Endogenous Risk of Stock Collapse and the Great Fish Pact.

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Abstract

Risk of stock collapse is an intuitive motivation for cooperative fisheries management. This study analyses the effect of an endogenously determined risk of stock collapse on the incentives to cooperate in a Great Fish War model. The model uses symmetric players and tests the Internal Stability of Grand Coalitions over a range of stock growth and discount rates. We numerically solve the model and establish that harvest strategies are non-linear in stock. We find that for very slow growing stocks, it is optimal to fish the stock to extinction. We find that Grand Coalitions are strictly stable for any number of players if the growth rate is low but not so low that it is optimal to fish the stock to extinction. The results thus show conditions under which a Great Fish War is in fact a Great Fish Pact.

Keywords: fish war, renewable resource exploitation, dynamic game, fish stock collapse, endogenous risk.

JEL codes: C72, C73, Q22.

1. Introduction

Regional Fisheries Management Organisations (RFMOs) are the principal tool for the management of high seas fisheries. High seas fisheries are a classic example of a common-pool resource where private property rights cannot be established. From an economic perspective, social welfare resulting from such a common-pool resource is maximised under cooperative management. However, free-rider incentives may prevent cooperation, interfere with the objectives of RFMOs and contribute to overfishing.

Globally, from 1950 to 2000, 366 fisheries collapsed and the collapses are generally attributed to over-fishing (Mullon et al., 2005). The risk of stock collapse is likely to be important in determining the strategic harvest choices of fishing nations (Hannesson, 2014). Avoiding stock collapses is an important motivation for the formation of RFMOs, which are the principal institutions through which high seas fish stocks are managed.

A significant body of research has tested the theoretical potential for cooperation in RFMOs (see Bailey et al. (2010) for a summary). The number of players in a fisheries game is arguably the most important factor in determining the success of cooperation. A negative relationship between the number of players and the success of cooperation in fisheries was first established by Hannesson (1997) and has been found repeatedly over many studies. Cooperation between greater numbers of players can be facilitated by allowing players to be asymmetric in costs of fishing (e.g. Pintassilgo et al., 2010), using sequential move games (e.g. Long and Flaaten, 2011) or with alternative solution concepts (e.g. Breton and Keoula, 2012).

Much of the literature does not consider that stocks fished to levels marginally greater than zero might collapse entirely. This paper proposes that endogenous determination of such a risk of stock collapse constitutes an intuitive motivation for cooperation. This potential importance of risk of stock collapse is evidenced, outside of the fisheries literature, by studies of uncertainty in the climate agreements literature. The importance of the risk of catastrophe for the success of climate treaties has been considered by Barrett (2013), Kolstad (2007) and Dellink and Finus (2012).

The objective of this study is therefore to analyse the stability of cooperative agreements when a risk of stock collapse is endogenously determined by stock size and therefore by harvest. The aim is to demonstrate that the risk of stock collapse is an important incentive for cooperation. This study uses symmetric players and does not invoke transfer payments. It therefore also aims to show the successful cooperation for larger numbers of players does not necessarily require asymmetric players and transfer payments. Transfers (or "side" payments) have met much resistance in the policy world in general (Folmer et al., 1993) and are not implemented in direct financial terms in fisheries agreements (Munro, 2008). It is therefore always questionable when the success of cooperation in theoretical models relies on behaviour which is, strictly speaking, not observed in reality.

We adopt a variant of the Great Fish War model of Levhari and Mirman (1980) (henceforth referred to as L&M) to estimate Stochastic Markov Perfect Nash Equilibrium (SMPNE) harvest rules. We consider an irreversible collapse such that the stock after the collapse is zero, and remains zero, for all time periods after the collapse. We find that the risk of stock collapse results in non-linear harvest rules. Due to the technical difficulties in analytically solving for non-linear harvest strategies (Antoniadou et al., 2013), we adopt a numerical approach[1]. Our numerical model is validated by removing the endogenous risk from the model and statistically analysing the similarity of the numerically derived harvest rules to those from existing analytical solutions. This demonstrates the robustness of the model to numerical error and validates our approach.

Our model calculates the Internal Stability of Grand Coalitions across a range of growth and discount rates and for any number of players. In turn, this allows us to determine if an endogenous risk of stock collapse affects the potential for successful cooperation.

In addition to the literature on cooperation in fisheries management, our study relates to the literature on uncertainty in resource management such as Clarke and Reed (1994) and Tsur and Zemel (1998). Specific to the L&M model, exogenous uncertainty has been considered in three studies. Firstly and secondly, Antoniadou et al. (2013) and Agbo (2014) consider exogenous uncertainty in stock dynamics. Thirdly, Fesselmeyer and Santugini (2013) consider exogenous uncertainty in the quality of the resource as well as the probability of regime shifts in the growth rate of the stock.

Endogenous risk has been considered in Sakomoto's (2014) analysis of the subclass of dynamic renewable resource games of Sorger (2005). This subclass is defined by its growth and utility functions. Specifically, a constant natural growth rate is assumed and utility is derived from both the resource stock size as well as from consumption (depletion) of the resource. Sakamoto (2014) finds that endogenous risk can reduce harvest when stock size is large. However, if the stock size is too small, then endogenous risk encourages more aggressive resource use.

