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OUTPUT VERSUS INPUT CONTROLS UNDER UNCERTAINTY: THE CASE OF A FISHERY

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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.

KEY WORDS: Fisheries management, bioeconomic model, multiple uncertainties.

1. Introduction. A fundamental issue when managing common-pool resources is whether to control the inputs or efforts of resource users or their actual level of use or harvest. In a deterministic world with perfect information and enforcement, both approaches generate identical outcomes. However, in a world of uncertainty the two methods

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of regulation differ in their effects just as prices and quantities differ in their impacts (Weitzman [1974], Jensen and Vestergaard [2003]).

We address the problem of how to manage renewable resources 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. 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, the uncertainty between fishing effort and harvest, and the uncertainty between the fish stock and the level of recruitment or growth in the fishery. In this paper, we confine our analysis to how the uncertainty affects the relative efficiency between TAC and TAE controls. Focusing on uncertainty, we show what circumstances favor TAC versus TAE controls.

A TAC provides direct control over harvesting mortality but only indirectly controls the effort expended by harvesters, whereas a TAE directly limits effort and only indirectly limits the amount harvested. In the case of TAE control, fishers may be able to substitute to unregulated inputs to offset the limits imposed by managers (Dupont [1991]), but ineffective monitoring and enforcement will limit the ability of a TAC to control the harvests of fishers. Both approaches can be established as market-based instruments. In the case of total harvest (under TAC control) rights can be allocated as individual transferable harvesting quotas, whereas for total fishing effort (under TAE control), rights can be allocated in the form of individual transferable effort quotas.

The existing literature shows that the more uncertain is the relationship between current stocks and future recruitment, the more difficult it becomes to effectively set a TAC control. Similarly, 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. Although these are important insights, there remain several important questions to be answered when comparing the two instruments. For instance, to what extent can trade-offs be made between the total catch level and the risk of overfishing? To what extent do uncertainties in both the stock recruitment and harvest–effort relationships 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 knowledge gaps, 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.

The paper is organized as follows. In Section 2, we describe the results from previous modeling and describe our own "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. A discussion of the results is given in Section 5 and Section 6 provides concluding remarks.

2. Modeling TAC and TAE controls. 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] showed 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. They also found that, as fishing cost decreases, the constant effort strategy becomes less profitable. 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 relative variability in the growth of the stock to the catch per unit of effort is low, then a TAC is preferred to a TAE. In an extension of Danielsson's work, Kompas et al. (2008) developed a dynamic model utilizing data from the Northern Tiger Prawn fishery of Australia. They find that given the estimated variability in the stock–recruitment relationship and catch per unit of effort that the use of a TAC is preferred in that fishery because both expected profits and the stock are higher at the steady state with a TAC, and because the variation in the stock is always less with the TAC than TAE.

We develop a bioeconomic model based on the models in Hannesson and Steinshamn [1991] and Danielsson [2002]. This permits us to compare and contrast our results to previous studies. To compare TAC and TAE controls, we specify a monotonic harvest–effort relationship represented by the general form given in equation (1)

$$h_t = f(E_t, x_t) = qE_t^{\gamma 1} x_t^{\gamma 2} \tag{1}$$

where h_t is the harvest level at time t. The function f is the deterministic harvest function with the effort level E_t, biomass level x_t, and a constant catchability coefficient q at time t. The parameters $\gamma 1$ and $\gamma 2$ determine the importance of effort and stock levels in the harvest function. We define $\gamma 2$ as a stock effect. Given the assumption of $\partial h_t / \partial E_t > 0$, the effort function, or the inverse of (1) is:

$$\begin{aligned} E_t &= f^{-1}(h_t, x_t) \\ &= g(h_t, x_t) \\ &= \left(\frac{h_t}{q x_t^{\gamma 2}} \right)^{\frac{1}{\gamma 1}} . \end{aligned} \tag{2}$$

Uncertainty is introduced by including random variables in the harvest and effort functions, respectively, that is,

$$h_t = F\big(E_t, x_t z_t^h\big) = z_t^h q E_t^{\gamma 1} x_t^{\gamma 2} \tag{3}$$

and

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

where F and G are, respectively, the harvest and effort functions with the random variables z_t^h and z_t^e interpreted as "policy implementation errors," respectively, in the TAE and TAC controls. In other words, z_t^h is realized only when the TAE control is implemented, and z_t^e is realized only when the TAC control is used as an instrument.

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

$$x_{t+1} - x_t = z_t^g r x_t \left(1 - \frac{x_t}{K} \right)^{\alpha} - h_t , \tag{5}$$

where r is the intrinsic growth rate, K is the carrying capacity, and α represents the skewness of the growth function. 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_t^g represents unknown variability in the growth in the biomass.

