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# Fisheries enforcement with a stochastic response function

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## Abstract

Fishers' response to the enforcement of fisheries management rules is generally not known with certainty. There are many reasons for this. Different fishers have different risk attitudes and the composition of active fishers is usually not known beforehand. Fishers' profit functions are usually imperfectly known and parameters such as prices are variable over time and, to some extent at least, stochastic from the perspective of the fisheries manager.

It follows that the enforcement of fisheries rules is usefully perceived as a stochastic problem. This paper investigates some of the implications. Among other things, it attempts to derive and explain certain necessary modifications to rules of optimal enforcement. To illustrate these principles it produces numerical stochastic simulation results. Finally, the paper discusses the practical issue of incorporating this stochasticity in practical fisheries models.


Keywords:
JEL classification codes:

## 0. Introduction

This paper considers the problem of optimal enforcement of fisheries rules where the response of fishers to the enforcement activity is uncertain. In order to focus the attention on what I see as essential aspects of the situation, a couple of important simplifications are adopted. First, we consider the case where the only management control to be enforced is the harvest rate. This corresponds to an IQ or more generally TAC management regime. Second, we will for the most part ignore the dynamic aspects of the situation. Both of these simplifications are easily relaxed (and are therefore theoretically immaterial) but only at a substantial cost in presentational clarity.

The theory of fisheries enforcement is somewhat underdeveloped. There is a substantial volume of literature on enforcement developed in general economics. The key initiator was Becker (1968). Other early contributions were by Stiegler (1970), Becker and Stiegler (1974) and Polinski and Shavell (1979). The existing theory is summarized by Garoupa (1997) and Polinski and Shavell (2000). In fisheries economics, notable applications of this basic theory have inter alia been by Sutinen and Andersen (1985), Anderson and Lee (1986), Milliman (1986), Charles et al. (1999), Arnason (2003), Hatcher (2005) and Hansen et al. (2006). None of these applications deal explicitly with the stochastic aspects of enforcement.

Very few empirical studies of the problem of fisheries enforcement have been published and those that have are quite limited (OECD 2003, Schrank et al. 2003, Hatcher and Gordon 2005). No comprehensive empirically based models of fisheries enforcement have to my knowledge been published, although a number of the above studies contain elements of such a model. The most accomplished model of this kind that I could locate was the one developed by MRAG et al (2004) for the European Union.

This paper is based on the fundamental economic enforcement theory first developed by Becker (1968). It begins by extending this theory to comprise the basic elements of a general fisheries enforcement theory. This theory is compatible with what has already been done in this field (see the references above) but is hopefully more systematic and more easily empirically applicable. A key element of this theory is the fishers' response function — a function which describes the fishers' response to enforcement activity. Rarely will the fisheries managers know this function with certainty. Hence, from their perspective, it may be seen as being stochastic. The implications of this are explored in section 3 of the paper. A numerical example of enforcement under a stochastic response function is provided in section 4. Finally, in section 5, the main results of the paper are summarized.

## 1. The basic model

Let the *social benefits of fishing* be defined by the function:

(1) $B(q,x)-\lambda\cdot q$.

In this expression, the function $B(q,x)$ represents the *private benefits from fishing* (profits, surplus salary etc.). The variable $q$ represents extraction and $x$ biomass. The variable $\lambda$

represents the shadow value of biomass, so $\lambda \cdot q$ is the social resource depletion charge.[1] The function $B(q,x)$ is assumed to be jointly concave in its arguments, monotonically increasing in $x$ and at least ultimately declining in $q$. From the concavity of $B(q,x)$ it follows that the social benefit function as a whole is concave in extraction, $q$, and biomass, $x$. It is convenient for representational purposes to assume $B(q,x)$ to be differentiable.

The management tool is taken to be $q$. This obviously corresponds exactly to a TAC regime. All fisheries management systems except the biological ones (mesh sizes, marine protected areas etc.) attempt to control $q$ directly or indirectly. For instance, effort restrictions attempt to do that by controlling effort—an important determinant of $q$.

