ECONOMIC DISCUSSION PAPERS

Efficiency Series Paper 09/2003

Econometric Estimation of Fishing Production Functions when Stock is Unknown: A Monte Carlo Analysis

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Available online at: www.uniovi.es/economia/edp.htm

UNIVERSIDAD DE OVIEDO

DEPARTAMENTO DE ECONOMÍA

PERMANENT SEMINAR ON EFFICIENCY AND PRODUCTIVITY

ECONOMETRIC ESTIMATION OF FISHING PRODUCTION FUNCTIONS WHEN STOCK IS UNKNOWN: A MONTE CARLO ANALYSIS

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Abstract: In fisheries economics it is quite common to include a measure of fish stock as an argument of the production function. Given that this information is not available in many cases, researches use stock proxies. In this paper we show that a common proxy based on average catch of all (or some) boats in a given period is biased. However, a proxy based on seasonal dummy variables works better. An empirical section that uses Monte Carlo illustrates the theoretical results.

Keywords: fish stock, production function, Monte Carlo analysis.

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The author thanks Carlos Arias, Joaquín Millán, Luis Orea, David Roibás and Peter Schmidt for their helpful comments.

1. Introduction

In fisheries economics it is quite common to include a measure of fish stock as an argument of the production function. The idea is that the more fish exists the higher the catch will be. Therefore it seems logical to include an estimate of stock as an environmental factor in the production function. Given that this information is not available in many cases, researches use stock proxies. This approach raises some interesting modelling issues.

In this paper we compare two alternative proxies for fish stock within the primal parametric framework of production analysis. The first proxy is the 'catch per unit effort' (CPUE) which estimates stock in a given period as the average catch of all (or some) boats in that period. The second proxy uses seasonal dummy variables to account for temporal variation in the stock. The main finding of the paper is that the proxy that estimates stock based on average catch is shown to be biased, while the seasonal dummies allow for unbiased estimation of the production function parameters.

The paper is organized as follows. Section 2 discusses the general role of stock in a production function. Section 3 studies two different proxies for fish stock. Section 4 performs Monte Carlo analysis which allows to asses the extent of the biases. Section 5 contains a discussion of the implications of the paper for empirical analysis. Section 6 contains some conclusions.

2. The Role of Stock in Fishing Production Functions

The analytical framework is based on a simple production model where fishing output of boat i at time t (y_{it}) is a function of variable inputs (Z_{it}) and fish stock (S_t), which is assumed to be common to all boats. Additionally, catches depend on luck and other stochastic effects (u_{it}). Therefore, the fishing production function can be written as:

$$y_{it} = f(Z_{it}, S_t) + u_{it} \qquad (1)$$

If the model is linear, we have:

$$y_{it} = \mu + \alpha Z_{it} + \beta S_t + u_{it} \quad (2)$$

It is assumed that luck is uncorrelated with stock and with inputs, i.e., $Cov(S_t,u_{it})=Cov(Z_{it},u_{it})=0$. The correlation of stock and inputs is an empirical issue. If the inputs are time invariant, as it is the case with boat characteristics (length, engine power, …), then $Z_{it}=Z_i$, and by construction, $Cov(Z_i,S_t)=0$[1]. On the other hand, if Z_{it} changes over time, then it can be correlated with S_t, as it would be the case if producers choose inputs depending on the stock level (e.g. bait,…).

If there are data on fish stock, then S_t should be included as an explanatory variable.[2] Since stock is not known in most cases, the simplest way to deal with this problem is to model stock as a random variable uncorrelated with inputs. In this case, the model (2) becomes:

$$y_{it} = \mu + \alpha Z_{it} + v_{it} \quad \text{where } v_{it} = \beta S_t + u_{it} \quad (3)$$

If the objective is to estimate the effect of boat characteristics on output, ordinary least squares applied to equation (3) will yield an unbiased estimate of α if $Cov(Z_{it},S_t)=0$. Otherwise, failing to control for stock can lead to bias.

However, if there is interest in estimating the effect of stock on catches (β), the researcher has to use some kind of proxy for stock in the production function. In general, there are two cases. If boats fish in the same area, then a variation in fish stock will affect all fishermen equally. In this case, the problem calls for a stock measure common to all producers. Therefore, the effects of changes in fishing stock are similar to those of technical change, since an increase in the stock allows all fishers to catch more fish at any level of input use. On the other hand, if boats fish on different grounds, the stock measure should take this

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[1] A similar argument can be made with potentially time-varying inputs that in practice are almost fixed over time (net length, crue size, …).