2.1 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. This assumption is not restrictive to our objective of comparing the relative biological and economic payoffs between the two fisheries instruments under various forms of uncertainty. Indeed, the two instruments can be more explicitly compared if the choice of instrument is not switched over time because our simulations will depend on the performance of only each instrument at a time.[1]

The regulator's optimization problem is to maximize the objective function (6) subject to constraints (7) to (9).

$$\max_{Et \text{ or } h_t} \mathbb{E} \sum_{t=0}^{\infty} \beta^t \pi_t \tag{6}$$

subject to

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

$$x_0 = x(0) \tag{8}$$

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

where $\mathbb{E}$ is the mathematical expectation operator and $\beta \in (0,\, 1)$ is the time discount factor. We define π_t as the net profit at time t and $\pi_t = p(h_t)h_t - cE_t$, where $p(h_t)$ 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, whereas under a TAE control the regulator sets the optimal effort quota. Our model disregards costs connected with monitoring and enforcement for the two different instruments and the ability of fishers to substitute to nontargeted species or unregulated inputs. As in Danielsson [2002], this allows us to focus on the effects of uncertainties in the stock–recruitment relationship and the harvest–effort relationship on the relative efficiency of TAC and TAE controls.

The inverse demand function is specified as $p(h_t) = \bar{p}h_t^{-1/\delta}$, where δ is the price elasticity of the demand and $\bar{p}$ is a parameter. This specification is commonly used in bioeconomic modeling (Clark 1990) and can encompass various forms of the demand function depending on the parameter δ. For example, as $\delta \to \infty$, $p(h_t) \to \bar{p}$, and the price converges to a constant. Given the inverse demand function, the total revenue and cost functions are, respectively, defined as $R_t = \bar{p}h_t^{-1/\delta} \times h_t$ and $C_t = cE_t$.

Our model implicitly indicates the importance of including both the population dynamics and different forms of uncertainty when the two fisheries instruments are compared. Given strict convexity of the harvest and concavity of the effort functions, it follows from Jensen's inequality that with a given stock level $x_t = x_t^*$, $F(E_t, x_t^*, \mathbb{E}[z_t^h]) < \mathbb{E}[F(E_t, x_t^*, \mathbb{E}[z_t^h])]$ and $\mathbb{E}[G(h_t, x_t^*, z_t^e)] < G(h_t, x_t^*, \mathbb{E}[z_t^e])$.[2] This result implies that, with a fixed stock level, harvest control will yield a smaller catch and also a smaller effort level on average under the stochastic environment. However, the inequalities do not always hold because of the random variable z_t^g that varies the biomass over time. For example, assume that F is an increasing and G is a decreasing function of the biomass and $x_t^* > \tilde{x}_t$, then $F(E_t, x_t^*, \mathbb{E}[z_t^h]) < \mathbb{E}[F(E_t, \tilde{x}, z_t^h)]$ and $\mathbb{E}[G(h_t, \widetilde{x}_t, z_t^e)] < G(h_t, x_t^*, \mathbb{E}[z_t^e])$ can hold, respectively. Consequently, a model that accounts for uncertainty in the growth function and the population dynamics over time will yield different results than a one-period model.

The recursive form of the problem for each control variable is as follows: for TAE control, it takes the following form:

$$V^e(x_t) = \max_{E_t} \left(\mathbb{E}\left[p \cdot z_t^h q E_t^{\gamma 1} x_t^{\gamma 2}\right] - cE_t + \beta \mathbb{E} V^e\left(x_{t+1}, z_{t+1}^g\right)\right) \tag{10}$$

and for TAC controls it is:

(11)

$$V^h(x_t) = \max_{h_t} \left(ph_t - \mathbb{E}\left[c \cdot z_t^e \left(\frac{h_t}{q x_t^{\gamma 2}} \right)^{\frac{1}{\gamma 1}} \right] + \beta \mathbb{E} V^h \left(x_{t+1}, z_{t+1}^g \right) \right) \Bigg|,$$

where the left hand side of both equations (10) and (11) represents the value function, which is the maximum attainable objective function at time t. The right hand side of the equations has two parts. The first two terms are the expected net profit at time t ($\mathbb{E}\pi_{\mathrm{t}}$), and the last term $\beta \mathbb{E} V^i(x_{t+1},\, z_{t+1}^g)$, $i \in \{e,\, h\}$ is the discounted expected value function at time $t + 1$. 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 fishery.[3] It is one of the world's largest fisheries in terms of total harvest and generates landings of approximately 1.2 million metric tons per year (Langley et al. [2005]). The fish are harvested primarily by purse seine vessels that are highly capital intensive, although some skipjack is also caught by pole-and-line vessels. Overall, the fishery is characterized as a high volume but low value fishery per unit harvested (Barclay and Cartwright [2007]). Although concerns have been raised about the sustainability of other tuna species (in particular bigeye), the biomass of skipjack still remains above its maximum sustained yield (Langley et al. [2005]).

The management of the fishery is overseen by the Western and Central Pacific Fisheries Commission (WCPFC)—a regional fisheries management organization (Parris and Grafton [2006]). The WCPFC acts on behalf of its member nations, which include coastal states and distant water fishing nations, and sets "meta" rules for its members that apply to both EEZ and the high-seas zones of the fishery. Its decisions are binding on member states 60 days after their adoption. Decisions are, in the first instance, to be made by consensus, and if this is not possible and only after all efforts to reach a decision by consensus have been exhausted, decisions can be made by a three-fourths majority of members.