Once a value for the management tool has been selected, i.e. a management measure imposed, it needs to be enforced provided of course it is binding. We consider two components of the enforcement activity:

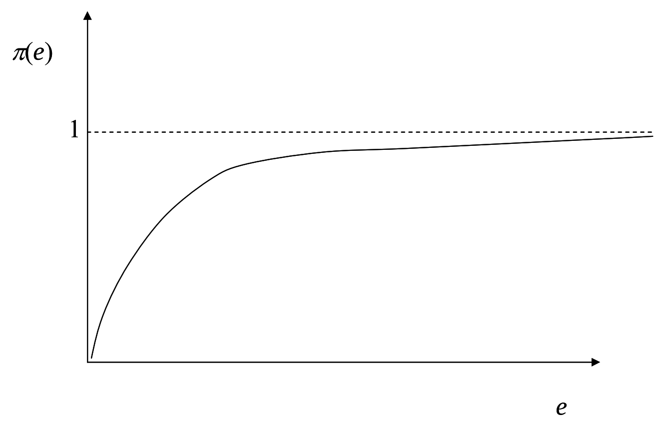
1. Enforcement effort, *e*.
   This is basically what is often referred to as the monitoring, control and surveillance (MCS) activity. This can be effected by many means at-sea or on-land. It is generally quite demanding and, therefore, costly in terms of manpower and equipment.
2. Sanctions, *f*.
   For fisheries violations it is reasonable to think of the sanctions as fines. However, in principle, sanctions may represent any type of penalty. In what follows, the sanctions will be taken as exogenous constants. To impose the sanctions generally requires certain administrative and legal proceedings. It is analytically convenient to think of these processes as a part of the enforcement effort.

The enforcement effort generates a certain probability of a violation of a management measure being detected and the violator apprehended (cited). It also generates a certain probability of having to suffer a sanction if apprehended. Let us represent this composite probability of having to suffer a penalty if one violates a management measure by the following probability function, which may be referred to as the *penalty probability function*:

(2) $\pi(e)$, $\pi(0)=0$, $\lim_{e\to\infty}\pi(e)=1$.

Most likely this function will look like the one depicted in Figure 1. This, obviously, is a concave smooth, monotonically increasing function.

Figure 1
**The penalty probablity function: Illustration**

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[1] This, of course, can reflect both fisheries and conservation values as well as other stock related concerns such as risk. There is a slight theoretical weakness in this formulation in that the appropriate $\lambda$ is generally an endogenous variable depending among other things on the enforcement effort.

Clearly, the main purpose of the enforcement activity is to increase the penalty probability function. For a given enforcement technology, this can only be done by increasing enforcement effort.

There will of course be costs associated with the enforcement activity. Let us describe these costs by the *enforcement cost function*:

(3) $C(e)$.

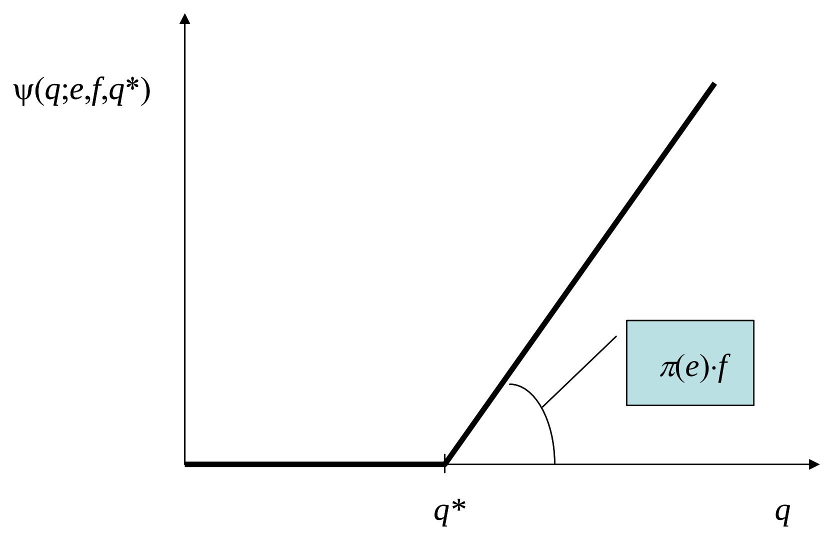
This function may be taken to be increasing in the enforcement effort and at least weakly convex.

