

# Empirical characterisation , of a commercial fishing cycle using structural time series methods

A. **David McDonald\*** Senior Research Scientist CSIRO Division of Fisheries PO Box 1538, Hobart Tasmania 7001 Australia  
Phone: +(61-02) 325 201  
Fax: +(61-02) 325 199  
E-mail: [David.McDonald@ml.csiro.au](mailto:David.McDonald@ml.csiro.au)

## Abstract

Structural time series methods are applied to modeling endogenous fishing effort in the German North Sea shrimp fishery. The effects on fishing effort of shrimp price, catch per unit effort and environmental variation are examined. Preliminary results suggest that fishing firms do not respond much to price changes but they are highly responsive to variation in catch per unit effort and environmental conditions, which have a significant impact on the fish stock.

## 1. Introduction

Central to the commercial success of fishing firms is the information that they use, and manner in which they use it, to determine the amount of effort they expend in a fishery. In attempting to evaluate the bio-economic stability of the North Sea shrimp stock, McDonald and Hanf (1992) specified fishing effort as a control variable. The decision-making process was then modeled by assuming that fishing firms choose the level of effort that maximizes the net present value of harvests over time. The stochastic control framework used yields a non-linear stochastic differential equation for effort which implies that effort is determined endogenously by fishing firms in response to information on output price, the firm's production function and the abundance of fish.

The model used by McDonald and Hanf (1992) provided the basis for analyzing annual data to address the question of stock stability. It also provides guidance as to plausible relationships between fishing effort and the state of the fishery's bio-economic system when monthly data are available. Naturally, the use of monthly data leads to a new set of modelling considerations that were not addressed in the above-mentioned study. Formal modelling of the intra-year variation in effort could clearly command a great deal of thought, for example. In the meantime, an empirical study might be of considerable interest. This is the point of departure for the present paper.

Available monthly data for the German North Sea shrimp fishery consist of 257 observations during the period March 1970 - July 1991 on fishing effort, shrimp price, catch per unit effort (CPUE), mean daily seawater temperature and rainfall. Examination of these data reveals persistent seasonal cycles. Structural time series modelling (Harvey, 1989; Harvey and Shepherd, 1993) is therefore a natural means by which one might characterize cyclical patterns in effort; perhaps as the prologue to a more ambitious use of stochastic control methods for development of a detailed

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structural econometric model.

## 2. An empirical model of the annual cycle in the German north sea shrimp fishery

As mentioned above, previous modelling of the German North Sea shrimp fishery has suggested that fishing effort is determined by fishers, to varying degrees, in response to shrimp price, catchability and the abundance of fish. The available data include shrimp price and a number of variables that, as a set, are proxies for catchability and abundance. At first blush in an empirical study of cyclical patterns in fishing effort, therefore, it is tempting to simply regress effort on price, CPUE, seawater temperature and rainfall to see whether these patterns can be explained adequately using such explanatory variables. Unfortunately, such action is likely to yield misleading results because of features, those are common to effort and the regressors. That is, because they have common features that arise from common causes, the ability of the regressors to explain effort may be exaggerated when using standard regression techniques<sup>1</sup>.

The risk of obtaining spurious evidence of causal relationships between effort and the regressors can be diminished by taking account of common features and then, examining the power of the regressors in explaining effort. Within the structural time series framework of Harvey (1989), the features found to be common to effort, seawater temperature, shrimp price, rainfall and CPUE for the German North Sea shrimp fishery are a local trend, a monthly seasonal effect and a non-specific cyclical effect. These common features can be combined linearly to form a general structural model (GSM).

The GSM for each variable takes the form of a measurement equation and a multivariate stochastic equation of motion that includes dynamic unobservable variables. Each pair of differential equations within the multivariate stochastic equation of motion satisfies a pair of difference equations with trigonometric transition matrices, thus admitting periodicity. The general form of the GSM for the present application is given by:

$$Y_t = U_t + \psi_t^s + \psi_t + \sigma_y dz_y \quad (1)$$

where  $U_t$  is a trend that represents long-term movements in the data which can be extrapolated into the future,  $\psi_t^s$  is a seasonal component,  $\psi_t$  is an unobserved cyclical component with frequency  $\lambda$  radians and damping factor  $\alpha$ , and  $z_y$  is a standard Wiener process (that is,  $dz_y$  is white noise). The unobserved cyclical component evolves according to the stochastic differential equation.