Our study is the first exploration of non-linear harvest rules in the L&M model and the first study to explicitly consider endogenous risk from a coalition theory perspective. By comparing harvest rules derived under endogenous risk to harvest rules from the original L&M model, we find that harvest is either lower under exogenous risk, or, in the case of slower growing stocks, greater, to the extent that the stock is harvested to extinction. We term the deterministic choice to harvest the stock to extinction "pre-emptive depletion". By testing the stability of the Grand Coalition over a range of growth and discount rates, we find that, in general, an endogenous risk of stock collapse increases Grand Coalition stability. This is particularly the case if the Grand Coalition is harvesting less in response to the risk and a deviation from the Grand Coalition would result in pre-emptive depletion. When this is the case the incentive to cooperate is so great that the Grand Coalition is stable for any number of players.

2. Model

We will first define the biology of the system, then introduce the objective functions. The objective functions determine the payoff of different coalition membership choices across different parameterisations, which are then used to define coalition stability across these parameterisations.

Let us first define escapement (the stock remaining after harvest) in a given period, e_t as

$$e_t \equiv x_t - H_t, \qquad (1)$$

where H_t is the sum of harvest of all players in period *t*. Fish stock grows according to the following rule;

$$x_{t+1} = \beta e_t^{\alpha}, \qquad (2)$$

where $\beta > 0$ and $0 < \alpha < 1$. If there is no harvest, x_t increases to its unfished steady state, which is given by

$$\bar{x} = \beta^{\frac{1}{1-\alpha}}. \qquad (3)$$

The probability of the fish stock surviving into the next period, $0 \leq r_{t+1} < 1$, is endogenously determined by the escapement and is given by

$$r_{t+1} = max\left(0, 1 - \frac{\gamma\bar{x}}{e_t}\right), \qquad (4)$$

where $0 < \gamma < 1$. The parameter γ determines the critical escapement level $\gamma\bar{x}$, below which collapse is certain. For escapement larger than the critical level, there is a strictly positive survival probability which is increasing in escapement at an increasing rate. This means that there is a risk of stock collapse even for very large stock sizes, though a very small one. This is reasonable because, for certain species, pressures from habitat loss or invasive species may mean that a risk of stock collapse is present even in the absence of any fishing (Field et al., 2009, Gjøsæter et al., 2009).

The stability of Grand Coalitions is determined by comparing the payoff of membership versus non-membership. We test for stability across a parameter space given by $\Theta = (n, \theta)$ where $\theta = (\alpha, \rho)$. The parameter ρ is the discount rate where $0 < \rho \leq 1$. We consider a range of parameters[2] for α and ρ such that $\alpha \in A = [0.01, 0.02, \dots, 0.99]$ and $\rho \in P = [0.01, 0.02, \dots, 1]$ and denote the set of all possible θ as Ω such that $\Omega = A \times P$. The disaggregation of A and P allows us to determine the stability of coalitions across a full range of parameters and therefore to acquire insights of a similar depth to those provided by analytical results. We do not analyse $\alpha = 1$ in order to retain strict concavity in the growth function. This simplifies the numerical modelling.

The set of N identical players represents n nations i who, in a given period t, choose harvest level $h_{i,t}$. The instantaneous utility function for player i at time t is given by $max\left(0, ln(h_{i,t})\right)$. This utility function avoids the problem of utility being equal to negative infinity when harvest is zero[3].

We adopt the standard assumption of a two-stage game, such that coalition structure is fixed in the first stage. In the second stage players choose their harvest. Players choose harvest to maximise their value functions, which are in the form of Bellman equations. Value is a function of x_t and depends on the parameterisation set Θ. The value function $U_j(x_t; \Theta)$ for a coalition member j is derived from maximising the sum of coalition member utilities,

$$U_j(x_t; \Theta) = \frac{1}{m} \max_{\sum h_{j,t}} \left\{ m \left(\max\left(0, ln\left(\frac{\sum h_{j,t}}{m}\right)\right) + \frac{r_{t+1}}{1+\rho} U_j(x_{t+1}; \Theta) \right) \right\} \quad \forall \ j \in M \ , \tag{5}$$

where M which is the set of players in the coalition and $m = |M|$. The value function for a free-rider $k \in N \backslash M$ playing against a coalition is given by

$$U_k(x_t; \Theta) = \max_{h_{k,t}} \left\{ \max\left(0, ln(h_{k,t})\right) + \frac{r_{t+1}}{1+\rho} U_k(x_{t+1}; \Theta) \right\}. \tag{6}$$

Value functions (5) and (6) are maximised subject to $x_{t+1} = \beta(x_t - H_t)^\alpha$ to estimate Stochastic Markov Perfect Nash Equilibrium (SMPNE) harvest rule. We estimate the value functions using backward induction and value function iteration. We impose a time-horizon and then backwardly induce to estimate the infinite time-horizon solution. The imposition of a time horizon ensures that the harvest for a given stock size decreases through the iteration procedure until the effect of imposing a time horizon no longer has an effect on harvest. When the harvest becomes constant over time, the mapping from stock to harvest constitutes SMPNE harvest rule $c_i(x)$.