The last basic component of this simple enforcement model is the cost to private operators, the fishers, of violating a management measure. Given the inherent uncertainty of having to suffer a penalty, this must be an expected cost. We refer to this expected cost function as the *private costs of violations* and write it simply as:[2]

(4)
$$\psi(q;e,f,q^*) = \pi(e)\cdot f\cdot(q-q^*), \text{ if } q\geq q^*.$$
$$\psi(q;e,f,q^*) = 0 \quad , \text{ if } q<q^*,$$

where $q^*$ is some management measure. On course, as already indicated, the second case, where $q<q^*$ is of limited interest. The shape of private costs of violations function as a function of the extraction level is illustrated in Figure 2. Note the non-smoothness of this function at $q=q^*$. This is mathematically a bit awkward but theoretically trivial. Clearly, the slope of this function beyond $q^*$, defined by $\pi(e)\cdot f$, is a major determinant of the deterrence against violating fisheries rules. Note that this increases with the penalty level, $f$, and the enforcement effort.

Figure 2
**Private costs of violations function: Illustration**




[2] Note that this formulation makes several implicit simplifying assumptions: (i) it assumes that the management measure can be expressed as an upper bound, (ii) it assumes that the penalty depends linearly on the amount of violations and (iii) it implies risk neutrality by the fishers. The first assumption is, I believe, trivial in the sense that it can obviously be easily relaxed. The second and third are somewhat more intricate. To relax them, however, would, I believe, not change the essence of the analysis, only render it more complicated and less transparent.

Combining (1) and (3) we obtain the *social benefits of fishing under costly enforcement*:

(5) $B(q,x)-\lambda\cdot q - C(e)$.

It is important to realize that this is the appropriate function for the management authority to maximize. If enforcement is costly, i.e. $C(e)$ not identically equal to zero, the traditional recommendation in the literature, namely to maximize the function in (1) (Gordon 1954, Clark 1976, Hannesson 1993) is inappropriate. It represents a fisheries management mistake which depending on the actual situation may be very costly.

Expressions (1) and (4) imply the *private benefits from fishing under binding management*.

(6) $B(q,x)-\pi(e)\cdot f\cdot(q-q^*)$.

If the management restriction is binding, this is the function private operators, i.e. the fishers, will try to maximize at each point of time.

## 2. Analysis

We are now in a position to examine the situation analytically and draw certain useful conclusions.

***Private behaviour***

Private behaviour (under restrictive management) is defined by the following:

(7) $q = \arg\max(B(q,x) - \pi(e)\cdot f\cdot(q-q^*))$

Assuming sufficient smoothness this implies the solution:

$B_q(q,x)- \pi(e)\cdot f=0$,

which implicitly defines the behavioural equation:

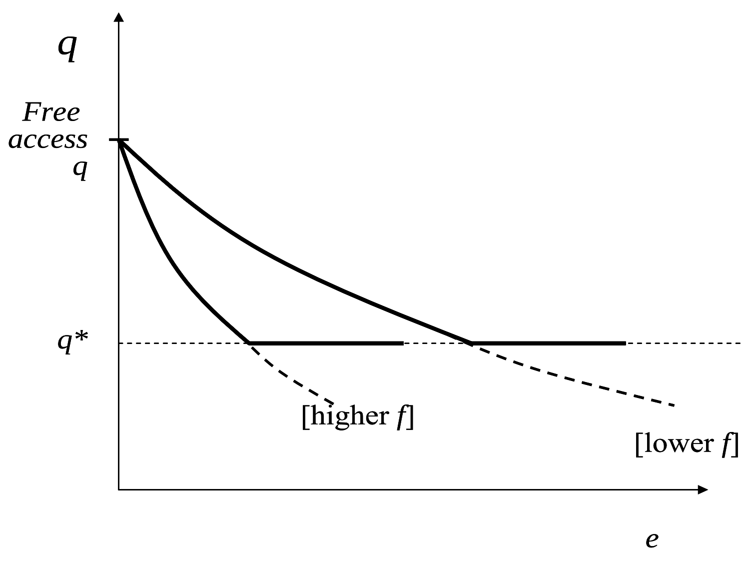
(8) $q=Q(e,f,x)$.