[2] Only a few papers include a measure of fish stock obtained as an independent estimate from external sources. See, for example, Kirkley *et al.* (1995, 1998), Grafton *et al.*(2000) and Pascoe *et al.* (2001).

factor into account and be boat-specific. In the next section we study two proxies for fish stock considering that stock is common to all producers.

3. Proxies for Fish Stock

The point is how to include biomass stock in the production function when data are not available for it. In previous papers, two main proxies for fish stock have been used in empirical work. One is average catches in a given period, what is called ‘catch per unit of effort’ (CPUE). The other is to use time dummies to account for temporal variations of the stock.

a) Catch per unit of effort

In this approach, the stock in a given period is estimated as the average catch of all (or some) boats in that period. That is,

$$\hat{S}_t = \frac{\sum_i y_{it}}{N} \tag{4}$$

For example, Eggert (2001) calculated a stock proxy as “the overall average landing value per unit effort on a monthly basis”. Pascoe and Coglan (2002) used a stock index calculated as the geometric mean of the “value of catch per hour fished for the boats that operated in the same month in the same area using the same gear”.

The rational for this proxy is based in the traditional specification of a production function in fisheries economics, where catch (y) is a function of fishing effort (E) and stock (S). That is:

$$y = qES \tag{5}$$

where q is the coefficient of catchability. Since q is usually considered constant, it is easy to see that catch per unit effort (y/E) is proportional to the stock.

We will now study the implications of this proxy in the context of the production function. Using equation (2) the stock index in (4) becomes:

$$\hat{S}_t = \mu + \alpha \bar{Z}_t + \beta S_t + \bar{u}_t \tag{6}$$

where $\bar{u}_t$ is the average luck of all boats in period t. It should be noticed that $\bar{u}_t$ is not necessarily zero, since in a given period of time, it is not likely that the random components of all boats cancel out. However, taking expectations over time, the mean value should be zero, i.e., E[$\bar{u}_t$]=0.

In equation (6) one can solve for βS_t and substitute this value in equation (2):

$$y_{it} = \alpha(Z_{it} - \bar{Z}_t) + \hat{S}_t + (u_{it} - \bar{u}_t) \tag{7}$$

This is the expression of the production function implied by the functional relationship between the stock index and the true stock given in (6). Equation (7) can now be compared to the estimated production function, which is :

$$y_{it} = \mu' + \alpha' Z_{it} + \beta' \hat{S}_t + v_{it} \tag{8}$$

Comparing these last two equations it is easy to see that the estimated β' should be close to 1. This is because the construction of the stock index based on catches implies that any variation in the stock will be captured. This is a very important underlying assumption.

The same result is obtained if a Cobb-Douglas production function is estimated using the geometric mean of catches as a proxy for stock. The geometric mean of catches is:

$$\tilde{S}_t = \sqrt[N]{y_{it} \cdots y_{Nt}} \tag{9}$$

Taking logs, the temporal average of the log of catches is obtained:

$$\ln \tilde{S}_t = \frac{1}{N} \sum_i \ln y_{it} = \overline{\ln y_t} \tag{10}$$

Summing over i and dividing by N in equation (2) written in logs, yields:

$$\overline{\ln y_t} = \mu + \alpha \overline{\ln Z_t} + \beta \ln S_t + \bar{u}_t \tag{11}$$

Solving for $\beta \ln S_t$ and substituting back:

$$\ln y_{it} = \alpha(\ln Z_{it} - \overline{\ln Z_t}) + \ln \tilde{S}_t + (u_{it} - \bar{u}_t) \tag{12}$$

It can be seen that if a model in logs is estimated using the geometric mean of catches as a proxy for stock, one will get a coefficient close to one for this variable.

Also, on econometric grounds, introducing a proxy of fish stock based on average catches can sometimes lead to endogeneity problems. This problem resembles the most general question of explaining individual behavior by the group average. Manski (1995; ch. 7) analyzes the specification and estimation problems of this approach.

b) Time dummies

This approach has been used in several papers. For example, Coglan et al. (1998) or Campbell and Hand (1998).[3] If stock is common to all boats, one can write:

$$y_{it} = \mu + \alpha Z_{it} + \gamma_t + u_{it} \tag{13}$$

where γ_t are time effects, i.e. the coefficients of the seasonal dummy variables. Note that this formulation implies that there is one excluded category and the coefficients of the dummies have to be interpreted as the differential effect on output with respect to the omitted category.[4] If the panel data set is short in the time direction, the time dummies will probably pick up only the effect of stock changes, otherwise they will also pick up pure neutral technical change.

