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Abstract

The paper compares the management outcomes with a total allowable catch (TAC) and a total allowable effort (TAE) in a fishery under uncertainty. Using a dynamic programming model with multiple uncertainties and estimated growth, harvest and effort functions from one of the world's largest fisheries, the relative economic and biological benefits of a TAC and TAE are compared and contrasted in a stochastic environment. This approach provides a decision and modeling framework to compare instruments and achieve desired management goals. A key finding is that neither instrument is always preferred in a world of uncertainty and that regulator's risk aversion and weighting in terms of expected net profits and biomass and the trade-offs in terms of expected values and variance determine instrument choice.

Keywords: Fisheries management, bioeconomic model, multiple uncertainties

JEL Classification: C26, D81, Q22

1 Introduction

A fundamental issue in managing common-pool resources is whether to control the inputs or efforts of harvesters or their actual level of catch. In a deterministic world with perfect information and enforcement both approaches generate identical outcomes. However, in a world of uncertainty the two methods of regulation differ in their effects just as prices and quantities differ in their impacts in terms of pollution with uncertainty (Weitzman 1974).

We address the problem of how to manage under uncertainty by comparing two high-order methods of regulation: a total allowable catch (TAC) that limits the total harvest and a total allowable effort (TAE) that regulates the total level of effort expended by harvesters. A TAC provides direct control over harvesting mortality but only indirectly controls the effort expended by harvesters while a TAE directly limits effort and only indirectly limits the amount harvested. Both approaches can be established as market-based instruments if either the total harvest (under TAC control) or the total fishing effort (under TAE control) were allocated as individual and transferable rights in the form individual transferable harvesting quotas (ITQs) or individual transferable effort quotas (IEQs).

Whether a TAC or TAE is preferred depends on the relative costs in monitoring and enforcement, the ability of fishers to substitute to non-ITQ species or unregulated fishing inputs, and the uncertainty between fishing effort and harvest and the uncertainty between the fish stock and the level of recruitment or growth in the fishery. The more uncertain is the relationship between current stocks and future recruitment the more difficult it becomes to effectively set a TAC control while the less predictable is the relationship between fishing inputs and level of catch the less effective is a TAE control in obtaining the desired level of harvest.

A small but important literature has developed over the relative merits of TAC and TAE controls in fisheries. Using a one period model with uncertainty in terms of the current biomass, Hannesson and Steinshamn (1991) find that the actual difference between a constant

catch quota and constant effort is very small and the most important determinant of the relative profitability between them is the size of the stock effect in the harvest function. Quiggin (1992) extended the Hannesson and Steinshamn model to show that there is a constant effort rule that generates a higher economic return for every constant catch rule. Danielsson (2002) subsequently developed a dynamic model to compare the relative efficiency of TAC and TAE controls and also added an additional level of uncertainty. He finds that if the price elasticity of demand is low and the relative variability in the growth of the stock to the catch per unit of effort (CPUE) is low, then a TAC is preferred to a TAE. However, TAE control is superior if the price elasticity of demand is high and there is high variability in the biomass relative to the catch per unit of effort. In an extension of Danielsson's work, Kompas, Che, and Grafton (in press) developed a dynamic model utilizing annual time series database from the Northern Prawn fishery (NPF) of Australia. They find that given the estimated variability in the stock recruitment relationship and CPUE that the use of a TAC is preferred because both expected profits and the stock is higher at the steady state with a TAC, and because the variation in the stock is always less with the TAC than TAE.

The previous studies provide useful insights about regulatory choice but several important questions remain. To what extent can tradeoffs be made between the total catch level and the risk of overfishing? To what extent do uncertainties in both the stock recruitment relationship affect the choice of TAC versus TAE control? To what extent do comparisons of the instruments using cumulative density functions rather than expected values provide added insights about regulatory choice under uncertainty? To address these questions, we employ a dynamic programming model under multiple uncertainties with estimated growth, harvest and effort functions to simulate the economic and biological benefits under TAC and TAE controls. Using cumulative density functions the two instruments are compared by varying uncertainty in terms of the price, the stock-growth relationship and the harvest-effort function.