This equation is in many respects central to the analysis of fisheries enforcement. It may be called the *enforcement response function*. Given our previous specifications it is easy to show the following:

$\frac{\partial q}{\partial e}<0,\ \frac{\partial q}{\partial f}<0,\ \frac{\partial q}{\partial x}>0,$ provided $B_{qx}>0$, i.e. biomass helps harvesting.

The likely shape of the enforcement response function is illustrated in Figure 3. Two curves are drawn, one for a relatively high penalty and one for a lower penalty. When there is no enforcement, harvest is essentially unregulated and the situation becomes one that is often characterized as free access. This point is independent of the penalty level as illustrated in the diagram. For positive levels of enforcement harvest declines, until at sufficiently high level of enforcement effort, there are no violations; actual harvest is equal to the allowed harvest, $q^*$.

Figure 3
**Likely shape of the enforcement response function**




As illustrated in Figure 3, the enforcement response functions are non-smooth. They have corners at points where actual catch is equal to $q^*$. These corner points correspond to a regime shift; a binding harvest constraint becomes non-binding. At the corresponding level of enforcement effort and beyond it is optimal for the fishers not to violate at all. These points are formally defined by the condition $B_q(q^*,x)-\pi(e)\cdot f=0$. At these $q^*$s there is a discontinuity in the marginal enforcement response function — $Q_e \equiv \partial q/\partial e$ jumps from a negative value to zero. This discontinuity, although a mathematical feature, has fairly important practical implications. From this point of discontinuity onwards, there is no response by fishers to increases in management effort. In a fundamental sense additional management effort is wasted. This is a practical problem because under full compliance, i.e. at $q^*$ it is difficult for the enforcement authorities to figure out whether they are using excessive enforcement effort or not. Hence, to err on the save side there would be a tendency for excessive enforcement effort. For this reason it is advisable from a practical perspective never to generate full compliance and by that enjoy the convenience of a continuous marginal enforcement response function. The reader should realize that since $q^*$ can be arbitrarily set by the enforcer, less than perfect compliance can still correspond exactly to the socially optimal harvest level!

Note finally that the greater (numerically) the slope of the enforcement response function, the more effective the enforcement effort. It is easy to see (by differentiating the private behavioural rule) that this slope is (numerically) increasing in the penalty, *f*. This immediately implies the important practical result that by the simple expedient of increasing the penalty, the enforcement effort can be made mode effective. How much the penalty needs to be increased to have the desired impact is, however, an empirical question.

***Social Optimality***

The social problem is to maximize the social benefit function subject to the enforcement response function and other relevant constraints. More formally the social problem in the current context is:

$$\underset{e}{Max}\ B(q,x)\text{-}\lambda\cdot q - C(e).$$

Subject to: $q= Q(e,f,x)$
$e\geq 0$
$f$ fixed
$x$, $\lambda$ predetermined.

Assuming sufficient smoothness and an interior solution, the solution to this problem may be written as:

(9) $$(B_q(q,x)-\lambda)\cdot Q_e(e,f,x)=C_e(e).$$

Equation (9) defines the socially optimal enforcement effort level, $e_{opt}$, say. By implication it also provides a measure of the socially optimal compliance level as

(10) $$\Omega_{opt}=\frac{q*}{Q(e_{opt},f,x)}.$$

Obviously, the socially optimal compliance level would only rarely be unity.

Now, ignoring management costs (and assuming 100% compliance) implies the social optimality condition:

(11) $$B_q(q,x)=\lambda.$$

We immediately draw the following important conclusions:

I Under costly enforcement, socially optimal harvesting levels will be greater than otherwise.

