Essays on Risk and Renewable Resource Management

by

Kwabena Bediako Boateng

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Department of Economics

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Abstract

Sustainable management of natural resources such as fish is important as millions of people rely on such resources for food, source of income, and well-being. It is increasingly challenging, however, for institutions and stakeholders to induce a sustainable exploitation of such resources due to factors arising from environmental, biological, and economic conditions (e.g., uncertainty, strategic behavior, and resource displacement). This thesis develops three articles to formally address such issues. The paragraphs below provide a summary of such articles.

Stability of international fisheries agreements under stock growth uncertainty: Scientific evidence reveals that renewable resource stock dynamics are subject to uncertainty due to changes in environmental conditions. Despite its critical impacts on management, little is known about the effects of such uncertainty on the formation of regional fisheries management organizations (RFMOs). In this paper, we design a dynamic stock recruitment framework to examine this issue in a common pool setting. We find that stock growth uncertainty critically affects equilibrium behaviors under both open loop membership and dynamic membership. For instance, we delineate conditions under which uncertainty induces full non-cooperation in equilibrium. Strategic behaviors may also shift equilibrium outcomes from full non-cooperation under deterministic conditions to full cooperation under uncertainty when countries anticipate a small environmental variability. Moreover, strategic interactions to extract the resource stock may lead to higher individual payoffs under uncertainty. We also outline the differences in equilibrium responses of membership, harvest, and payoff to variations in environmental conditions under both open loop membership and dynamic membership.

Learning and uncertainty in spatial resource management: Natural resources such as fish, and wildlife have the ability to move across different areas within an ecosys-

tem. Such movements are subject to random changes in environmental conditions (e.g., nutrients, temperature, oxygen). Although empirical evidence suggests that learning about such movements helps improve management, the related economic literature concentrates on scenarios in which the resource population lives in a closed area and cannot migrate. In this paper, we develop a spatial bioeconomic model to examine a renewable resource harvester's responses to learning about fish movements. Our baseline is the scenario in which the harvester is fully informed about the distribution of fish movements. We find that introducing uncertainty and learning about fish movements critically affects extraction incentives. For instance, we show that uncertainty and learning may increase harvest in a patch and reduce harvest in another patch when the marginal harvesting cost function is constant. In the stock dependent marginal harvesting cost case, we delineate conditions under which uncertainty and learning increase harvest in all patches. We also show how harvest responses to learning change with the distribution of uncertainty.

Effectiveness of regional fisheries management organizations: Evidence from the general fisheries commission for the mediterranean: The 1995 United Nations Fish Stocks Agreement urges countries to exploit straddling and highly migratory fish stocks cooperatively through regional fisheries management organizations (RFMOs). Although this recommendation is being implemented across jurisdictions, little is known about the effectiveness of RFMOs to carry out their mandate of conservation. Using panel data on fish stock overuse in national exlusive economic zones (EEZs), we compare overfishing within EEZs of member countries of the General Fisheries Commission for the Mediterranean (GFCM) to that of a synthetic counterfactual. Our results indicate that the GFCM's management policies has been ineffective in reducing overfishing among member countries. Further, analysis of the share of collapsed stocks and rebuilding stocks supports our conclusion. Robustness checks conducted using different

sub-samples of our control group support these results. We elaborate on policy implications of our results, most significantly, the importance of identifying and addressing the issues that undermine the performance of RFMOs.

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1 Introduction

Biological and environmental conditions as well as the quality of institutions are important factors for the effective management of a renewable resource. Environmental conditions are susceptible to change overtime. Such changes present a number of challenges to natural resource management. For instance, environmental variations such as El-Niño southern oscillation entail random changes in the biological growth and migration pattern of renewable resources (e.g., fish stocks). In this context, a manager would have to rely on limited information to make extraction decisions.

Moreover, there are increasing concerns regarding severe overexploitation of internationally shared fish stock within the high seas and the adjacent exclusive economic zones of coastal nations. In order to address such a transboundary problem, the United Nations Organization recommends that coastal nations cooperate through the formation of regional fisheries management organizations (RFMOs). However, the formation, stability, and effectiveness of these organizations are influenced by uncertainty about environmental conditions; migration of fish stock; strategic behavior such as free-riding; and weaknesses in the enforcement ability of RFMOs. Understanding the nature, scope and how economic agents may respond to these challenges helps contribute to a sustainable use of natural resources. The dissertation proposes three essays to formally investigate the aforementioned issues.

The first essay develops a bioeconomic framework to examine countries' incentives to cooperate to sustainably exploit a common pool renewable resource. We explicitly take into account the fact that harvest and variations in environmental conditions randomly affect stock growth. To shed light on this type of uncertainty, we separately examine the fixed membership and dynamic membership scenarios. We find that stock growth uncertainty may result in more cooperation, leading to enhanced conservation of fish stock. Moreover, strategic interactions to extract the resource stock may lead to higher individual payoffs under uncertainty.

In the second essay, we design a bioeconomic model to address the optimal management of renewable resource populations that migrate across areas (patches). Changes in environmental conditions inflict random shocks to resource movements and growth. We account for asymmetry in biological, economic, and environmental conditions. In this context, we investigate the effects of Bayesian learning about resource movements on harvest incentives. Our baseline is the scenario in which the distribution of the random shock is fully known. We delineate conditions under which uncertainty and learning about such a distribution increases harvest in one patch while reducing harvest in the other patch. We also find that a mean preserving spread may have heterogeneous effects on harvest across patches.

The third essay empirically investigates effectiveness of RFMOs in reducing the overexploitation of fish stocks. Economic theory suggests that cooperation between agents in the exploitation of an open access resource always leads to less harvest relative to the scenario where they operate non-cooperatively. However, in the real world setting, factors such as illegal, unreported, and unregulated fishing, environmental variabilites, and the absence of a precautionary and ecosystem based approach undermine the ability of RFMOs to prevent overexploitation of fish stock. We use the generalized synthetic control method (GSCM) with cross-country data from 1950 to 2014 to analyze the effectiveness of the General fisheries commission for the Mediterranean (GFCM). Our results indicate that the GFCM's management policies has been ineffective in reducing overfishing among member countries. Further, analysis of the share of collapsed stocks and rebuilding stocks supports our conclusion.

The remainder of the dissertation is organized as follows. In Chapter 2, we investigate the impact of uncertainty about the reproduction of a renewable resource on incentives to join RFMOs. Chapter 3 analyzes the effects of learning about the movement of a renewable resource across patches on management. Chapter 4 deals with the empirical analysis of the effectiveness of RFMOs in mitigating overfishing among member countries.

2 Stability of international fisheries agreements under stock growth uncertainty

2.1 Introduction

The persistence of overfished stocks is a permanent concern for policy makers. The fraction of the world's overexploited marine fish stocks has increased continuously from 10% in 1974 to 33.1% in 2015 with dramatic ecological and economic consequences (FAO, 2018). A major international fisheries policy undertaken to address this issue is the 1982 UN Convention on the Law of the Sea (UNCLOS). A key feature of this management approach is that by allowing coastal states to exercise authority over the area extending up to 200 nautical miles into the sea (i.e., Exclusive Economic Zones), it reduces the open access to internationally shared marine resources (UN, 1982).

One important issue that the UNCLOS failed to address is the management of fish stocks that migrate across coastal EEZs (i.e., straddling fish stocks) and highly migratory fish stocks. This issue resulted in persistent overexploitation over decades of such fish stocks (Pintassilgo et al., 2010). Further effort to supplement the UNCLOS led to a new international agreement known as the UN Fish Stocks Agreement, ratified in 1995 (UN, 1995). A core principle of this new agreement is that the management of straddling fish stocks and highly migratory fish stocks must be undertaken cooperatively through regional fisheries management organizations (RFMOs). RFMOs usually set total allowable catches (TACs) for member countries.[1] These TACs are critical for the conservation of some species. Yet, these conservation prospects are affected by the strategic behavior of outsiders, countries that are not RFMO members. The decision to

[1]For instance, the Northwest Atlantic Fisheries Organization is a RFMO that sets TACs annually for member countries. Each year, coastal nations unilaterally decide whether to join or leave the organisation (Fisheries and Oceans Canada, 2016).

sign in an RFMO or not is a free-will decision. Importantly, the presence of uncertainty influences the strategic behavior of all countries (RFMO members and non-members).

Despite evidence that random environmental shocks (e.g., changes in temperature, nutrient) lower our ability to predict fish stock dynamics,[2] the effects of associated uncertainty have been largely ignored in the economic literature on the formation of RFMOs. Given current problems with environmental variability and overfishing, a number of research questions are critical for policies aimed at contributing to a sustainable use of renewable resources. How does stock growth uncertainty affect stable RFMOs? What are implications on harvest strategies? Can stock growth uncertainty raise the net present value of utility? In this paper, we address these and related questions.

Our analysis builds on two strands of economic research that examines resource extraction under uncertainty. The first strand concentrates on a renewable resource harvester's extraction responses to several types of uncertainty. For instance, Mirman (1971), Reed (1979), Singh et al. (2006), Costello and Polasky (2008), and Springborn and Sanchirico (2013) focus on the stock growth uncertainty case whereas Costello and Kaffine (2008) address scenarios in which future ownership is uncertain. Clark and Kirkwood (1986) and Sethi et al. (2005) investigate scenarios in which the harvester faces managerial uncertainty (e.g., measurement errors) and environmental uncertainty (e.g., stock growth uncertainty). In a common pool context where several harvesters operate non-cooperatively in all periods, the second strand investigates the effects of stock growth uncertainty (Pindyck, 1984; Antoniadou et al., 2013) or uncertainty about a possible spatial shift in the resource distribution (Costello et al., 2019).[3]

Our analysis has important ramifications within the economic literature on renewable

[2]Some fish species (e.g., cod, herring, tuna) are subject to random growth variability associated with the El Ninio southern oscillation (ENSO), the effects of which span from severe to beneficial (Tibbetts, 1996).

[3]See also Long (2010) for a survey.

resource management under the threat of regime shift. Interesting contributions include Polasky et al. (2011), Fesselmeyer and Santugini (2013), Sakamoto (2014), Miller and Nkuiya (2016), and Diekert (2017). These papers focus on scenarios in which the initial state of the ecosystem may permanently and randomly shift to another state characterized by a lower resource growth function. Following Reed (1979), we concentrate on ecosystems (e.g., high sea) in which the resource growth function can randomly shift between a continuum of states due to changes in environmental conditions (e.g., temperature, salinity, nutrients). In this setting, our analysis suggests that strategic interactions to extract the resource stock yield novel equilibria.

Our analysis suggests that the decision to join or leave a RFMO (or a coalition) is driven by two opposing mechanisms. On the one hand, each coalition member would like to defect as individual coalition members gain less relative to counterpart non-coalition members. This mechanism is called the "free riding effect" and reduces incentives to join the coalition. On the other hand, leaving the coalition lowers the next period's expected resource stock, which reduces each player's expected payoff. This mechanism is called the "conservation effect" and raises incentives to join the coalition.

To determine the relative strength of the two mechanisms, we first examine the effects of stock growth uncertainty on the stability of RFMOs under open-loop membership. In this setting, countries decide whether or not to join a RFMO in the initial period and such membership decisions remain unchanged in all subsequent periods. When the elasticity of inter-temporal substitution is greater than one, countries are likely to choose sufficiently heterogenous harvest levels over time. In this context, when the biological return of the resource is high and the number of countries is small, we find that the conservation effect dominates the free-riding effect for large coalitions such that full cooperation occurs in equilibrium. Full non-cooperation happens in equilibrium when countries anticipate a sufficiently high variability in biological growth. In this context, uncertainty lowers the level of cooperation relative to the deterministic scenario. Small mean preserving spreads may shift the equilibrium from full non-cooperation to full cooperation. In response to an increase in uncertainty, the interplay between the free riding effect and conservation effect may lower individual harvests even if the elasticity of inter-temporal substitution is high.

We also examine how stock growth uncertainty affects the stability of RFMOs under the dynamic membership scenario. In this case, each player is allowed to reconsider his membership and harvest strategy every period. Our analysis suggests that any variation of the resource stock generates a change of the same magnitude on the free riding effect and conservation effect. As a result, equilibrium coalitions do not depend on the resource stock. When the elasticity of inter-temporal substitution is greater than one, our analysis identifies several equilibrium outcomes. We delineate economic, environmental, and biological conditions under which any increase in the resource stock by one unit leads to a higher individual payoff under full cooperation relative to scenarios of unilateral defection. In such contexts, the coalition constituted of all countries forms in equilibrium. By substantially reducing the expected return from conserving the resource stock, a high level of uncertainty dramatically diminishes economic benefits from joining the coalition, which leads to full non-cooperation in equilibrium. In this setting, uncertainty reduces equilibrium coalitions relative to the deterministic environmental condition case. In response to small mean preserving spreads, strategic interactions may lower the net present value of utility.[4]

The remainder of the paper is organized as follows. Section 2.2 provides a literature review on the formation of RFMOs. Section 2.3 sets up the model. Section 2.4 focuses on the stability of RFMOs under open-loop membership. Section 2.5 concentrates on

[4] Focusing on numerical simulations, McKelvey et al. (2003) examine how two players exploiting non-cooperatively (in all periods) a shared fish stock respond to environmental uncertainty relative to the fully cooperative scenario.

the dynamic membership case. Section 2.6 relies on numerical simulations to further illustrate the stability of RFMOs and how such stability changes in response to stock growth uncertainty. Section 2.7 summarizes the results and provides relevance for policy. Section 2.8 concludes.

2.2 Literature review on the stability of RFMOs

Since the decision to sign in an RFMO is voluntary, the extent of participation by countries and their ability to sustain membership and abide by the organizations' regulations are key concerns on the management of shared fish stocks. A growing body of economic research addresses these issues within a dynamic common property resource game.

In a context where the decision to cooperate is exogenous, Levhari and Mirman (1980), Dutta and Radner (2004), and Nkuiya (2015) find that full non-cooperation leads to over-extraction relative to the fully cooperative case. This incentive for over-extracting can be prevented through the use of history-dependent punishment strategies. Specifically, Dockner et al. (1996), Hannesson (1997), Polasky et al. (2006), Tarui et al. (2008), Dutta and Radner (2009), Mason et al. (2017) show that full cooperation can be achieved through trigger strategies in a dynamic game. Using linear quadratic games under deterministic conditions, Dockner and Long (1993) and Nkuiya and Plantinga (2021) find that the cooperative solution can be reached in a Markov Perfect Nash equilibrium when players commit to non-linear strategies. Unlike these studies, we do not rely on any punishment strategy in our model and we make use of the partial cooperative approach such that full-cooperation, partial cooperation, or full non-cooperation can arise, but only as equilibrium outcomes.

A number of economic papers have addressed the formation of RFMOs within a partial cooperative framework. While the studies by Pintassilgo and Lindroos (2008), Pintassilgo et al. (2010), Long and Flaaten (2011), and Finus et al. (2020) represent important contributions on this issue, they concentrate on deterministic conditions only and do not account for the effects of stock dynamics in their analysis.[5] Kwon (2006) concentrates only on the open loop membership case under deterministic conditions. In this context, he argues that stable coalitions are constituted of no more than two agents when players elaborate their harvest strategies simultaneously. The recent paper by Miller and Nkuiya (2016) finds that this result remains valid even if players face an exogenous threat of regime shift or are allowed to reconsider their membership and harvest strategies every period. In addition to extending these papers to the CRRA utility and CES growth functions case and considering the effects of the stock dynamics, this paper also examines players' responses to random changes in environmental conditions.

2.3 Model

A group of $N \geqslant 3$ identical and sovereign countries exploit a shared renewable resource stock over $T + 1$ discrete time periods. The time index is denoted by $t = 0, 1, 2, ..., T$. The resource stock at the outset of period t is denoted by X_t whereas h_{it} represents the harvest level for country $i = 1, 2, \ldots, N$ in that period. The resource stock can replenish and changes in environmental conditions (temperature, nutrients, salinity) affect the biological growth of the resource. More precisely, the resource stock evolves following the law of motion

$$X_{t+1} = Z_t g(y_t), \tag{2.1}$$

where $y_t = X_t - \sum_{i=1}^{N} h_{it}$ represents total escapement (the residual stock after harvest). We consider the growth function

$$g(y) = \left[\alpha y^{1-\frac{1}{v}} + (1-\alpha)\,\phi^{1-\frac{1}{v}}\right]^{\frac{v}{(v-1)}}, \tag{2.2}$$

[5] While they rely on a static model, Walker and Weikard (2016) examine the effects of random changes in catchability coefficients on players' incentive to join RFMOs.

where $\upsilon > 0$, $\phi > 0$, and $\alpha \in (0,1)$. In condition (2.1), Z_t is a random variable, which captures the effects of sudden shifts in period-t environmental conditions. Denote by $E(.)$ the expected value operator. We assume that elements of the sequence $\{Z_t, \quad t = 0,1,2,...\}$ are independent and identically distributed with $E(Z_t) = m > 0$ for all $t \geqslant 0$.

As in Antoniadou et al. (2013), country i's willingness to harvest the resource is represented by the constant relative risk aversion (CRRA) utility function:

$$u\left(h_i\right) = \frac{h_i^{1-\frac{1}{\eta}} - 1}{1 - \frac{1}{\eta}}, \text{ if } \eta \neq 1. \tag{2.3}$$

As a limiting value $u\left(h_i\right) = \ln\left(h_i\right)$ for $\eta = 1$.[6] The parameter η represents the elasticity of inter-temporal substitution.

To obtain analytical solutions, as in Antoniadou et al. (2013), we restrict our attention in the remainder of this paper to scenarios in which the equality $\upsilon = \eta$ holds.[7] An important body of economic papers on renewable resource management in addition to making use of such an assumption (i.e., $\upsilon = \eta$), focuses on simplifying economic and biological conditions. For instance Levhari and Mirman (1980) and Miller and Nkuiya (2016) consider the growth and utility functions $u(h) = \ln(h)$ and $g(y) = y^{\alpha}$. Conditions (2.2) and (2.3) retrieve these growth and utility functions whenever $\eta = \upsilon = 1$ and $\phi = 1$.

The expected net present value of utility for country i is given by

$$E\left(\sum_{t=0}^{\infty} \delta^t u\left(h_{it}\right)\right),$$

[6]The utility function in Eq.(2.3) represents country i's social welfare. In this paper, we consider the normative approach to be consistent with the fact that, in the real world setting, decisions to join or leave RFMOs are made by governments.

[7]This condition suggests that the inter-temporal elasticity of substitution in harvest coincides with the elasticity of substitution in the reprodution process of the resource.

where $\delta \in (0,1)$ is the discount factor.

2.4 The fixed membership case

In this section, we examine incentives of countries to ratify a RFMO over an infinite planning horizon (i.e., $T = +\infty$). Such a process operates in two stages. In the first stage (membership game), each country decides non-cooperatively at the beginning of the initial period whether or not to join a RFMO. In all subsequent periods, each coalition member or non-coalition member maintains his membership decision.

In the second stage (harvest game), given the outcome of the membership game, each non-coalition member non-cooperatively chooses current harvest so as to maximize his expected net present value of utility. Each coalition member chooses his current harvest, taking the current harvest level of non-coalition members as given, so as to maximize the sum of the expected net present value of utility for all coalition members. Depending on environmental conditions and the state of the system (the resource stock), each player (coalition member or non-coalition member) can reconsider his harvest decision in every period. We rely on the Cournot approach in which coalition members and non-coalition members simultaneously choose their harvest strategies. We make use of the backward induction approach to derive the equilibrium of the game. That is, we first derive the solution of the harvest game and use such a solution to fully characterize the equilibrium of the game.

2.4.1 Harvest game

For now, we assume that the membership game described above results in a coalition of K countries and n is the size of K. The Bellman equation for the problem faced by a coalition member $i \in K$ can be written as

$$W\left(X_t\right)=\max_{h_{it}}\left\{\sum_{\ell\in K}u\left(h_{\ell t}\right)+\delta E(W(X_{t+1}))\right\},\tag{2.4}$$

subject to Eq.(2.1). The first-order condition for the maximization problem in Eq.(2.4) can be written as

$$u'\left(h^o_{it}\right)=\delta E(Z_t g'\left(y_t\right)W'\left(Z_t g\left(y_t\right)\right)),\ \text{for all } i\in K,\tag{2.5}$$

where the superscript "o" stands for open-loop membership. This relation unveils interesting properties of strategic behaviors. At the equilibrium, all coalition members have identical harvest levels, denoted by h^o_{mt} because the expression on the right-hand side of Eq.(2.5) does not explicitly depend on h^o_{it}. Eq.(2.5) shows that the optimal harvest for a coalition member depends on the environmental shock Z_t, the biological growth of the resource, and the discount factor. Eq.(2.5) is an inter-temporal arbitrage condition which shows that at the equilibrium, the marginal benefit from harvesting today is equal to the value lost by coalition members by harvesting today rather than conserving the resource stock for future harvest.

The Bellman equation for the dynamic optimization problem faced by a non-coalition member $j \notin K$ reads

$$W_{nc}\left(X_t\right)=\max_{h_{jt}}\left\{u\left(h_{jt}\right)+\delta E(W_{nc}(X_{t+1}))\right\},\tag{2.6}$$

subject to Eq.(2.1). The subscript "nc" refers to a non-coalition member. The first-order condition is given by

$$u'\left(h^o_{jt}\right)=\delta E(Z_t g'\left(y_t\right)W'_{nc}(Z_t g(y_t))).\tag{2.7}$$

Since the right-hand side of Eq.(2.7) does not explicitly depend on h^o_{jt}, non-coalition members have identical harvest levels, denoted by h^o_{nct}. Condition (2.7) also suggests that at the equilibrium, a non-coalition member's current harvest equates his marginal utility from harvesting with his discounted marginal cost measured in terms of future utility lost (because current harvest reduces future resource stocks).

Lemma 2.1. *(i) The equilibrium harvest for a coalition member is a solution to*

$$u'\left(h^o_{mt}\left(X\right)\right) = \delta E\{\left[Z_t g'\left(y\right) u'\left(h^o_{mt}\left(Z_t g\left(y\right)\right)\right)\right]\left[1-\left(N-n\right) h^{o\prime}_{nct}\left(Z_t g\left(y\right)\right)\right]\}, \qquad (2.8)$$

where $y = X - nh^o_{mt}(X) - (N-n)h^o_{nct}(X)$.

(ii) The equilibrium harvest for a non-coalition member satisfies

$$u'\left(h^o_{nct}\left(X\right)\right) = \delta E\{\left[Z_t g'\left(y\right) u'\left(h^o_{nct}\left(Z_t g\left(y\right)\right)\right)\right]\left[1-nh^{o\prime}_{mt}\left(Z_t g\left(y\right)\right)-\left(N-n-1\right) h^{o\prime}_{nct}\left(Z_t g\left(y\right)\right)\right]\}. \qquad (2.9)$$

Proof. See Appendix 4.8.

Lemma 2.1 further characterizes the equilibrium harvest strategies. Despite the fact that the planning horizon is infinite, Eq.(2.8) and Eq.(2.9) suggest that equilibrium harvest rules are solutions of a two-period model. Eq.(2.8) and Eq.(2.9) also reveal that equilibrium harvest rules are time independent and only depend on the current resource stock. This is the case because the optimization problems (2.4) and (2.6) are autonomous. That is, the planning horizon is infinite, the instantaneous utility function and the growth function depend on harvest and the resource stock (do not explicitly depend on current time period).

Although non-linear equilibria might exist, in the remainder of this section we restrict our attention to linear harvest strategies only. In other words, we focus our attention on harvest rules of the form $h_m(X) = \omega_m X$ and $h_{nc}(X) = \omega_{nc} X$. A challenge is that linear strategies may not exist over a set of the parameter space. For example, in response to a severe environmental shock that depletes the resource stock, it can be beneficial for coalition members not to harvest at all. Moreover, it would be difficult to determine which equilibrium is more appropriate if several sets of linear strategies exist. We formally address these issues in the following proposition.

Proposition 2.1. *If $0 \leqslant \alpha\delta\xi < 1$, there exists a unique linear Markov perfect Nash equilibrium defined as follows;*

$$h_m(X) = \omega_m X, \quad \text{for all} \quad X > 0, \tag{2.10}$$

$$h_{nc}(X) = \omega_{nc} X, \quad \text{for all} \quad X > 0, \tag{2.11}$$

where $\omega_m > 0$ and $\omega_{nc} \in \left(0, \frac{1}{N-n+1}\right)$ satisfy

$$\omega_{nc} = n\omega_m \quad \text{and} \quad (1 - n\omega_m(N-n+1))^{\frac{1}{\eta}} = \alpha\delta\xi\left(1 - n\omega_m(N-n)\right), \tag{2.12}$$

where $\xi = E\left(Z^{1-\frac{1}{\eta}}\right)$.

Proof. See Appendix 4.8.

A violation of the condition $0 \leqslant \alpha\delta\xi < 1$ rules out the existence of a linear Markov-perfect Nash equilibrium.[8] For this reason, we assume in the remainder of this paper that model parameters satisfy $0 \leqslant \alpha\delta\xi < 1$. Conditions (2.10) and (2.11) represent the harvest decision rules for a coalition member and a non-coalition member respectively. Since ω_m and ω_{nc} are positive, individual players always increase current harvest in

[8] This condition is a restriction on the transformed shock $\xi = E\left(Z^{1-\frac{1}{\eta}}\right)$ of the model. The condition can be re-written as $\xi < \frac{1}{\alpha\delta}$. Notice that the support of the shock in the model is unbounded from above. Therefore, without the above restriction on the transformed shock, the existence of a solution is violated for some values of ξ.

response to an exogenous increase in the current resource stock. Moreover, Eq.(2.12) suggests that $\omega_{nc} > \omega_m$. In particular, a representative non-coalition member harvests as much as the entire coalition. As such, for $2 \leqslant n < N$, each coalition member harvests less relative to individual non-coalition members. Denote by $H_t^o(n) = n\omega_m X_t + (N-n)\omega_{nc} X_t$ period-t total harvest as a function of n. The first term represents harvest of the entire coalition while the second term is the harvest for non-coalition members. In the following lemma, we examine how changes in the coalition size affect period-t total harvest.

Lemma 2.2. *The following result holds:* $H_t^o(1) > H_t^o(2) > ... > H_t^o(N)$.

Proof. See Appendix 4.8.

Lemma 2.2 indicates that current total harvest declines as the size of a coalition increases. The intuition for this can be deduced from Eq.(2.12) which indicates that each non-coalition member harvests as much as the entire coalition. Therefore, when there is a higher number of non-coalition members, total harvest is relatively higher. With a fixed and finite number of countries sharing the resource, a larger coalition size necessarily implies a smaller number of non-coalition members and this reduces the level of total harvest.

As shown in Appendix 4.8, the expected net present value of utility for a coalition member can be written as

$$W_m\left(X,n\right) = \frac{\omega_m^{-\frac{1}{\eta}}}{n}\left[1-\left(N-n\right)\omega_{nc}\right]\frac{X^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}} + \frac{w_m^{1-\frac{1}{\eta}}-1}{(1-\delta)(1-\frac{1}{\eta})} + \frac{\beta}{n^{1-\frac{1}{\eta}}}, \tag{2.13}$$

where

$$\beta = \delta w_{nc}^{-\frac{1}{\eta}}(1-(N-n)\omega_{nc})\frac{[\alpha\xi(1-(N-n+1)\omega_{nc})^{1-\frac{1}{\eta}} + (1-\alpha)\,\xi\phi^{1-\frac{1}{\eta}} - 1]}{(1-\delta)(1-\frac{1}{\eta})}.$$

The expected net present value of utility for a non-coalition member reads

$$W_{nc}(X,n) = \omega_{nc}^{-\frac{1}{\eta}} \left[1-(N-n)\,\omega_{nc}\right] \frac{X^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}} + \frac{w_{nc}^{1-\frac{1}{\eta}}-1}{(1-\delta)(1-\frac{1}{\eta})} + \beta. \tag{2.14}$$

Contemplating conditions (2.13) and (2.14), it is an easy matter to show that for any coalition of size $2 \leqslant n \leqslant N-1$, individual non-coalition members gain more than each coalition member. This finding may explain why some countries could have incentives not to join the coalition. We next formally address this issue.

2.4.2 The membership game

Since the resource stock is exploited by sovereign agents, the decision to join or leave the RFMO must be driven by the gain. To derive the equilibrium for the membership game, our approach draws from early economic research that relies on the concept of stability by d'Aspremont et al. (1983) to investigate the stability of RFMOs (e.g., Kwon, 2006; Miller and Nkuiya, 2016). More precisely, a coalition of size n^* is stable if it is both internally and externally stable.

A coalition of size n is internally stable if a coalition member cannot benefit from free riding. That is, a coalition of size n is internally stable if

$$W_m(X_0,n) \geqslant W_{nc}(X_0,n-1).$$

A coalition of size n is externally stable if a non-coalition member cannot benefit from joining the coalition. That is, a coalition of size n is externally stable if

$$W_{nc}(X_0,n) \geqslant W_m(X_0,n+1).$$

It is possible to recover internal and external stability conditions through the stability function defined as

$$S\left(X_0,n\right)=W_m\left(X_0,n\right)-W_{nc}\left(X_0,n-1\right). \tag{2.15}$$

Indeed, the largest coalition of size n^* satisfying $S\left(X_0,n\right)\geqslant 0$ is stable for two reasons. First, by construction, n^* satisfies the internal stability condition. Second, since n^* is the largest coalition size satisfying $S\left(X_0,n\right)\geqslant 0$, we necessarily have $S\left(X_0,n^*+1\right)<0$ (or equivalently $W_{nc}\left(X_0,n^*\right)>W_m\left(X_0,n^*+1\right)$). That is, the coalition of size n^* is externally stable as well. Consequently, in the remainder of this paper, we define the equilibrium coalition as the largest coalition of size n^* satisfying the internal stability condition.

The following proposition further unveils implications of strategic interactions.

Proposition 2.2. *Full cooperation is the equilibrium of the game as long as the model parameters satisfy*

$$N<\hat{N}\equiv\left[\frac{\mu(1-\mu)^{-\eta}}{1-(\alpha\delta\xi)^{\eta}}\right]^{\frac{1}{\eta-1}} \quad \textit{and } (1-\alpha)\phi^{1-\frac{1}{\eta}}\geqslant\overline{\phi}, \quad \textit{and} \quad \eta>1, \tag{2.16}$$

where μ and $\overline{\phi}$ endogenously depend on $\delta,\alpha,N,\xi,$ and η, and are given in Appendix 4.8.

Proof. See Appendix 4.8.

We have also shown in Appendix 4.8 that the equilibrium coalition size equals 2 if $N\leqslant\bar{N}$ and $\eta=1$, where $\bar{N}>0$ is defined in Eq.(25). Moreover, the balance between current economic gain and conservation leads to full non-cooperation in equilibrium if $N>\bar{N}$ and $\eta=1$. These results and findings of Proposition 2.2 shed new light on economic research, which examines the stability of RFMOs in a context where countries elaborate their harvest strategies simultaneously (in a Cournot fashion). For instance, concentrating on the open-loop membership case and deterministic conditions with $\eta = \phi = 1$, the paper by Kwon (2006) finds that the size of any stable coalition cannot be greater than two.

In this section, we also consider the open-loop membership approach in which countries make harvest decisions in a Cournot fashion. In our context of CRRA utility function and CES biological growth, not yet investigated, our analysis suggests that such conventional wisdom does not necessarily hold when $\eta > 1$. In particular, as shown in Proposition 2.2, the coalition constituted of all countries is stable when condition (2.16) holds.[9] The intuition underlying this result is that countries make a tradeoff between benefits from free-riding and benefits from cooperation. By raising current harvest, free-riding enhances private utility. In this framework, the benefit from cooperation stems from the fact that it enhances future resource stocks (which benefits all countries). Since a large coalition substantially diminishes private utility for member countries, these findings suggest that a large coalition forms today when member countries anticipate that the associated loss will be compensated for by a substantial increase in future harvest.

For scenarios in which the elasticity of inter-temporal substitution equals one ($\eta = 1$), countries are averse to inter-temporal harvest sequences (h_{it}, h_{it+1}) in which h_{it} and h_{it+1} differ substantially. As a result, coalitions constituted of more than two members cannot form in equilibrium. When the elasticity of inter-temporal substitution is high ($\eta > 1$), countries are more likely to choose harvest sequences (h_{it}, h_{it+1}) in which h_{it} and h_{it+1} differ considerably. In the presence of this inter-temporal substitution, individual cooperation benefits under less competition and a higher biological return in future periods actually dominate the prospect of gains from free-riding. As such, each country's

[9] Assuming that Z_t follows the log-normal distribution defined below and using the set of parameters $m = 1.4$, $\sigma^2 = 0.1$, $\delta = 0.95$, $\alpha = 0.9$, $X_0 = 100$, and $\eta = 2$, numerical simulations reveal that $\hat{N} = 24.3526$ and $\bar{\phi} < 0$ for any $3 \leqslant N \leqslant \hat{N}$. This numerical finding shows that, for this set of parameters, the conditions in (2.16) hold for any $\phi > 0$ and $3 \leqslant N \leqslant 24$.

dominant strategy is to join the RFMO as shown in Proposition 2.2.

In the particular case where N is arbitrarily large, we have shown in Appendix 4.8 that the grand coalition is not internally stable when X_0 or ϕ is high and $\eta > 1$. This result reveals that the likelihood of full cooperation highlighted in Proposition 2.2 collapses when N becomes sufficiently large.

In the particular setting of $\eta = 1$ and $\phi = 1$, it can be shown that $u(h) = \ln(h)$ and $g(y) = y^{\alpha}$. In this context, the only variable capturing random changes in environmental conditions takes the value one (i.e., $\xi = 1$). This finding along with conditions (2.10), (2.11), (2.13), and (2.14) show that individual harvests and payoffs, and thus, equilibrium coalitions are not affected by uncertainty in equilibrium when $\eta = 1$.

