during the time period studied and did not fish for at least three months during the same time period. In addition, no one single individual within the data set selected one alternative the entire time. Therefore, this data set, although it only encompasses a small sample of commercial fishermen within southern Florida, provides an interesting panel of switching behavior on which to develop our model.

Results

In addition to the three revenue expectation models estimated, we estimated a static model of targeting decisions which fully discounts future periods ($\delta = 0$). The results from the static model are contained in Table 2. The most important determinants of targeting behavior are the revenues the fishermen expect to derive from each of the four fisheries, γ_1, as well as the state dependence variables, α_n. The revenue coefficient indicates that when the rent differential between fisheries increases it is more likely that a fisherman will switch out of one fishery and into another. Given that all five state dependence variables are statistically significant, it is evident that fishermen are reluctant to switch from one fishery to another if it is a fishery they have participated in over the past four months. This "sticky" behavior is consistent with the fisheries literature on spatial choice (Holland and Sutinen 2000; Smith 2005) and illustrates that this behavior is also prevalent in fishermen targeting decisions.

In the myopic model, only one of the switching variables is statistically significant, θ_3, which indicates that within the stone crab fishery the fixed costs incurred while switching from gillnets or hook-and-line gear (i.e., having fished for either king mackerel or snapper/grouper the month before) to traps reduces the probability that a fishermen will fish for stone crab in the current month. For the other three

fisheries, the gear switching variables are not statistically significant suggesting that their capital is predominately malleable and easily converted across fisheries. The final parameter estimated, λ_1, represents the baseline utility each fishermen derives from electing to not fish in a given month. Combining this with the statistically significant and positive coefficient on α_5 indicates that fishermen are reluctant to resume fishing once they have elected to leave the fisheries and obtain utility from alternative activities.

The results for the three dynamic models estimated are shown in Table 3. Given that the naïve model uses the same data as the static choice model, a likelihood ratio test can be conducted on the null hypothesis that $\delta = 0$. The results for this test reject the null hypothesis (LR test statistic = 352.16) and indicate that dynamic behavior is present within the fishery. In the revenue expectations model, the coefficient on the previous months revenues, ρ_1, combined with the lagged months revenues, ρ_2, indicate a downward trend in fisherman's expectations regarding the revenues derived in each fishery. This is different than the formation of revenue expectations assumed in the naïve model and the likelihood ratio statistic suggests that the revenue expectation model is a better empirical fit for fishermen behavior. Comparing the DRUM to the other two models is not feasible because it uses different data, however, the log-likelihood results indicate that its performance is on par with the other two models. This may be important from a policy perspective because the DRUM (as well as the naïve model) is not subject to the curse of dimensionality thereby greatly simplifying the computational requirements of the model.

The model parameter estimates for the dynamic models (lower part of Table 3) are generally consistent with those obtained in the static model. The magnitudes of the coefficients are unilaterally lower in the dynamic models than in the static model (similar results have been found in Hicks and Schnier 2006, 2008). This is due to the fact that the coefficients are fitting behavior for the contemporaneous as well as future optimal behavior simultaneously versus just the contemporaneous utility in the static model. All three dynamic models possess a positive coefficient on the expected revenues derived in each fishery; however, the coefficient is only statistically significant within the revenue expectation and naïve expectation models. Furthermore, within the revenue expectation model the coefficient is only statistically significant at the 90% level. By far the most statistically significant coefficients in all three dynamic models are the state dependence variables for each fishery and the non-fishing alternative. This is consistent with previous literature on fishery selection decisions (Eggert and Tvetras 2004) and fishermen spatial behavior (Holland and Sutinen 2000; Smith 2005).

Focusing on the revenue expectation model it is evident that fishermen participating in these fisheries expect fishery revenues to gradually decrease over the time horizon with a strong negative

correction occurring if the revenues obtained in a fishery were large two months prior to the current decision period. Within the empirical model all of the revenues were scaled by a factor of 1,000. Combining this with the variance parameter estimated in the revenue expectations model ($\sigma^2 = 0.5433$) indicates that there exists substantial variation in a fisherman's expectations regarding future returns in each fishery. Combined, these phenomenon warrant further investigation and we intend to examine the impacts of these predictions in future analysis. One obvious limitation is that the empirical model we utilize does not impose any additional structure on the revenues feeding into the Bellman equation (Equation 3), that is, that they must be positive at all realizations of the state space. Perhaps this lack of structure is generating the erratic profile of revenue expectations observed in the model.[8]

Given that the primary purpose of developing an intra-annual species selection model is to be able to forecast fishermen responses to potential policy changes the within sample, predictive accuracy of the models is of paramount importance. Figures 2(a) and 2(b) graphically illustrate the within sample predictive accuracies of the myopic (static) model and the revenue expectation model for a randomly selected fisherman. The DRUM and naïve expectation models are not illustrated because they generate a similar profile of switching behavior to that predicted by the revenue expectation model. As illustrated, the dynamic models outperform the static model of species selection (the circular plots overlap more indicating better predictions). For the fisherman selected, the myopic model inaccurately predicts 13 of the 48 choices whereas each of the three dynamic models only misses four times. However, these numbers are slightly larger for the myopic model relative to the sample average, which accurately predicts behavior 76.3% of the time. In addition, the accurate predictions for the dynamic models are slightly above the 86.1%, 84.5% and 85.3% average accurate predictions for the revenue expectation, DRUM and naïve expectations models, respectively. One important phenomenon worth noting is that none of the models successfully predict behavior which is starkly different from previous behavior. This is evident in month 42 (June 1998) where the fisherman shifted from fishing for snapper/grouper to the non-fishing alternative (likely due to the El Nino event; D. Gregory, pers. comm..) and then back to the snapper/grouper fishery. Therefore, erratic fishing behavior such as may be caused by exogenous environmental events is not readily captured in the model.

