Title

Fisheries Management Implications of Intrinsic Under Identification of Growth Equation Parameters

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Abstract

Fisheries are subject to multiple forms of uncertainty. One of these, parameter uncertainty, has been largely ignored in the fisheries economics literature even though it is known elsewhere (*e.g.,* macroeconomics) to play an important role in models with a similar structure. We model management of a renewable resource with unknown growth parameters and simulate estimation of the key parameters of the growth equation. Even with predictability high by typical standards and the true data generating process serving as the model, management of the fishery is problematic. A simple heuristic alternative making less intensive use of the data performs better.

Keywords: *Fishery management, simulation, estimation*

INTRODUCTION

Fisheries managers when making decisions almost always assume that the parameters of the growth function are statistically identified and temporally stable. If both of the conditions hold then the usual political economy story of agency capture is the most plausible one for the declining state of fisheries in many places. However, if the growth function's parameters are either not identified in the available data or the system they are in is not stable then there may be fundamental problems that institutional changes and changes in management objectives, such as those suggested by the recent Pew Oceans Commission and the U.S. Commission on Oceans Policy, will not solve. Several recent papers have looked at the case where the growth function parameters vary over time in a cyclical fashion (Carson, *et al.*, 2009; Costello, 2000). Here we look at a diferent case where the parameters of a time-invariant function are only weakly identified in any feasible data set available.

The standard natural resource economics textbook treatments of how to optimally manage a fishery implicitly assume that biologists have delivered to them the "true" underlying parameters of a stable biological growth function (Fisher, 1981; Clark, 1990; Hartwick and Olewiler, 1998; Perman, *et al.*, 2003; Tietenberg, 2002). Indeed, most economic analysis is done as if there is not even a random element to changes in fish stocks. While this has allowed economists to concentrate on the "economic" part of the management problem, serious issues arise if the underlying biological parameters upon which decisions are being made are substantially wrong. Indeed, the basic theme of this paper is that the estimates of the biological parameters will usually be sufficiently far from their true values in such a manner that economists cannot ignore the implications of this issue in providing policy advice. It is also a theme of this paper that the problem is much deeper and structural in nature than simply admitting uncertainty and invoking some notion of the precautionary principle to cut back on allowable catch limits.

To be sure, economists have not completely ignored the issue of uncertainty, although "relative" neglect is probably a fair assessment. Much of this neglect stems from a perceived division of labor between biologists and economists and a line of work begun by Reed (1979). Reed's work suggested that if one simply tacked on a random term to the current period of growth, then the optimal policy was still the deterministic constant escapement rule of Gordon (1954). The reason for this is that if the error term was i.i.d. with an expected value of zero and observable then it was optimal to adjust to each shock by setting harvests to keep the stock size constant. Clark and Kirkwood (1986) made the more realistic assumption that the error component was not observed contemporaneously so that there was effectively error in the stock size measurement.

Recently, there has a been renewed interest in looking at uncertainty, some of which is stimulated by a provocative biologically oriented paper by Roughgarden and Smith (1996) that argued that the large amount of uncertainty in biological modeling called for the use of some variant of the precautionary principle in fisheries management. This has led some economists, most notably Sethi, *et al.* (2005) to reexamine the uncertainty issue.[1] Sethi *et al.* use three independent sources of uncertainty, growth, stock size measurement, and harvest implementation each modeled as a contemporaneous error

[1] Other recent papers looking at the role of uncertainty in fisheries management and the behavior of fisherman include Singh, Weninger and Doyle (2006) and Smith, Zhang, and Coleman (2008). More generally there is a growing recognition that economists need to become more actively involved in modeling the complete bioeconomic system. Smith(2008) points out that small changes in parameter values in non-linear fisheries can have a large influence on the underlying dynamics and that econometric understanding of these implications are woefully inadequate.

term. In this sense, Sethi *et al.* encompasses the Reed, Clark and Kirkwood results and the more formal parts of Roughgarden and Smith. They find that uncertainty with respect to stock size measurement matters the most. In particular, they find constant escapement rules that attempt to hold the stock size at the level that maximizes sustainable yield, and which often characterize fisheries management, lead to substantially lower profit and a higher probability that the fish stock being managed will go extinct than under the adaptive policy they find to be optimal.

Sethi, *et al.* (2005) suggest that uncertainty is more important than economists previously thought but at its heart is still a stable deterministic growth function with contemporaneous uncorrelated i.i.d. error terms added to the growth, stock measurement, and harvest equations. There are two other interesting possibilities to explore. The first is that the system is not stable over time in the sense of having clear time series dynamics either in the deterministic (Carson, *et al.,* 2009) or stochastic (Costello, 2000) part of the model. Here, we look at the other possibility that the system is stable but the parameters being used for policy purposes are fundamentally different from the true ones.

This remainder of the paper has three parts. First, we introduce the basic model and discuss some of the fisheries biology literature on estimating growth equations. This literature shows that even simple Gordon-Shaefer logistic growth models typically produce poor estimates and that there has been a tendency to move to ever more complicated models that improve in-sample but typically not out-of-sample forecasting ability. Economists have paid surprisingly little attention to the technical estimation problems the biologists have long faced. Various shades of macroeconomic modeling and forecasting issues come to mind here (Hamilton, 1994). The fundamental problem is that errors are propagated through a non-linear dynamic system, with the issue being exacerbated by a high degree of correlation between many variables, imperfect observability of some key variables, and a relatively short time series available on which to estimate model parameters.

While the parameters of the growth equation are technically identified, we show that they are often only weakly identified so because of the typical lack of substantial variation in the stock size and because of the tightly coupled relationship between the growth rate and the carrying capacity. In samples of the size often used for the purpose, parameter estimates may be almost arbitrarily far from their true values and the property of asymptotic consistency of little practical import. This under identification becomes even more troublesome if one allows various economic factors associated with catch per unit of effort measurements to be correlated with the unobserved random shocks, as seems likely.