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 tuna species that will restrict 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, the scheme 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 fishery. 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 growth function and the harvest function. The intrinsic growth rate (r) and the parameter in the growth function (α) are estimated as $r = 1.31$ and $\alpha = 0.89$. The goodness of the fit for the growth function is 0.58, and both parameters are statistically significant at 5% level. The parameters in the harvest function are estimated as $\ln(q) = -1.93$, $\gamma_1 = 1.37$, and $\gamma_2 = 0.27$. The goodness of the fit for the harvest function is 0.91. The catchability coefficient (q) and the parameter (γ_1) are statistically significant at 5% level, but the stock effect (γ_2) is not significant. Hence, we first set $\gamma_2 = 0$ to obtain base case results and then apply $\gamma_2 = 0.27$ for the sensitivity analysis of the stock effect in the harvest function. For ease of exposition, the carrying capacity (K) is normalized to unity such that the biomass (x) represents density rather than 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 $c = 14.5$. Due to the lack of adequate price data, the parameter in the inverse demand function ($\bar{p}$) is initially set at 50 to ensure the existence of a unique steady state, and sensitivity analysis is then undertaken. The base-case results are derived with the statistically significant estimated parameters, and alternative parameters are applied for a sensitivity analysis. This allows us to investigate how the relative efficiencies between the two instruments change depending on the parameter values.

The stochastic factors z^h, z^e, and z^g are specified as $z^i = 1 + (2u - 1)\varepsilon^i$, $i \in \{h, e, g\}$, where u is uniformly discretized with 10 grids (a 10-state Markov transition). The term ε determines the size of variations

TABLE 1. Estimation results of the growth function and the harvest function.

Parameter	Coefficient	T ratio
	Growth function	
r	1.31	8.50
		(0.154)
α	0.89	2.25
		(0.396)
Number of observations	30	
R^2	0.58	
	Harvest function	
$\ln(q)$	−1.93	−1.97
		(0.978)
$\gamma 1$	1.37	−16.71
		(0.082)
$\gamma 2$	0.27	−1.34
		(0.202)
Number of observations	31	
R^2	0.91	
p-value (F-stat)	0.000	

Note: Numbers in parentheses are standard errors.

in the harvest and effort functions and growth function. It lies between 0 and 1, indicating from 0–100% variations. An underlying assumption in the uncertainty is that resource managers do not have exact information of the variation in the fish growth function and harvest and effort functions, 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 300 state space grids.[4] 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" (uncertainty in the harvest and effort functions) 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" (uncertainty in the growth function). At each iteration (updated from the previous iteration), the optimal policy rule function ($\Phi : \mathbb{R}_+ \times \mathbb{R}_{++} \rightarrow \mathbb{R}_+|$) is determined to maximize the objective function for each of the current states and the realization of the growth uncertainty ($x_{t+1} = \Phi(x_t,\, z_t^g)$). 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, z^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 $0 \leq h_t^* \leq K$, $0 \leq E_t^*$, $0 \leq x_t^* \leq K$, and $0 \leq \pi_t^*$, which implies that these variables are nonnegative and the harvest and biomass cannot exceed the carrying capacity. Due to the normalization of carrying capacity (K), the units of the biomass and harvest are defined as densities, and the units of the effort and net profit become indexes. Consequently, the domain for the biomass and harvest is from 0 to 1 for both TAC and TAE controls, but the domains for the effort and net profit vary, depending on the instrument choice, the values of the parameters, and the relative size of the uncertainty in the growth and harvest–effort functions.

The steady state values of the biomass, net profits, harvest, and effort levels under the deterministic case, where $\varepsilon^h = 0$, $\varepsilon^e = 0$ and $\varepsilon^g = 0$, are presented in Table 2.[5] Without any stochasticity in 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.

4.1 TAC versus TAE control. In order to determine the superiority among the two fisheries instruments in a stochastic environment, a reference point must be assigned. This is because the superiority between the fisheries instruments may change, depending on the different realizations of uncertainties. Kompas et al. (2008) use expected values

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

	Biomass	Net profit	Harvest	Effort
TAC	0.946	11.040	0.092	0.720
TAE	0.946	11.040	0.092	0.720

Note: The carrying capacity is normalized, and thus each variable has the following domains: $0 \leq x \leq 1$, $0 \leq \pi \leq 11.040$, $0 \leq h \leq 1$, and $0 \leq E \leq 4.094$.

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 perfectly general reference point to compare the two instruments. This is because of the relatively small difference between the expected values derived from the two control variables at given parameter values.[6] 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.