The observed fishery participation decisions and model predictions are illustrated in the top panel of Table 4 and are summarized in Figure 3. Model predictions were determined by assigning the fishery selection decision to that fishery which possessed the highest probability of visitation. The within sample prediction results indicate that in general the static model tends to under-predict participation in the

[8] It is also possible that there is exists a high degree of variance for each fisheries revenues, but due to computational difficulties we were not able to estimate a separate set of revenue expectations for each fishery. Therefore, the revenues expectation parameters can be thought of as a representative average of the individual fishery parameters. This may be invoking a degree of bias we are unable to correct for within our analysis.

snapper/grouper and king mackerel fisheries and over-predict participation in the spiny lobster and no fishing alternatives. On the other hand the three dynamic models generate predictions that are all very close to the observed behavior, with the largest prediction errors occurring with the king mackerel fishery. Combined, the empirical results indicate that the three dynamic models estimated generate a more reliable profile of the fishermen participating in these fisheries. The ramification of this will be discussed in more detail in the following section when we simulate alternative policies and changes in the state space to predict fishermen responses.

Fishery Simulations

Conducting policy simulations following the estimation of a structural dynamic discrete choice model has proven to be advantageous in a number of different settings. They have been used to investigate the linkage between education level and lifetime utility (Keane and Wolpin 1997), participation in welfare programs (Keane and Moffitt 1998), the impact of educational subsidies in Mexico (Todd and Wolpin 2006), the link between social security and retirement (Rust and Phelan 1997) and recreational demand responses to policy (Provencher and Bishop 1997) to cite a few. To investigate the impacts of potential policy changes and economic shocks on the targeting decisions of fishermen in Key West, Florida, we simulate four hypothetical changes to the state space and compare the predicted behavior of the dynamic models to the static model. The predictions from each of the four policy changes are summarized in Table 4 and Figure 4.

The first proposed policy removes the season constraints on stone crab and spiny lobster for the first month of seasonal closures for each fishery. The static model predicts a reduction in snapper/grouper months (i.e., the number of months fishermen are found to target snapper/grouper) of roughly 9% and a reduction in the king mackerel months by 22%. These monthly reductions generate an increase in stone crab and spiny lobster months by 11% and 13%, respectively, with a marginal increase in non-fishing activities. Compared to the static model, the dynamic models predict a different profile of participation decisions. The predicted reduction in snapper/grouper months is not nearly as dramatic and the changes in the king mackerel fishery are mixed. The revenue expectations model predicts a decrease in months spent fishing for king mackerel, whereas the DRUM and naïve predict an increase relative to the baseline observed choices.[9] Compared to the static model, predictions from the dynamic models indicate a larger increase in stone crab months and a lower decrease in the spiny lobster months. The most substantial difference between the static and dynamic models is the predicted number of non-fishing months. The

[9] All three dynamic models predict a reduction in the King mackerel months relative to their initial baseline predictions.

static model predicts a much higher number of non-fishing months than any of the dynamic models. Given that the stone crab and spiny lobster fisheries absorb this inactive effort, the dynamic models generate a different profile of over capacity within these fisheries, which was one of the reasons for seasonal constraints in these fisheries (Hutchinson 2003).

The second simulation conducted reduces revenues from the spiny lobster fishery by 15%. This simulation was conducted to test the sensitivity of behavior to a potential lifting of the import restrictions in southern Florida, which if lifted could reduce the value of the fishery.[10] Once again, the static and dynamic models generate a different profile of predicted changes. The static model predicts a net reduction in fishing (i.e., fewer months targeting) for snapper/grouper and king mackerel with an increase in fishing for spiny lobster and the non-fishing alternative relative to the observed behavior. However, relative to the baseline within sample predictions, the static model predicts a slight increase in snapper/grouper activity. Although the static model predicts an increase in spiny lobster fishing months relative to the observed when the revenues are assumed to fall, it is important to note that it predicts a decrease in months spent fishing for spiny lobster (187 versus 195) relative to the baseline predictions from the static model. These phenomenon reflect the low predictive power of the static model.

The dynamic models, on the other hand, predict a different profile of fishermen responses to the reduction in value of spiny lobsters. On average, the three models predict an increase in the number of months spent fishing for snapper/grouper as well as king mackerel. These models predict a 10% greater number of snapper/grouper months and 20% greater for the king mackerel fishery relative to the static model's predictions. These predicted changes result from a modest reduction in the number of months spent fishing for stone crab and spiny lobster and the no-fishing alternative. The modest reduction in the number of months spent not fishing predicted by the dynamic models provides one of the starkest contrasts with the static model. The non-fishing alternative is selected, on average, about 27 fewer months than in the static model. This results in a substantially different profile of species selection that would generate different policy implications resulting from the price change in spiny lobsters. This is because the dynamic model predicts a shifting of effort toward the other species and not an increase in non-fishing activities.

The third simulation increases the revenues derived from fishing in the snapper/grouper fishery by 15%. As was the case with a decrease in the spiny lobster revenues, the static model predicts an outcome that is opposite of what would be expected relative to the observed behavior. Instead of predicting more activity in the snapper/grouper fishery, the static model predicts that fewer months will

[10] 15% was *ad hoc* selected. Currently, the impacts of lifting the import restrictions (which happened after the modeling horizon) are not known. The purpose of this simulation is merely to illustrate behavioral responses and a more accurate value reduction would be required before any policy recommendations could be made.

be spent targeting snapper/grouper when the revenues increase relative to the observed choices. However, once again, it is important to note that the predicted number of months fished for snapper/grouper is greater than the baseline static predictions (228 versus 222). On the other hand, all three dynamic models generate results in accordance with our expectations. The most interesting result from the dynamic models is that they all predict a relatively constant level of no fishing activity and a small rise in the level of snapper/grouper, which replaces months spent fishing primarily for stone crabs and spiny lobster. This reduction in fishing activity for stone crab and spiny lobster may be of interest to management because of the overcapacity concerns present within these two fisheries (Hutchinson 2003). However, in general, the dynamic models predict that not much change will actually take place if the revenues from snapper/grouper increase, which is presumably due to the fact that snapper/grouper were already being intensively fished.

