Essays on International Fisheries Management

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Abstract

This thesis consists of three chapters on the economics of international fisheries management.

The first chapter explores the economic and biological effects of exploiter and species interactions in a multinational and multispecies fishery. The Northeast Atlantic pelagic complex fishery (Norwegian spring-spawning herring, mackerel, and blue whiting) is harvested by several countries, and the species are ecologically interdependent through, for example, predation and competition for food. I develop a stylized bioeconomic model of the pelagic complex fishery, and estimate the outcomes of different types of fishery management. Specifically, I consider (1) whether exploiters ignore or take into account species interactions, and (2) whether countries cooperate or compete in the fishery. I consider three major exploiters: Norway, the European Union, and Iceland, which differ in terms of harvesting costs and ex-vessel prices. In the cooperative case, applying multispecies management increases the net present value of the fishery by over 20 percent compared to single-species management. The global optimum (i.e., cooperation and multispecies management) increases net present value by over 91 percent compared to the situation where both the common property and biological externality are uninternalized. Non-cooperative management leads to poor biological outcomes, such as depletion of the mackerel stock, irrespective of the type of biological management adopted.

The second chapter examines empirically the effectiveness of Regional Fisheries Management Organizations (RFMOs). The fraction of overexploited and collapsed international fish stocks has grown over the past decades, but has international management improved sustainability of managed stocks? The purpose of RFMOs is to promote sustainable use and conservation of international fisheries within their purview. To elicit whether RFMOs have a conservation effect, I examine if RFMO management

has reduced the probability of stock collapse. I exploit global fisheries data bases, and construct a large panel data set on stock status of 87 RFMO-managed species during 1950–2014. I use a differences-in-differences strategy that compares probability of collapse in managed fisheries before and after RFMO establishment to collapse of other international stocks. I find some tentative evidence to suggest that RFMOs may have improved the sustainability of managed stocks, but the effect differs across individual RFMOs.

The third chapter studies to what extent the number of exploiters in international fisheries contributes to overexploitation. The number of harvesting countries may be a key determinant of biological and economic outcomes in international fisheries. Theory predicts that an increase in the number of independent harvesting countries increases the probability of poor resource management. I combine information on the number of harvesting countries and stock status in almost 1,300 internationally shared ocean fish stocks. I use global fisheries catch data to construct indicators of stock status, and estimate an ordered dependent variable model, controlling for key economic and ecological variables. I complement the catch data analysis by studying a smaller set of international fish stocks using biomass data. When using the catch data, the results suggest that more harvesting countries is associated with a higher probability that stocks are overexploited or collapsed. When using the biomass data, the results suggest that an increase in the number of harvesting countries leads to (1) an increase in the odds of overexploitation, and (2) a reduction in total biomass.

Ágrip

Þessi ritgerð samanstendur af þremur sjálfstæðum köflum um hagfræði alþjóðlegrar fiskveiðistjórnunar.

Fyrsti kaflinn fjallar um hagrænar og lifræðilegar afleiðingar af samspili fiskveiðiþjóða og fiskistofna í uppsjávarfiskikerfinu (norsku vorgotssíldarinnar, makríls og kolmunna) í Norður-Atlantshafi. Nokkur þjóðríki nýta þessa uppsjávarfiskikerfi til fiskveiða og fiskistofnarnir hafa áhrif hver á annan m.a. með afráni og fæðusamkeppni. Ég byggi upp lífhagfræðilegt líkan af þessum fiskveiðum og nota líkanið til að meta árangur af mismunandi stjórnun fiskveiðanna. Nánar tiltekið kanna ég (1) hvort veiðiþjóðirnar taka tillit til líffræðilegs samspils stofnanna og (2) hvort þjóðirnar samhæfi veiðar sínar eða keppi hver við aðrar. Líkanið tekur til þriggja veiðiþjóða: Noregs, Evrópusambandsins og Íslands, sem eru mismunandi hvað snertir veiðikostnað og aflaverð. Sé gert ráð fyrir því að þessar þjóðir samhæfi veiðar sínar gefur líkanið til kynna að virði fiskveiðanna hækki um meira en 20% ef beitt er margstofnafiskveiðistjórnun fremur en einsstofnastjórnun sem ekki tekur tillit til líffræðilegs samspil stofnanna. Hagkvæmasta nýting (þ.e. samhæfðar veiðar og margstofnafiskveiðistjórnun) hækkar núvirði veiðanna um meira en 91% miðað við það núvirði sem fengist úr samkeppnisveiðum án tillits til líffræðilegs samspils stofnanna.

Í öðrum kaflanum eru raungögn notuð til þess að kanna skilvirkni þess fyrirkomulags við stjórnun alþjóðlegra fiskveiða sem nefnt má Svæðisbundin Samtök um Fiskveiðistjórnun (SSF; enska Regional Fisheries Management Organizations eða RFMOs). Hlutfall alþjóðlegra fiskistofna sem taldir eru hafa hrunið hefur vaxið jafnt og þétt undanfarna áratugi. Hlutverk SSF er að tryggja sjálfbæra nýtingu og verndun fiskistofna á sínum svæðum. Samkvæmt hagfræðikenningum er hins vegar erfitt fyrir SSF að koma á aðhaldssamri fiskveiðistjórnun vegna fríþegahvatanna í alþjóðlegum fiskveiðum. Til að varpa ljósi á hvort SSF hafi áhrif í fiskverndunarátt skoðum við

hvort tilvera þeirra dragi úr líkunum á stofnhruni. Í þessu skyni hagnýtum við okkur fyrirliggjandi gagnasöfn um alþjóðlegar fiskveiðar og setjum saman stórt tímaraða-þverksurðar gagnamengi um stofnstærðir yfir 150 alþjóðlegrar fiskitegunda á tímabilinu 1950–2014. Annar hluti gagnamengisins, viðfangshópurinn, eru stofnar þessara tegunda sem hafa komist í umsjón SSF einhvern tíma á tímabilinu. Hinn hlutinn, samanburðarhópurinn, eru stofnar sem aldrei hafa verið undir stjórn SSF. Tölfræðileg kennsl eru borin á samhengið með hjálp aðferðar aðstoðarbreyta, þar sem alþjóðlegar skuldbindingar viðkomandi þjóðríkja eru notaðar sem aðstoðarbreyta fyrir tilveru SSF. Niðurstaðan er að ekki séu neinar vísbendingar um að tilvist SSF minnki líkur á stofnhruni. Þessi niðurstaða helst óbreytt þótt viðfangsshópnum og samanburðarhópnum sé breytt.

Í þriðja kaflanum er grafist fyrir um að hvaða marki fjöldi veiðiþjóða í alþjóðlegum fiskveiðum stuðli af ofnýtingu fiskistofna. Vera kann að fjöldi nýtingarþjóða ráði miklu um líffræðilegar og efnahagslegar afleiðingar alþjóðlegra fiskveiða. Forspá fræðikenninga er að líkur á slæmri fiskveiðistjórnun vaxi með fjölda nýtingarþjóða. Ég leiði saman gögn um fjölda nýtingarþjóða og stofnstærðir meira en 1300 alþjóðlegra fiskistofna. Ég nota alþjóðleg gögn um fiskafla til að útbúa mælikvarða á stofnstærð og met líkan fyrir raðaða háða breytu (e. ordered dependent variable model) þar sem fallsamhengið tekur einnig tillit til hagrænna og lífríkis- lykilbreyta. þessari athugun til viðbótar bæti ég annarri þar sem háða breytan er mælingar á raunverulegum stofnstærðum en fjöldi athugana hins vegar miklu færri. Þegar aflagögn eru notuð til að meta stofnstærðir benda niðurstöður til þess að fleiri veiðiþjóðir auki líkur á ofnýtingu og stofnhruni. Þegar beint stofnmat er notað benda niðurstöður til þess að fleiri veiðiþjóðir leiði til (1) meiri líkinda á ofnýtingu og (2) minnkunar í stofnstærð.

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Introduction

The international fishery is an archetypal common property resource. As with any natural resource, there is an optimal way to utilize the international fishery so that it, for example, maximizes long-term economic yield. A key source of inefficiency in the use of the fishery–domestic or international–arises when the property right is shared between several users. In the absence of effective fisheries management, the incentive to conserve the resource is quickly dissipated, because every fish left in the ocean may be exploited by another user. Of course, there are also other sources of inefficiency which may be relevant to the international fishery, such as ecological interactions in exploited ecosystems. This raises the question of what is the impact of multiple sources of inefficiency on an international fishery's economic and ecological outcomes. Moreover, in the international fishery, the resource users are sovereign countries. Many international fisheries are jointly managed by countries in fisheries organizations. This raises the question whether international fisheries management has been successful in preventing overexploitation of managed fish stocks. Finally, a key result in fisheries economics is the tendency of common property fisheries to be overfished. This raises the question to what extent the number of harvesting countries in international fisheries impacts the severity of overexploitation. This thesis addresses the questions raised above in three independent chapters.

The *international* fishery does not have one exact definition. The Food and Agriculture Organization of the United Nations (FAO) uses the term *shared* fishery, which is further divided into subgroups according to the distributional pattern of the fish stock (FAO, 2003). Throughout this thesis, the focus is on *straddling* and/or *highly migratory* fish stocks. Straddling stocks are found in the exclusive economic zones (EEZs) of one or more coastal states, and in the adjacent high seas. Highly migratory stocks are a subset of the straddling stocks, and consists most notably of the major tuna species. All highly migratory species are listed in Annex I of the 1982 United Nations Convention on the Law of the Sea (UN, 1982). Chapter 1 studies the pelagic complex fishery in the Northeast Atlantic, which consists of Norwegian spring-spawning herring, mackerel, and blue whiting. The pelagic complex is an example of a straddling fishery. The stocks are widely distributed and migrate through the EEZs of several countries in the region, such as Iceland, Faeroe Islands, the United Kingdom, and Norway. In addition, the stocks are present in high seas areas, such as in the "Banana Hole" between mainland Norway and Jan Mayen (Bjørndal and Ekerhovd, 2014). In Chapter 2, which studies the performance of international fisheries organizations, the emphasis is on highly migratory stocks. Many of these organizations have a strong focus on the management of tuna and tuna-like species. Chapter 3 analyzes exploitation outcomes in a large number of both straddling and highly migratory stocks.

Serious concern about the overexploitation of ocean fisheries did not arise until the first half of the 20th century. Prior to this, ocean fisheries were seen as practically inexhaustible, and biological overfishing therefore not possible. The development of new and more effective fishing technologies changed this view, and after World War II it was obvious that ocean fisheries needed to be regulated in order to prevent overexploitation (Munro, 2008). A natural way to manage common resources is to create property rights. A pivotal milestone in fisheries management was the UN Third Conference on the Law of the Sea (1973–1982), which produced the UN Convention on the Law of the Sea (1982). The main outcome of the Convention was the creation property rights through establishment of EEZs. The EEZs extend 200 nautical miles off the coast of coastal states, i.e., countries with a significant marine coast line. Coastal states have property rights to the fishery resources within their respective EEZs. However, many ocean fisheries are widely distributed and mobile, and therefore present in multiple EEZs, as well as in the high seas (i.e., ocean areas adjacent to the EEZs and beyond national jurisdictions) (Munro, 2008). Therefore, EEZs do not solve the common property problem in international fisheries.

After the management problem of international fish stocks was recognized, the UN Fish Stocks Conference (1993–1995) was convened, and from this the UN Fish Stocks Agreement (1995) was born. The Agreement stipulates that straddling and highly migratory fish stocks should be managed on a regional basis in Regional Fisheries Management Organizations (RFMOs), in which the relevant harvesting countries are members. Harvesting countries include both coastal states and countries fishing solely on the high seas (distant water fishing states) (Munro, 2008). Whether RFMOs have improved the management situation remains unclear. Currently one third of the world's marine fish stocks are overfished, and the problem of overfishing appears to be particularly acute for straddling and highly migratory fishery resources (FAO, 2018). Since as much as one third of marine capture production originates from international fish stocks (Munro et al., 2004), questions on how international fisheries are managed are clearly of significant importance.

Strategic interactions between harvesting countries is at the core of international fisheries management. Game theory, which is the study of strategic interaction, therefore plays an essential part in the analysis of international fisheries management. The theory and examples from real-world shared fisheries demonstrate that non-cooperation is economically and biologically wasteful (Clark, 1980; Levhari and Mirman, 1980; Bailey et al., 2010). In Chapter 1, I use the concept of differential games to estimate the effects of non-cooperation and cooperation in a real-world fishery (i.e., the pelagic complex). In Chapter 2, I examine empirically whether real-world cooperative efforts have been successful in preventing overexploitation. In Chapter 3, I test empirically a prediction derived from non-cooperative fisheries games, namely, that the probability of overexploitation increases with more independent exploiters (e.g., Arnason, 1990).

Two key methodological components of this thesis are bioeconomic modeling and econometrics. In Chapter 1, a bioeconomic model is used to analyze one specific fishery, albeit an assemblage of three interconnected species. Biological growth and economic profit functions are estimated using simple statistical techniques with biological and economic data on the pelagic complex fishery. Chapter 1 is, to the best of my knowledge, the first attempt to study the impact of multiple externalities in the pelagic complex fishery. First, the chapter corroborates a finding by Ekerhovd and Steinshamn (2016) that economic performance in the pelagic complex can be improved if fisheries management takes species interactions into consideration. Specifically, more fishing effort should be exerted in the mackerel fishery. Second, the results suggest that the biological externality matters little if the common property externality is present, i.e., the fishery is non-cooperatively harvested. The chapter contributes to a hitherto scarce literature on fishery games in which broader ecosystem considerations are taken into account.

In contrast to Chapter 1, Chapters 2 and 3 employ reduced form analysis to study two important questions in international fisheries using longitudinal (panel) data on hundreds of fish stocks. Chapter 2 provides the first large-scale econometric analysis of the impact of RFMO management on ecological outcomes. RFMO fisheries are compared to unmanaged international fisheries in a differences-in-differences empirical framework. The analysis, which includes over 900 international fish stocks, finds tentative evidence of beneficial impacts of RFMO management on stock sustainability. Chapter 2 contributes to a growing literature on empirical analyses of the effectiveness of international environmental agreements (IEAs). Lastly, Chapter 3 is one of very few empirical analyses of the impact of number of exploiters on ecological outcomes in international common property resources. Two different data sources and a range of econometric models are used to empirically show that more harvesting countries is associated with an increase in the probability of overexploitation. The chapter complements and extends a paper by McWhinnie (2009), which is a study on how the number of EEZs a fishery is harvested in affects stock outcomes.