4.2 Optimal time paths. Figure 1 presets the sample optimal time path for the harvest and effort levels under two different scenarios.[7] In the first case, the relative uncertainty in the growth function is small relative to the harvest–effort function ($\varepsilon^g = 0.01$, $\varepsilon^h = 0.05$, and $\varepsilon^e = 0.05$), but in the second case there is much more uncertainty in the growth function relative to the harvest–effort function ($\varepsilon^g = 0.05$, $\varepsilon^h = 0.01$, and $\varepsilon^e = 0.01$).[8] The dotted line is the optimal time path under the deterministic environment with no uncertainty ($\varepsilon^g = 0$, $\varepsilon^h = 0$, and $\varepsilon^e = 0$). 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, whereas the harvest in the TAE is indirectly determined by setting the optimal effort quota. Figure 1 also shows that the variations in the harvest and effort levels are greater when the uncertainty in the harvest–effort function is relatively large. Moreover, the time paths under the stochastic environment, especially the harvest with the TAC and the effort level with the TAE, tend to be lower than those under the deterministic case. This is because with a stochastic environment and a strictly concave profit function, the harvest and effort quotas are set to a lower level to avoid overfishing.

Figures 2.1 and 2.2 illustrate how 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: $\varepsilon^g = 0.01$, $\varepsilon^h = 0.05$, and $\varepsilon^e = 0.05$), the relative economic payoff favors the TAC control. 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: $\varepsilon^g = 0.05$, $\varepsilon^h = 0.01$, and $\varepsilon^e = 0.01$), 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 larger is the variation in the harvest level with a TAE control that, in turn, contributes to over- or underfishing. 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 thereby reducing its efficacy as a policy instrument.

Figures 3.1 and 3.2 provide a comparison between TAC and TAE controls in terms of the average biomass.[9] In both cases, a TAC control delivers a higher average biomass. The larger 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

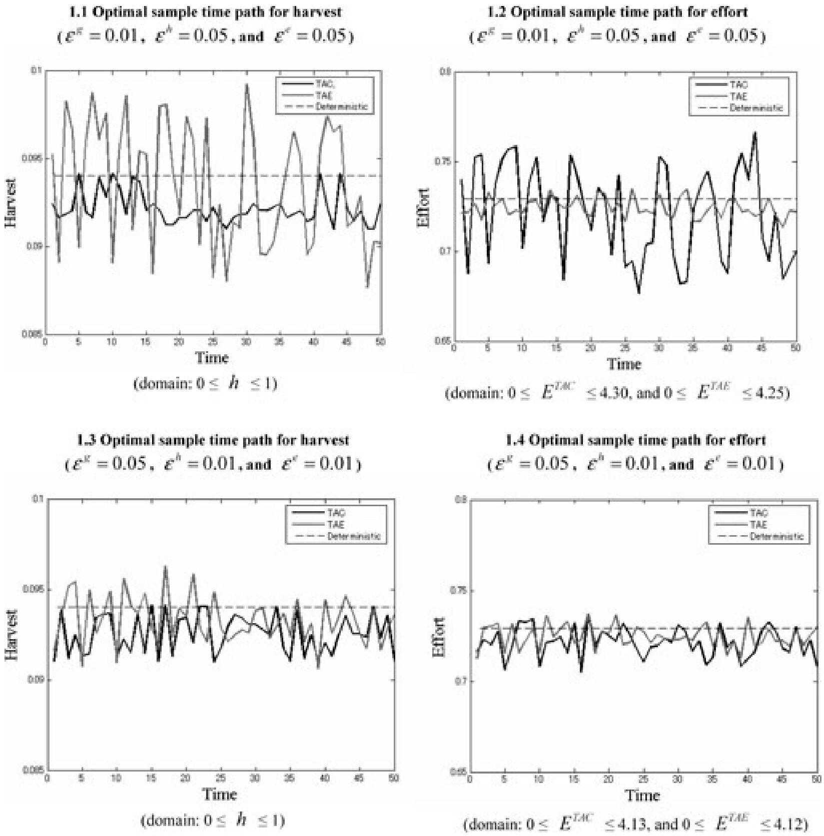

FIGURE 1. Optimal sample time paths for the harvest and fish effort under stochastic environment.

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.

4.3 Sensitivity analysis: Stock effect. The estimated value of the stock or biomass dependency parameter, $\gamma 2$, in the harvest function

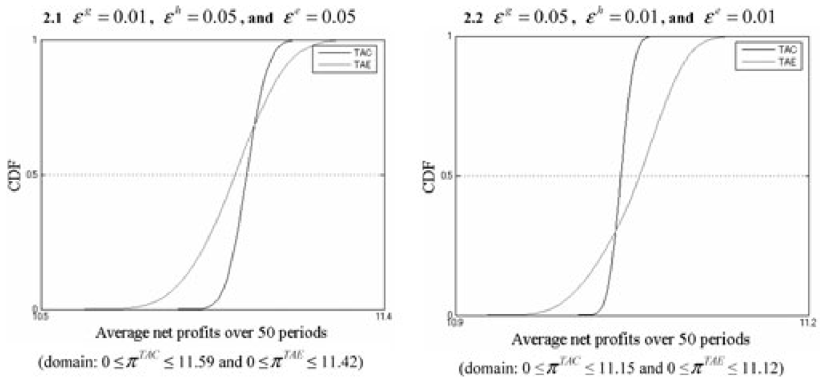

FIGURE 2. CDF of average net profit with different size of uncertainties ($\gamma 2 = 0.0$). (domain: $0 \leq \pi \leq 11.040$.)