To further illustrate the effect of uncertainty, in the remainder of this section, we assume that Z_t follows a log-normal distribution. Specifically, the random variable $\ln(Z_t)$ is normally distributed with the mean equal to $\tilde{\mu}$ and variance σ^2. To maintain the mean of Z_t, $m = \exp(\tilde{\mu} + \frac{\sigma^2}{2})$, constant as σ^2 changes, we assume that $\tilde{\mu} = \ln(m) - \sigma^2/2$. An increase in σ^2 raises the variance $\text{Var}(Z_t) = m^2(\exp(\sigma^2) - 1)$, of Z_t. We find that $\xi = \exp\left((1 - \frac{1}{\eta})\ln(m) - \frac{\sigma^2}{2\eta}(1 - \frac{1}{\eta})\right)$ and our derivations give rise to the following results.

Proposition 2.3. *(i) Full non-cooperation is the equilibrium under uncertainty when σ^2 is sufficiently high and $\eta > 1$. (ii) Full cooperation is the equilbrium under deterministic conditions when $N < \hat{N}_{|\xi = m^{1-\frac{1}{\eta}}}$ and $(1-\alpha)\phi^{1-\frac{1}{\eta}} \geqslant \tilde{\phi} \equiv \bar{\phi}_{|\xi = m^{1-\frac{1}{\eta}}}$.*

Proof. See Appendix 4.8.

Result (i) of Proposition 2.3 reveals that countries can respond to uncertainty like risk averse agents. Specifically, they reduce investments in future resource stock by operating non-cooperatively when $\eta > 1$ and they anticipate a sufficiently high variability in biological growth. Result (i) of Proposition 2.2 holds under both deterministic $(\sigma^2 = 0)$

and uncertain ($\sigma^2 > 0$) environmental conditions. Result (ii) of Proposition 2.3 is the restriction of such a finding to scenarios in which environmental conditions are deterministic.[10] For scenarios in which $\eta > 1$, these results suggest that if countries anticipate a dramatic and uncertain shift in biological conditions, they will be less likely to cooperate relative to the deterministic case.

Note that in contrast to Antoniadou et al. (2013) who examine the strategic management of a common pool renewable resource in scenarios where countries exogenously operate non-cooperatively in all periods, in this paper, the decision to cooperate is endogenous. In this setting, never explored, our analysis reveals that novel forms of cooperation can happen in equilibrium. For example, as shown in Propositions 2.2 and 2.3, we have delineated conditions under which full cooperation occurs in equilibrium under both deterministic and uncertain conditions.

2.5 The Dynamic Membership Case

In Section 2.4, we have focused our attention on scenarios in which the RFMO is negotiated in the initial period only. For most RFMOs (e.g., Northwest Atlantic Fisheries Organization), member and non-member countries can revise their membership and harvest decisions every one or two years. To shed light on the effects of such renegotiations, in this section, we extend our analysis to cases in which countries reconsider their membership and harvest decisions at the outset of each period. For the sake of tractability, this section relies on a three-period model. The initial period is denoted by $t-2$ while $t-1$ and t represent the second and third periods. In each period, countries play a two-stage game. In the first stage, countries decide unilaterally whether or not to join the

[10] Using the set of parameters $\eta = 2, \delta = 0.95, \alpha = 0.27, X_0 = 100, m = 15, \sigma^2 = 0$, our numerical analysis reveals that $\hat{N}_{|\xi = m^{1-\frac{1}{\eta}}} = 9.7316$ and $\bar{\phi}_{|\xi = m^{1-\frac{1}{\eta}}} = \tilde{\phi} < 0$ for all $3 \leqslant N < \hat{N}_{|\xi = m^{1-\frac{1}{\eta}}}$. Hence, in this setting, full cooperation occurs in equilibrium under deterministic conditions for all $\phi > 0$ and any $3 \leqslant N \leqslant 9$.

RFMO. In the second stage, given the coalition resulting from the first stage, while each coalition member chooses his harvest so as to maximize the aggregated expected net present value of utility for all coalition members, each non-coalition member chooses his harvest so as to maximize his own expected net present value of utility. The equilibrium is obtained by solving backwards, starting from the last period (i.e., period t).

In period t (third period), given the current resource stock, countries negotiate a RFMO, which results in a coalition K_t of size n_t. A coalition member $i \in K_t$ solves

$$\max_{h_i} \sum_{i \in K_t} u\left(h_i\right), \tag{2.17}$$

subject to Eq.(2.1).

A non-coalition member solves

$$\max_{h_j} u\left(h_j\right), \tag{2.18}$$

subject to Eq.(2.1). Since the utility function is increasing in harvest and t is the final period, current total harvest is equal to period t resource stock. That is,

$$n_t h_{mt} + \left(N - n_t\right) h_{nct} = X_t. \tag{2.19}$$

In order to be consistent with previous derivations, we assume that $h_{nct} = n_t h_{mt}$. Substituting this equality into Eq.(2.19) gives

$$h_{mt} = \frac{X_t}{n_t\left(N - n_t + 1\right)}, \quad \text{and} \quad h_{nct} = \frac{X_t}{N - n_t + 1}. \tag{2.20}$$

The equilibrium payoffs (as a function of n_t) for the representative coalition member and non-coalition member can be written as

$$W_{mt}\left(X_t, n_t\right) = \frac{\left(\frac{X_t}{n_t(N-n_t+1)}\right)^{1-\frac{1}{\eta}} - 1}{1-\frac{1}{\eta}} \quad \text{and} \quad W_{nct}\left(X_t, n_t\right) = \frac{\left(\frac{X_t}{N-n_t+1}\right)^{1-\frac{1}{\eta}} - 1}{1-\frac{1}{\eta}}. \tag{2.21}$$

Using the above calculations, we derive the following findings.

Result 1. *In period t the following result holds under dynamic membership.*

(i) Full non-cooperation is the equilibrium ($n_t^* = 1$). (ii) The equilibrium individual harvest can be written as

$$h_{mt}^* = \frac{X_t}{N} = h_{nct}^*.$$

Proof. See Appendix 4.8.

The intuition underlying the findings of this Result is as follows. Cooperation allows to conserve the resource stock. Countries do not have any incentives to conserve the resource stock in period t because it is the final period and each country's utility function is monotonically increasing in harvest. These factors explain why full non-cooperation is the equilibrium in period t irrespective of the shape of the growth function and the size of period-t resource stock.

The period-t equilibrium payoff is:

$$W_{mt}\left(X_t, n_t^*\right) = W_{nct}\left(X_t, n_t^*\right) = \frac{\left(\frac{X_t}{N}\right)^{1-\frac{1}{\eta}} - 1}{1-\frac{1}{\eta}}. \tag{2.22}$$

Eq.(2.22) along with Result 1 suggests that period-t individual harvest and payoff decline as the number of countries N increases. Moreover, individual harvest and payoff increase as the resource stock rises.

We now turn to the analysis of incentives to join or leave a RFMO in periods $t-2$ and $t-1$. Following Miller and Nkuiya (2016), we assume that countries do not commit to membership across periods. In particular, we assume that in period $s = t-2, t-1$, irrespective of their membership status (coalition member or non-coalition member) countries have the same future expected payoff.[11] More precisely, in period $s = t-2, t-1$, the payoff that each country expects to get in period $s+1$ can be written as follows

$$\psi_{s+1}\left(X_{s+1}\right) = \frac{n^*_{s+1}}{N} W_{ms+1}\left(X_{s+1}, n^*_{s+1}\right) + \frac{\left(N - n^*_{s+1}\right)}{N} W_{ncs+1}\left(X_{s+1}, n^*_{s+1}\right), s = t-2, t-1. \tag{2.23}$$

Utilizing the fact that full non-cooperation is the equilibrium in period t (i.e. $n^*_t = 1$), for $s = t-1$, this expression gives rise to

$$\psi_t\left(X_t\right) = \frac{\left(\frac{X_t}{N}\right)^{1-\frac{1}{\eta}} - 1}{1 - \frac{1}{\eta}} \text{ and } \psi_t'\left(X_t\right) = \left(\frac{1}{N}\right)^{1-\frac{1}{\eta}} X_t^{-\frac{1}{\eta}}. \tag{2.24}$$

We next use this formula to fully characterize the equilibrium of the game in period $t-1$.

Following the approach of period t, assume for now that a RFMO game is played at the beginning of period $t-1$, which gives rise to a coalition K_{t-1} of size n_{t-1}. A coalition member $i \in K_{t-1}$ makes his harvest decisions according to

$$W_{t-1}\left(X_{t-1}\right) = \max_{h_{it-1}} \left\{ \sum_{k \in K_{t-1}} u\left(h_{kt-1}\right) + n_{t-1}\delta E\left[\psi_t\left(X_t\right)\right] \right\},$$

subject to Eq.(2.1). The first-order condition for this maximization problem can be

[11] A wide array of economic papers on dynamic coalition formation rely on this assumption. See for instance Nkuiya (2012) or Nkuiya et al. (2015) for a survey.

written as

$$u'\left(h_{mt-1}\right) = n_{t-1}\delta E\left[Z_{t-1}g'\left(y_{t-1}\right)\psi_t'\left(X_t\right)\right]. \tag{2.25}$$

The problem to address by a non-member of the coalition reads

$$W_{nct-1}\left(X_{t-1}\right) = \max_{h_{jt-1}} u\left(h_{jt-1}\right) + \delta E\left[\psi_t\left(X_t\right)\right],$$

subject to Eq.(2.1). The first order condition is given by

$$u'\left(h_{nct-1}\right) = \delta E\left[Z_{t-1}g'\left(y_{t-1}\right)\psi_t'\left(X_t\right)\right]. \tag{2.26}$$

Notice that for $n_{t-1} \geqslant 2$, the right hand side of Eq.(2.25) is greater than that of Eq.(2.26). This result implies that $u'\left(h_{mt-1}\right) > u'\left(h_{nct-1}\right)$. Since marginal utility is decreasing in harvest, we necessarily have $h_{mt-1} < h_{nct-1}$. Consequently, the equilibrium harvest by a coalition member is lower than the equilibrium harvest by a non-coalition member.

Contemplating Eq.(2.25) and Eq.(2.26), we find that the equality $u'(h_{mt-1}) = n_{t-1}u'(h_{nct-1})$ holds. This result yields

$$h_{nct-1} = n_{t-1}^{\eta} h_{mt-1}. \tag{2.27}$$

Substituting (2.24) and (2.27) into (2.25) provides the period $t-1$ harvest rule for a representative coalition member

$$h_{mt-1}\left(X_{t-1}\right) = \omega_{mt-1}X_{t-1} = \frac{X_{t-1}}{\left(\alpha\delta\xi n_{t-1}\right)^{\eta} N^{1-\eta} + n_{t-1} + \left(N - n_{t-1}\right) n_{t-1}^{\eta}}. \tag{2.28}$$

Likewise, substituting (2.24) and (2.27) into (2.26) provides the period $t-1$ harvest rule for a representative non-coalition member

$$h_{nct-1}\left(X_{t-1}\right) = \omega_{nct-1}X_{t-1},\ \ \omega_{nct-1} = n_{t-1}^{\eta}\omega_{mt-1}. \tag{2.29}$$

Notice that we have not used any functional guess to derive these harvest rules. As such, linear strategies defined in (2.28) and (2.29) constitute the unique Markov Perfect Nash equilibrium in period $t-1$.

As shown in Appendix 4.8, each coalition member's expected net present value of utility associated with the harvest rules (2.28) and (2.29) reads

$$W_{mt-1}\left(X_{t-1},n_{t-1}\right)=A_{mt-1}(n_{t-1})X_{t-1}^{1-\frac{1}{\eta}}+B_{mt-1}(n_{t-1}), \tag{2.30}$$

where,

$$A_{mt-1}(n_{t-1})=\frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[\left(N\omega_{nct-1}\right)^{1-\frac{1}{\eta}}n_{t-1}^{1-\eta}+\alpha\delta\xi\left(1-\left(n_{t-1}^{1-\eta}+N-n_{t-1}\right)\omega_{nct-1}\right)^{1-\frac{1}{\eta}}\right],$$
$$B_{mt-1}(n_{t-1})=\frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}[(1-\alpha)\,\delta\xi\phi^{1-\frac{1}{\eta}}-(1+\delta)\,N^{1-\frac{1}{\eta}}].$$

Derivations done in the appendix suggest that the expected net present value of utility for an individual non-coalition member can be written as

$$W_{nct-1}\left(X_{t-1},n_{t-1}\right)=A_{nct-1}(n_{t-1})X_{t-1}^{1-\frac{1}{\eta}}+B_{mt-1}(n_{t-1}), \tag{2.31}$$

where,

$$A_{nct-1}(n_{t-1})=\frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[\left(N\omega_{nct-1}\right)^{1-\frac{1}{\eta}}+\alpha\delta\xi\left(1-\left(n_{t-1}^{1-\eta}+N-n_{t-1}\right)\omega_{nct-1}\right)^{1-\frac{1}{\eta}}\right].$$

Using the equilibrium payoff functions defined above, it is possible to derive stable coalitions as well as the sensitivity of such coalitions with respect to the current resource stock. The results are summarized in the following Proposition.

Proposition 2.4. *The following results hold in period $t-1$.*

(i) Changes in the current resource stock X_{t-1} do not affect the equilibrium coalition size n^*_{t-1}.

(ii) If $\eta > 1$, full cooperation is the equilibrium in period $t-1$ when

$$N^{\frac{1}{\eta}-1}[1+(\alpha\delta\xi)^{\eta}]^{\frac{1}{\eta}} \geqslant \frac{1+(\alpha\delta\xi)^{\eta}N^{1-\eta}}{\left[(\alpha\delta\xi)^{\eta}N^{1-\eta}+(N-1)^{1-\eta}+1\right]^{1-\frac{1}{\eta}}}. \tag{2.32}$$

(iii) If $0 < \eta < 1$, full cooperation is the equilibrium in period $t-1$ when

$$N^{\frac{1}{\eta}-1}[1+(\alpha\delta\xi)^{\eta}]^{\frac{1}{\eta}} \leqslant \frac{1+(\alpha\delta\xi)^{\eta}N^{1-\eta}}{\left[(\alpha\delta\xi)^{\eta}N^{1-\eta}+(N-1)^{1-\eta}+1\right]^{1-\frac{1}{\eta}}}. \tag{2.33}$$

Proof. See Appendix 4.8.

To better understand the intuition underlying the results of Proposition 2.4, we decompose the stability function as follows

$$S(X_{t-1}, n_{t-1}) = \text{Free Riding} + \text{Conservation Effect},$$

where Free Riding $=[u(h_{mt-1}(n_{t-1})) - u(h_{nct-1}(n_{t-1}-1))]$ and Conservation Effect$=$ $\delta E\left[\psi_t(X_{t(n_{t-1})}) - \psi_t(X_{t(n_{t-1}-1)})\right]$.

Assume that a player decides to join a coalition of size $n_{t-1}-1$. Such a decision entails two opposite effects. First, his instantaneous utility declines because period $t-1$ harvest $(h_{mt-1}(n_{t-1}))$ for such a player is smaller relative to his harvest before such a change in membership decision $(h_{nct-1}(n_{t-1}-1))$. Free Riding is negative and represents the free riding effect (i.e., the incentive not to join the coalition). Second, a larger coalition gives rise to a higher expected resource stock and a higher expected utility. The conservation effect called Conservation Effect is positive and represents the incentive to join the coalition. Condition (2.32) holds if and only if $\frac{\partial W_{mt-1}}{\partial X_{t-1}}(X_{t-1}, N) > \frac{\partial W_{nct-1}}{\partial X_{t-1}}(X_{t-1}, N-1)$. Consequently, Result (ii) shows that in the scenario where $\eta > 1$, the conservation effect always dominates for the grand coalition (i.e., full cooperation prevails in equilibrium) when the individual shadow price of the resource stock under full cooperation is higher compared to the shadow price associated with the problem faced by a country that unilaterally defects. However, if $0 < \eta < 1$, result (*iii*) reveals that full cooperation happens in equilibrium when the individual shadow price of the resource stock for the grand coalition is smaller relative to the case where a country unilaterally defects.

Our analysis suggests that a variation of the current resource stock X_{t-1} generates the same magnitude of change on both the incentive to join and leave the coalition. As a result, such a variation does not affect equilibrium coalitions. Results (*ii*) and (*iii*) of Proposition 2.4 delineate conditions under which each player's incentive to leave the grand coalition is outweighed. In the particular case where N is arbitrarily large, it can be shown that conditions (2.32) and (2.33) are violated. This result implies that the likelihood of full cooperation falls apart when N becomes sufficiently large.

For scenarios in which $\eta = 1$ and $\phi = 1$, it can be shown that $u(h) = \ln(h)$ and $g(y) = y^{\alpha}$. In this context, our analysis reveals that the interplay between the free-riding effect and the conservation effect gives rise to full non-cooperation in equilibrium as shown in Appendix 4.8. The only variable capturing random changes in environmental conditions takes the value one (i.e., $\xi = 1$) as long as $\eta = 1$. This result along with conditions (2.28), (2.29), (2.30), and (2.31) reveal that individual harvests and payoffs, and thus, equilibrium coalitions are not affected by uncertainty in equilibrium when $\eta = 1$.

To further isolate the effects of uncertainty, in the remainder of this paragraph, we focus our attention on scenarios in which Z_t follows the log-normal distribution presented in Section 2.4.2. We find that strategic interactions lead to full non-cooperation in equilibrium when σ^2 is sufficiently high and $\eta > 1$.[12] Using an approach similar to Proposition 2.4, we find that full cooperation forms in equilibrium under deterministic conditions when any increase in the resource stock by one unit generates greater individual payoffs under full cooperation compared to the scenario of a single defection. Relative to

[12]Interested readers can refer to Appendix 4.8 for the proof.

the deterministic scenario, these findings suggest that cooperation incentives are smaller when countries anticipate highly uncertain environmental variabilities.

Our results stating that incentives to cooperate fall apart under the dynamic and open loop membership cases when players anticipate uncertain and large shifts in environmental conditions is in line with facts observed in real world fisheries. For example, variability in environmental conditions, like those expected from climate change, often generates serious threats to the stability of RFMOs (e.g., the North East Atlantic mackerel conflict between the EU, Norway, Iceland, and the Faroe Islands documented by Ellefsen et al. (2017)). Our analysis sheds more light on this issue, arguing that one of the potential causes of such instability is the high level of uncertainty associated with the return from conserving the resource stock.

We next turn our attention to the initial period (i.e., period $t-2$). Recall that in this dynamic membership setting, each country reconsiders his membership and harvest decisions every period. For $s = t-2$, condition (2.23) suggests that in period $t-2$, each player's continuation value can be written as

$$\psi_{t-1}\left(X_{t-1}\right) = \frac{n^*_{t-1}}{N} W_{mt-1}\left(X_{t-1}, n^*_{t-1}\right) + \frac{\left(N - n^*_{t-1}\right)}{N} W_{nct-1}\left(X_{t-1}, n^*_{t-1}\right).$$

Using the expressions of $W_{mt-1}\left(X_{t-1}, n^*_{t-1}\right)$ and $W_{nct-1}\left(X_{t-1}, n^*_{t-1}\right)$ defined in (2.30) and (2.31), this formula simplifies to

$$\psi_{t-1}\left(X_{t-1}\right) = \left[\frac{n^*_{t-1}}{N} A_{mt-1}(n^*_{t-1}) + \left(1 - \frac{n^*_{t-1}}{N}\right) A_{nct-1}(n^*_{t-1})\right] X_{t-1}^{1-\frac{1}{\eta}} + B_{mt-1}(n^*_{t-1}).$$

Differentiating this formula with respect to the resource stock X_{t-1}, we obtain

$$\psi'_{t-1}\left(X_{t-1}\right) = \nu(n^*_{t-1}) X_{t-1}^{-\frac{1}{\eta}}, \tag{2.34}$$

where $\nu(n^*_{t-1}) = \left(1-\frac{1}{\eta}\right)\left[\frac{n^*_{t-1}}{N}A_{mt-1}(n^*_{t-1}) + \left(1-\frac{n^*_{t-1}}{N}\right)A_{nct-1}(n^*_{t-1})\right]$.

In period $t-2$, the problem solved by member i of the coalition K_{t-2} of size n_{t-2} reads

$$W_{t-2}\left(X_{t-2}\right) = \max_{h_{it-2}} \sum_{k\in K_{t-2}} u\left(h_{kt-2}\right) + n_{t-2}\delta E\left[\psi_{t-1}\left(X_{t-1}\right)\right],$$

subject to Eq.(2.1). The first-order condition can be written as

$$u'\left(h_{mt-2}\right) = n_{t-2}\delta E\left[Z_{t-2}g'\left(y_{t-2}\right)\psi'_{t-1}\left(X_{t-1}\right)\right]. \tag{2.35}$$

Non-coalition member j solves

$$W_{nct-2}\left(X_{t-2}\right) = \max_{h_{jt-2}} u\left(h_{jt-2}\right) + \delta E\left[\psi_{t-1}\left(X_{t-1}\right)\right],$$

subject to Eq.(2.1). The first-order condition reads

$$u'\left(h_{nct-2}\right) = \delta E\left[Z_{t-2}g'\left(y_{t-2}\right)\psi'_{t-1}\left(X_{t-1}\right)\right]. \tag{2.36}$$

Contemplating the right hand-sides of equations (2.35) and (2.36), it can be shown that $u'(h_{mt-2}) = n_{t-2}u'(h_{nct-2})$. This result along with condition (2.3) yields

$$h_{nct-2} = n^{\eta}_{t-2}h_{mt-2}. \tag{2.37}$$

Following the approach used for the derivation of equilibrium harvest rules in period $t-1$, we substitute (2.37) and (2.34) into (2.35), which provides the period $t-2$ harvest rule for a representative coalition member

$$h_{mt-2}\left(X_{t-2}\right) = \omega_{mt-2}X_{t-2} = \frac{X_{t-2}}{\left(\alpha\delta\xi n_{t-2}\nu(n^*_{t-1})\right)^{\eta} + n_{t-2} + \left(N-n_{t-2}\right)n^{\eta}_{t-2}}. \tag{2.38}$$

Likewise, substituting (2.37) and (2.34) into (2.36) provides the period $t-2$ harvest rule for a representative non-coalition member

$$h_{nct-2}\left(X_{t-2}\right) = \omega_{nct-2} X_{t-2}, \quad \omega_{nct-2} = n_{t-2}^{\eta} \omega_{mt-2}. \tag{2.39}$$

Harvest rules (2.38) and (2.39) provide three important properties of equilibrium behaviors. First, such harvest rules constitute the unique Markov Perfect Nash equilibrium for period $t-2$. Second, they illustrate a tradeoff between period $t-2$ individual harvests and the next period's expected marginal payoff (i.e., $\psi'_{t-1}\left(X_{t-1}\right)$). Specifically, as the next period's expected marginal payoff rises, period $t-2$ individual harvests decline. Third, in period $t-2$, each coalition member harvests less relative to individual non-coalition members.

The precautionary principle urges a cautious management strategy for potentially harmful problems when information about the consequences of solutions is limited or entirely unknown. This principle has been adopted by policy makers for a wide array of issues including international agreements on climate change and the use of new products (e.g., medication, tools). In our context of climate variability, known to increase uncertainty about resource growth (Miller et al., 2013), we next investigate this issue. We rely on the concept of second-order stochastic dominance which allows to rank risky assets. Such a concept suggests that if $\tilde{P}$ and $\hat{P}$ are two random variables with $E(\tilde{P}) = E(\hat{P})$, $\hat{P}$ is more uncertain than $\tilde{P}$ if $E(f(\hat{P})) \leqslant E(f(\tilde{P}))$, whenever $f(.)$ is a concave function. Our results are summarized in the following proposition.

Proposition 2.5. *Assume that $\hat{Z}_s$ is a random variable with $E(Z_s) = E(\hat{Z}_s)$ and $\hat{Z}_s$ is more uncertain than Z_s. The following results hold under dynamic membership.*

(i) if $\eta > 1$, the harvest rate of a coalition member or a non-coalition member associated with $\hat{Z}_s$ is greater compared to Z_s. (ii) If $0 < \eta < 1$, the harvest rate of a coalition

member or a non-coalition member associated with $\hat{Z}_s$ is lower relative to Z_s. (iii) If $\eta = 1$, individual harvests associated with $\hat{Z}_s$ and Z_s are equal.

Proof. See Appendix 4.8.

Our analysis suggests that, η captures individual attitude towards risk. For the case where $\eta > 1$, result (i) of Proposition 2.5 implies that countries behave like risk averse agents because in response to an increase in uncertainty, they lower investment in future resource stock (i.e., increase individual harvest). On the other hand, when $0 < \eta < 1$, result (ii) suggests that countries operate as risk loving agents. This is the case because, in this context, they always increase investment in future resource stock (i.e., reduce individual harvest) in response to any increase in uncertainty. For the scenario where $\eta = 1$, result (iii) of Proposition 2.5 reveals that countries behave like risk neutral agents because they do not change their investment in future resource stock in response to uncertainty.

In order to fully characterize the equilibrium of the game, it is useful to determine equilibrium payoffs as a function of X_{t-2} and n_{t-2}. Using a similar method as the period $t-1$ case, it can be shown that the expected net present value of utility (associated with harvest rules in (2.38) and (2.39)) for a representative coalition member is

$$W_{mt-2}\left(X_{t-2}, n_{t-2}\right) = A_{mt-2}(n_{t-2}) X_{t-2}^{1-\frac{1}{\eta}} + B_{mt-2}, \tag{2.40}$$

where,

$$A_{mt-2}(n_{t-2}) = \frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[\left(N\omega_{nct-2}\right)^{1-\frac{1}{\eta}} n_{t-2}^{1-\eta} + \alpha\delta\xi(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n_{t-1}^{*})\left(1-\left(n_{t-2}^{1-\eta}+N-n_{t-2}\right)\omega_{nct-2}\right)^{1-\frac{1}{\eta}}\right],$$

$$B_{mt-2} = \frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[(1-\alpha)\delta\xi\phi^{1-\frac{1}{\eta}}\left[(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n_{t-1}^{*})+\delta\right]-(\delta^2+\delta+1)N^{1-\frac{1}{\eta}}\right].$$

Similarly, the expected net present value of utility for an individual non-coalition member reads

$$W_{nct-2}\left(X_{t-2}, n_{t-2}\right) = A_{nct-2}(n_{t-2})X_{t-2}^{1-\frac{1}{\eta}} + B_{mt-2}, \tag{2.41}$$

where,

$$A_{nct-2}(n_{t-2}) = \frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[(N\omega_{nct-2})^{1-\frac{1}{\eta}} + \alpha\delta\xi(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n_{t-1}^{*})\left(1-\left(n_{t-2}^{1-\eta}+N-n_{t-2}\right)\omega_{nct-2}\right)^{1-\frac{1}{\eta}}\right].$$

Using the above calculations, we derive the following results.

Proposition 2.6. *The following results hold in period $t-2$.*

(i) The current resource stock X_{t-2} does not affect the equilibrium coalition size n_{t-2}^{*}.

(ii) If $\eta > 1$, full cooperation is the equilibrium in period $t-2$ when

$$\frac{N^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}(1-1/\eta)}{[N^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}]^{1-\frac{1}{\eta}}} \geqslant \frac{1 + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}(1-1/\eta)}{[1+(N-1)^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}]^{1-\frac{1}{\eta}}}.$$

(iii) If $0 < \eta < 1$, full cooperation is the equilibrium in period $t-2$ when

$$\frac{N^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}(1-1/\eta)}{[N^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}]^{1-\frac{1}{\eta}}} \leqslant \frac{1 + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}(1-1/\eta)}{[1+(N-1)^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}]^{1-\frac{1}{\eta}}}.$$

Proof. See Appendix 4.8.

Result (i) of Proposition 2.6 is driven by the fact that any variation of the current resource stock X_{t-2} produces the same scale of change on both the free riding effect and conservation effect. Results (ii) and (iii) of Proposition 2.6 provide economic, environmental, and biological conditions under which the free riding effect associated with the grand coalition is dominated by the conservation effect. The intuition underlying these results is similar to that of Proposition 2.4. Specifically, Result (ii) reveals that if $\eta > 1$, then all countries join the coalition in equilibrium when any increase in the resource stock by one unit leads to a higher payoff under full cooperation relative to the scenario where there is a unilateral defection. Likewise, Result (iii) shows that if $\eta < 1$, then the coalition constituted of all countries forms in equilibrium when the shadow price associated with the problem faced by a country under full cooperation is smaller than the shadow price associated with a unilateral defection.

2.6 Numerical Simulations

This section relies on simulations to shed more light on the effects of random changes in environmental conditions. We assume that Z_t follows the log-normal distribution defined in Section 2.4.2. More precisely, the random variable $\ln(Z_t)$ is normally distributed with the mean equal to $\tilde{\mu}$ and variance σ^2. To keep the mean of Z_t, $m = \exp(\tilde{\mu} + \frac{\sigma^2}{2})$, constant as σ^2 changes, we assume that $\tilde{\mu} = \ln(m) - \sigma^2/2$. In this setting, an increase in σ^2 raises the variance, $\text{Var}(Z_t) = m^2(\exp(\sigma^2) - 1)$, of Z_t. As such, any increase in σ^2 constitutes a mean preserving spread. In the remainder of this section, we define a mean preserving spread as an increase in σ^2. Values of σ^2 used in simulations are defined as follows: $\sigma_j^2 = \sigma_{j-1}^2 + s$, $j = 1, 2, ..., 400$ with $\sigma_0^2 = 0$ and $s = 0.01$.

Table 2.1: Set of initial parameters used in simulations

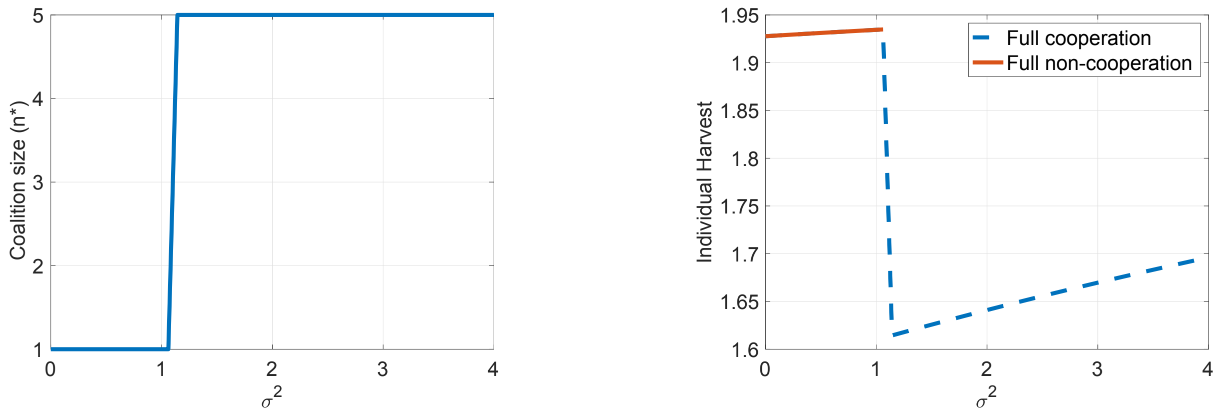
Description	Value
Utility function parameter	$\eta = 1.2$
Discount factor	$\delta = 0.95$
Growth function Parameters	$\phi = 100$ and $\alpha = 0.3$
Mean of Z_t	$m = 0.8$
Total number of countries	$N = 5$
Initial resource stock	$X_0 = 10$

2.6.1 Open-Loop Membership Case

This section examines how changes in model parameters affect the equilibrium outcome under the open-loop membership scenario. Using the initial set of parameters provided in Table 2.1, we examine the effects of mean preserving spreads. Numerical results illustrated in Figure 2.1 show that the interplay between the free riding effect and conservation effect gives rise to full non-cooperation under the deterministic scenario (which corresponds to $\sigma^2 = 0$). Starting from this deterministic scenario, a mean preserving spread does not change this result as long as σ^2 lies below a threshold, denoted by $\bar{\sigma}^2$. Above such a threshold (i.e., for $4 \geqslant \sigma^2 > \bar{\sigma}^2$), full cooperation is the equilibrium. These results imply that relative to the deterministic scenario, uncertainty does not change the equilibrium coalition size when σ^2 falls short of the threshold $\bar{\sigma}^2$. However, uncertainty associated with $4 \geqslant \sigma^2 > \bar{\sigma}^2$ substantially raises the equilibrium coalition size. In response to a mean preserving spread, interactions between the free riding effect and conservation effect always raise individual payoffs (net present value of utility).

Our numerical analysis also help shed further light on the papers by Mirman (1971) and Antoniadou et al. (2013), which only focus on the single player case or scenarios in which players exogenously act non-cooperatively in all periods. In these contexts, the authors find that for $\eta > 1$, mean preserving spreads always increase individual harvests. Simulations suggest that such a standard result does not necessarily hold when players endogenously decide whether or not to cooperate. Specifically, for $\eta = 1.2$ (as we are using the initial set of parameters), simulations show that a mean preserving spread from σ^2 smaller than $\bar{\sigma}^2$ to σ^2 lying between $\bar{\sigma}^2$ and 4, shifts the equilibrium from full-non cooperation to full cooperation. As a result, any mean preserving spread from σ^2 lower than $\bar{\sigma}^2$ to σ^2 lying between $\bar{\sigma}^2$ and 4, diminishes individual harvests as illustrated in Figure 2.1.