We proceed to generate synthetic data for the parameter values used for growth rate, carrying capacity and stock size in the fisheries example in Perman, *et al.* (2003), a popular graduate textbook. Our example shows a frightening degree of parameter dispersion, and even with almost thirty years of data some of the parameter estimates still display considerable bias.

For our manager we adopt a realistic objective[2] of maximizing the sum of catches subject to maintaining positive stock levels with a minimum probability of collapse. We

[2] This is not the economic optimum but rather, maximum sustainable yield. This is quite realistic as a target for the manager as many current US fishery management plans mandate that the stock be maintained at or near maximum sustainable yield or a fraction thereof. Examples include the Mid-Atlantic Flounder (Mid-Atlantic Fisheries Management Council, 1999), the Bering Sea and Aleutian Islands Groundfish (Witherell, 1997) and the California White Seabass (Larson, *et al.,* 2002).

look at catches in management simulations treating the parameter estimates as truth as well as two heuristic rules of thumb one based on stock size and one based on catch.

Traditional management is adaptive in the sense that its uses estimates of maximum sustainable yield (MSY) from models that are periodically updated with accumulated harvest and stock size or effort data. We assume the various parameter estimates from the previous section are treated as truth by the management agency in setting catch limits. This is done repeatedly with different draws on the vector of random error terms for the growth function. This allows us to trace out various outcome distributions. In particular, we focus on average catch and the present discounted value of catches. We also evaluate the probability the fish stock goes extinct. As a baseline we manage the fishery using the true biological model parameters and the same specification for random contemporaneous shocks over the five years management period. The profit distribution is not at all concentrated around that achieved if the true biological growth function parameters were used and, in cases were profit is high, the probability of low stock size and even extinction is high.

The last part compares the performance of traditional management to a simple rule of thumb scheme that forsakes an effort at formal estimation of the growth function parameters. This too is similar to the direction that some of the macroeconomic literature has taken when it is clear that the true model parameters are unknown (Brock, *et al.,* 2007). Here rather than assuming that the parameters of the growth function are known or even knowable, we make the much weaker assumption than is typical and assume only that the growth function is stable and is single peaked. Ourrule of thumb looks at the difference between stock (or catch) over two periods and then determines what side of the peak one is on and takes a step toward it. Because there is a true stochastic component to growth it is always possible to take a step in the wrong direction. Essentially, this is an adatpive gradient pursuit method which is always on average moving in the correct direction. We show that this rule of thumb can lead to higher expected yields than does traditional management and a lower likelihood of collapse.

MODEL

The standard textbook fisheries example is the Gordon-Schaefer model with a logistic growth equation (Clark, 1990; Perman, *et al.,* 2003). The growth equation is usually represented as:

(1) $G(X_t) = rX_t(1 - X_t/K),$

where $G(X_t)$ is the net natural growth in the fish stock at time t, X_t, r is the growth rate and K is the carrying capacity. $X_{t+1} = X_t + G(X_t) - F_t$, where F_t is the quantity of fish harvested. A sustainable yield occurs where $F_t = G(X_t)$. Maximizing sustainable yield (*MSY*), which is the explicit or implicit objective written into much fisheries legislation, occurs when the population is set at $½K$ and is equal to $rK/4$. Adding an economic actor such as a rent maximizing sole owner shifts the *MSY* formulation of stock size a bit higher or lower to take account of how costs depend on stock size (stock size larger than *MSY* and increasing as degree of dependence increases) and the magnitude of the positive discount rate (stock size smaller than *MSY* and decreasing as discount rate increases). The optimal harvest size though is still typically driven to a large degree by the underlying *MSY* biology, as these two factors often roughly offset each other. What is crucial for the argument we advance is the dependence of current policies on knowing K to set the optimal stock size and *rK* to set the optimal harvest. Similar dependence exists for most of the other growth functions commonly used in making fisheries management decisions so the conceptual issues can all be well illustrated using the logistic function. Further, we note that while the Gordon-Shaefer logistic growth model can be criticized for not being realistic enough to fit empirical data, it is an entirely different matter if we generate data as if that model were true and then try to fit it. Now the Gordon-Shaefer logistic model with stock assumed to be observable represents the best case of having to fit *only* two parameters relative to the available time dimension of the dataset.[3] While our simple model has but a single species and ignores spatial/temporal heterogeneity, the complications that arise from accounting for these factors make estimation all the more difficult and consequently reinforce our argument.

The main problem is that K in the logistic growth equation is fundamentally under identified unless r is known (and to a lesser degree vice versa for r unless K is known). The main reason for this is that unless there is substantial variation in X_t, then observing X_t and $G(X_t)$ only identifies the ratio r/K. Since fisheries managers often try to hold X_t constant, which is optimal for *MSY* with i.i.d. environmental shocks to the growth equation (Reed 1979), little variation in S_t is generally observed. Under identification of K and r is not a new argument. It is developed at some length by Hilborn and Walters 1992, but the argument does not seem to have permeated thinking in the economics literature on fisheries management. Instead, one sees explorations of other sources of uncertainty and of the implications of the precautionary principle.

[3] In practice stock is at best observed with considerable measurement error. Zhang and Smith (2011) examine statistical issues related to this problem in the context of the Gordon-Shaefer model.

This fundamental under identification of the parameters of the growth equation has a counterpart in the environmental valuation literature, where it is well known that because observed conditions do not vary sufficiently one must induce experimental variation (often in a stated preference context) in the attributes such as cost to statistically identify the parameters of interest with enough precision to be useful for policy purposes. In the fisheries context, this would require intentionally encouraging very large swings in $G(X_t)$ by setting different harvest levels in order to learn about r and K. This is unlikely to happen as it would be fought in either direction by different interest groups.