The harvest rule allows us to determine the steady state stock size with harvesting as the stock size x^* for which the following equality holds;

$$x^* = \beta(x^* - \sum_{i \in N} c_i(x^*))^\alpha. \quad (7)$$

Due to discounting, once the harvest rule has been applied for a sufficient number of periods, the value functions are no longer a function of time, only of stock, and thus have converged. Evaluating the converged value functions at x^* gives payoffs, which determine Grand Coalition stability. We use an Internal Stability solution concept, under which the Grand Coalition is stable if the payoff to a Grand Coalition member is greater than that of a free-rider playing against the remaining coalition members. The Grand Coalition is therefore internally stable if

$$U_j(x^*; \Theta) \geq U_k(x^*; \Theta) \qquad \text{where } j \in M = N. \quad (8)$$

We therefore calculate payoffs for the $m = n$ case, i.e. the Grand Coalition, and the $m = n - 1$ case, which we will refer to as the "free-rider" case. The stability condition in Equation (8) implicitly assumes that players make membership choices based on the payoffs in the steady state and do not account for payoffs during the transition path to the steady state. This simplification allows us to calculate a unique payoff for a given membership choice which is independent of the stock size when the game begins.

In addition to estimating SMPNE harvest rules we also consider the sole-owner case in order to illustrate certain properties of the model in the simplest setting. The sole-owner model uses Equation (6) where $k = N$. For more details and discussion of the numerical techniques used, see Appendix 2.

3. Results

We begin by validating the model as explained in Appendix 1. The validation demonstrates high statistical similarity of harvest rules from a numerical L&M model with analytically derived L&M harvest rules. We thus proceed to analyse the numerical model of endogenous risk. We find that x^* is unique for very low values of γ. We therefore set $\gamma = 0.01$. We find that the risk of stock collapse results in harvest rules which are non-linear in stock. This is different from the original L&M result where harvest rules are always linear in stock as shown by Kwon (2006)[4]. This is illustrated in Figure 1.

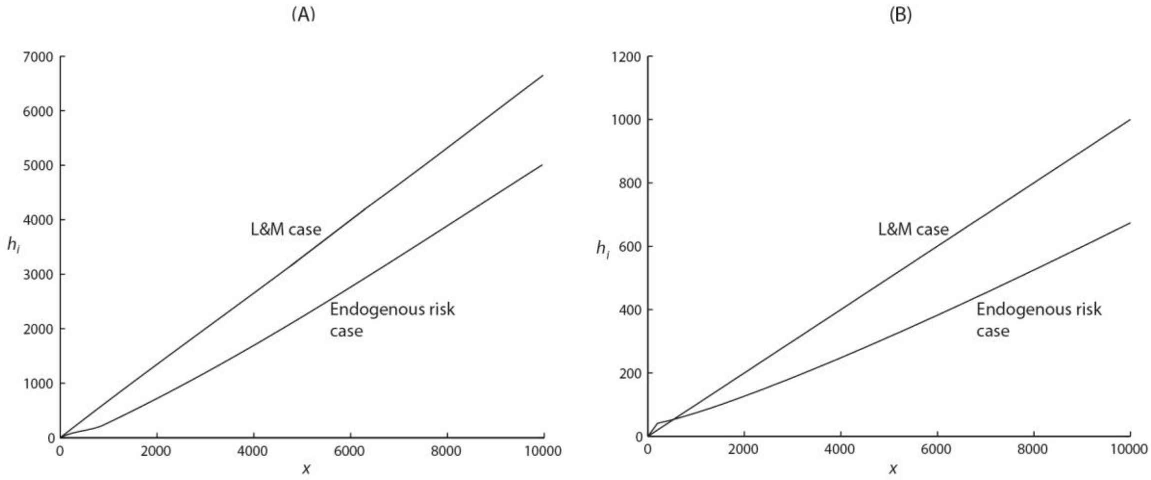
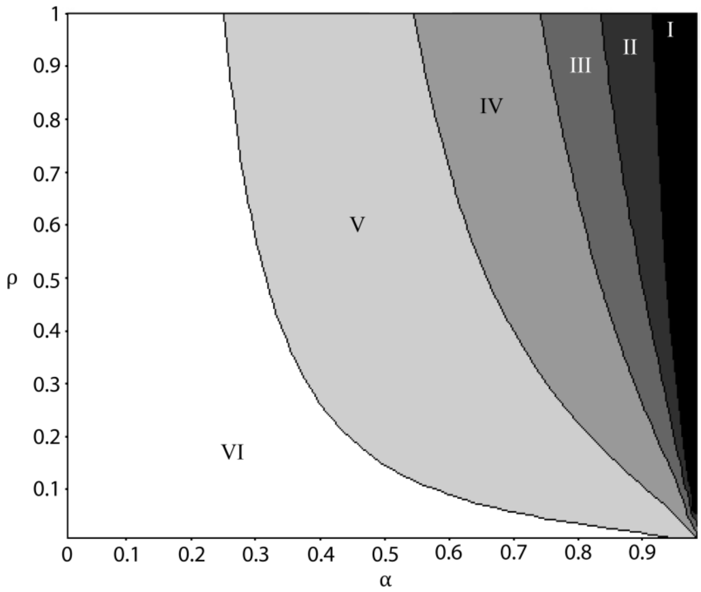


Figure 1: Examples of harvest rules for the original L&M specification (for comparison) and the endogenous risk case described in the model section. The examples are taken from the sole-owner case where $\bar{x}$ =10,000. In Panel (A), $\alpha = 0.5$ and $\rho = 0.5$. In Panel (B), $\alpha = 0.99$ and $\rho = 0.10$. The L&M cases display linear harvest rules and the endogenous risk cases display non-linear harvest rules.