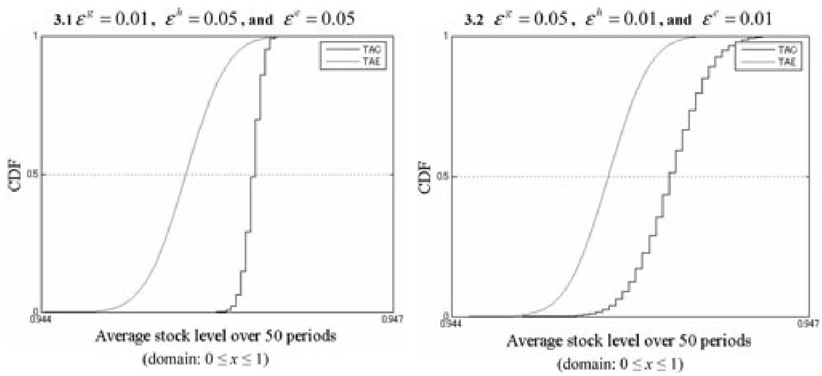

FIGURE 3. CDF of average biomass with different size of uncertainties ($\gamma 2 = 0.0$).

was not significantly 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.[10] 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

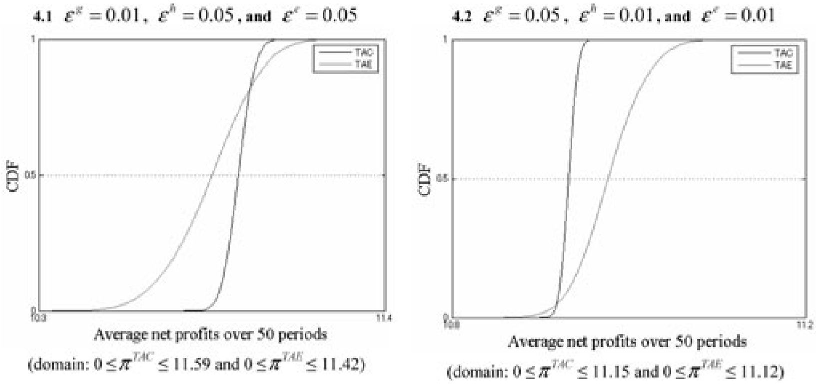

FIGURE 4. CDF of average net profit with a stock effort in harvest and effort functions ($\gamma 2 = 0.27$).

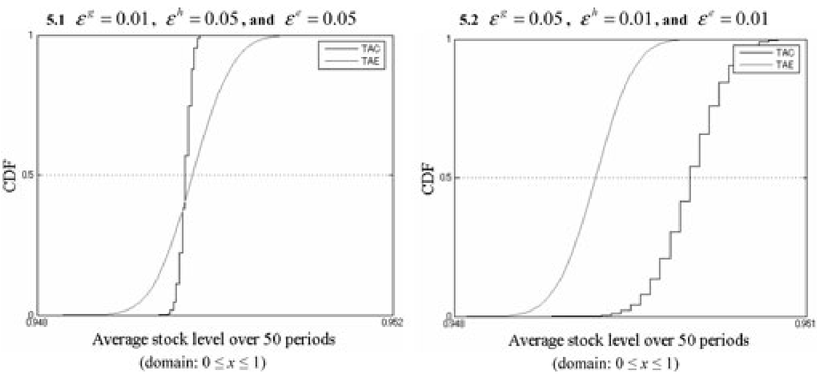

FIGURE 5. CDF of average biomass with a stock effect in harvest and effort functions ($\gamma 2 = 0.27$).

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 underfishing.

4.4 Sensitivity analysis: Price elasticity of demand. To investigate how the price elasticity affects the result, different values of

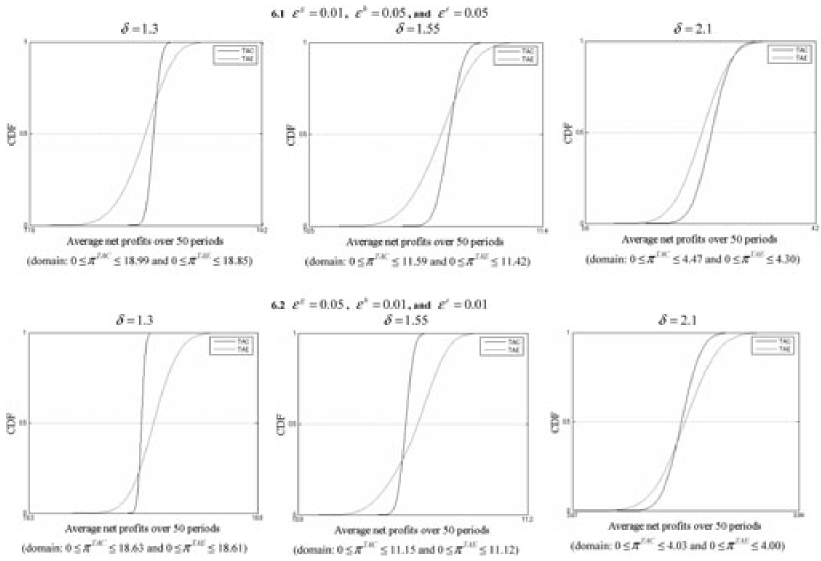

FIGURE 6. CDF of average net profit with different price elasticity ($\gamma 2 = 0.0$).

the price elasticity of demand ($\delta = 1.3$ and $\delta = 2.1$) are applied. The simulation results are shown in Figures 6 and 7. Again, the difference to the base-case results in Figures 2 and 3 are 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 a TAE control as it only indirectly controls the harvest.