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<sup>1</sup> This is the well-documented problem of spurious regression that arises frequently in time series. See, for example, Davidson and MacKinnon (1993) and Greene (1993) for discussion of this problem.

$$\begin{bmatrix} d\Psi_t \\ d\Psi_t^* \end{bmatrix} = \begin{bmatrix} \ln(\alpha) & \lambda \\ -\lambda & \ln(\alpha) \end{bmatrix} \begin{bmatrix} \Psi_t \\ \Psi_t^* \end{bmatrix} dt + \begin{bmatrix} \sigma & 0 \\ 0 & \sigma^* \end{bmatrix} \begin{bmatrix} dz_\Psi \\ dz_{\Psi^*} \end{bmatrix} \quad (2)$$

where  $0 < \alpha < 1$  for a stationary cyclical process. The evolution of  $U_t$  is given by

$$\begin{bmatrix} du_t \\ du_t \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_t \\ u_t^* \end{bmatrix} dt + \begin{bmatrix} \sigma & 0 \\ 0 & \sigma^* \end{bmatrix} \begin{bmatrix} dz_u \\ dz_u \end{bmatrix} \quad (3)$$

and the trigonometric seasonal component,  $\psi_t^s$ , takes the form of equation (2) for each of 6 monthly pairs, with  $\alpha$ , set equal to one and  $\lambda$ , set to the required seasonal frequency<sup>2</sup>. These components or features are estimated using a Kalman filter, with the Wiener-process errors assumed to be independent.

The solution of equation (2), for example, makes it clear that this equation facilitates the modelling of cyclical components that may exist in the data series  $y_t$ . The transition (co-efficient) matrix of the solution to equation (2) contains trigonometric terms that are clearly cyclical. Conditioned on the most recent data point, this solution satisfies the difference equation

$$\begin{bmatrix} \Psi_t \\ \Psi_t^* \end{bmatrix} = \alpha \begin{bmatrix} \cos \lambda & \sin \lambda \\ -\sin \lambda & \cos \lambda \end{bmatrix} \begin{bmatrix} \Psi_{t-1} \\ \Psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} n_t \\ n_t \end{bmatrix} \quad (4)$$

where the error-vector covariance matrix is

$$\frac{(1-\alpha^2)}{-2\ln(\alpha)} \begin{bmatrix} \alpha^2 & 0 \\ 0 & \alpha^2 \end{bmatrix} \quad (5)$$

The task now is to make use of this structural time series framework to characterize the principal patterns and causal linkages in the German North Sea shrimp fishery effort data. The main point to be made is that there is interest in examining the common features in the time series on effort, seawater temperature, shrimp price, rainfall and CPUE and then, investigating whether the remaining

<sup>2</sup> the appropriate seasonal pairs are for the  $\lambda$  values  $\pi / 6$ ,  $\pi / 3$ ,  $\pi/2$ ,  $5\pi / 6$  and  $\pi$ .

variation in effort can be explained by the remaining variation in the other variables.

On the assumption that fishing effort is an endogenous control variable, the stochastic control framework used by McDonald and Hanf (1992) suggests that the amount of fishing effort chosen by fishers depends not only on shrimp prices and shrimp abundance but also on the level of uncertainty surrounding prices and abundance. This dependency is potentially nonlinear and is complicated further when one considers monthly data with common cyclical features. The empirical characterization reported in the present paper is based on an arbitrary nonlinear relationship between effort and price, seawater temperature, rainfall and CPUE. Natural logarithms are used for all variables except seawater temperature. This imposes nonlinearly and guarantees non-negative predictions for all variables that can take only non-negative values.

Parameter estimates are obtained and inferences are made in two steps. The first step involves fitting the GSM to all variables either independently or jointly as a seemingly unrelated set with the common structural time series features given by equations (1) - (3). The second step entails using residuals from the price, seawater temperature, rainfall and CPUE GSM's as explanatory variables in the model for effort. This second step requires estimation of the effort equation

$$y_t = U_t + \psi_t^s + \psi_t + XB + \sigma_y dz_y \quad (6)$$

where  $B$  is a **vector** of regression coefficients corresponding to the columns of the regression matrix  $X$ , which are the above-mentioned GSM residuals and their interactions.<sup>3</sup>

### 3. Results

The first step in characterizing the commercial fishing cycle for the German North Sea shrimp fishery involved fitting a common GSM to the variables effort, price, seawater temperature, rainfall and CPUE. This was done using equations (1) - (3) for each of these variables individually and also, as a seemingly unrelated system. The parameter estimates for the system were very similar to those for each variable treated separately, except for the damping-factor and frequency parameters of the non-specific cycle. The residual diagnostics, especially those concerned with serial correlation, were better for the separate analyses, however. In addition, analyzing the variables separately (but using the same GSM) is more compatible with the second step in which, for consistency of parameter estimates, any stochastic regressors must be uncorrected with the effort-equation residuals. For these reasons, the first-step results are reported in Table 1 for each of the variables analyzed separately.