The paper is organised as follows. In Section 2, we develop a 'benchmark' bioeconomic model under multiple uncertainties. Section 3 describes the simulation method and estimates

the model parameters using annual time series data from the skipjack fishery in the Western and Central Pacific Ocean. Numerical results, the trade-offs between TAC and TAE controls and the effects of uncertainty on the relative payoffs are explored in section 4. Section 5 provides concluding remarks.

2 Modeling TAC and TAE Controls

To compare TAC and TAE controls we specify a monotonic harvest-effort relationship represented by the general form given in (1)

$$h_t = f(E_t, x_t) = qE_t^{\gamma_1} x_t^{\gamma_2} \quad (1)$$

where h is the harvest level and f is the deterministic harvest function with the effort level E , x is the biomass level and q is a constant catchability coefficient at time t . The parameters γ_1 and γ_2 determine the importance of effort and stock level in the harvest function. The effort function, or the inverse of (1), is defined by:

$$\begin{aligned} E_t &= f^{-1}(h_t, x_t) \\ &= g(h_t, x_t) \\ &= \left(\frac{h_t}{qx_t^{\gamma_2}} \right)^{\frac{1}{\gamma_1}} \end{aligned} \quad (2)$$

Uncertainty is introduced by including random variables in the harvest and effort functions, i.e.,

$$h_t = F(E_t, x_t, z_t^h) = z_t^h q E_t^{\gamma_1} x_t^{\gamma_2} \quad (3)$$

and

$$E_t = G(h_t, x_t, z_t^e) = z_t^e \left(\frac{h_t}{qx_t^{\gamma^2}} \right)^{\frac{1}{\gamma^1}} \quad (4)$$

where $F(\square)$ and $G(\square)$ are respectively the harvest and effort functions with the random variables z^h and z^e that can be interpreted as policy implementation errors, respectively in the TAC and TAE controls.

We also specify a stock density dependent stochastic growth function defined as follows:

$$\begin{aligned} x_{t+1} - x_t &= G(x_t, z_t^g) - h_t \\ &= z_t^g r x_t \left(1 - \frac{x_t}{K} \right)^\alpha - h_t \end{aligned} \quad (5)$$

where r is the intrinsic growth rate, K is the carrying capacity, and α represents the skewness of the logistic growth function G . The change in the biomass over a period is the difference between the harvest level and the random growth in the stock. The random variable z^g represents unknown variability in the growth in the biomass.

Objective Function and Constraints

For both TAC and TAE controls we assume the regulator wishes to maximize the discounted net profits from fishing over an infinite time horizon and that the choice of which instrument to use cannot be changed. Our objective is to compare the relative biological and economic payoffs under various forms of uncertainty. The regulator's optimization problem is to maximize (6) subject to constraints (7)-(9).

$$\max_{E_t \text{ or } h_t} E \sum_{t=0}^{\infty} \beta^t \pi_t \quad (6)$$

subject to

$$x_{t+1} - x_t = z_t^g r x_t \left(1 - \frac{x_t}{K}\right)^\alpha - h_t \quad (7)$$

$$x_0 = x(0) \quad (8)$$

$$z_0^i = z^i(0) \quad i = \{h, e, g\} \quad (9)$$

where E is the mathematical expectation operator and $\beta \in (0,1)$ is the time discount factor. We define π as the net profit and $\pi = p(h)h - cE$, where $p(h)$ is the inverse demand function and c is cost per unit of effort. In a TAC controlled fishery the regulator seeks to set an optimal harvest quota to maximize discounted net profits while under TAE control the regulator sets the optimal effort quota.

The inverse demand function is specified as $\bar{p}h_t^{-1/\delta}$, where δ is the price elasticity of the demand and $\bar{p}$ is a parameter. Thus, the total revenue and cost functions are, respectively, defined as $R_t = \bar{p}h_t^{-1/\delta} \times h_t$ and $C_t = cE_t$.