The final policy simulation conducted, and perhaps the most dramatic, closes the snapper/grouper season in November and December. These months were selected for closure because they contain the overlapping months of closure for the deep and shallow water grouper assemblages in 2004. A more refined empirical model could directly investigate the switching between these two broad species groups, but that is beyond the scope of this research. Given that the snapper/grouper assemblage was targeted roughly 32% of the time in the data set, this closure stands to have the most substantial impact on other fisheries as effort is displaced from the snapper/grouper fishery.

The first prominent difference in the policy simulations is the predicted number of months fishermen will fish for snapper/grouper. The static model predicts a 16.5% reduction in the number of months fished for snapper/grouper.[11] On the other hand, the dynamic models predict a reduction in the number of snapper/grouper months by 31.3% on average, which is nearly twice the predicted reduction within the static model. In addition to these differences, the static and dynamic models also generate a different profile for the displaced effort. The static model predicts that most of the displaced effort will be absorbed by the spiny lobster fishery and by fishermen selecting not to fish. However, the increase in the spiny lobster effort is not due to the snapper/grouper closure, it is a result of the poor baseline within sample predictions. Therefore, one can conclude that the static model predominately shifts all displaced effort into the non-fishing alternative. The dynamic models predict that displaced effort will result in a slight increase in the months spent fishing for stone crabs and spiny lobsters (depending on the dynamic model), with most of the displaced effort deciding not to fish or to fish for king mackerel. In fact the

[11] It is important to note the static model only generates an 8.6% reduction in the number of months spent fishing for the snapper/grouper relative to its baseline within sample predictions of behavior. Given that all three dynamic models possess better within sample predictions, the reductions predicted by these models should carry even more weight.

number of months spent fishing for king mackerel increases on average by 62.2% (note, however, the small baseline participation rates) and the non-fishing days increase by 14.8%.

The asymmetry between these two predictions may be important to fisheries managers because they have already had to address overcapacity issues in the spiny lobster fishery (see Hutchinson 2003). To illustrate the difference in the predicted strategies, Figures 5(a) and 5(b) illustrate the predicted differences in behavior resulting from the policy change for the static and revenue expectation models, respectively. The fisherman selected predominately fished in the snapper/grouper fishery. For this particular fisherman the static model predicts that they will predominately shift to the no fishing alternative when the snapper/grouper fishery is closed, whereas the revenue expectation model illustrates that they will shift out of the snapper/grouper fishery and into the king mackerel and stone crab fishery. However, this only occurs for half of the four closure periods simulated where the other half they switch to the non fishing alternative. Despite this similarity with the static model it does provide a different profile of fishery selection responses that highlights the importance of using a structurally dynamic model of fishermen behavior.

Conclusion

This research addresses an important question as we begin to push toward an ecosystem based fisheries management policy, that is, how do fishermen select which fishery to participate in and how will policy enacted in one fishery spillover to others within the larger ecosystem? Furthermore, the discrete choice model developed here determines the switching behavior of fishermen using a structurally dynamic discrete choice model that allows fishermen to make their current fishery selection decisions incorporating future optimal behavior. This model generates a more accurate profile of fishermen behavior, as measured by within sample predictions, which we used to simulate out-of sample behavior resulting from different alternative management policies and alterations of the state space. Given the differences in the predicted future responses, our model illustrates the pitfalls of using static discrete choice models to conduct policy simulations in an inherently dynamic system.

Although this research was conducted on just a small sample of the entire fishing population in southern Florida (i.e., those fishing out of Key West), a more complex model could be developed to help guide policy provided that a more complete data set is utilized. It is too early to suggest what the full ramifications of beginning to model behavior in this manner may be, but this initial investigation suggests that the dynamic modeling of species targeting decisions is a fruitful area for future econometric modeling in fisheries. Furthermore, the use of a dynamic model generates a more robust profile of behavioral responses to potential policy which may have a profound impact on policy development.

Future research will investigate the application of this model using a larger, more information rich data set on fishermen behavior to facilitate fisheries management.

References

Arcidiacono, P. 2004. Ability sorting and the returns to college major. *Journal of Econometrics* 121: 343-375.

Arnason, R. 1998. Ecological fisheries management using individual transferable share quotas. *Ecological Applications* 8(1): S151-S159.

Arnason, R. 2000. Economic instruments for achieving ecosystem objectives in fisheries management. *ICES Journal of Marine Science* 57: 742-51.

Baerenklau, K.A. and B. Provencher. 2005. Static modeling of dynamic recreational behavior: implications for prediction and welfare estimation. *Journal of Environmental Economics and Management* 50:617-36.

Baldursson, F.M. and G. Magnusson. 1997. Portfolio fishing. *Scand avian Journal of Economics* 99(3):389-403.

Bellman, R. 1957. *Dynamic Programming*. Princeton: Princeton University Press.

Ben-Akiva, M. and S.R. Lerman. 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press: Cambridge, Mass.

Bockstael, N. and J. Opaluch. 1983. Discrete modeling of supply response under uncertainty: the case of the fishery. *Journal of Environmental Economics and Management* 10:125-37.

Curtis, R. and R.L. Hicks. 2000. The cost of sea turtle preservation: the case of Hawaii's pelagic longliners. *American Journal of Agricultural Economics* 82:1191-97.

Dupont, D.P. 1993. Uncertainty, expectations formation and fishers' location choice. *Marine Resource Economics* 8:219-47.