Keeping other initial parameters unchanged, we also address the effects of changing the elasticity of inter-temporal substitution to $\eta = 0.7$. In this case, simulations suggest that full non-cooperation is the equilibrium for all values of σ^2 considered. In this scenario, any mean preserving spread lowers individual harvests and increase the expected net present value of utility.



(a) **(b)**

Figure 2.1: Effects of mean preserving spreads for $\eta = 1.2$

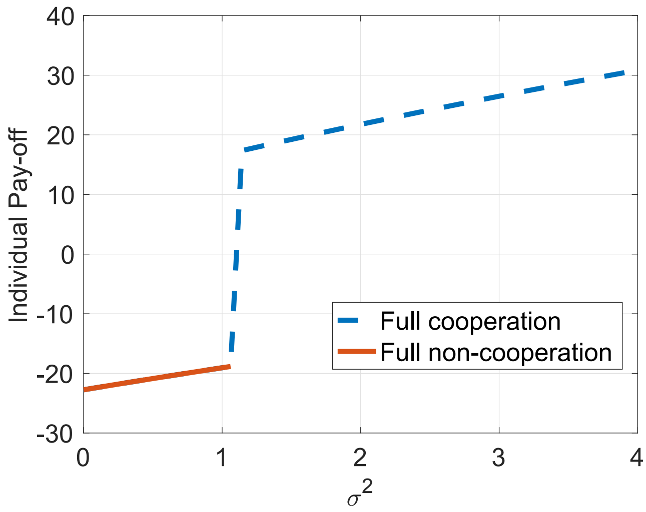


Figure 2.2: Effect of a Mean-preserving spread on payoffs if $\eta = 1.2$

2.6.2 Dynamic Membership Case

In this section, we rely on simulations to examine how sensitive the equilibrium under dynamic membership is to changes in environmental conditions. Making use of the initial set of parameters portrayed in Table 2.1, numerical simulations indicate that dynamic interactions between the free riding effect and conservation effect entail full cooperation in both periods $t-2$ and $t-1$ for all values of σ^2 considered.[13] This result along with findings in Section 2.6.1 suggest that the possibility to revise membership and harvest decisions in each period raises incentives to join the RFMO relative to the open loop membership case. Any mean preserving spreads increases individual harvest in period $t-2$ (holding the current resource stock constant) as illustrated in Figure 2.3b. This finding is consistent with Result (i) of Proposition 2.5. Unlike the open loop membership case, the expected net present value of utility (initial period's payoff) declines in response to any mean preserving spreads. Keeping other initial parameters unchanged, these results remain qualitatively valid if the initial discount factor is reduced to $\delta = 0.75$ as illustrated in Figures 2.3b and 2.4b.

Holding other initial parameters unchanged, we also examine the effects of diminishing the elasticity of inter-temporal substitution to $\eta = 0.7$. In this setting, simulations show that full cooperation is the equilibrium in periods $t-2$ and $t-1$. In contrast to the case where $\eta = 1.2$, a mean preserving spread actually lowers individual harvests. This finding is in line with Result (ii) of Proposition 2.5. Moreover, mean preserving spreads increase the net present value of utility. These results qualitatively hold even if the initial discount factor is diminished to $\delta = 0.75$ as illustrated in Figures 2.3a and 2.4a.

2.7 Summary of results and relevance for policy

RFMOs impose TACs that may be critical for fish conservation. Understanding how uncertainty affects RFMO participation and TACs is important since there is evidence that climate instability may increase in the near future.

We find that equilibrium coalitions depend critically on the initial resource stock under open-loop membership. However, this result is reversed under the dynamic membership case because changes in the resource stock equally affect free riding incentives and

[13] This result is consistent with Result (ii) of Proposition 2.4.

incentives to conserve the resource stock. Simulations suggest that mean preserving spreads always increase individual expected net present values of harvest under open-loop membership. This result does not hold under the dynamic membership scenario. We derive three equilibrium outcomes that hold under both the open-loop and dynamic membership scenarios and when the elasticity of inter-temporal substitution is high. By substantially reducing the expected return from conserving the resource stock, a high level of uncertainty dramatically diminishes economic benefits from forming a coalition, which leads to full non-cooperation in equilibrium. In this context, uncertainty reduces equilibrium coalitions relative to the deterministic environmental condition case. In response to small mean preserving spreads, the interplay between the free-riding effect and the conservation effect may raise individual harvests.

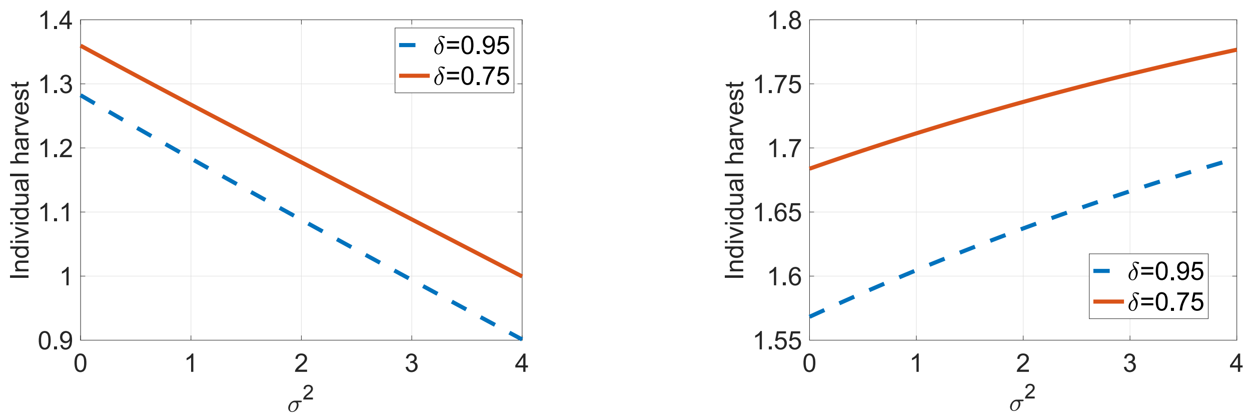
Our analysis sheds new light on factors that shape incentive to join RFMOs within dynamic common pool renewable resource games in contexts where players make their harvest decisions following the Cournot fashion. Several economic papers argue that equilibrium coalitions cannot support more than two members under deterministic conditions (e.g., Kwon, 2006; Miller and Nkuiya, 2016) or exogenous uncertainty (Miller and Nkuiya, 2016). Other prominent contributions (e.g., Polasky et al., 2006; Tarui et al., 2008) find that the fully cooperative solution can be reached in a sub-game perfect Nash equilibrium when punishment strategies are allowed. In this paper, we identify two novel elements that can also be critical factors in the ability to achieve large scale RFMOs. First, under the CRRA utility and CES growth functions, strategic interactions may give rise to full cooperation in equilibrium as shown in Propositions 2.2, 2.3, and 2.4. Second, uncertainty in the context of CRRA utility and CES growth functions, can shift the equilibrium outcome from full non-cooperation under deterministic conditions to full cooperation under uncertainty.

Our analysis contributes to an ongoing international policy debate regarding management of shared fish stocks. To mitigate over-exploitation related problems, the United Nations urges to manage marine resources in international waters through RFMOs. Meanwhile, the growth rates of such resources are subject to random shocks generated by environmental variability. This paper provides a novel attempt to formally investigate the effects of climate variability on countries' willingness to join RFMOs and associated harvest decisions. As such, our results may help inform governments, social scientists and societal stakeholders about potential conservation benefits and economic returns associated with membership in RFMOs (e.g., the North Pacific Anadromous Fish Commission).

2.8 Conclusion

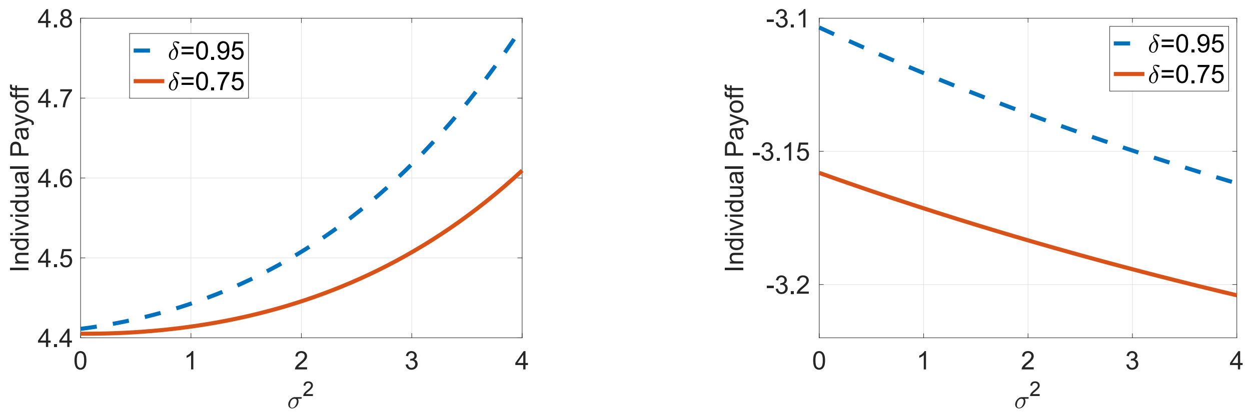
Scientific evidence suggest that changes in environmental conditions affect the growth rate of renewable resources (e.g., marine species). In ecosystems such as the high sea, consequences span from severe to beneficial and such changes occur abruptly. In this regard, this paper has developed a stochastic dynamic game to examine incentives of sovereign countries to join or leave RFMOs under stock growth uncertainty. We have explicitly accounted for the fact that intensifying current harvest lowers the next period resource stock. To better understand implications of strategic interactions, we have separately examined how stock growth uncertainty affects the equilibrium coalition, harvest, and net present value of utility under both the open-loop membership and dynamic membership scenarios.

Extensions of our model may give rise to new perspectives for renewable resource management. For example, we have restricted our attention to scenarios in which countries are identical. Several forms of heterogeneity capable of playing important roles in resource management include asymmetry in the discount rate, beliefs about stock growth, elasticity of inter-temporal substitution, and extraction costs. While we have concentrated on the risk neutral players case, our findings might change if players are risk averse. Moreover, to examine the dynamic membership scenario, we have restricted our attention to a finite horizon game for the sake of tractability. Our findings might, however, change if one considers an infinite horizon game. Our framework can be enhanced to address the effects of the above or other features on incentives to join or leave RFMOs and associated harvest policies.



(a) $\eta = 0.7$ **(b)** $\eta = 1.2$

Figure 2.3: Effects of mean preserving spreads on harvest.



(a) $\eta = 0.7$ **(b)** $\eta = 1.2$

Figure 2.4: Effects of mean preserving spreads on individual expected payoffs.

Bibliography

Antoniadou, E., C. Koulovatianos, and L. J. Mirman (2013). Strategic exploitation of a common-property resource under uncertainty. *Journal of Environmental Economics and Management 65*(1), 28–39.

Clark, C. W. and G. P. Kirkwood (1986). On uncertain renewable resource stocks: Optimal harvest policies and the value of stock surveys. *Journal of Environmental Economics and Management 13*(3), 235 – 244.

Costello, C., B. Nkuiya, and N. Quérou (2019). Spatial renewable resource extraction under possible regime shift. *American Journal of Agricultural Economics 101*(2), 507–527.

Costello, C. and S. Polasky (2008). Optimal harvesting of stochastic spatial resources. *Journal of Environmental Economics and Management 56*(1), 1 – 18.

Costello, C. J. and D. Kaffine (2008). Natural resource use with limited-tenure property rights. *Journal of Environmental Economics and Management 55*(1), 20–36.

d'Aspremont, C., A. Jacquemin, J. J. Gabszewicz, and J. A. Weymark (1983). On the stability of collusive price leadership. *Canadian Journal of economics*, 17–25.

Diekert, F. K. (2017). Threatening thresholds? the effect of disastrous regime shifts on the non-cooperative use of environmental goods and services. *Journal of Public Economics 147*, 30–49.

Dockner, E. J. and N. V. Long (1993). International pollution control: cooperative versus noncooperative strategies. *Journal of environmental economics and management 25*(1), 13–29.

Dockner, E. J., N. Van Long, and G. Sorger (1996). Analysis of nash equilibria in a class of capital accumulation games. *Journal of Economic Dynamics and Control 20*(6-7), 1209–1235.

Dutta, P. K. and R. Radner (2004). Self-enforcing climate-change treaties. *Proceedings of the National Academy of Sciences 101*(14), 5174–5179.

Dutta, P. K. and R. Radner (2009). A strategic analysis of global warming: Theory and some numbers. *Journal of Economic Behavior & Organization 71*(2), 187–209.

Ellefsen, H., L. Grønbæk, and L. Ravn-Jonsen (2017). On international fisheries agreements, entry deterrence, and ecological uncertainty. *Journal of environmental management 193*, 118–125.

FAO (2018). The state of world fisheries and aquaculture 2018 - meeting the sustainable development goals. rome. Technical report, Food and Agriculture Organization of the United Nations.

Fesselmeyer, E. and M. Santugini (2013). Strategic exploitation of a common resource under environmental risk. *Journal of Economic Dynamics and Control 37*(1), 125–136.

Finus, M., R. Schneider, and P. Pintassilgo (2020). The role of social and technical excludability for the success of impure public good and common pool agreements: The case of international fisheries. *Resource and Energy Economics 59*, 101122.

Fisheries and Oceans Canada (2016). Northwest Atlantic Fisheries Organization. https://www.dfo-mpo.gc.ca/international/media/bk_nafo-opano-eng.htm. Accessed: 2019-08-15.

Hannesson, R. (1997). Fishing as a supergame. *Journal of Environmental Economics and Management 32*(3), 309–322.

Kwon, O. S. (2006). Partial international coordination in the great fish war. *Environmental and Resource Economics 33*(4), 463–483.

Levhari, D. and L. J. Mirman (1980). The Great Fish War: An Example Using a Dynamic Cournot-Nash Solution. *The Bell Journal of Economics 11*(1), 322–334.

Long, L. K. and O. Flaaten (2011). A stackelberg analysis of the potential for cooperation in straddling stock fisheries. *Marine Resource Economics 26*(2), 119–139.

Long, N. V. (2010). *A survey of dynamic games in economics*, Volume 1. World Scientific.

Mason, C. F., S. Polasky, and N. Tarui (2017). Cooperation on climate-change mitigation. *European Economic Review 99*, 43–55.

McKelvey, R., K. Miller, and P. Golubtsov (2003). Fish-wars revisited: a stochastic incomplete-information harvesting game. *Risk and Uncertainty in Environmental and Natural Resource Economics*, 93–112.

Miller, K. A., G. R. Munro, U. R. Sumaila, and W. W. L. Cheung (2013). Governing marine fisheries in a changing climate: A game-theoretic perspective. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 61*(2), 309–334.

Miller, S. and B. Nkuiya (2016). Coalition formation in fisheries with potential regime shift. *Journal of Environmental Economics and Management 79*, 189–207.

Mirman, L. J. (1971). Uncertainty and optimal consumption decisions. *Econometrica 39*(1), 179.

Nkuiya, B. (2012). The effects of the length of the period of commitment on the size of stable international environmental agreements. *Dynamic Games and Applications 2*(4), 411–430.

Nkuiya, B. (2015). Transboundary pollution game with potential shift in damages. *Journal of Environmental Economics and Management 72*, 1–14.

Nkuiya, B., W. Marrouch, and E. Bahel (2015). International environmental agreements under endogenous uncertainty. *Journal of Public Economic Theory 17*(5), 752–772.

Nkuiya, B. and A. J. Plantinga (2021). Strategic pollution control under free trade. *Resource and Energy Economics 64*, 101218.

Pindyck, R. S. (1984). Uncertainty in the theory of renewable resource markets. *The Review of Economic Studies 51*(2), 289–303.

Pintassilgo, P., M. Finus, M. Lindroos, and G. Munro (2010). Stability and success of management organizations. *Environmental and Resource Economics 46*(3), 377–402.

Pintassilgo, P. and M. Lindroos (2008). Coalition formation in straddling stock fisheries: a partition function approach. *International Game Theory Review 10*(03), 303–317.

Polasky, S., A. De Zeeuw, and F. Wagener (2011). Optimal management with potential regime shifts. *Journal of Environmental Economics and management 62*(2), 229–240.

Polasky, S., N. Tarui, G. M. Ellis, and C. F. Mason (2006). Cooperation in the commons. *Economic Theory 29*(1), 71–88.

Reed, W. J. (1979). Optimal escapement levels in stochastic and deterministic harvesting models. *Journal of environmental economics and management 6*(4), 350–363.

Sakamoto, H. (2014). Dynamic resource management under the risk of regime shifts. *Journal of Environmental Economics and Management 68*(1), 1–19.

Sethi, G., C. Costello, A. Fisher, M. Hanemann, and L. Karp (2005). Fishery management under multiple uncertainty. *Journal of Environmental Economics and Management 50*(2), 300 – 318.

Singh, R., Q. Weninger, and M. Doyle (2006). Fisheries management with stock growth uncertainty and costly capital adjustment. *Journal of Environmental Economics and Management 52*(2), 582–599.

Springborn, M. and J. N. Sanchirico (2013). A density projection approach for non-trivial information dynamics: Adaptive management of stochastic natural resources. *Journal of Environmental Economics and Management 66*(3), 609–624.

Tarui, N., C. F. Mason, S. Polasky, and G. Ellis (2008). Cooperation in the commons with unobservable actions. *Journal of Environmental Economics and Management 55*(1), 37–51.

Tibbetts, J. (1996). Farming and fishing in the wake of el nino. *Bioscience*, 566–569.

UN, U. N. (1982). United nations convention on the law of the sea. [UN Doc. A/Conf 61/122].

UN, U. N. (1995). United nations conference on straddling and highly migratory fish stocks. agreement for the implementation of the united nations convention on the law of the sea of 10 december 1982 relating to the conservation and management of straddling and highly migratory fish stocks. UN Doc. A/Conf 164/37.

Walker, A. N. and H.-P. Weikard (2016). Farsightedness, changing stock location and the stability of international fisheries agreements. *Environmental and Resource Economics 63*(3), 591–611.

3 Learning and uncertainty in spatial resource management

3.1 Introduction

Renewable resource stocks (such as fish and wildlife) have the ability to migrate across different areas (patches). These movements are driven by random changes in environmental conditions, such as temperature, food abundance, and water salinity among others. For instance, the bluefin tuna moves according to food abundance and water temperature (Miranda, 2007). Lea and Rosenblatt (2000) note that, as a result of the global El-Niño event of 1997-98 which resulted in the persistence of warm-water conditions, a significant proportion of Panamic (eastern tropical Pacific, along the coast of countries such as Ecuador and Peru) fish migrated to the California coast. While it is possible to learn about the migration pattern of several species, accounting for the associated information may help improve their management.

Learning about spatial movements of species is an important feature that requires significant consideration when making optimal exploitation strategies. However, such a feature has been largely ignored within the economic literature on renewable resource management. The goal of this paper is to design a bio-economic model to formally examine this issue. We account for three modeling features that differentiate our work from prior economic research. First, fish populations are distributed across zones or patches in a setting where fish migration and growth are subject to random climatic shocks. As fish move across patches, the manager learns about their movements. Second, we explicitly account for the fact that resource stocks across patches increase or decrease depending on harvest intensity, environmental conditions, and growth. Third, economic conditions (e.g., the resource price, extraction costs) and biological returns may differ across patches.

Our analysis builds on three strands of economic literature related to renewable resource management, each relying on economic frameworks that differ with respect to environmental, biological, political, or economic conditions. The first strand addresses, in an aspatial context without any possibility to learn, renewable resource management under uncertainty. For instance, Reed (1979), Weitzman (2002), and Costello et al. (2001) concentrate on optimal exploitation under stock growth uncertainty, whereas Fesselmeyer and Santugini (2013) focus on the strategic management scenario under the threat that random changes in environmental conditions may irreversibly deteriorate resource quality. Diop et al. (2018) find that the harvest rule based on the optimization of the net present value of harvest performs better when resource growth is subject to random shocks entailed by climate change. Moreover, Clark and Kirkwood (1986) and Sethi et al. (2005) examine the combined effect of stock growth uncertainty and managerial uncertainty. Our analysis complements these studies by examining the effects of learning in a context of resource populations moving across space.

The second strand examines, in the absence of learning, the extraction of spatially connected renewable resources (e.g., birds, fish populations). The early contribution by Sanchirico and Wilen (1999) concentrates on management under open access and deterministic conditions. Fabbri et al. (2020) address the effects of assigning Territorial User Rights among resource owners who are spatially connected through resource movements. While Costello et al. (2019) examines the strategic management case under the prospect of spatial regime shift, Costello and Polasky (2008) investigate optimal management under stock growth uncertainty. By contrasting management with and without learning, heterogenous economic, or biological conditions, we shed light on the role these fishery features play in making optimal exploitation strategies.

The third strand of literature, in aspatial contexts, investigates the effects of learning on renewable resource extraction. For instance, Costello et al. (2001) ask how the prediction of the future biological growth function affects optimal management. Based on Brock and Mirman (1972), Koulovatianos et al. (2009) investigate the impact of Bayesian learning on optimal consumption and investment strategies. Springborn and Sanchirico (2013) compare the optimal harvest rule under adaptive management with the passive learning and no-learning scenarios. Costello et al. (1998) develop a bioeconomic model to quantify the benefits of forecasting El niño events on optimal management.[1] Unlike these studies, we account for spatial connectivity and heterogenous biological and economic returns across patches. To the best of our knowledge, a general economic framework that incorporates factors that shape spatial mobility, environmental and biological conditions, and explicitly accounts for learning does not yet exist. This paper fills this gap.

To illustrate the effects of Bayesian learning, our baseline is the scenario in which the planner is fully informed about the distribution of the shock. We first examine scenarios in which the marginal harvesting cost function is constant. In this context, our results are driven by structural uncertainty, which illustrates the fact that by updating prior information about the fraction of fish stock moving from one patch to the other, learning changes the distribution of uncertainty. Such changes in turn alter the structure of the economic problem. Formally, structural uncertainty represents the curvature of the mean of the dispersal shock with respect to the unknown parameter. Our analysis reveals that when such a mean is linear, the expected marginal revenue of investment remains unchanged across patches, leaving harvest unchanged in response to learning. Bayesian learning increases harvest in a patch and reduces harvest in the other patch when the mean is either convex or concave.

We revisit the results of this latter paragraph in the presence of the stock effect. That is, the marginal harvesting cost function decreases in the resource stock. In this context,

[1] Interested readers may refer to LaRiviere et al. (2020) for a survey of studies on the effects of uncertainty and learning in natural resource management.

in addition to facing structural uncertainty, the manager also faces uncertainty due to the anticipation of learning. The latter form of uncertainty affects, depending on the curvature of the marginal harvesting costs, the expected marginal utility of investment, giving rise to changes in harvest. Our analysis reveals that the interplay between both mechanisms may lead to new insights relative to the constant marginal harvesting cost case. For instance, even if the mean of the dispersal shock is linear, the manager can actually reduce harvest in both patches under learning.

We also address the sensitivity of our results with respect to model parameters. Our analysis shows that, if the resource price is not patch specific, escapement in each patch is not price dependent when utility is linear in harvest. This result is reversed when the resource price differs across patches. In the presence of the stock effect, we find that escapement depends on the resource price even if the price across patches does not vary. A mean preserving spread in the distribution of the dispersal shock does not affect optimal escapement when utility is linear in harvest. However, this result does not necessarily hold in the presence of the stock effect. Our analysis also reveals that a mean preserving spread in the distribution of prior beliefs about the unknown parameter does not result in a change in optimal harvest when the mean of the dispersal shock is linear. A mean preserving spread increases harvest in a patch while reducing harvest in the other patch when the mean is either convex or concave.

The remainder of the paper is organized as follows. Section 3.2 describes the model in detail. Section 3.3 examines optimal management under full information. Section 3.4 concentrates on optimal management under learning. Section 3.5 is devoted to the equilibrium under stock dependent marginal cost of harvest. Section 3.6 concludes.

3.2 Model

A planner (economic agent) manages a mobile renewable resource stock scattered within an ecosystem constituted of two zones (or patches) A and B. We consider a discrete time approach with an infinite planning horizon. In period t, the planner chooses the harvest level h_{it} in patch $i = A, B$, so as to maximize the sum across both patches of individual expected net present values of harvest. The variable X_{it} represents the resource stock in patch i at the beginning of period t whereas $y_{it} = X_{it} - h_{it}$ stands for patch i's resource stock conserved for future use (i.e., escapement or investment in future resource stock).

At the end of period-t harvesting season, the resource stock naturally grows. The biological growth function in each patch is subject to random variations of environmental conditions (rainfall, nutrients, temperature). Following Reed (1979) and Costello et al. (2008), these features determine patch i's growth function as follows

$$Q_{it} = Z_{it}^{p} g_i(y_{it}), \tag{3.1}$$

where Z_{it}^{p} is a random variable. The variables Z_{it}^{p} are independently and identically distributed with known distributions, expected value $E(Z_{it}^{p})$ equal to 1 and support bounded above by $\kappa < \infty$ and below by 0. The growth function $g_i(.)$ satisfies standard properties: it is increasing, concave, and twice continuously differentiable.

Mobility of the resource induces a spatial connection across patches. The period-t dispersion of the resource population across patches is represented by the 2×2 dispersal matrix (ψ_{ijt}), $i, j = A, B$. More precisely, in period t, the fraction $\psi_{ijt} \geqslant 0$ of patch i's resource stock migrates to patch j while the fraction $\psi_{iit} > 0$ remains in patch i. To be consistent with discrete time models of migratory biological resources (Costello et al., 2019), we assume that $\psi_{ijt} + \psi_{iit} \leqslant 1$. Random changes in environmental conditions (e.g. prevailing winds and ocean currents) heterogeneously affect resource migration across patches.

Specifically, while such changes improve environmental conditions (raise in-migration) in one patch, they can deteriorate environmental conditions (raise out-migration) in the other patch. This phenomenon accords, for example, with the migration of cyprinid fish from lakes to streams in one season and return in another season. Depending on goals (e.g., spawning, foraging or escaping predators), such migration may involve partial migration (where a part of the population migrates while the other remains resident) or the entire population (Brönmark et al., 2014). To capture this feature, we assume that $\psi_{ABt} = (a - Z_t)D_{AB}$, $\psi_{AAt} = D_{AA}$, $\psi_{BAt} = Z_t D_{BA}$, $\psi_{BBt} = D_{BB}$, where $a \geqslant 0$, Z_t is a random variable with support $F = [0, a]$, where $D_{ij} \geqslant 0$ are constant and deterministic terms. The probability density function (p.d.f.) of Z_t is given by $\phi(z_t|\theta^*)$, where z_t is the actual realization of Z_t, θ^* denotes parameter(s) of the p.d.f. of Z_t.

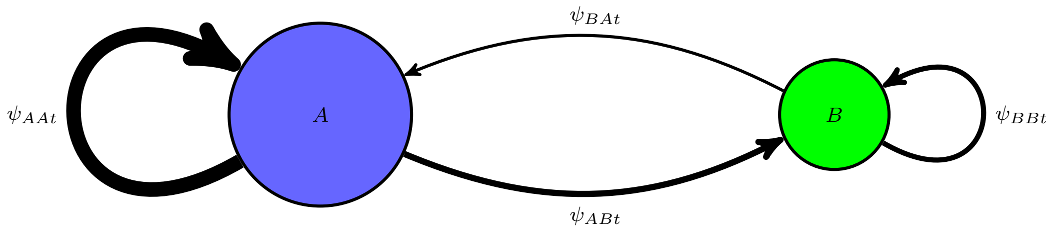


Diagram of dispersal of resource populations across and within patches.

The resource stock dynamics evolve according to the difference equation

$$X_{jt+1} = \sum_{i=A,B} \psi_{ijt} Q_{it} \tag{3.2}$$

This formula reveals that patch $j's$ escapement grows (Q_{it}), and scatters according to the dispersal matrix (ψ_{ijt}).

Since harvest can be expressed in terms of escapement as $h_{it} = X_{it} - y_{it}$, choosing y_{it} is equivalent to choosing h_{it}. Therefore, we consider escapement as the control variable in the remainder of this paper.

The expected net present value of harvest across patches can be written as

$$E(\sum_{t=0}^{\infty} \beta^t \sum_{i=A,B} p_i(X_{it} - y_{it})),$$

where $\beta \in (0, 1)$ is the discount factor. Following Reed (1979); Costello et al. (2001); Costello and Polasky (2008); Costello et al. (2019), we assume that patch i's resource price p_i is constant and may be patch specific.

3.3 Full information Planner

Under full information, although the planner knows the parameter θ^* attached to the p.d.f. of Z_t, the realization of Z_t remains unknown before period-t harvest or escapement decision is made. Consequently, the Bellman equation for the optimization problem associated with the full information planner can be written as

$$W_f(\mathbf{X}_t, \theta^*) = \max_{\mathbf{y}_{ft}} \{ \sum_{i=A,B} p_i(X_{it} - y_{ift}) + \beta \int_F W_f(\mathbf{X}_{t+1}; \theta^*) \phi(z_t|\theta^*) dz_t \}, \tag{3.3}$$

where $\mathbf{X}_t = (X_{At}, X_{Bt})$, $\mathbf{y}_{ft} = (y_{Aft}, y_{Bft})$, and the subscript "$f$" stands for full information. The problem in (3.3) is subject to the equation of motion defined in (3.2). The first right-hand side term in (3.3) represents period-t total revenue from harvesting in both patches. The second right-hand side term in (3.3) stands for the continuation value of the problem.

For an interior solution, the first-order conditions for the optimization problem in (3.3) reads

$$p_i = \beta \int_F \Big(\sum_{j=A,B} \frac{\partial W_f(\mathbf{X}_{t+1};\theta^*)}{\partial X_{jt+1}} \frac{\partial X_{jt+1}}{\partial y_{ift}} \Big) \phi(z_t|\theta^*) dz_t, i = A, B. \quad (3.4)$$

Condition (3.4) suggests that at the optimum, the planner harvests up to the escapement level that equates marginal revenue p_i from harvesting in patch i to the value lost by harvesting today rather than allowing the resource to grow for future harvests. Despite the fact that the resource is exploited over more than two periods, conditions (3.3) and (3.4) suggest that period-t optimal escapements are solutions to a two-period model. Equation (3.4) suggests that the optimal escapement level may not depend on the current resource stock, since the right-hand side term does not explicitly depend on $\mathbf{X}_t$. We next investigate this issue in the following lemma.

Lemma 3.1. *(i) Optimal escapement in patch A is the solution to*

$$p_A = \beta g'_A(y_{Aft}) \left(p_A D_{AA} + p_B (a - \mu(\theta^*)) D_{AB} \right), \quad (3.5)$$

where $\mu(\theta^*) = \int_F z_t \phi(z_t|\theta^*) dz_t$ *represents the mean of* Z_t.

(ii) Optimal escapement in patch B is defined as

$$p_B = \beta g'_B(y_{Bft})(p_A \mu(\theta^*) D_{BA} + p_B D_{BB}). \quad (3.6)$$

Proof. See Appendix 4.8.

The results of Lemma 3.1 show that optimal escapement depends on the resource price, biological, and environmental conditions and illustrate two important properties of the optimum. First, in the absence of spatial movement, the golden rule of growth in resource management suggests that the financial rate of return equals the expected biological growth of the stock when the resource stock is optimally exploited. In our context of spatial management and learning, never investigated, such a golden rule of growth should be adjusted to account for biophysical conditions $(\mu(\theta^*), D_{ij})$ and inter-connectivity across patches. Second, Lemma 3.1 sheds light on the importance of asymmetry. For example, conditions (3.5) and (3.6) reveal that optimal escapement does not depend on the resource price as long as the resource price is not patch specific. This result is, however, reversed if the resource price differs across patches. An increase in patch $B's$ resource price raises patch $B's$ financial rate of return (i.e., $p_B/\beta(p_A\mu(\theta^*)D_{BA}+p_BD_{BB})$). Consequently, the planner optimally lowers patch $B's$ escapement in response to any increase in p_B. We also find that an increase in patch $A's$ resource price increases escapement in patch B.

3.4 Learning planner

In constrast to the full information planner's case, the learning planner is uncertain about the parameter θ^* associated with $\phi(z_t|\theta^*)$. As a result, he forms initial beliefs regarding the distribution of θ^*. Such beliefs are represented by the prior p.d.f. $\xi(\theta)$ with support $\Theta \subset \mathbb{R}^+$. Moreover, after observing the shock, the planner utilizes the actual realization z_t of the shock to formulate posterior beliefs using the Bayesian method. According to Baye's rule, the planner's posterior beliefs (updated beliefs) are represented by the p.d.f.

$$\hat{\xi}(\theta|z_t) = \frac{\phi(z_t|\theta)\xi(\theta)}{\int_{\Theta}\phi(z_t|x)\xi(x)dx}.$$

The planner is rational as he anticipates the effects of learning on both future resource stocks and beliefs. Anticipation of learning in period t is captured by the fact that the payoff in period $t+1$ is a function of updated beliefs $\hat{\xi}(.|z_t)$ about θ^*. As such, the value function associated with the learning planner's case satisfies the Bellman equation

$$W_l(\mathbf{X}_t, \xi) = \max_{\mathbf{y}_{lt}} \{ \sum_{i=A,B} p_i(X_{it} - y_{ilt}) + \beta \int_F W_l(\mathbf{X}_{t+1}, \hat{\xi}(.|z_t))[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t\}, \quad (3.7)$$

where $\mathbf{X}_t = (X_{At}, X_{Bt})$ is a state vector of resource stock, $\mathbf{y}_{lt} = (y_{Alt}, y_{Blt})$ is a control vector of escapement in period t and the subscript "l" stands for learning. The optimization problem in (3.7) is subject to (3.2).