Hilborn and Walters (1992) note that in many empirical fishing models, because of the statistical imprecision in parameter estimates, K is set to the largest observed stock size (usually estimated via sampling or some other method). This, of course, technically resolves the statistical identification problem. However, the other parameter estimates can now be grossly wrong as a consequence, and hence, may result in policy prescriptions that are grossly wrong. In particular, assuming a value of K which is too small (*e.g.*, because fishing effort before X_t was well estimated) will results in an estimate of r that is too large and a recommendation to set X_t too small, which can be potentially disastrous.

SIMULATION STRUCTURE AND PARAMETER ESTIMATORS

Consider a fishery manager charged with estimation of MSY with 30 years[4] of fish stock data (observed with noise). We choose to focus on MSY rather than maximum economic yield for three reasons, ignoring discounting and dependence of harvest costs on stock

[4] This is a plausible sample size and, perhaps even larger than typical, for estimation. For example, the Bottomfish Stock Assessment for the Western Pacific in Ralston, *et al.* (2004) made use of 12 years of fishery dependent data; the Southeast Data Assessment (2003) for Black Sea Bass and Vermillion Snapper used 33 years; and the Southeast Data Assessment (2004) for the Gulf of Mexico Red Snapper used no more than 12 years.

size and discounting simplifies the analysis, their inclusion typically results in a rule calling for some fraction of MSY, and; many management documents in the United States still mention MSY or a fraction of MSY as the target harvest.

Suppose that the data generating process for the fishery is known to be given by;

(2)
$$\begin{aligned} X_{t+1} &= X_t + G(X_t) - F_t + \varepsilon_{t+1} \\ &= X_t + rX_t(1 - \frac{X_t}{K}) - F_t + \varepsilon_{t+1} \end{aligned}$$

The fish biomass at time t is given by X_t, the quantity harvested by F_t, the intrinsic growth rate by r, and the carrying capacity by K. If our manager performs OLS on 30 years of stacked data we obtain;

(3)
$$\begin{bmatrix} X_{15} \\ \vdots \\ X_1 \end{bmatrix} = \begin{bmatrix} X_{14} \\ \vdots \\ X_0 \end{bmatrix} \begin{bmatrix} 1 + r \end{bmatrix} + \begin{bmatrix} X_{14}{}^2 \\ \vdots \\ X_1^2 \end{bmatrix} \begin{bmatrix} \frac{-r}{K} \end{bmatrix} - F_t + \begin{bmatrix} \varepsilon_{15} \\ \vdots \\ \varepsilon_1 \end{bmatrix}$$
$$\equiv \mathbf{X}\beta_1 + \mathbf{X}^2\beta_2 - \mathbf{F} + \varepsilon$$

A consistent[5] estimate of the maximum of the growth curve is then given by;

(4)
$$MSYOLS = \frac{(\beta_1 - 1)^2}{-4\beta_2}$$

An immediate statistical difficulty is that the two OLS parameters of interest are highly correlated as noted by Hilborn and Walters (1992). It is also the case that as a nonlinear function of the regression coefficients can be shown to be biased in finite samples. In addition to being biased, the denominator *4r/K* is likely to be quite small, particularly, for longer lived species (such as cod and orange roughy) which can lead to empirical under identification (Kenny, 1979).

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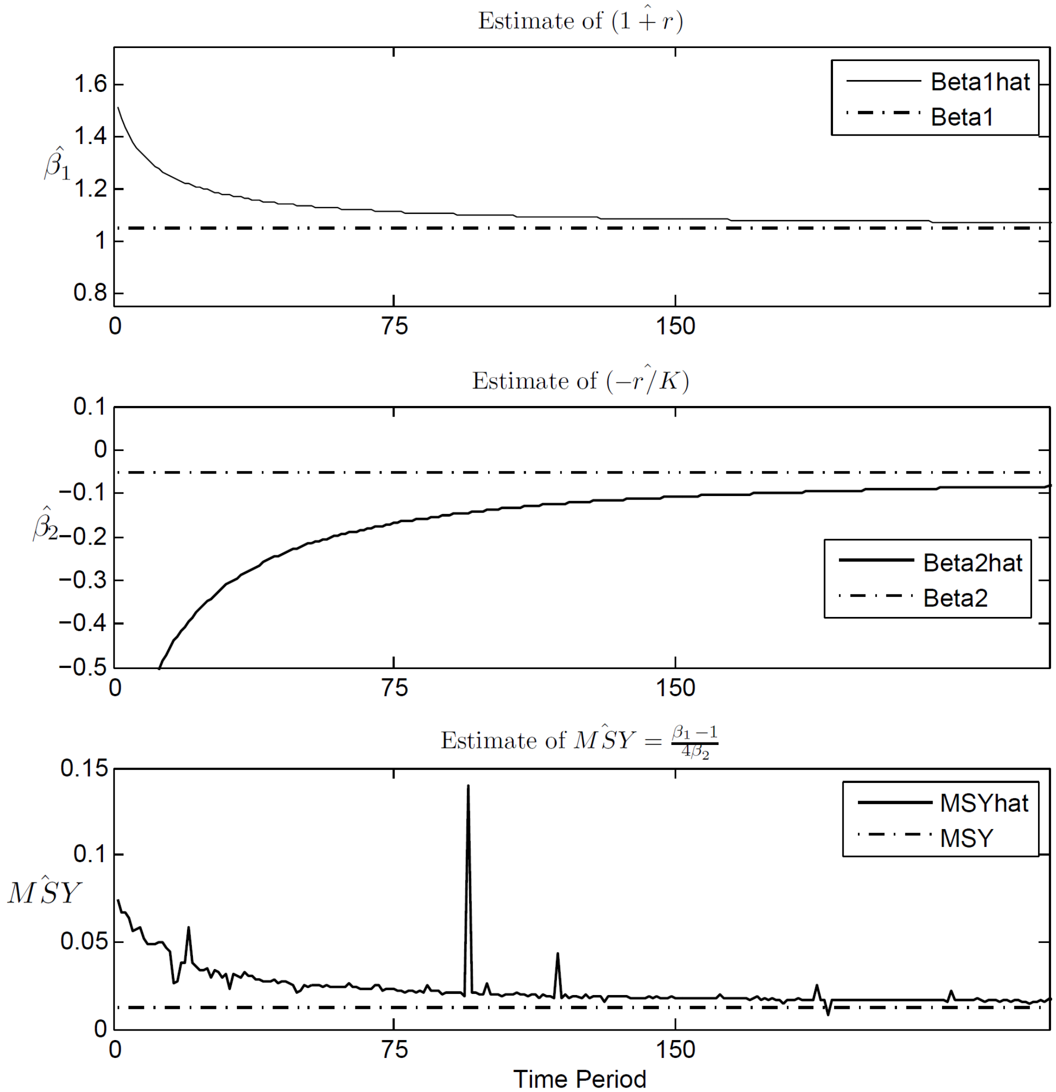
[5] This follows from Slutsky's theorem (Wooldridge, 2002, p. 37) and is confirmed by simulation results below.