In Panel (A), the harvest rule in the endogenous risk case shows that lower stocks are fished less in the present period in order to increase the probability of being able to fish in future periods. Panel (B) shows a case of higher discount rates and a slower growing stock. In this case, the harvest rule for the endogenous risk case involves greater harvest than the L&M case for small stock sizes. This implies that when stock is low, it is better to harvest more now because of the risk of collapse.

All harvest rules result in unique steady states across all parameterisations for both the Grand Coalition and free-rider cases. The steady states for the Grand Coalition and the free-rider case for $n = 2$ are illustrated in Figure 2.

(A) x^* in the Grand Coalition case



(B) x^* in the free-rider case

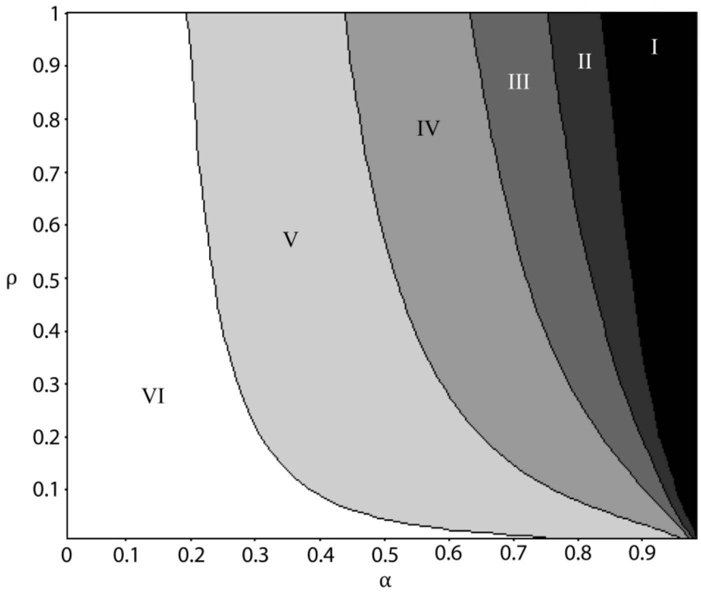
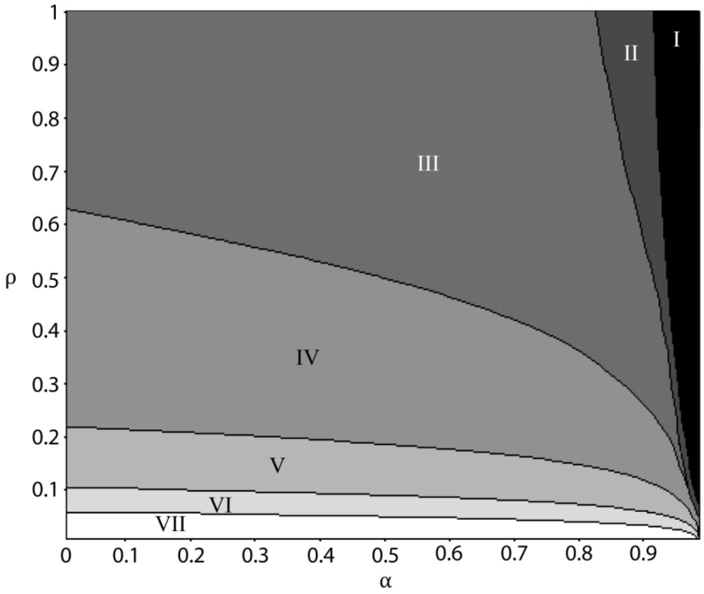


Figure 2: Steady state stock with harvesting x^* in the Grand Coalition case (Panel A) and the free-rider case (Panel B) in Ω space where $n = 2$, as an example. Using x_I^* to denote the steady state stock in Region I, x_{II}^* to denote the steady state stock in Region II and so on, the regions are defined as x_I^* =0, 0< x_{II}^* ≤1000, 1000< x_{III}^* ≤2000, 2000< x_{IV}^* ≤4000, 4000< x_V^* ≤7000 and 7000≤ x_{VI}^* <10000.

Both panels in Figure 2 include a Region I, in which $x^* = 0$. This means that it is optimal to fish the stock to extinction rather than waiting in the hope that stocks will increase and thus the risk of collapse will drop. We refer to this effect as "pre-emptive depletion". Pre-emptive depletion occurs when harvest rules are similar to the one shown in Figure 1(B). It is important to note that pre-emptive depletion is the result deterministic choice to harvest all of the stock and not by stock collapse. Pre-emptive depletion cannot occur in the original L&M model[5]. As will become clear, the existence of pre-emptive depletion, and in particular the different sizes of Region I between Panels A and B in Figure 2, drive our most interesting results.