Partially differentiating (3.7) with respect to y_{ilt}, we obtain the first-order conditions for an interior solution as follows

$$p_i = \beta \int_F \sum_{j=A,B} (\frac{\partial W_l(\mathbf{X}_{t+1}, \hat{\xi}(.|z_t))}{\partial X_{jt+1}} \frac{\partial X_{jt+1}}{\partial y_{ilt}})[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t, \; i = A, B. \quad (3.8)$$

The difference between conditions (3.8) and (3.4) is that the learning planner does not know the parameter θ^* and therefore replaces the p.d.f. $\phi(z_t|\theta^*)$ with the expected p.d.f. $\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta$ with respect to beliefs $\xi(\theta)$.

As shown in the appendix, the value function for the problem faced by the learning planner takes the form

$$W_l(\mathbf{X}_t, \xi) = \sum_{j=A,B} p_j(X_{jt} - y^*_{jl}(\xi)) + \nu(\xi), \quad (3.9)$$

where $y^*_{jl}(\xi)$ is optimal escapement in patch j and $\nu(\xi)$ represents the continuation value of the problem. Using (3.9), we characterize optimal escapement as summarized in the following lemma.

Lemma 3.2. *(i) Optimal escapement in patch A is the solution to*

$$g'_A(y_{Alt}) = \frac{p_A}{\beta(p_A D_{AA} + (a - \int_{\Theta}\mu(\theta)\xi(\theta)d\theta)p_B D_{AB})}. \tag{3.10}$$

(ii) Optimal escapement in patch B is defined as

$$g'_B(y_{Blt}) = \frac{p_B}{\beta(p_B D_{BB} + p_A D_{BA}\int_{\Theta}\mu(\theta)\xi(\theta)d\theta)}. \tag{3.11}$$

Proof. See Appendix 4.8.

The results in Lemma 3.2 indicates that the resource is optimally exploited if for each patch the financial rate of return equals the rate of growth of the fish stock. Therefore, any factor that raises patch $j's$ financial rate of return lowers patch $j's$ escapement. For example, patch A's escapement declines (resp. increases) in response to any increase in p_A (resp. p_B) because any increase in p_A (resp. p_B) increases (resp. reduces) patch A's financial rate of return.

Comparing results of Lemma 3.1 and Lemma 3.2 sheds light on the force driving the effects of Bayesian learning. Since the learning planner anticipates that updating prior beliefs changes the structure of the economic problem, we call the expression $\int_{\Theta}\mu(\theta)\xi(\theta)d\theta$ structural uncertainty. This force drives heterogeneous response to learning across patches. For example, in response to any variation of environmental conditions that raises structural uncertainty, the learning planner optimally reduces escapement in patch A and increases that of patch B.

Contemplating (3.5) and (3.10), and (3.6) and (3.11), it is possible to compare optimal escapement under full information to that of learning. Our analysis indicates that if $\int_{\Theta}\mu(\theta)\xi(\theta)d\theta > \mu(\theta^*)$, then optimal escapement under learning is greater in patch A and smaller in patch B. If $\int_\Theta \mu(\theta)\xi(\theta)d\theta < \mu(\theta^*)$, then optimal escapement under learning is lower in patch A and higher in patch B. Moreover, if $\int_\Theta \mu(\theta)\xi(\theta)d\theta = \mu(\theta^*)$, then learning does not affect optimal escapement relative to the full information case. These results suggest that the effects of learning critically depend on the magnitude of structural uncertainty. We next use these findings to shed further light on the implications of learning in the context where beliefs about the unknown parameter are unbiased.

Proposition 3.1. *When beliefs about the unknown parameter are unbiased, (i.e. $\theta^* = \int_\Theta \theta\xi(\theta)d\theta$), the following results hold:*

(i) If $\mu(\theta)$ is convex, then $y_{Af}(\theta^*) > y^*_{Al}(\xi)$ and $y_{Bf}(\theta^*) < y^*_{Bl}(\xi)$.

(ii) If $\mu(\theta)$ is concave, then $y_{Af}(\theta^*) < y^*_{Al}(\xi)$ and $y_{Bf}(\theta^*) > y^*_{Bl}(\xi)$.

(iii) If $\mu(\theta)$ is linear, then $y_{if}(\theta^*) = y^*_{il}(\xi)$ for $i = A, B$.

Proof. See Appendix 4.8.

The results of Proposition 3.1 are driven by the magnitude of structural uncertainty and show three different ways the curvature of $\mu(\theta)$ affects management under learning relative to the full information case. First, if $\mu(\theta)$ is convex in θ, by Jensen's inequality, structural uncertainty is sufficiently high (i.e., $\mu(\theta^*) < \int_\Theta \mu(\theta)\xi(\theta)d\theta$). As such, learning reduces escapement in patch A and increases escapement in patch B. Second, for scenarios in which $\mu(\theta)$ is concave in θ, structural uncertainty is sufficiently small (i.e., $\mu(\theta^*) > \int_\Theta \mu(\theta)\xi(\theta)d\theta$). In this context, learning increases escapement in patch A and lowers escapement in patch B. Third, in the case where $\mu(\theta)$ is linear in θ, structural uncertainty equals $\mu(\theta^*)$ (i.e., $\mu(\theta^*) = \int_\Theta \mu(\theta)\xi(\theta)d\theta$). As a result, learning does not affect escapement.

Evidence suggests that environmental events such as climate change and El-Niño southern oscillation are expected to be on the rise (Cai et al., 2021). Such events will have critical effects on fish movement and growth. To shed light on this issue, we next examine how sensitive our results are to changes in the distribution of the random shocks and beliefs.

Definition 1. *For any two p.d.f.s ω and $\tilde{\omega}$, ω first-order stochastically dominates $\tilde{\omega}$, if for every non decreasing function $\gamma : \mathbb{R} \to \mathbb{R}$, the inequality $\int_{\mathbb{R}} \gamma(x)\omega(x)dx \geqslant \int_{\mathbb{R}} \gamma(x)\tilde{\omega}(x)dx$ holds (i.e., the expected value associated with ω is higher).*

Denote by $\tilde{\phi}(z_t|\theta)$ another distribution for the random shock Z_t, with $\tilde{\mu}(\theta) = \int_F z_t\tilde{\phi}(z_t|\theta)dz_t$ and $y^*_{il}(\tilde{\phi})$ as the associated mean and escapement. Likewise, consider $\tilde{\xi}$ another distribution for prior beliefs with $y^*_{il}(\tilde{\xi})$ the resulting escapement. The effects of changing the mean of the distribution of random shock ϕ on optimal escapement of the learning planner is summarised in the following proposition.

Proposition 3.2. *If ϕ first-order stochastically dominates $\tilde{\phi}$, then $y^*_{Al}(\phi) \leqslant y^*_{Al}(\tilde{\phi})$ and $y^*_{Bl}(\phi) \geqslant y^*_{Bl}(\tilde{\phi})$.*

Proof. See Appendix 4.8.

The results of Proposition 3.2 is driven by structural uncertainty. Indeed, structural uncertainty associated with ϕ is higher relative to structural uncertainty associated with $\tilde{\phi}$ whenever ϕ first-order stochastically dominates $\tilde{\phi}$. As such, patch A's escapement associated with ϕ is lower than the one associated with $\tilde{\phi}$ and the reverse scenario holds in patch B.

We also examine the effects of changing the mean of the p.d.f. of prior beliefs on optimal escapement. Our results are summarized in the following proposition.

Proposition 3.3. *If ξ first-order stochastically dominates $\tilde{\xi}$, then the following results hold: i) If $\mu' > 0$, then $y^*_{Al}(\xi) \leqslant y^*_{Al}(\tilde{\xi})$ and $y^*_{Bl}(\xi) \geqslant y^*_{Bl}(\tilde{\xi})$.*

(ii) If $\mu' < 0$*, then* $y^*_{Al}(\xi) \geqslant y^*_{Al}(\tilde{\xi})$ *and* $y^*_{Bl}(\xi) \leqslant y^*_{Bl}(\tilde{\xi})$.

(iii) If $\mu' = 0$ *, then* $y^*_{il}(\xi) = y^*_{il}(\tilde{\xi})$ *for* $i = A, B$.

Proof. See Appendix 4.8.

Results of Proposition 3.3 hinges on the magnitude of structural uncertainty. In particular, structural uncertainty under ξ exceeds the one under $\tilde{\xi}$ whenever $\mu' > 0$ and ξ first-order stochastically dominates $\tilde{\xi}$. In such a scenario, patch A's escapement associated with ξ is lower than the one associated with $\tilde{\xi}$ while patch B's escapement associated with ξ exceeds the escapement associated with $\tilde{\xi}$. On the other hand, structural uncertainty under ξ is lower relative to the one under $\tilde{\xi}$ when $\mu' < 0$. In this case, patch A's escapement is higher under ξ relative to $\tilde{\xi}$ but patch B's escapement is lower under ξ in comparison to $\tilde{\xi}$.

To shed further light on how changes in the distribution of random shocks and beliefs affect the planner's behavior, we next investigate the effects of mean preserving spreads. To facilitate our discussion, we utilize the following definition.

Definition 2. *For any two p.d.f.s* ω *and* $\tilde{\omega}$*,* $\tilde{\omega}$ *is a mean preserving spread of* ω*, if* ω *and* $\tilde{\omega}$ *have the same mean and for every concave function* $\gamma : \mathbb{R} \to \mathbb{R}$*, the inequality* $\int_{\mathbb{R}} \gamma(x)\omega(x)dx \geqslant \int_{\mathbb{R}} \gamma(x)\tilde{\omega}(x)dx$ *is satisfied.*

This definition provides a tool that can help rank risky assets. For example, it states that if we consider two lotteries U and V with the same mean, a risk averse agent would prefer U over V if V is a mean preserving spread of U. Using Definition 2, we outline the effects of mean preserving spreads with respect to the distribution of the dispersal shock.

Proposition 3.4. *If* $\tilde{\phi}$ *is a mean preserving spread of* ϕ*,* $y^*_{il}(\phi) = y^*_{il}(\tilde{\phi})$ *for* $i = A, B$.

Proof. See Appendix 4.8.

Proposition 3.4 states that a mean preserving spread of the distribution of dispersal shocks does not affect optimal escapement under learning. The intuition underlying this result is as follows. Structural uncertainty depends only on the mean of dispersal shocks $\mu(\theta)$ and the p.d.f. ξ of prior beliefs. Consequently, any change in the distribution of dispersal shocks that preserves its mean does not alter structural uncertainty. As such, any mean preserving spread does not affect optimal escapement under learning.

Although an increase in riskiness of dispersal shocks has no impact on escapement, Proposition 3.5 suggests that mean preserving spreads of the distribution of prior beliefs about the unknown parameter does affect escapement.

Proposition 3.5. *If $\tilde{\xi}$ is a mean preserving spread of ξ, then the following results hold:*

(i) If $\mu''(\theta) < 0$, then $y^*_{Al}(\xi) \leqslant y^*_{Al}(\tilde{\xi})$ and $y^*_{Bl}(\xi) \geqslant y^*_{Bl}(\tilde{\xi})$.

(ii) If $\mu''(\theta) > 0$, then $y^*_{Al}(\xi) \geqslant y^*_{Al}(\tilde{\xi})$ and $y^*_{Bl}(\xi) \leqslant y^*_{Bl}(\tilde{\xi})$.

(iii) If $\mu''(\theta) = 0$, then $y^*_{il}(\xi) = y^*_{il}(\tilde{\xi})$ for $i = A, B$.

Proof. See Appendix 4.8.

The results of Proposition 3.5 outline three different ways the curvature of $\mu(\theta)$ affects optimal escapement under learning. If $\mu(\theta)$ is concave, a mean preserving spread in beliefs reduces structural uncertainty (i.e., $\int_\Theta \mu(\theta)\xi(\theta)d\theta > \int_\Theta \mu(\theta)\tilde{\xi}(\theta)d\theta$). As such, optimal escapement in patch A (resp. patch B) is higher (resp. lower) under $\tilde{\xi}$ relative to ξ. In scenarios where $\mu(\theta)$ is convex, a mean preserving spread in beliefs increases structural uncertainty (i.e., $\int_\Theta \mu(\theta)\xi(\theta)d\theta < \int_\Theta \mu(\theta)\tilde{\xi}(\theta)d\theta$). Consequently, in this context, patch A's (resp. patch B's) escapement associated with $\tilde{\xi}$ is lower (resp. higher) than the one associated with ξ. However, in the case where $\mu(\theta)$ is linear, structural uncertainty remains unchanged in response to a mean preserving spread in ξ (i.e.,

$\int\limits_{\Theta}\mu(\theta)\xi(\theta)d\theta = \int\limits_{\Theta}\mu(\theta)\tilde{\xi}(\theta)d\theta)$. As a result, in this context, optimal escapement is not sensitive to mean preserving spreads.

3.5 Stock dependent marginal cost

The stock effect is a standard feature in natural resource economics which states that marginal harvesting costs increase as the resource stock decreases. In previous sections, we have derived important results under the constant marginal harvesting cost function case. The intuition gleaned will allow us to understand implications of the stock effect to which we now turn.

3.5.1 Full information planner

In this setting, the Bellman equation for the optimization problem of the full information planner can be written as

$$W_f(\mathbf{X}_t, \theta^*) = \max_{\mathbf{y}_{ft}} \{ \sum_{i=A,B} [p_i(X_{it} - y_{ift}) - \int_{y_{ift}}^{X_{it}} c_i(r)dr] + \beta \int\limits_{F} W_f(\mathbf{X}_{t+1}; \theta^*)\phi(z_t|\theta^*)dz_t \}, \tag{3.12}$$

subject to the equation of motion defined in (3.2). The first right-hand side term in (3.12) represents the period-t total profit from harvesting in both patches, while the second right-hand side term is the continuation value of the problem. In condition (3.12) , $c_i(r)$ represents the marginal harvesting cost function. We assume that marginal cost of harvest, $c_i(r)$, is decreasing in the resource stock (i.e., $c_i'(r) < 0$).

For an interior solution, the first-order conditions for the optimization problem in (3.12) reads

$$p_i = c_i(y_{ift}) + \beta \int\limits_{F} (\sum_{j=A,B} \frac{\partial W_f(\mathbf{X}_{t+1}; \theta^*)}{\partial X_{jt+1}} \frac{\partial X_{jt+1}}{\partial y_{ift}}) \phi(z_t|\theta^*) dz_t \ \forall i. \tag{3.13}$$

Condition (3.13) reveals that at the optimum, the planner chooses her escapement level to equate the resource price in each patch with the augmented marginal cost, which consists of the direct marginal harvesting cost and the value lost by harvesting today rather than allowing the resource to grow for future harvests. Since $\mathbf{X}_{t+1}$ depends on y_{At} and y_{Bt} and does not explicitly depend on the current resource stock in either patch, optimal escapement in each patch can be stock and time independent. We verify this in the following lemma.

Lemma 3.3. *(i) Optimal escapement in patch A is the solution to*

$$\begin{aligned} p_A = c_A(y_{Aft}) + \beta g'_A(y_{Aft})\{p_A D_{AA} + p_B D_{AB}(a - \mu(\theta^*)) \\ - \int_F (c_A(X_{At+1})D_{AA} + c_B(X_{Bt+1})(a - z_t)D_{AB})\phi(z_t|\theta^*)dz_t\}. \end{aligned} \tag{3.14}$$

(ii) Optimal escapement in patch B satisfies

$$\begin{aligned} p_B = c_B(y_{Bft}) + \beta g'_B(y_{Bft})\{p_A D_{BA}\mu(\theta^*) + p_B D_{BB} \\ - \int_F (c_A(X_{At+1})z_t D_{BA} + c_B(X_{Bt+1})D_{BB})\phi(z_t|\theta^*)dz_t\}. \end{aligned} \tag{3.15}$$

Proof. See Appendix 4.8.

Conditions (3.14) and (3.15) suggest that optimal escapements, y_{Aft} and y_{Bft} are stock and time independent. Moreover, optimal escapement depends on marginal costs of harvest, resource prices, biological returns, environmental conditions, and random shocks affecting resource movement across patches. Our analysis reveals that accounting for the stock effect can give rise to new incentives. For example, in contrast to the constant marginal harvesting cost case, conditions (3.14) and (3.15) show that optimal escapement actually depends on the resource prices even if such prices are identical across patches.

3.5.2 Learning Planner

The value function associated with the learning planner's economic problem satisfies the Bellman equation

$$W_l(\mathbf{X}_t, \xi) = \max_{\mathbf{y}_t} \{ \sum_{i=A,B} [p_i(X_{it} - y_{it}) - \int_{y_{it}}^{X_{it}} c_i(r)dr] + \beta \int_F W_l(\mathbf{X}_{t+1}, \hat{\xi}(.|z_t))[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t\}, \tag{3.16}$$

which is subject to the equation of motion defined in (3.2).

Partially differentiating (3.16) with respect to y_{ilt} yields the first-order conditions for an interior solution

$$p_i - c_i(y_{ilt}) = \beta \int_F (\sum_{j=A,B} \frac{\partial W_l(\mathbf{X}_{t+1}, \hat{\xi}(.|z_t))}{\partial X_{jt+1}} \frac{\partial X_{jt+1}}{\partial y_{ilt}})[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t \ \forall i. \tag{3.17}$$

Condition (3.17) suggests that optimal escapement in patch i is obtained when the net marginal revenue $p_i - c_i(y_{ilt})$ from harvest in the current period equals the expected discounted marginal cost, in terms of the forgone value of harvestable stock in the next period. Optimal escapement in each patch can be stock independent, as shown in the following lemma.

Lemma 3.4. *(i) Optimal escapement in patch A is the solution to*

$$p_A - c_A(y_{Alt}) = \beta g'_A(y_{Alt})\{p_A D_{AA} + p_B D_{AB}(a - \int_\Theta \mu(\theta)\xi(\theta)d\theta) - \int_F (c_A(X_{At+1})D_{AA} + c_B(X_{Bt+1})(a - z_t)D_{AB})[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t\}. \tag{3.18}$$

(ii) Optimal escapement in patch B satisfies

$$p_B - c_B(y_{Blt}) = \beta g_B'(y_{Blt})\{p_A D_{BA}\int_{\Theta}\mu(\theta)\xi(\theta)d\theta + p_B D_{BB} - \int_{F}(c_A(X_{At+1})z_t D_{BA} + c_B(X_{Bt+1})D_{BB})[\int_{\Theta}\phi(z_t|\theta)\xi(\theta)d\theta]dz_t\}. \tag{3.19}$$

Proof. See Appendix 4.8.

Comparing (3.10) and (3.11) to (3.18) and (3.19), we observe two mechanisms through which learning affects optimal escapement relative to the full information scenario. The first mechanism is structural uncertainty (i.e., $\int_{\Theta}\mu(\theta)\xi(\theta)d\theta$). A higher structural uncertainty under learning tends to reduce patch A's escapement and tends to raise patch B's escapement, relative to the full information scenario. The second mechanism — uncertainty due to anticipation of learning (i.e., $\int_{\Theta}\phi(z_t|\theta)\xi(\theta)d\theta$) — affects optimal escapement through the stock dependent marginal cost function. A higher uncertainty due to anticipation of learning tends to reduce optimal escapement in each patch.

Proposition 3.6. *When beliefs about the unknown parameter are unbiased, (i.e., $\theta^* = \int_{\Theta}\theta\xi(\theta)d\theta$), the following results hold:*

(i) If $\mu(\theta)$ is linear and $\phi(.|\theta)$ is convex in θ, then $y_{if}(\theta^*) > y_{il}^*$ for $i = A, B$.

(ii) If $\mu(\theta)$ is linear and $\phi(.|\theta)$ is concave in θ, then $y_{if}(\theta^*) < y_{il}^*$ for $i = A, B$.

Proof. See Appendix 4.8.

Recall that in the absence of the stock effect, when $\mu(\theta)$ is linear, as shown in Proposition 3.1, learning does not affect escapement because structural uncertainty vanishes in this case. Proposition 3.6 suggests that such a result does not necessarily hold in the presence of the stock effect. The forces underlying the results of Proposition 3.6 work as follows.

When $\phi(.|\theta)$ is convex in θ, by Jensen's inequality, uncertainty due to anticipation of learning is high (i.e., $\int_{\Theta}\phi(z_t|\theta)\xi(\theta)d\theta > \phi(z_t|\theta^*)$). As such, learning reduces escapement in both patches as compared to the full information scenario. However, when $\phi(.|\theta)$ is concave in θ, uncertainty due to anticipation of learning is small (i.e., $\int_{\Theta}\phi(z_t|\theta)\xi(\theta)d\theta < \phi(z_t|\theta^*)$). Consequently, optimal escapement in both patches increases as a result of learning.

Using a method similar to the one applied for the constant marginal cost case, we investigate implications of mean preserving spreads. It is useful to introduce the "augmented marginal harvesting cost" function $f_A(z_t) = c_A(X_{At+1})D_{AA} + c_B(X_{Bt+1})(a - z_t)D_{AB}$ for patch A. Likewise, the "augmented marginal harvesting cost" function for patch B can be written as $f_B(z_t) = c_A(X_{At+1})z_tD_{BA} + c_B(X_{Bt+1})D_{BB}$. Our analysis reveals that when the "augmented marginal harvesting cost" in patch j is convex, a mean preserving spread with respect to $\phi(.|\theta)$ lowers escapement in patch j. For scenarios in which the "augmented marginal harvesting cost" in patch j is concave, a mean preserving spread with respect to $\phi(.|\theta)$ raises escapement in patch j.

Our derivations also show that the effects of a mean preserving spread with respect to $\xi(.)$ critically depends on the curvature of $\phi(.|\theta)$. Specifically, when $\phi(.|\theta)$ is concave in θ and $\mu(\theta)$ is linear in θ, we find that a mean preserving spread with respect to $\xi(.)$ diminishes uncertainty due to the anticipation of learning which increases optimal escapement in both patches. Moreover, if $\phi(.|\theta)$ is convex in θ and $\mu(\theta)$ is linear in θ, a mean preserving spread with respect to $\xi(.)$ raises uncertainty due to the anticipation of learning which lowers individual escapements.

3.6 Conclusion

Mobility across space, a key feature of living resources, is influenced by changes in environmental conditions. The random nature of such environmental changes induces considerable uncertainty about the migration pattern and location of these resources. Our ability to predict resource movements is improving and such information can help enhance resource management. With this in mind, this paper has extended standard natural resource models to examine how learning about spatial resource movements affect optimal management. We have explicitly accounted for heterogeneous environmental, economic, and biological conditions.

Our analysis reveals that accounting for spatial movements represents an important contribution. Prior economic research concentrates on scenarios in which the resource population lives in a single patch and cannot migrate. In our context where the resource stock moves across spatially connected patches (which may differ in terms of environmental, biological, and economic conditions), we find that a planner's optimal response to learning depends on factors arising from individual patches. For example, our analysis reveals that the planner may optimally increase harvest in a patch and reduce harvest in another patch in response to learning when marginal harvesting costs are constant. However, in the stock dependent marginal harvesting cost scenario, we delineate conditions under which the planner optimally reduces harvest in all patches in response to learning.

Our quantitative analysis also reveals that changes in the distribution of the random shock may critically affect harvest responses to uncertainty and learning. For example, a random shock with a higher mean diminishes patch A's optimal escapement under learning and raises patch B's optimal escapement under learning. This result remains valid even if the planner is fully informed about the distribution of the random shock. The planner's responses to mean preserving spreads depend on the shape of the marginal harvesting cost function. For example, a mean preserving spread of the random shock does not affect optimal escapement under learning in each patch when marginal harvesting costs are constant. This result is reversed under scenarios where marginal harvesting costs are stock dependent. Specifically, a mean preserving spread of random shock may lower optimal escapement under learning in each patch when the augmented marginal harvesting cost functions are convex across patches.

Bibliography

Brock, W. and L. Mirman (1972). Optimal economic growth and uncertainty: The discounted case. *Journal of Economic Theory 4*(3), 479–513.

Brönmark, C., K. Hulthén, P. Nilsson, C. Skov, L.-A. Hansson, J. Brodersen, and B. Chapman (2014). There and back again: migration in freshwater fishes. *Canadian Journal of Zoology 92*(6), 467–479.

Cai, W., A. Santoso, M. Collins, B. Dewitte, C. Karamperidou, J.-S. Kug, M. Lengaigne, M. J. McPhaden, M. F. Stuecker, A. S. Taschetto, et al. (2021). Changing el niño–southern oscillation in a warming climate. *Nature Reviews Earth & Environment 2*(9), 628–644.

Clark, C. W. and G. P. Kirkwood (1986). On uncertain renewable resource stocks: Optimal harvest policies and the value of stock surveys. *Journal of Environmental Economics and Management 13*(3), 235 – 244.

Costello, C., S. D. Gaines, and J. Lynham (2008). Can catch shares prevent fisheries collapse? *Science 321*(5896), 1678–1681.

Costello, C., B. Nkuiya, and N. Quérou (2019). Spatial renewable resource extraction under possible regime shift. *American Journal of Agricultural Economics 101*(2), 507–527.

Costello, C. and S. Polasky (2008). Optimal harvesting of stochastic spatial resources. *Journal of Environmental Economics and Management 56*(1), 1 – 18.

Costello, C., S. Polasky, and A. Solow (2001). Renewable resource management with environmental prediction. *Canadian Journal of Economics/Revue canadienne d'économique 34*(1), 196–211.

Costello, C. J., R. M. Adams, and S. Polasky (1998). The value of el niño forecasts in the management of salmon: a stochastic dynamic assessment. *American Journal of Agricultural Economics 80*(4), 765–777.

Diop, B., N. Sanz, Y. J. J. Duplan, F. Blanchard, J.-C. Pereau, L. Doyen, et al. (2018). Maximum economic yield fishery management in the face of global warming. *Ecological Economics 154*, 52–61.

Fabbri, G., S. Faggian, and G. Freni (2020). Policy effectiveness in spatial resource wars: A two-region model. *Journal of Economic Dynamics and Control 111*, 103818.

Fesselmeyer, E. and M. Santugini (2013). Strategic exploitation of a common resource under environmental risk. *Journal of Economic Dynamics and Control 37*(1), 125–136.

Koulovatianos, C., L. J. Mirman, and M. Santugini (2009). Optimal growth and uncertainty: learning. *Journal of Economic Theory 144*(1), 280–295.

LaRiviere, J., D. Kling, J. N. Sanchirico, C. Sims, and M. Springborn (2020). The treatment of uncertainty and learning in the economics of natural resource and environmental management. *Review of Environmental Economics and Policy*.

Lea, R. N. and R. Rosenblatt (2000). Observations on fishes associated with the 1997-98 el niño off california. *Reports of California Cooperative Oceanic Fisheries Investigations 41*, 117–129.

Miranda, J. P. (2007). *Handbook of operations research in natural resources*, Volume 99. Springer Science & Business Media.

Reed, W. J. (1979). Optimal escapement levels in stochastic and deterministic harvesting models. *Journal of environmental economics and management 6*(4), 350–363.

Sanchirico, J. N. and J. E. Wilen (1999). Bioeconomics of spatial exploitation in a patchy environment. *Journal of Environmental Economics and Management 37*(2), 129–150.

Sethi, G., C. Costello, A. Fisher, M. Hanemann, and L. Karp (2005). Fishery management under multiple uncertainty. *Journal of Environmental Economics and Management 50*(2), 300 – 318.

Springborn, M. and J. N. Sanchirico (2013). A density projection approach for non-trivial information dynamics: Adaptive management of stochastic natural resources. *Journal of Environmental Economics and Management 66*(3), 609–624.

Weitzman, M. L. (2002). Landing fees vs harvest quotas with uncertain fish stocks. *Journal of environmental economics and management 43*(2), 325–338.

4 Effectiveness of regional fisheries management organizations: Evidence from the general fisheries commission for the mediterranean

4.1 Introduction

The overexploitation of internationally shared fish stocks has attracted much attention from numerous stakeholders in the last few decades.[1] A popular example is the eventual collapse of the cod *Gadus morhua* in Canada in 1992 (Tsikliras et al., 2015). This catastrophic event resulted in about 30,000 job losses and the displacement of hundreds of coastal communities that depended on the fishery (Higgins, 2008).

Due to severe overexploitation in the late 80s through the early 90s, the UN convened an international conference solely aimed at improving the management of straddling and highly migratory fish stocks. The conference resulted in an agreement widely known as the 1995 UN Fish Stocks Agreement (United Nations, 1995). The agreement urged countries to cooperate through regional fisheries management organizations (RFMOs), in the exploitation of straddling and highly migratory fish stocks (United Nations, 1995). Examples of such RFMOs include the Northwest Atlantic Fisheries Organization (NAFO), Northeast Atlantic Fisheries Commission (NEAFC), and the General Fisheries Commission for the Mediterranean (GFCM) among others.

While RFMOs have the mandate to adopt conservation and management measures that are legally binding on its members, their effectiveness in carrying out this mandate remains in question (Hoel, 2011; Haas et al., 2019, 2020).[2] Indeed, there are indications

[1] Evidence of rising levels of overexploitation is depicted in Figure 4.1 by continent.

[2] In the case of the GFCM for example, members have 120 days, post notification, to raise objections to new policies and regulations. After such a period has elapsed, countries must incorporate the regulations into their national legislation. This implies that nationals cannot disregard such regulations as member countries will be able to legally enforce them (Srour et al., 2020).

that weaknesses in RFMOs are the reason for the decline in most shared fish stocks (Cullis-Suzuki and Pauly, 2010). Such weaknesses include disparity between organization intent (policies on paper) and action (actual implementation). For instance, member countries of most RFMOs have the right to object and opt-out from the obligation to implement an agreed upon measure (Haas et al., 2020). Such rights constitute a major drawback of RFMOs as it is likely to result in 'lowest common denominator' regulations that are weak and unable to address the substantial overexploitation problems.[3] Moreover, illegal, unreported, and unregulated (IUU) fishing by outsiders (with the incentive to overfish) undermine the effectiveness of RFMOs. As a result, the ability of RFMOs to effectively ensure sustainable management requires deliberate effort to prevent IUU fishing.

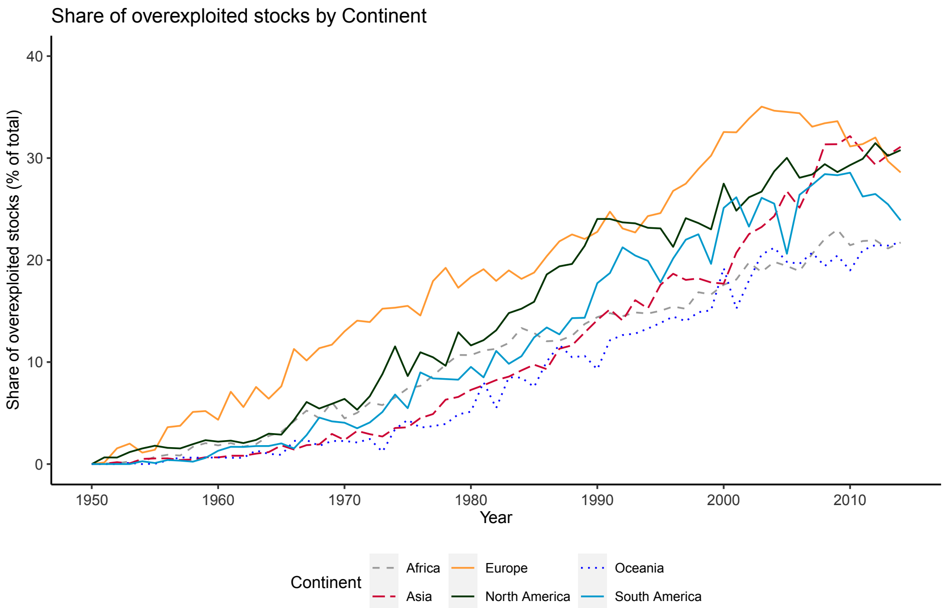


Figure 4.1: Average share of overexploited stocks by Continent over the period 1950 to 2014. This graph shows the average share (across the sample period) of stocks that are overexploited in the EEZ(s) for all countries in a given continent. Note that some countries have more than one EEZ.

In this paper we study the effectiveness of RFMOs in improving the management of

[3]It is considered best practice to require countries to explain in detail the reasons for their objections to the proposed measure, while implementing alternative measures that achieve the same objectives as the one to which objections are raised (Haas et al., 2020). To the best of my knowledge, the GFCM is yet to follow such best practice, unlike other RFMOs such as the South Pacific Regional Fisheries Management Organization (SPRFMO).

shared fish stocks by leveraging the generalized synthetic control method (GSCM). This method facilitates a robust assessment of an RFMO by accounting for the inherent selection bias associated with RFMO membership. The empirical analysis is based on a quasi-experiment involving an amendment to the mandate of the general fisheries commission for the Mediterranean (GFCM). Analyzing data on the share of overexploited stocks, the GSCM allows for comparison of the outcome for countries that are legally bound by the GFCM management measures to their expected business-as-usual outcome (i.e., the expected outcome in the absence of a change in the mandate of the GFCM). This contribution applies a newly developed approach, never explored in the context of RFMOs to investigate the extent to which RFMOs improve the status of fish stocks under their supervision.

Our results show that the amendment to the mandate of the GFCM has no effect on the share of overexploited stocks of member countries. The estimated average treatment effect on the treated (ATT) is between -0.74 and -2.96 percent with standard errors of between 2.56 and 5.19 percent, implying that the GFCM's management measures are not associated with a statistically significant reduction in overexploitation. We verify the robustness of these results by implementing several sensitivity analyses. Specifically, we analyze the share of collapsed, and rebuilding stocks in the period of consideration and our results suggest that the change in the mandate of the GFCM did not have a statistically significant effect on these variables.