Given strict convexity of the harvest function and concavity of the effort function it follows from Jensen's inequality that with a given stock level that $x_t = x_t^*$, $F(E_t, x_t^*, E[z_t^h]) < E[F(E_t, x_t^*, z_t^h)]$ and $E[G(h_t, x_t^*, z_t^e)] < G(h_t, x_t^*, E[z_t^e])$.¹ This result implies that, with a fixed stock level, harvest control will yield a smaller catch and also a smaller effort level on average in a stochastic environment. However, the inequalities do not always hold because of the random variable z^g that varies the biomass over time. For example, assume that $F(\square)$ is increasing and $G(\square)$ is decreasing function of the biomass and if $x_t^* > \tilde{x}_t$, then $F(E_t, x_t^*, E[z_t^h]) > E[F(E_t, \tilde{x}_t, z_t^h)]$ and $E[G(h_t, \tilde{x}_t, z_t^e)] > G(h_t, x_t^*, E[z_t^e])$ can hold, respectively. Consequently a model that accounts for uncertainty in the growth function and how it changes the biomass over time will yield different results than a one-period model.

The dynamic recursive form of the problem defined by (6)-(9) for TAE control takes the following form:

$$V^e(x_t) = \max_{E_t \geq 0} \left(E \left[p \cdot z_t^h q E_t^{\gamma_1} x_t^{\gamma_2} \right] - c E_t \right) + \beta E V^e(x_{t+1}, z_{t+1}^g) \quad (10)$$

and for TAC control,

$$V^h(x_t) = \max_{h_t \geq 0} \left(p h_t - E \left[c \cdot z_t^e \left(\frac{h_t}{q x_t^{\gamma_2}} \right)^{\frac{1}{\gamma_1}} \right] + \beta E V^h(x_{t+1}, z_{t+1}^g) \right) \quad (11)$$

The solution to the optimization problems in (10) and (11) yields, respectively, the optimal effort level and harvest level in each period. As a result of the random variables the optimal levels of effort and harvest may not equal their actual levels.

3 Western and Central Pacific Skipjack Fishery

The problem of instrument choice is applied to the Western and Central Pacific skipjack fisheries. This is one of the world's largest with estimated total harvest of approximately 1.2 million metric tons per year (Langley et al. 2005). The fish are harvested primarily from purse seine and pole and longline vessels. The management of the fishery is overseen by the Western and Central Pacific Fisheries Commission (WCPFC) — a regional fisheries management organization (Parris and Grafton 2005). The WCPFC acts on behalf of its member nations that include coastal states and distant water fishing nations and sets 'meta' rules for its members that apply to both the exclusive economic zones (EEZs) and the high seas components of the fishery.

To address concerns over higher than desired levels of fishing mortality for yellowfin, and especially bigeye tuna, members of the WCPFC have agreed to implement a type of TAE in the form of a vessel Day Scheme (VDS) for these species that restricts the number of days fished to an average over the 2001-2004 period. Although fishing effort for skipjack tuna is not directly controlled by the VDS it will also regulate the skipjack fishery as bigeye and

yellowfin are important bycatches.

The economic and biological parameters for our model are estimated by using annual time series data (1972-2002) from the skipjack tuna purse seine fisheries. The effort level is measured by days at sea fishing and searching for fish. Details of the estimation are provided in Table 1 for both the harvest function and the growth function. For ease of exposition the carrying capacity K is normalized to unity such that the biomass x represents density rather than the actual weight of fish. The price elasticity of demand and the cost parameter are obtained from Bertignac *et al.* (2000). The price elasticity is set at $\delta = 1.55$ and the cost parameter is set at $c_1 = 14.5$. There is a large variation in the cost of purse seine fisheries, and thus an alternative cost parameter $c_2 = 2.4$ is also applied in the analysis. The price parameter is set at 50 to ensure the existence of a unique steady state. The base case results are derived from the estimated parameters, and alternative parameters are applied to investigate how the relative efficiencies between the two instruments change.

[Table 1 is about here]

The stochastic factors $z^{h/e}$ and z^g are specified as $z^i = 1 + (2u - 1)\varepsilon^i$, $i = \{h, e, g\}$, where u is uniformly discretized with 10 grids (a 10-state Markov transition). The term ε determines the size of variations in the harvest and effort functions and growth function. It lies between 0 and 1, indicating from 0 per cent to 100 per cent variations. We set $\varepsilon = 0.01$ (1 per cent variation) for ‘small’ and $\varepsilon = 0.05$ (5 per cent variation) for ‘large’ uncertainty. An underlying assumption in the uncertainty is that the resource managers do not have exact information of the variation in the fish growth and implementation of their policies, but they do know about the source of uncertainty (which variables contain unpredictable variations) and their distributions (how large the variations would be).