The existence of unique steady states allows us to calculate the payoffs across the parameter space. These are shown in Figure 3.

(A) $U_j(x^*;\Theta)$



(B) $U_k(x^*;\Theta)$

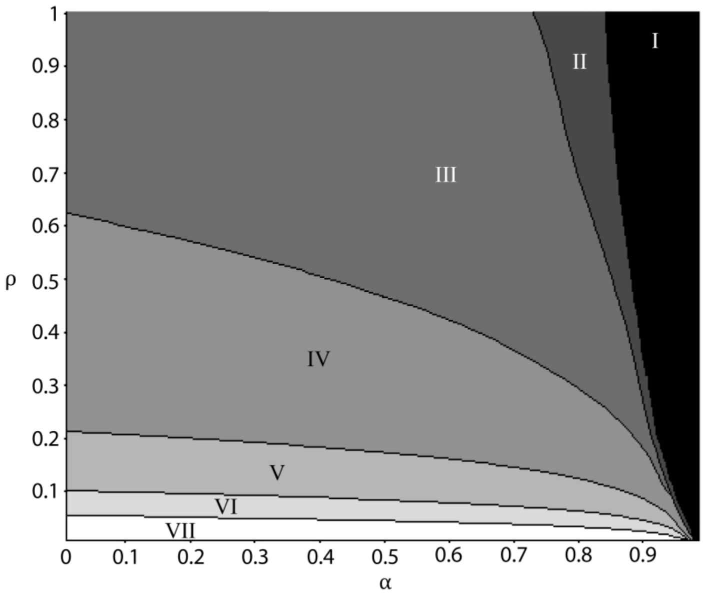


Figure 3: Payoffs for a free-rider (Panel A) and a coalition member (Panel B) in Ω space where $n = 2$, as an example. Using U^I to denote the payoff value in Region I, U^{II} to denote the payoff in Region II and so on, the regions are defined as $U^I = 0$, $0 < U^{II} \leq 10$, $10 < U^{III} \leq 20$, $20 < U^{IV} \leq 40$, $40 < U^V \leq 70$, $70 < U^{VI} \leq 110$ and $U^{VII} > 110$. Region I thus refers to parameterisations for which pre-emptive depletion occurs.

Both panels in Figure 3 show the same general pattern. Payoff increases as the discount rate decreases. The marginal effect of the discount rate is very significant at low discount rates. Also, payoff decreases as α increases. High α means that the stock grows slowly. We also see an area for very high α where payoff is zero due to pre-emptive depletion.

To further the analysis, it is useful to formally define the payoff threshold in the parameter space Ω which determines where payoffs change from non-zero to zero due to pre-emptive depletion. We achieve this via Definition 1, which defines the length of a payoff threshold.

Definition 1: *z is the number of values of* P *for which there exists a* $U(x^*;\Theta) = 0$ *for at least one* $\alpha \in A$.

Definition 2: *For a given n, a payoff threshold is a vector of length z, indexed l, whereby the* l^{th} *element is the smallest element of A such that* $U(x^*;\Theta) = 0$, *where* $\theta = (\alpha, \rho_l)$.

Definition 1 is required because the payoff threshold may not exist for all ρ. Using Definition 2, we can define payoff thresholds for both the Grand Coalition and free-rider cases. In turn, we observe in Figure 3 that, for all *l*, the free-rider payoff threshold consists of smaller values of α than the coalition payoff threshold. This means that pre-emptive depletion occurs for a larger area of Ω. This is because free-riding reduces x^*. In turn, this increases the risk of stock collapse and provides greater incentives to harvest the entire stock to avoid this risk. Thus, there are fewer parameterisations in the Grand Coalition case for which the stock is pre-emptively depleted.

We see then that the risk of stock collapse has different effects depending on whether a free-rider is present. Free-riding reduces x^* which increases risk. As x^* reduces, risk increases at an increasing rate due to the functional form of Equation (4). This means that reductions in x^* due to free-riding can lead to increases in risk which are disproportionally larger than the reduction in x^*. In turn, this reduces the payoff of free-riding relative to Grand Coalition membership. We term this the “risk cost”.

In order to analyse the stability of Grand Coalitions for different numbers of players *n*, we calculate payoffs in the free-rider and Grand Coalition cases in Ω space for each *n*. We can then explain how the risk cost affects and changing numbers of players affects the stability of the Grand Coalition.