Further, we make use of different sub-samples of our control group by selecting countries that (1) are located on the same continent as the treated group, (2) have a given number of RFMO memberships. Under both scenarios, our results buttress the fact that the GFCM's management has not improved fish conservation among member countries. Moreover, we investigate how our results change when we construct separate control groups for our sample of treated EEZs based on continent. Thus, for the treated EEZs in a given continent, we include only EEZs in that continent in our control group. In general, these robustness checks support our main results.

In addition to providing evidence on the ineffectiveness of the GFCM in reducing over-exploitation in its area of competence, our paper makes two important contributions. First, we provide a first attempt of leveraging the GSCM to analyze the effectiveness of international fisheries agreements. We add to the existing literature on the effectiveness of RFMOs by rigorously addressing the issue of endogeneity arising from the inherent selection bias associated with RFMO formation. Second, our study complements ongoing research on the effectiveness of international environmental agreements (IEAs), which operates similar to RFMO agreements (Barrett, 1994; Mitchell, 2003; Vollenweider, 2013; Grunewald and Martinez-Zarzoso, 2016; Almer and Winkler, 2017).

The rest of the paper is organized as follows. Section 4.2 provides a review of the literature on RFMOs. Section 4.3 provides detailed background information about the GFCM and the estimation method, the GSCM. Section 4.4 describes the data sources and the final sample for the analysis. Section 4.5 discusses the empirical strategy. Section 4.6 reports the results and Section 4.7 deals with robustness checks. Section 4.8 concludes.

4.2 Literature review of RFMOs

4.2.1 Theoretical Literature

While focusing on theoretical analysis, a growing body of economic papers investigate the formation and stability of RFMOs. Such papers employ a combination of game theory, dynamic optimization, and numerical simulations to address various issues. For example, Kaitala and Munro (1997) analyze the threat posed by new members to existing coalition members. Hannesson (1997) and Tarui et al. (2008) study the prospects of achieving full cooperation through the threat of punishments in a dynamic game setting. Pintassilgo

(2003) studies the extent to which positive externalities enjoyed by free riders due to the formation of RFMOs undermine the stability of such RFMOs. Kwon (2006) extends the Levhari and Mirman (1980) framework with two countries to a multi-country setting to analyze the prospects of partial cooperation. Miller and Nkuiya (2016) build on Kwon (2006) to analyze the stability of RFMOs when countries can revise their membership decision in each period while facing the threat of an irreversible decline in resource growth. Pintassilgo et al. (2010) extend the analysis by Pintassilgo and Lindroos (2008) to scenarios in which players are asymmetric with respect to unit effort cost.[4] The recent paper by Bediako and Nkuiya (2022) shows that a higher elasticity of intertemporal substitution is likely to result in the success and stability of RFMOs.

The general consensus in the theoretical literature is that the formation of RFMOs always leads to more conservation of stocks, relative to the scenario where countries act non-cooperatively. However, in the real world setting, several factors such as illegal, unreported, and unregulated fishing, environmental variabilites, and the absence of a precautionary and ecosystem based approach (Hoel, 2011; Haas et al., 2019, 2020) undermine the ability of RFMOs to deliver on their mandate of conservation and sustainable management. In this paper, we provide a rigorous empirical investigation of this issue in the context of the GFCM.

4.2.2 Empirical Literature

In this section, we review the existing empirical literature on the effectiveness of RFMOs and highlight the gaps our present paper seeks to fill. These gaps are a result of two missing pieces. One is the fact that selection bias is not sufficiently addressed. Secondly, these studies are mainly descriptive and rely on an exogenous threshold for comparison. Cullis-Suzuki and Pauly (2010) assess the effectiveness of 18 RFMOs by examining the

[4]Interested readers may refer to Pintassilgo et al. (2015) for a more detailed overview of this literature.

current state as well as trends through time of fish stocks under the management of each RFMO. Their results indicate low performance of RFMOs in terms of policies that are in place as well as actual implementation of those policies. Specifically, they find that approximately two-thirds of stocks under RFMO management are either overexploited or collapsed. Although they show trends that depict continuous declines in the biomass of managed stocks, one should not rely solely on such trends to conclude that RFMOs have been ineffective. We address this concern by formulating an appropriate counterfactual to serve as a benchmark for comparison.

Tsikliras et al. (2015) conduct an evaluation of the status of the Mediterranean Sea and the Black Sea fisheries for the period 1970 - 2010, using indicators such as total catches, number of recorded stocks, and stock classification methods among others. Their findings show evidence of overexploitation in the Mediterranean and Black Sea (i.e., the areas under the control of the GFCM). Although these results represent important contributions to the literature on fisheries overexploitation, their analysis does not necessarily address the role of RFMOs and in particular the GFCM in the overexploitation that has occured in the Mediterranean and Black Seas.

The paper by Gilman et al. (2014) analyzes the effectiveness of 13 RFMOs in regulating bycatch (non-targeted catch) and find results suggesting poor performance. While their study represents an important contribution, it has some limitations. They only concentrate on cross-sectional analyses of RFMOs' performance by ranking them based on an exogenous threshold. In this paper, we propose a method of comparison, the GSCM, which does not rely on an exogenous threshold. Further, they do not account for heterogeneity in the membership of different RFMOs. This is a cause for concern as member countries engage in self-selection informed by their own country size, level of economic development, location, and the extent of overfishing. Consequently, their results may be biased due to self selection into RFMO membership. Our contribution addresses these concerns using a panel dataset with time varying controls on 94 countries.

4.3 Background

4.3.1 The General Fisheries Commission for the Mediterranean

The establishment of RFMOs to oversee fisheries governance and enhance cooperation among fishing nations began as a series of post-World War II conventions negotiated between two or more coastal states. The main aim was to provide scientific support for fisheries management to member countries (Srour et al., 2020). This predates the 1982 United Nations Convention on the Law of the Sea (UNCLOS) which provided guidelines for managing marine resources by establishing the concept of exclusive economic zones (EEZs) within which coastal states can exercise the right to fish (United Nations, 1982).[5] However, the UNCLOS did not emphasize the role of RFMOs in managing stocks that straddle multiple EEZs and the high seas. It was not until the United Nations Fish Stocks Agreement (UNFSA) in 1995 when the UN recognized the role of RFMOs in the management of internationally shared living marine resources. The UNFSA called for the management of shared (straddling) fish stocks to be undertaken on a region by region basis through RFMOs, constituted by coastal states with interest in the said fish stock (United Nations, 1995). After the adoption of the UNFSA, the mandates of existing RFMOs needed to be revised to accommodate some of the recommendations laid out in the agreement.

Several RFMOs that existed prior to the UNCLOS including the GFCM were under the Food and Agriculture Organization. The GFCM was created in 1949 as one of the post-World War II advisory bodies devoid of management powers. Its role was mainly to provide scientific advice to member countries with interest in the fish stocks located in

[5] An exclusive economic zone (EEZ) extends up to 200 nautical miles (370 km) from the shore of a coastal nation (Munro, 2007).

the Mediterranean and Black Seas. In 1997 a revision of the mandate of the GFCM was initiated to allow the implementation of management measures that would be binding on member countries. However, actual implementation of this new mandate commenced in 2004 (Srour et al., 2020).

Although the amendment contained specific provisions for addressing IUU fishing, its aim was to enable the commission to effectively fulfill its core mandate of ensuring optimum utilization, rational management, and conservation of fishery resources within the area of competence (NAFO, 2004). As a consequence, the GFCM formulated measures such as (1) procedures for listing of fishing vessels engaged in IUU fishing, (2) the establishment of an authorized vessels list, (3) the reduction of fishing effort on some threatened species, (4) the establishment of restricted areas to fishing, and (5) establishment of appropriate specifications of fishing technology, among others (Srour et al., 2020; GFCM, 2010).

The GFCM differs from other RFMOs in three different ways. First, its mandate covers not only EEZs of member countries but also all the types of species within their geographical range, unlike most other RFMOs that operate in the high seas with limited species coverage. Second, the change in its mandate provides a natural experiment for analyzing its effectiveness after the implementation of their new mandate. Lastly, it comprises of 23 contracting parties (members), a relatively large sample of countries affected by a change in policy. These features make the GFCM a strong candidate for our analysis.

4.3.2 Generalized synthetic control method

In order to assess policy effectiveness, economists usually compare the post-policy outcomes to the outcome that would have been realized in the same period in the absence of such a policy. This amounts to nothing more than estimating an appropriate counterfactual (i.e., the would-have been outcome). To this end, some studies rely on regression based approaches (such as regression discontinuity, instrumental variables etc.). However, in most cases, a policy implementation or change may not be exogenous (which is a standard assumption of regression based approaches). Examples of such scenarios include environmental agreements, international fisheries agreements, adoption of individual tradable quotas, etc. The voluntary nature of these policy changes results in selection bias arising from the fact that reasons for the implementation of such policies may differ from one entity (i.e., government, state, etc) to another and may be influenced by each entity's specific characteristics. To account for this selection problem, a number of studies employ the difference-in-differences (DID) approach (for example, Isaksen and Richter, 2019, employ DID to analyze the effectiveness of individual tradable quota systems (ITQs) in reducing overfishing.). However, the main problem with this method is two-fold. First, selection of control group is ad hoc and subjective. Second, it relies on the parallel trends assumption which states that in the absence of the treatment, the average outcome of interest for the treated and control units should have followed parallel trends. This assumption is difficult to verify directly and in most cases does not appear to be supported by data (Xu, 2017).

There are several approaches in the literature that attempt to address this problem. One of them is the synthetic control method introduced by Abadie and Gardeazabal (2003) in their analysis of the effects of civil unrest on economic outcomes.[6] The idea behind this approach is based on the fact that a weighted combination of control units that most closely resembles a treated unit (before treatment occured) serves as a better counterfactual than any single unit on its own. An interesting feature of this approach is that it does not rely on the assumption of parallel trends, as the choice of the synthetic control does not require any knowledge of post-treatment outcomes. It utilizes only pre-treatment predictors and the pre-treatment outcome(s) in constructing the sythetic

[6] Interested readers may refer to Abadie et al. (2010) for a detailed treatment of the sythetic control method.

counterfactual. However, its major limitation is that it applies to the scenario where there is only one treated unit. The generalized synthetic control method (GSCM), as the name implies, is a more general approach and permits the study of several treated units at different treatment periods.

4.4 Data

We compile data on stock status, harvest, fish value, environmental conditions and economic indicators. The data on stock status, harvest, and fish value are drawn from the Sea Around Us (SAU) project. The stock status data include the share of stocks that are collapsed, overexploited, developing, rebuilding, and exploited at the level of national exclusive economic zones (EEZs) from 1950 - 2014. In our analysis, we make use of the share of overexploited stocks, and two of the other measures (collapsed and rebuilding) to infer the extent of improvement in the status of stocks within the area of competence of the GFCM. The data on harvest contains catch per species in tonnes across EEZs. The value of fish provides information on the market value of fish in real 2010 US dollars. We include data on sea surface temperature obtained from Isaksen and Richter (2019) in order to capture any potential effects of environmental conditions on harvest, which in turn affects the stock status of species across EEZs. [7]

The data on economic indicators are obtained from the Penn World table (version 10.0) as well as the World Bank's world development indicators (WDI). The variables we include in our analysis are: real GDP per capita; population size in millions; and agriculture, forestry, and fishing value added as a percentage of GDP. An observation in the data is constituted by each EEZ-Country-year pair. Finally, we obtain information on

[7] According to the SAU project, a stock is overexploited in a particular year if catch falls within 50% and 10% of the maximum catch recorded since 1950. A stock is deemed collapsed if the harvest in a particular year is less than 10 percent of peak harvest and the year is after the peak year. A stock is classified as rebuilding if harvest is between 10 percent and 50 percent of peak harvest and the year in question is after the post-peak minimum harvest (Pauly D. and Palomares, 2020).

the membership of the GFCM from the food and agriculture organization (FAO). The data provides information on all 23 member countries including the European union. Our baseline analysis incorporates data on 11 countries due to lack of data for the remaining countries. Out of the 11 countries, we have 12 EEZs in the final dataset due to the fact that Turkey has two EEZs that fall within the area of operation of the GFCM. The contol group comprises 103 EEZs located within 83 countries.

Table 4.1 shows a high variation in the dependent variables (Overexploited, Collapsed, and Reguilding) utilized in the paper. The range of the share of overexploited stocks spans from 0 percent to 81 percent. The share of rebuilding stocks ranges between 0 percent to 54.6 percent. In the case of collapsed stocks the shares fall between 0 percent and 100 percent. El Salvador is an outlier, having collapsed shares up to 100 percent. Excluding El Salvador in the robustness checks in Section 4.7, we find results that are not qualitatively different from our main results that includes El Salvador.[8]

The plot in Figure 4.2 shows the shares of overexploited stocks for the control group (on the left) and the treated group (on the right) with their averages superimposed on each panel over the period of analysis. The average overexploitation for both rose between 1950 and 2005 but thereafter the control group average levels off while that of the treated group declines. This plot, however, does not control for any covariates and the role of the GFCM as a fisheries management body. Hence, the following econometric analysis attempts to clarify whether this correlation over time holds when quasi-experimental methods are applied.

[8]In terms of time varying controls such as Total harvest, Real GDP per capita, and population with very high standard deviations and spanning relatively wide ranges, we apply log transformation in the estimated models in order to control the impact of such large variations.

Table 4.1: Summary statistics of variables

Statistic	N	Mean	Min	Max	St. Dev.
Overexploited (% out of total stock)	9,657	12.77	0	81	14.56
Collapsed (% out of total stock)	9,657	9.32	0	100	13.39
Exploited (% out of total stock)	9,657	25.14	0.00	100.00	19.48
Rebuilding (% out of total stock)	9,458	2.79	0.00	54.55	5.40
Total harvest (tonnes)	4,952	892.97	1.09	28,002.34	2,055.44
Value of harvest (million, real 2010 USD)	4,952	16.17	4.56	26.29	3.09
Fish value added (in constant 2010 USD)	5,206	14.47	0.37	79.04	12.23
Sea surface temperature (degree celcius)	6,887	21.52	−0.38	29.90	8.09
Real GDP per Capita (in constant 2010 USD)	7,684	13,543.15	150.77	204,345.40	15,648.82
Population (in millions)	7,500	49.5	0.977	1,364.3	127.7

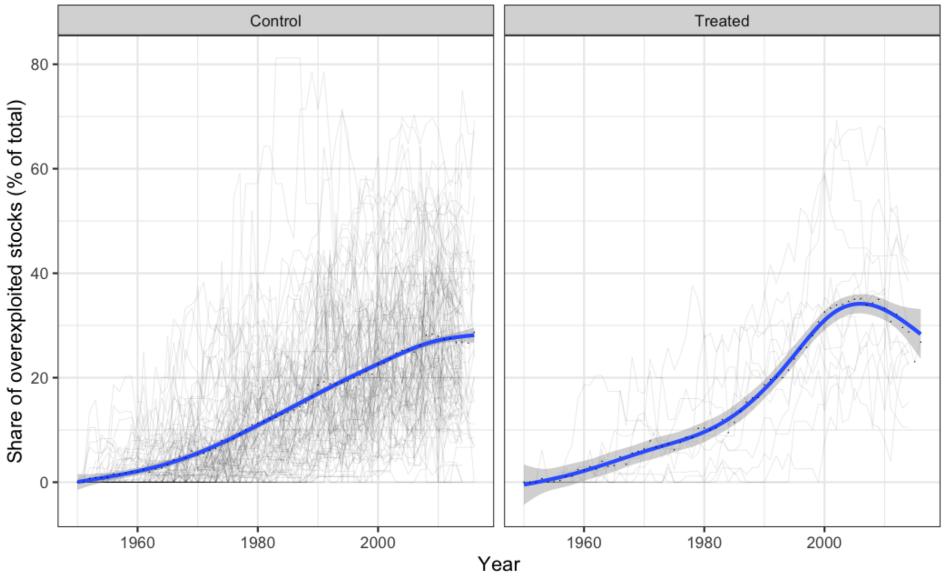


Figure 4.2: The share of overexploited stocks among control vs. treated group.
The lines in dark grey represents the share of overexploited stocks for each EEZ across the period of analysis. The blue smooth line is the line that best fits the average share of overexploited stocks. Note that while the average for the control group increases smoothly at the initial stages and levels off close to the end, that of the treated group increases sharply and declines towards the year 2014.

4.5 Empirical Strategy

We employ the generalized synthetic control method (GSCM) in order to quantify the effects of the GFCM's regulations on overexploitation among its member countries. Our treatment group comprises members of the GFCM, while the control group is constituted by other coastal nations globally.[9]

The method generally proceeds as follows: (1) an interactive fixed effects (IFE) model is estimated using pre-treatment data from the control group, while withholding a small part of the data; (2) The potential outcomes for the withheld portion of the data is then predicted and compared to the actual outcomes observed in the witheld portion of the data; (3) Steps (1) and (2) are repeated, each time with an additional unobserved factor and the corresponding mean squared prediction error (MSPE) obtained. The model that minimizes the MSPE (i.e., with the most accurate predictions) is selected; (4) Next, the algorithm estimates factor loadings for each treated unit; (5) The algorithm then imputes treated counterfactuals based on the estimated factors and factor loadings. During this step, the coefficients of the model are generated, with standard error estimates imputed with bootstrapping techniques (with 1000 simulations); (6) Finally, the difference between the actual outcomes of the treated group is compared to that of the estimated counterfactual to obtain the average treatment effect on the treated (ATT).

Following Xu (2017) and Maamoun (2019), the IFE model we estimate takes the following form:

$$Y_{ijt} = \delta_{ijt} D_{ijt} + X'_{jt}\beta + \gamma'_{ij} f_t + \varepsilon_{ijt}, \tag{4.1}$$

where, i references EEZ, j indicates country, and t denotes year. The variable Y_{ijt} is the independent variable (Overexploited, Collapsed, or Rebuilding stocks). The treatment indicator D_{ijt} equals 1 if unit i has been exposed to the treatment at time t and equals

[9] Refer to Appendix 4.8 for a list of countries in the final sample of analysis.

0 otherwise. Time varying independent variables X_{jt} are at the country level. Further, f_t is a vector of unobserved common factors, γ_{ij} is a vector of unknown factor loadings. The factor component $\gamma'_{ij} f_t$ has a linear additive form by assumption, and has unit and time fixed effects as special cases.[10] The term ε_{ijt} represents unobserved idiosyncratic shocks and has zero mean.

The parameter of interest is δ_{ijt} which captures the treatment effect. This parameter captures the difference between the outcome $Y_{ijt}(1)$ of a treated EEZ in a given year and the potential (i.e., would-have been) outcome in the absence of treatment $Y_{ijt}(0)$ of that EEZ in year t. Thus, $Y_{ijt}(1) = \delta_{ijt} + X'_{jt}\beta + \gamma'_{ij} f_t + \varepsilon_{ijt}$ and $Y_{ijt}(0) = X'_{jt}\beta + \gamma'_{ij} f_t + \varepsilon_{ijt}$. Therefore, the treatment effect on a treated unit i is:

$$\delta_{ijt} = Y_{ijt}(1) - Y_{ijt}(0),\ t > T_0, \tag{4.2}$$

where T_0 represents all time periods before treatment occurs.

Denote the number of treated units by N_{tr}, and the set of treated units by τ. The main result of the GSCM is the average treatment effect on the treated (ATT) at time t, expressed as follows:

$$\text{ATT}_{t,t>T_0} = \frac{1}{N_{tr}} \sum_{i \in \tau} [Y_{ijt}(1) - Y_{ijt}(0)] = \frac{1}{N_{tr}} \sum_{i \in \tau} \delta_{ijt}. \tag{4.3}$$

Since $Y_{ijt}(1)$ is observed for treated units in our sample for the posttreatment period, our objective is to make use of the GSCM to construct appropriate counterfactuals (i.e., $Y_{ijt}(0)$ for i in τ and $t > T_0$) for each treated unit in the post treatment periods. The GSCM computes the predicted value of $Y_{ijt}(0)$ in three steps. The first step involves

[10] To see that the factor component has unit and time fixed effects as special cases, note that $\gamma'_{ij} f_t = \gamma_{ij1} f_{1t} + \gamma_{ij2} f_{2t} + ... + \gamma_{ijr} f_{rt}$. If we set $f_{1t} = 1$ and $\gamma_{ij2} = 1$ and rewrite $\gamma_{ij1} = \alpha_{ij}$ and $f_{2t} = \eta_t$, then we have $\gamma_{ij1} f_{1t} + \gamma_{ij2} f_{2t} = \alpha_{ij} + \eta_t$ (Xu, 2017). For this reason, we do not explicitly include unit and time fixed effects.

choosing a fixed number of unobserved common factors. The second step is to estimate factor loadings. Based on the estimated factors and factor loadings in steps 1 and 2, a counterfactual is estimated for each treated unit in the post treatment period. The identifying assumptions necessary to obtain unbiased estimates or a causal effect with the above functional form are as follows:

Assumption 1: Strict exogeneity. This means that the error term of any EEZ in any country at any time period is not affected by treatment assignment, varying independent variables, unobserved common factors, and factor loadings. In other words, our model satisfies conditional mean independence, i.e., $\mathbb{E}[\varepsilon_{ijt}|D_{ijt}, X_{jt}, \gamma_{ij}, f_t] = \mathbb{E}[\varepsilon_{ijt}|X_{jt}, \gamma_{ij}, f_t] = 0$.

Assumption 2: Weak serial dependence of the error terms. Although Assumption 2 permits weak serial correlations, it allows us to rule out strong serial dependence. That is, there are no unit root processes, and errors of different EEZs are uncorrelated. In other words, we assume that error terms are independent both across units and over time, in addition to being independent of varying controls, factors, and factor loadings.

Assumption 3: The error terms are cross-sectionally independent and homoscedastic.

We estimate 5 variations of Eq.(4.1) based on the time varying controls included in each model. Different models are presented for the purpose of checking sensitivity of our results to potential omitted variables. The choice of our preferred model is guided by the following considerations: (i) observations must be available for as many treated and control countries and for as many time periods as possible. (ii) The model should control for the underlying variation in the ability of countries to regulate overfishing in their EEZs as much as possible. Thus, variables should be able to capture economic power, industry structure, and institutional quality. (iii) Finally, the model should be as simple as possible, i.e., it should include the least number of controls since the whole point of using the GSCM is to imitate a natural experiment. Based on the above considerations, we use Model 1 as our baseline model while the remaining models (Models 2-5) are used to check the robustness of our results.

4.6 Results

4.6.1 Main results

This section reports the average treatment effects of the GFCM's management measures on overexploitation within its area of competence. Our results suggest that the change in the mandate of the GFCM has been ineffective in reducing the share of overexploited stocks within their area of operation relative to the counterfactual scenario representing the absence of management measures. Results shown in Table 4.2 indicate that the ATT is between -0.74 and -2.96 percent. However, standard errors of between 2.56 and 5.19 percent imply that the change in the mandate of the GFCM is not associated with a statistically significant change in overexploitation at conventional levels.

Figure 4.3 is obtained from model 1 of Table 4.2 and shows the average treatment effect of the change in the mandate of the GFCM on the treated group. The thick horizontal line at point zero represents the counterfactual while the actual share of overexploited stocks of the treated group is shown by the black curve, lying between a 95% confidence interval. This curve indicates the extent of deviation from the estimated counterfactual. The thick vertical line represents the beginning of the treatment period (2004).

Table 4.2: Effect of the GFCM on the share of overexploited stocks.

Variable	Overexploited stocks (In % of total stocks)				
	Model 1	Model 2	Model 3	Model 4	Model 5
ATT	-0.742	-1.469	-1.342	-2.094	-2.961
	(4.26)	(5.19)	(5.13)	(5.15)	(2.56)
Ln Real GDP per capita	-0.912	-2.082	-2.552		-16.252
	(9.48)	(14.00)	(13.99)		(11.63)
Ln (real GDP per capita) squared	0.168	0.284	0.309		1.059
	(0.58)	(0.81)	(0.81)		(0.71)
Ln Population	-1.318	0.271	0.383	6.442	-4.493
	(3.68)	(4.81)	(4.74)	(3.67)	(4.99)
Ln Harvest (in tonnes)		-0.000			
		(0.00)			
Ln Value			0.073		
			(0.129)		
Fishing value added				0.000	
				(0.05)	
Sea surface temperature					-0.152
					(0.50)
MSPE	20.59	19.11	19.12	23.45	20.673
Unobserved factors	5	5	5	2	4
Treated units	12	6	6	12	12
Control Units	110	62	62	109	98
Observations	8174	4556	4556	6897	6270

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 5, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2014. Treatment year is 2004.

The difference in overexploitation trends between the treated group and the counterfactual is depicted in Figure 4.4 where the counterfactual overexploitation levels (i.e., the dashed blue line) do not exhibit a pronounced increase in the share of overexploited stocks compared to the actual level of overexploitation of the treated group (i.e., the dark solid line). Based on the estimations of the GSCM after conditioning on the additive fixed effects and the included unobservable factors, the average treatment effect on the treated (ATT) EEZs is not statistically significant. These results provide evidence to the effect that the change in the mandate of the GFCM has not yielded significant reduction in the share of overexploited fish stocks within its area of competence.

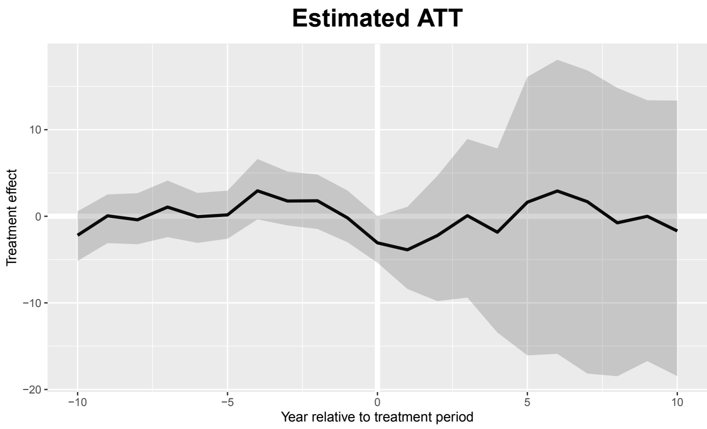


Figure 4.3: The gap in the share of overexploited stocks between the treated group and the counterfactual. The figure shows how the treated group's average share of overexploited stocks diverge from the counterfactual over time. The horizontal line (=zero) represents the counterfactual and the black line represents the share of overexploited stocks of the treated group. The vertical line at 0 is the treatment year. The grey shaded area is the 95% confidence interval.

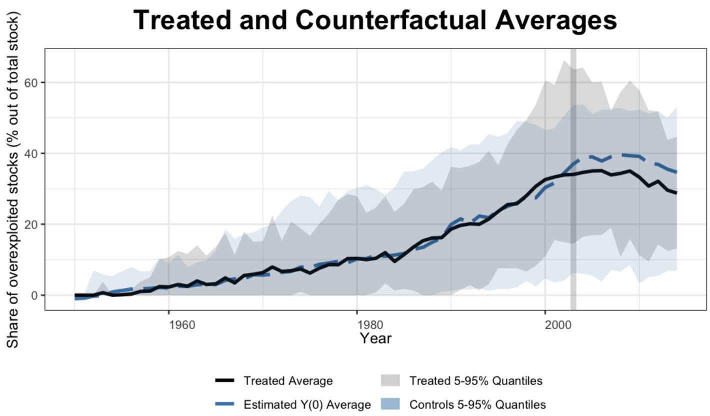


Figure 4.4: The share of overexploited stocks of the treated group and the counterfactual. The black solid line represents the share of overexploited stocks of the treated group and the blue dashed line represents the share of the overexploited stocks of the synthetic counterfactual. Treatment period (starting 2004) begins at the vertical line after the year 2000 mark shaded in dark grey.

To gain more insight on these results, it is imperative we understand the factors that influence the performance of RFMOs and in particular the GFCM. These factors fall under 5 broad themes: (1) precautionary and ecosystem approach; (2) decision making; (3) members; (4) transparency; and (5) scientific advice and data (Haas et al., 2020). One factor that is particularly worth examining in this context is the closure of certain habitats to harvest, which falls under the precautionary and ecosystem approach. Such a policy may not be fully implemented or could be undermined due to dispersion of fish in the presence of bottom trawl fishing. This is the case because bottom trawls harvest all kinds of fish including those that are classified as threatened species. In this context, conservation efforts have very little effect on overexploitation. Moreover, most RFMOs and in particular the GFCM lack clearly outlined bycatch mitigation policies that would ensure that non-target fish that are harvested are returned to their habitat (Gilman et al., 2014). In the case of the GFCM, we find evidence suggesting that the use of bottom trawl and other industrial fishing gear responsible for larger, non-selective harvest did not decline after 2004, with the exception of pelagic trawls. In fact, there was a slight increase in harvest from bottom trawl fishing as shown in Figure 4.5.

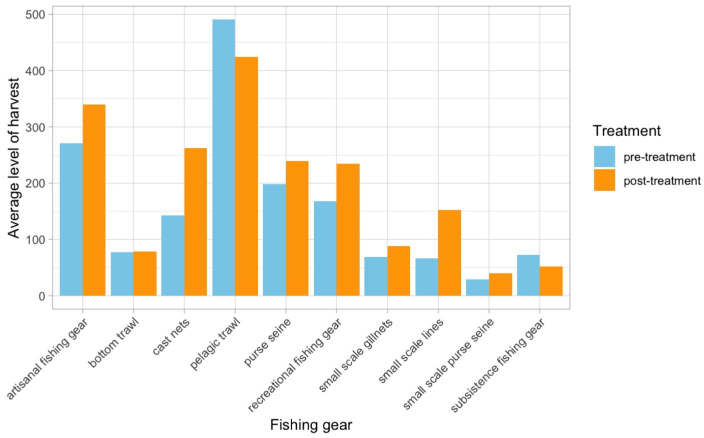


Figure 4.5: Harvest(tonnes) by gear type among treated countries.
In this graph we illustrate the average harvest for all treated countries before 2004 (pre-treatment) and after 2003 (post-treatment) by the top ten (based on harvest intensity) gear types used among treated countries.

4.7 Robustness checks

4.7.1 The share of collapsed stocks and rebuilding stocks

In this section, we report on how the change in the mandate of the GFCM affected the share of collapsed stocks as well as rebuilding stocks. We make use of the share of collapsed stocks as it serves as a more conservative measure of overfishing relative to the share of overexploited stocks (Erhardt, 2018). Intuitively, one would expect a reduction in the share of collapsed stocks after the implementation of the amendment to the GFCM's mandate if such an amendment was effective. On the other hand, we use the share of rebuilding stocks to assess whether the change in the GFCM's mandate affected stocks that were already collapsed before the coming into force of the amendment. In

Table 4.3: Effect of the GFCM on the share of collapsed stocks.

Variable	Collapsed stocks (In % of total stocks)				
	Model 1	Model 2	Model 3	Model 4	Model 5
ATT	-3.89	-2.375	-2.404	1.589	-0.169
	(2.38)	(2.72)	(2.72)	(4.06)	(1.69)
Ln Real GDP per capita	-35.476***	-38.166***	-37.469***		-31.216***
	(8.14)	(12.49)	(12.46)		(8.43)
Ln (real GDP per capita) squared	1.996***	1.969***	1.937***		1.746***
	(0.48)	(0.70)	(0.70)		(0.49)
Ln Population	-5.02***	-10.187**	-9.854**	-9.047***	-6.69**
	(2.87)	(4.06)	(4.13)	(3.39)	(2.99)
Ln Harvest (in tonnes)		-0.000			
		(0.00)			
Ln Value			-0.168		
			(0.19)		
Fishing value added				0.052	
				(0.06)	
Sea surface temperature					0.452
					(0.32)
MSPE	9.89	7.31	7.40	15.30	8.84
Unobserved factors	5	3	3	4	4
Treated units	12	6	6	12	12
Control Units	110	62	62	109	98
Observations	8174	4556	4556	6897	6270

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 5, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.

this scenario, an increase in the share of rebuilding stocks constitutes effectiveness of the new management measures adopted by the GFCM after 2004.

As shown in Table 4.3, the estimated ATT ranges between -3.89 percent and 1.59 percent. However, these estimates are not statistically significant at conventional levels. Therefore, similar to our main results in Table 4.2, we conclude that the change in the mandate of the GFCM has not been effective in reducing overfishing among member countries. Figures 4.6 and 4.7 are obtained from Model 1 of Table 4.3 and depicts the actual share of collapsed stocks relative to the estimated counterfactual over both the pre-treatment and post-treatment periods.

Results in Table 4.4 indicate that the estimated ATT on the share of rebuilding stocks

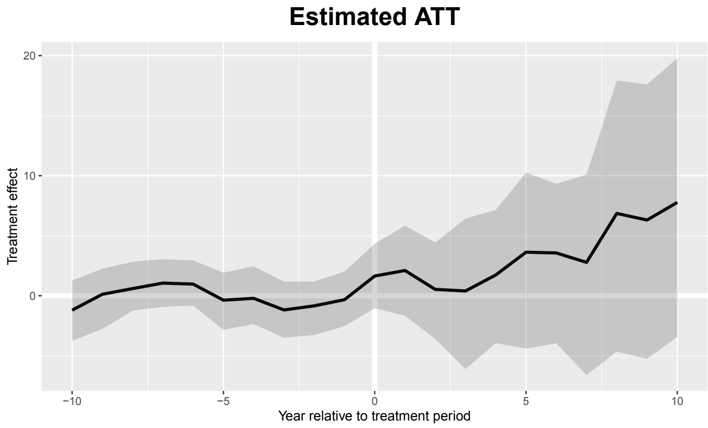


Figure 4.6: The gap in the share of collapsed stocks between the treated group and the counterfactual.
The figure shows how the treated group's average share of collapsed stocks diverge from the counterfactual over time. The horizontal line (=zero) represents the counterfactual and the black line represents the share of collapsed stocks of the treated group. The vertical line at 0 is the treatment year. The grey shaded area is the 95% confidence interval.