This model can be estimated by subtracting temporal means.

$$\bar{y}_t = \mu + \alpha \bar{Z}_t + \gamma_t + \bar{u}_t \tag{14}$$

This is equivalent to the "within" transformation for panel data, but with the roles of *i* and *t* reversed. Thus,

$$y_{it} - \bar{y}_t = \alpha(Z_{it} - \bar{Z}_t) + (u_{it} - \bar{u}_t) \tag{15}$$

[3] In a similar vein, Salvanes and Steen (1994) use a time trend to control for variations in fish stock.

[4] Another possibility is to specify the model without a general constant and include as many dummies as seasonal categories. That is, $y_{it} = \alpha Z_{it} + \gamma_t + u_{it}$

Equation (15), where we have removed anything that varies only over *t* (not over *i*), such as S, basically states that the difference in catches for boat *i* in period *t* from average catch in that period will be due to the difference in boat characteristics with respect to their mean. Ordinary least squares applied to equation (15) will yield unbiased estimates of α.

The time effects can be recovered using the following expression:

$$\gamma_t = \bar{y}_t - \alpha\bar{Z}_t - \bar{u}_t \tag{16}$$

Therefore, since E[$\bar{u}_t$]=0, a consistent estimator of the time effects will be:

$$\hat{\gamma}_t = \bar{y}_t - \hat{\alpha}\bar{Z}_t \tag{17}$$

Now we proceed to compare the two estimators for fish stock: catch per unit effort ($\hat{S}_t$) or time dummies ($\hat{\gamma}_t$). The difference between the two estimators of fish stock can be seen calculating their respective expected values. The expected value of $\hat{S}_t$ in equation (6) is:

$$E(\hat{S}_t) = \mu + \alpha\bar{Z}_t + \beta S_t \tag{18}$$

This implies that $\hat{S}_t$ (CPUE) is a biased estimator of S_t, since what it is fished on average depends on the average fishing effort ($\bar{Z}_t$).

On the other hand, the expected value of $\hat{\gamma}_t$ in equation (17) is:

$$E(\hat{\gamma}_t) = E(\bar{y}_t) - \bar{Z}_t E(\hat{\alpha}) \tag{19}$$

Since, $\hat{S}_t = \bar{y}_t$, substituting equation (18) into equation (19) yields:

$$E(\hat{\gamma}_t) = \mu + \beta S_t \tag{20}$$

Therefore, the expected value of the estimated time effects ($\hat{\gamma}_t$) equals the effect of stock on output (βS_t) plus the effect of the true (unknown) constant. This is not a problem since the estimated constant ($\hat{\mu}_t$) incorporates the effect of the omitted seasonal dummy. For this reason, the effect of stock on output (βS_t) is calculated as the difference between the estimated effect and the estimated constant. Therefore, the time effects can be considered unbiased estimators of the effects of fish stock on output.

4. Empirical application

In this section we will show the empirical implications of the theoretical results obtained above. Two are the main issues to be analysed. One, is the importance of the estimation biases that arise using CPUE as a measure of fish stock. The other is to check the consistency of time dummies as proxies for stock. However, the exact results of section 3 will be difficult to reproduce in most data sets due to problems caused by multicollinearity between inputs and the stock proxy, and also to the presence of noise. For this reason, we have decided to use a simulated data set.[5]

We construct a panel data set considering a situation with 50 boats and 12 time periods which are assumed to be months. Therefore, there are 600 observations.[6] We estimate both the linear and the Cobb-Douglas production models. That is, the equations to be estimated are:

$$\begin{aligned} y_{it} &= \mu + \alpha Z_{it} + \beta S_t + u_{it} \\ \ln y_{it} &= \mu + \alpha \ln Z_{it} + \beta \ln S_t + u_{it} \end{aligned} \tag{21}$$

The random term *u* is generated from a N(0,1). Since we estimate the models using ordinary least squares, it should be noted that the variance of *u* does not affect the estimated parameters (only the R^2). The population parameters take the following values in the simulation: μ=1, α=0.2, β=0.8. Effort is generated from a uniform distribution (0,1) in order to assure that it is always positive. The stock is generated with seasonal variation, assuming that it is highest in summer and lowest in winter. Therefore, the stock for month t, denoted by S_t, will be S_t=1 for t=1-3, S_t=1.5 for t=4-6, S_t=1.75 for t=7-9 and S_t=1.25 for t=10-

[5] Other papers that use artificial data sets in fisheries are Pascoe and Robinson (1996), Lee and Holland (2000), or Herrero and Pascoe (2004).