The ecological status of international fish stocks is a key piece of information in this thesis. Because actual stock (biomass) data are available for a relatively limited number of fish stocks worldwide, harvest indices are frequently used to infer the biological state of fish stocks (Froese and Kesner-Reyes, 2002; Worm et al., 2006; Froese et al., 2012). I exploit long time series (1950–2014) of multinational harvests from the Sea Around Us catch database (SAU) (Sea Around Us, 2015), which allows me to assign stocks a unique exploitation status in each year. The SAU data are used in Chapters 2 and 3. Chapter 3 additionally uses biomass data on a smaller set of international fish stocks from the RAM Legacy Stock Assessment Database (Ricard et al., 2011) as complementary data. Chapter 1 uses stock data on the pelagic complex from the International Council for the Exploration of the Sea (ICES, 2015).

To sum up, this thesis uses a variety of methods and data sources to study topics in international fisheries management. Methods include bioeconomic modeling, differential games, statistical estimations, and econometric analysis. The data include large panels on catch (Chapter 2 and 3) and biomass (Chapter 3), as well as ecological and economic data on three specific North Atlantic pelagic fisheries in Chapter 1. The mix of methods partly reflects the multifaceted nature of the study object, the international fishery, which consists of both a social-economic and an ecological component. It is well-established that many international fisheries are in a poor state, exhibiting dissipated economic rents, overfishing, and stock collapse to a growing extent. In light of this current situation, different types of analyses contributing to the understanding of the economics of international fisheries management are called for.

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Chapter 1

International management of North Atlantic pelagic fisheries: The role of competing species and exploiters[1]

[1] A version of this chapter is published in *Fisheries Research*, 203:12–21, 2018.

1.1 Introduction

In shared multispecies fisheries, interactions can occur between both harvesters and the exploited fish populations that have potential to cause economic inefficiencies and be ecologically damaging. In a fishery shared among several exploiters, the harvesting of each exploiter will affect the population dynamics of the fish stock, and thus the harvest and future profits of all other exploiters. In an open-access or non-cooperative fishery this will lead to excess effort, overfishing, and suboptimal economic and biological performance. If the species of a multispecies fishery are ecologically interdependent, there will also be interactions between the harvested populations. Also biological interdependencies have the potential to significantly influence a fishery's economic and ecological outcomes. The effect of these interactions will depend on the ecosystem in question and on the management regime in place. The ecosystem defines the type of biological interaction between the species, which can be competition for food and other resources, predator-prey interactions, or various types of symbiotic relationships. The management regime determines whether species interactions are taken into account (multispecies management) or ignored (single-species management), and whether fishing is cooperative or competitive among the exploiters.

This paper studies the individual and joint effect of exploiter and biological interactions using a Northeast Atlantic assemblage of pelagic fish as a case study. This fish assemblage consists of Norwegian spring-spawning (NSS) herring[2] (*Clupea harengus*), mackerel (*Scomber scombrus*), and blue whiting (*Micromesistius poutassou*). To perform this task a stylized bioeconomic model is developed, which allows for interaction between both species and exploiters. This implies three types of interaction

1. Exploiters interact with species through the harvesting process,
2. Species interact with each other through different ecological relationships, and
3. Exploiters interact with each other by either cooperating or competing in the fishery.

Because the three fisheries are closely intertwined through ecological factors, they are sometimes referred to as the "pelagic complex" of the Northeast Atlantic (Bachiller

[2] Also known as Atlanto-Scandian herring.

Table 1-1. Management scenarios

1. Cooperation Multispecies management (MSM)
2. Cooperation Single-species management (SSM)
3. Non-cooperation Multispecies management (MSM)
4. Non-cooperation Single-species management (SSM)

Note: Cooperation and non-cooperation apply to the whole pelagic complex, i.e., all three fisheries.

et al., 2016). The pelagic complex is an interesting case study because of the uninternalized externalities potentially present in this fishery. First, each of the fisheries in question has from from time to time been subject non-cooperative harvesting due to a failure to reach or maintain agreements on the sharing of harvest quotas (Bjørndal and Ekerhovd, 2014). This is the common property externality. Second, single-species management, which is the prevailing management regime nationally and internationally, neglects ecosystem considerations, such as ecological interactions between the species. This is the biological externality.

The analysis considers three major exploiters of these fisheries: Norway, the European Union (EU), and Iceland, which differ in harvesting costs and prices for fish. I compare different management scenarios where the exploiters either cooperate or compete in all fisheries, and employ either single-species (SSM) or multispecies management (MSM) when making harvesting decisions. MSM is modeled by using a multispecies model of the three-species fishery. This model includes explicit relationships between the harvested species, i.e., species interactions are taken into account in fisheries management. In SSM the agents optimize three single-species models which do not include interspecific interactions. Consequently, fisheries management ignores interactions between species.[3] Under cooperation the three exploiters are maximizing joint benefits from the fishery, while under non-cooperation the agents are playing a competitive game against each other. The four management scenarios considered are presented in Table 1-1.

[3]For similar applications comparing outcomes from single- and multispecies models in exploited ecosystems, see e.g., Conrad and Adu-Asamoah (1986), Kasperski (2015), and Ekerhovd and Steinshamn (2016).

Very few empirically based studies exist that study interactions between both exploiters and harvested species. The current paper aims to fill this gap in the literature. I contribute to two important areas in the fisheries economics literature. The first is the use of ecosystem models instead of the traditional single-species model in bioeconomic analysis of fisheries. The second is the use of game theory to analyze the strategic interactions between, for example, several countries participating in international fisheries. The importance of moving towards ecosystem based fisheries management has been widely acknowledged (e.g., Arnason, 1998; Sinclair et al., 2002), while game theory has become a standard tool in the analysis of fisheries with more than one stakeholder (Munro, 2009). In an empirical study, Hjermann et al. (2004) find that Barents Sea capelin can collapse as a result of overexploitation by competing fishermen and predation by herring, whereas predation by cod may slow recovery of the collapsed capelin stock. These are findings that illustrate the importance of accounting broadly for ecological and economic aspects when assessing fisheries management outcomes.

1.1.1 Related literature

Existing literature combining game theoretic tools and multispecies modeling is fairly scarce. Fischer and Mirman (1996) analyze cooperation and non-cooperation in an exploited ecosystem with different types on interactions between two species of fish. The authors compare their results to earlier studies where only competing exploiters (Levhari and Mirman, 1980) or biological interactions (Fischer and Mirman, 1992) are studied. The authors call these interactions a dynamic and biological externality, respectively.[4] Using an analytical model, Fischer and Mirman (1996) draw some general conclusions on the impact of the interplay between the biological and dynamic externality. However, it is not always clear what this impact is going to be as it will depend on specific parameters. The aim of the current paper is to show how these impacts can be elucidated for a specific ecosystem when plausible biological and economic parameters are available.

Kronbak and Lindroos (2011) is another analytical study which combines game theory and multispecies modeling. The authors study a two-species ecosystem with

[4]Levhari and Mirman (1980) also acknowledge a third type of interaction, which they call a "market" externality. This occurs when the market price for fish is affected by the landings of all exploiters. I do not consider this last effect in my analysis, because I assume constant prices.

different ecological interactions, and derive the maximum number of non-cooperative exploiters that preserve all species in the ecosystem. My paper, apart from being an application to a real world fishery, differs from Kronbak and Lindroos (2011) and Fischer and Mirman (1996) in that it focuses on impacts on economic performance in addition to exploring impacts on harvest levels and implications for biological viability.

My empirical application is the same as in Ekerhovd and Steinshamn (2016), who develop a multispecies model of the pelagic complex where species growth is limited by a common environmental carrying capacity. However, their model is optimized only from a sole owner perspective. Sumaila (1997) is an application to the Barents Sea with two exploiters and two species, cod and capelin, which are in a predator-prey relationship. One player harvests only cod, and the other player harvests only capelin. The study concentrates on the inefficiencies arising from the separate fishing of two interlinked species of fish by non-cooperating exploiters. My study differs from this paper in that all exploiters participate in all fisheries. A more recent empirically based study is Nieminen et al. (2016), who combine multispecies modeling (cod, herring, and sprat in the Baltic Sea) with game theory, specifically stability analysis of international fisheries agreements. I am not concerned with if and how the cooperative solution is reached. Rather, I focus on the comparison of long-run economic and biological consequences of cooperation and non-cooperation.

1.2 The pelagic complex fishery in the Northeast Atlantic

Species interactions between NSS herring, mackerel, and blue whiting include spatial and dietary overlap, as well as interspecific predation on eggs, larvae, and juveniles (Huse et al., 2012; ICES, 2015).[5] There is strong evidence of interspecific competition for food between the species of the pelagic complex, in particular between NSS herring and mackerel. The herring is thought to be more negatively affected from this competition, because mackerel is a faster and more effective predator (ICES, 2015, and references therein). Furthermore, mackerel predating on herring larvae may have a regulatory effect on the herring population by influencing recruitment (Skaret et al., 2015). Mackerel also feeds on blue whiting eggs, larvae, and juveniles, to the extent that it may

[5] Trenkel et al. (2014) provide a good overview of the comparative ecology of NSS herring, mackerel, blue whiting, and other pelagic species in the North Atlantic.

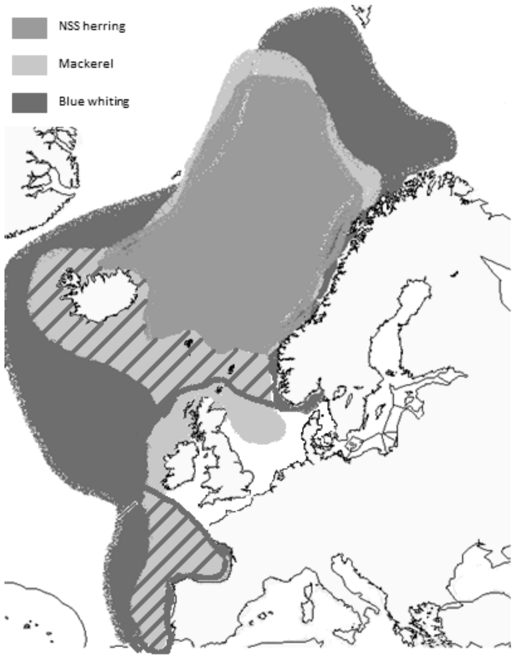

Figure 1-1. Schematic map of overlapping feeding areas of adult NSS herring, mackerel, and blue whiting. All three species overlap in the Norwegian Sea and adjacent areas. The striped areas indicate overlap between mackerel and blue whiting.

have a regulatory impact on the juvenile blue whiting population. For example, studies have found that juvenile blue whiting constitute the main prey of mackerel off the coast of Portugal (Payne et al., 2012). Thus, ecological interactions between the small pelagic species of the Northeast Atlantic may be an important determinant of the dynamics of these fisheries. For example, it has been found that in the North Sea, pelagic fish feeding on other pelagic fish has a larger potential to influence population dynamics than removal by the fishery or predation by marine mammals and sea birds (Furness, 2002). Figure 1-1 shows the spatial overlap of feeding areas for species in the pelagic complex.

The main exploiters of the pelagic complex are the EU, Norway, Iceland, Faeroe Islands, Russia, and more recently Greenland. The migratory nature of the pelagic complex poses a challenge to international management. During their annual migrations the stocks enter the exclusive economic zones (EEZs) of several coastal states, and they are also present in international waters (high seas). When distribution is variable it is difficult to agree on the share of a fish stock each party is entitled to. Indeed, for all fisheries considered here, reaching and maintaining international fisheries agreements (IFAs) has proved challenging from time to time. Reaching an IFA often means that the exploiters agree on a total allowable catch (TAC), and how to share that catch between them on an annual basis. Mackerel began entering the Icelandic EEZ during its summer migrations in mid-2000, and the fishery has been under dispute ever since. Parties have not been able to agree on how to share the harvest, and have been setting unilateral quotas which have exceeded the scientific advice in most years. Also the international management of the NSS herring fishery has experienced disagreements in recent years. There was no agreed TAC during the period 2013–2015, with parties setting their quotas unilaterally. The sum of the individual quotas exceeded the level indicated in the management plan (ICES, 2015). The blue whiting fishery was virtually unregulated until 2006, when the first IFA for this fishery was agreed upon (Bjørndal and Ekerhovd, 2014).[6]

1.3 The model

1.3.1 Single and multispecies dynamics

I now develop a partial ecosystem model (multispecies model) and three single-species models of the Northeast Atlantic pelagic complex. The purpose of these models is to simulate the growth of NSS herring, mackerel, and blue whiting. In the multispecies model the emphasis is on capturing the interspecific dynamics between the species. The basis for the multispecies model is the Schaefer surplus production model for a single species in discrete time

$$X_{i,t+1} = X_{i,t} + r_i X_{i,t}\left(1 - \frac{X_{i,t}}{K_i}\right) - \sum_{l=1}^{m} H_{i,t} \tag{1.1}$$

where $X_{i,t}$ is biomass of species i at time t, r_i is the intrinsic growth rate, K_i is the environmental carrying capacity, and H_i is harvest. $i = 1,...,n$ are the species being fished, and $l = 1,..,m$ are the exploiters harvesting in the fishery.

The multispecies dynamics are modeled by supplementing the logistic growth with the Gause model (see e.g., Clark, 1990) of interspecific competition

$$X_{i,t+1} = X_{i,t} + r_i X_{i,t}\left(1 - \frac{X_{i,t}}{K_i}\right) + \sum_{j\neq i}^{n-1} \alpha_{ij} X_{i,t} X_{j,t} - \sum_{l=1}^{m} H_{i,t} \tag{1.2}$$

[6] Bjørndal and Ekerhovd (2014) is a fairly recent review of the international management of the pelagic complex.

where r_i is again the growth rate of species i, K_i is the carrying capacity of species i in the absence of other species, and H_i is harvest. The expression for logistic growth represents intraspecific competition, and the interaction term, $\sum_{j \neq i}^{n-1} \alpha_{ij} X_{i,t} X_{j,t}$, embodies all interspecific interactions. $X_{i,t}$ is biomass of species i, and $X_{j,t}$ is biomass of competitor, predator, or prey species j. In this model the different populations affect each other's growth through the interaction terms. The type and magnitude of interactions are determined by the sign and size of the interaction coefficients α_{ij} and α_{ji} for species i and j, respectively. If the species are competitors, and interactions thus mutually detrimental, then $\alpha_{ij} < 0$ and $\alpha_{ji} < 0$. If $\alpha_{ij} > 0$, $\alpha_{ji} < 0$, then prey species j has a positive impact on the growth of predator species i, while the predator impedes the growth of the prey. If $\alpha_{ij} > 0$ and $\alpha_{ji} > 0$, then the two species are in a symbiotic relationship.