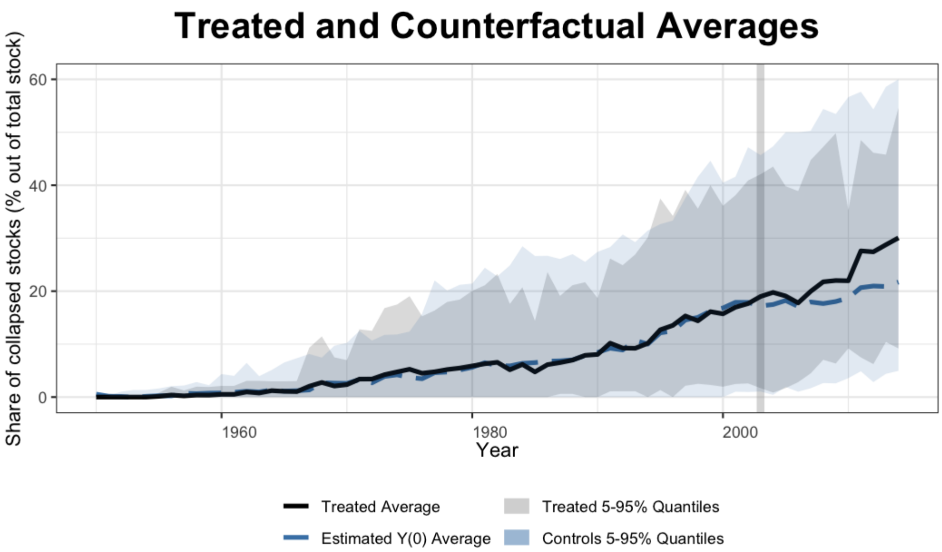


Figure 4.7: The share of collapsed stocks of the treated group and the counterfactual.
The black solid line represents the share of collapsed stocks of the treated group and the blue dashed line represents the share of the collapsed stocks of the synthetic counterfactual. Treatment period (starting 2004) begins at the vertical line after the year 2000 mark shaded in dark grey.

Table 4.4: Effect of the GFCM on the share of rebuilding stocks.

Variable	Rebuilding stocks (In % of total stocks)				
	Model 1	Model 2	Model 3	Model 4	Model 5
ATT	0.168	-3.91	-3.847	1.558	0.676
	(4.15)	(3.02)	(2.94)	(1.68)	(1.22)
Ln Real GDP per capita	-2.564	-7.442*	-7.069*		1.632
	(4.15)	(4.09)	(4.02)		(4.09)
Ln (real GDP per capita) squared	0.079	0.316	0.299		0.033
	(0.24)	(0.24)	(0.23)		(0.24)
Ln Population	-3.779**	-2.414	-2.293	-3.832**	-3.333*
	(1.74)	(1.55)	(1.55)	(1.75)	(1.77)
Ln Harvest (in tonnes)		-0.000			
		(0.00)			
Ln Value			-0.074		
			(0.07)		
Fishing value added				0.001	
				(0.016)	
Sea surface temperature					-0.008
					(0.11)
MSPE	1.55	1.49	1.49	2.35	1.34
Unobserved factors	4	4	4	1	5
Treated units	12	6	6	12	12
Control Units	109	61	61	108	98
Observations	8107	4489	4489	6840	6270

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 5, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.

lies between -3.91 and 1.56 percent. From Figures 4.8 and 4.9, notice that the share of rebuilding stocks increased after 2004 among treated EEZs for a number of years but declined later on. This could explain why the average effect is not economically and statistically significant at conventional levels. In a nut shell, the lack of statistical significance in these robustness checks serves to buttress our main finding that the change in the mandate of the GFCM has not been effective in mitigating overfishing.

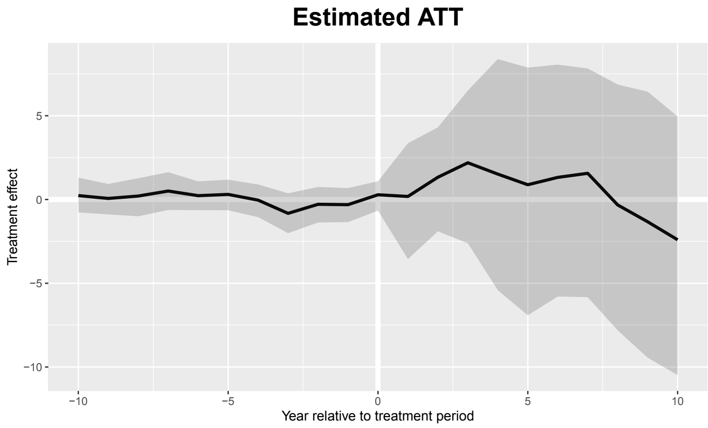


Figure 4.8: The gap in the share of rebuilding stocks between the treated group and the counterfactual.
The figure shows how the treated group's average share of rebuilding stocks diverge from the counterfactual over time. The horizontal line (=zero) represents the counterfactual and the black line represents the share of rebuilding stocks of the treated group. The vertical line at 0 is the treatment year. The grey shaded area is the 95% confidence interval.

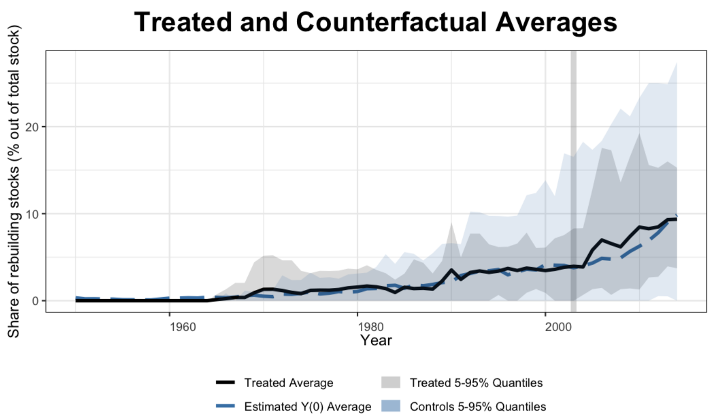


Figure 4.9: The share of rebuilding stocks of the treated group and the counterfactual.
The black solid line represents the share of rebuilding stocks of the treated group and the blue dashed line represents the share of the rebuilding stocks of the synthetic counterfactual. Treatment period (starting 2004) begins at the vertical line after the year 2000 mark shaded in dark grey.

4.7.2 Using Africa, Asia, and Europe as control group

One of the main challenges facing empirical studies on international agreements is the endogeneity problem arising from the voluntary decision of countries to ratify an agreement or in this case join an RFMO. The endogeneity arises from the fact that countries may have ratified the agreement based on previous levels of overfishing, which induces pre-selection bias and takes away the randomness of treatment. By using a synthetic counterfactual, we reduce the selection bias as the unobservable factors that are present for a treated unit are theoretically the same factors present in the estimated counterfactual. However, such a selection bias may not be completely eliminated (Billmeier and Nannicini, 2013; Maamoun, 2019).

To ensure the robustness of our results to such a concern, one may proceed in several ways. The location of a country near the Mediterranean or Black Sea should be taken into consideration as it is the basis on which countries are legally bound by the GFCM's management measures. More time-varying independent variables can be used to account for differences in location of the treated group and the control group. However, not many covariates exist that could justifiably be included to account for all manner of individual heterogeneity. In Model 5 of our results, we include sea surface temperature to account for differences between environmental conditions of the Mediterranean and Black Seas and other areas such as, for instance, the North Atlantic ocean. We further address this concern by including only the EEZs within Africa, Asia, and Europe in our control group, since they present a more comparable group to the treated EEZs, given their common location.[11]

Our results as presented in Figures 4.10 and 4.11 as well as Table 4.5 suggest that

[11] A counter argument to this point is that some of the control countries located closer to the treated countries might have been affected by the GFCM as fish straddle across EEZs. To alleviate concerns of such potential contamination, I present results in Appendix 4.8 where a control group of countries outside Africa, Asia, and Europe is utilized in the construction of a counterfactual.

overall the GFCM's impact on overexploitation is not statistically different from zero. The similarity in the treatment effects using different control groups provides evidence of the robustness of our main results in Table 4.2. Essentially, these results suggest that the estimated counterfactual does not change significantly when we change the composition of our control group. Therefore, the concerns of selection bias potentially contaminating our results are to a large extent addressed.

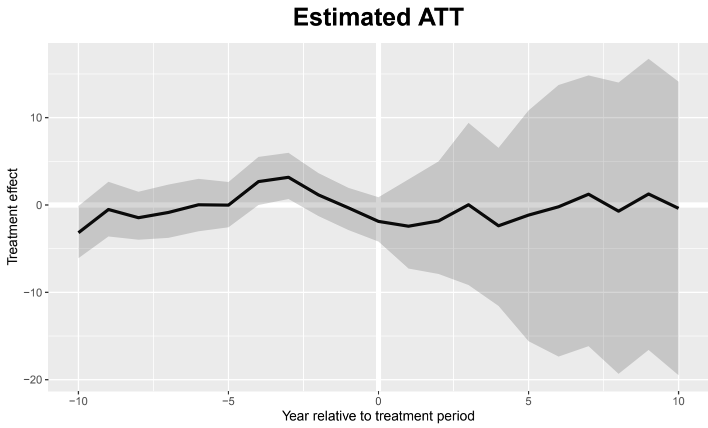


Figure 4.10: The gap in the share of overexploited stocks between the treated group and the counterfactual - EEZs of countries outside Africa, Asia, and Europe excluded from the control group.
The figure shows how the treated group's average share of overexploited stocks diverge from the counterfactual over time. The horizontal line (=zero) represents the counterfactual and the black line represents the share of overexploited stocks of the treated group. The vertical line at 0 is the treatment year. The grey shaded area is the 95% confidence interval.

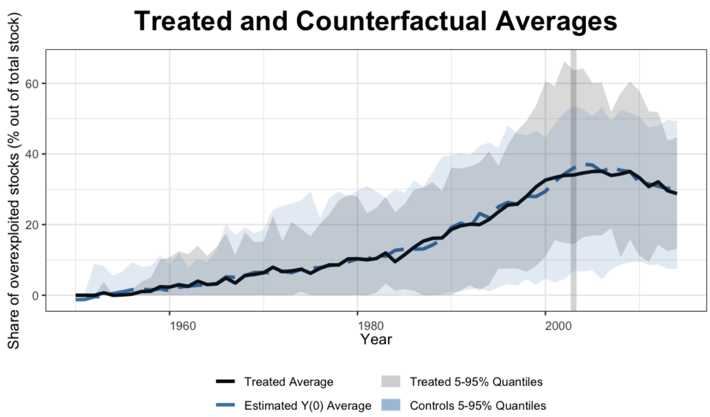


Figure 4.11: The share of overexploited stocks of the treated group and the counterfactual - EEZs of countries outside Africa, Asia, and Europe excluded from the control group.
The black solid line represents the share of overexploited stocks of the treated group and the blue dashed line represents the share of the overexploited stocks of the synthetic counterfactual. Treatment period (starting 2004) begins at the vertical line after the year 2000 mark shaded in dark grey.

Table 4.5: Effect of the GFCM on the share of overexploited stocks - Africa, Asia, Europe as control.

Variable	Africa, Asia, Europe as control group				
	Model 1	Model 2	Model 3	Model 4	Model 5
ATT	−1.069	2.445	2.618	8.745	-0.572
	(4.15)	(5.24)	(5.24)	(11.38)	(2.66)
Ln Real GDP per capita	7.183	6.361	6.032		-7.816
	(10.03)	(14.89)	(14.74)		(12.33)
Ln (real GDP per capita) squared	-0.319	-0.177	-0.147		0.542
	(0.62)	(0.86)	(0.86)		(0.76)
Ln Population	-3.369	0.121	-0.086	4.037	-8.067
	(4.49)	(5.71)	(5.61)	(3.88)	(5.07)
Ln Harvest (in tonnes)		0.001			
		(0.00)			
Ln Value			0.313		
			(0.25)		
Fishing value added				-0.064	
				(0.047)	
Sea surface temperature					0.183
					(0.61)
MSPE	21.48	21.13	21.22	19.39	19.94
Unobserved factors	4	5	5	5	5
Treated units	12	6	6	12	12
Control Units	74	46	46	74	65
Observations	5762	3484	3484	4902	4389

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 5, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.

4.7.3 Choosing control group based on RFMO membership

The number of RFMOs a country joins potentially influences the stock status of that country and vice-versa. There are countries in our sample who are members of up to 18 regional fisheries bodies (for example, USA). The incentives presented to such countries to reduce overexploitation may be relatively higher especially when membership is influenced by a depleted stock status. This is the case even when the species being managed by different agreements are not necessarily the same. In order to separate the potential effects of ratifying several international fisheries agreements, we exclude countries that have ratified more than 6 international fisheries agreements from the control group.

The results presented in Table 4.6 as well as Figures 4.12 and 4.13 indicate that except for Models 2 and 3 the ATT are in general not qualitatively different from those based on the entire data sample (as shown in Table 4.2). Results in Models 2 and 3 of Table 4.6 indicate an increase in overexploitation and are statistically significant at 10 percent. However, there are two reasons why these results should be interpreted with caution. First, these results are not robust to the different robustness checks in Table 4.6 as well as those conducted throughout the paper. Second, the positive ATT of Models 2 and 3 may seem counter intuitive at first glance as it points to the fact that the GFCM's change in mandate exacerbated overexploitation among affected countries. However, that may not be necessarily true. The statistical significance of the ATT falls short of the generally acceptable threshold of 5 percent needed to support such a direct conclusion.

Table 4.6: Effect of the GFCM on the share of overexploited stocks - Membership in 6 or less RFMOs as control.

Variable	Membership in 6 or less RFMOs as control group				
	Model 1	Model 2	Model 3	Model 4	Model 5
ATT	−3.307	11.11*	11.07*	-2.663	-1.936
	(3.73)	(6.51)	(6.51)	(8.10)	(2.94)
Ln Real GDP per capita	3.479	13.276	12.61		-8.548
	(10.22)	(19.24)	(19.76)		(11.74)
Ln (real GDP per capita) squared	-0.127	-0.67	-0.629		0.608
	(0.61)	(1.07)	(1.11)		(0.70)
Ln Population	2.751	-6.346	-6.139	3.299	-9.183
	(4.13)	(4.82)	(4.83)	(4.26)	(5.53)
Ln Harvest (in tonnes)		-0.000			
		(0.00)			
Ln Value			0.103		
			(0.25)		
Fishing value added				-0.044	
				(0.05)	
Sea surface temperature					-0.055
					(0.71)
MSPE	20.98	21.89	21.84	25.58	22.06
Unobserved factors	5	5	5	3	4
Treated units	12	6	6	12	12
Control Units	74	35	35	74	65
Observations	5762	2747	2747	4902	4389

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 5, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.

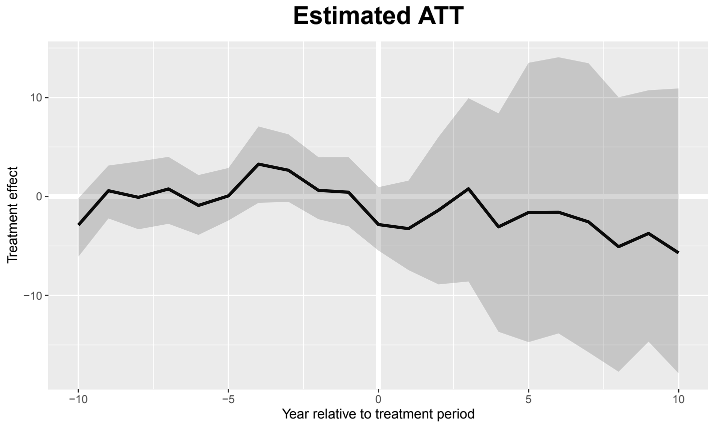


Figure 4.12: The gap in the share of overexploited stocks between the treated group and the counterfactual - EEZs of countries with membership in more than 6 RFMOs excluded from the control group.
The figure shows how the treated group's average share of overexploited stocks diverge from the counterfactual over time. The horizontal line (=zero) represents the counterfactual and the black line represents the share of overexploited stocks of the treated group. The vertical line at 0 is the treatment year. The grey shaded area is the 95% confidence interval.

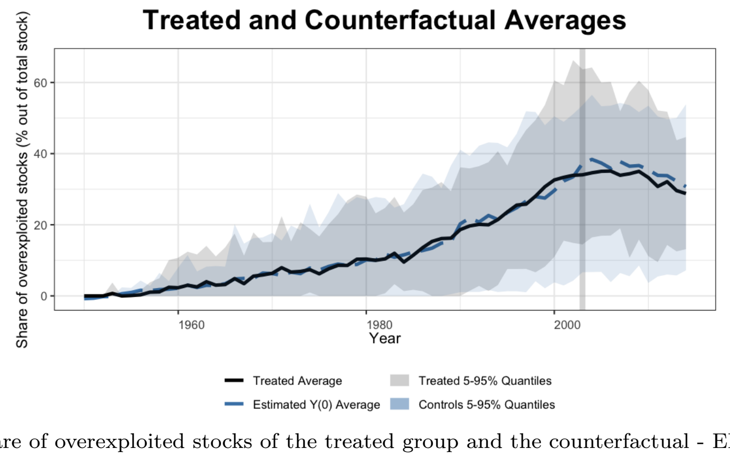


Figure 4.13: The share of overexploited stocks of the treated group and the counterfactual - EEZs of countries with membership in more than 6 RFMOs excluded from the control group.
The black solid line represents the share of overexploited stocks of the treated group and the blue dashed line represents the share of the overexploited stocks of the synthetic counterfactual. Treatment period (starting 2004) is the vertical line after the year 2000 mark shaded in dark grey.

4.8 Conclusion

The 1995 UN Fish Stocks Agreement stipulates that the management of shared fish stocks should be managed on a region by region basis through regional fisheries management organizations (RFMOs). However, their effectiveness in preventing severe overfishing still remains in question. Although, in theory, the formation of RFMOs are expected to bring about improvement in the management of shared fish stocks, empirical evidence suggests otherwise. The general fisheries commission for the Mediterranean (GFCM), one of the most important RFMOs that exist today, is of no exception to this debate. Studies have shown evidence of overexploitation in the Mediterranean and Black Sea, which constitutes the area of competence of the GFCM.

An important feature of the GFCM is that its mandate as a management body commenced in 2004 (with the authority to make binding decisions on member countries). Prior to 2004, it existed as an advisory body, providing scientific support to member countries. In this paper, we examine the effectiveness of this amendment to the mandate of the GFCM in reducing overexploitation among member countries by constructing a synthetic counterfactual. Using the generalized synthetic control method (GSCM), we compare the share of overexploited stocks in the exclusive economic zones (EEZs) of member countries after the change in the mandate of the GFCM to a synthetic counterfactual that represents the expected share of overexploited stocks that would have pertained in the absence of the change. The GSCM facilitates a more robust comparison between the treated group and the control group, while simulataneously accounting for the collective nature of international fisheries agreements.

Our results show that the amendment to the mandate of the GFCM has not resulted in a significant (both economic and statistical) effect on the share of overexploited stocks relative to the expected share of overexploited stocks that would have pertained in the absence of such an amendment. Our results are robust to different sensitivity analysis. First, excluding countries that are located outside Africa, Asia, and Europe (i.e., continents where member countries of the GFCM are located) from the control group showed a similar effect. Second, we find that over the same period of analysis, there was no improvement in the status of stocks that had undergone collapse. Lastly, we find that the change in the mandate did not reduce overexploitation in the scenario where our control group comprises of countries with none or fewer membership in regional fisheries bodies.

Our results provide clear evidence pointing to the fact that further steps are needed to bridge the gap between the adoption of best practices on paper and actual implementation of those policies. In fact Gilman et al. (2014) notes that RFMOs have large governance deficits. These include the lack of explicit performance standards against which to assess efficacy; deficiencies in surveillance methods required to assess compliance with binding measures; and difficulties in reaching concensus among member countries etc. In the context of the GFCM, it is important to also note the inherent difficulty in the implementation of management policies as the area of operation encompasses the EEZs of member countries. Since countries have complete autonomy over their own EEZs, they have the incentive to deviate from the rules and regulations of the GFCM without being detected, or not necessarily reporting their domestic vessels that violate rules within their EEZs. For these reasons, it is not too surprising that the effects of the amendment to the mandate of the GFCMs mandate is largely nonexistent.

Bibliography

Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of the American statistical Association 105*(490), 493–505.

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the basque country. *American economic review 93*(1), 113–132.

Almer, C. and R. Winkler (2017). Analyzing the effectiveness of international environmental policies: The case of the kyoto protocol. *Journal of Environmental Economics and Management 82*, 125–151.

Barrett, S. (1994). Self-enforcing international environmental agreements. *Oxford Economic Papers*, 878–894.

Bediako, K. and B. Nkuiya (2022). Stability of international fisheries agreements under stock growth uncertainty. *Journal of Environmental Economics and Management 113*, 102664.

Billmeier, A. and T. Nannicini (2013). Assessing economic liberalization episodes: A synthetic control approach. *Review of Economics and Statistics 95*(3), 983–1001.

Cullis-Suzuki, S. and D. Pauly (2010). Failing the high seas: a global evaluation of regional fisheries management organizations. *Marine Policy 34*(5), 1036–1042.

Erhardt, T. (2018). Does international trade cause overfishing? *Journal of the Association of Environmental and Resource Economists 5*(4), 695–711.

GFCM (2010). GFCM's response to UN - Capacity building in ocean affairs & the law of the sea including marine science. https://www.un.org/Depts/los/general_assembly/contributions_2010/GFCM.pdf. Reference: LOS/ICP/2010 dated 11 December 2009].

Gilman, E., K. Passfield, and K. Nakamura (2014). Performance of regional fisheries management organizations: ecosystem-based governance of bycatch and discards. *Fish and Fisheries 15*(2), 327–351.

Grunewald, N. and I. Martinez-Zarzoso (2016). Did the kyoto protocol fail? an evaluation of the effect of the kyoto protocol on co2 emissions. *Environment and Development Economics 21*(1), 1–22.

Haas, B., M. Haward, J. McGee, and A. Fleming (2019). The influence of performance reviews on regional fisheries management organizations. *ICES Journal of Marine Science 76*(7), 2082–2089.

Haas, B., J. McGee, A. Fleming, and M. Haward (2020). Factors influencing the performance of regional fisheries management organizations. *Marine Policy 113*, 103787.

Hannesson, R. (1997). Fishing as a supergame. *Journal of Environmental Economics and Management 32*(3), 309–322.

Higgins, J. (2008). Economic impacts of the cod moratorium. https://www.heritage.nf.ca/articles/economy/moratorium-impacts.php. [Online; accessed March 15, 2021].

Hoel, A. H. (2011). Performance reviews of regional fisheries management organizations. In *Recasting Transboundary Fisheries Management Arrangements in Light of Sustainability Principles*, pp. 449–472. Brill Nijhoff.

Isaksen, E. T. and A. Richter (2019). Tragedy, property rights, and the commons: investigating the causal relationship from institutions to ecosystem collapse. *Journal of the Association of Environmental and Resource Economists 6*(4), 741–781.

Kaitala, V. and G. Munro (1997). The conservation and management of high seas fishery resources under the new law of the sea. *Natural resource modeling 10*(2), 87–108.

Kwon, O. S. (2006). Partial international coordination in the great fish war. *Environmental and Resource Economics 33*(4), 463–483.

Levhari, D. and L. J. Mirman (1980). The Great Fish War: An Example Using a Dynamic Cournot-Nash Solution. *The Bell Journal of Economics 11*(1), 322–334.

Maamoun, N. (2019). The kyoto protocol: Empirical evidence of a hidden success. *Journal of Environmental Economics and Management 95*, 227–256.

Miller, S. and B. Nkuiya (2016). Coalition formation in fisheries with potential regime shift. *Journal of Environmental Economics and Management 79*, 189–207.

Mitchell, R. B. (2003). International environmental agreements: a survey of their features, formation, and effects. *Annual review of environment and resources 28*(1), 429–461.

Munro, G. R. (2007). Internationally shared fish stocks, the high seas, and property rights in fisheries. *Marine Resource Economics 22*(4), 425–443.

NAFO, N. A. F. O. (2004). *Convention on Future Multilateral Cooperation in the Northwest Atlantic Fisheries*. Northwest Atlantic Fisheries Organization.

Pauly D., Z. and M. Palomares (2020). Sea around us concepts, design and data. http://www.seaaroundus.org/data/#/eez/12/stock-status. [Online; accessed April 27, 2021].

Pintassilgo, P. (2003). A coalition approach to the management of high seas fisheries in the presence of externalities. *Natural Resource Modeling 16*(2), 175–197.

Pintassilgo, P., M. Finus, M. Lindroos, and G. Munro (2010). Stability and success of organizations. *Environmental and Resource Economics 46*(3), 377–402.

Pintassilgo, P., L. G. Kronbak, and M. Lindroos (2015). International fisheries agreements: A game theoretical approach. *Environmental and Resource Economics 62*(4), 689–709.

Pintassilgo, P. and M. Lindroos (2008). Coalition formation in straddling stock fisheries: a partition function approach. *International Game Theory Review 10*(03), 303–317.

Srour, A., N. Ferri, and A. Carlson (2020). The general fisheries commission for the mediterranean and the fight against illegal, unreported, and unregulated fishing through better compliance. *Ocean Yearbook Online 34*(1), 412–427.

Tarui, N., C. F. Mason, S. Polasky, and G. Ellis (2008). Cooperation in the commons with unobservable actions. *Journal of Environmental Economics and Management 55*(1), 37–51.

Tsikliras, A. C., A. Dinouli, V.-Z. Tsiros, and E. Tsalkou (2015). The mediterranean and black sea fisheries at risk from overexploitation. *PloS one 10*(3), e0121188.

United Nations, U. (1982). United nations convention on the law of the sea. [UN Doc. A/Conf 61/122].

United Nations, U. (1995). United nations conference on straddling and highly migratory fish stocks. agreement for the implementation of the united nations convention on the law of the sea of 10 december 1982 relating to the conservation and management of straddling and highly migratory fish stocks. UN Doc. A/Conf 164/37.

Vollenweider, J. (2013). The effectiveness of international environmental agreements. *International Environmental Agreements: Politics, Law and Economics 13*(3), 343–367.

Xu, Y. (2017). Generalized synthetic control method: Causal inference with interactive fixed effects models. *Political Analysis 25*(1), 57–76.

Appendices

The fixed membership case

Proof of Lemma 2.1

(i) Condition (2.4) suggests that at the equilibrium, the value function of the coalition can be written as

$$W(X) = nu\left(h^o_{mt}(X)\right) + \delta E\left(W\left(Z_t g\left(X - nh^o_{mt}(X) - (N-n)\, h^o_{nct}(X)\right)\right)\right). \tag{4}$$

Differentiating both sides of this relation and using condition (2.5), we get

$$W'(X) = \delta\left[1 - (N-n)\, h'_{nct}(X)\right] E\left(Z_t g'(y)\, W'(Z_t g(y))\right). \tag{5}$$

Substituting condition (2.5) into (5) yields

$$W'(X) = u'\left(h^o_{mt}(X)\right)\left[1 - (N-n)\, h^{o\prime}_{nct}(X)\right] \quad \text{for all} \quad X > 0. \tag{6}$$

Evaluating this relation at $X = Z_t g(y)$, we get

$$W'(Z_t g(y)) = u'\left(h^o_{mt}(Z_t g(y))\right)\left[1 - (N-n)\, h^{o\prime}_{nc}(Z_t g(y))\right], \tag{7}$$

Substituting Eq.(7) into Eq.(2.5), Result (i) of Lemma 2.1 follows.

(ii) Condition (2.6) shows that at the equilibrium, the value function for a non-coalition member reads

$$W_{nc}(X) = u\left(h^o_{nct}\right) + \delta E\left(W_{nc}\left(Zg\left(X - nh^o_{mt}(X) - (N-n-1)\, h^o_{nct}(X) - h^o_{nct}\right)\right)\right), \tag{8}$$

Differentiating both sides of this equality and using condition (2.7), we find that

$$W'_{nc}(X) = \delta\left[1 - nh^{o\prime}_{mt}(X) - (N-n-1)\, h^{o\prime}_{nct}(X)\right] E\left(Z_t g'(y)\, W'_{nc}(Zg(y))\right). \tag{9}$$

Combining Eq.(9) with Eq.(2.7) yields

$$W'_{nc}(X) = u'(h_{nc}(X))\left[1 - nh'_m(X) - (N-n-1)\, h'_{nc}(X)\right] \quad \text{for all} \quad X > 0. \tag{10}$$

Evaluating both sides of this formula at $X = Z_t g(y)$ gives rise to

$$W'_{nc}(Zg(y)) = u'(h_{nc}(Zg(y)))\left[1 - nh'_m(Zg(y)) - (N-n-1)\, h'_{nc}(Zg(y))\right].$$

Substituting this relation into Eq.(2.7), Result (ii) of Lemma 2.1 follows.

Proof of Proposition 2.1

We are interested in linear harvest rules: $h^o_{mt}(X) = \omega_m X$ and $h^o_{nct}(X) = \omega_{nc} X$. In this context, we have

$$y = X - n\omega_m X - (N-n)\omega_{nc} X, \quad g(y) = \left(\alpha y^{1-\frac{1}{\eta}} + (1-\alpha)\,\phi^{1-\frac{1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, \tag{11}$$

$$g'(y) = (1 - n\omega_m - (N-n)\,\omega_{nc})^{-\frac{1}{\eta}} X^{-\frac{1}{\eta}} \alpha \left(\alpha y^{1-\frac{1}{\eta}} + (1-\alpha)\,\phi^{1-\frac{1}{\eta}}\right)^{\frac{1}{\eta-1}}. \tag{12}$$

Substituting Eq.(11) and Eq.(12) into Eq.(2.8), we find that

$$(1 - n\omega_m - (N-n)\,\omega_{nc})^{\frac{1}{\eta}} = \alpha\delta\xi\left[1 - (N-n)\omega_{nc}\right]. \tag{13}$$

Substituting Eq.(11) and Eq.(12) into Eq.(2.9) and simplifying the result, we get

$$(1 - n\omega_m - (N-n)\,\omega_{nc})^{\frac{1}{\eta}} = \alpha\delta\xi\left[1 - n\omega_m - (N-n-1)\,\omega_{nc}\right], \tag{14}$$

where $\xi = E\left(Z_t^{1-\frac{1}{\eta}}\right)$. Equating the right hand side of Eq.(13) and Eq.(14), we find that $\omega_{nc} = n\omega_m$. Using this result along with (14), the result follows.

Proof of Lemma 2.2

Total harvest is defined as $H_t^o(n) = n\omega_m X_t + (N-n)\omega_{nc} X_t$. Using the fact that $\omega_{nc} = n\omega_m$, this expression simplifies to $H_t^o(n) = (N-n+1)\omega_{nc} X_t$. This can be re-written as $H_t^o(n) = \tau_n X_t$, where $\tau_n = (N-n+1)\omega_{nc}$. Our objective is to show that $\tau_n > \tau_{n+1}$ for $2 \leqslant n \leqslant N-1$. Using the expression for τ_n, we can eliminate ω_{nc} from Eq.(2.12) to obtain

$$(1-\tau_n)^{\frac{1}{\eta}} = \alpha\delta\xi\left(1 - \frac{N-n}{N-n+1}\tau_n\right). \tag{15}$$

Denote by $L(\tau) = (1-\tau)^{\frac{1}{\eta}}$ the left-hand side of (15) and $R_n(\tau) = \alpha\delta\xi\left(1 - \frac{N-n}{N-n+1}\tau\right)$ the right hand side of (15). Note that $R_n(\tau)$ is linear and decreasing in τ and $R_{n+1}(\tau) > R_n(\tau)$ for all $\tau > 0$. Moreover, $L(\tau) \leqslant 1$ for all $0 \leqslant \tau \leqslant 1$ and $L(\tau)$ is decreasing in τ. These results suggest that $\tau_n > \tau_{n+1}$ as illustrated in Figure 14.

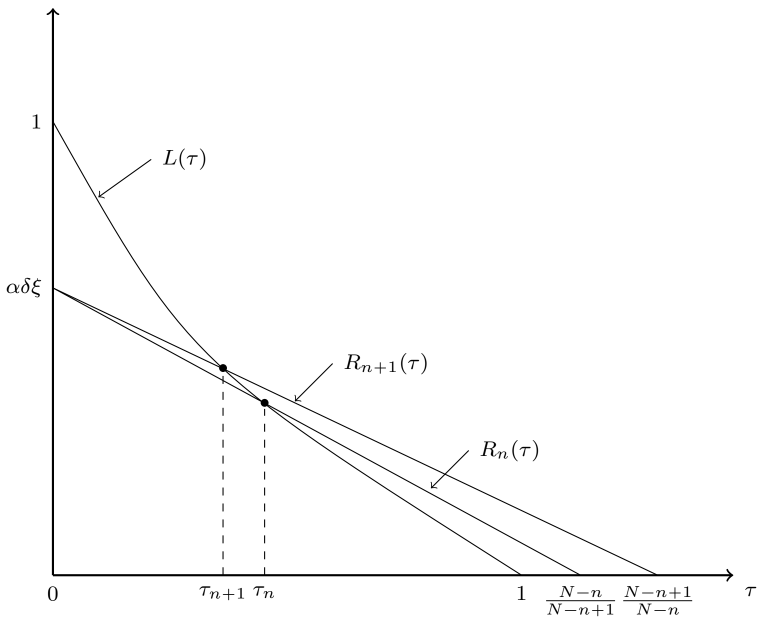


Figure 14: Proof that $\tau_n > \tau_{n+1}$.

