Regulatory Objectives in the North Pacific Halibut Fishery:

How Far is the Regulator from the Economists' Ideal?

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1 Introduction

Beginning with Gordon (1954) economists have pointed out that open access to fisheries results in dissipation of economic rents, hypothesized about optimal fisheries management by a sole owner, and studied how harvest levels should be set to maximize economic yield.[1] The declaration of 200-mile zones of extended fisheries jurisdiction in 1976 made explicit fisheries management reality in that most important fisheries were brought under the authority of adjacent coastal nations. Economic research has proposed regulations that would steer fisheries toward the rent maximizing ideal. While economists have been influential in incorporating socioeconomic goals into fisheries management, much of real world fisheries policy has been shaped by biological goals and short-term political considerations. The question then arises of how real world regulations comply with the economists' ideal of rent maximization.

We examine regulatory objectives in the North Pacific Halibut fishery, one of the fisheries with the longest history of regulation.[2] The International Pacific Halibut Commission (IPHC) has regulated the halibut fishery since the early 1930's. The IPHC states that its objective is to attain the optimum sustainable yield, but does not specify what is considered optimum. The regulator's objective might be to maximize the sustainable biological yield, the current economic rents, or the expected present discounted value of the flow of rents. We do not know the regulator's objective function. However, we seek to measure how the regulator's behavior complies with the ideal of rent maximization.

[1] Other examples include Scott (1955), Turvey and Wiseman (1957), and Crutchfield and Zellner (1962).

[2] Homans and Wilen (1997) have previously studied regulation in the North Pacific Halibut fishery. They assume that a goal-oriented regulator chooses harvest levels according to a safe stock concept.

We assume that the regulator solves a stochastic dynamic optimization problem to maximize the expected present discounted value of rents. We derive the stochastic Euler equations that define the solution to the regulator's problem. From the Euler equations, we estimate the discount factor that is consistent with our assumptions and the regulator's observed behavior. The estimated discount factor provides an index of regulatory behavior. A zero discount factor implies that the regulator maximizes current net revenue. A discount factor equal to one makes no distinction between current and future net revenue, implying the objective of maximum sustainable yield. The results show the extent to which the regulator's objective deviates from discounted rent maximization. The results can be used to compute the welfare costs of following a suboptimal management policy.

Since Hansen and Singleton's (1982) contribution, the generalized method of moments has become the mainstay method in estimating stochastic Euler equations. The data based empirical likelihood method suggested by Owen (1988, 1991), Qin and Lawless (1994), and Mittelhammer, Judge, and Miller (2000) is a new method that readily lends itself to Euler equation estimation. We compare the results from estimating a stochastic dynamic model using the traditional generalized method of moments and nonlinear two-stage least squares procedures, and the empirical likelihood method.

The study's objectives parallel those of Fulton and Karp (1989) and Fernandez (1996). Fulton and Karp study the objectives of a public firm in the uranium industry. They estimate a linear control rule and state equations in an optimal control model in order to determine how the firm balances different objectives. Fernandez examines the objectives of a public waste water treatment plant, using maximum entropy to estimate a dynamic model. In the linear-quadratic setting of Fulton and Karp and Fernandez, the maximum entropy method avoids the restrictions needed by two-stage least squares and other traditional methods. The empirical likelihood method provides the same advantage without forcing the economic model into an entropy framework.

The paper is organized as follows. Section 2 states the regulator's optimization problem, determines the optimal harvest level, and develops hypotheses about the regulator's behavior. Section 3 describes data for the North Pacific Halibut fishery. Section 4 presents the empirical analysis. Section 5 examines the welfare implications of the regulatory program, and section 6 concludes.

2 The Bioeconomic Model

We use the bioeconomic model of a seasonal fishery developed by Clark (1971) and employed by Clark (1972), Clark (1973), Spence and Starrett (1975), Levhari, Michener and Mirman (1981), Hannesson (1997), and others. The biological model is deterministic. Let X_t denote the size of the fish stock at the beginning of the fishing season in period *t*. The regulator sets a harvest quota Q_t prior to commencement of harvest, after having observed the stock X_t. Harvesting then takes place, and once the quota has been reached, the fishery is closed for the season. The size of the stock left behind after harvesting is referred to as the escapement level S_t. Neglecting natural mortality during the fishing season, the relation between the initial stock X_t, the harvest quota Q_t, and the escapement level S_t is $X_t - Q_t = S_t$. The growth of the fish stock is a function of the escapement S_t. The escapement spawns at the end of the season, and produces $F(S_t)$ recruits available to harvest in period $t+1$. Recruitment to the stock follows a Beaverton-Holt type stock recruitment relation

(1) $$X_{t+1} = aS_t - bS_t^2,$$

where *a* and *b* are biological growth parameters.