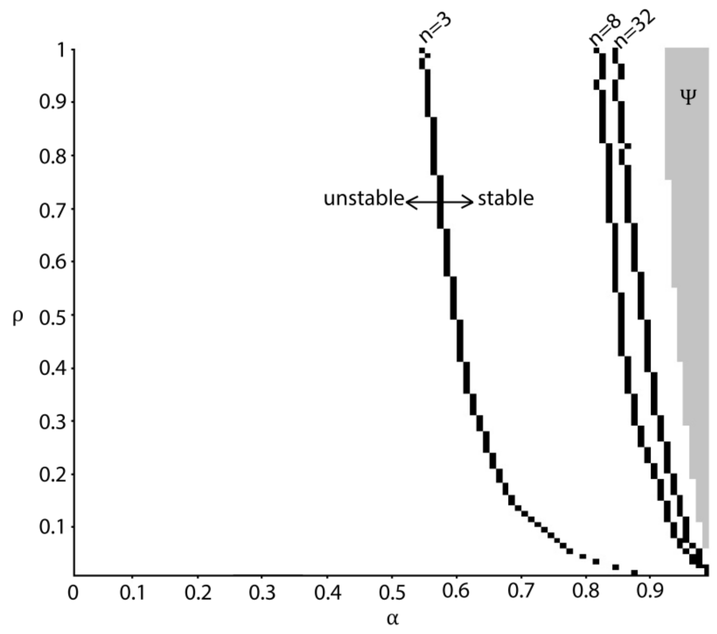


Figure 4: Stability thresholds between stable and unstable Grand Coalitions for selected numbers of players in Ω space. We illustrate the interpretation of the thresholds explicitly for $n = 3$. For all stability thresholds, to the left of the stability threshold, the Grand Coalition is unstable. To the right of the stability threshold, the Grand Coalition is stable. For $n = 2$ the Grand Coalition is stable for all parameters. Some estimation error exists for stability thresholds where $3 < n < 8$, but the general pattern always holds. See Appendix 1 for more detail on estimation error. The grey area, marked ψ, is the subset of θ for which $U_j(x^*; \Theta) = U_k(x^*; \Theta) = 0$, i.e. where pre-emptive depletion occurs in both the Grand Coalition and free-rider cases.

We will discuss Figure 4 according to the effects of change of changing, α, ρ and n and finally, we discuss the area marked ψ. Concerning α, in general, we see that for a given ρ, as α increases, the Grand Coalition can shift from being unstable to being stable. Higher α means a lower growth rate which in turns results in a lower x^*. Grand Coalitions maintain a higher x^* than when free-riding occurs. In this way, the risk cost penalises free-riding disproportionally more than cooperation. Accordingly, increasing α can result in a shift from unstable to stable.

Concerning ρ, in general, we see that for a given α, as ρ increases, the Grand Coalition can shift from being unstable to being stable. This is caused again, by the risk cost. Higher ρ means that the future is less valuable. Therefore, players prefer current harvest proportionately more than future harvest. Accordingly, x^* decreases, the risk cost increases and concurrently, Grand Coalition stability increases. Note also that the risk cost explains the curved shape of the thresholds in Figure 4. This is because the risk cost becomes larger at an increasing rate as the ρ reduces.

Concerning n, we see that in general, increasing the number of players decreases number of parameterisations for which the Grand Coalition is stable. Grand Coalition stability relies on internalising the externalities of fishing, which are two-fold. Firstly, harvest by one player reduces the amount of fish available for the other player in the future. The second is the risk cost. Grand Coalitions internalize these externalities, but the benefits to each player of doing so are reduced as n increase because the socially optimal catch must be shared by more members. Thus, as the n increases, we see a decrease in the number of parameterisations for which the Grand Coalition is stable.

As n increases from 3 to 32, the stability threshold approaches the free-rider payoff threshold (Definition 2a) in progressively smaller steps. At $n = 32$, the stability threshold is identical to the free-rider payoff threshold[6]. This means that the payoff is zero for a free-rider and non-zero for a coalition member. As n increases beyond 32, the socially optimal harvest must be shared by more players, but always remains non-zero, while the free-rider payoff remains zero. Hence, the stability threshold does not change for $n \geq 32$.

We now discuss the grey area ψ in Figure 4, which refers to the subset of θ for which $U_j(x^*; \Theta) = U_k(x^*; \Theta) = 0$, i.e. where pre-emptive depletion occurs in both the Grand Coalition and free-rider cases. When this is the case, stability is trivial because, when payoffs are evaluated in the steady state, it is no longer logical for players to consider fishing either in or out of the coalition. This allows our final result; that Grand Coalitions are non-trivially stable for some values of Ω for all $n > 1$. Grand Coalitions are non-trivially stable for stocks which are slow growing, but not so slow growing that the stock is pre-emptively depleted. This result is due to the inclusion of endogenous risk.

4. Conclusions

This study has analysed the classic Levhari and Mirman model of the Great Fish War (1980) under an endogenous risk of stock collapse. The objective was to analyse the effects of endogenous risk on the stability of Grand Coalitions. The results show that a risk of stock collapse increases the potential for cooperation. Further, the results show that cooperation can be sustained for large numbers of players if the stock is sufficiently slow growing, but not so slow growing that the exploitation is not sustainable in the long run (i.e. if pre-emptive depletion occurs). For fast growing stocks however, the potential for a stable Grand Coalition is no greater than when there is no risk of stock collapse. As the number of players increases, the potential for cooperation decreases, but this effect stops at 32 players.

The result relating to the growth rate α has interesting management implications, particularly for deep-water fisheries which are often slow growing (Gordon, 2003). Slow growing stocks are more vulnerable to over-exploitation (Roberts, 2002, Neubauer et al. 2013). This paper supports this proposition for very slow growing stocks, indeed, the results suggests that the stock would be fished to extinction. However, because Grand Coalitions are non-trivially stable for slow (not very slow) growing stocks regardless of the number of players, the potential for sustainable management is somewhat less bleak.