Details for the payoff functions (open-loop membership)

Condition (6) suggests that

$$W'(X) = (\omega_m X)^{-\frac{1}{\eta}} [1 - (N-n)\,\omega_{nc}], \quad \text{for all} \quad X > 0.$$

Integrating this differential equation yields

$$W(X) = \omega_m^{-\frac{1}{\eta}} [1 - (N-n)\,\omega_{nc}] \frac{X^{1-\frac{1}{\eta}} - 1}{1 - \frac{1}{\eta}} + C_m, \quad \text{and} \quad W(1) = C_m. \tag{16}$$

Notice that condition (4) holds for all $X > 0$. Evaluating (4) at $X = 1$ and using $W(X)$ defined in (16), we find that

$$C_m = n \frac{w_m^{1-\frac{1}{\eta}} - 1}{(1-\delta)(1-\frac{1}{\eta})} + n^{\frac{1}{\eta}}\beta,$$

where

$$\beta = \delta w_{nc}^{-\frac{1}{\eta}}(1-(N-n)\omega_{nc})\frac{\left[\alpha\xi(1-(N-n+1)\omega_{nc})^{1-\frac{1}{\eta}} + (1-\alpha)\,\xi\phi^{1-\frac{1}{\eta}} - 1\right]}{(1-\delta)(1-\frac{1}{\eta})}$$

The expected net present value of utility for each coalition member is given by $W_m(X) = \frac{1}{n}W(X)$.

Condition (10) reveals that

$$W'_{nc}(X) = (\omega_{nc}X)^{-\frac{1}{\eta}}\left[1 - n\omega_m - (N-n-1)\,\omega_{nc}\right]$$

Using the fact that $\omega_{nc} = n\omega_m$ and integrating this expression, we get

$$W_{nc}(X) = \omega_{nc}^{-\frac{1}{\eta}}\left[1-(N-n)\,\omega_{nc}\right]\frac{X^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}} + C_{nc}, \quad \text{and} \quad W_{nc}(1) = C_m. \tag{17}$$

Notice that (8) is valid for all $X > 0$. Using the expression of $W_{nc}(X)$ provided in (17), we evaluate condition (8) at $X = 1$, which gives rise to

$$C_{nc} = \frac{w_{nc}^{1-\frac{1}{\eta}} - 1}{(1-\delta)(1-\frac{1}{\eta})} + \beta.$$

Proof of Proposition 2.2

(i) For the case where $n = N$, condition (2.12) implies $\omega_{m(N)} = \omega_{m|n=N} = \frac{1-(\alpha\delta\xi)^{\eta}}{N}$. Denote by μ the positive and unique root of (2.12) associated with $n = N-1$. Formally, μ is the solution to $(1-2\mu)^{\frac{1}{\eta}} = \alpha\delta\xi(1-\mu)$.

Using these notations, condition (2.13) suggests that the payoff for a country under full cooperation can be rewritten as

$$W_m\left(X_0, N\right) = \frac{\omega_{nc(N)}^{-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}}\frac{X_0^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}} + \frac{\left(\frac{\omega_{nc(N)}}{N}\right)^{1-\frac{1}{\eta}}-1}{(1-\delta)(1-\frac{1}{\eta})} + \frac{\beta_{(N)}}{N^{1-\frac{1}{\eta}}}, \tag{18}$$

where $\omega_{nc(N)} = \omega_{nc|n=N} = N\omega_{m(N)}$, and $\beta_{(N)} = \beta_{|n=N} = \frac{\delta(w_{nc(N)})^{-\frac{1}{\eta}}}{(1-\delta)(1-\frac{1}{\eta})}[\alpha\xi(1-\omega_{nc(N)})^{1-\frac{1}{\eta}} + (1-\alpha)\,\xi\phi^{1-\frac{1}{\eta}} - 1]$.

Using condition (2.14), the payoff of a member who unilaterally deviates from the grand coalition can be written as

$$W_{nc}\left(X_0, N-1\right) = \mu^{-\frac{1}{\eta}}(1-\mu)\frac{X_0^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}} + \frac{\mu^{1-\frac{1}{\eta}}-1}{(1-\delta)(1-\frac{1}{\eta})} + \beta_{(N-1)}, \tag{19}$$

where $\beta_{(N-1)} = \beta_{|n=N-1} = \frac{\delta\mu^{-\frac{1}{\eta}}(1-\mu)}{(1-\delta)(1-\frac{1}{\eta})}[\alpha\xi(1-2\mu)^{1-\frac{1}{\eta}} + (1-\alpha)\,\xi\phi^{1-\frac{1}{\eta}} - 1]$.

The grand coalition is stable if

$$S\left(X_0, N\right) = W_m\left(X_0, N\right) - W_{nc}\left(X_0, N-1\right) \geqslant 0.$$

Substituting (18) and (19) into this inequality, we find that $S\left(X_0, N\right) \geqslant 0$ if and only if

$$S(X_0,N)=\frac{X_0^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}}\left[\frac{\omega_{nc(N)}^{-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}}-\mu^{-\frac{1}{\eta}}(1-\mu)\right]+\frac{\left(\frac{\omega_{nc(N)}}{N}\right)^{1-\frac{1}{\eta}}-\mu^{1-\frac{1}{\eta}}}{(1-\delta)(1-\frac{1}{\eta})}+$$
$$\frac{\alpha\delta\xi}{(1-\delta)(1-\frac{1}{\eta})}[\frac{\omega_{nc(N)}^{-\frac{1}{\eta}}(1-\omega_{nc(N)})^{1-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}}-\mu^{-\frac{1}{\eta}}(1-2\mu)^{1-\frac{1}{\eta}}(1-\mu)]+$$
$$\frac{\delta}{(1-\delta)(1-\frac{1}{\eta})}\left[\mu^{-\frac{1}{\eta}}(1-\mu)-\frac{\omega_{nc(N)}^{-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}}\right]+\frac{\delta(1-\alpha)\xi\phi^{1-\frac{1}{\eta}}}{(1-\delta)(1-\frac{1}{\eta})}\left[\frac{\omega_{nc(N)}^{-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}}-\mu^{-\frac{1}{\eta}}(1-\mu)\right]\geqslant 0 \tag{20}$$

This formula reveals that for the inequality $S(X_0,N)\geqslant 0$ to hold, it suffices for model parameters to satisfy $(1-\alpha)\phi^{1-\frac{1}{\eta}}\geqslant\overline{\phi}$, where $\overline{\phi}$ is defined as

$$\overline{\phi}=\frac{1-\delta}{\xi\delta}\left[1-X_0^{1-\frac{1}{\eta}}+\frac{\delta}{(1-\delta)}\right]-\frac{\omega_{nc(N)}^{1-\frac{1}{\eta}}-\mu^{1-\frac{1}{\eta}}N^{1-\frac{1}{\eta}}}{bN^{1-\frac{1}{\eta}}(1-\delta)(1-\frac{1}{\eta})}$$
$$-\frac{\alpha\delta\xi}{bN^{1-\frac{1}{\eta}}(1-\delta)(1-\frac{1}{\eta})}\left[\omega_{nc(N)}^{-\frac{1}{\eta}}(1-\omega_{nc(N)})^{1-\frac{1}{\eta}}-N^{1-\frac{1}{\eta}}\mu^{-\frac{1}{\eta}}(1-2\mu)^{1-\frac{1}{\eta}}(1-\mu)\right],$$

with $b\equiv\frac{\delta\xi}{(1-\delta)(1-\frac{1}{\eta})}\left[\frac{\omega_{nc(N)}^{-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}}-\mu^{-\frac{1}{\eta}}(1-\mu)\right]>0$. Since $\eta>1$ by assumption, this condition (i.e., $b>0$) holds if and only if the inequality $\frac{\omega_{nc(N)}^{-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}}-\mu^{-\frac{1}{\eta}}(1-\mu)>0$ is valid. Using the fact that $\omega_{nc(N)}=1-(\alpha\delta\xi)^{\eta}$, this latter inequality can be rewritten as $N<\hat{N}\equiv\left[\frac{\mu(1-\mu)^{-\eta}}{1-(\alpha\delta\xi)^{\eta}}\right]^{\frac{1}{\eta-1}}$. It is important to notice that $\hat{N}$ does not depend on N.

(ii) If $\eta=1$, condition (2.12) implies that

$$\omega_{nc1}=\omega_{nc|\eta=1}=n\omega_{m1}=n\omega_{m|\eta=1}\text{ and }\omega_{nc1}=\frac{1-\alpha\delta}{1+(N-n)(1-\alpha\delta)}. \tag{21}$$

Using (21) along with (4) and (16), we derive the value function of a representative member of the coalition

$$W_m(X) = \frac{1}{1-\alpha\delta} \ln X + C_{m1}, \tag{22}$$

where $C_{m1} = C_{m|\eta=1} = (1-\delta)^{-1} \ln \omega_{m1} + \beta_1$, and

$$\beta_1 = \beta_{|\eta=1} = \frac{\delta}{(1-\delta)(1-\alpha\delta)} \left[E(\ln Z) + (1-\alpha)\ln\phi + \alpha\ln(1+(N-n)(1-\alpha\delta))\right].$$

Using (21) along with (8) and (17), the value function of a non-coalition member is given by

$$W_{nc}(X) = \frac{1}{1-\alpha\delta} \ln X + C_{nc1}, \tag{23}$$

where $C_{nc1} = C_{nc|\eta=1} = (1-\delta)^{-1} \ln \omega_{nc1} + \beta_1$. A coalition of size n is internally stable if

$$S(X_0, n) = W_m(X_0, n) - W_{nc}(X_0, n-1) \geqslant 0.$$

Using (22) and (23), this condition holds if and only if

$$\ln(n) \leqslant \frac{1}{1-\alpha\delta} \ln\left(1 + \frac{1-\alpha\delta}{1+(N-n)(1-\alpha\delta)}\right). \tag{24}$$

Since ln(.) is a concave function, it can be shown that $\ln(1+a) \leqslant a$. Therefore,

$$\ln\left(1 + \frac{1-\alpha\delta}{1+(N-n)(1-\alpha\delta)}\right) \leqslant \frac{1-\alpha\delta}{1+(N-n)(1-\alpha\delta)}.$$

Thus, from (24) we can write

$$\ln(n) \leqslant \frac{1}{1-\alpha\delta} \ln\left(1 + \frac{1-\alpha\delta}{1+(N-n)(1-\alpha\delta)}\right) \leqslant \frac{1}{1+(N-n)(1-\alpha\delta)}.$$

Since $N \geqslant n$, the fraction $\frac{1}{1+(N-n)(1-\alpha\delta)}$ is less or equal to one. However, for $n \geqslant 3$, $\ln(n) > 1$. This implies that any coalition of size $n \geqslant 3$ is not internally stable. A coalition of size $n^* = 2$ is internally stable if and only if

$$\ln(2) \leqslant \frac{1}{1-\alpha\delta} \ln\left(1 + \frac{1-\alpha\delta}{1+(N-2)(1-\alpha\delta)}\right)$$

This can be re-written as

$$N \leqslant \bar{N} = \frac{1}{2^{1-\alpha\delta}-1} + \frac{1-2\alpha\delta}{1-\alpha\delta}. \tag{25}$$

(iii) From (ii), it follows that full non-cooperation arises in equilibrium when $N > \bar{N}$.

Proof that full cooperation may not hold if N is high

For the particular case where N goes to infinity, the stability function defined in (20) simplifies to

$$\begin{aligned} S(X_0, N) = &- \mu^{-\frac{1}{\eta}}(1-\mu)\frac{X_0^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}} - \frac{\mu^{1-\frac{1}{\eta}}}{(1-\delta)(1-\frac{1}{\eta})} - \alpha\delta\xi\frac{[\mu^{-\frac{1}{\eta}}(1-2\mu)^{1-\frac{1}{\eta}}(1-\mu)]}{(1-\delta)(1-\frac{1}{\eta})} \\ &+ \frac{\delta\mu^{-\frac{1}{\eta}}(1-\mu)}{(1-\delta)(1-\frac{1}{\eta})} - \frac{(1-\alpha)\delta\xi\phi^{1-\frac{1}{\eta}}}{(1-\delta)(1-\frac{1}{\eta})}\mu^{-\frac{1}{\eta}}(1-\mu) \end{aligned}$$

This can be re-written as

$$\begin{aligned} S(X_0, N) =& [1-(1-\delta)X_0^{1-\frac{1}{\eta}} - \mu(1-\mu)^{-1} - \alpha\delta\xi(1-2\mu)^{1-\frac{1}{\eta}} - (1-\alpha)\delta\xi\phi^{1-\frac{1}{\eta}}] \\ &\times \frac{\mu^{-\frac{1}{\eta}}(1-\mu)}{(1-\delta)(1-\frac{1}{\eta})} \end{aligned}$$

Since $0 < \mu < 1$, this condition shows that the grand coalition is not internally stable (i.e., $S(X_0, N) < 0$) when X_0 or ϕ is high and $\eta > 1$.

Proof of Proposition 2.3

(i) If σ^2 is sufficiently large, then for $\eta > 1$, $\xi \approx 0$. Therefore, condition (2.12) implies that

$$\omega_{nc} \approx n\omega_m \text{ and } \omega_{nc} \approx \frac{1}{N-n+1}. \tag{26}$$

Using (26) along with (2.13), we derive the value function of a representative member of the coalition

$$W_m(X) \approx \left(\frac{1}{n(N-n+1)}\right)^{1-\frac{1}{\eta}} u(X) + \frac{u(\frac{1}{n(N-n+1)})}{1-\delta} + \frac{\beta_n}{n^{1-\frac{1}{\eta}}}, \tag{27}$$

where $\beta_n = -\frac{\delta}{(1-\delta)(1-\frac{1}{\eta})}\left(\frac{1}{N-n+1}\right)^{1-\frac{1}{\eta}}$. Using (26) along with (2.14), the value function of a non-coalition member is given by

$$W_{nc}(X) \approx \left(\frac{1}{N-n+1}\right)^{1-\frac{1}{\eta}} u(X) + \frac{u(\frac{1}{N-n+1})}{1-\delta} + \beta_n. \tag{28}$$

Substituting (27) and (28) into the expression of the stability function in (2.15), we obtain the following expression

$$\begin{aligned} S(X_0, n) \approx &\left[\left(\frac{1}{n(N-n+1)}\right)^{1-\frac{1}{\eta}} - \left(\frac{1}{N-n+2}\right)^{1-\frac{1}{\eta}}\right] u(X_0) + \\ &\frac{u(\frac{1}{n(N-n+1)}) - u(\frac{1}{N-n+2})}{1-\delta} + \frac{\beta_n}{n^{1-\frac{1}{\eta}}} - \beta_{n-1} \end{aligned}$$

Using algebraical manipulations, the above expression can be re-written as

$$S(X_0, n) \approx AX_0^{1-\frac{1}{\eta}} - A + \frac{A}{(1-\delta)} - \frac{A\delta}{(1-\delta)},$$

where $A = u(\frac{1}{n(N-n+1)}) - u(\frac{1}{N-n+2})$. The condition $S(X_0, n) \geqslant 0$ holds if and only if

$A \geqslant 0$. Since $u(.)$ is increasing and $N \geqslant 3$, it follows that for $n \geqslant 2$, $A < 0$. Therefore, full non-cooperation arises in equilibrium when σ^2 is sufficiently high and $\eta > 1$.

(ii) The result of Proposition 2.2 and condition (2.16) hold under uncertain and deterministic conditions. Moreover, under deterministic conditions, $\xi = m^{1-\frac{1}{\eta}}$. Therefore, full cooperation holds under deterministic conditions when condition (2.16) is valid with $\xi = m^{1-\frac{1}{\eta}}$. This result can be rewritten as full cooperation occurs in equilibrium under deterministic conditions when $N < \hat{N}_{|\xi=m^{1-\frac{1}{\eta}}}$ and $(1-\alpha)\phi^{1-\frac{1}{\eta}} \geqslant \tilde{\phi} \equiv \bar{\phi}_{|\xi=m^{1-\frac{1}{\eta}}}$.

The Dynamic Membership Case

In the second-stage we use the optimal policy functions to obtain the equilibrium payoff for a coalition member:

$$W_{mt}\left(X_t, n_t\right) = u\left(h_{mt}(X_t)\right) = \frac{\left(\frac{X_t}{n_t(N-n_t+1)}\right)^{1-\frac{1}{\eta}} - 1}{1-\frac{1}{\eta}}.$$

In similar fashion, we obtain the equilibrium payoff of a non-member of the coalition as:

$$W_{nct}\left(X_t, n_t\right) = u\left(h_{nct}(X_t)\right) = \frac{\left(\frac{X_t}{(N-n_t+1)}\right)^{1-\frac{1}{\eta}} - 1}{1-\frac{1}{\eta}}$$

Proof of Result 1

(i) It suffices to show that $S\left(X_t, n_t\right) = W_{mt}\left(X_t, n_t\right) - W_{nct}\left(X_t, n_t - 1\right) < 0$ for all $2 \leqslant n_t \leqslant N$. Using (2.21) this condition can be re-written as

$$S\left(X_t, n_t\right) = \frac{X_t^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}}\left[\left(\frac{1}{n_t\left(N-n_t+1\right)}\right)^{1-\frac{1}{\eta}} - \left(\frac{1}{N-n_t+2}\right)^{1-\frac{1}{\eta}}\right] < 0.$$

Notice that the inequality $n_t(N-n_t+1) > N-n_t+2$ holds for all $2 \leqslant n_t \leqslant N$ and the function $X^{1-\frac{1}{\eta}}/(1-\frac{1}{\eta})$ is increasing in X. These results suggest that

$$\frac{\left(\frac{1}{N-n_t+2}\right)^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}} > \frac{\left(\frac{1}{n_t(N-n_t+1)}\right)^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}}$$

Hence, $S(X_t, n_t) < 0$ for all $2 \leqslant n_t \leqslant N$. As such, full non-cooperation is the equilibrium in period t.

(ii) From (i) it follows that $n_t^* = 1$. Therefore, (2.20) implies that $h_{mt}^* = \frac{X_t}{N} = h_{nct}^*$.

Details for the payoff functions in period $t-1$

Substituting conditions (2.24), (2.28), and (2.29) into the optimization problem faced by a coalition member, we get

$$W_m(X_{t-1}, n_{t-1}) = \frac{(h_{mt-1}(X_{t-1}))^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}} + \delta E\left(\frac{\left(\frac{X_t}{N}\right)^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}}\right).$$

Using (2.1) and (2.2), this expression simplifies to

$$W_{mt-1}(X_{t-1}, n_{t-1}) = A_{mt-1}(n_{t-1})X_{t-1}^{1-\frac{1}{\eta}} + B_{mt-1}, \tag{29}$$

where, $A_{mt-1}(n_{t-1}) = \frac{1}{N^{1-\frac{1}{\eta}}(1-\frac{1}{\eta})}\left[(N\omega_{nct-1})^{1-\frac{1}{\eta}} n_{t-1}^{1-\eta} + \alpha\delta\xi\left(1-\left(n_{t-1}^{1-\eta}+N-n_{t-1}\right)\omega_{nct-1}\right)^{1-\frac{1}{\eta}}\right]$,
$B_{mt-1} = \frac{1}{N^{1-\frac{1}{\eta}}(1-\frac{1}{\eta})}[(1-\alpha)\delta\xi\phi^{1-\frac{1}{\eta}} - (1+\delta)N^{1-\frac{1}{\eta}}]$.

Substituting conditions (2.24), (2.28), and (2.29) into the optimization problem faced by a non-coalition member, we obtain

$$W_{nc}(X_{t-1}, n_{t-1}) = \frac{(\omega_{nct-1}X_{t-1})^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}} + \delta E\left(\frac{\left(\frac{X_t}{N}\right)^{1-\frac{1}{\eta}}-1}{1-\frac{1}{\eta}}\right),$$

Using (2.1) and (2.2), algebraical manipulations lead to

$$W_{nct-1}\left(X_{t-1},n_{t-1}\right)=A_{nct-1}(n_{t-1})X_{t-1}^{1-\frac{1}{\eta}}+B_{mt-1}, \tag{30}$$

where,

$$A_{nct-1}(n_{t-1})=\frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[\left(N\omega_{nct-1}\right)^{1-\frac{1}{\eta}}+\alpha\delta\xi\left(1-\left(n_{t-1}^{1-\eta}+N-n_{t-1}\right)\omega_{nct-1}\right)^{1-\frac{1}{\eta}}\right].$$

Proof of Proposition 2.4

(i) Here, the stability function can be written as

$$S\left(X_{t-1},n_{t-1}\right)=W_{mt-1}\left(X_{t-1},n_{t-1}\right)-W_{nct-1}\left(X_{t-1},n_{t-1}-1\right).$$

Using conditions (29) and (30), this relation implies

$$S\left(X_{t-1},n_{t-1}\right)=X_{t-1}^{1-\frac{1}{\eta}}\left[A_{mt-1}(n_{t-1})-A_{nct-1}\left(n_{t-1}-1\right)\right], \tag{31}$$

where $A_{nct-1}\left(n_{t-1}-1\right)=A_{nct-1}(n_{t-1})_{|n_{t-1}=n_{t-1}-1}$. Since X_{t-1} is positive, $X_{t-1}^{1-\frac{1}{\eta}}$ does not affect the sign of the right-hand side of Eq.(31). This result implies that the sign of the stability function does not depend on X_{t-1}. Therefore, the equilibrium coalition size in period $t-1$ does not depend on the values of $X_{t-1}>0$.

(ii) The grand coalition is stable if and only if

$$S\left(X_{t-1},N\right)=X_{t-1}^{1-\frac{1}{\eta}}\left[A_{mt-1}(N)-A_{nct-1}\left(N-1\right)\right]\geqslant 0. \tag{32}$$

Algebraical manipulations yield

$$S\left(X_{t-1},N\right)=\frac{X_{t-1}^{1-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[\left(N\omega_{nct-1}(N)\right)^{1-\frac{1}{\eta}}N^{1-\eta}-\left[N\omega_{nct-1}(N-1)\right]^{1-\frac{1}{\eta}}+\alpha\delta\xi\left(\rho_{t-1}(N)-\rho_{t-1}(N-1)\right)\right] \tag{33}$$

where

$$\omega_{nct-1}(N) = \omega_{nct-1|nct-1=N} = \frac{1}{(\alpha\delta\xi)^{\eta} N^{1-\eta} + N^{1-\eta} + N - N} = \frac{1}{[1 + (\alpha\delta\xi)^{\eta}] N^{1-\eta}},$$

$$\omega_{nct-1}(N-1) = \omega_{nct-1|nct-1=N-1} = \frac{1}{(\alpha\delta\xi)^{\eta} N^{1-\eta} + (N-1)^{1-\eta} + N - N + 1} = \frac{1}{(\alpha\delta\xi)^{\eta} N^{1-\eta} + (N-1)^{1-\eta} + 1},$$

$$\rho_{t-1}(N) = \left[1 - N^{1-\eta}\omega_{nct-1}(N)\right]^{1-\frac{1}{\eta}} = \left[\frac{(\alpha\delta\xi)^{\eta}}{1 + (\alpha\delta\xi)^{\eta}}\right]^{1-\frac{1}{\eta}},$$

$$\rho_{t-1}(N-1) = \left[1 - \left[(N-1)^{1-\eta} + 1\right]\omega_{nc(N-1)}\right]^{1-\frac{1}{\eta}} = \left[\frac{(\alpha\delta\xi)^{\eta} N^{1-\eta}}{(\alpha\delta\xi)^{\eta} N^{1-\eta} + (N-1)^{1-\eta} + 1}\right]^{1-\frac{1}{\eta}}.$$

Therefore, for $\eta > 1$, the condition in Eq.(33) is satisfied if

$$(N\omega_{nct-1}(N))^{1-\frac{1}{\eta}} N^{1-\eta} - [N\omega_{nct-1}(N-1)]^{1-\frac{1}{\eta}} + \alpha\delta\xi\left(\rho_{t-1}(N) - \rho_{t-1}(N-1)\right) \geqslant 0. \tag{34}$$

The first term in Eq.(34) can be rewritten as

$$(N\omega_{nct-1}(N))^{1-\frac{1}{\eta}} N^{1-\eta} = \left[\frac{N}{[1 + (\alpha\delta\xi)^{\eta}] N^{1-\eta}}\right]^{1-\frac{1}{\eta}} N^{1-\eta} = \left[\frac{1}{1 + (\alpha\delta\xi)^{\eta}}\right]^{1-\frac{1}{\eta}}.$$

The second term in Eq.(34) can be rewritten as

$$[N\omega_{nct-1}(N-1)]^{1-\frac{1}{\eta}} = \left[\frac{N}{(\alpha\delta\xi)^{\eta} N^{1-\eta} + (N-1)^{1-\eta} + 1}\right]^{1-\frac{1}{\eta}}.$$

The third term in Eq.(34) can be rewritten as

$$\alpha\delta\xi\left(\rho_{t-1}(N) - \rho_{t-1}(N-1)\right) = \alpha\delta\xi\left\{\left[\frac{(\alpha\delta\xi)^{\eta}}{1 + (\alpha\delta\xi)^{\eta}}\right]^{1-\frac{1}{\eta}} - \left[\frac{(\alpha\delta\xi)^{\eta} N^{1-\eta}}{(\alpha\delta\xi)^{\eta} N^{1-\eta} + (N-1)^{1-\eta} + 1}\right]^{1-\frac{1}{\eta}}\right\},$$

Using these last three results, condition (34) simplifies to

$$N^{\frac{1}{\eta}-1}[1 + (\alpha\delta\xi)^{\eta}]^{\frac{1}{\eta}} \geqslant \frac{1 + (\alpha\delta\xi)^{\eta} N^{1-\eta}}{[(\alpha\delta\xi)^{\eta} N^{1-\eta} + (N-1)^{1-\eta} + 1]^{1-\frac{1}{\eta}}}.$$

(iii) In the case where $0 < \eta < 1$, the condition in Eq.(33) is satisfied when Eq.(34)$\leqslant 0$. Following the same approach used in (ii) yields

$$N^{\frac{1}{\eta}-1}[1 + (\alpha\delta\xi)^{\eta}]^{\frac{1}{\eta}} \leqslant \frac{1 + (\alpha\delta\xi)^{\eta} N^{1-\eta}}{[(\alpha\delta\xi)^{\eta} N^{1-\eta} + (N-1)^{1-\eta} + 1]^{1-\frac{1}{\eta}}}.$$

If $\eta = 1$, condition (2.12) implies that

$$\omega_{nct-1} = n_{t-1}\omega_{mt-1} \text{ and } \omega_{nct-1} = \frac{1}{1 + \alpha\delta + N - n_{t-1}}. \quad (35)$$

The payoff function for a representative coalition member is given by

$$W_{mt-1}(X_{t-1}, n_{t-1}) = (1 + \alpha\delta)\ln(X_{t-1}) - \ln(n_{t-1}(1 + \alpha\delta + N - n_{t-1})) + B_{mt-1}, \quad (36)$$

where, $B_{mt-1} = \alpha\delta \ln\left(\frac{\alpha\delta}{1+\alpha\delta+N-n_{t-1}}\right) + \delta[E\ln(Z_{t-1}) + (1-\alpha)\ln(\phi) - \ln(N)]$.

The payoff function for a non coalition member in this context (where $\eta = 1$) reads

$$W_{nct-1}(X_{t-1}, n_{t-1}) = (1 + \alpha\delta)\ln(X_{t-1}) - \ln(1 + \alpha\delta + N - n_{t-1}) + B_{mt-1}. \quad (37)$$

Substituting (36) and (37) into (2.15), the stability function in this context reads

$$S(X_{t-1}, n_{t-1}) = \ln(2 + \alpha\delta + N - n_{t-1}) - \ln(n_{t-1}(1 + \alpha\delta + N - n_{t-1})). \quad (38)$$

Since $n_{t-1}(1 + \alpha\delta + N - n_{t-1}) > (2 + \alpha\delta + N - n_{t-1})$ for $N \geqslant 3$ and $N \geqslant n_{t-1} \geqslant 2$, it follows that $S(X_{t-1}, n_{t-1}) < 0$ for $n_{t-1} \geqslant 2$. This result reveals that any coalition of size greater than or equal to two is not stable. Therefore, full non-cooperation arises in equilibrium in period $t-1$ when $\eta = 1$.

Proof that full non-cooperation is the equilibrium in period $t-1$ if σ^2 is high

If σ^2 is sufficiently large, then for $\eta > 1$, $\xi \approx 0$. Therefore, individual harvest rates reads

$$\omega_{nc} \approx n_{t-1}^{\eta}\omega_{mt-1} \text{ and } \omega_{nct-1} \approx \frac{1}{n_{t-1} + (N - n_{t-1})n_{t-1}^{\eta}}. \tag{39}$$

Substituting (39) into the expression of the stability function in condition (31), we obtain the following expression

$$S(X_{t-1}, n_{t-1}) \approx \frac{X_{t-1}}{1-\frac{1}{\eta}}\left[\left(\frac{n_{t-1}^{\eta}}{n_{t-1} + (N - n_{t-1})n_{t-1}^{\eta}}\right)^{1-\frac{1}{\eta}} n_{t-1}^{1-\eta} - \left(\frac{(n_{t-1}-1)^{\eta}}{n_{t-1} - 1 + (N - n_{t-1} + 1)(n_{t-1}-1)^{\eta}}\right)^{1-\frac{1}{\eta}}\right]$$

Given the fact that $\eta > 1$, the term $\frac{X_{t-1}}{1-\frac{1}{\eta}}$ is positive. Therefore, the condition $S(X_{t-1}, n_{t-1}) \geqslant 0$ holds as long as the bracketed term is nonnegative. Using this result, algebraical manipulations reveal that the condition $S(X_{t-1}, n_{t-1}) \geqslant 0$ holds if and only if $n_{t-1} + (N - n_{t-1})n_{t-1}^{\eta} \leqslant (n_{t-1}-1)^{1-\eta} + N - n_{t-1} + 1$. This condition is not satisfied for $n_{t-1} > 1$. Therefore, full non-cooperation arises in equilibrium when σ^2 is sufficiently high and $\eta > 1$.

Condition (2.32) holds under both uncertain and deterministic environmental conditions. For scenarios in which environmental conditions are deterministic $\xi = m^{1-\frac{1}{\eta}}$. In this context, condition (2.32) provides conditions under which full cooperation happens in equilibrium under deterministic conditions.

Proof of Proposition 2.5

Recall that by assumption, $E(\hat{Z}_s) = E(Z_s)$ and $\hat{Z}_s$ is more uncertain than Z_s.

According to the harvest rules (2.38) and (2.39), a change in the random shock Z_s that raises ξ reduces individual harvests. Denoting by $f(z) = z^{1-\frac{1}{\eta}}$, it is easy to verify that $f(z)$ is convex whenever $0 < \eta < 1$ and is concave if $\eta > 1$.

(i) Notice that in this case, $\eta > 1$. Since $\hat{Z}_s$ is more uncertain than Z_s and $f(x)$ is concave in x, by definition, we have $\xi(\hat{Z}_s) = E(f(\hat{Z}_s)) < E(f(Z_s)) = \xi(Z_s)$. Therefore, individual harvests associated with $\hat{Z}_s$ are higher relative to the scenario associated with Z_s.

(ii) Notice that in this case, $0 < \eta < 1$. Since $\hat{Z}_s$ is more uncertain than Z_s and $f(.)$ is convex in this case, by definition, we have $\xi(\hat{Z}_s) = E(f(\hat{Z}_s)) > E(f(Z_s)) = \xi(Z_s)$. Therefore, individual harvests associated with $\hat{Z}_s$ are lower relative to the scenario associated with Z_s.

(iii) Notice that in this case, $\eta = 1$. Since $\hat{Z}_s$ is more uncertain than Z_s and $f(.)$ is linear in this case, by definition, we have $\xi(\hat{Z}_s) = E(f(\hat{Z}_s)) = E(f(Z_s)) = \xi(Z_s)$. Therefore, individual harvests associated with $\hat{Z}_s$ and Z_s are equal.

Proof of Proposition 2.6

Here, the stability function reads

$$S\left(X_{t-2}, n_{t-2}\right) = W_{m,t-2}\left(X_{t-2}, n_{t-2}\right) - W_{nc,t-2}\left(X_{t-2}, n_{t-2} - 1\right).$$

Using the expression of $W_{m,t-2}\left(X_{t-2}, n_{t-2}\right)$ and $W_{nc,t-2}\left(X_{t-2}, n_{t-2} - 1\right)$ defined in Eq.(2.40) and Eq.(2.41), this expression simplifies to

$$S\left(X_{t-2}, n_{t-2}\right) = X_{t-2}^{1-\frac{1}{\eta}}\left[A_{mt-2}(n_{t-2}) - A_{nct-2}\left(n_{t-2} - 1\right)\right]. \tag{40}$$

(i) Since the current resource stock X_{t-2} is always positive, condition (40) reveals that X_{t-2} does not affect the sign of the stability function. As such, any variations of X_{t-2} do not change equilibrium coalitions.