4.5 Sensitivity analysis: Harvesting costs. Alternative cost parameters ($c = 8$ and $c = 2.4$) are applied to analyze how the results alter with changes in harvesting costs. The simulations are presented in Figures 8 and 9.[11] The results are very different from 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

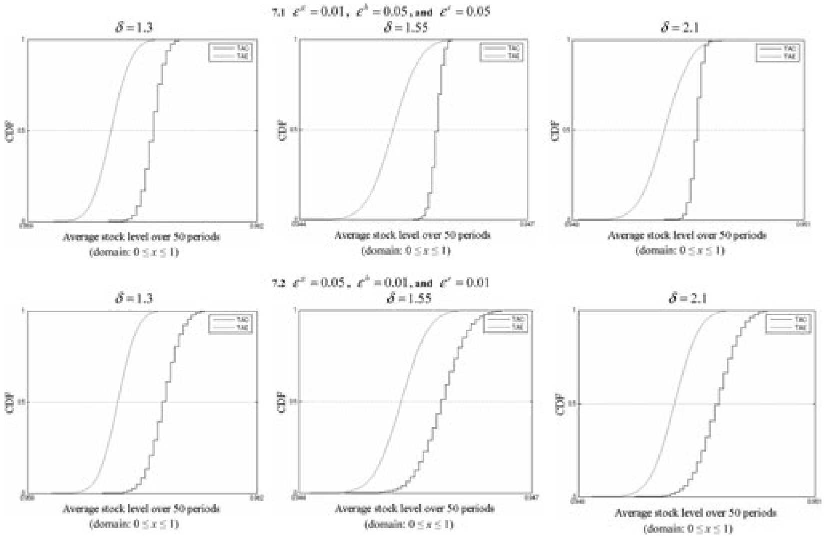

FIGURE 7. CDF of average biomass with different price elasticity ($\gamma 2 = 0.0$).

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.

Our finding contrasts with the findings of Hannesson and Steinshamn [1991], who show that as fishing cost decreases, the constant effort strategy becomes relatively less profitable than the constant catch management. Their result comes from the fact that they employed a one period model with a strictly convex cost function. 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 with a stock effect. 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.

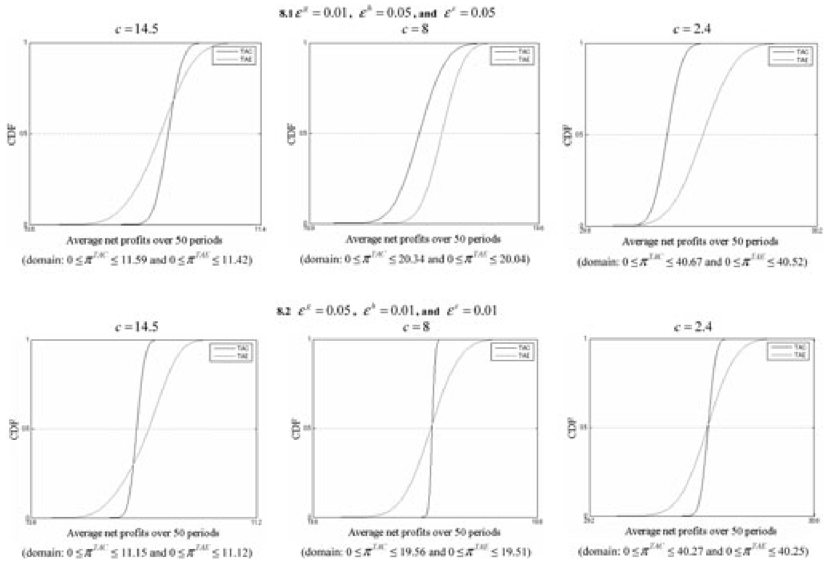

FIGURE 8. CDF of average net profit with different cost parameters ($\gamma 2 = 0.0$).

4.6 Sensitivity analysis: Price effect. A similar result to the costs effect is obtained with higher price parameters of fish ($\bar{p} = 85$ and $\bar{p} = 100$) but with the same price elasticity of demand, as shown in Figures 10 and 11. 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.