4 Model Results

To solve the recursive problems in (10) and (11) numerically, the value function iteration is utilized with evenly discretized 200 state space grids.² This is implemented using a numerical method and two expectation terms are calculated. One is the expectation of the net returns for the ‘implementation uncertainty’ for all possible combinations of the state variables in the current (x_t) and next period (x_{t+1}). The other is the expected value of the value function for the ‘growth uncertainty’. At each iteration (updated from the previous iteration), the optimal policy rule is determined to maximize the value function for each of the current states ($x_{t+1} = \Phi(x_t, z_t^g)$). The value function is iterated until a convergence criterion is satisfied ($\|V^{l+1} - V^l\| < e^{-10}$).

Using information from the converged value function (V^*) with a given initial stock and tracking the Markov transitions in $z^{h/e}$ and z^g , 50,000 sets of time series are simulated for the optimal policy rule, stock level, and economic returns for the TAC and TAE. These calculated values are restricted to $0 \leq h_t^* \leq K$, $0 \leq E_t^* < \infty$, $0 \leq x_t^* \leq K$ and $0 \leq \pi_t^* < \infty$, which imply that these variables are non-negative and the harvest and biomass cannot exceed the carrying capacity.

The steady state values of the biomass, net profits, harvest and effort levels under the deterministic case, where $\varepsilon^{h/e} = 0$ and $\varepsilon^g = 0$, are presented in Table 2.³ Without any stochasticity in the growth, and harvest-effort functions, both the optimal net profits and fish stock level are identical for the TAC and TAE. This is because under perfect information, enforcement and without any implementation error, the fishery manager can optimally control the harvest and effort level to maximize the discounted net profits by using either instrument.

[Table 2 is about here]

TAC versus TAE Control

In order to determine the superiority among the two fisheries instruments in a stochastic environment, a reference point needs to be assigned. This is because the superiority between

the fisheries instruments may change, depending on the different realizations of uncertainties. Kompas, Che and Grafton (in press) use expected values to compare TAC and TAE controls. A problem with their approach, however, is that a single value of the expected value of the outcomes (net profits and biomass) does not provide a sensible reference point to compare the two instruments. This is because of the minimal difference between the expected values derived from the two control variables.⁴ We overcome this deficiency by constructing a cumulative density function (CDF) of the outcomes averaged over 50 periods to capture the difference in the two instruments.

The CDF describes the probability distribution of all possible outcomes and for each instrument is drawn from the 50,000 simulations. In each CDF figure the point where CDF = 0.5 represents the average value of the 50,000 simulations, and thus it is the expected value of the outcomes. The intersection of the two functions derived from each fisheries instrument represents the point at which the outcomes from the two instruments are identical. If the intersection is either below or above the point where CDF = 0.5 then one of the instruments is superior to the other with a higher probability in terms of the outcome measures.

Optimal Time Paths

Figure 1 presets the sample optimal time path for the harvest and effort levels under two different scenarios⁵. In the first case the relative uncertainty in the growth function is small relative to the harvest-effort function ($\varepsilon^{h/e} = 0.05$ and $\varepsilon^g = 0.01$) while in the second the other there is much more uncertainty in the growth function relative to the harvest-effort function ($\varepsilon^{h/e} = 0.01$ and $\varepsilon^g = 0.05$). The dotted line is the optimal time path under the deterministic environment with no uncertainty. When the uncertainty in the harvest and effort functions is relatively large, the harvest level with the TAE has a greater variation than that with the TAC but the variation in the level of effort is smaller than with the TAC. This is because the TAC directly controls the harvest level, while the harvest in the TAE is indirectly determined by setting the optimal effort quota. The figure also shows that the variations in the

harvest and effort levels are greater when the uncertainty in the harvest-effort function is relatively large.