Eales, J. and J.E. Wilen. 1986. An examination of fishing location choice in the pink shrimp fishery. *Marine Resource Economics* 4:331-51.

Edwards, S.F., Link, J.S. and B.P. Rountree. 2004. Portfolio management of wild stocks. *Ecological Economics* 49:317-29.

Eggert, H. and R. Tveteras. 2004. Stochastic production and heterogeneous risk preferences: commercial fishers' gear choices. *American Journal of Agricultural Economics* 86(1):199-212.

Felthoven, R.G., Horrace, W.C., and K.E. Schnier. 2007. Estimating heterogeneous capacity and capacity utilization in a multi-species fishery. *Working paper, Department of Environmental and Natural Resource Economics, University of Rhode Island*.

Gilleskie, D.B. 1998. A dynamic stochastic model of medical care use and work absence. *Econometrica* 66(1):1-45.

Gregory, D. 2008. Personal Communication. Florida Sea Grant College Program, Monroe County Extension, University of Florida. Key West, FL. 17 July 2008.

Gönul, F.F. 1999. Estimating price expectations in the OTC medicine market: an application of dynamic discrete choice models to scanner panel data. *Journal of Econometrics* 89:41-56.

Gönul, F.F. and M.Z. Shi. 1998. Optimal mailing of catalogs: a new methodology using estimable structural dynamic programming models. *Management Science* 15(3):262-79.

Hanna, S.S. 1998. Institutions for marine ecosystems: economic incentives and fishery management. *Ecological Applications* 8(1):S170-S174.

Hicks, R.L., Kirkley, J. and I.E. Strand. 2004. Short-run welfare loss from essential fish habitat designations for the surf-clam and ocean quahog fisheries. *Marine Resource Economics* 19:113-44.

Hicks, R.L. and K.E. Schnier. 2008. Eco-labeling and dolphin avoidance: a dynamic model of Tuna fishing in the Eastern Tropical Pacific. *Journal of Environmental Economics and Management* 56: 103-116.

Hicks, R.L and K.E. Schnier. 2006. Dynamic random utility modeling: a Monte Carlo analysis. *American Journal of Agricultural Economics* 88(4):816-35.

Holland, D.S. and J.G. Sutinen. 2000. Location choice in New England trawl fisheries: old habits die hard. *Land Economics* 76:133-49.

Hutchinson, S.D. 2003. An economic analysis of multi-species participation among commercial fishers in south Florida. *Ph.D. Dissertation, Department of Food and Resource Economics, University of Florida.*

Keane, M.P. and R. Moffitt. 1998. A structural model of multiple welfare program participation and labor supply. *International Economic Review* 39(3):553-89.

Keane, M.P. and K.L. Wolpin. 1997. The career decisions of young men. *Journal of Political Economy* 105(3):473-522.

Keane, M.P. and K.L. Wolpin. 1994. The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence. *The Review of Economics and Statistics* 76(4):648-672.

Lauck, T.C., Clark, C.W., Mangel, M. and G.R. Munro. 1998. Implementing the precautionary principle in fisheries management through marine reserves. *Ecological Applications* 8(1):S72-S78.

Marasco, R.J., Goodman, D., Grimes, C.B., Lawson, P.W., Punt, A.E. and T.J. Quinn II. 2007. Ecosystem-based fisheries management: some political suggestions. *Canadian Journal of Fisheries and Aquatic Sciences* 64:928-39.

McFadden, D. 1973. Conditional logit analysis of qualitative choice behavior, in P. Zarembka ed., *Frontiers in Econometrics* Academic Press. New York, NY.

Miranda, M. and G. Schnitkey. 1995. An empirical model of asset replacement in dairy production. *Journal of Applied Econometrics* 10:541-556.

Mistiaen, J.A. and I.E. Strand. 2000. Location choice of commercial fishermen with heterogeneous risk preferences. *American Journal of Agricultural Economics* 82:1184-90.

Morrison Paul, C.J. and R. Nehring. 2005. Product diversification, production systems, and economic performance in U.S. agricultural production. *Journal of Econometrics* 126(2):525-48.

Orea, L., Alvarez, A. and C.J. Morrison Paul. 2005. Modeling and measuring production processes for a multi-species fishery: alternative technical efficiency estimates for the northern Spain hake fishery. *Natural Resource Modeling* 18(2):183-213.

Pascoe, S., Koundouri, P. and T. Bjorndal. 2007. Estimating targeting ability in multi-species fisheries: a primal multi-output distance function approach. *Land Economics* 83(3):382-97.

Pauly, D., Christensen, J., Dalsgaard, R., Froese, R., and R. Torres Jr. 1998. Fishing down marine food webs. *Science* 279:860-63.

Pauly, D., Christensen, V., Guenette, S., Pitcher, T.J., Sumalia, U.R., Walters, C.J., Watson, R., and D. Zeller. 2002. Towards sustainability in world fisheries. *Nature* 418:689-95.

Perruso, L., Weldon, R.N. and S.L. Larkin. 2005. Predicting optimal targeting strategies in multispecies fisheries: a portfolio approach. *Marine Resource Economics* 20:25-45.

Provencher, B. 1995. Structural versus reduced from-estimation of optimal stopping problems. *American Journal of Agricultural Economics* 79:357-68.

Provencher, B. and R.C. Bishop. 1997. An estimable dynamic model of recreation behavior with an application to Great Lakes angling. *Journal of Environmental Economics and Management* 33:107-127.

Rust, J. 1987. Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica* 55:999-1033.

Sanchirico, J.N., Smith, M.D. and D.W. Lipton. 2008. An empirical approach to ecosystem-based fishery management. *Ecological Economics* 64(3):586-596.

Sanchirico, J.N. and J.E. Wilen. 2001. A bioeconomic model of marine reserve creation. *Journal of Environmental Economics and Management* 42(3):257-67.