At a given price p_t, the revenue R_t obtained from harvest Q_t in period *t* is

(2) $$R_t = p_t Q_t = p_t(X_t - S_t).$$

The p_t are stochastic. The unit cost of additional harvest at any stock level x is c/x, where c is the unit cost of fishing effort.[3] The total cost TC_t of harvesting the stock from the initial level X_t down to S_t in period t equals

$$(3) \qquad TC_t = \int_{S_t}^{X_t} \frac{c}{x} dx = c(\ln X_t - \ln S_t).$$

The period t net revenue to the fishery is $\pi_t = R_t - TC_t = p_t(X_t - S_t) - c(\ln X_t - \ln S_t)$. The expected present value $E_t J$ of the stream of net revenues π_s for an infinite time horizon, given the information available at period t, is

$$(4) \qquad E_t J = E_t\left[\sum_{s=t}^{\infty} \alpha^s \{p_s(X_s - S_s) - c(\ln X_s - \ln S_s)\}\right],$$

where α is the discount factor and $\{p_s\}$ is a stochastic sequence of prices. If the regulator sets the quota Q_t, or equivalently the escapement S_t, to maximize $E_t J$ subject to the stock dynamics $X_{t+1} = aS_t - bS_t^2$, the first order condition is

$$(5) \qquad E_t\left\{p_t - \frac{c}{S_t} - \alpha(a - 2bS_t)\left[p_{t+1} - \frac{c}{(aS_t - bS_t^2)}\right]\right\} = 0.$$

Expectations are assumed to be formed rationally. E_t then denotes both the mathematical conditional expectation and the regulator's subjective expectations as of date t.

[3] This cost function obtains if the unit cost of fishing effort is constant and the catch per unit of effort is proportional to the size of the stock available to harvest. This is obviously a special case, but widely used in fisheries economics.

3 The North Pacific Halibut Fishery

The North Pacific Halibut fishery provides a good case study of regulatory behavior: it has a long history of regulation, dating back to the 1930s. The International Pacific Halibut Commission (IPHC) was established in 1923 by a convention between Canada and the United States for the preservation of the halibut, as the first international agreement providing for the joint management of a marine resource. The first regulations enacted by the IPHC went into effect in 1932. Since then, harvest quotas have been set by the IPHC annually. The empirical analysis investigates the regulator's objectives by estimating equations (1) and (5) using halibut data. The IPHC has collected data extensively throughout the entire regulatory period, and relatively long time series exist on biomass estimates, quota targets, annual harvests (catches) and prices, and other economic variables. Quotas are published by IPHC annually. A logbook program has been in effect since the beginning of the regulation to collect catch and effort statistics from fishermen, and information from fish processors has been collected to maintain accurate records of the commercial catch.

We assembled data from sources published by the IPHC over the 1935-1977 period. We constructed a series for a management area referred to as Area 2, which includes waters off British Columbia and up to Cape Spencer in Southeastern Alaska.[4] The period was truncated in 1977, after which Area 2 was divided into separate Canadian and U.S. waters, each with new management methods and data collection procedures. We used biomass estimates from Quinn et al. (1985) as a measure of beginning of the season stock X_t. Quinn et al. derived the biomass estimates using catch-age and catch per unit of effort (CPUE) data, which were collected from logbook entries over the entire regulatory program. The estimates were computed ex post, i.e. catch-age and CPUE data for year t were used to compute an estimate of biomass in exploitable in year t. We assume that they are unbiased representations of estimates used by the regulatory authority for annual regulation decisions prior to commencement of harvest. Quotas and harvests were derived from a summary in Hoag et al (1983). Quotas were summarized from the IPHC regulation pamphlets for each year, and the catches were compiled from records from fish

[4] Homans and Wilen (1997) also relied on these data.

processors and from logbooks of fishing vessels. Prices were obtained from a summary in IPHC annual report 1978, Appendix 2. The prices are prices paid to the fishermen, as reported by fish processors. Prices were deflated by a producer price index with base year 1982 (Bureau of Labor Statistics, http://146.142.4.24/gi-bin/surveymos). No timeseries is available for the unit cost of fishing effort, and we are hence forced to treat the cost c as an unknown parameter.