(ii) The grand coalition is stable if and only if we have

$$S\left(X_{t-2}, N\right) = X_{t-2}^{1-\frac{1}{\eta}}\left[A_{mt-2}(N) - A_{nct-2}\left(N-1\right)\right] \geqslant 0. \tag{41}$$

Using the expression of $A_{mt-2}(n_{t-2})$ defined below condition (2.40), we derive

$$\begin{aligned} A_{mt-1}(N) = & \frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[\left(N\omega_{nct-2(N)}\right)^{1-\frac{1}{\eta}} N^{1-\eta}\right. \\ & \left. + \alpha\delta\xi(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n_{t-1}^{*})(1-N^{1-\eta}\omega_{nct-2(N)})^{1-\frac{1}{\eta}}\right]. \end{aligned} \tag{42}$$

Using the expression of $A_{nct-2}(n_{t-2})$ defined below condition (2.41), we get

$$\begin{aligned} A_{nct-2}(N-1) = & \frac{1}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[\left(N\omega_{nct-2(N-1)}\right)^{1-\frac{1}{\eta}}\right. \\ & \left. + \alpha\delta\xi(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n_{t-1}^{*})\left\{1-((N-1)^{1-\eta}+1)\omega_{nct-2(N-1)}\right\}^{1-\frac{1}{\eta}}\right], \end{aligned} \tag{43}$$

Substituting equations (42) and (43) into Eq.(41) and simplifying yields

$$\begin{aligned} S\left(X_{t-2}, N\right) = & \frac{X_{t-2}^{1-\frac{1}{\eta}}}{N^{1-\frac{1}{\eta}}\left(1-\frac{1}{\eta}\right)}\left[\left(N\omega_{nct-2(N)}\right)^{1-\frac{1}{\eta}} N^{1-\eta} - \left[N\omega_{nct-2(N-1)}\right]^{1-\frac{1}{\eta}}\right. \\ & \left. + \alpha\delta\xi(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n_{t-1}^{*})\left(\rho_{t-2(N)} - \rho_{t-2(N-1)}\right)\right] \geqslant 0, \end{aligned} \tag{44}$$

where,

$$\omega_{nct-2(N)} = \frac{1}{\left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta} + N^{1-\eta} + N - N} = \frac{1}{N^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}},$$

$$\omega_{nct-2(N-1)} = \frac{1}{\left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta} + (N-1)^{1-\eta} + N - N + 1} = \frac{1}{1 + (N-1)^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}},$$

$$\rho_{t-2(N)} = \left[1 - N^{1-\eta}\omega_{nct-2(N)}\right]^{1-\frac{1}{\eta}} = \left[\frac{\left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}}{N^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}}\right]^{1-\frac{1}{\eta}},$$

$$\rho_{t-2(N-1)} = \left\{1 - \left[(N-1)^{1-\eta} + 1\right]\omega_{nct-2(N-1)}\right\}^{1-\frac{1}{\eta}} = \left[\frac{\left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}}{1 + (N-1)^{1-\eta} + \left(\alpha\delta\xi\nu(n_{t-1}^{*})\right)^{\eta}}\right]^{1-\frac{1}{\eta}}.$$

Therefore, for $\eta > 1$, condition Eq.(44) is satisfied if and only if

$$\left(N\omega_{nct-2(N)}\right)^{1-\frac{1}{\eta}} N^{1-\eta} - \left[N\omega_{nct-2(N-1)}\right]^{1-\frac{1}{\eta}} + \alpha\delta\xi(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n^*_{t-1})\left(\rho_{t-2(N)} - \rho_{t-2(N-1)}\right) \geqslant 0. \tag{45}$$

The first term in Eq.(45) can be re-written as

$$\left(N\omega_{nct-2(N)}\right)^{1-\frac{1}{\eta}} N^{1-\eta} = \left[\frac{N}{N^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}}\right]^{1-\frac{1}{\eta}} N^{1-\eta}.$$

The second term in Eq.(45) can be re-written as

$$\left[N\omega_{nct-2(N-1)}\right]^{1-\frac{1}{\eta}} = \left[\frac{N}{1 + (N-1)^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}}\right]^{1-\frac{1}{\eta}}.$$

The third term in Eq.(45) can be re-written as

$$\begin{aligned}&\alpha\delta\xi(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n^*_{t-1})\left(\rho_{t-2}(N) - \rho_{t-2}(N-1)\right) = \\ &\alpha\delta\xi(1-1/\eta)N^{1-\frac{1}{\eta}}\nu(n^*_{t-1})\left\{\left[\frac{\left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}}{N^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}}\right]^{1-\frac{1}{\eta}} - \left[\frac{\left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}}{1 + (N-1)^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}}\right]^{1-\frac{1}{\eta}}\right\},\end{aligned} \tag{46}$$

Making use of these last three results, Eq.(45) simplifies to

$$N^{1-\frac{1}{\eta}}\frac{\left[N^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}(1-1/\eta)\right]}{\left[N^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}\right]^{1-\frac{1}{\eta}}} - N^{1-\frac{1}{\eta}}\frac{\left[1 + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}(1-1/\eta)\right]}{\left[1 + (N-1)^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}\right]^{1-\frac{1}{\eta}}} \geqslant 0$$

This expression can be rewritten as

$$\frac{N^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}(1-1/\eta)}{\left[N^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}\right]^{1-\frac{1}{\eta}}} \geqslant \frac{1 + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}(1-1/\eta)}{\left[1 + (N-1)^{1-\eta} + \left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}\right]^{1-\frac{1}{\eta}}}.$$

(*iii*) In the case where $0 < \eta < 1$, the condition in Eq.(44) is satisfied when the inequality in (45) is reversed. Therefore, it follows from (ii) that

$$\frac{N^{1-\eta}+\left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}(1-1/\eta)}{\left[N^{1-\eta}+\left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}\right]^{1-\frac{1}{\eta}}} \leqslant \frac{1+\left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}(1-1/\eta)}{\left[1+(N-1)^{1-\eta}+\left(\alpha\delta\xi\nu(n^*_{t-1})\right)^{\eta}\right]^{1-\frac{1}{\eta}}}.$$

The costant marginal cost case

Proof of Lemma 3.1

Evaluating (3.3) at the optimum, we get

$$W_f(\mathbf{X}_t, \theta^*) = \sum_{i=A,B} p_i(X_{it} - y^*_{ift}) + \beta \int_F W_f(\mathbf{X}_{t+1}; \theta^*)\phi(z_t|\theta^*)dz_t. \tag{47}$$

Following Costello et al. (2019), we restrict our attention to stock-independent escapement strategies. In this context, according to (3.2), the second right-hand side term of (47) does not depend on $\mathbf{X}_t$. This result implies that

$$\frac{\partial W_f(\mathbf{X}_t; \theta^*)}{\partial X_{jt}} = p_j \tag{48}$$

Since this formula holds for all $\mathbf{X}_t$ in the relevant range, evaluating (48) at $\mathbf{X}_{t+1}$, we get $\frac{\partial W_f(\mathbf{X}_{t+1};\theta^*)}{\partial X_{jt+1}} = p_j$. Moreover, differentiating (3.2) with respect to y_{ift} yields $\frac{\partial X_{jt+1}}{\partial y_{ift}} = Z^p_{it} g'_i(y_{ift})\psi_{ijt}$. Substituting these last two results into (3.4) and using the fact that the mean of Z^p_{it} equals one, the result follows.

Details for the value function of the learning planner

Suppose the value function of the learning planner at the optimum takes the form conjectured in (3.9). Substituting optimal escapements, $y^*_{il}(\xi)$, and the conjecture, (3.9) into (47), we get

$$\begin{aligned} W_l(\mathbf{X}_t, \xi) = &\sum_{i=A,B} p_i[X_{it} - y^*_{il}(\xi)] \\ &+ \beta \int_F (\sum_{i=A,B} p_i(X_{it+1} - y^*_{il}(\xi)) + \nu(\hat{\xi}(.|z_t)))[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t. \end{aligned} \tag{49}$$

Conditions (49) and (3.9) imply that

$$\nu(\xi) = \beta \int_F \Big(\sum_{i=A,B} p_i(X_{it+1} - y^*_{il}(\xi)) + \nu(\hat{\xi}(.|z_t)) \Big) \Big[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta \Big] dz_t. \tag{50}$$

Suppose the solution to $\nu(\xi)$ takes the following form:

$$\nu(\xi) = \int_\Theta A(\theta)\xi(\theta)d\theta. \tag{51}$$

Updating (51) to period $t+1$, we get

$$\nu(\hat{\xi}(.|z_t)) = \int_\Theta A(\theta)\hat{\xi}(\theta|z_t)d\theta. \tag{52}$$

According to the Baye's rule, the updated prior beliefs can be written as

$$\hat{\xi}(\theta|z_t) = \frac{\phi(z_t|\theta)\xi(\theta)}{\int_\Theta \phi(z_t|x)\xi(x)dx}.$$

Substituting this rule into (52), we obtain

$$\nu(\hat{\xi}(.|z_t)) = \int_\Theta A(\theta) \frac{\phi(z_t|\theta)\xi(\theta)}{\int_\Theta \phi(z_t|x)\xi(x)dx} d\theta. \tag{53}$$

Substituting (51) and (53) into (50) and simplifying, we get

$$(1-\beta)\int_\Theta A(\theta)\xi(\theta)d\theta = \beta \int_F \sum_{i=A,B} p_i(X_{it+1} - y^*_{il}(\xi)) \Big[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta \Big] dz_t. \tag{54}$$

This expression can be re-written as

$$\int_{\Theta}(1-\beta)A(\theta)\xi(\theta)d\theta = \int_{\Theta}\beta\int_{F}\sum_{i=A,B}p_i(X_{it+1}-y^*_{il}(\xi))\phi(z_t|\theta)\xi(\theta)dz_t d\theta.$$

Equalizing terms in the integral sign gives rise to

$$A(\theta) = \frac{\beta}{1-\beta}\int_{F}\sum_{i=A,B}p_i(X_{it+1}-y^*_{il}(\xi))\phi(z_t|\theta)dz_t. \tag{55}$$

Substituting (55) into (51), we obtain

$$\nu(\xi) = \frac{\beta}{1-\beta}\int_{\Theta}\int_{F}\sum_{i=A,B}p_i(X_{it+1}-y^*_{il}(\xi)\phi(z_t|\theta dz_t)\xi(\theta)d\theta. \tag{56}$$

Proof of Lemma 3.2

The proof of this lemma is very similar to the proof of Lemma 3.1. As such, we will provide a sketch of the proof only. Partially differentiating (3.9) with respect to X_{jt} and updating the result to period $t+1$, we get $\frac{\partial W_l(\mathbf{X}_{t+1},\hat{\xi}(.|z_t))}{\partial X_{jt+1}} = p_j$. Using equation (3.2), we derive $\frac{\partial X_{jt+1}}{\partial y_{ilt}} = Z^p_{it}g'_i(y_{ilt})\psi_{ijt}$ for $i = A, B$. Utilizing these results allow us to re-write condition (3.8) so as to obtain (3.10) and (3.11).

Proof of Proposition 3.1

(i) Notice that by assumption $\mu(\theta)$ is convex in θ and $\theta^* = \int_{\Theta}\theta\xi(\theta)d\theta$. In this context, Jensen's inequality leads to $\mu(\theta^*) < \int_{\Theta}\mu(\theta)\xi(\theta)d\theta$. Using this result along with conditions (3.5) and (3.10) and the fact that $g_A(.)$ is concave, we find that $y_{Af}(\theta^*) > y^*_{Al}(\xi)$. Making use of conditions (3.6) and (3.11) along with the facts that $g_A(.)$ is concave and the inequality $\mu(\theta^*) < \int_{\Theta}\mu(\theta)\xi(\theta)d\theta$ holds, we establish that $y_{Bf}(\theta^*) < y^*_{Bl}(\xi)$.

(ii) Here, by assumption, $\mu(\theta)$ is concave and $\theta^* = \int_\Theta \theta\xi(\theta)d\theta$. Then, Jensen's inequality gives rise to $\mu(\theta^*) > \int_\Theta \mu(\theta)\xi(\theta)d\theta$. Utilizing conditions (3.5) and (3.10) and the fact that $g_A(.)$ is concave, we show that $y_{Af}(\theta^*) < y^*_{Al}(\xi)$. In the case of patch B, if we compare conditions (3.6) and (3.11), coupled with the fact that $g_A(.)$ is concave, and the inequality $\mu(\theta^*) > \int_\Theta \mu(\theta)\xi(\theta)d\theta$ is valid, we show that $y_{Bf}(\theta^*) > y^*_{Bl}(\xi)$.

(iii) When $\mu(\theta)$ is linear in θ and $\theta^* =\int_\Theta \theta\xi(\theta)d\theta$, the inequality $\mu(\theta^*) = \int_\Theta \mu(\theta)\xi(\theta)d\theta$ always holds. In this context, conditions (3.5) and (3.6) reveal that Patch A's optimal escapement under full information and learning are equal. Likewise, using conditions (3.6) and (3.11), we find that Patch B's optimal escapement under full information and learning are identical.

Proof of Proposition 3.2

If ϕ has a higher mean than $\tilde{\phi}$, then $\mu(\theta) = \int_F z_t\phi(z_t|\theta)dz_t \geqslant \tilde{\mu}(\theta) = \int_F z_t\tilde{\phi}(z_t|\theta)dz_t$. This inequality can be rewritten as follows $a - \int\limits_\Theta \mu(\theta)\xi(\theta)d\theta \leqslant a - \int\limits_\Theta \tilde{\mu}(\theta)\xi(\theta)d\theta$. Since $g_i(.)$ is concave, using this inequality and condition (3.10), we get $y^*_{Al}(\phi) \leqslant y^*_{Al}(\tilde{\phi})$. Likewise, utilizing condition (3.11) and the inequality $\int\limits_\Theta \mu(\theta)\xi(\theta)d\theta \geqslant \int\limits_\Theta \tilde{\mu}(\theta)\xi(\theta)d\theta$, we establish that $y^*_{Bl}(\phi) \geqslant y^*_{Bl}(\tilde{\phi})$.

Proof of Proposition 3.3

(i) Since by assumption, ξ first-order stochastically dominate $\tilde{\xi}$ and $\mu' > 0$, then the inequalities $(a - \int\limits_\Theta \mu(\theta)\xi(\theta)d\theta) < (a - \int\limits_\Theta \mu(\theta)\tilde{\xi}(\theta)d\theta)$ and $\int\limits_\Theta \mu(\theta)\xi(\theta)d\theta > \int\limits_\Theta \mu(\theta)\tilde{\xi}(\theta)d\theta$ hold. Hence, the expected marginal return on investment in patch A is lower under ξ than $\tilde{\xi}$. Since $g_A(.)$ is concave, condition (3.10), reveals that the escapement under ξ is lower relative to that of $\tilde{\xi}$.

Likewise, since the inequality $\int\limits_\Theta \mu(\theta)\xi(\theta)d\theta > \int\limits_\Theta \mu(\theta)\tilde{\xi}(\theta)d\theta$ holds, the expected marginal return on investment in patch B is higher under ξ than $\tilde{\xi}$. Since $g_B(.)$ is concave, condition (3.11) shows that escapement under ξ is higher than that of $\tilde{\xi}$.

The proofs for (ii) and (iii) follows similar reasoning.

Proof of Proposition 3.4

Since $\tilde{\phi}$ is a mean preserving spread of ϕ, then both distributions have the same mean. That is, $\mu(\theta) = \tilde{\mu}(\theta)$. Consequently, optimal escapements defined in conditions (3.10) and (3.11) remain unchanged whether the planner faces the distribution ϕ or $\tilde{\phi}$. In other words, $y_{il}(\phi) = y_{il}(\tilde{\phi})$ for all $i \in \{A, B\}$.

Proof of Proposition 3.5

(i) Since $\tilde{\xi}$ is a mean preserving spread of ξ and $\mu'' < 0$, the following inequality $\int_{\Theta} \mu(\theta)\xi(\theta)d\theta > \int_{\Theta} \mu(\theta)\tilde{\xi}(\theta)d\theta$ is necessarily valid.

Using this inequality and condition (3.10) along with the fact that g_A is concave, we find that patch A's optimal escapement under ξ is lower compared to optimal escapement under $\tilde{\xi}$. Likewise, using that inequality and condition (3.11) along with the fact that g_B is concave, we find that patch B's optimal escapement under ξ is higher compared to optimal escapement under $\tilde{\xi}$.

(ii) Suppose $\tilde{\xi}$ is a mean preserving spread of ξ and $\mu'' > 0$. It follows that the inequality $\int_{\Theta} \mu(\theta)\xi(\theta)d\theta < \int_{\Theta} \mu(\theta)\tilde{\xi}(\theta)d\theta$ is valid.

Utilizing this inequality along with the fact that g_A is concave, contemplating condition (3.10), we find that patch A's optimal escapement under ξ is greater or equal to optimal escapement under $\tilde{\xi}$. Contemplating condition (3.11) while noting that the above inequality holds and that g_B is concave, we find that patch B's optimal escapement under ξ is no greater than optimal escapement under $\tilde{\xi}$.

(iii) By assumption, $\tilde{\xi}$ is a mean preserving spread of ξ , and μ is linear in θ. Therefore, the inequality $\int\limits_{\Theta}\mu(\theta)\xi(\theta)d\theta = \int\limits_{\Theta}\mu(\theta)\tilde{\xi}(\theta)d\theta$ always holds. In this context, condition (3.10) reveals that Patch A's optimal escapement under ξ and $\tilde{\xi}$ are equal. Likewise, contemplating condition (3.11), we find that Patch B's optimal escapement under ξ and $\tilde{\xi}$ are identical.

The stock dependent marginal cost case

Proof of Lemma 3.3

The proof of this lemma is very similar to the proof of Lemma 3.1. As such, we will provide a sketch of the proof only. Partially differentiating (3.12) with respect to X_{jt} and updating the result to period $t+1$, we get $\frac{\partial W_f(\mathbf{X}_{t+1},\theta^*)}{\partial X_{jt+1}} = p_j - c_j(X_{jt+1})$. Using equation (3.2), we obtain the explicit form of $\frac{\partial X_{jt+1}}{\partial y_{ift}}$ for $i = A, B$. Utilizing these results, condition (3.13) can be re-written for $i = A, B$ to retrieve (i) and (ii) respectively.

Proof of Lemma 3.4

The proof of this lemma is very similar to the proof of Lemma 3.1. As such, we will provide a sketch of the proof only. Partially differentiate (3.16) with respect to X_{jt} and update the result to period $t+1$ to obtain $p_j - c_j(X_{jt+1})$. Also, partially differentiate (3.2) for all j with respect to y_{ilt} for $i = A, B$. Substituting these results into (3.17) for $j = A, B$ allow us to retrieve (3.18) and (3.19).

Proof of Proposition 3.6

(i) Notice that by assumption $\mu(\theta)$ is linear, $\phi(.|\theta)$ is convex in θ and $\theta^*= \int_{\Theta}\theta\xi(\theta)d\theta$. In this context, $\mu(\theta^*) = \int\limits_{\Theta}\mu(\theta)\xi(\theta)d\theta$ and Jensen's inequality implies $\int\limits_{\Theta}\phi(.|\theta)\xi(\theta)d\theta > \phi(.|\theta^*)$. Holding escapement constant, these inequalities have two implications. First, the right-hand side of (3.14) is greater than the right-hand side of (3.18). Second, the right-hand side of (3.15) is greater than the right-hand side of (3.19). These results imply that $y_{if}(\theta^*) > y^*_{il}$ for $i = A, B$.

(ii) By assumption $\mu(\theta)$ is linear in θ, $\phi(.|\theta)$ is concave in θ, and $\theta^* = \int_\Theta \theta\xi(\theta)d\theta$. As such, $\mu(\theta^*) = \int\limits_\Theta \mu(\theta)\xi(\theta)d\theta$ and by Jensen's inequality $\int\limits_\Theta \phi(.|\theta)\xi(\theta)d\theta < \phi(.|\theta^*)$. Holding escapement constant, these inequalities have two consequences. First, the right-hand side of (3.14) is lower than the right-hand side of (3.18). Second, the right-hand side of (3.15) is lower than the right-hand side of (3.19). Hence, $y_{if}(\theta^*) < y^*_{il}$, $i = A, B$.

Adaptive learning

Adaptive learning harvester

Under adaptive learning, the planner is not fully informed about the true value of θ. Similar to the learning planner, the adaptive learning planner forms initial beliefs about the distribution of θ. These two planners differ only in terms of their anticipation of learning. The adaptive learning planner updates his beliefs across periods. However, in making escapement decisions, he does not account for the fact that his future beliefs may change. Concentrating on the scenario where the marginal harvesting costs are stock dependent, the problem solved by the adaptive learning planner is represented by the Bellman equation

$$\begin{aligned} W_a(\mathbf{X}_t, \xi) = \max_{\mathbf{y}_{at}} \{ \sum_{i=A,B} [p_i(X_{it} - y_{iat}) - \int_{y_{iat}}^{X_{it}} c_i(r)dr] \\ + \beta \int\limits_F W_a(\mathbf{X}_{t+1}, \xi)[\int\limits_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t\}, \end{aligned} \quad (57)$$

where $\mathbf{X}_t = (X_{At}, X_{Bt})$, $\mathbf{y}_{at} = (y_{Aat}, y_{Bat})$, and the subscript "$a$" stands for adaptive learning. The planner solves (57) subject to (3.2). The first-order condition for an interior solution to (57) is obtained by taking the partial derivative with respect to y_{iat}

and is given by

$$p_i - c_i(y_{iat}) = \beta \int_F (\sum_{j=A,B} \frac{\partial W_a(\mathbf{X}_{t+1}, \xi)}{\partial X_{jt+1}} \frac{\partial X_{jt+1}}{\partial y_{iat}})[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t \ \forall i. \tag{58}$$

Condition (58) suggests that the adaptive planner's expected net present value of harvest is maximized when net marginal revenue $p_i - c_i(y_{iat})$ in patch i equals expected discounted marginal return from investment (i.e., allowing the resource stock to grow) for harvest in the next period. The marginal return from investment is the additional return obtained from conserving one more unit of the resource for harvest in the next period. Following an approach similar to that of the learning planner's scenario presented in Section 3.5, optimal escapement in each patch can be stock independent, as shown in the following lemma.

Lemma .1. *(i) Optimal escapement in patch A is the solution to*

$$\begin{aligned} p_A - c_A(y_{Aat}) = \beta g'_A(y_{Aat})\{p_A D_{AA} + p_B D_{AB}(a - \int_\Theta \mu(\theta)\xi(\theta)d\theta) \\ - \int_F (c_A(X_{At+1})D_{AA} + c_B(X_{Bt+1})(a - z_t)D_{AB})[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t\}. \end{aligned} \tag{59}$$

(ii) Optimal escapement in patch B satisfies

$$\begin{aligned} p_B - c_B(y_{Bat}) = \beta g'_B(y_{Bat})\{p_A D_{BA} \int_\Theta \mu(\theta)\xi(\theta)d\theta + p_B D_{BB} \\ - \int_F (c_A(X_{At+1})z_t D_{BA} + c_B(X_{Bt+1})D_{BB})[\int_\Theta \phi(z_t|\theta)\xi(\theta)d\theta]dz_t\}. \end{aligned} \tag{60}$$

These results lead to the following proposition.

Proposition .1. $y^*_{il}(\xi) = y^*_{ia}(\xi)$ *for all* $i \in \{A, B\}$

The proof of this proposition is straightforward. Conditions (3.18) and (59) reveal that patch A's optimal escapements under the learning and adaptive scenarios are equal. Likewise, conditions (60) and (3.19) show that patch B's optimal escapements under the learning and adaptive scenarios are identical.

Countries

List of Countries

Treated: Cyprus, Egypt, Spain, France, Greece, Croatia, Italy, Morocco, Malta, Tunisia, Turkey.

Control: Angola, Anguilla (UK), United Arab Emirates, Argentina, Antigua Barbuda, Australia, Bangladesh, Bahamas, Brazil, Barbados, Canada, Chile, China, Cote d'Ivoire, Colombia, Comoros Isl., Cape Verde, Costa Rica, Germany, Denmark, Dominican Republic, Ecuador, Egypt, Spain, Estonia, Finland, Fiji, France, Gabon, United Kingdom, Ghana, Guinea, Guinea-Bissau, Equatorial Guinea, Guatemala, Honduras, Haiti, Indonesia, India, Ireland, Iran, Iceland, Jamaica, Japan, Korea, Liberia, Sri Lanka, Morocco, Madagascar, Maldives, Mexico, Myanmar, Mozambique, Mauritania, Mauritius, Malaysia, Namibia, Nigeria, Nicaragua, Netherlands, Norway, New Zealand, Oman, Pakistan, Panama, Peru, Philippines, Portugal, Russia, Saudi Arabia, Sudan, Senegal, Sierra Leone, El Salvador, Sao Tome Principe, Suriname, Sweden, Seychelles, Thailand, Trinidad Tobago, Tanzania, Ukraine, Uruguay, USA, Venezuela, Viet Nam, Yemen, South Africa.

Robustness checks

Countries outside Africa, Asia, and Europe as control group

In Section 4.7.2, we use a control group defined based on EEZs located only in Africa, Asia, and Europe, given the location of the treated EEZs. Some of the control countries might have been affected by the GFCM as fish straddle across EEZs. In order to alleviate concerns of such potential contamination, I consider a set of countries outside Africa, Asia, and Europe in the control group. In general, our results support the conclusion of our main results in Table 4.2 as well as that of our sensitivity analysis in Table 4.5. We

Table 7: Effect of the GFCM on the share of overexploited stocks - outside Africa, Asia, Europe as control.

Variable	Countries outside Africa, Asia, Europe as control group				
	Model 1	Model 2	Model 3	Model 4	Model 5
ATT	2.763	4.181	1.881	0.008	-2.544
	(4.27)	(6.70)	(6.39)	(4.46)	(3.54)
Ln Real GDP per capita	-50.77	-82.647*	-81.079*		-38.084
	(36.28)	(49.73)	(47.78)		(37.47)
Ln (real GDP per capita) squared	2.73	4.379	4.309		2.255
	(2.02)	(2.83)	(2.68)		(2.15)
Ln Population	13.19	10.864	10.699	42.873***	8.386
	(9.22)	(15.79)	(14.51)	(11.43)	(11.12)
Ln Harvest (in tonnes)		0.000			
		(0.00)			
Ln Value			00.378		
			(0.27)		
Fishing value added				0.236	
				(0.16)	
Sea surface temperature					-0.369
					(0.72)
MSPE	29.68	46.34	45.15	43.46	26.36
Unobserved factors	4	5	3	4	5
Treated units	12	6	6	12	12
Control Units	36	16	22	35	33
Observations	3216	1430	1430	2679	2565

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 5, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.

do note that the MSPEs for the results in Table 7 are higher than that of its counterpart in Table 4.5, which indicates that countries in Africa, Asia, and Europe present a better counterfactual to our treated group. Nonetheless, both results point to the fact that the GFCM has not been effective in reducing overfishing among member countries.

Sensitivity analysis based on RFMO membership

In this Section, we present results for the scenario where our control group consists of countries with membership in more than 6 RFMOs. These results are presented to provide a more complete picture of our results in Section 4.7.3 where we use a control group consisting of countries with membership in 6 or less RFMOs. Our results shown in Table 8 largely indicate a negative ATT for the treated group. However, the results lacks statistical significance at conventional levels. We notice that the MSPEs for the results in Table 8 are almost identical to its counterpart in Table 4.6, and therefore implies that RFMO membership may not necessarily be a confounding factor for our main results.

Table 8: Effect of the GFCM on the share of overexploited stocks - Membership in more than 6 RFMOs as control.

Variable	Membership in more than 6 RFMOs as control group				
	Model 1	Model 2	Model 3	Model 4	Model 5
ATT	-1.069	-1.925	-2.127	6.611	-4.635
	(4.56)	(5.20)	(5.04)	(8.13)	(3.11)
Ln Real GDP per capita	-18.436	-34.270	-35.292		-55.998**
	(24.58)	(34.49)	(34.60)		(28.04)
Ln (real GDP per capita) squared	1.223	2.235	2.327		3.557**
	(1.56)	(2.11)	(2.10)		(1.70)
Ln Population	6.671	11.899	12.617	16.573*	17.981*
	(10.93)	(14.38)	(14.18)	(10.08)	(9.53)
Ln Harvest (in tonnes)		0.000			
		(0.00)			
Ln Value			-0.051		
			(0.35)		
Fishing value added				-0.196	
				(0.17)	
Sea surface temperature					-0.54
					(0.72)
MSPE	19.57	21.03	20.93	28.98	23.56
Unobserved factors	5	5	5	3	5
Treated units	12	6	6	12	12
Control Units	36	27	27	35	33
Observations	3216	2145	2145	2679	2565

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 5, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations.. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.

Additional robustness checks

In the following robustness checks, we investigate whether our main results are affected by averaging out the treatment effect for all 12 treated EEZs. Moreover, we ameliorate concerns of significant differences between treated EEZs and the control group. Theoretically, this should not be a concern as the GSCM computes a counterfactual that is as close as possible to the treated outcome before the treatment occurred. Nonetheless, we investigate how our results change when we construct different control groups for our sample of treated EEZs based on continental location. Specifically, for the treated EEZs in Africa, we include only countries in Africa in our control group; for those in Asia we include only EEZs in Asia; and for those in Europe we have only EEZs in Europe in our control group.

Results shown in Table 9 indicate positive ATT for treated EEZs in Africa, but these results are not statistically significant. Although there is an improvement in the accuracy of the estimated counterfactual for Models 1 and 5 based on their MSPEs relative to that of Table 4.2, the results show no effect of the GFCM on the share of overexploited stocks among member countries.

Results shown in Table 10 indicate a negative ATT in overexploitation for Models 1 and 2. The estimated treatment effect in Model 1 is significant at 10 percent level. Although this constitutes a statistically significant decline (at the 10 percent level) in overexploitation, unsurprisingly, it is not robust to small changes in the estimated model as shown in Model 3. For this reason, we interpret this decline with caution.

In Table 11, we show results for the EEZs in our sample located in Europe. Although, the results in Models 1 – 3 indicate a positive ATT in overexploitation, they are not statistically significant. Model 4 shows a negative ATT but again the estimated ATT is not statistically significant. Ultimately, these robustness checks do not generally contradict our main results that the GFCM's change in mandate has not improved the management of fish stocks (measured in terms of overexploited, collapsed, and rebuilding stocks) in their area of competence.

Table 9: Effect of the GFCM on the share of overexploited stocks - treated and control units in Africa.

Variable	Treated and control units in Africa				
	Model 1	Model 2	Model 3	Model 4	Model 5
ATT	2.472	14.63	12.84	4.58	5.109
	(4.05)	(10.08)	(9.58)	(4.82)	(4.29)
Ln Real GDP per capita	15.149	23.36	21.225		3.226
	(25.03)	(37.64)	(39.01)		(28.87)
Ln (real GDP per capita) squared	-0.747	-0.755	-0.622		-0.156
	(1.56)	(2.37)	(2.46)		(1.76)
Ln Population	-11.759	-5.105	-5.421	6.079	-24.323
	(9.13)	(10.06)	(10.43)	(7.92)	(11.49)
Ln Harvest (in tonnes)		0.001			
		(0.00)			
Ln Value			0.582		
			(0.74)		
Fishing value added				-0.048	
				(0.07)	
Sea surface temperature					-0.179
					(1.29)
MSPE	15.88	51.65	50.76	19.71	12.74
Unobserved factors	5	4	5	3	4
Treated units	3	1	1	3	3
Control Units	31	18	18	31	26
Observations	2278	1235	1235	1938	1653

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 5, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.

Table 10: Effect of the GFCM on the share of overexploited stocks - treated and control units in Asia.

Variable	Treated and control units in Asia		
	Model 1	Model 2	Model 3
ATT	-19.59*	-9.26	0.111
	(11.37)	(13.33)	(10.09)
Ln Real GDP per capita	-14.155		-32.759
	(16.93)		(22.618)
Ln (real GDP per capita) squared	0.714		1.91
	(0.97)		(1.32)
Ln Population	-5.454	-5.799	-15.448*
	(7.22)	(9.22)	(8.74)
Ln Harvest (in tonnes)			
Ln Value			
Fishing value added		0.169	
		(0.16)	
Sea surface temperature			0.925
			(3.19)
MSPE	12.72	13.92	11.32
Unobserved factors	5	5	5
Treated units	2	2	2
Control Units	29	29	25
Observations	2077	1767	1539

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. In model 2, we replace real GDP per capita with agriculture, forestry, and fishing value added in constant 2010 USD as a percentage of GDP. In model 3, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.

Table 11: Effect of the GFCM on the share of overexploited stocks - treated and control units in Europe.

Variable	Treated and control units in Europe			
	Model 1	Model 2	Model 3	Model 4
ATT	1.205	1.366	0.919	-2.863
	(6.641)	(9.81)	(9.57)	(4.62)
Ln Real GDP per capita	-110.002	-165.384	-161.773	-174.972**
	(75.12)	(148.53)	(176.94)	(76.21)
Ln (real GDP per capita) squared	6.141	8.153	8.113	9.46**
	(3.79)	(7.39)	(8.86)	(4.03)
Ln Population	-21.33	-9.647	-15.552	-10.256
	(18.44)	(7.39)	(43.43)	(19.36)
Ln Harvest (in tonnes)		-0.006		
		(0.019)		
Ln Value			-0.103	
			(2.15)	
Fishing value added				
Sea surface temperature				-0.417
				(0.96)
MSPE	43.83	41.94	41.98	51.97
Unobserved factors	5	3	4	5
Treated units	7	5	5	7
Control Units	14	8	8	14
Observations	1407	845	845	1197

The symbol * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level. Ln Harvest included in model 2 is the natural log of total harvest 3 years prior to the current year. Ln Value in model 3 is the natural log of fish value in real 2010 USD. In model 4, we control for changes in sea surface temperature. Standard error estimates in parentheses below each estimated coefficient are imputed with bootstrapping based on 1000 simulations. MSPE is mean squared prediction error and indicates the accuracy of the estimated counterfactual (smaller values indicates better estimation of counterfactual). Years of analysis include 1950 through 2016. Treatment year is 2004.