Sanchirico, J.N. and J.E. Wilen. 1999. Bioeconomics of spatial exploitation in a patchy environment. *Journal of Environmental Economics and Management* 37(2):129-50.

Shivlani, M.P. and J.W. Milon. 2000. Sociocultural effects of a market-based fishery management program in the Florida Keys. *Coastal Management* 28:133-147.

Smith, M.D. 2005. State dependence and heterogeneity in fishing location choice. *Journal of Environmental Economics and Management* 50:319-40.

Smith, M.D. and B. Provencher. 2003. Spatial search in marine fisheries: A discrete choice dynamic programming approach. *Proceedings of the AERE 2003 Summer Workshop: Spatial Theory, Modeling, and Econometrics in Environmental and Resource Economics*.

Smith, M.D. and J.E. Wilen. 2003. Economic impacts of marine reserves: the importance of spatial behavior. *Journal of Environmental Economics and Management* 46:183-206.

Smith, V.L. 1969. On models of commercial fishing. *Journal of Political Economy* 77:181-198.

Todd, P.E. and K.I. Wolpin. 2006. Assessing the impact of a school subsidy program in Mexico: using a social experiment to validate a dynamic behavioral model of child schooling and fertility. *American Economic Review* 96(5):1384-1417.

U.S. Commission on Ocean Policy. 2004. *An Ocean Blueprint for the 21st Century*.

Walters, C., Christensen, V. and D. Pauly. 1997. Structuring dynamic models of exploited ecosystems from trophic mass-balanced assessments. *Reviews in Fish Biology and Fisheries* 7:139-172.

Table 1: Descriptive Statistics on Monthly Data

	Mean		Number of Choices		
Alternative	Revenues	Std. Deviation	Mean	Minimum	Maximum
Snapper/Grouper	3,270.90	986.40	15.19	0	42
King Mackerel	3,798.20	4,070.60	3.25	1	18
Stone Crab	6,584.70	3,110.00	2.25	0	17
Spiny Lobster	7,347.90	4,484.60	11.13	0	30
No Fishing	n.a.	n.a.	16.19	3	32

Table 2: Static MNL Results

	Coefficient	Standard Errors
Parameters:		
γ_1 = Revenues expected from fisheries	0.2071**	0.023
α_1 = State dependence in snapper/grouper	1.2364**	0.097
θ_1 = Gear switching for snapper/grouper	-0.4357	0.518
α_2 = State dependence in King mackerel	1.4887**	0.184
θ_2 = Gear switching for King mackerel	0.1727	0.465
α_3 = State dependence in stone crab	1.7140**	0.267
θ_3 = Gear switching for stone crab	-1.7792**	0.737
α_4 = State dependence in spiny lobster	1.1664**	0.097
θ_4 = Gear switching for spiny lobster	-0.1171	0.391
λ_1 = Baseline utility from not fishing	1.6654**	0.343
α_5 = State dependence for non-fishing	0.8627**	0.118
Model Statistics:		
Log-likelihood	-440.290	
N. obs	768	

*indicates statistically significant at the 90% level; ** indicates statistically significant at the 95% level.

Table 3: Dynamic Modeling Results

	Estimated Coefficients (Std. Errors)		
	Revenue Expectation	DRUM	Naïve
Parameters:			
ρ_1	1.8240**	N/A	1.0000
	(0.09)		(N/A)
ρ_2	-1.2167**	N/A	0.0000
	(0.12)		(N/A)
σ_m^2	0.5433	N/A	0.0000
			(N/A)
Parameters:			
γ_1	0.0244*	0.0467	0.0196**
	(0.014)	(0.03)	(0.008)
α_1	1.0578**	1.0439**	1.0524**
	(0.07)	(0.07)	(0.08)
θ_1	-0.4343	-0.5872	-0.6291
	(0.73)	(0.70)	(0.70)
α_2	1.0851**	1.0972**	1.0910**
	(0.07)	(0.08)	(0.08)
θ_2	-0.6033	-0.3044	-0.5463
	(0.69)	(0.60)	(0.61)
α_3	1.5970**	1.4728**	1.4921**
	(0.10)	(0.12)	(0.11)
θ_3	-0.7113	-0.0435	0.2885
	(0.76)	(0.80)	(0.81)
α_4	1.5383**	1.3560**	1.3610**
	(0.10)	(0.09)	(0.09)
θ_4	1.0144	0.8075	0.9916
	(0.73)	(0.62)	(0.60)
λ_1	0.9556**	1.0805**	1.0349**
	(0.42)	(0.52)	(0.52)
α_5	0.7892**	0.7707**	0.7666**
	(0.08)	(0.10)	(0.10)
Model Statistics:			
Log-likelihood	-225.754	-266.275	-264.211
N. obs	768	768	768
Time horizon (M)	12	12	12

*indicates statistically significant at the 90% level; ** indicates statistically significant at the 95% level.

Table 4: Observed Choices, Baseline Predictions, and Policy Simulation Results (i.e., number of months and percentage of total) by Model