The next section describes the performance of a fishery managed using OLS estimates obtained from simulated data. We then proceed to compare these statistical decisions under identical draws from the error terms are to the performance of heuristic management.

Statistical Management

Parameter estimates are calculated by simulating sample data according to the model outlined above. The harvest data are generated to mimic an unmanaged fishery by using a uniformly distributed variable that can be thought of as exogenously varying fishing effort. Each period, a a uniformly distributed fraction of the fish stock is removed as harvest. Figure 1 shows the average parameter estimates over 10,000 simulations for 200 periods each. The regression coefficients are consistent for their true values, and converge smoothly. The small-sample bias in the regression coefficients leads to some problematic behavior in the estimates of the policy variable; estimates of MSY are consistent but exhibit a much less regular approach to the true value with large spikes in error during approach. This fits with empirical underidentification described above (Kenny 1979).

Figure 1: Consistency of Estimates

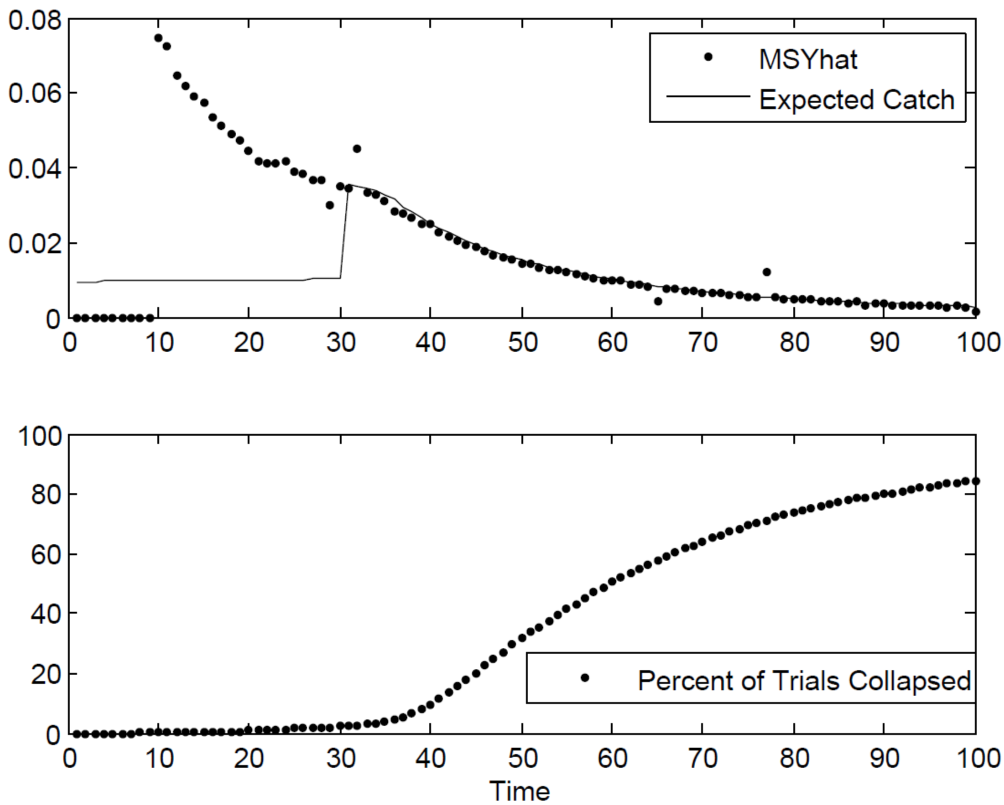


The simulations above are presented to confirm that OLS estimates for this model are consistent. Using these estimates for policy is a different matter. Figure 2 demonstrates the performance of a statistical management regime that allows harvesting of the estimated value for MSY beginning at period 30.[6] When statistical management begins, catches immediately increase and the rate of collapse (stock reaching zero) increases, rising to nearly 90% by the 100th period. While there may exist discount rates

[6] 30 years is an unusually large sample to have both catch and stock data. For example, a recent study (Erisman et al, 2011) made use of some of the largest such datasets in Southern California and the largest sample in this paper contained 30 years.

for which this catch profile is supported as optimal, the fact remains that most fishery management legislation contains a mandate to prevent collapse of the resource. Statistical management, even for a correctly specified model with unrealistically high-quality data, performs poorly.