To see this, it is sufficient to note that (9) implies $B_q=\lambda+C_e/Q_e$ and the last term is, according to our assumptions, negative. Therefore, $B_q<\lambda$ and since $B_{qq}$<0 $q$ must now be higher.

II. Only when 100% compliance is achieved costlessly, will socially optimal harvesting levels be defined by (13).

This obviously happens in two cases: (i) the cost of enforcement is actually zero, (ii) the effectiveness of enforcement is infinite (vertical cost of violations function see Figure 2 or equivalently vertical enforcement response function see Figure 3) so infinitely small enforcement effort is sufficient to ensure 100% compliance.

## 3. Optimal enforcement under uncertainty

Now, let us assume that the fishers' behavioural function is known only with uncertainty and that this uncertainty may be represented in the following simple way:

(12) $q = Q(e, x, f) \cdot g(u)$,

where $u$ is a random variable and $g(u)$ is some function of this random variable. The strong assumption contained in (12) is that the stochastic term is multiplicatively separable from the fishers' behavioural equation. One convenient specification is that $g(u) = e^u$, $u \sim N(0, \sigma_u^2)$, so that $g(u)$ has the log normal distribution. In this case the most likely (although not the expected) harvest is given by the non-stochastic response function, $q = Q(e, x, f)$.

Proceeding in general terms, the problem is to

$$\underset{e}{Max}\ E(B(Q(e,x,f)\cdot g(u),x) - \lambda \cdot q - C(e)),$$

where $E(.)$ is the usual stochastic expectations operator (Hogg and Craig 1970).

A necessary condition for solving this problem is:

(13) $E(B_q(Q(e,x,f)\cdot g(u),x) - \lambda)\cdot Q_e(e,x,f),x)\cdot g(u) - C_e) = 0$.

This should be compared to the non-stochastic necessary condition, equation (9) above.

Expression (13) is a complicated function of the stochastic term, $g(u)$, while in (9) this term is arbitrarily set equal to unity. It should be obvious that only under very exceptional circumstances would these two conditions, (13) and (9) yield the same enforcement level.

Let $e^*$ be the solution to the properly defined stochastic problem (5) and $e°$ the solution to the non-stochastic problem, i.e. (6). To find the difference between the two is in general an extremely complicated exercise. To get some idea we may proceed as follows:

Consider the expression $E(B_q - \lambda)\cdot Q_e \cdot E(g(u))$, which is basically the marginal social benefit of enforcement effort with the two stochastic functions, $B_q(Q(e,x,f)\cdot g(u),x,f)$ and $g(u)$ being replaced by their expectations. Subtract this expression from both sides of (13) and rearrange to obtain:

(14) $E((B_q - \lambda)\cdot Q_e \cdot (g(u) - E(g(u)))) = C_e - E(B_q - \lambda)\cdot Q_e \cdot E(g(u))$.

The left hand side of (14) is simply the covariance between the marginal social benefits of enforcement effort, $(B_q - \lambda)\cdot Q_e$, and the stochastic term, $g(u)$. So, more concisely, (14) may be written as:

(15) $Cov((B_q - \lambda)\cdot Q_e, g(u)) = C_e - E(B_q - \lambda)\cdot Q_e \cdot E(g(u))$.

The right hand side of (14) (and (15)) is the (negative) of the net marginal benefits of enforcement with stochastic functions replaced by their expectations. Thus, we immediately deduce the following result:

**Result 1** (for the simple enforcement model)

If and only if $Cov((B_q - \lambda)\cdot Q_e, g(u)) = 0$ will optimal enforcement be characterized by the condition $E(B_q - \lambda)\cdot Q_e \cdot E(g(u)) - C_e = 0$.