	Snapper / Grouper	King Mackerel	Stone Crabs	Spiny Lobster	No Fishing
Observed Choices:	243	52	36	178	259
	(31.64%)	(6.78%)	(4.69%)	(23.18%)	(33.72%)
Baseline Predictions:					
Static/Myopic Model	222	43	33	195	275
	(28.90%)	(5.60%)	(4.29%)	(25.39%)	(35.81%)
Revenue Expectation	247	50	31	184	256
	(32.16%)	(6.51%)	(4.04%)	(23.96%)	(33.33%)
DRUM	250	62	26	173	257
	(32.55%)	(8.07%)	(3.39%)	(22.53%)	(33.46%)
Naïve Model	250	65	28	176	249
	(32.55%)	(8.46%)	(3.64%)	(22.39%)	(32.42%)
Policy Simulation 1:					
Static/Myopic Model	222	41	40	201	264
	(28.90%)	(5.34%)	(5.21%)	(26.17%)	(34.38%)
Revenue Expectation	237	37	54	202	238
	(30.86%)	(4.82%)	(7.03%)	(26.30%)	(30.99%)
DRUM	241	59	42	186	240
	(31.38%)	(7.68%)	(5.47%)	(24.22%)	(31.25%)
Naïve Model	244	61	46	185	232
	(31.77%)	(7.94%)	(5.99%)	(24.09%)	(30.21%)
Policy Simulation 2:					
Static/Myopic Model	225	43	33	187	280
	(29.30%)	(5.60%)	(4.30%)	(24.35%)	(36.46%)
Revenue Expectation	248	49	31	186	254
	(32.29%)	(6.38%)	(4.04%)	(24.22%)	(33.07%)
DRUM	253	62	26	170	257
	(32.94%)	(8.07%)	(3.39%)	(22.13%)	(33.47%)
Naïve Model	252	65	28	174	249
	(32.81%)	(8.46%)	(3.65%)	(22.66%)	(32.42%)
Policy Simulation 3:					
Static/Myopic Model	228	42	33	195	270
	(29.69%)	(5.47%)	(4.30%)	(25.39%)	(35.16%)
Revenue Expectation	248	47	30	170	253
	(32.29%)	(6.12%)	(3.91%)	(22.14%)	(35.54%)
DRUM	252	62	26	174	254
	(32.81%)	(8.07%)	(3.39%)	(22.66%)	(33.07%)
Naïve Model	255	62	28	174	249
	(33.20%)	(8.07%)	(3.65%)	(22.66%)	(32.42%)
Policy Simulation 4:					
Static/Myopic Model	203	50	33	195	287
	(26.43%)	(6.51%)	(4.30%)	(25.39%)	(36.37%)
Revenue Expectation	177	67	41	186	297
	(23.05%)	(8.72%)	(5.34%)	(24.22%)	(38.67%)
DRUM	167	85	34	178	304
	(21.74%)	(11.07%)	(4.43%)	(23.18%)	(39.58%)
Naïve Model	157	101	37	177	296
	(20.44%)	(13.15%)	(4.82%)	(23.05%)	(38.54%)

Figure 1: Mean Revenue Plots by Fishery and Month

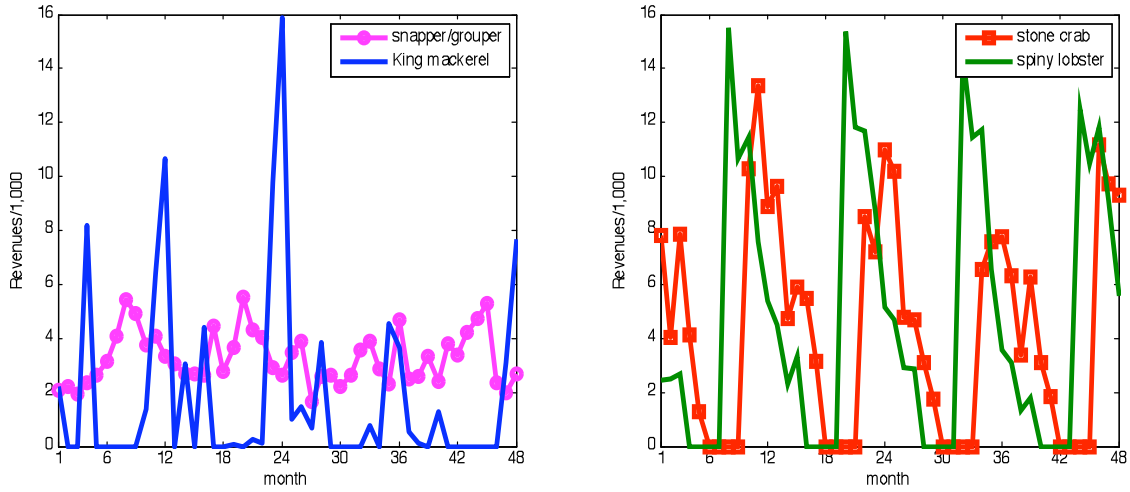
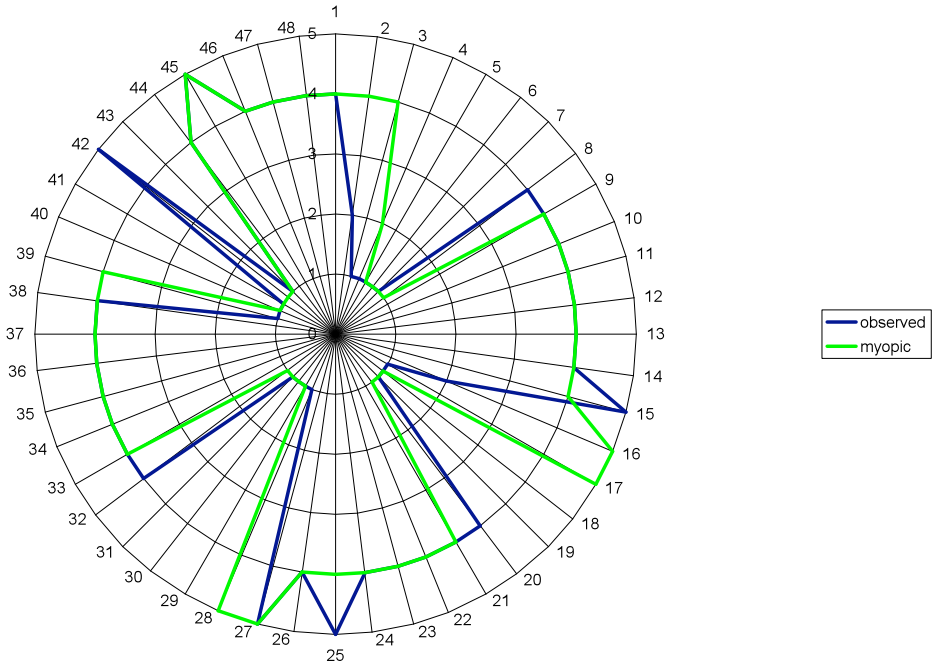