Figure 2: Statistical Management



Heuristic Management

Acompeting management regime is a simple "rule of thumb" management program using only the most recent three period's stock and catch data to perform a rudimentary gradient search for the stock which yields MSY. The motivation for the gradient search is that with knowledge of the stock, much can be learned from three data points about the current position of the stock if we presume only that $G(X_t)$ has a unique local maximum value greater than zero and $G(X_t) = 0$ for $X_t = 0$ and $X_t = 0$ for some unknown $K > 0$. The goal is to set catch levels to send the stock level to that which maximizes the growth function. If the noise term can be considered small and stock values and catch values are known, then we can infer that $G(X_t) = (X_{t-1} - X_t) - Y_{t-1.}$ So at time period s, given data: $\{Y_s, Y_{s-1}, Y_{s-2}, X_{s,} X_{s-1}, X_{s-2}\}$, we can rewrite to obtain our estimates of the realized growth in the previous two periods:

$G(X_{s-1}) = (X_s - X_{s-1}) - Y_{s-1}$ and $G(X_{s-2}) = (X_{s-1} - X_{s-2}) - Y_{s-2}$. We now have four cases, two of which are informative:

1. $X_{s-1} > X_s$ and $G(X_{s-1}) > G(X_s)$: This implies that the single peak occurs at some X greater than X_s.

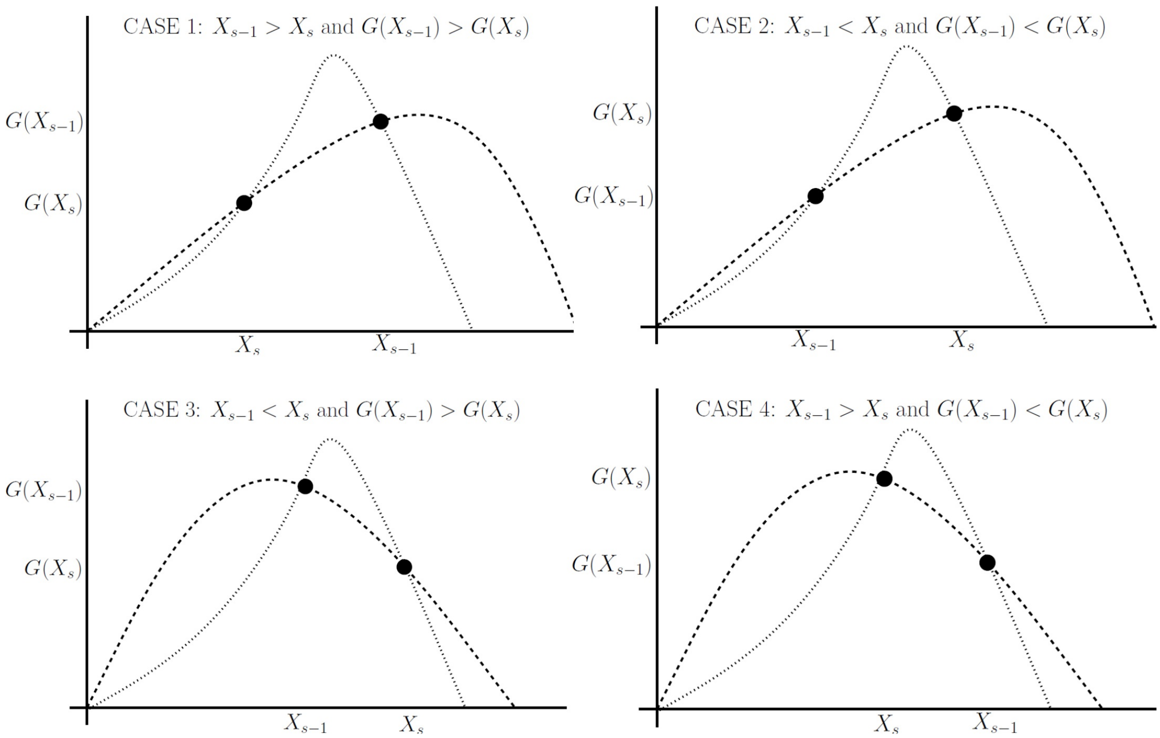
2. $X_{s-1} < X_s$ and $G(X_{s-1}) < G(X_s)$: This is not enough information to determine location of the peak.

3. $X_{s-1} < X_s$ and $G(X_{s-1}) > G(X_s)$: This implies that the single peak occurs at some X greater than Xs.

4. $X_{s-1} > X_s$ and $G(X_{s-1}) < G(X_s)$: This is not enough information to determine the location of the peak.

Figure 3 summarizes the 4 cases outlined above.

Figure 3: The four possibilities for 3 data points for any single-peaked growth curve



Our rule-of-thumb decision rule makes use of the implications of each case above. In the informative cases 1 and 2 the rule increases or decreases the harvest by a factor, γ, assigned arbitrarily to be .5 in our simulations below. To summarize, the rule of thumb set's period *s* catch as follows:

1. Set $Y_s = (1-\gamma)Y_{s-1}$
2. Set $Y_s = Y_{s-1}$
3. Set $Y_s = (1+\gamma)Y_{s-1}$
4. Set $Y_s = Y_{s-1}$

Motivated by the statements in many fishery management plans we also track the probability of stock collapse. Many management plans contain statements mandating a maintenance of stocks at or near that which yields *MSY* coupled with a mandate to prevent the stock from crashing and to prevent the stock from dropping below some threshold as in Lee (2003).

Figures 4, 5, 6 and 7 present averages of 100,000 trials for 100 periods of for managing fishery under different regines. Figure 4 shows the baseline of OLS statistical management beginning at period 15. Figures 5 and 6 show the results of preceding OLS statistical management by 15 and 30 years (respectively) of tule-of-thumb (gradient) management. Figure 7 shows the results of using our ule-of-thumb management approach for the entire sample. In every case, statistical management is dominated by our simple heuristic rule. Most strikingly, our rule of thumb gradient approach maintains high average catch levels and the longer it is used relative to the standard OLS statistical management regime, the more the probability of a fishery collapse declines.