5. Discussion. The results suggest that, in terms of uncertainty considerations, TAC control is likely to be preferred versus TAE for the Western and Central Pacific skipjack tuna fishery. This is because there is a well-defined and estimated growth function for the fishery and considerable uncertainty in terms of the harvest–effort relationship. For instance, there have been large and unexpected increases in catch per unit of effort in recent years in this fishery (Barclay and

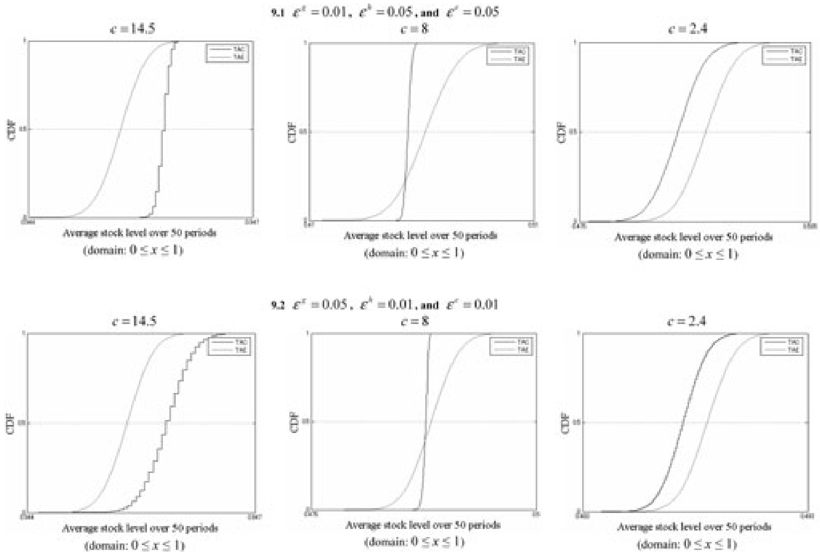

FIGURE 9. CDF of average biomass with different cost parameters ($\gamma 2 = 0.0$).

Cartwright [2007]). Consequently, Figures 2.1 and 3.1 (corresponding to $\varepsilon^g = 0.01$, $\varepsilon^h = 0.05$, and $\varepsilon^e = 0.05$) are likely to be a better reflection of the differences between TAC and TAE control in the skipjack fishery than Figures 2.2 and 3.2 (corresponding to $\varepsilon^g = 0.05$, $\varepsilon^h = 0.01$, and $\varepsilon^e = 0.01$). As a result, Figures 2.1 and 3.1 imply that a TAC control is preferred over a TAE control as it generates both highest expected profits and higher expected stock levels. Changes in the various parameters (stock effect, price elasticity, cost parameter, price effect), however, change the relative desirability of the instruments. Nevertheless, using a price elasticity of 1.55 and a cost parameter of 14.5 obtained from Bertignac et al. [2000], expected net profits still remain higher with a TAC, and this result is reinforced the lower is the price of skipjack, which has declined in real terms since the 1980s (Asian Development Bank [2003]). Given that the skipjack fishery is not overexploited and its biomass is above its maximum sustained yield, and the expected net profits is the primary economic consideration of the purse seine fleet, it would seem that a TAC control is, on the basis

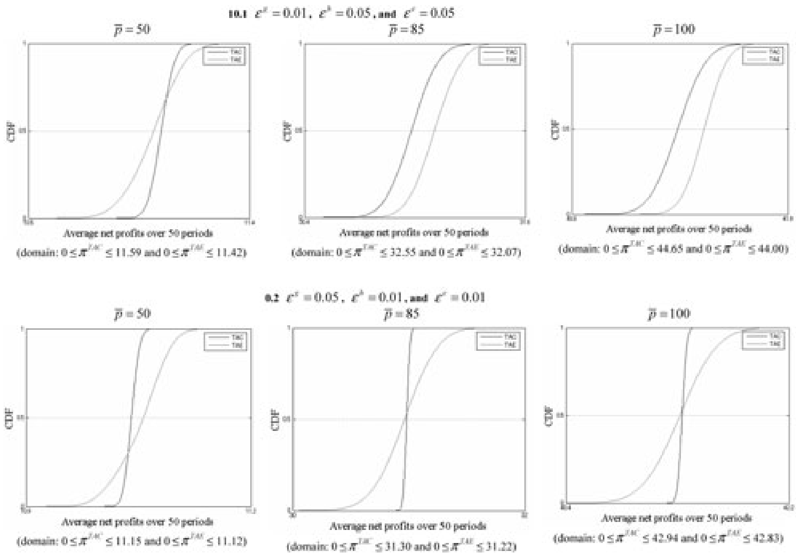

FIGURE 10. CDF of average net profit with different price parameters ($\gamma 2 = 0.0$).

of our uncertainty analysis, preferred relative to TAE control for this fishery.