To estimate the parameters in equation 1.1 and equation 1.2, I use biomass and harvest data on NSS herring, mackerel, and blue whiting from the period 1981–2015 (ICES, 2015). The single-species models were estimated using ordinary least squares (OLS). The multispecies model, which consists of a system of three interdependent growth equations, was estimated using seemingly unrelated regression (SUR) (Zellner, 1962). Unobserved factors that influence growth, such as environmental and climatic conditions, will likely affect all species in the pelagic complex. SUR, which is a generalized least squares estimator, provides efficient estimates when the set of estimating equations are related through contemporaneously correlated error terms. SUR has previously been used to estimate parameters in multispecies systems by, for example, Agnarsson et al. (2008) and Kasperski (2015).

Table 1-2 lists the estimated parameter values for the single-species models, and Table 1-3 lists the parameters for the multispecies model. Details on the results from the statistical estimations are found in the Appendix (Table A-1 and Table A-2). The estimated growth parameters in Table 1-2 are in line with parameters obtained in other empirical studies on the North Atlantic pelagic fisheries (see Arnason et al., 2000; Ekerhovd and Steinshamn, 2016, for examples).

Reliability of the multispecies coefficients is more uncertain, because there are no previous results with which to compare. The species interactions are of particular interest. The last three rows of Table 1-3 form an interaction matrix, where each species' interaction coefficients with respect to the other species are displayed. Mackerel is in a

Table 1-2. Biological parameter values used in the single-species models

Symbol	Definition	NSS herring	Mackerel	Blue whiting	Unit
r_i	Intrinsic growth rate	0.62	0.40	0.35	
K_i	Carrying capacity	7.64	8.73	36.00	Million tonnes
$X_{i,t}$	Initial biomass	4.87	3.22	3.43	Million tonnes

Table 1-3. Biological parameter values used in the multispecies model

Symbol	Definition	NSS herring	Mackerel	Blue whiting	Unit
i	Subscript	1	2	3	
r_i	Intrinsic growth rate	0.78	0.17	0.51	
K_i	Carrying capacity	8.55	8.00	24.21	Million tonnes
$X_{i,t}$	Initial biomass	4.87	3.22	3.43	Million tonnes
α_{ij}	Interaction coefficient				Unit biomass^{-1}
	with herring	-	0.0233	0.0004	
	with mackerel	-0.0548	-	-0.0427	
	with blue whiting	0.0153	0.0192	-	

predator-prey relationship with both herring and blue whiting. Herring and blue whiting appear to be in a symbiotic relationship, although the positive impact of herring on blue whiting is very small. These results do not necessarily line up perfectly with the ecology of the pelagic complex and there are even some counterintuitive results.[7] Moreover, most of the interaction coefficients in the multispecies model are not statistically significant. However, because I am lacking better empirical information, I will use these parameters in the MSM analysis. The parameters may still serve the role as an example of a biological externality.

The initial biomass levels, which are used in the simulations and reported in Table 1-2 and Table 1-3, are historical averages of spawning stock biomass (SSB) over approximately 30 years.

1.3.2 Economic model

Next, a model is developed to describe harvesting behavior of the exploiters. First, I describe the fishery production function, which relates harvest to two factors of produc-

[7] Kasperski (2015) also finds counterintuitive signs in his three-species interaction model. It may be that the Gause model is better suited for more simple ecological relationships, such as predator-prey. In contrast, the relationships between the pelagic species are more complex, which may make it difficult to fit the model to the data.

tion, fishing effort and the fish stock. The Cobb-Douglas harvest function is often used in empirical studies to model production in pelagic fisheries (e.g., Bjørndal and Conrad, 1987; Nøstbakken, 2008). The Cobb-Douglas function is thus used to model harvest in the NSS herring, mackerel, and blue whiting fisheries

$$H_{i,t} = q_i E_{i,t}^{a_i} X_{i,t}^{b_i} \tag{1.3}$$

where E_i is the amount of effort exerted in the fishery, X_i is the size of the fish stock, and q, a, and b are parameters. The parameter q is a catchability coefficient which represents the efficiency of the fishing fleet. Catch elasticity with respect to effort and stock size is described by a and b, respectively. This functional form is suitable for modeling pelagic fisheries because it allows capturing the effect of schooling behavior of pelagic species on the yield function. For schooling fisheries the parameter b is often assumed to be less than unity and close to zero. Fish stocks that form schools can be fished at very low stock levels, because the density of individual schools is not dependent on overall stock size (e.g., Hannesson, 1993).

The unit of fishing effort is determined as one vessel day, so the effort variable, E_i, is a product of the number of boats and days at sea. At the beginning of the season, the fishery manager chooses the amount of vessel days to employ in each fishery during the season. Since the cost per unit of effort, i.e., the cost of operating one vessel for one day, is assumed to be constant, the total seasonal cost in fishery i is simply $C_{i,t} = c_i E_{i,t}$. Further, assuming a constant price for fish, the per-season revenue from each fishery is given by $R_{i,t} = p_i H_{i,t}$.

In all three fisheries, three exploiters usually account for 80–90 percent of the annual catches (ICES, 2015). The EU, Norway, and Iceland are the three major harvesters of NSS herring and mackerel. Norway, the EU, and Russia catch most of the blue whiting. This is the motivation to restrict the analysis to three players when comparing non-cooperative management with cooperative management. I consider Norway, the EU, and Iceland because of their central role in the pelagic complex fishery, and because of available cost and price data on these three exploiters.

Data on the Norwegian purse seine fleet (Table 1-4) is used to parameterize the harvest and cost functions. This means that the three exploiters have identical harvesting

Table 1-4. Data on the Norwegian pelagic purse seine fishery, 1998–2007

Year	X_1	H_1	X_2	H_2	X_3	H_3	E	TC
1998	5818	218	2005	52	3595	514	12136	4806
1999	5681	234	2180	53	4327	471	12915	5746
2000	4733	234	2141	58	4196	461	12080	6882
2001	3940	155	2029	65	4563	490	12096	7071
2002	3491	170	1949	71	5444	452	14076	6310
2003	4157	184	2005	69	6875	698	14194	8189
2004	5292	209	2476	67	6791	792	13570	11218
2005	5447	263	2308	49	6062	595	11546	11169
2006	5461	249	2378	51	5875	495	9844	10412
2007	7092	327	2412	57	4687	427	9990	11095

Notes: Subscripts 1, 2, and 3 denote NSS herring, mackerel, and blue whiting, respectively. Biomass (X) and harvest (H) are in thousand tonnes. E denotes total effort (vessel days) employed by the purse seine fleet. TC (thousand Norwegian kronor, NOK) is total annual variable costs of an average vessel in the purse seine fleet.
Source: Directorate of Fisheries (2016).

technologies. However, the unit cost of harvesting differs between the exploiters. In this fleet segment the species of the pelagic complex usually constitute 80–90 percent of the catch (Directorate of Fisheries, 2016). I know total seasonal effort, but not how it is divided between the three species. Therefore, I simply assume that effort on a given species is proportional to the share of that species in the total catch. Using the same logic, I assume that the share of total seasonal variable costs attributed to a given fishery is proportional to that fishery's share of total catch. These are naturally crude approximations, since the stocks are not necessarily equally accessible to a given country. For example, a stock that has to be fetched over long distances requires more effort and leads to higher costs for the fishery.

Total variable cost in each of the fisheries, where c_i is the unit cost of effort in fishery i, is given by

$$C_i = c_i \left(\frac{H_{i,t}}{q_i X_{i,t}^{b_i}} \right)^{\frac{1}{a_i}} \tag{1.4}$$

Given the assumptions on effort and cost described above, it is possible to estimate the harvest equation parameters for the three fisheries, and the corresponding unit costs of effort.[8] This is done in two steps. First, the system of three harvest equations (equation 1.3) is estimated using seemingly unrelated regression. Second, the obtained harvest equation parameters and data on total variable cost are used to estimate the unit cost parameters in equation 1.4 using nonlinear least squares. All economic parameters used in the subsequent simulations are displayed in Table 1-5.[9] Details on the statistical estimation of the harvest functions are found in the Appendix (Table A-3). The estimated catch elasticity parameters are in line with what is to expected of schooling species fisheries, although the stock parameter b is not statistically significant in the three cases.

The unit prices of fish used in the analysis are averages that the three exploiters fetched during 2007–2011 (Lappo, 2013). Norway has the highest price in all three fisheries. The unit costs of effort estimated above apply to the Norwegian purse seine fleet. I do not have similar data on the EU and Iceland. However, Lappo (2013) reports on average cost per tonne harvested for these three exploiters.[10] According to this data, the UK pelagic fleet has the highest, and the Icelandic fleet the lowest cost per tonne harvested. The cost of the Norwegian purse seine fleet is between these two. I use the Norwegian estimates from above as the base case, and calculate the EU and Icelandic cost parameters according to relative values given by the data in Lappo (2013). Thus, the EU and Icelandic cost parameters are obtained by multiplying the Norwegian cost parameter by 1.85 and 0.52, respectively. Iceland has strikingly low costs, but similarly low fish prices. This could point to some inconsistency in the way prices and costs have been determined across countries. This is not a cause of great concern in the present context. Country-specific costs are crucial when studying whether cooperation can actually be achieved. In this study, however, the purpose is merely to compare cooperative and competitive outcomes.

[8] There are some caveats in the econometric estimation of the Cobb-Douglas harvest function (see Gordon, 2015). Number of vessel days, which is a proxy variable for fishing effort, will be correlated with other production inputs not included in the model. This means that it is not possible to retrieve a consistent estimate of the catch elasticity parameter a in equation 1.3. Further, as the measures for stock abundance from ICES are subject to measurement error, the estimate of the catch elasticity parameter b is also likely inconsistent.

[9] Ekerhovd and Steinshamn (2016) also estimate economic parameters for the pelagic complex fishery, but these are not directly comparable to mine because of a different cost function applied. However, reassuringly, Ekerhovd and Steinshamn (2016) also report a higher unit cost for blue whiting than for herring and mackerel.

[10] Lappo (2013) analyzes North Atlantic pelagic fisheries in Norway, the UK, and Iceland. For my purposes, the UK data suffices to represent the EU.

Table 1-5. Economic parameters

Symbol	Definition	NSS herring	Mackerel	Blue whiting	Unit
i	Subscript	1	2	3	
q_i	Catchability	0.062	0.064	0.078	
a_i	Output elasticity, E_i	0.87	0.90	0.81	
b_i	Output elasticity, X_i	0.23	0.20	0.21	
p_i	Unit price of fish				NOK/tonne
	Norway	3832	10190	2101	
	EU	3325	8356	2023	
	Iceland	1484	2015	1095	
c_i	Unit cost of effort				Thousand NOK
	Norway	74	61	83	
	EU	137	113	153	
	Iceland	39	32	43	
δ	Discount factor, where $\delta = \frac{1}{1+\rho}$				
ρ	Discount rate $= 0.05 \Rightarrow 5\%$				
T	Time horizon $= 30$				Years

Note: Prices and costs are expressed in Norwegian kronor (NOK).

1.3.3 Cooperative management

The optimization problem of the exploiter will vary depending on the type of management adopted. Recall that I am interested in two dimensions of fishery management: single-species (SSM) versus multispecies management (MSM), and non-cooperative versus cooperative management.

The solution to the dynamic optimization problem is an open loop control rule. This means that at the beginning of the planning horizon the resource manager chooses a vector of effort levels and sticks to it. The time horizon is set to 30 years. The typical approach in studies of this kind is to solve the model for a 20–50-year time period (e.g., Sumaila, 1997; Kennedy, 2003; Bjørndal and Lindroos, 2004). The optimization problem is solved numerically in MATLAB using the fmincon toolbox, which is a set of algorithms used to find a minimum of constrained nonlinear multivariable functions.

I begin by investigating the cooperative setting in which the objective is to maximize the sum of all three exploiters' benefits from the fishery. The exploiters are denoted by $l = 1,..,m$, and the species by $i = 1,...,n$. Hence, in the cooperative and SSM case, the objective is to maximize the sum of joint discounted net benefits from the three fisheries over a time horizon of length T by choosing fishing effort

$$J_{coop,SSM} = \max_{E_{l,i,t}} \sum_{t=1}^{T} \sum_{l=1}^{m} \frac{\sum_{i=1}^{n} p_{l,i} H_{l,i,t} - c_{l,i} E_{l,i,t}}{(1+\rho)^{t-1}} \tag{1.5}$$

subject to Eq. (1.1)

$X_i(0) = X_{i,0}, \quad E_{l,i,t} \geq 0 \quad \forall l, i.$

The denominator is the discount factor with discount rate ρ. The constraints are the single-species state equations (equation 1.1), initial constraint for the state variables, and a non-negativity constraint for the control variable. Note that because the optimization is constrained by single-species growth dynamics, the resource manager overlooks possible interactions between the species when choosing the harvest levels.