[Figure 1 is about here]

Figures 2.1 and 2.2 illustrate the relative economic payoffs between the two instruments changes according to the relative size of the uncertainty. If the uncertainty in the growth function is small (Figure 2.1: $\varepsilon^{h/e} = 0.05$ and $\varepsilon^g = 0.01$), the relative economic payoff favours the TAC. This is shown in Figure 2.1 by the intersection of the TAC and TAE CDFs at a point greater than 0.5. By contrast, if the uncertainty in growth function is large (Figure 2.2: $\varepsilon^{h/e} = 0.01$ and $\varepsilon^g = 0.05$), the TAE has a higher payoff than the TAC with a higher probability as shown by the intersection of the CDFs at a point less than 0.5. The greater is the variation in the harvest- effort function then the larger is the variation in the harvest level with a TAE control that, in turn, contributes to over or under fishing. On the other hand, the greater is the variation in the biomass growth function the larger is the regulator's error in predicting the following period's stock level such that TAC control is set at either at too high or too low a level reducing its efficacy as a policy instrument.

[Figure 2 is about here]

Figures 3.1 and 3.2 provide a comparison between TAC and TAE controls in terms of the average biomass. In both cases a TAC control delivers a higher average biomass. The large the variation in the biomass growth function relative to the variation in the harvest-effort function the larger is the average biomass associated with TAC control compared to TAE control. This is because with a relatively high realization in the biomass a TAC control increases the likelihood of harvesting less than what is optimal relative to a TAE control. This more than offsets the case of lower than expected realization in the biomass with a TAC that results in greater than optimal fishing and greater overfishing than with TAE control. As a result, the TAC maintains on average a greater biomass than TAE control.

[Figure 3 is about here]

Sensitivity Analysis: Stock Effect

The estimated value of the stock or biomass dependency parameter, γ_2 , in the harvest function was not statistically significant different from zero at the 5% level of significance. However, the ‘stock effect’ has been shown to be important in some fisheries so we assess the sensitivity of the results to changes in this parameter.⁶ Figures 4 and 5 show how the results change when there is a weak link ($\gamma_2 = 0.27$) between the harvest and the biomass. Although there is not a substantial change in the results, the introduction of stock effect favors TAE control versus TAC control in terms of net profits because a smaller level of effort is needed to maintain the same level of harvest. Given a smaller level of effort, there is less variation in the harvest level in the TAE, and it is less likely there will be over or under fishing.

[Figure 4 is about here]

[Figure 5 is about here]

Sensitivity Analysis: Price Elasticity of Demand

The greater price elasticity of demand, the more responsive is price to changes in the total harvest. To investigate how the price elasticity affects the result, a larger value of the price elasticity of demand ($\delta = 2.1$) is applied. The simulation results are shown in Figures 6 and 7. Again, the difference to the base-case results in Figures 2 and 3 is not large. However, Figure 6 does show that as the price elasticity increases, the payoffs in terms of net profits increase for TAC versus TAE control. This is because the more responsive is the price to change in the harvest the less desirable is TAE control as it only indirectly controls the harvest.

[Figure 6 is about here]

[Figure 7 is about here]

Sensitivity Analysis: Harvesting Costs

An alternative and substantially smaller cost parameter ($c = 2.4$) is applied to analyze how the results alter with changes in harvesting costs. The simulations are presented in Figures 8 and 9. The results are very different to Figures 2 and 3. As the cost parameter decreases the cost of fishing becomes lower and the optimal harvest level increases. A larger harvest, however, increases the risk of overfishing and because the TAE control only indirectly limits the harvest it is optimal to have a lower level of fishing effort to avoid such an outcome. By contrast, the TAC control limits the harvest level directly and there is less need to compensate with lower harvests if it can be controlled directly. Consequently, the TAE is relatively favored in terms of the average payoffs and generates a higher biomass to the TAC relative to the base case scenario. This finding contradicts Hannesson and Steinshamn (1991) who find that, as fishing cost decreases, the constant effort strategy becomes relatively less profitable than the constant catch management. Their results comes from the fact that in a one period model with a strictly convex cost function, the smaller is the fishing cost, the less is the relative fishing cost in the TAC. By contrast, in our dynamic model with time varying biomass, this relationship does not always hold. For instance, if the constant effort strategy conserves a greater biomass, then the fishing cost with the TAC could be greater than that with the TAE. Thus, in our results as fishing costs decrease, the TAE level is reduced as it only indirectly controls harvest and the probability of overfishing increases with higher optimal harvests. Consequently, the harvest and effort levels with the TAE become relatively smaller than those with the TAC leading to higher average biomass and net profits relative to TAC control.