[6] The results are not very sensitive to the number of boats. We have performed the empirical analysis for N=10, 50, and 100 and the results do not differ much.

12.[7] Finally, the output (catch) is calculated using the production functions in (21).[8]

We estimate each production model using the true stock (S_t), CPUE ($\hat{S}_t$) and seasonal dummies (γ_t). In order to infer the sampling distribution of the estimators we perform a Monte Carlo analysis estimating the model 1000 times. In each new estimation, the random term *u*, the output and, therefore, CPUE are generated but the values of stock and effort are fixed. We first estimate both production models without correlation between effort and stock. Then, we allow for different degrees of correlation between both variables.

a) Inputs and stock are uncorrelated[9]

The results of the Monte Carlo exercise are summarized in Table 1, where we show the means of the estimated coefficients using the "true" stock and CPUE for both the linear and the Cobb-Douglas production functions. The results illustrate some interesting points. As expected, in both models the use of the true stock allows to recover all the technology parameters. Also, as predicted by the theoretical discussion in section 3, the estimated coefficient for CPUE is equal to one. Both models are able to recover the coefficient of effort. A "strange" result is that the use of CPUE also results in a biased estimate of the constant term. The reason is that CPUE incorporates the effect of effort on catches. In the linear case, comparing equations (7) and (8) it is clear that the estimated constant when using CPUE is equivalent to $-\alpha\overline{Z}_t$. Since the mean of effort is 0.50 and α=0.2, we have that $-0.2*\overline{Z}_t = -0.10$, which is the estimated constant. Similarly, in the Cobb-Douglas case, it can be seen in equation (12)

[7] We also allowed for some random variability in the stock. In this case the stock for month t was generated as a random draw from an $N(m_t,0.5)$, where m_t=1if t=1-3, m_t=1.5 for t=4-6, m_t=1.75 for t=7-9 and m_t=1.25 for t=10-12. The results are not much different from the ones obtained using a deterministic stock and are not presented here.

[8] Even though the data has the structure of a balanced panel, the independence of the draws implies that we are treating it as a "pooled" model. That is, there is independence across boats and over time. The boat effect is likely to be important for empirical analysis with real data. However, we believe that it is not relevant for the issues discussed in the paper.

[9] The lack of correlation in this case is driven by the independence of the drawings for both variables. In fact, the variables are not orthogonal, although the correlation (-0.02) is not statistically different from zero.

that the estimated constant will be $\hat{\mu} = -\alpha \overline{\ln Z_t}$, which is 0.201. Therefore, the predictions of the theoretical model hold when using empirical data.

Table 1. Estimates of the production function using stock proxies

	Stock proxy	Constant	Stock	Effort
Linear model	True Stock	1.00	0.80	0.20
	CPUE	-0.10	1.00	0.19
Cobb-Douglas model	True Stock	1.00	0.80	0.20
	CPUE	0.20	1.00	0.19

Means of 1000 replications

We now estimate the two models using seasonal dummy variables, leaving the winter dummy out (months 1-3). The results can be seen in Table 2. The coefficient of effort is again recovered with precision by both models.

Table 2. Estimates of the linear model with time dummies

	Constant	Spring	Summer	Fall	Effort
Linear model	1.80	0.39	0.60	0.20	0.19
Cobb-Douglas model	1.01	0.33	0.45	0.18	0.20

Means of 1000 replications

However, the interpretation of the estimated coefficients for the dummy variables is not direct. We are interested in checking whether the dummy variables capture the effect of stock on output. In the linear model this effect is given by βS_t. Therefore, the true effects in the four seasons will be: 0.8x1=0.8 for winter, 0.8x1.5=1.2 for spring, 0.8x1.75=1.4 for summer, and 0.8x1.25=1.0 for fall. Now, from equation (20) we see that the estimated time effects <u>in levels</u> are confounded with the constant. Since the coefficients of dummy variables in linear models show the differential effect with respect to the omitted category, the calculated effects of stock in each season with respect to the effect in winter are given by

$$\hat{\gamma}_j = \beta S_j - \beta S_W \qquad (22)$$

where S_W is the stock in winter and j denotes seasons (j=spring, summer and fall). Table 3 shows that the estimated time effects are almost identical to the true stock effects, measured with respect to the effect on output of winter stock. Note that the effect of winter cannot be recovered in this setting since it is confounded with the constant.[10]