In the cooperative and MSM setting, the exploiters maximize the joint net present value of the aggregate pelagic complex fishery by simultaneously selecting effort levels for all three fisheries subject to multispecies population dynamics (equation 1.2). Using the discount factor $\delta = \frac{1}{1+\rho}$, and the more compact expressions for total revenue and cost, the objective function takes the form

$$J_{coop,MSM} = \max_{E_{l,i,t}} \sum_{t=1}^{T} \sum_{l=1}^{m} \sum_{i=1}^{n} \{R_{l,i,t} - C_{l,i,t}\} \delta^t \tag{1.6}$$

subject to Eq. (1.2)

$X_i(0) = X_{i,0}, \quad E_{l,i,t} \geq 0 \quad \forall l, i.$

1.3.4 Non-cooperative exploitation

Next, I explore the non-cooperative situation where exploiters need to acknowledge the harvesting of their competitors, and how it affects the dynamics of the biological system, and thus their prospective economic welfare. The exploiters optimize under the assumption that all others do the same. The three exploiters are asymmetrical as they face different harvesting costs and prices. All players apply either SSM or MSM in a given scenario. Under SSM and MSM, the players maximize equation 1.7 and equation

1.8, respectively

$$J_{noncoop,SSM} = \max_{E_{l,i,t}} \sum_{t=1}^{T} \frac{\sum_{i=1}^{n} p_{l,i} H_{l,i,t} - c_{l,i} E_{l,i,t}}{(1+\rho)^{t-1}} \tag{1.7}$$

subject to Eq. (1.1)

$$J_{noncoop,MSM} = \max_{E_{l,i,t}} \sum_{t=1}^{T} \frac{\sum_{i=1}^{n} p_{l,i} H_{l,i,t} - c_{l,i} E_{l,i,t}}{(1+\rho)^{t-1}} \tag{1.8}$$

subject to Eq. (1.2)

To study the interaction between the exploiters, I apply the concept of differential games, which is the appropriate tool for analyzing strategic interactions in dynamic settings. The goal is to find an equilibrium where no exploiter finds it profitable to change effort level given the effort levels of the other exploiters. The set of fishing efforts that satisfy this condition constitutes a Nash equilibrium. Formally

$$J_l(X_i, E^*_{l,i}, E^*_{-l,i}) \geq J_l(X_i, E_{l,i}, E^*_{-l,i}) \quad \forall X, E, i, l$$

where J_l are the payoff functions for the three exploiters as shown in equation 1.7 for SSM, and equation 1.8 for MSM. Note that $E_{l,i}$ is a vector. In this case the relevant equilibrium concept is the open loop Nash equilibrium. An open loop information structure means that the players commit themselves to their harvesting decisions at the start of the game. The open loop equilibrium can be motivated by the fact that the state of the fish stocks and the harvesting decisions of the exploiters are only imperfectly observed (Diekert et al., 2010). An iterative optimization procedure is applied, where players in turn update their best responses to their competitors' decisions and the state of the biological system. Such a procedure lets the harvesting decisions of the exploiters converge to the open loop equilibrium paths (Diekert et al., 2010).

Table 1-6. Overview of payoffs (NPV) in the different scenarios

	NSS herring	Mackerel	Blue whiting	Sum (exploiter)
A. Cooperation, MSM (global optimum)				
Norway	15.735	219.769	6.992	242.497
EU	0.949	25.363	0.358	26.671
Iceland	1.218	5.841	0.362	7.422
Sum (total NPV)	17.903	250.973	7.714	**276.588**
B. Cooperation, SSM				
Norway	49.836	127.720	29.036	206.589
EU	0.846	11.388	1.490	13.722
Iceland	1.061	2.608	1.894	5.561
Sum (total NPV)	51.741	141.714	32.418	**225.871**
C. Non-cooperation, MSM				
Norway	16.750	53.673	16.237	86.658
EU	4.267	37.146	2.389	43.801
Iceland	6.599	8.971	8.317	23.885
Sum (total NPV)	27.614	99.789	26.941	**154.344**
D. Non-cooperation, SSM				
Norway	18.671	48.810	15.215	82.695
EU	4.931	33.536	3.002	41.467
Iceland	5.403	7.600	7.979	20.980
Sum (total NPV)	29.003	89.944	26.194	**145.141**

Note: NPV = net present value (billion NOK); MSM = multispecies management; SSM = single-species management.

1.4 The results

In this section, I present the results from the numerical simulations. Table 1-6 summarizes the economic results by reporting the net present values (NPV) in the four different management scenarios. In each scenario, NPV is reported for each individual fishery and for the pelagic complex fishery as a whole. Total NPV in each scenario is reported in the bottom right-hand corner of each panel. The payoffs for each of the exploiters are also reported, although this is not a primary concern of this study. Figure 1-2 and Figure 1-3 illustrate the biological results by showing the evolution of fish stock biomass and the time paths for aggregate harvest.

1.4.1 Effect of the biological externality

1.4.1.1 Cooperation

The potential source of inefficiency in the cooperative scenario are the ignored biological interactions between the harvested species. By comparing panels A and B of Table 1-6, we see the effect of species interactions on total and fishery-specific NPV in the cooperative case. Total NPV is increased by 22 percent, from 226 to 277 billion NOK, when applying MSM in the pelagic complex fishery. This increase stems from a higher profitability of the mackerel fishery. Figure 1-2 shows harvest and biomass levels under SSM and MSM in the cooperative case. There is a clear change in the allocation of harvest between the species when moving to MSM: harvest of mackerel is increased, while harvest of its prey species, herring and blue whiting, is decreased. In the SSM framework, the stocks reach equilibrium after about ten years. In the MSM framework, herring and mackerel reach equilibrium quickly, whereas blue whiting appears to be excluded from the ecosystem in the long run.

There are no significant changes in the way harvest is allocated between the exploiters in the two scenarios. In both cases, Norway, as the most efficient exploiter, stands for the majority of harvesting. The NPV under the global optimum is estimated to be 277 billion NOK.[11]

1.4.1.2 Non-cooperation

Figure 1-3 shows harvest and biomass levels under SSM and MSM in the non-cooperative case. In both scenarios, mackerel is depleted in the beginning of the simulation period. The high value of the mackerel and the specification of the harvest function both contribute to this result.[12] The harvesting of herring follows a similar pattern in both SSM and MSM scenarios with high initial harvests which almost deplete the stock. The blue whiting stock, on the other hand, remains healthy in both scenarios.[13] By comparing panels C and D of Table 1-6, we see that the difference in NPV between the SSM and MSM scenarios is quite small (6 percent higher under MSM) when exploiters act non-

[11]Ekerhovd and Steinshamn (2016) estimate the NPV of a multispecies managed pelagic complex to be 129 billion NOK over a 15-year period.

[12]A catch elasticity parameter which is close to zero means that the cost of harvesting is not sensitive to the size of the stock.

[13]Blue whiting has "favorable" parameter values, such as low price, high cost, and high environmental carrying capacity.

cooperatively.

The non-cooperative results are in contrast to cooperative management, where acknowledging the biological externality has a clearer impact on harvesting strategies, i.e., harvest allocation between species, and on attainable profits from the fishery as a whole. Intuitively, a likely explanation for the similar outcomes of SSM and MSM under non-cooperative management is that when the exploiters are competing against each other for the fish resources, accounting for species interactions is of secondary importance.

1.4.2 Effect of the common property externality

1.4.2.1 Economic impacts

The common property externality incurs significant loss in long-run NPV under both MSM and SSM. In the former case the loss is 44 percent and in the latter case the loss is 36 percent of NPV. Non-cooperation under SSM means that there are two sources of inefficiency present in the fishery: (1) the overlooked species interactions, and (2) the competitive harvesting strategies. Comparing this situation with the global optimum, the loss of NPV is up to 48 percent. Nonetheless, fairly high profits are made also in the non-cooperative scenario because of high initial harvests of especially mackerel and herring. Non-cooperative exploitation also leads to more harvesting by the other players, the EU and Iceland.

Cooperation is always superior to non-cooperation in terms of aggregate NPV attainable from the fishery. However, because of the interplay between biological and exploiter interactions, profits in the herring and blue whiting (i.e., the prey) fisheries can be higher under non-cooperation than in the global optimum. This is because the MSM policy prescribes less harvesting of the prey species, which reduces their contribution to NPV. In the (non-cooperative) SSM case, the biological interaction is simply ignored, which leads to more harvesting of the prey. In the (non-cooperative) MSM case, the exploiter interaction is stronger than the biological interaction when making harvesting decisions. That is, although a MSM policy is applied (less harvesting of prey), the non-cooperative harvesting strategies (more overall harvesting) result in more harvesting of herring and blue whiting than in the global optimum. Thus, profits in prey fisheries may be larger under non-cooperation if MSM is applied under cooperation. Profits in the mackerel (predator) fishery, on the other hand, are always higher under cooperation, irrespective of the type of biological management. This is because the MSM policy prescribes more harvesting of mackerel which increases its contribution to NPV.

1.4.2.2 Biological impacts

The non-cooperative harvest profiles of mackerel and herring contain an element of pulse fishing (Figure 1-3) compared to the more smooth harvest profiles of the cooperative solution (Figure 1-2).[14] In the non-cooperative case, the fishery is depleted if it is profitable. The mackerel stock is depleted in the very beginning of the time period under both SSM and MSM. As in the cooperative case, harvesting of mackerel increases under MSM. The herring stock is mined down to a very low level (around 100 thousand tonnes) under both MSM and SSM, but is let to recover toward the end of the period, after which it is fished down again. The competitive blue whiting harvest is more smooth. Further, in the MSM framework the blue whiting stock is larger in the non-cooperative scenario because its predator (mackerel) is removed from the ecosystem.

The biological results are broadly in line with the analytical studies by Fischer and Mirman (1992, 1996). These papers find that internalizing the biological externality in a predator-prey system leads to more fishing of the predator, and adding a dynamic externality (competition between harvesters) leads to even more fishing of the predator. This pattern can be observed in my analysis by studying Figure 1-4, which shows the time paths of aggregate fishing effort in the four different scenarios (note the different scales on the y-axis in upper and lower panels). We see how fishing effort exerted on mackerel increases when moving from panel (b) to (a) to (c). Indeed, in panel (c) the effort is so high that the mackerel stock is depleted. Further, Fischer and Mirman (1996) point out that what happens to the prey in the predator-prey setting is ambiguous, because the dynamic externality increases fishing, but the biological externality, when accounted for, reduces fishing. In my analysis, by comparing panels (b) and (c) in Figure 1-4, we see that the dynamic externality increases effort on herring well beyond the SSM cooperative level. For blue whiting the effect is qualitatively the same, but the increase in effort is much smaller.

[14] Bjørndal and Lindroos (2004) report a similar result from the North Sea herring fishery, with pulse fishing as the non-cooperative solution, and a smooth harvesting path in the cooperative solution.

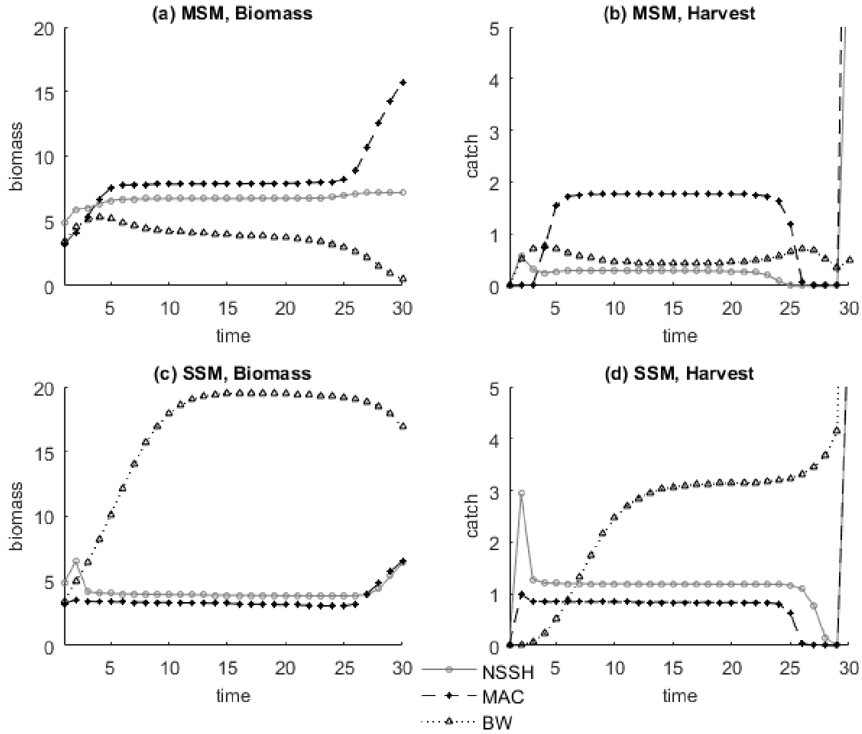

Figure 1-2. The cooperative solution. Long-run harvest and biomass levels (in million tonnes) under multispecies management (a–b) and single-species management (c–d).

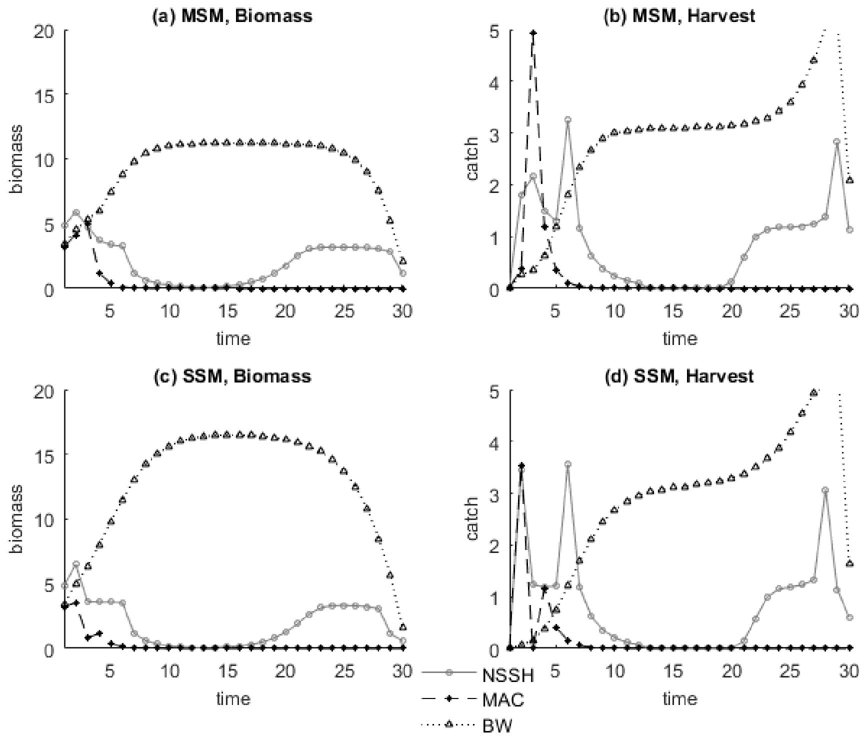

Figure 1-3. The non-cooperative solution. Long-run harvest and biomass levels (in million tonnes) under multispecies management (a–b) and single-species management (c–d).