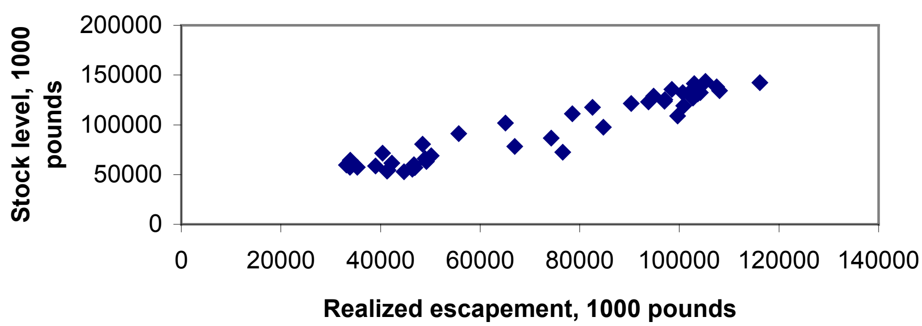
The quotas and realized harvests differ, due to delays in closing the fishery, cheating, and measurement errors, with discrepancies of up to 37 %. To account for the difference, we computed two escapement measures. The realized escapement, denoted by S_t^R, equals the difference between the initial biomass and the realized harvest H_t: $S_t^R = X_t - H_t$. The target escapement S_t^T equals the difference between the initial biomass and the quota: $S_t^T = X_t - Q_t$. We constructed series of realized escapements and target escapements from the data on the biomass estimates, annual harvests, and quotas.

Table 1 displays summary statistics for the data. Figure 1 shows the relation between the initial stock and the previous year's realized escapement. The relation is consistent with the quadratic Beaverton-Holt specification – it is plausible that the recruitment levels have been on the increasing portion of the recruitment relation throughout the halibut program.

Table 1. Summary Statistics

Variable	Mean	Standard Deviation	Min	Max
Stock, 1000 pounds	97296	32504	52973	143619
Quota, 1000 pounds	22795	4410	11000	28000
Harvest, 1000 pounds	23728	7219	8820	36240
Realized escapement, 1000 pounds	73568	27596	33130	116190
Target escapement, 1000 pounds	73807	28737	34563	117119
Difference between quota and harvest, %	-5	13	-37	29
Price, dollars per 1000 pounds (deflated)	860	390	70	1700

Figure 1. Relation between stock level and previous year's realized escapement



4 The Econometric Model

The econometric model consists of the biological stock recruitment relation in equation (1), and the first order condition to the regulator's optimization problem in equation (5). The error term in the stock growth equation encompasses shocks in recruitment. Appending an additive error term, the stock growth equation (1) becomes

$$(6)\qquad X_{t+1} - aS_t + bS_t^2 = \eta_{t+1}\,.$$

In our econometric estimation of the first order condition in (5), we interpret

$$(7)\qquad \varepsilon_{t+1} = p_t - \frac{c}{S_t} - \alpha(a - 2bS_t)\left[p_{t+1} - \frac{c}{(aS_t - bS_t^2)}\right]$$

as the disturbances, arising from mistakes made by the regulator in setting the optimal escapement. The first order condition to the regulator's problem equals

$$(8)\qquad E_t[\varepsilon_{t+1}] = E_t\left\{p_t - \frac{c}{S_t} - \alpha(a - 2bS_t)\left[p_{t+1} - \frac{c}{(aS_t - bS_t^2)}\right]\right\} = 0\,.$$

The parameters to be estimated are the cost parameter *c,* the discount factor α, and the biological growth parameters *a* and *b.* Given the sources of variation, there is no reason to assume that the error terms η_{t+1} and ε_{t+1} are correlated. Nor is there simultaneity in equations (6) and (8). The regulator's first order condition (8) determines the target escapement level, and once the escapement has been realized, recruitment to the stock occurs following (6). We impose the cross-equation restriction that the growth parameters *a* and *b* are the same in both equations. Assuming that the cross-equation restriction holds is the only way to identify the parameters *c* and α in equation (8), which is highly nonlinear in parameters. It is then not possible to test the cross-equation restriction.

There are marked differences between the realized escapements and the target escapements. Rather than approximate the realized escapement by the target escapement or vice versa, we use the realized escapements S_t^R to estimate (6) and the target escapements S_t^T to estimate (8). The regulator chooses a target escapement level that satisfies

(5) and sets the quota based on this target, while the stock equation (1) states a biological relationship between the escapement actually realized and the recruitment to the stock.

We estimate equation (6) using ordinary least squares (OLS). The parameter estimates for *a* and *b* are inserted into equation (8), which is then estimated using the generalized method of moments (GMM), nonlinear two-stage least squares (NL2SLS), and the empirical likelihood method (EL).