Most importantly, the results offer counter-evidence to a long-running implicit conclusion in the literature, namely that the number of players is the most important determinant of potential for stable Grand Coalitions. This model shows that when there are greater than 32 players, further increases in the number of players has no effect on the number of parameterisations for which the Grand Coalition is stable. The reason for this is that in previous models, increasing the number of players results in lower steady state stocks and these low steady states can be sustained *ad infinitum* with no risk that the stock might collapse. The result presented in this paper regarding the independence of stability from the number of players is entirely a result of relaxing this very common, yet fairly nonsensical, assumption.

In general, this study contributes to the discussion regarding what makes coalitions in fisheries management stable. We observe empirically that coalitions can be stable for large numbers of players but theoretical models tend to be more pessimistic (Hannesson, 2011). Breton and Keoula (2014) refer to this as the “puzzle of small coalitions” and show that larger coalitions can be achieved by using asymmetry players in a game with first mover advantage, thus partly solving the puzzle. Asymmetric players can contribute to solving the puzzle (e.g. Pintassilgo et al. 2010), as can the type of solution concept used (e.g. Breton and Keoula, 2012). Additionally, Hannesson (2014) suggests that quasi-cooperation may play an important role in solving the puzzle.

We have also shown how asymmetric players are not *per se* necessary for large Grand Coalitions to be stable. A useful benchmark to compare to is Pintassilgo et al. (2010). Using the internal stability concept in a deterministic setting, this study shows that cooperation can be sustained for greater numbers of players as the degree of asymmetry between players increases. This also means that, to explain stability, asymmetry must become more extreme as the number of players increase. This makes sense up to a point, because the assumption of symmetry is a restrictive assumption. However, extreme asymmetry is, from a positivist perspective, also undesirable. This study shows that cooperation can be theoretically sustained for very large numbers of players without any asymmetry between players.

Our study shows that whether the Great Fish War is in fact a Great Fish Pact depends heavily on the growth rate. When the stock is subject to an endogenous risk of stock collapse, growth rates can be such that the puzzle of small coalitions can be solved entirely, cooperation can be sustained for any number of players, and the Great Fish War becomes a Great Fish Pact.

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Appendix 1. The Utility Function and Numerical Accuracy.

In order to evaluate the numerical accuracy of our model, we numerically solve the deterministic (original) L&M model and evaluate the similarity of the numerically derived harvest rule to the analytical solution of the original L&M model. We consider the sole-owner case and consider all harvest rules in Ω space. For the 1-player deterministic game, it would be possible to increase numerical accuracy by exploiting certain properties of the model. However, in stochastic $n > 1$ cases, these exploitable properties no longer exist. In order not to bias the tests of numerical accuracy, we simply remove the stochastic element from our code and make no other changes.

To test the similarity, we calculate a standard R^2 statistic to evaluate the extent to which the numerical harvest rule can be explained by the analytical harvest rule. The results are reported in the following figure, Figure A1.1.

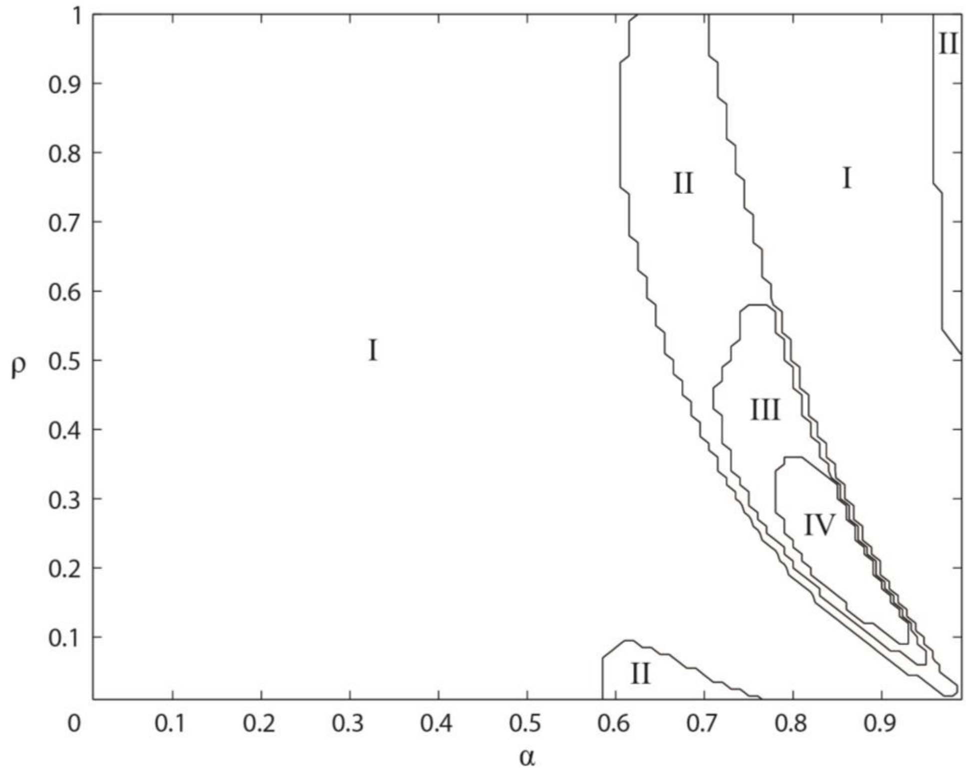

Figure A1.1: R^2 statistics in Ω space determining the accuracy of a numerical 1-player deterministic L&M model. Each region (I through IV) represents a range of R^2 statistics. Using R_I^2 to denote the R^2 value in Region I, R_{II}^2 to denote the R^2 in Region II and so on, the regions are defined as $0.9998 < R_I^2 \leq 1$, $0.9994 < R_{II}^2 \leq 0.9998$, $0.9990 < R_{III}^2 \leq 0.9994$ and $0.9984 \leq R_{IV}^2 \leq 0.9990$.