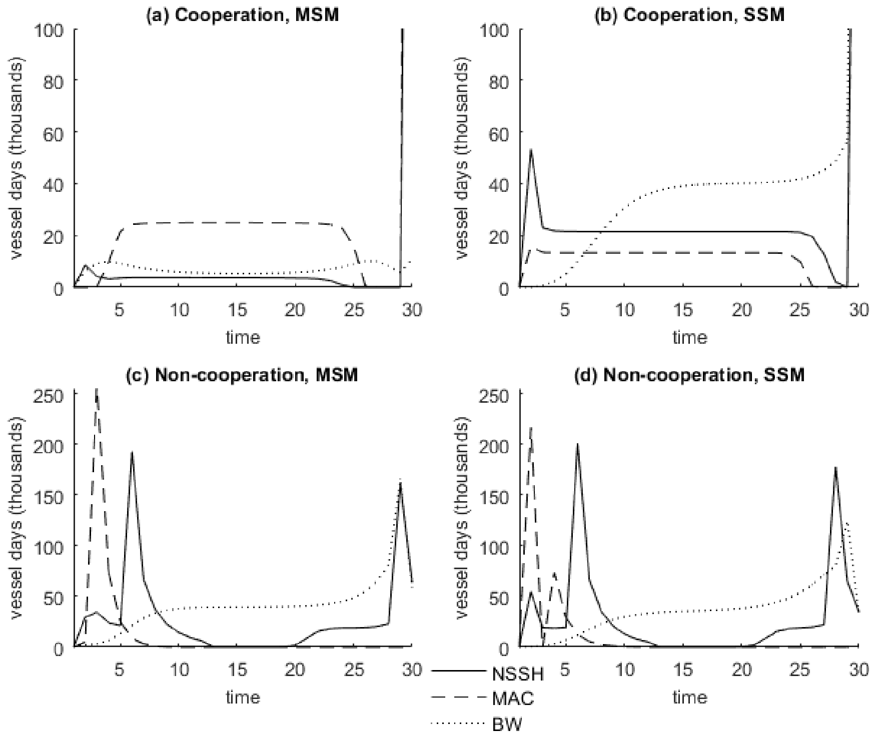

Figure 1-4. The time paths of fishing effort under single-species and multispecies management in the cooperative (a–b) and non-cooperative (c–d) scenario. Note the different scales on the y-axis in upper and lower panels.

The SSM non-cooperative case (Figure 1-4, panel (d)) is not considered in the analyses by Fischer and Mirman (1992, 1996). In my analysis, this scenario does not differ significantly from the MSM non-cooperative case in terms of stock health: mackerel is fully depleted and herring severely overexploited in both scenarios. Still, although the change is small, MSM has the effect of increasing effort on mackerel and decreasing effort on herring. This finding suggests how multispecies management has the potential to exacerbate overfishing of some species, whereas mitigate overfishing of other species in a non-cooperative setting.

1.4.3 Alternative model configurations

Here, I test the sensitivity of aggregate profits to changes in selected biological and economic parameters. The results of the sensitivity analysis are reported in Table 1-7. There is obvious uncertainty surrounding the specific type and magnitude of ecological interactions between the species in the pelagic complex. In this study, I have hypothesized that the primary interaction is between a predator (mackerel) and its prey (herring and blue whiting). First, I test the impact of modifying some of the interactions in the multispecies model.

Reducing the negative interaction (predation) between mackerel and NSS herring and blue whiting by 50 percent, increases NPV in the global optimum by 13 percent to 312.7 billion NOK. The difference between SSM and MSM in the non-cooperative scenario is somewhat larger than in the base case. Reducing the positive interaction between the prey (NSS herring and blue whiting) and mackerel by 75 percent lowers the global optimum NPV by 43 percent to 156.4 billion NOK. The outcome from this case differs from previous results in that MSM produces less NPV than SSM in the non-cooperative scenario. I also test the effect of initial biomass by running the simulations with year 2007 biomass levels. This implies a higher initial biomass for NSS herring (7.092 million tonnes) and blue whiting (4.687 million tonnes), and lower biomass for mackerel (2.412 million tonnes). This improves profitability in the MSM cooperative scenario, but in the MSM non-cooperative scenario the effect is negligible. This confirms results from the base case, namely, that the impact of SSM versus MSM in a non-cooperative setting is small compared to a cooperative setting. It has previously been found that initial biomass has a significant impact on cooperative benefits in a fishery (e.g., Bjørndal and Lindroos, 2014).

Next, I explore the effect of changes in costs, prices, and the rate of discount. Increasing all cost parameters by half and reducing all fish prices by 25 percent lowers the NPV in the global optimum by 39 percent to 168.3 billion NOK. In this case, mackerel is still depleted in the beginning of the non-cooperative simulation, but is not fished to extinction as in the base case. The stock stays at very low levels (some ten thousand tonnes) for a long time, but is let to recover toward the end of the simulation until there is another fishing pulse. As expected, changing the discount rate has a significant impact on the NPV obtained in the different scenarios. A two percent discount rate produces less smooth harvesting paths in the cooperative setting, and an even stronger emphasis on the valuable mackerel than in the base case. A higher discount rate of eight percent results in more uniform harvesting of the three species, although mackerel is still the most important fishery. In the non-cooperative scenarios there are no significant qualitative changes compared to the base case from using different rates of discount.

Table 1-7. Sensitivity analysis of payoffs (NPV) earned in the different scenarios

Management regime	Base case	$\alpha_{12}: -50\%$ $\alpha_{32}: -50\%$	$\alpha_{21}: -75\%$ $\alpha_{23}: -75\%$	$X_{i,2007}$	Cost: $+50\%$ price: -25%	$r = 2\%$	$r = 8\%$
Cooperation							
SSM	225.9	213.8	115.1	221.7	117.0	352.1	156.8
MSM	276.6	312.7	156.4	318.5	168.3	434.7	182.1
Non-cooperation							
SSM	145.1	153.3	130.0	131.8	78.1	179.6	121.2
MSM	154.3	180.5	125.8	155.9	96.2	192.5	127.3

Note: NPV = net present value (billion NOK). MSM = multispecies management, SSM = single-species management.

1.5 Discussion and conclusion

In this paper, I show how acknowledging or ignoring species interactions has the potential to affect the outcomes of cooperative and non-cooperative management. I use a quasi-empirical model of the pelagic complex fishery in the Northeast Atlantic as a case study. The difference between SSM and MSM on the fishery is fairly significant under cooperative management, whereas under non-cooperative management the effect on profits and stock health is rather small. In the cooperative case, economic performance can be improved by adjusting fishing effort on the different species according to a multispecies policy scheme. This means putting more fishing effort on the mackerel fishery. This is also the policy recommendation prescribed by Ekerhovd and Steinshamn (2016), although they use a different model which emphasizes food competition between the species. Because my model treats herring and blue whiting as prey species of mackerel, the MSM policy prescribes lower harvest rates of these species than a SSM policy. The estimated improvement in economic performance from applying multispecies management in the pelagic complex fishery is of the same magnitude in the current paper and in the paper by Ekerhovd and Steinshamn (2016), i.e., 20–25 percent.

A cooperative fishery improves economic performance by 56 percent in the SSM case, and by 79 percent in the MSM case. Accounting for both the common property and biological externality improves profitability by 91 percent. This study confirms the importance of both exploiter and biological interactions which are potentially present in international fisheries, and demonstrates the inefficiencies they result in. Most previous empirically based bioeconomic studies deal with one or the other of these inefficiencies. This paper is one of very few studies to analyze the effect of both inefficiencies simultaneously.

A limitation of using MSM in practice is that policy prescriptions hinge strongly on the type and magnitude of biological interactions, i.e., the ecosystem configuration. At the same time there will always be a great deal of uncertainty surrounding the ecological interdependencies present in exploited ecosystems. The more accurate knowledge we get on ecological interactions in multispecies fisheries, the more relevant are the results from bioeconomic analyses that explicitly model these interactions. That is why it is essential to gain better empirical knowledge on the ecology of exploited ecosystems.

Also completely ignoring relevant ecological interactions may, apart from loss in economic rents, have ecological consequences. If we assume that the multispecies model is the "true" model of the ecosystem, then applying a policy prescribed by a single-species model can in the worst case lead to stock extinctions, even in the absence of competition between harvesters (see Kasperski, 2015). For example, harvest quotas may be too large if a species' role as prey is not considered.

I differentiate between three major exploiters (Norway, the EU, and Iceland) in the pelagic complex fishery. However, I do not explore further the harvesting and economic benefits that accrue to the individual exploiters. The focus is on aggregate economic performance and the long-run outcomes of cooperative and non-cooperative management. A natural extension of this study is to analyze how species interactions affect the possibility of reaching and maintaining fisheries agreements that ensure the cooperative solutions.

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Appendix: Estimation results

Table A-1. Results from statistical estimation of the single species models

Species	Parameter	Estimate	Standard error	t-statistic	p-value
NSS herring	r	0.6215	0.1696	3.665	0.0009
	η	-0.0814	0.0376	-2.166	0.0379
Mackerel	r	0.4020	0.0716	5.617	3.29e-06
	η	-0.0460	0.0223	-2.064	0.0472
Blue whiting	r	0.3464	0.0935	3.703	0.0008
	η	-0.0096	0.0260	-0.370	0.7140

Notes: Estimation method: ordinary least squares. The parameter r is the intrinsic growth rate and η is a parameter relating to the environmental carrying capacity, $K = \frac{r}{\eta}$.

Table A-2. Results from statistical estimation of the multispecies model

Species	Parameter	Estimate	Standard error	t-statistic	p-value
NSS herring	r	0.7790	0.4418	1.7635	0.0880
	η	-0.0911	0.0432	-2.1081	0.0435
	α_{mac}	-0.0548	0.0989	-0.5539	0.5837
	α_{bw}	0.0153	0.0653	0.2349	0.8159
Mackerel	r	0.1693	0.09567	1.7695	0.0870
	η	-0.0212	0.0214	-0.9888	0.3307
	α_{her}	0.0233	0.0094	2.4941	0.0184
	α_{bw}	0.0192	0.0141	1.3615	0.1835
Blue whiting	r	0.5142	0.2210	2.3266	0.0269
	η	-0.0212	0.0327	-0.6502	0.5205
	α_{her}	0.0004	0.0216	0.0176	0.9861
	α_{mac}	-0.0427	0.0495	-0.8637	0.3946

Notes: Estimation method: seemingly unrelated regression. The parameter r is the intrinsic growth rate and η is a parameter relating to the environmental carrying capacity, $K = \frac{r}{\eta}$. The interaction coefficients for the three species are denoted α_{her}, α_{mac}, and α_{bw}.

Table A-3. Results from statistical estimation of the harvest functions

Species	Parameter	Estimate	Standard error	t-statistic	p-value
NSS herring	q	-2.7884	0.195086	-14.2933	1.9513e-06
	a	0.8659	0.197373	4.38688	0.0032
	b	0.2250	0.2014	1.1171	0.3008
Mackerel	q	-2.7492	0.1925	-14.2824	1.9614e-06
	a	0.9023	0.1232	7.3222	0.0002
	b	0.2031	0.2615	0.7767	0.4627
Blue whiting	q	-2.5565	0.2369	-10.7917	1.2919e-05
	a	0.8146	0.1342	6.0682	0.0005
	b	0.2130	0.1219	1.7467	0.1242

Notes: Estimation method: seemingly unrelated regression. The parameter q denotes catchability, a denotes catch elasticity with respect to effort, and b denotes catch elasticity with respect to stock size.

Chapter 2

Do international agreements prevent fisheries collapse? Evidence from RFMOs

2.1 Introduction

It is well-established that shared or common property natural resources are prone to overexploitation (Gordon, 1954; Hardin, 1968; Hanley et al., 2016). Many valuable fish stocks are international common property in the sense that they are found in the EEZs (exclusive economic zones) of two or more coastal states and/or outside national EEZs, where they may be fished by any fishing nation. I refer to these stocks as international fish stocks. Joint management by the countries harvesting from international fish stocks is essential in order to avoid negative outcomes associated with competitive exploitation—a situation often referred to as a tragedy of the commons (Hardin, 1968).

Management of many of the world's commercially important international fish stocks is conducted by RFMOs (Regional Fisheries Management Organizations), in which key harvesting countries are members. International fish stocks are non- or poorly excludable public goods, which can create incentives for some countries to free ride on the management efforts of others. Unlike many international environmental agreements (IEAs), RFMOs are not voluntary, since participation in RFMO-managed fisheries requires compliance with regulations (United Nations, 1995). RFMOs may therefore be viewed as institutions which are meant to address common problems of voluntary agreements, such as free riding. However, the poor ecological state of many international fisheries has given reason to question the effectiveness of RFMOs in this task (Cullis-Suzuki and Pauly, 2010). Still, it is possible that the situation would have been even worse in the absence of RFMO management. A rigorous empirical analysis of the effect of RFMOs on the sustainability of fish stocks is currently lacking.

This paper asks whether RFMOs, in accordance with their management task, are effective in promoting sustainable use and conservation of managed fish stocks. To answer this question, I study whether RFMO management has reduced the probability of stock collapse. A collapsed stock is one where the biomass level is a small fraction (usually less than 10 percent) of the unfished biomass (Worm et al., 2009). In the absence of data on biomass, historical catch records may be used to infer the status of fish stocks (Froese and Kesner-Reyes, 2002; Worm et al., 2006; Froese et al., 2012). Applying this approach, I use global catch data from the Sea Around Us catch database (Sea Around Us, 2015) to construct a panel data set on the exploitation of 942 international fish stocks from 1950 to 2014. I study the overall (average) and individual performance of eight multispecies RFMOs established between 1969 and 2009.

I report the following results. First, the initial differences-in-differences (DD) analysis suggests that RFMO management has had no effect on the probability of collapse. Second, excluding the poorest performing RFMO (according to an earlier assessment of RFMO performance) yields a different result: the included RFMOs have had a noticeable and significant beneficial impact on sustainability of managed stocks. These findings point to heterogeneity across RFMOs. The results from eight DD analyses on the individual RFMOs are more inconclusive, partly due to smaller samples sizes. I find weak evidence of beneficial impacts on sustainability in the case of three RFMOs. Taken together, the results of this paper question the general claim that RFMOs have failed in their management task, and call for further empirical analysis into successes and failures of RFMOs.