4.1 Generalized Method of Moments and Two-Stage Least Squares Estimation

The Euler equations (8) imply a set of population orthogonality conditions that depend in a nonlinear way on observed variables and the unknown parameters. A widely used method for estimating the parameters is constructing nonlinear instrumental variables estimators using the sample versions of the orthogonality conditions. The procedure was proposed by Amemiya (1974, 1977), Jorgenson and Laffont (1974), Hansen (1982), and Hansen and Singleton (1982). Let $\mathbf{z}_t$ denote an *M* dimensional vector of variables that are in the regulator's information set at time *t* and included in the data. In Hansen's (1982) notation, the $\mathbf{z}_t$ are the instrumental variables. Assume that the ε_{t+1} and $\mathbf{z}_t$ have finite second moments. The optimization model then implies the population orthogonality conditions

$$(9)\qquad E\left\{\left[p_t - \frac{c}{S_t} - \alpha(a - 2bS_t)\left[p_{t+1} - \frac{c}{(aS_t - bS_t^2)}\right]\right]\boldsymbol{z}_t\right\} = E[\boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c)] = 0,$$

which can be estimated by making the sample versions close to zero according to a certain metric. The generalized method of moments suggested by Hansen and Hansen and Singleton uses the estimated variance of $\boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c)$ as the metric. The nonlinear two-stage least squares estimator suggested by Amemiya uses the identity matrix.

As instrumental variables in the estimation of (9), we considered p_t, S_{t-1}^T, S_{t-2}^T, X_t, X_{t-1}, S_{t-1}^R and S_{t-2}^R. Table 2 displays the correlation coefficients for these variables and the dependent variable $S_t = S_t^T$ in equation (9). The choice of instruments is problematic in that the potential instrumental variables are highly correlated with each other, with most of the correlation coefficients close to one. We chose the stock X_t and the price p_t as instruments. The stock is the independent variable most highly correlated with the dependent variable S_t^T. The price has the smallest correlation with the stock.

Table 2. Correlation Matrix for Model Variables

ρ	S_t^T	p_t	S_{t-1}^T	S_{t-2}^T	X_t	X_{t-1}	S_{t-1}^R	S_{t-2}^R
S_t^T	1.000							
p_t	-0.497	1.000						
S_{t-1}^T	0.983	-0.486	1.000					
S_{t-2}^T	0.936	-0.466	0.983	1.000				
X_t	0.996	-0.565	0.978	0.931	1.000			
X_{t-1}	0.983	-0.543	0.996	0.979	0.985	1.000		
S_{t-1}^R	0.970	-0.458	0.995	0.986	0.964	0.991	1.000	
S_{t-2}^R	0.915	-0.438	0.970	0.995	0.909	0.964	0.977	1.000

Table 3 displays the estimation results. The estimates for a and b are significant at the 1% level. The GMM and NL2SLS estimates of c and α are numerically equal. Since the two methods use a different metric in setting the sample orthogonality conditions close to zero, the estimated standard errors differ. As expected, the standard deviations for the GMM estimates are smaller than for NL2SLS. For GMM both c and α are significant at the 1% level. For NL2SLS c is significant at the 1% level but α only at the 10% level. The signs of all the parameter estimates are as expected, and the magnitudes are reasonable.

The Durbin-Watson statistics indicate that autocorrelation may be present in both equations (6) and (9). While autocorrelation requires careful consideration in future work, we do not to correct for it here. Adjusting the stock equation (6) for first order autocorrelation provided no significant improvement in the Durbin-Watson statistic. The positive test for autocorrelation in (6) may indicate that a more complicated age structured model better predict the population dynamics. Since our focus is on the regulator's behavior, and the limited data set provides restricted information on the population dynamics, we choose to retain the simple population model of equation (6).We do not know the form of the possible autocorrelation in (9). No reliable information would be gained by assuming some form of autocorrelation. We hence retain the present model.

Table 3. Parameter Estimates from OLS/GMM and NL2SLS Estimation

Method	Parameter	Estimate	Standard error	t-statistic
OLS	a	1.5395	.077571	19.8460
	b	$2.5935*10^{-6}$	$.8345*10^{-6}$	3.1080
GMM	c	$46586*10^{3}$	$6929*10^{3}$	6.7236
	α	.38320	.132354	2.8953
NL2SLS	c	$46586*10^{3}$	$12203*10^{3}$	3.8175
	α	.38320	.214653	1.7852

Durbin-Watson statistic for OLS estimation of equation (6)	.2235
Durbin-Watson statistic for NL2SLS estimation of equation (9)	.9278
Durbin-Watson statistic for GMM estimation of equation (9)	.9278