Now, of course, the $Cov((B_q - \lambda)\cdot Q_e, g(u))$ involves $g(u)$ in both terms. Hence, it is extremely unlikely that this covariance is ever zero. On reasonable assumptions, it appears very likely that $Cov((B_q - \lambda)\cdot Q_e, g(u)) > 0$. When $g(u)$ is relatively high $q = Q(e,x,f)\cdot g(u)$ is also high. Therefore, by the concavity of the benefit function, $B_q$ would be smaller, the difference $(B_q - \lambda)$ a higher negative number and, therefore, $(B_q - \lambda)Q_e$ also higher. For unusually low $g(u)$, the opposite happens. By the (assumed) concavity of the social benefit function, the right hand side of (8) is increasing in enforcement, *e*. We thus deduce:

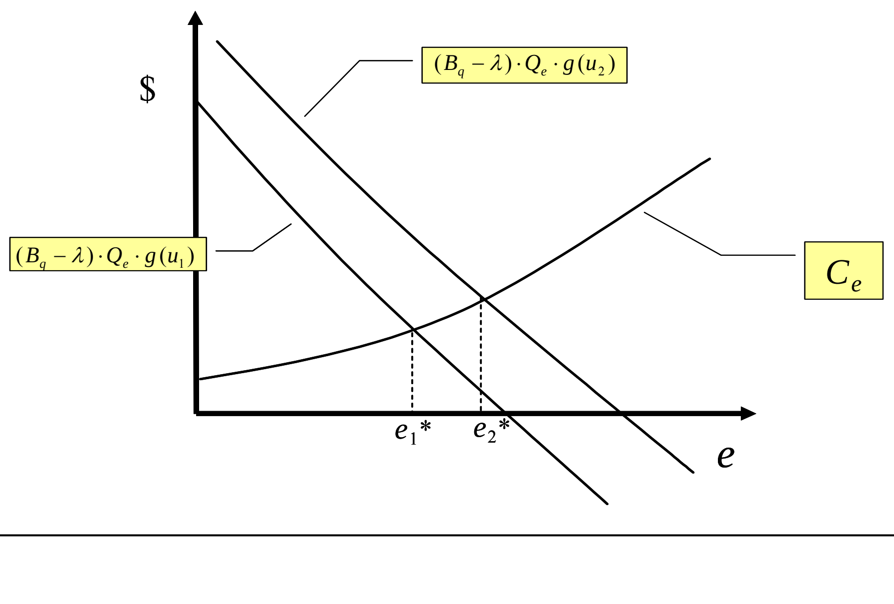
**Result 2** (for the simple enforcement model)

If $Cov((B_q - \lambda)\cdot Q_e, g(u)) > 0$ then $e^* > e^\circ$ and vice versa.

It is important to correctly interpret this result. Its message is that under the conditions given (i.e. $Cov((B_q - \lambda)\cdot Q_e, g(u)) > 0$) the enforcement level that maximizes expected social benefits from fishing will be greater than the one that maximizes social benefits where the two stochastic terms, $(B_q(Q(e,x,f)\cdot g(u),x) - \lambda)$ and $g(u)$ have been replaced by their expectations. Note, however, that since $E(B_q - \lambda)\cdot Q_e \cdot E(g(u)) - C_e \neq B_q(Q\cdot g(E(u),x) - \lambda)\cdot Q_e \cdot g(E(u))$, Result 2 does not directly inform us of the error made by replacing the random variable in the first order maximality condition by its expectation.

The economic rationale for Result 2 is not difficult to understand. According to the specification in equation (4), a high $g(u)$ implies that the marginal productivity of enforcement effort, $Q_e \cdot g(u)$ has become higher. Thus, *ceteris paribus*, it is economically appropriate to use more enforcement effort. The basic relationship is illustrated in Figure 4.

Figure 4
**The effect of a high random term** ($u_2 > u_1$)



**4. Optimal enforcement under uncertainty: A numerical example**

Let us now illustrate the foregoing theory with a numerical example. Consider the following fisheries enforcement model which functional forms are in accordance with the basic theory of section 1.

*Private fisheries profit function*:

$$p \cdot q - c \cdot \frac{q^2}{x} - f \cdot \pi(e) \cdot q,$$

where *p* is price, *q* harvest, *x* biomass, *c* a cost parameter , *f* the value of the penalty and $\pi(e)$ the probability of having to suffer the penalty.

*Fisheries social benefit function*:

$$(p-\lambda) \cdot q - c \cdot \frac{q^2}{x} - a \cdot e^2,$$

where λ represents the shadow value of biomass and $a \cdot e^2$ represents the cost of enforcement.