The remainder of the paper proceeds as follows. The next section reviews related literature on this subject. In section 3, I provide a brief overview of the background and role of RFMOs in international fisheries management. Section 4 describes the data. Section 5 presents the estimation strategy and the estimation results. Section 6 concludes.

2.2 Related literature

The literature on international fisheries agreements is concerned with the formation and stability of agreements and their impacts on resource use. The typical approach is to employ a bioeconomic model of an international fishery and within that framework study a specific agreement. Early examples of empirical studies in this vein are Arnason et al. (2000) and Pintassilgo (2003).[1] A key message arising from this literature is that fisheries agreements are seldom self-enforcing, and that some form of legal regime is needed to foster cooperative management between countries. In international fisheries, the RFMO exemplifies such a legal regime. Yet, the question whether RFMOs have had a beneficial impact on resource use remains to some extent unclear.

Several studies have investigated the effectiveness of international environmental

[1] For a survey of these studies, see Pintassilgo et al. (2015).

agreements (IEAs). These papers employ econometric methods, such as differences-in-differences and instrumental variables, to study whether agreements have improved on managed outcomes.[2] The evidence from this literature appears somewhat mixed: some agreements have resulted in lower emissions, whereas other have not improved on the outcomes that would have occurred in their absence. My paper contributes to this strand of literature by specifically studying the impact of international agreements (in the form of RFMOs) in fisheries.

My paper is also related to a growing literature on policy evaluation, employing reduced form and/or structural methods, in fisheries specifically. Abbott and Wilen (2010) study the success of a voluntary program on by-catch reduction in the Bering Sea flatfish fishery. Diekert and Schweder (2017) study the effect of abolishing the open access management regime on biomass and profits in the Norwegian coastal cod fishery. In addition, several recent papers use the Sea Around Us data to construct measures of stock sustainability. Costello et al. (2008, 2010) and Isaksen and Richter (2019) study the impact of catch share programs on the probability of stock collapse. Erhardt (2018) and Eisenbarth (2018) study how international trade impacts overfishing and stock collapse. I contribute to this literature by studying the impact of RFMO policies on stock collapse.

RFMO effectiveness has previously been studied by Cullis-Suzuki and Pauly (2010). This, however, is not a formal statistical study, but instead consists of a qualitative and a quantitative assessment. The quantitative assessment examines current biomass and fishing mortality compared to reference points (maximum sustainable yield) in 48 RFMO stocks. The results suggest overall weak performance of RFMOs, because biomass levels have often declined in spite of RFMO management. My paper complements this study by applying a more formal statistical methodology in the assessment. Specifically, RFMO stocks are compared to a control group to reveal what would have happened in the absence of management.

[2]Papers that study IEAs on pollution reduction include Bratberg et al. (2005): Sofia Protocol (nitrogen oxide), Aichele and Felbermayr (2012): Kyoto Protocol (CO2), Kellenberg and Levinson (2014): Basel Convention (hazardous waste), and Isaksen (2020): SO2, NOx and VOCs.

2.3 RFMOs and international fisheries management

2.3.1 The establishment of RFMOs: The UN Fish Stocks Agreement

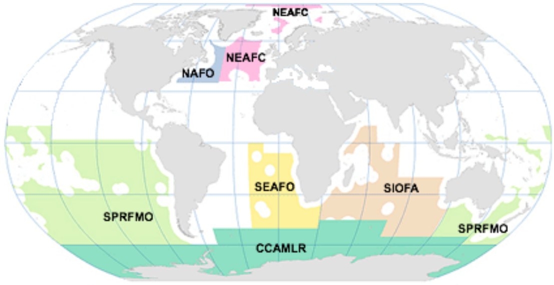
By establishing 200 nautical mile exclusive economic zones, the United Nations (UN) Convention on the Law of the Sea (UNCLOS), ratified in 1982, constituted a major step toward assigning national property rights over marine fish stocks. This convention, however, did not assign national rights to straddling and high seas fish stocks which, consequently, became subject to more intense international fishing pressure. A widespread international desire to close this gap led to the UN conference on straddling and highly migratory fish stocks, which resulted in an international agreement on the utilization of straddling and high seas fish stocks known as the UN Fish Stocks Agreement (United Nations, 1995). Since 2001, when it had gained a sufficient number of signatories, the UN Fish Stocks Agreement has had the status of international treaty law (Bjørndal and Munro, 2003).

A major provision of the UN Fish Stocks Agreement (Article 8) is that all coastal states and distant water states with a "real interest in the fisheries concerned" should cooperate in the management of these stocks within the so-called Regional Fisheries Management Organization (RFMO). To date, the RFMOs are the only management bodies with legal mandates to regulate fish stocks in the high seas (Cullis-Suzuki and Pauly, 2010).

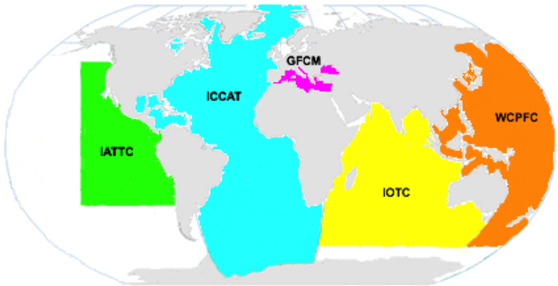
The UN Fish Stocks Agreement stipulates that membership in an RFMO should be open to all countries that wish to participate in the fisheries managed by the RFMO. This applies both to the relevant coastal states and to states fishing for the stocks on the high seas (distant water states). Countries that are not original members of a RFMO but later wish to participate in the fisheries should also be able to join (Article 8). Such countries are referred to as new members (Article 11). Only member countries, or those that follow the regulations set forth by the RFMO, are allowed to access the fishery resources subject to said regulations (Article 8).

2.3.2 Overview of current RFMO management

As of today, there are 18 RFMOs in operation, responsible for the management of some 150 different marine species around the world (Cullis-Suzuki and Pauly, 2010; Sea



(a)



(b)

Figure 2-1. Two schematic maps showing the regulatory areas of the major multi-species RFMOs. The upper map depicts RFMOs whose regulatory areas include only the high seas. The lower map depicts RFMOs whose regulatory areas include both EEZs and the high seas. Source: Maps modified from FAO (2016a).

Around Us, 2015). All current RFMOs in operation are listed in Table A-1 in the Appendix. The vast majority of RFMO-managed species are fish, but there are also some crustaceans (crabs, lobsters, shrimp) and molluscs (clams, oysters, squids). Some RFMOs (e.g., the IATTC) also address the by-catch of marine mammals, such as dolphins (Jefferies, 2016). One RFMO (the IWC) deals with the management of whaling. The oldest RFMO, the IPHC, was established in 1923 and the most recent is the SIOFA established in 2012. There is also great variability in the number of managed species and the number of signatory (member) countries. Some RFMOs manage only one or a few species, whereas others manage dozens of fisheries in a geographical area. RFMO-managed stocks are typically of high commercial value, when measured in average landings price (Sea Around Us, 2015). The regulatory areas of some of the major RFMOs are illustrated in Figure 2-1. From this figure, we see that most of the global oceans, including both EEZs and high seas, are covered by at least one RFMO.

RFMOs have a formal management mandate—not merely an advisory role—to implement binding conservation and management measures based on scientific advice (United Nations, 1995). RFMOs may decide to jointly conduct scientific research and establish management measures, such as total allowable catches (TACs), national catch quotas, area closures, and gear restrictions. RFMOs are also mandated to combat illegal fishing and address impacts from fishing activities on other living resources and the ocean habitat. Further, the UN Fish Stocks Agreement provides an enforcement regime, which allows RFMO member states to undertake enforcement measures against non-member vessels (see United Nations, 1995, Articles 5 and 10, for an overview of the functions of RFMOs).

The key management objective is similar across the different RFMOs, namely, the conservation of stocks of interest within their area of competence (Cullis-Suzuki and Pauly, 2010).[3] However, many fish stocks have continued to decline despite the establishment of RFMOs (Cullis-Suzuki and Pauly, 2010). On the other hand, there are also positive signs from international fisheries in different parts of the world, such as reduced fishing rates and restoration of overfished stocks (Fernandes and Cook, 2013; FAO, 2016b). Moreover, the recovery of some international fisheries is attributed specifically to the implementation of RFMOs.[4] There may also be substantial differences in the performance across individual RFMOs. Thus, the qualitative evidence of the impact of RFMOs on international stocks is far from clear.

2.4 Data

In this paper, global catch data are used to construct measures of stock abundance. The data source is the Sea Around Us database (Sea Around Us, 2015), which provides data on fisheries exploitation. The data contain information on year, species, fishing country, weight of catch, and landed value of catch. The catch data are reconstructed, which means they contain both official reported data and estimates of unreported data, such as major discards. The time span covers 1950–2014, but depending on data availability the length of the time series varies between fish stocks. Also, it is not uncommon that there are missing years in the time series for a given fish stock.

When working with catch data, the researcher "defines" the fish stock by choosing

[3] For example, the objective of the NEAFC is "to ensure the long-term conservation and optimum utilization of the fishery resources within its area of competence, providing sustainable economic, environmental and social benefits" (FAO, 2013).

[4] Bjørndal and Munro (2003) argue that the establishment of the NEAFC, an RFMO in the Northeast Atlantic, in the early 1980s provided the necessary framework for successful cooperation in the Norwegian spring-spawning herring fishery after a long period of international overexploitation.

the spatial area from which catches are extracted. In the case of many international stocks, it is not unambiguous what is the appropriate spatial scale. Therefore, I apply here a uniform approach and always extract the catch data on an FAO area basis. The FAO statistical areas encompass both EEZs and the high seas. I use data from FAO areas in the Atlantic, Pacific, Indian, and Antarctic Oceans (see Figure A-1 in the Appendix). Thus, a fish stock (fishery) is defined as a unique species-FAO area combination. This is arguably a crude approximation and how appropriate it is will depend on the stock in question. In the Northeast Atlantic, for example, this definition is more feasible for blue whiting than for Atlantic herring, since the latter consists of several distinct stocks. The FAO-area-species definition may be feasible for highly migratory stocks. However, in some cases, species of tuna in multiple adjacent FAO areas is considered a single stock (e.g., southern bluefin tuna).

2.4.1 RFMO and non-RFMO stocks

In this paper, I focus on multispecies RFMOs that manage straddling and highly migratory stocks. I exclude single-species RFMOs, RFMOs for anadromous species (salmon), and RFMOs for which catch data are insufficient. Firstly, this focus yields a more uniform set of RFMOs for the overall DD analysis. Secondly, the individual RFMO analyses benefit from having multiple managed stocks to consider. Out of the 18 RFMOs listed in Table A-1, eight are included in the analysis: ICCAT, NAFO, CCAMLR, NEAFC, IOTC, SEAFO, WCPFC, and SPRFMO.

For each RFMO, I check which FAO areas are included in its area of competence.[5] In some cases, the RFMO area of competence corresponds roughly to one FAO area, such as with NEAFC in the Northeast Atlantic. In other cases, the RFMO area of competence encompasses several FAO areas, such as with ICCAT in the Atlantic Ocean (see Figure 2-1). I check which species the RFMOs manage and subsequently define the RFMO stocks (area-species combinations). A full list of managed species by RFMO is available from Sea Around Us.

To construct a control group, I need international fish stocks which have never been subject to RFMOs or similar management. All species in a given FAO area not managed

[5] Note that the area of competence and regulatory area may differ. The areas of competence of the NAFO and the NEAFC are the Northwest and Northeast Atlantic Oceans, respectively, but only the high seas portions are their regulatory areas, where they may regulate fishing activities (FAO, 2013, 2015).

by a RFMO are non-RFMO species and subsequently preliminary non-RFMO stocks. Because I extract data on an FAO area basis (EEZs and high seas), these data also include catches of strictly domestic stocks. Therefore, I retain only those non-RFMO stocks that are harvested in both EEZs and high seas. Further, I drop non-RFMO stocks which in spite of their wide distribution have only one harvesting country throughout the time period. I cannot be fully certain that the non-RFMO stocks are not internationally managed in any way. However, as the RFMO is the primary management body for international fisheries worldwide, it seems feasible to assume that most fisheries in the control group are indeed unmanaged.

To check for balance across RFMO and non-RFMO fisheries, I gather information on stock- and year-specific number of harvesting countries and landings price from Sea Around Us. I also collect data on species-specific covariates from the FishBase databank (FishBase, 2018). These covariates are dummy variables indicating highly migratory species, highly commercial species, tropical/subtropical species, and species with low/very low biological resilience. Many RFMO managed species are highly migratory and/or of high commercial value, such as tunas and mackerels. RFMO managed species are also often tropical or subtropical. Tropical species are typically fast-growing with a high intrinsic rate of population increase. Such fast-growing species may be especially prone to collapse when overfished (Pinsky and Byler, 2015). RFMOs also manage many species with low biological resilience (which here means a long doubling time for biomass), which may predispose to stock collapse.

2.4.2 Estimating stock status

The Sea Around Us database does not contain estimates of stock size. Following criteria developed by Froese and Kesner-Reyes (2002) and Froese et al. (2012), I assign exploitation status to stocks in each year on the basis of catch relative to maximum catch in previous years. This approach of inferring stock status from the catch record is common practice in studies of this kind (see e.g., Worm et al., 2006; Costello et al., 2008, 2010; Sakai, 2017; Eisenbarth, 2018; Erhardt, 2018; Isaksen and Richter, 2019). Specifically, I use the catch record to define the following six exploitation categories for all stocks in the sample in every year: (1) underdeveloped, (2) developing, (3) fully exploited, (4) overexploited, (5) collapsed, and (6) rebuilding. The exploitation category central to this study is collapsed, which is defined as a catch level less than 10 percent of the previous maximum catch. The criteria for assigning exploitation status and definitions of the different exploitation categories are given in Table A-2 and Table A-3, respectively, in the Appendix.