4.2 Empirical Likelihood Estimation

The empirical likelihood approach (EL) suggested by Owen (1988, 1991), Qin and Lawless (1994), and Mittelhammer, Judge, and Miller (2000) provides another way to estimate the unknown parameters in the moment equations (9). The moment equations can be interpreted as representing the expectation of the M dimensional unbiased vector estimating function

$$\text{(10)}\qquad \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c) = \left\{\left[p_t - \frac{c}{S_t} - \alpha(a - 2bS_t)\left[p_{t+1} - \frac{c}{(aS_t - bS_t^2)}\right]\right]\boldsymbol{z}_t\right\}.$$

We can combine the information in the unbiased estimating functions with the concept of empirical likelihood to define an empirical likelihood function for (α, c). Maximizing the empirical likelihood function yields maximum empirical likelihood (MEL) estimates. The first-order asymptotic sampling properties of the MEL estimator are similar to those for parametric likelihood methods. Since the empirical likelihood method is not widely known, we next review the technique in some detail. The exposition follows Mittelhammer, R. , Judge, G. and Miller, D. J. (2000).

The concept of empirical likelihood begins with the joint empirical probability distribution $\prod_{t=1}^{T} v_t$ that is supported on the sample data. The parameter v_t denotes the probability of observing the *t*th sample outcome, $\{p_t, p_{t+1}, S_t, \mathbf{z}_t\}$. To define the value of the empirical likelihood function for (α, c), the v_t are chosen to maximize $\prod_{t=1}^{T} v_t$, subject to the constraints defined by the moment conditions (9). Since the v_t's represent a probability distribution, the maximization problem is subject to the additional constraints $\sum_{t=1}^{T} v_t = 1$ and $v_t > 0 \ \forall t$. The maximization procedure assigns the maximum probability possible to the sample outcome actually observed, subject to the information represented by the moment equations. The moment equations link the data, the population distribution, and the parameters.

Using the empirical probabilities v_t, the moment equations (9) can be represented empirically as the $(M \times 1)$ vector equation

$$
\begin{aligned}
&\sum_{t=1}^{T} v_t \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c) \\
&= \sum_{t=1}^{T} v_t \left\{ \left[p_t - \frac{c}{S_t} - \alpha(a - 2bS_t) \left[p_{t+1} - \frac{c}{(aS_t - bS_t^2)} \right] \right] \boldsymbol{z}_t \right\} = \mathbf{0},
\end{aligned} \tag{11}
$$

with the observations ranging from 1 to *T*. Using a logarithmic transformation of $\prod_{t=1}^{T} v_t$ and scaling by $1/T$, the constrained maximization problem can then be defined as

$$
\begin{aligned}
&\frac{1}{T} \ln(L_{EL}(\alpha, c; \boldsymbol{p}, \boldsymbol{p}_{+1}, \boldsymbol{S}, \boldsymbol{Z})) \\
&\equiv \max_v \left[\frac{1}{T} \sum_{t=1}^{T} \ln(v_t) \text{ s.t. } \sum_{t=1}^{T} v_t \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c) = 0 \text{ and } \sum_{t=1}^{T} v_t = 1 \right].
\end{aligned} \tag{12}
$$

The Lagrange function associated with the constrained maximization problem can be represented as

$$(13) \qquad L(\mathbf{v},\eta,\boldsymbol{\lambda}) \equiv \left[\frac{1}{T}\sum_{t=1}^{T}\ln(v_t) - \eta\left(\sum_{t=1}^{T} v_t - 1\right) - \boldsymbol{\lambda}'\sum_{t=1}^{T} v_t \mathbf{h}(p_t, p_{t+1}, S_t, \mathbf{z}_t, \alpha, c)\right].$$

To solve for (α, c), we need to recover a specific functional form for the log-empirical likelihood in (13) in terms of (α, c). We first solve for the optimal $\mathbf{v}, \eta$ and $\boldsymbol{\lambda}$ in the Lagrange form of the problem in (13), and then substitute the optimal values for $\mathbf{v}$ back into the objective function in (12). This yields the concentrated or profile empirical likelihood function in terms of (α, c).

The first order conditions with respect to the v_t's are

$$(14) \qquad \frac{\partial L(\mathbf{v},\eta,\lambda)}{\partial v_t} = \frac{1}{T}\frac{1}{v_t} - \eta - \sum_{m=1}^{M}\lambda_m h_m(p_t, p_{t+1}, S_t, z_{mt}, \alpha, c) = 0, \quad \forall\, t.$$

Multiplying both sides of (14) by v_t, summing over *t*, and using (11) yields

$$(15) \qquad \sum_{t=1}^{T} v_t \frac{\partial L(\mathbf{v},\eta,\lambda)}{\partial v_t} = \frac{1}{T}T - \eta = 0\,.$$