Figure 4: Pure Statistical Management with delay

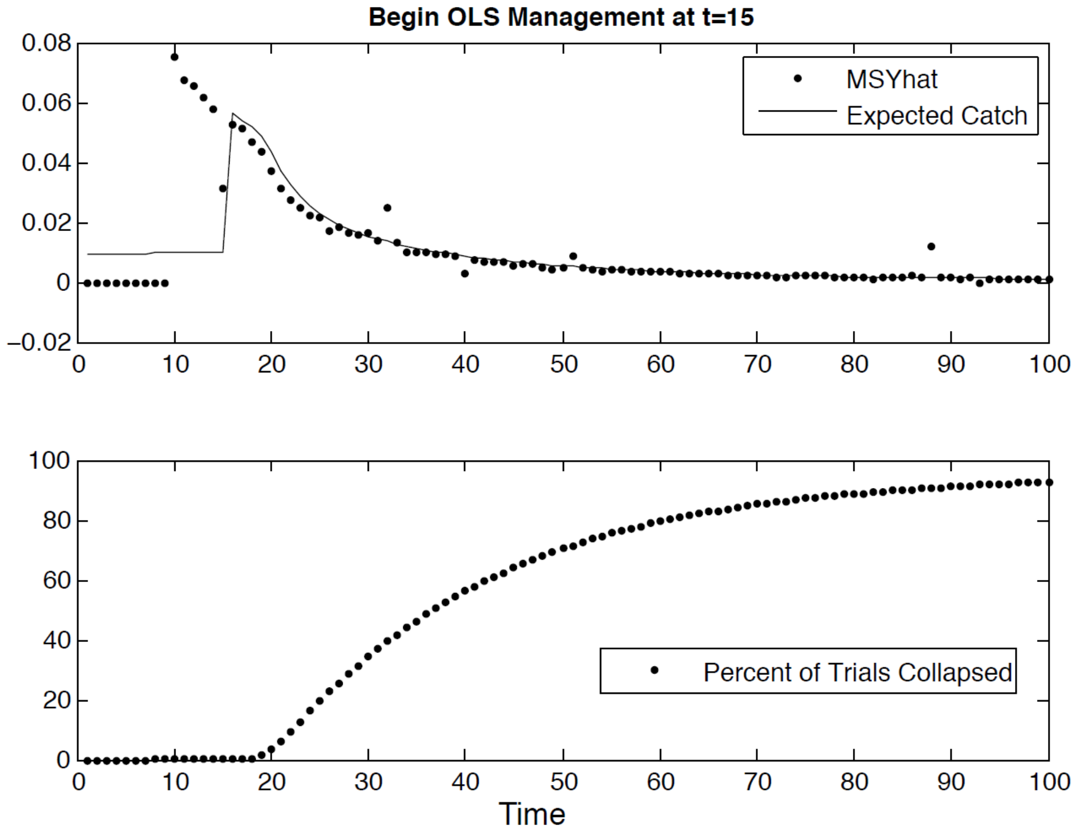


Figure 5: Mixed Management, Short Horizon