Figure 2. Circular Plots of Observed and Predicted Monthly Targeting for a Randomly Selected Fishermen

2(a): observed and predicted from myopic



model

2(b): observed and predicted from revenue expectation model

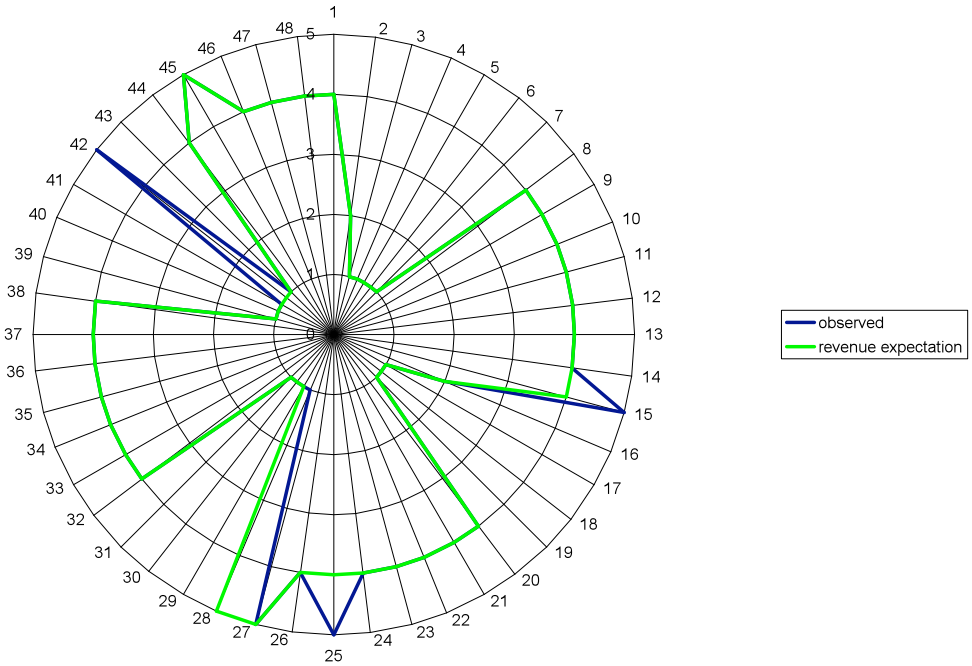


Figure 3. Difference between Predicted Monthly Targeting and Observed Targeting by Model

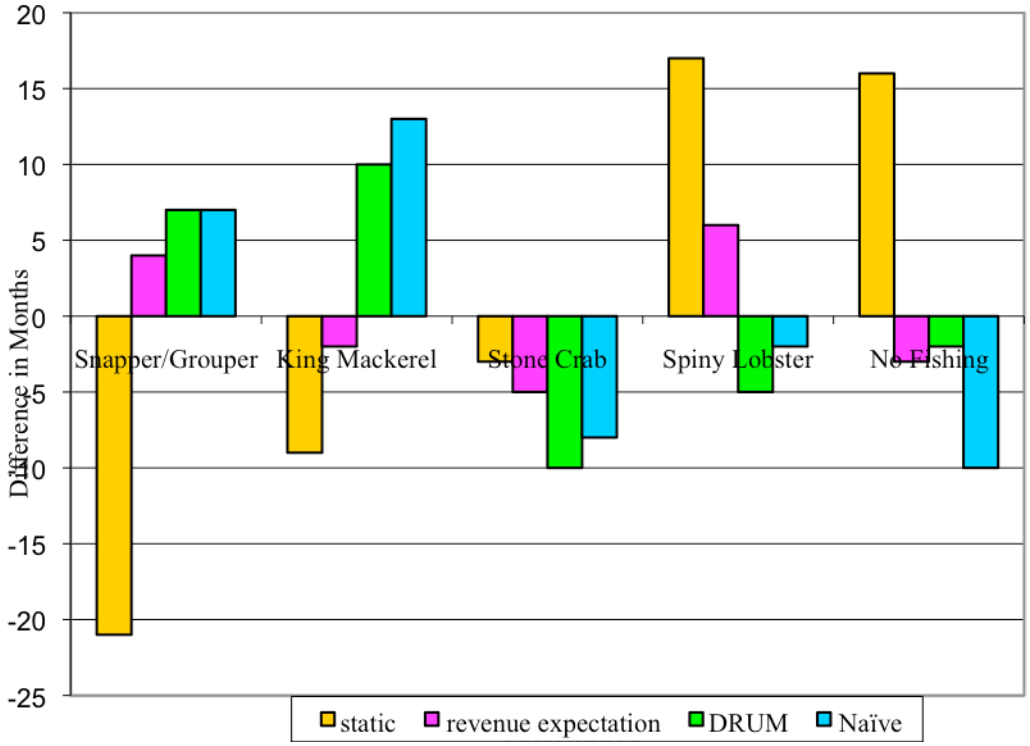


Figure 4. Summary of Policy Simulation Impacts on the Predicted Number of Months by Target for each Model