Equation (15) implies $\eta = 1$. Solving for the v_t from the first order conditions $\partial L / \partial v_t = 0$ yields the optimal weights v_t as a function of α, *c* and λ :

$$(16) \qquad v_t(\alpha, c, \lambda) = \left[T\left(\sum_{m=1}^{M}\lambda_m h_m(p_t, p_{t+1}, S_t, z_{mt}, \alpha, c) + 1\right)\right]^{-1}.$$

Substituting (16) into the empirical moment condition (11) defines the Lagrange multipliers λ as a function of α and *c*. The multipliers λ have to satisfy the empirical moment conditions

$$
(17) \quad \begin{aligned}
&\sum_{t=1}^{T} v_t \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c) \\
&= \sum_{t=1}^{T} T^{-1} \left(\sum_{m=1}^{M} \lambda_m h_m(p_t, p_{t+1}, S_t, z_{mt}, \alpha, c) + 1 \right)^{-1} \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c) = 0.
\end{aligned}
$$

From (17), the multipliers $\boldsymbol{\lambda}$ are defined as a solution to an implicit function of (α, c),

$$
(18) \quad \boldsymbol{\lambda}(\alpha, c) = \arg_{\lambda} \left[\frac{1}{T} \sum_{t=1}^{T} \left(\frac{1}{1 + \lambda' \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c)} \right) \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c) = \mathbf{0} \right].
$$

Substituting $\boldsymbol{\lambda}(\alpha, c)$ into (16) defines the optimal empirical probabilities evaluated at (α, c) as

$$
(19) \quad v_t(\alpha, c, \lambda(\alpha, c)) = \left[T \left(\sum_{m=1}^{M} \lambda_m(\alpha, c) h_m(p_t, p_{t+1}, S_t, z_{mt}, \alpha, c) + 1 \right) \right]^{-1}.
$$

Finally, substitution of the optimal empirical probabilities into the objective function $\sum_{t=1}^{T} \ln(v_t)$ in (13) yields the expression for the log-empirical likelihood function evaluated at (α, c):

$$
(20) \quad \ln(L_{EL}(\alpha, c, p_t, p_{t+1}, S_t, \boldsymbol{z}_t)) = -\sum_{t=1}^{T} \ln \left[T \left(\boldsymbol{\lambda}(\alpha, c)' \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c) + 1 \right) \right].
$$

The maximum empirical likelihood (MEL) estimator of (α, c) is defined by choosing the value of (α, c) that maximizes the log-empirical likelihood function (20). The MEL estimator can be found using numerical optimization techniques.

Qin and Lawless (1994) and Mittelhammer et al. (2000) note two principal ways in which the empirical likelihood solution may be computed. First, the optimal parameters (α, c) and the Lagrange multipliers $\boldsymbol{\lambda}$ may be simultaneously selected to maximize the empirical likelihood function. This problem is defined by (13) after substituting (16) for the v_t 's :

$$(21) \qquad L(\mathbf{v},\eta,\lambda) \equiv -\frac{1}{T}\sum_{t=1}^{T} \ln\left[T\left(\boldsymbol{\lambda}'\mathbf{h}(p_t, p_{t+1}, S_t, \mathbf{z}_t, \alpha, c) + 1\right)\right].$$

The solution must satisfy the constraints $v_t > 0$, or $T\left(\sum_{m=1}^{M} \lambda_m h_m(p_t, p_{t+1}, S_t, z_{mt}, \alpha, c) + 1\right) > 0$. Second, an initial estimate of the Lagrange multipliers $\boldsymbol{\lambda}_1$ could be computed using (18) and an initial starting value $(\alpha, c)_0$ for the parameter vector. A numerical gradient-search maximization algorithm could then be used to sequentially iterate to the optimal values of (α, c) and $\boldsymbol{\lambda}$ that maximize the empirical likelihood function in (20).

Qin and Lawless (1994) show that the MEL estimator is consistent and asymptotically normal under general regularity conditions. The present example satisfies the conditions of the twice continuous differentiability of $\boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c)$ with respect to (α, c) and the boundedness of $\boldsymbol{h}$ and its first and second derivatives, both in the neighborhood of the true parameter vector $(\alpha, c)_0$, and the requirement that the row rank of $E\left[\partial \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c) / \partial(\alpha, c)\big|_{(\alpha,c)_0}\right]$ equal the number of parameters to be estimated. The covariance matrix Σ of the limiting normal distribution can be consistently estimated by