Table 3. Calculated seasonal effects of stock on output (with respect to winter)

	Effect	Spring	Summer	Fall
Linear model	True: βS_j-βS_W	1.2 - 0.8 = 0.4	1.4 – 0.8 = 0.6	1.0 – 0.8 = 0.2
	Calculated: $\hat{\gamma}_t$	0.39	0.6	0.2
Cobb-Douglas	True: $\beta \ln S_j$-$\beta \ln S_W$	0.32 – 0 = 0.32	0.44 – 0 = 0.44	0.17 – 0 = 0.17
	Calculated: $\hat{\gamma}_t$	0.33	0.45	0.18

In the Cobb-Douglas case, the stock effect is given by $\beta \ln S_t$. Therefore, the true effects of each season will be: 0.8xln1=0 for winter, 0.8xln1.5=0.32 for spring, 0.8xln1.75=0.44 for summer, and 0.8xln1.25=0.17 for fall. Again, the effect of winter is confounded with the estimated constant and is not retrievable. The estimated effect of each season is given by:

$$\hat{\gamma}_j = \beta \ln S_j - \beta \ln S_W \quad (23)$$

In Table 3 it is easy to check that the estimated values and the true effects are very close.[11]

b) Inputs and stock are correlated

We now impose correlation between effort and stock. In particular, the assumed relationship between the two is the following:

[10] Since in the simulation we know the true value of the constant (μ=1), we could also recover the effect of stock for winter subtracting the theoretical constant from the estimated constant (1.80), which yields the theoretical value of 0.80.

[11] Since the variables are in logs the interpretation of the time effects in the Cobb-Douglas model is not straightforward. Suits (1983) shows that the interpretation of the coefficient of a dummy variable in this model is the percentage difference in output with respect to the omitted category. This value can be calculated as: $e^{\hat{\gamma}_j} - 1$.

$$Z_{it} = \theta S_t + \varepsilon_{it}$$

The correlation between Z and S is given by:

$$Corr(Z,S) = \theta \frac{\sigma_s}{\sigma_z}$$

where σ_s and σ_z are the standard deviations of S and Z respectively.

Three cases were considered: low (0.20), medium (0.50), and high (0.80) correlation. The results of the estimation of the linear and Cobb-Douglas models using the true stock and CPUE can be seen in Table 4.

Table 4. Estimates of the production models with stock proxies when inputs are correlated

	Stock proxy	Constant	Stock	Effort
Corr(Z,S) = 0.20				
Linear model	True Stock	1.00	0.80	0.20
	CPUE	-0.03	0.98	0.20
Cobb-Douglas model	True Stock	1.00	0.81	0.20
	CPUE	0.27	0.93	0.19
Corr(Z,S) = 0.50				
Linear model	True Stock	1.00	0.80	0.19
	CPUE	-0.01	0.95	0.17
Cobb-Douglas model	True Stock	1.00	0.79	0.20
	CPUE	0.18	0.90	0.18
Corr(Z,S) = 0.80				
Linear model	True Stock	1.00	0.79	0.20
	CPUE	0.03	0.91	0.15
Cobb-Douglas model	True Stock	0.99	0.80	0.20
	CPUE	0.08	0.92	0.13

Means of 1000 replications

The estimates in Table 4 show that correlation does not affect the estimation when the true stock is used. Both the linear and the Cobb-Douglas models are able to track with precision the theoretical estimates. However, when using CPUE, the estimates of all coefficients in both functional forms are biased and the biases increase with the level of correlation. Since with real data it is always the case that inputs are correlated, it is not surprising that the empirical papers that have used CPUE have not estimated a value of 1 for the coefficient of this variable.

In Table 5 we present the estimates of both models when using time-dummies as proxies for stock under the three degrees of correlation. In this case the estimated coefficients for all the variables (constant, time dummies, and effort) are very similar to those obtained when there is no correlation between effort and stock (see Table 2).