*Probability of paying the penalty*:

$$\pi(e) = \frac{e}{b+e},$$

where b is a parameter.

Under these model specifications, it is easy to verify that the fishers' response function is:

$$Q(e,x,f) = \frac{(p - f \cdot \pi(e)) \cdot x}{2 \cdot c}.$$

Now, we want to make this function (as seen by the enforcers) stochastic. There are many reasons why that might be the case. There are normally a substantial number of fishers with presumably somewhat different risk attitudes. The application of the enforcement effort depends on the enforcement personnel and quite possibly various stochastic environmental conditions. The prices which enter the functions vary stochastically and so on. Let the stochastic version of the behavioural function be:

$$Q(e,x,f) = \frac{(p - f \cdot \pi(e)) \cdot x}{2 \cdot c} \cdot exp(u),\ u \sim N(0,\sigma_u^2).$$

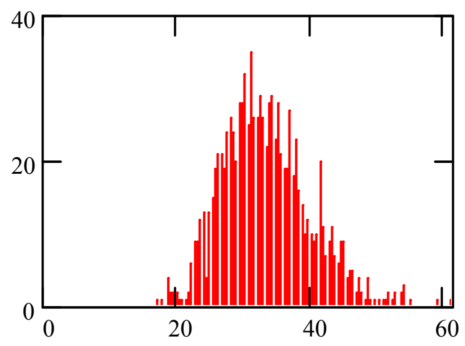
So, the stochastic term is taken to be log-normally distributed.

The numerical assumptions are listed in Table 1:

| Table 1<br>**Numerical assumptions** | |
|---|---|
| Parameters | Values |
| $p$ | 1 |
| $c$ | 1 |
| $f$ | 1 |
| $\lambda$ | 0.4 |
| $a$ | 0.05 |
| $b$ | 2 |
| $x$ | 100 |
| $\sigma_u$ | 0.2 |

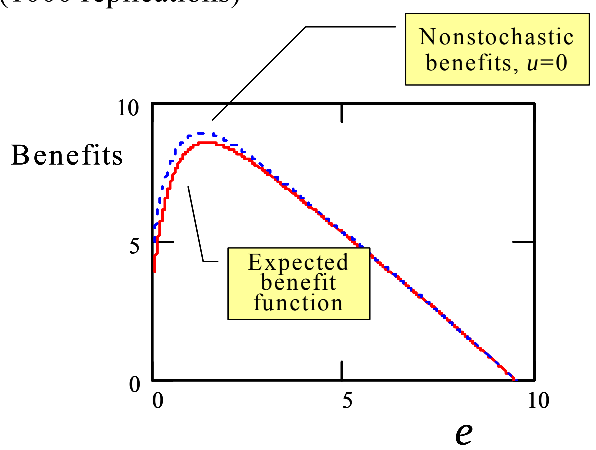
The distribution of harvests for the values of the parameters given in Table 1 and an arbitrary enforcement effort level of $e$=1 is described in Figure 5. As indicated in the diagram the distribution (a log-normal one) is slightly skewed to the left (stretched to the right) The average in the sample is 34.2 units of harvest with a standard deviation of 6.9 units. This should be compared to the non-stochastic catch level of 33.3. units for the same level of enforcement and the non-stochastic harvest level under no enforcement of 50 units.

Figure 5
**Distribution of catches**
(1000 replications. Enforcement level $e$=1.0)




The expected social benefit function and the one obtained by setting the random variable $u$ at its expected level of zero are illustrated in Figure 6. As shown in the diagram, there is a clear difference between the two curves, especially at low level of enforcement effort. At high levels of enforcement effort the catches are relatively small so the deviations cannot be great (remember the stochastic term is multiplied by the catch level).