[Figure 8 is about here]

[Figure 9 is about here]

Sensitivity Analysis: Price Effect

A similar result to the costs effect is obtained with a higher price of fish ($p = 100$) but with the same price elasticity of demand. As the value of a landed fish increases, the optimal

harvest level rises. At a larger harvest the risk of overfishing becomes greater and because a TAE only controls the harvest indirectly, it is optimal to limit total effort more than total harvest. This is equivalent to a decrease in the cost parameter and favors TAE control relative to TAC control in terms of average net profits and the biomass.

[Figure 10 is about here]

[Figure 11 is about here]

5 Discussion

We contribute to the literature on instrument choice by examining multiple uncertainties in an actual fishery using a dynamic model and also provide a decision making framework in the form of CDFs. The approach offers a substantial improvement over earlier work and generates additional insights. For instance, Hannesson and Steinshamn (1991, p. 88), argue that the most important determinant as to which instrument is preferred is the size of the stock effect in the harvest function. Our analysis suggests that other factors, such as the level of the costs and price parameters are equally important in determining the preferred instrument.

Danielsson (2002) provides the most complete analytical set of results regarding instrument choice but to obtain his results he was limited to examining the case of only one form of uncertainty — in either the biomass growth function or in terms of catch per unit of effort, but not both. By employing numerical methods we are able to examine multiple uncertainties. Our findings support the results of Danielsson (2002) and we also find that modeling several forms of uncertainty is required to make adequate comparisons between the instruments. Our approach has most in common with Kompas, Che, and Grafton (in press). They also use a dynamic model and estimate parameters from the Northern Prawn fishery of Australia to compare TAC and TAE controls. They do not, however, undertake sensitivity analysis in terms of cost and price parameters or the price elasticity of demand, and restrict themselves to comparisons of expected values and standard deviations in the biomass and net profits which is not an adequate means of comparison.

The principal management implications from our results is that TAC control generates wider risk boundaries for the average biomass than does TAE control. However, a TAC has the advantage that it results in a lower variation in both biomass and net profits than a TAE. We also find there are tradeoffs between the harvest level and the risk of overfishing. If the regulator sets a high harvest level, either with a TAC or TAE, the expected net profits will also increase for a given sufficient stock level. However, higher harvests increase the risk of overfishing and cause a less than optimal biomass level which lowers future net profits. Harvesting less today also reduces the possibility of overfishing but at the cost of net profits today.

Overall, our analysis provides a decision framework to balance higher expected net profits with lower expected biomass levels, and to show how TAC and TAE controls generate different outcomes. Indeed, a key finding of our modeling is that the larger is the harvest level then the greater is the variance in the net profits associated with TAE versus TAC control, but the higher is the expected biomass.

We fix the instrument choice at the beginning period and do not allow for a policy switch. Our results imply, however, that as costs and prices change in a fishery the relative preference for a given method of control may change. This suggests the possibility that a portfolio of instruments could be applied to optimize the management of fisheries. In such a scenario, fishers could be allocated both shares in a TAE and a TAC. Only one of the instruments would be binding in any period but it would allow the option to switch into a different policy regime as conditions in the fishery changed. For example, in the Eastern and Tuna Billfish fishery in Australia fishers will be assigned shares (denominated in hooks) of a TAE beginning 1 January 2008, but they could subsequently be allocated individual harvesting rights as a share of TAC control if such rights were assigned in the same ratio as individual effort shares.

6 Concluding Remarks

One of the most difficult aspects of managing fisheries is to cope with the inherent uncertainties in stock-recruitment and the harvest-effort relationships. Depending on the relative magnitudes of the uncertainties in these relationships and the price and cost parameters, managers can trade-off expected net profits and biomass levels with their variability.

Using parameter estimates from one of the world's largest fisheries, Western and Central Pacific skipjack tuna, we analyze multiple uncertainties and compare the use of a total harvest control with a total effort control. Using a decision framework not previously used in this context we compare the payoffs of the two instruments using cumulative density functions. A key finding is that neither instrument is always preferred in a world of uncertainty and that regulator's risk aversion and weighting in terms of expected net profits versus biomass, and trade-offs in terms of expected values and variance determine the instrument choice. Our analysis also shows that as harvesting costs decrease and the price of fish rises the desirability of a total effort control increases relative to that of a total harvest control in terms of expected net profits and biomass. Overall, our results provide a decision and modelling framework by regulators to compare instruments and to achieve desired management goals.