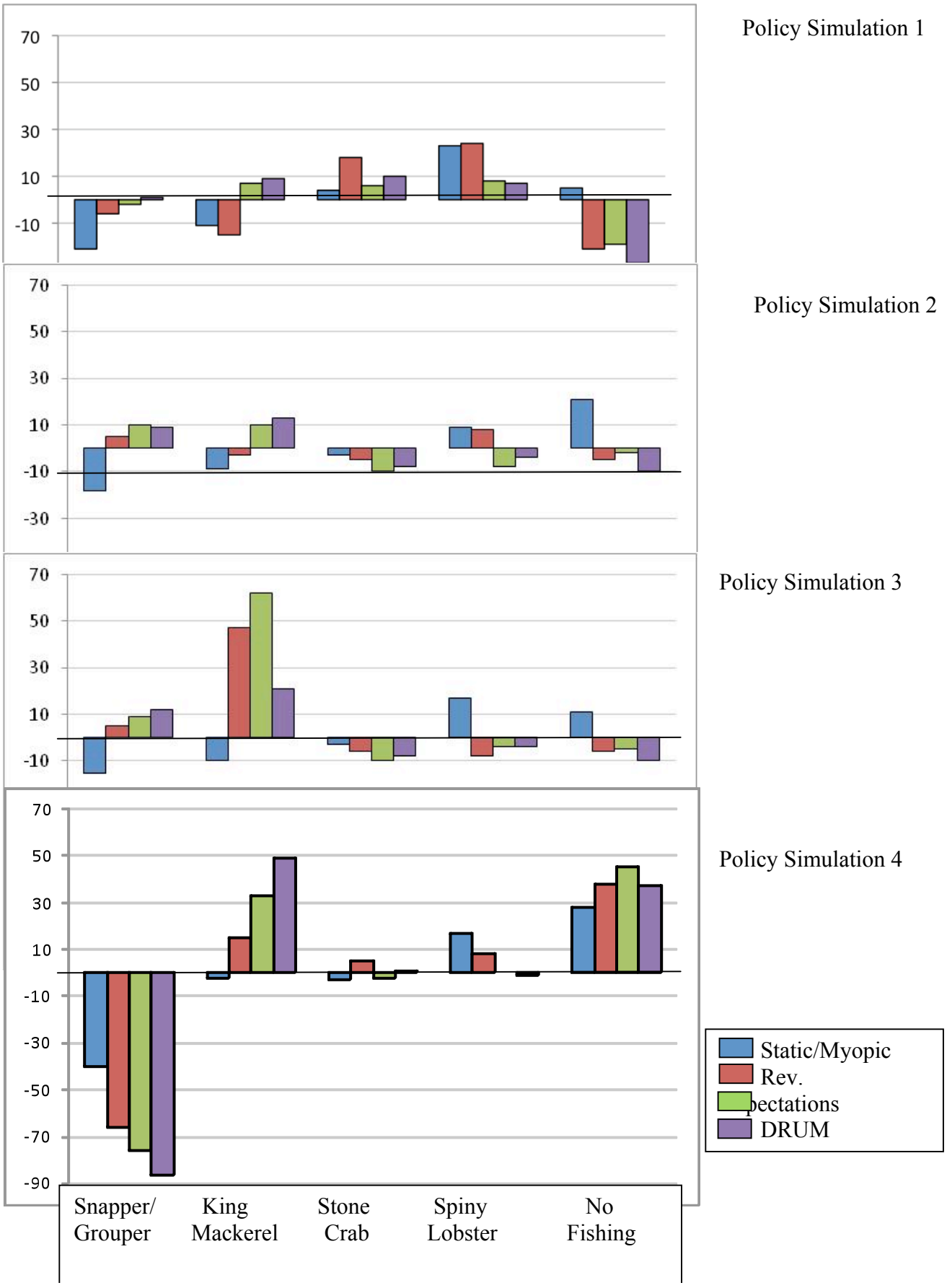
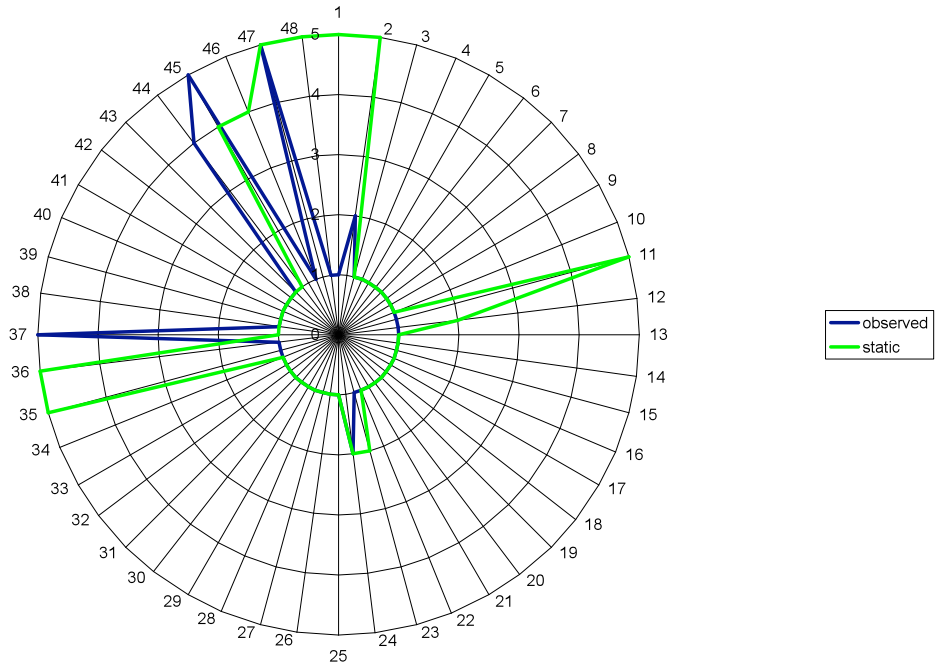


Figure 5. Circular Plots of Observed and Predicted Monthly Targeting under Policy Simulation 4 for a Randomly Selected Fishermen

5(a): static predictions relative to the observed behavior



5(b): revenue expectation predictions relative to the observed behavior