$$\hat{\Sigma} =$$

$$(22) \quad \left[\left[\sum_{t=1}^{T} \hat{v}_t \frac{\partial \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c)}{\partial(\alpha, c)}\Big|_{(\alpha,c)_{\mathrm{EL}}}\right]\left[\sum_{t=1}^{T} \hat{v}_t \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c)\boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c)'\right]^{-1} \times \left[\sum_{t=1}^{T} \hat{v}_t \frac{\partial \boldsymbol{h}(p_t, p_{t+1}, S_t, \boldsymbol{z}_t, \alpha, c)}{\partial(\alpha, c)'}\Big|_{(\alpha,c)_{\mathrm{EL}}}\right]\right]^{-1},$$

where the $\hat{v}_t$'s are the MEL estimates of the empirical probability distribution $\boldsymbol{v}$, computed from (19) using $\hat{\alpha}_{EL}, \hat{c}_{EL}$ and $\hat{\boldsymbol{\lambda}}_{EL} = \boldsymbol{\lambda}(\hat{\alpha}_{EL}, \hat{c}_{EL})$.

We computed the MEL estimates by simultaneously selecting the (α, c) and $\boldsymbol{\lambda}$ that maximize (21). We used the NSolve procedure in Mathematica 3.0 to solve the first order conditions for maximizing (21) with respect to (α, c) and $\boldsymbol{\lambda}$. The numerical procedure requires starting values to begin the iteration. We used the GMM/NL2SLS estimates $(\alpha, c)_{GMM}$ and $\boldsymbol{\lambda} = \mathbf{0}$. Table 4 presents the results.

Table 4. Parameter Estimates from OLS/MEL Estimation

Method	Parameter	Estimate	Standard error	t-statistic
OLS	a	1.5395	.077571	19.8460
	b	$2.5935*10^{-6}$	$.8345*10^{-6}$	3.1080
MEL	c	$45365*10^{3}$	$11885*10^{3}$	
	α	.40023	.245728	
	$\boldsymbol{\lambda}$	**0**		

The MEL estimates for α and c differ slightly from the GMM and NL2SLS estimates, but the magnitudes are the same. The standard deviation of the MEL estimator for α is larger than the GMM and NL2SLS standard deviations. The standard deviation of the MEL estimator for c is greater than the GMM but smaller than the NL2SLS estimate. The Lagrange multiplier $\boldsymbol{\lambda}$ equals zero to a numerical approximation, and the moment constraints hence are not binding. Each sample observation then has equal empirical probability, with ν_t equal to T^{-1}.

5 Welfare Implications

The results imply a discount factor of $\alpha = 0.38$ to $\alpha = 0.40$, or a discount rate of 150% to 163%. The implied discount rate is markedly higher than a level commonly considered reasonable in natural resource management. The regulator is taking future revenues into account to some extent, rather than simply maximizing current net revenue, but future revenues are discounted heavily. We computed the welfare costs of following a sub-optimal policy, using 10% as the social rate of discount. We solved for the steady state at the average price. The resulting socially optimal escapement level would be $110\,914$ thousand pounds. Assuming that all the additional fish would stay in Area 2, socially optimal management would yield annual profits of $13.5 million. At the estimated discount rate of 150% (MEL), the regulator's optimal escapement level is 66 281 thousand pounds, and the annual profits $6.2 million. At the discount rate of 163% (GMM/NL2SLS), the regulator's optimal escapement is 62 157 thousand pounds, and the annual profits $6 million. The profits at the estimated discount rate are markedly below those obtained using the social rate of discount, indicating that the regulator's use of a high discount rate results in a substantial welfare loss. The annual profits could be doubled if more fish were allowed to escape the fishery, producing higher stock levels and thus reducing costs of harvest. Over the period 1954-1963 the realized escapement exceeded $100\ 000$, which suggests that Area 2 could in fact support a larger stock.

6 Discussion

One explanation for the regulator's high discount rate is incomplete control of future stocks. For example, fleets from outside the authority of the commission members may have access to the fishery. Indeed, Japanese fleets targeted the halibut fishery prior to 1952. In 1952, Japan agreed to abstain from fishing halibut along the coast of North America under the Convention between Canada, Japan, and the United States that established the North Pacific Fisheries Commission (INPFC) (IPHC Technical Report No. 16).[5] Incidental catch taken by fishermen targeting other species is also outside the commission's authority. Although regulations require that incidentally caught halibut be returned to the sea, many of the fish die from injuries. Unfortunately, no acceptable estimates are available for incidental catch prior to 1962. Migrations of halibut do not seem to provide a reason for heavy discounting: the direction of migration is mainly from Area 3 to Area 2 (Hoag et al. 1983).[6]

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[5] In 1962 the INPFC allowed Japanese harvest in the Bering Sea. The area falls outside regulatory Area 2 investigated here.