Table 5. Estimates of the production model with time dummies when inputs are correlated

	Constant	Spring	Summer	Fall	Effort
Corr(Z,S) = 0.20					
Linear model	1.79	0.39	0.59	0.19	0.20
Cobb-Douglas model	1.00	0.32	0.45	0.18	0.20
Corr(Z,S) = 0.50					
Linear model	1.81	0.39	0.60	0.19	0.18
Cobb-Douglas model	1.01	0.32	0.44	0.17	0.20
Corr(Z,S) = 0.80					
Linear model	1.79	0.39	0.59	0.20	0.20
Cobb-Douglas model	1.00	0.33	0.44	0.18	0.19

Means of 1000 replications

Therefore, our simulation exercise shows that when there is no correlation between the inputs and the stock, the CPUE is a biased measure of stock and its estimate is equal to one, although it is possible to obtain a consistent estimate of the parameter associated with effort. When inputs are correlated with the stock, the use of CPUE generates biased estimates of all coefficients.

5. Discussion

Some papers in the fishing literature have been critical with the use of CPUE as a measure of biomass stock. For example, Richards and Schnute (1986) argue that the proportionality rule may be oversimplistic since the catchability coefficient may depend on some factors, such as fishing ground, or the behavior of fish and fishermen. Sharma and Leung (1998) refer to the use of CPUE in econometric work: "CPUE figures are commonly used as indicators of stock abundance. However, because of its dependence on other inputs (crew size, fuel, and gear type) … CPUE is not suitable to include as an input variable in production function analyses".

The previous sections contribute to show that CPUE is a biased measure of fish stock and that results in biased estimates of the coefficients of the production function. Therefore, in the framework of this paper (single species, one year of data) the use of time dummies is preferable to CPUE. However, the empirical application of seasonal dummy variables is not without problems. First of all, one has to choose the periodicity of the dummies. In many cases, the observations in the data sets belong to the fishing trip (which may not be the same for all boats) or may be aggregated at the monthly level. With respect to the case of trip level data, the empirical evidence shows that it is not necessary to include as many dummies as trip periods. In most cases, seasonal dummies (monthly at the most) are enough. Pascoe and Coglan (2002) point out that an additional problem may arise if the data set comprises several years. In this case, if the seasonal pattern of the fish stock is not the same over years, then the seasonal dummy variables have to be interacted with year dummies and the number of interactions needed could be substantial.[12]

One alternative, which is equivalent to the use of time dummies, is to model stock as a flexible function of time. For example, Orea, Alvarez and Morrison (2003) use a cubic function of time to model the seasonal pattern of stock in the

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[12] One referee pointed out that a similar problem arises in multi-species fisheries since the stock of different species may show different temporal patterns of variation.

framework of an output-oriented distance function. The advantage of this approach is that fewer parameters need to be estimated and the time trends can be interacted with other inputs in an easier way than time dummies. Orea et al. interact the parameters of a cubic polynomial time curve with output and gear variables.

Another important issue relates to the functional form of the production function. The paper has shown that if the production function is linear or Cobb-Douglas, then the coefficient of CPUE will be one if there is no correlation between stock and other explanatory variables. However, many papers use more flexible production functions, such as the translog (for example, Pascoe and Coglan, 2002; Sharma and Leung, 1998). The analytics of this problem for the translog production function are more complicated than in the linear and Cobb-Douglas functions and it does not seem possible to get such an exact result as in the other two cases (coefficient of CPUE equal to 1). Still, even though there is no exact result, it is clear that CPUE is a biased measure of stock. The nature of the bias does not depend on the functional form but on the way it is calculated.

The use of CPUE or time dummies is not the only way to account for stock in fishing production models. There are alternative ways to deal with the problem of controlling for unmeasured fish stock. For example, Pascoe and Herrero (2004) use Data Envelopment Analysis to estimate an index of stock abundance. Their measure is in fact a “stock effect” rather than a stock index. That is, it is an indicator of how much the changes in stock have affected the catch of each of the boats. This method was used by Herrero and Pascoe (2003) to normalise the dependent variable (catch) of a fishing production function instead of including it as an additional input.

6. Conclusions

This paper compares two alternative proxies for fish stock and studies their role in the framework of a production function. The theoretical analysis shows that time dummy variables are a better proxy for stock than average catch. In the empirical section we show that the predictions of the theoretical model are correct. That is, the coefficient of CPUE is shown to be equal to one in both linear and Cobb-Douglas models. The conclusion of the paper is that it is better to use time dummy variables as proxies for the unknown fish stock.

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