Table 1 reveals that there are significant cycle frequency and damping factors for all variables except CPUE. Interestingly, although not surprisingly, effort and seawater temperature have the most similar cyclical patterns. In addition, the variance estimates reveal very little randomness around the local trend, seasonal and cyclical features. Except for temperature, however, there is noticeable observation error. The diagnostic results point to heteroskedasticity in CPUE. The structural time series  $R^2$ , which is an indication of goodness of fit around the local

trend and seasonal components, indicates that price and CPUE are explained by the GSM least successfully.

The second step of the parameter, estimation and inference task involved adding explanatory variables to the effort equation, as per equation (4). These explanatory variables were constructed by subtracting the local trend, cycle and seasonal components from the variables price, seawater temperature, rainfall and CPUE. All interactions among these variables were also included. As alluded to above, these explanatory variables were added to assess whether, after taking account of common structural time series features, there is empirical evidence to support the view that commercial fishing decisions interactions are observation-by-observation products of the regressors. Two, three and four at a time are influenced directly by uncertain changes in economic, biological and physical variables.

The effort equation, including explanatory variables, was re-estimated in two ways. First, the structural time series hyper-parameters were constrained to equal the point estimates reported in Table 1 and the regression parameters were estimated, as reported in Table 2. Second, the effort equation, including the explanatory variables, was re-estimated as part of a seemingly unrelated set, yielding not only the regression parameters for the explanatory variables but also estimates of the hyper-parameters for a common trend, a common seasonal and a similar non-specific cycle. This ensures the same GSM for each equation, constraining the cyclical frequency and damping factor estimates to be the same for all equations, but it admits different degrees of departure from these common features, expressed as different variance estimates across equations. This also allows account to be taken of contemporaneous covariance among all (dependent) variables. Estimates for the second-step seemingly-unrelated equations are reported in Table 3.

The second-step results, for the effort equation reported in Tables 2 and 3, are broadly similar. The commonly significant explanatory variables are seawater temperature, CPUE and the interaction variables price-temperature, temperature-CPUE and price-temperature-rainfall. All of these variables are related positively to effort, as one would expect *a priori*. In addition to these commonly significant explanatory variables, Table 3 indicates a surprising significant negative impact of rainfall and a positive significant impact of temperature-CPUE. Also of note is the generous overlapping of 95% confidence intervals calculated for each coefficient, in turn, from Tables 2 and 3.

The diagnostic statistics for the effort equation are, in the main, similar, although some serial correlation appears to persist for the seemingly unrelated results reported in Table 3. A comparison of Table 1 with Table 3 also reveals a worsening of serial correlation, except for the seawater temperature equation.

#### **4. Concluding remarks**

The empirical results presented in Tables 1-3 provide a general characterization of the commercial fishing cycle in the German North Sea shrimp fishery. There is

strong evidence of seasonality, as one would expect, and superimposed on this is a non-specific cycle. Structural time series analysis is, therefore, a natural framework for tracing patterns in fishing activity. One might view this framework as providing a mechanism for mimicking the forecasting of fishers that leads to intended allocation of effort on a monthly basis. As information becomes available to fishers, however, these forecasts can be updated and effort allocation decisions modified. The second-step addition of explanatory variables in the effort equation is intended to reflect such information and resultant behavior modification.

The explanatory variables used are the GSM residuals for variables that proxy those postulated in previous work to be important in explaining effort. The natural conclusion to draw from the estimates in Tables 2 and 3 is that fishers respond only weakly to price changes but that they are much more responsive to changes in environmental conditions and fish abundance. In addition to common persistent seasonal and cyclical patterns, therefore, it is clear that effort is influenced directly by residual variation in economic, biological and environmental factors.