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Appendix

The purpose of this appendix is to show that when the harvest level increases from h_0 to h_1 , the percentage increase in the harvest level is greater than that in the corresponding effort level. In other words, we want to show that $\% \Delta h > \% \Delta E$ with $h_0 = qE_0^{\gamma_1} x^{\gamma_2}$ and $h_1 = qE_1^{\gamma_1} x^{\gamma_2}$.

$$\% \Delta h = \frac{h_1 - h_0}{h_0} = \frac{h_1}{h_0} - 1$$

$$\% \Delta E = \frac{E_1 - E_0}{E_0} = \frac{\left(\frac{h_1}{qx^{\gamma_2}} \right)^{1/\gamma_1} - \left(\frac{h_0}{qx^{\gamma_2}} \right)^{1/\gamma_1}}{\left(\frac{h_0}{qx^{\gamma_2}} \right)^{1/\gamma_1}} = \left(\frac{h_1}{h_0} \right)^{1/\gamma_1} - 1$$

Since $1/\gamma_1 < 1$, $h_1/h_0 < (h_1/h_0)^{1/\gamma_1}$ and $\% \Delta h > \% \Delta E$.

**Table 1 Estimation results of
the growth function and the harvest function**

Growth function		
Parameter	Coefficient	T ratio
r	1.31	8.50 (0.154)
α	0.89	2.25 (0.396)
Number of obs	30	
R-squared	0.59	
Harvest function		
Parameter	Coefficient	T ratio
$\ln(q)$	-1.93	-1.97 (0.978)
γ_1	1.37	-16.71 (0.082)
γ_2	0.27	-1.34 (0.202)
Number of obs	31	
R-squared	0.91	
P-value (F-stat)	0.000	

Note: Numbers in parentheses are standard errors.

**Table 2 Biomass, net profits, harvest and effort
at the steady state under a deterministic environment**

	Biomass	Net profits	Harvest	Effort
TAC	0.9447	11.0397	0.0941	0.7292
TAE	0.9447	11.0397	0.0941	0.7292

Figure 1 Optimal sample time paths for the harvest and fish effort under stochastic environment

1.1 Optimal sample time path for harvest
 $(\varepsilon^g = 0.01 \text{ and } \varepsilon^{h/e} = 0.05)$

1.2 Optimal sample time path for effort
 $(\varepsilon^g = 0.01 \text{ and } \varepsilon^{h/e} = 0.05)$

1.3 Optimal sample time path for harvest
 $(\varepsilon^g = 0.05 \text{ and } \varepsilon^{h/e} = 0.01)$

1.4 Optimal sample time path for effort
 $(\varepsilon^g = 0.05 \text{ and } \varepsilon^{h/e} = 0.01)$

Figure 2 CDF of average net profit with different size of uncertainties

Figure 3 CDF of average biomass with different size of uncertainties

Figure 4 CDF of average net profit with a stock effect in harvest and effort functions

Figure 5 CDF of average biomass with a stock effect in harvest and effort functions

Figure 6 CDF of average net profit with price elasticity $\delta = 2.1$

Figure 7 CDF of average biomass with price elasticity $\delta = 2.1$

Figure 8 CDF of average net profit with cost parameter $c = 2.4$

Figure 9 CDF of average biomass with cost parameter $c = 2.4$

Figure 10 CDF of average net profit with price parameter $p = 100$

Figure 11 CDF of average biomass with price parameter $p = 100$

End Notes:

1. The parameter γ_1 is estimated as $\gamma_1 = 1.37$, thus the restriction, $3.7 > \delta > 1$ is necessary to ensure the strict concavity of the profit function. Hence, the harvest and effort functions are, respectively, strictly convex and concave, and the revenue and cost functions are concave with respect to the control variables.
2. See Judd (1998) for further details.
3. The deterministic case is provided to show that a solution exists and that the system is stable and is not a benchmark.
4. This finding is consistent with the findings of Hannesson and Steinshamn (1991).
5. The same realizations in terms of the random variables are applied for both TAC and TAE controls.
6. For example, Kompas and Che (2006) estimated a harvest function that shows the relationship between the harvest and biomass in three of the tuna fisheries in the Western and Central Pacific.