Figure 6
**Benefits as a function of enforcement effort**
(1000 replications)



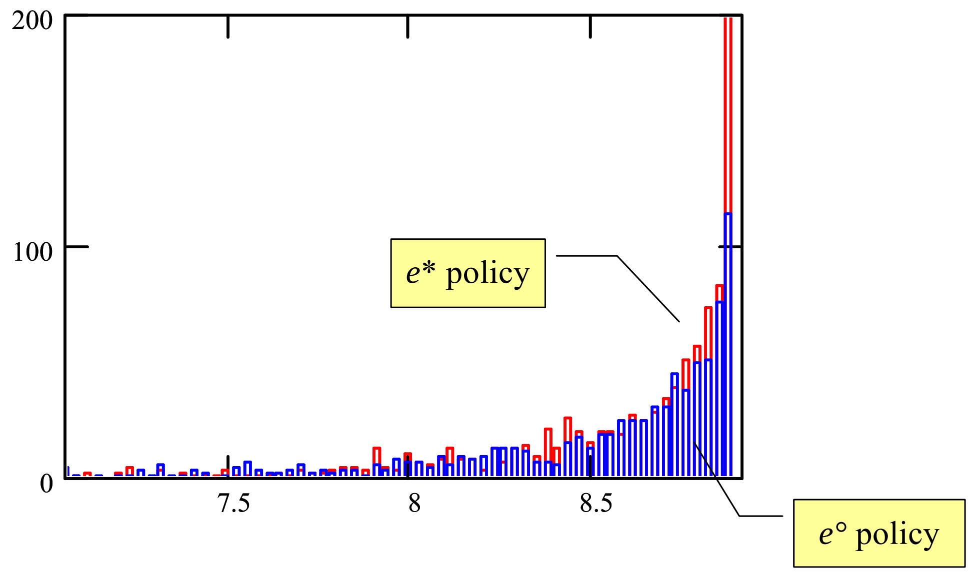

As is readily seen from Figure 6, the enforcement effort levels which maximize the non-stochastic and the stochastic expected benefit curves respectively are not identical. The two enforcement levels, the one that maximizes expected social benefits, $e^*$, and the one that maximizes the non-stochastic benefits, $e°$, and their respective expected outcomes are summarized in Table 2.

Table 2
**Optimal and suboptimal enforcement effort**
(1000 replications)

| Enforcement effort | Level | Expected harvest | Expected social benefits | Variance of social benefits |
|---|---|---|---|---|
| $e^*$ | 1.46 | 29.6 | 8.53 | 3.6% |
| $e°$ | 1.26 | 31.5 | 8.49 | 6.3% |

The numerical results in Table 2 verify the theoretical results. Under uncertainty, the benefit maximizing enforcement level is higher than under no uncertainty. Similarly the expected harvest is lower and expected social benefits are higher. In this particular numerical example, the gain in social benefits from adopting the optimal stochastic policy is not very great, however. There is a significant difference between the enforcement effort and the resulting expected harvest, but the difference in expected social benefits is relatively tiny. Interestingly, however, the variance in the expected social benefits under the suboptimal non-stochastic policy, $e°$ is much higher than under the optimal enforcement policy. One possible explanation is that with less harvest the relative variability in harvest is smaller. The following depicts the distribution of social benefits under the two policies

Figure 7
**Histograms of benefits under the stochastic policy, *e****, **and the nonstochastic policy *e°***




The two histograms illustrate the wider distribution of benefits under the sub-optimal policy. Note that since maximum benefits are non-stochastic (only the actual harvests are stochastic), both distributions have an absolute upper limit.

## 5. Conclusions

Ignoring uncertainty about actual catches, i.e. the fishers' response function to enforcement, will generally lead to (a) inappropriate levels of enforcement effort, (b) errors in selecting the (real) harvest target and (c) inefficient use of enforcement effort and (d) a loss in economic benefits from the fishery. The amount of social loss stemming from the omission depends on the particulars of the situation but could easily be high.

For reasonable specification of the actual catch uncertainty (skewed to the right, e.g. log-normal), it is likely that the optimal stochastic enforcement level will be higher than would otherwise be the case and therefore actual harvests lower and the cost of enforcement higher. As a result, the uncertainty about actual catches will reduce the maximum benefits attainable benefits from the fishery compared to the non-stochastic case. This is as expected. Uncertainty is generally economically costly.

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