Our findings also contribute to the general literature on instrument choice. By examining multiple uncertainties in an actual fishery using a dynamic model, we show how a decision-making framework in the form of CDFs can be utilized in fisheries management. This approach also offers additional insights. For instance, Hannesson and Steinshamn (1991, p. 88) argue that the most important factor that determines whether a total harvest or total effort control 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 finding 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

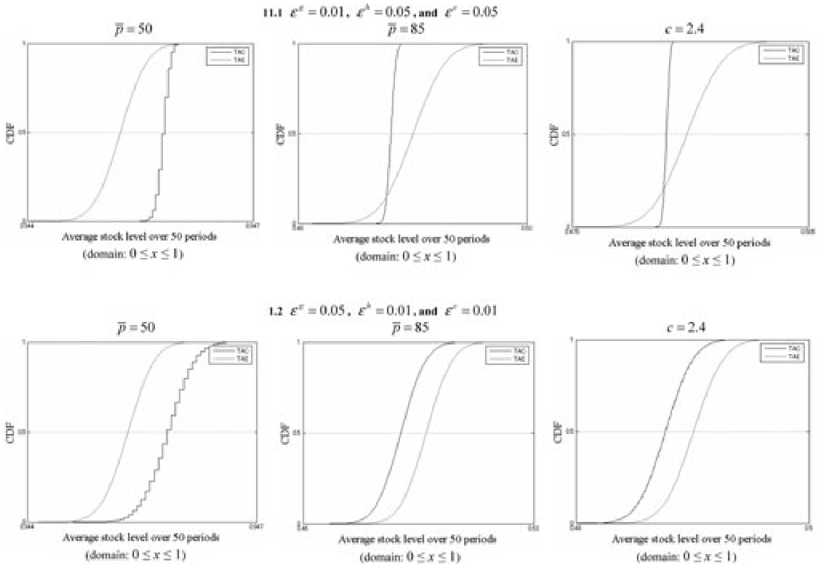

FIGURE 11. CDF of average biomass with different price parameters ($\gamma 2 = 0.0$).

uncertainties. We stress, however, that our results support the findings of Danielsson [2002] regarding relative size of "growth" and "implementation" uncertainties on instrument choice. We also show that modeling several forms of uncertainty is required to make adequate comparisons between the instruments. The only other study to employ a similar approach is Kompas et al. (2008), which they apply to the Northern Tiger Prawn fishery of Australia. However, they do not 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.

We find that TAC control has the advantage that it results in a lower variation in both biomass and net profits than does a TAE control. However, 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. On the other hand, higher harvests increase the risk of overfishing and cause a less then optimal biomass level that lowers future net profits. The alternative of harvesting less today 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 shows how TAC and TAE controls generate different outcomes. Indeed, a key finding of our modeling is that the larger is the harvest level, the greater is the variance in the net profits associated with TAE versus TAC control, but the higher is the expected biomass.

In our modeling, we fix the instrument choice at the beginning period and do not allow for a policy switch. However, even without policy switching, we show that as costs and prices change in a fishery, the relative preference for a given method of control may substantially 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, it is planned in the Eastern and Tuna Billfish fishery in Australia that fishers will be assigned shares (denominated in hooks) of a TAE before the end of 2008. However, they could subsequently be allocated individual harvesting rights as a share of TAC should circumstances change to favor the use of individual transferable harvesting rights.

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, the Western and Central Pacific skipjack tuna fishery, 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. Under most likely parameter values, and given the fishery is not currently overexploited, a total harvest control is favored to a total effort control if expected net profits are of primary consideration. Nevertheless, a key finding is that neither instrument is always preferred in a world of uncertainty and that a regulator's weighting in terms of the importance of expected net profits versus expected biomass, and trade-offs in terms of expected values and variance, will determine the instrument choice.

Our analysis shows that as harvesting costs decrease and the price of fish rises, the desirability of 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 modeling framework for regulators to compare instruments and to achieve desired management goals.

ENDNOTES

1. We restrict our modeling and analysis to a fixed policy instrument to make direct comparison to previous studies. Restricting the policy instrument also allows us to show how differences in a range of parameters can alter the preference for TAC versus TAE control

2. The parameter $\gamma 1$ 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. Under this restriction 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.

3. As with most other fisheries, the skipjack fishery is a multispecies fishery, and bycatch problems exist. However, this fishery is a good application of our model because skipjack is a relatively well-targeted species. We also note that in multi-species fisheries TAE control may lead to economic over- (and under-) fishing for some of the species in the absence of other forms of control.

4. See Judd (1998) for further details.

5. The deterministic case is provided to show that a solution exists and that the system is stable but it is not a benchmark.

6. This result is consistent with the findings of Hannesson and Steinshamn (1991).

7. The same realizations in terms of the random variables are applied for both the TAC and TAE.

8. The figures of the optimal time paths with $\varepsilon^g = \varepsilon^h = \varepsilon^e = 0.05$ and $\varepsilon^g = \varepsilon^h = \varepsilon^e = 0.01$ are available upon request. The key insights are the same as in Figure 1.

9. Note that the simulated stock level is the biomass consistent with a dynamic maximum economic yield (B_{MEY}). The average biomass is close to the carrying

capacity in Figures 3.1 and 3.2, which is due to the relative size in the price and cost parameter and also reflects that the fishery is, at present, not overexploited biologically.

10. 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 while Grafton et al. (2007) provide such estimates for bigeye and yellowfin tuna in the same fishery.

11. Because the density of the biomass is close to unity with benchmark parameters, sensitivity analysis that involves a higher price and lower cost (and thus a higher catch) provides a more useful comparison of the two policy instruments.

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