The results show that the numerical model can recreate analytical results to a high degree of accuracy. It also shows that particular areas of Ω space are more numerically challenging to estimate than others. The location of the area of largest error, consisting of the union of Regions III, IV and the larger of the two areas marked as Region II is particularly important. The stability thresholds for $3 < n < 8$ exist in the area of largest error and this reduces our confidence in their accuracy. Overall, the high R^2 values confer confidence in the accuracy of the numerical method.

Appendix 2. Numerical Methods.

The purpose of this appendix is to explain how we numerically solve for the payoffs. We will do so by explaining the algorithm which was used to solve the model for $n = 2$ player game. The algorithm for $n = 1$ is a simpler, special case of the $n > 1$ case and therefore does not require attention.

We begin by setting up the discrete state space. We found that numerical accuracy was increased by using large values for x because this precludes the increased difficulty of estimating optimal harvests which are close to zero. We therefore set $\beta = 10{,}000^{1-\alpha}$, which ensures that $\bar{x} = 10{,}000$ regardless of the value of α.

We also wish to have a sufficiently coarse discretisation to ensure fast computation times, but not so coarse as to prevent true functional forms of the converged value and harvest functions from being estimated. We therefore set the state space such that $x_t \in [0, 1000, 2000, \dots, 10000]$. In the case that the steady state x^* is less than 1000, the model increases the number of elements in the state space in order to accurately identify the steady state.

Discretisation of the state space means that $U(x_{t+1}; \Theta)$ is only known when $x_{t+1} \in [0, 1000, 20000, \dots, 10000]$. Almost always, x_{t+1} is not an element of the set $[0, 1000, 20000, \dots, 10000]$ and therefore we use interpolation to estimate $U(x_{t+1}; \Theta)$. Piecewise cubic Hermite interpolation was used because it produced results which were less prone to error.

Error in interpolation is the most important source of error in the model. It is important to note that the model including risk is likely to be less prone to error than the deterministic model discussed in Appendix 1. Consider that Appendix 1 shows that errors are greatest when the discount rate is lower. Interpolation error fails to properly estimate future value in the value function. Accordingly, low discount rates increase the effect of error on the estimation procedure. In the model including risk, the future is less valuable both due to discounting and risk. As such, the estimation procedure suffers less from interpolation errors.

We will now explain how strategic interaction is modelled. In contrast to the discretised state space, harvest is continuous. To derive SMPNEs, we set up a best-response function nested within a fixed-point calculation as described by Pakes and McGuire (1994). The inner function calculates best responses by player 1 to player 2's harvest using Brent's method (Brent, 1973) of maximisation. The outer function calculates the fixed-point given by the harvest by player 2 to which the best response by player 1 is equal to the harvest of player 2. The outer and inner functions use the built-in Matlab function-functions "fzero" and "fminbnd" respectively.

Footnotes

1. All Matlab codes are available from the corresponding author on request.

2. In the original L&M model the discount factor is between 0 and 1 whereas we test the discount rate between 0 and 1. This means that we test discount factors between 0 and 0.5.

3. Our instantaneous utility function does not result in negative utility when $0 < h_i < 1$ due to our scaling of stock sizes to very high numbers (see Appendix 2). Therefore, while h_i can be zero when $x = 0$, harvest is never less than 1 and greater than 0. We choose this function due to its similarity to the utility function used in L&M. A plausible alternative is $ln(h_{i,t} + 1)$. However, it is clear that, with appropriate scaling of x_t, $max\big(0, ln(h_{i,t})\big)$ is more similar to $ln(h_{i,t})$ than $ln(h_{i,t} + 1)$. This is intuition is reinforced in Appendix 1.

4. The linearity of the harvest rule in stock in the L&M model can be illustrated by showing the harvest rule in the All Singletons case where $\beta = 1$. This is given by $c_i(x_t) = x_t\left(\frac{1+\rho-\alpha}{(1+\rho-\alpha)n+\alpha}\right)$.

5. In the L&M model, the steady state with harvesting in a 2-player game, where $\beta = 1$ is given by
$\bar{x} = \left(\frac{\alpha}{2(1-\rho)-\alpha}\right)^{\frac{\alpha}{1-\alpha}}$.
It is easy to show that it is not possible for $\bar{x} = 0$ given the restrictions on α and ρ.

6. Due to potential estimation error, we cannot be entirely confident that $n = 32$ is the exact number of players at which the stability threshold does not change. We can however, be confident that the stability threshold is no longer a function of n at some $n \approx 32$.

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