[6] The low value of the discount factor may also indicate that an alternative model would more accurately describe the behavior of the regulator. One possible hypothesis we might entertain to describe the motivations of a regulatory authority would be that of rent seeking behavior.

A number of questions require further study and elaboration. We assumed that the discount factor is constant over time. It would be useful to allow the discount factor to change over time and study how environmental fluctuations and changes in the economic environment or the state of the fishing industry affect the regulator's behavior. Periods of slow economic growth or high unemployment may result in the regulator putting more weight to current profits. The exclusion of Japanese vessels in 1952 may have increased the weight given to stock conservation and future profits. It would be interesting to investigate differences in the regulator's behavior prior to 1952 and after 1952. Environmental shocks or pressure from environmental groups may also result in more conservationist policy.

Another limitation of this study is that we treat the unit cost of fishing as a parameter. Since no data are available for the measure, estimating the cost was the only way to recover the discount factor. The form of autocorrelation in the Euler equation and adjusting the model for autocorrelation also require additional research.

References:

Amemiya, T. (1974): The Nonlinear Two-Stage Least Squares Estimator. *Journal of Econometrics, 2, 105-110.*

Amemiya, T. (1977): The Maximum Likelihood and Nonlinear Three-Stage Least Squares Estimator in the General Nonlinear Simultaneous Equations Model. *Econometrica, 45, 955-968.*

Clark, C. W. (1971): Economically optimal policies for the utilization of biologically renewable resources. *Mathematical Biosciences, 12, 245-260.*

Clark, C. W. (1972): The dynamics of commercially exploited animal populations. *Mathematical Biosciences, 13,149-164.*

Clark, C. W. (1973): Profit Maximization and the Extinction of Animal Species. *Journal of Political Economy, 81, 950-961.*

Crutchfield, J. and Zellner, A. (1962): Economic Aspects of the Pacific Halibut Fishery. *U.S. Department of Interior, Fishery Industrial Research.* Washington, DC.

Fernandez, L. (1996): Estimation of Wastewater Treatment Objectives through Maximum Entropy. *Journal of Environmental Economics and Management, 32, 293-308.*

Fulton, M. and Karp, L. (1989): Estimating the Objectives of a Public Firm in a Natural Resource Industry. *Journal of Environmental Economics and Management, 16, 268-287.*

Gordon, H. S. (1954): The Economic Theory of a Common Property Resource: the Fishery. *Journal of Political Economy, 62, 124-142.*

Hannesson, R. (1997): Fishing as a supergame. *Journal of Environmental Economics and Management, 32, 309-322.*

Hansen, L. P. (1982): Large Sample Properties of Method of Moments Estimators, *Econometrica, 50, 1029-54.*

Hansen, L. P. and Singleton, K. (1982): Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models, *Econometrica, 50, 213-24.*

Hoag, S. H, Myhre, R. J, St-Pierre, G, and McCaughran, D. A. (1983): The Pacific Halibut Resource and Fishery in Regulatory Area 2. I. Management and Biology. International Pacific Halibut Commission Scientific Report No. 67.

Homans, F. R. and Wilen, J. E. (1997): A Model of Regulated Open Access Resource Use. *Journal of Environmental Economics and Management, 32, 1-21.*

International Pacific Halibut Commission (1978): Annual Report 1978.

Jorgenson, D. W. and Laffont, J. J. (1974): Efficient Estimation of Nonlinear Simultaneous Equations with Additive Disturbances. *Annals of Economic and Social Measurement, 3, 615-640.*

Levhari, D, Michener, R, and Mirman, L. J. (1981): Dynamic programming models of fishing: competition. *American Economic Review, 71, 649-661.*

Mittelhammer, R. C, Judge, G. G, and Miller, D. J. (2000): Econometric Foundations. Cambridge University Press, New York.

Owen, A. (1988): Empirical Likelihood Ratio Confidence Intervals for a Single Functional. *Biometrika, 75, 237-249.*

Owen, A. (1991): Empirical Likelihood for Linear Models, *The Annals of Statistics, 19, 1725-1747.*

Qin, J. and Lawless, J. (1994): Empirical Likelihood and General Estimating Equations, *The Annals of Statistics, 22, 300-325.*

Quinn, T, Deriso, R, and Hoag, S. (1985): Methods of Population Assessment of Pacific Halibut, International Pacific Halibut Commission Scientific Report No. 72.

Scott (1955): The fishery: The objectives of sole ownership. *Journal of Political Economy, 63,116-124.*

Spence, M, and Starrett, D. (1975): Most rapid approach paths in accumulation problems. *International Economic Review, 16,388-403.*

Turvey, R. and Wiseman, J. (eds) (1957): The economics of fisheries. FAO, Rome.