The stylized relationships revealed in this paper are consistent with previous stochastic-control based work on the German North Sea shrimp fishery. Despite the limitations of an empirical study of this type, it seems that a somewhat more ambitious use of the control framework in modelling commercial fishing cycles is likely to reveal insights of both theoretical and practical importance. Among other things, this would require explicit account to be taken of cost and production functions, seasonally and trends, as well as inter-annual economic cycles. Such work would need, therefore, to address temporal dynamics from both short-run and long-run perspectives. It would also require the setting of fishing cycles within a broader bio-economic context than has been achieved to date.

**Table 1: GSM Estimates (Step 1)**

Cycle Parameter		95% Confidence Interval for Each Equation				
		Effort	Price	Temperature	Rainfall	CPUE
$\alpha$ cycle damping		0.493-0.838	0.970-0.996	0.050-0.830	0.875-0.880	0.998-0.99
$\lambda$ cycle frequency		0.500-0.770	0.911-1.435	0.467-0.956	3.115-3,116	0.000-999
Variance Parameter		Point Estimate for Each Equation				
$\sigma^2$	local trend	0.001	0.040	0,000	0,000	0.055
$\sigma_{u^2}$	variances	0,000	0.000	0.000	0.000	0.000
$\sigma^2c$	cycle variance	0.0155	0.000	0.000	0.000	0,000
$\sigma^2s$	seasonal variance	0.001	(1.000	0.000	0.000	0.000
$\sigma^2y$	observation variance	0.013	0,003	0,000	0.381	0.030
Diagnostic Statistics						
Heteroskedasticity H(8l)~F(81,81)		1.193	0,315	1.277	1.112	3,477
Dirbin-Watson		1,940	2.010	2.000	1.856	1.967
Ljung-box Q05)~X <sup>2</sup> (9)		9.930	19.220	19.890	15.610	17.660
Structural Time Series R <sup>2</sup>		0.303	0.016	0.281	0.457	0.029

**Table 2:** Univariate Effort Equation Estimates (Step 2)

Explanatory Variable	Coefficient Estimate	Standard Error	Statistic
P (Price	-0.032	0,129	-0.248
T(Temperature)	11.230	2.676	4.197
R(Rainfall)	-0.034	0.047	-0.733
C(CPUE)	0.296	0.092	3,707
PT	39.327	10,608	
PR	0.043	0.206	0.210
PC	0.481	0.438	1.099
I'R	-4.339	3.823	-1.135
TC	9.628	6,450	1.493
RC	-0,038	0.154	-0.247
PTR	-2,385	13.672	-0.174
PTC	125.180	27.767	4.508
TRC	7,509	10.970	0.684
PTRC	15,249	54.705	0.279
Diagnostic Statistics			
Heteroskedasticity H(76) ~ F(76,76)	1.577		
Durbin-Watson	2.036		
Ljung-Box Q(14) ~ $X^2_{(8)}$	12.330		
Structural Time Series R <sup>2</sup>	0,510		



**Table 3:** Effort Equation Estimates from Seemingly Unrelated Set (Step 2)

Explanatory Variable	Coefficient Estimate	Standard Error	t Statistic		
P(Price)	0.163	0.120	1.351		
T( Temperature)	6.132	2.451	2.502		
R(Rainfall)	-0.379	0.042	-9.016		
C(CPUE)	0.291 44.477	0,085	3.419		
PT		9.675	4.597		
PR	-0-002	0.190	0.012		
PC	0-552	0.391	1.411		
TR	-3.979	3.605	-1.104		
TC	15.918	5.696	2.797		
RC	-0.038	0.143	0,269		
PTR	-4.292	12,386	-0.347		
PTC	114.170	26,190	4.359		
TRC	11.695	9.795	1.194		
PTRC	10.007	49.160	0.204		
Common cycle damping factor $\alpha=0.593$ Common cycle frequency $\lambda= 0,579$					
Diagnostic Statistics	Effort Eqn.	Price Eqn.	Temp Eqn.	Rainfall Eqn.	CPUE Eqn.
Heteroskedasticity H(76) ~ F(76,76)	1.604	0,384	1.143	0.995	3.231
Durbin-Watson	1.819	1.795	1.997	1.997	1.833
Ljung-Box Q(14) ~X <sup>2</sup> (8)	15,430	18.980	18.250	16.660	13.680
structural Time Series R <sup>2</sup>	0.450	0.048	0.286	0.469	0.237

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