There are of course shortcomings in the use of catch as a proxy for stock abundance. Other factors than fish abundance, such as fishing regulations, fuel costs, and natural disasters, may also influence the total amount of catch (Pauly et al., 2013). This means that using catch trends may overestimate the amount of collapsed stocks (Branch et al., 2011). Another concern is that the maximum catch is a poor reference point, since it may have been recorded at a time when harvesting was unsustainable. However, Froese et al. (2012) find that the historical maximum catch is often correlated with maximum sustainable yield. In my case, the chief concern is that collapse is mistaken for effective RFMO management. That is, the RFMO imposes a restrictive harvesting policy, which implies low catches (as does collapse). This is a cause of concern primarily if we were to observe a positive relationship between management and collapse. On the other hand, a positive correlation between management and collapse may also indicate that RFMO management is initiated as a response to overexploitation. Ideally we would be able to corroborate findings based on catch data with analysis using stock data. As this is not currently possible in my case, these data-related caveats have to accepted and acknowledged.

2.4.3 Data summary

From the combined data set (RFMO and non-RFMO stocks), I drop all stocks that have less than 30 years of observations to ensure sufficient observations before and after RFMO establishment. I also drop stocks with insignificant catches (less than one tonne annually) throughout the time period.

Figure 2-2 shows the number of stocks in each exploitation category in the RFMO and non-RFMO group in 1970 and 2010. In 1970 only ICCAT was established (in the previous year), whereas in 2010 all RFMOs included in the analysis were established. On the whole, the distribution of exploitation status is fairly similar in both groups in both years. In 1970, most stocks are still underdeveloped or developing, with only a few overexploited or collapsed stocks. In 2010, a substantial fraction of stocks are

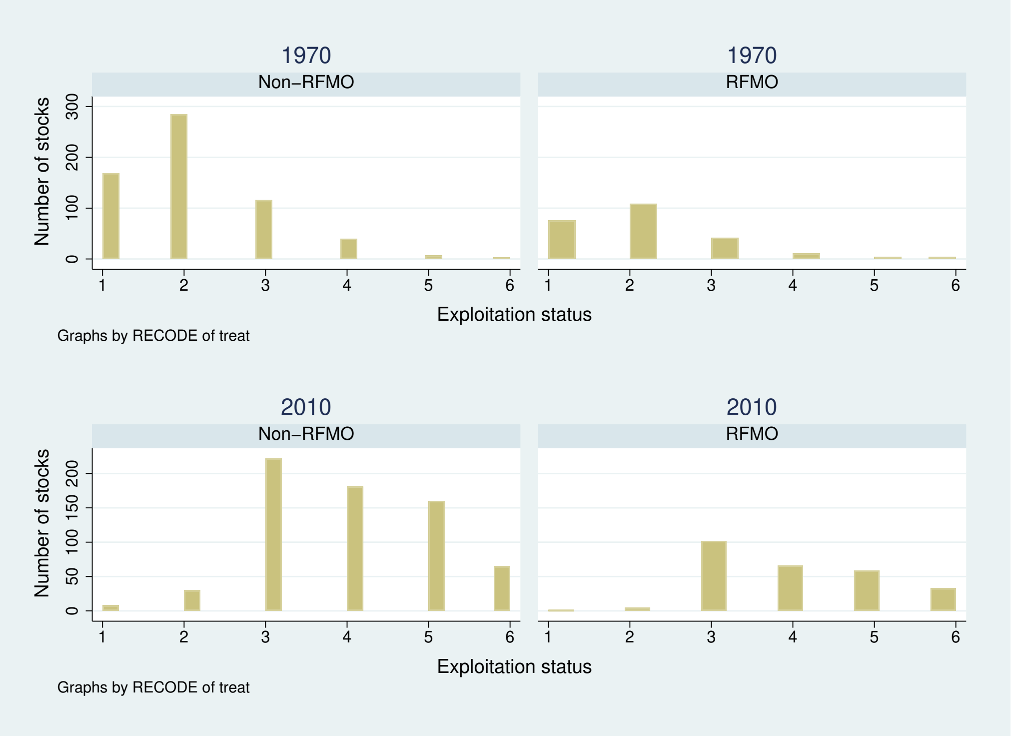


Figure 2-2. Frequency of exploitation status by the RFMO and non-RFMO group in 1970 and 2010. Note that the Non-RFMO and RFMO diagrams share the same vertical axis. Exploitation status code: 1=underdeveloped, 2=developing, 3=fully exploited, 4=overexploited, 5=collapsed, 6=rebuilding.

either collapsed or overexploited in both the RFMO and non-RFMO group.

Figure 2-3 compares the outcome of interest, stock collapse, in the RFMO and non-RFMO group over time. The figure shows the proportion of collapsed stocks in each group. The proportion of collapsed stocks has grown in both groups, but it appears that growth has been somewhat slower in the RFMO group since the 1990s. As already mentioned, the role of RFMOs in the management of straddling and highly migratory stocks was established in international law in 1995, i.e., around the time we see some divergence in the trends. At the end of the data period (in 2014), about 28 percent of non-RFMO stocks were collapsed, while the corresponding proportion for the RFMO-managed stocks was about 23 percent. This graphical analysis suggests that RFMO management may have had some beneficial effects on stock outcomes; however, this effect is far from clear and requires further investigation.

Means and standard deviations of variables in the data set are presented in Table 2-1. Summary statistics are reported for the total sample and in the RFMO and non-RFMO group. The dependent variable is a binary variable indicating whether a stock

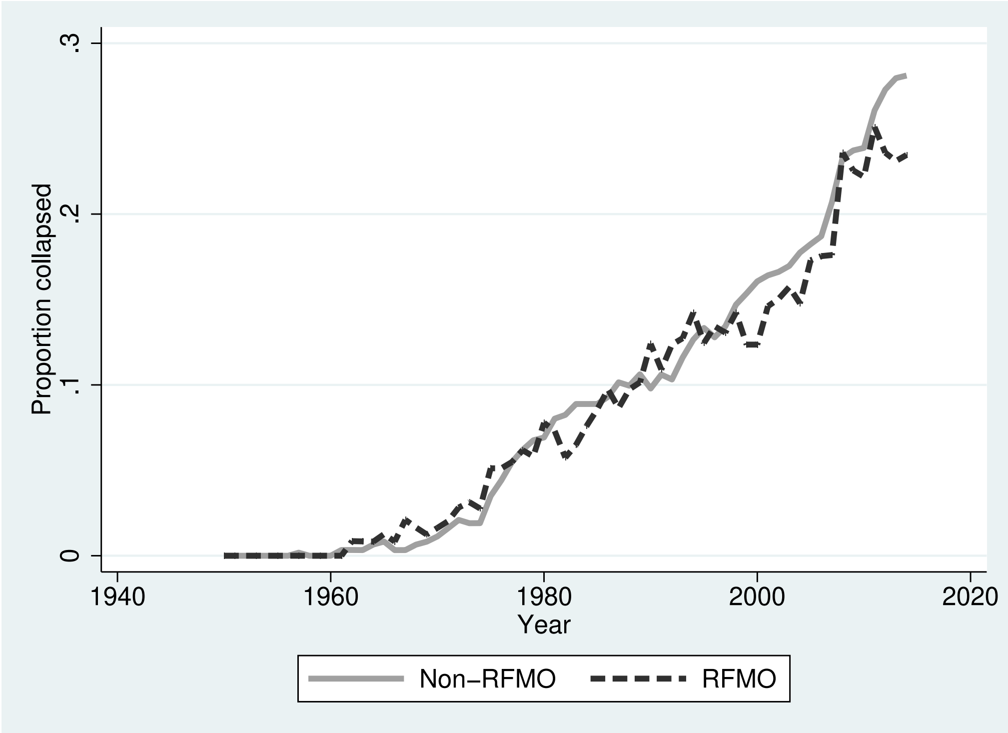


Figure 2-3. Comparison of proportion of collapsed stocks between the RFMO and non-RFMO group during the study period 1950–2014.

is collapsed. In the total sample and in both groups about 9 percent of observations represent a collapsed stock. The RFMO and non-RFMO groups are systematically different with respect to ecological and economic characteristics. RFMO stocks have higher average landings price and are harvested by more countries. RFMO stocks also more likely to be highly migratory, highly commercial, and tropical or subtropical, as well as a more likely to have low or very low biological resilience. Due to some of these characteristics RFMO stocks may be more prone to collapse than non-RFMO stocks.

Table 2-1. Summary statistics

	Total	RFMO	Non-RFMO
Collapsed dummy	0.092 (0.288)	0.089 (0.285)	0.092 (0.290)
Landings price (thousand 2005 US $)	1.974 (2.368)	2.259 (2.337)	1.861 (2.370)
Number of countries	6.3 (6.8)	7.4 (7.1)	5.9 (6.6)
Highly migratory dummy	0.231 (0.422)	0.560 (0.496)	0.101 (0.302)
Highly commercial dummy	0.187 (0.390)	0.399 (0.490)	0.103 (0.304)
(Sub)tropical dummy	0.337 (0.473)	0.659 (0.474)	0.210 (0.407)
(Very) low resilience dummy	0.183 (0.386)	0.320 (0.467)	0.128 (0.335)
Number of stocks	942	268	674
Number of species	387	87	300
Observations	57,263	16,240	41,023

Notes: Variable means and standard deviations (in parentheses) in the total sample and in the RFMO and non-RFMO group. Collapsed is the dependent variable; landings price, number of countries, highly migratory, highly commercial, (sub)tropical, and (very) low resilience are covariates.

2.5 Estimation: Differences-in-differences

The approach in this paper is to compare managed (RFMO) stocks to other international (non-RFMO) stocks, which have not been subject to RFMO management. The non-RFMO stocks represent a counterfactual: what would have happened to RFMO stocks had they not become subject to management at some point in time? Specifically, the differences-in-differences (DD) estimator compares the change in the probability of collapse in RFMO fisheries before and after RFMO establishment to the change in probability of collapse in non-RFMO fisheries during the same period. In contrast to the canonical DD setup, study subjects (fisheries) are exposed to the policy at different points in time as the RFMOs are gradually established. The DD estimator can be implemented by using the following generalized DD regression model

$$y_{i,t} = \delta RFMO_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t} \tag{2.1}$$

where $y_{i,t}$ is a dummy variable indicating whether a stock is collapsed or not, $RFMO_{i,t}$

is a dummy variable indicating the presence (or non-presence) of a RMFO managing the stock, α_i are fishery fixed effects, τ_t are year fixed effects, and $\varepsilon_{i,t}$ is an error term.

The year fixed effects control for fluctuations over time which affect collapse rates in all fisheries; for example, the development of new harvesting technologies. The fixed effects control for all unobserved and time-invariant heterogeneity between fish stocks which may be related to collapse. The coefficient of interest, δ, is the DD estimate of the effect of RFMO management on the probability of collapse. Equation 2.1 attributes changes in the probability of collapse within fisheries to changes in $RFMO_{i,t}$. The identifying assumption is that collapse in RFMO fisheries would have evolved similarly to non-RFMO fisheries in the absence of RFMO management (i.e., the collapse trends would have been the same). In other words, the DD estimator in equation 2.1 assumes that all of the difference in the collapse trends across RFMO and non-RFMO fisheries is due to RFMO management. To test for the robustness of my results, I address the possibility of RFMO fisheries-specific trends in different ways.

The trends in RFMO and non-RFMO fisheries may differ if the composition of the RFMO and non-RFMO group is related to ecological outcomes over time. We saw, for example, that RFMO stocks are more likely to comprise highly migratory species (such as tuna) and species with low biological resilience. If there is a growing demand for tuna over time, this may affect the collapse trends in RFMO stocks negatively compared to non-RFMO stocks. A changing climate may make RFMO stocks more prone to collapse, because a high fraction of RFMO species have low biological resilience. I address these possibilities by including species-specific control variables. Since the species-specific variables are time-invariant they are interacted with the year dummies so as not to be picked up by the fishery effects.[6]

There may also be geographical factors that cause fisheries to be on different trends. Geography is correlated with several factors that can potentially influence ecological outcomes, such as climate, biological productivity, and the set of countries participating in the fisheries. It is possible to control for geographical trends by including FAO area-

[6] I do not control for time-varying landings price. Price is potentially endogenous, since the outcome (collapse) and price are jointly determined by catch volume. I address differences in the economic values of fish stocks by including a dummy for highly commercial species. Also, I do not control for time-varying number of countries. Only RFMO member countries are allowed to participate in RFMO-managed fisheries. Therefore, number of countries is potentially affected by RFMO management and a channel through which management affects stock outcomes. Variables that are in fact outcomes of a variable of interest should not be included as controls (e.g., Angrist and Pischke, 2009).

specific time trends. However, even with FAO area-specific trends, identification still requires that there is no specific trend for RFMO-fisheries in a given area. It is possible to relax the common trends assumption by allowing specific trends for the RFMO and non-RFMO group, respectively, in each FAO area. In this model, the evidence for a RFMO effect comes from deviations from the trend that the group of managed fisheries is on in each area. With both species-specific control variables and area-specific trends, the estimating equation is

$$y_{i,t} = \delta RFMO_{i,t} + (X_i * \tau_t)\beta + \gamma_s t + \alpha_i + \tau_t + \varepsilon_{i,t} \tag{2.2}$$

where X_i are time-invariant control variables, t is a linear time trend, and γ_s are area-specific trend parameters. $y_{i,t}$, $RFMO_{i,t}$, δ, α_i τ_t, and $\varepsilon_{i,t}$ are defined as before. There are 17 area parameters ($\sum_{s=1}^{17} \gamma_s t$) when controlling only for FAO area-specific trends. There are 37 parameters ($\sum_{s=1}^{37} \gamma_s t$) when controlling for separate RFMO and non-RFMO trends in each FAO area.

I estimate the DD equations using OLS. The error terms in these linear probability models are necessarily heteroskedastic. To deal with this, the statistical inference is always based on heteroskedasticity-consistent (robust) standard errors.