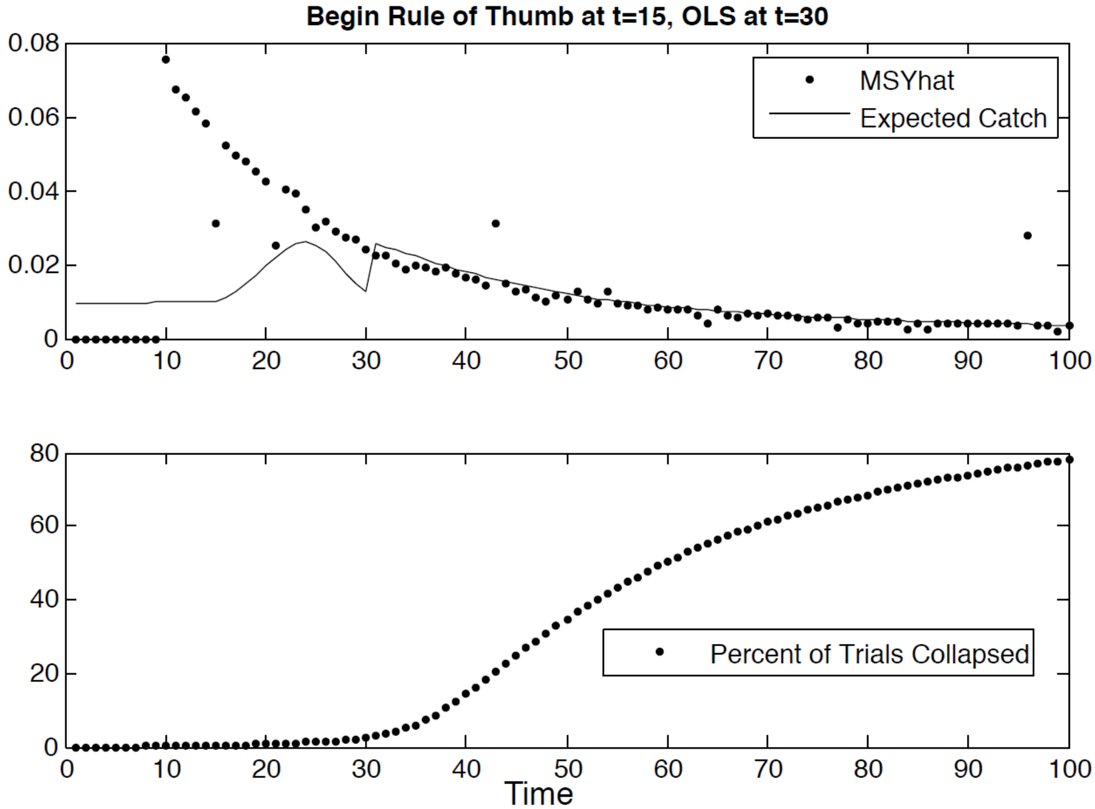


Figure 6: Mixed Management, Long Horizon

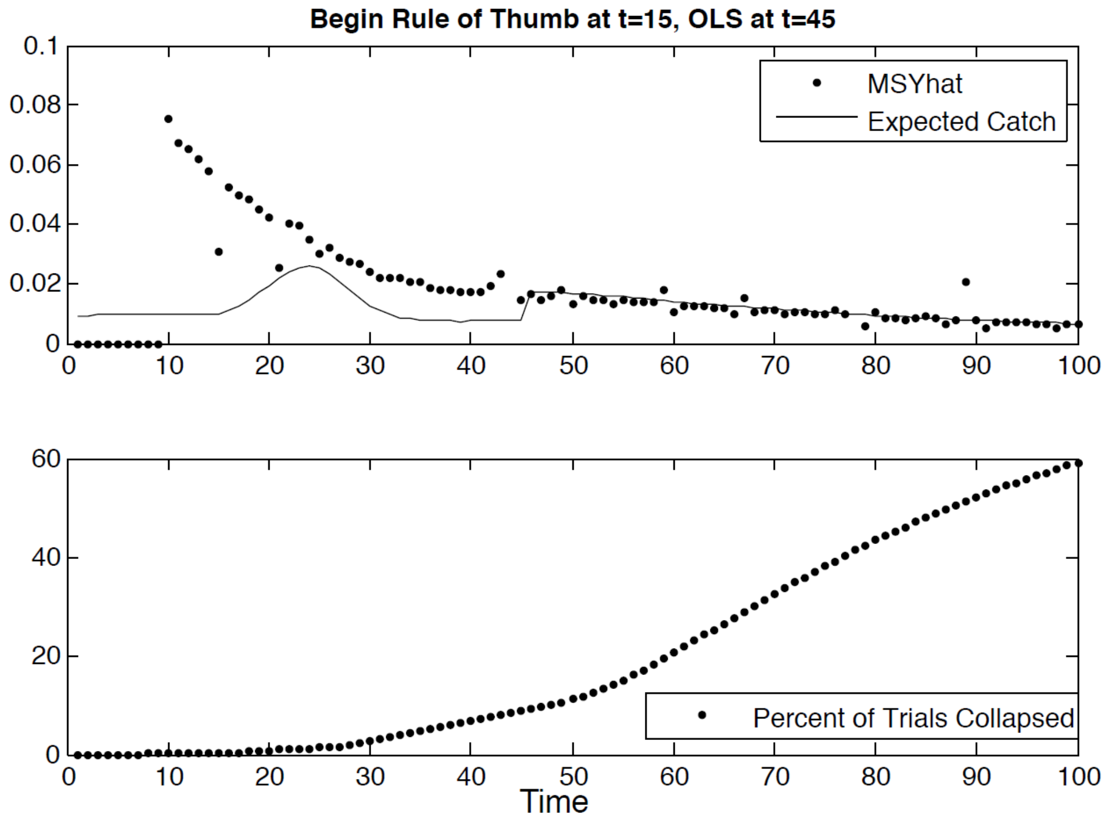
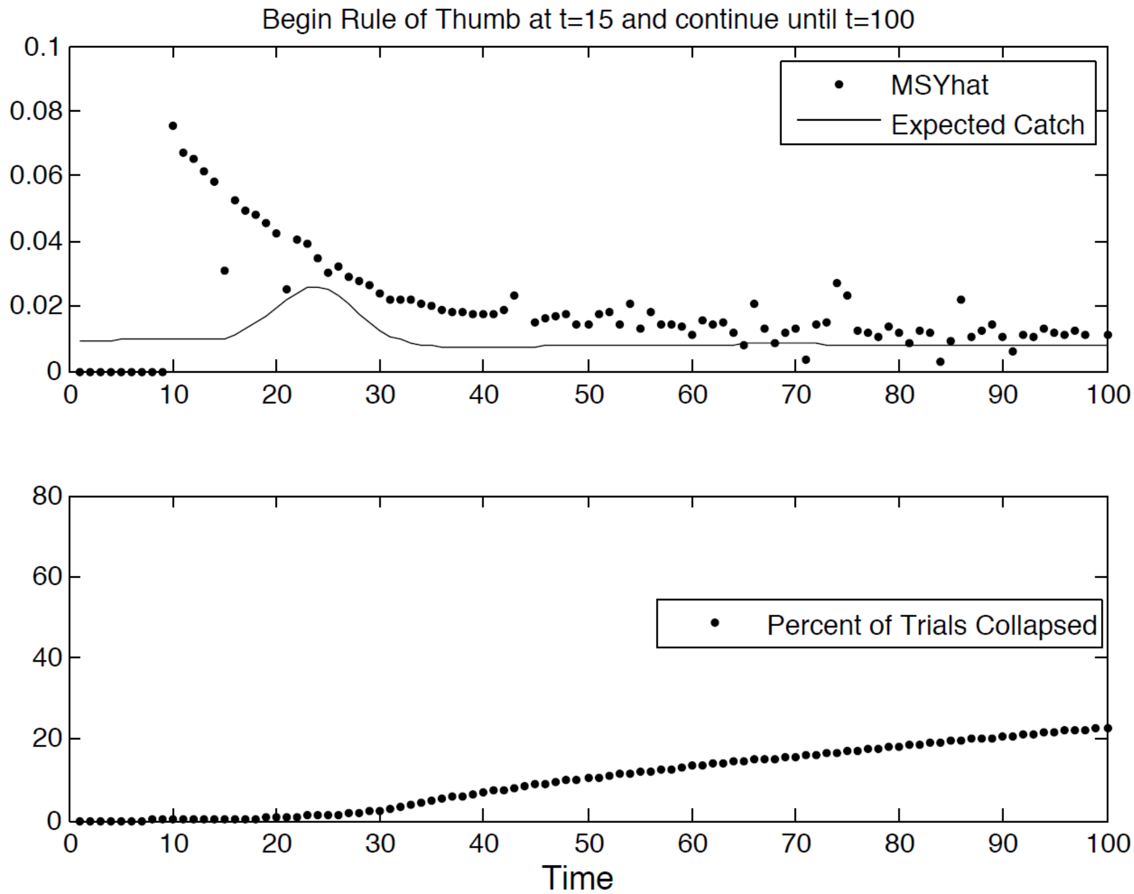


Figure 7: Pure Heuristic Management with delay



While we do not advocate the use our heuristic rule of thumb approach for real management with substantial further research; our results do suggest that it unlikely that any payoff-relevant information can be gained from statistical analysis of fishery data beyond that being used by our rule of thumb measure even if those data, by good fortune, were generated by the simplest model possible. It is important to remember that OLS is correctly specified for this model and the disturbance terms are *i.i.d.* normal, a rosy situation unlikely to occur in real management. Any change to the model to increase realism will only make the econometrician's task more difficult as there is no more realistic growth model with fewer parameters than two.

CONCLUDING REMARKS

Of necessity, the parameter estimates upon which fisheries management decisions are made must be wrong. That is because they are statistical estimates and not the true parameter values. Economists have largely ignored this issue. Indeed, most theoretical and applied work has taken the parameter estimates from biologists and treated them as truth. When economists have considered uncertainty, it is typically in the form of random environmental shocks to recruitment from the growth equation. In the simplest cases, i.i.d. error terms allow the appropriate adjustment each time period. Recently, Sethi *et al* (2005) have shown that other forms of error, such those results from having to measure stock size, can create much more substantial problems for managing fisheries. This paper is in that spirit.

Measurement error in the main biological parameters, growth rate, carry capacity, and maximum sustainable yield in our simple Gordon-Shaefer model tends to be fairly large. In part that is because the regression model has two covariates, stock size and stock size squared, which tend to be highly correlated. This high correlation is made much worse by the usual management practice of trying to maintain stock size at a particular level. The typical error in the parameter estimates increases rapidly in the underlying unexplained variance. More complex (and realistic) models either in terms of more parameters or more complex error structures are likely to create even worse statistical properties for the estimates used. Here, we have given the game away to the bioeconometrician; estimation is made as simple as possible by with the functional form fit being the one used to generate the data, the error component is generated independently and has low variance relative to many fisheries. Further, both catch and stock are assumed observable. Restricting ourselves to realistic sample sizes, it is possible to show that there is very little gain (if any) for using the full small sample relative throwing out 90% of the sample and using our simple rule of thumb.

Increasing the number of parameters will almost surely make the problem worse. Some readers may argue that real stock assessments rely on fishery independent data and our results only reinforce the importance of that source of information. Fisheries are highly dimensional dynamical systems and data on variables beyond catch and stock levels (such as length-frequency and length-at-age) may improve estimates but only if the out-of-sample predictive information they provide grows at a rate substantially larger than the number of extra parameters that must be fit. That is because the fundamental nature of the problem we point out is propagation of measurement error in the parameters throughout a non-linear optimization model.

One of the immediate results of our framework is that under- or overestimating the allowable catch by the same amount does not result in symmetric errors. That is because overestimation leads to higher catches now and, of necessity, fewer fish later, including substantially increasing the risk that the fishery collapses. For any given over and under estimate of the allowable catch there is typically a discount rate that would make one indifferent. Environmentalists and fishers, however, are likely to disagree on the discount rate and the social discount rate is also likely to be lower than the private discount rate. This discount rate story as a source of conflict is not new but what is new is the interaction between the level of parameter uncertainty and the discount rate in these sense that differences in discount rates are amplified by the level of uncertainty. Reducing the level of uncertainty can be Pareto improving for all groups and reduces (but does not eliminate) the degree of conflict. This insight may be useful in implementing more practical variants of the precautionary principle.

Given the poor performance of the standard statistical estimates of the relevant biological parameters, it is useful to ask if there is anyway to improve the situation as either over or underestimation of allowable catch can reduce welfare. Given that the problem is essentially one of high collinearity and small sample-size, one possibility is to limit the range of either the carrying capacity or growth rate parameters. Interesting opportunities for doing this appear to be available, particularly with the recent biological work on estimating historical population stocks before large scale commercial fishing (Jackson, *et al.,* 2001). A Bayesian framework (Gelman, *et al.,* 2003; Walters and Ludwig, 1994) is natural and pinning down a reasonable narrow range for one of these parameters can add a great deal of stability to the estimate of allowable catch.

Our framework suggests a different way of dealing with the issue that may be generally applicable situations where there is considerable uncertainty about the underlying biological growth function other than it being assumed to be single peaked. That is to use a rule of thumb type decision rule that simply tests what side of the peak one is likely to be on using very limited information and then pursued it using a fairly conservative step. Since there are stochastic shocks it is always possible to move in the wrong direction on any particular step. On average though one moves in the correct direction and this simple approach works reasonably well in the sense of being fairly close to using the growth function parameters estimated in the standard way when the parametric modeling being fit was the correct one. Further, there are clearly more sophisticated adaptive gradient pursuit methods that could be explored than the simple rule of thumb approach we use in this paper that may be more statistically efficient while maintaining a large degree of robustness. Another logical step would be to look at the performance of different adaptive gradient pursuit methods when the underlying parametric model being fit was the incorrect one so that there was both specification and parameter estimation error as is likely to be the case in realistic empirical applications.

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