2.5.1 Estimation results: The average RFMO effect

This section reports the average effect for the eight RFMOs included in the initial analysis. I report results from specifications with and without control variables and with different controls for trends. In addition, I report results when using an alternative control group, and I discuss the possibility of an endogenous RFMO variable.[7]

The result from the most basic DD estimator (equation 2.1) is reported in column 1 of Table 2-2. This specification includes fishery fixed effects, a full set of year dummies to capture the common time path, and a dummy to indicate whether a fishery is managed by a RFMO in a given year. The DD estimate is close to zero, which would suggest that

[7] In all regressions, standard errors are clustered at the fishery (species-FAO area) level to address over-precision in the estimates from serially correlated errors. Clustering at the fishery level does not take into account possible correlation in outcomes between RFMO fisheries and non-RFMO fisheries, respectively, within FAO areas. Non-independence of observations within areas could also lead to exaggerated precision in the DD estimates. However, as the number of areas is often low (depending on the setup, but 37 at most), I refrain from clustering at the area level. In fact, in some of the DD regressions for individual RFMOs the number of fisheries is only a few dozen, which could be perceived as too few clusters (e.g., Angrist and Pischke, 2009).

Table 2-2. Differences-in-differences estimates of the effect of RFMO management on the probability of collapse

	(1)	(2)	(3)	(4)
RFMO management	0.001	0.022	-0.005	-0.002
	(0.016)	(0.017)	(0.015)	(0.014)
Species-specific controls		Yes	Yes	Yes
Area-specific trends			Yes	
Area-by-treatment-specific trends				Yes
R^2	0.109	0.119	0.179	0.189
Fish stocks	942	942	942	942
Observations	57,263	57,263	57,263	57,263

Notes: All regressions include fishery and year fixed effects. Species-specific control variables are interacted with the year dummies. Area-specific trends allow for different trends for each FAO area. Area-by-treatment-specific trends allow for different trends for the RFMO and non-RFMO group, respectively, in each FAO area. Robust standard errors (in parentheses) clustered at the fishery (species-FAO area) level. Significance levels: *10%, **5%, ***1%.

RFMO management has had no effect on the probability of collapse. Columns 2 through 4 report results from different specifications of equation 2.2. Adding species-specific control variables makes the estimate substantially bigger, but not significantly different from zero. However, controlling for area-specific trends again yields coefficients close to zero, albeit with a negative sign. Taken together, the results in Table 2-2 provide no evidence that RFMO management has improved on the sustainability of managed stocks.

A reasonable question is whether the chosen non-RFMO stocks represent a good control group. Table 2-3 reports results when confining the control group only to species that are managed by a RFMO somewhere in the world. Because a fish stock is defined as a species-FAO area combination, a given species can be managed in one area and unmanaged in another area. Using only RFMO species makes the control group considerably smaller, but perhaps more comparable to the RFMO group. Another benefit of this control group is that it is perhaps less likely that the non-RFMO stocks are subject to some form of other international management. The reason being that we are focusing solely on species that are typically managed in RFMOs, such as tunas and other highly migratory species. The results do not change when using this alternative control group. The evidence still seems to suggest that the RFMO effect on probability of collapse is more or less zero.

Considering the graphical evidence in Figure 2-3, a DD estimate close to zero is not

Table 2-3. Differences-in-differences estimates with *RFMO species only* control group

	(1)	(2)	(3)	(4)
RFMO management	0.011	0.020	-0.005	0.001
	(0.017)	(0.017)	(0.016)	(0.015)
Species-specific controls		Yes	Yes	Yes
Area-specific trends			Yes	
Area-by-treatment-specific trends				Yes
R^2	0.099	0.122	0.175	0.199
Fish stocks	430	430	430	430
Observations	25,972	25,972	25,972	25,972

Notes: All regressions include fishery and year fixed effects. Species-specific control variables are interacted with the year dummies. Area-specific trends allow for different trends for each FAO area. Area-by-treatment-specific trends allow for different trends for the RFMO and non-RFMO group, respectively, in each FAO area. Robust standard errors (in parentheses) clustered at the fishery (species-FAO area) level. Significance levels: *10%, **5%, ***1%.

surprising. Both graphical and statistical evidence seem to suggest that RFMO management has not decreased the incidence of stock collapse. Still, there may be factors leading to an underestimation of the RFMO effect. If deterioration in the state of the stocks is a driver of RFMO establishment, the OLS estimate could be downward biased. In particular, countries may address overexploitation or collapse of shared stocks by establishing a RFMO. Second, if the RFMO variable is measured with error the coefficient of interest would be biased toward zero. For example, all currently managed species did not necessarily become subject to management at precisely the time of RFMO establishment.

I have attempted to address potential endogeneity of the RFMO variable by applying an instrumental variables (IV) strategy. I use the *average* number of signed international environmental agreements among harvesting countries as an instrument for RFMO management.[8] I hypothesize that the more countries with a history of signing many IEAs that participate in a fishery, the more likely that the fishery is subject to RFMO management. Because cooperative management is the key to sustainable fisheries, and such management takes place primarily within RFMOs, it is feasible to assume no direct effect of country characteristics (which determine the instrument) on sustainability outcomes. The results from the IV estimation are inconclusive (no table provided). First, there is a strong positive relationship between the instrument and

[8]Information on how many IEAs a country has signed is available from the International Environmental Agreements database (Mitchell, 2018).

RFMO management only when using exclusively RFMO species in the control group. Second, although the IV estimate is negative and of a reasonable magnitude (coefficient: -0.025, s.e.: 0.189), the estimate is too imprecise to be informative. Specifically, the 95% confidence interval does not preclude the zero effect obtained from the OLS estimation. Thus, the best available evidence still points to an overall RFMO effect of zero.

2.5.2 Estimation results: The role of individual RFMOs

The average RFMO effect may mask considerable heterogeneity across RFMOs. Some RFMOs may have had no effect on sustainability outcomes, whereas others have had a positive effect. If RFMOs are established as a response to overexploitation, the result could be spurious correlation between management and a negative effect on sustainability. These three cases would imply zero, negative, and positive DD point estimates. Therefore, we need to explore what lies behind this aggregate effect.

As a point of departure, let us return to the assessment of RFMO performance by Cullis-Suzuki and Pauly (2010), a paper discussed in the literature section. In this assessment, the authors rank RFMOs based on current fishing mortality (F) and biomass (B) relative to maximum sustainable yield (MSY). For example, $F/F_{MSY} > 1$ implies overfishing. In addition, the authors examine the evolution of biomass in relation to the time of RFMO establishment. Table 2-4 shows performance scores given to RFMOs in Cullis-Suzuki and Pauly (2010).[9] These are relative scores: although CCAMLR has the highest score, it does not necessarily mean that the CCAMLR has performed exceedingly well. Nonetheless, this ranking presents an interesting starting point for examining the effect of individual RFMOs. For example, what would be the impact on the average RFMO effect if we would omit ICCAT, the lowest performing RFMO, from the analysis? The average score among all RFMOs assessed by Cullis-Suzuki and Pauly (2010) is 48.9. ICCAT is well below the average, whereas all the other RFMOs in my analysis have performance scores above the average.

Figure 2-4 compares again the evolution of the proportion of collapsed stocks in the RFMO and non-RFMO group, but this time excluding ICCAT from the group of RFMOs. Compared to Figure 2-3, there is now a clearer difference between RFMO

[9] No scores for SEAFO and SPRFMO are provided

Table 2-4. Relative performance scores by Cullis-Suzuki and Pauly (2010)

RFMO	Q Score (%)	Assessed stocks
CCAMLR	100	1
IOTC	77.8	3
NEAFC	77.2	6
WCPFC	66.7	4
NAFO	53.5	5
ICCAT	37.5	8

Notes: The ranking is based on current fishing mortality and biomass relative to MSY (maximum sustainable yield), and the evolution of biomass abundance over time.

and non-RFMO stocks. Specifically, it looks like the overall growth in proportion of collapsed stocks has been slower in the RFMO group. Intriguingly, the evolution in the RFMO group appears to alternate between periods of no growth and fast growth in the proportion of collapsed stocks. This could point to periods of poor management being succeeded by periods of good management, and vice versa. If the downward trend in the final years of the time series has continued remains to be seen.

Table 2-5 reports DD estimates when excluding ICCAT from the RFMO group. The most basic DD estimator in column 1 yields a substantive negative, albeit somewhat imprecise, coefficient (-0.035). Controlling for species-specific characteristics yields a slightly smaller coefficient, which gets even smaller when controlling for FAO area-specific trends. However, the final specification, controlling for different trends for the RFMO and non-RFMO group in each area, yields a substantive negative coefficient. Moreover, the coefficient is now precisely estimated. This DD estimate suggests that RFMO management has decreased the probability of stock collapse by 3.5 percentage points. Compared to a collapse rate of 9.2 percent in the non-RFMO group, this result suggests that RFMO management has decreased the probability of collapse by 38 percent.[10]

Again, I rerun the regressions using the alternative control group defined earlier. The qualitative results do not change markedly. When using only RFMO species (Table 2-6), the coefficients are of similar magnitude in all specifications compared to using the baseline control group. The coefficients are slightly more imprecise, however, since the

[10]NAFO is the second lowest performing RFMO according to the ranking by Cullis-Suzuki and Pauly (2010). Running the DD regressions excluding both ICCAT and NAFO yields even larger coefficients. Coefficients and standard errors in specifications 1 through 4 (excluding ICCAT and NAFO) are as follows: -0.07 (0.019), -0.05 (0.022), -0.02 (0.020), -0.04 (0.017).

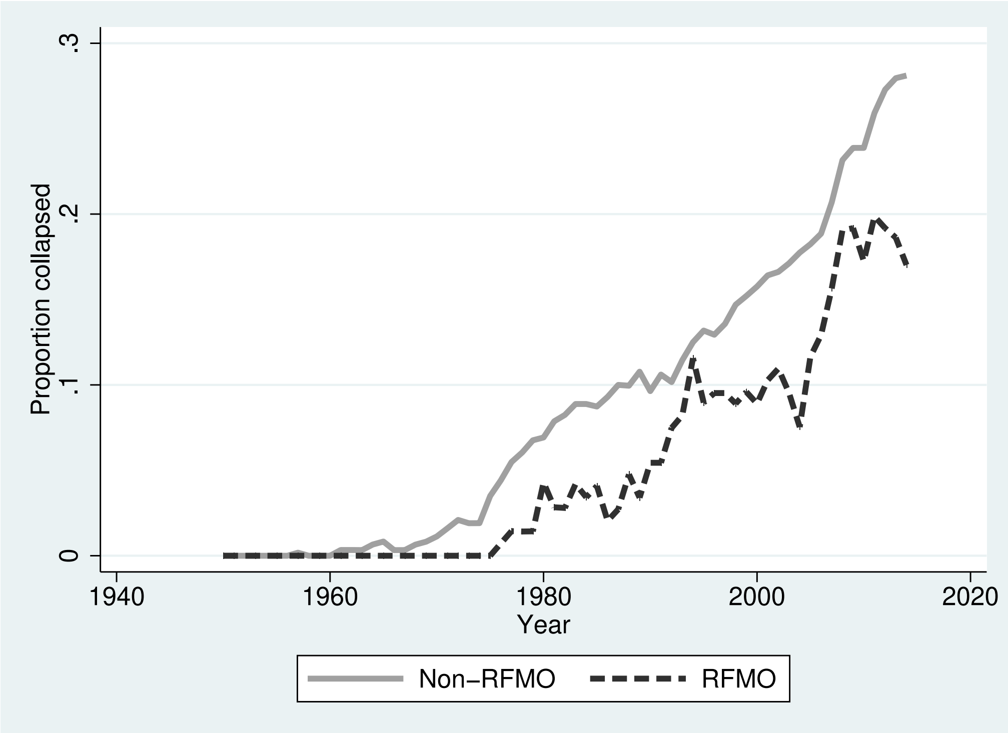


Figure 2-4. Comparison of proportion of collapsed stocks between the RFMO and non-RFMO group (excl. ICCAT).

number of stocks is less than half of the baseline.

2.5.3 Estimation results: Effectiveness of eight RFMOs

Finally, I turn to the analysis of the effectiveness of the individual RFMOs. I run DD regressions using equations 2.1 and 2.2 for each of the eight RFMOs in my data sample. These estimators are more akin to the canonical DD setup, since there is a single period in time when RFMO stocks become subject to the policy. The control group in each case consists of international stocks in the RFMO's area of competence (FAO area(s)) that are not managed by any RFMO. A weakness of limiting the control group to the area of competence is that the total number of stocks in the samples can be low (e.g., in the case of CCAMLR in the Antarctic), which can lead to imprecise estimates. On the other hand, the most appropriate counterfactual for CCAMLR-managed stocks are arguably non-managed stocks in the Antarctic Ocean.

The results from the regressions are reported in Table 2-7. There appears to be substantial heterogeneity across RFMOs, because we observe DD estimates ranging from negative to positive. Also, there is more variation across specifications than when studying all RFMOs jointly, which reduces confidence in some of the RFMO estimates.

Table 2-5. Differences-in-differences estimates of the effect of RFMO management on the probability of collapse (excl. ICCAT)

	(1)	(2)	(3)	(4)
RFMO management	-0.035	-0.026	-0.008	-0.035**
	(0.022)	(0.024)	(0.021)	(0.017)
Species-specific controls		Yes	Yes	Yes
Area-specific trends			Yes	
Area-by-treatment-specific trends				Yes
R^2	0.113	0.129	0.197	0.200
Fish stocks	821	821	821	821
Observations	49,941	49,941	49,941	49,941

Notes: All regressions include fishery and year fixed effects. Species-specific control variables are interacted with the year dummies. Area-specific trends allow for different trends for each FAO area. Area-by-treatment-specific trends allow for different trends for the RFMO and non-RFMO group, respectively, in each FAO area. Robust standard errors (in parentheses) clustered at the fishery (species-FAO area) level. Significance levels: *10%, **5%, ***1%.

Table 2-6. Differences-in-differences estimates with *RFMO species only* control group (excl. ICCAT)

	(1)	(2)	(3)	(4)
RFMO management	-0.025	-0.026	0.008	-0.029
	(0.025)	(0.024)	(0.021)	(0.018)
Species-specific controls		Yes	Yes	Yes
Area-specific trends			Yes	
Area-by-treatment-specific trends				Yes
R^2	0.106	0.156	0.228	0.236
Fish stocks	309	309	309	309
Observations	18,650	18,650	18,650	18,650

Notes: All regressions include fishery and year fixed effects. Species-specific control variables are interacted with the year dummies. Area-specific trends allow for different trends for each FAO area. Area-by-treatment-specific trends allow for different trends for the RFMO and non-RFMO group, respectively, in each FAO area. Robust standard errors (in parentheses) clustered at the fishery (species-FAO area) level. Significance levels: *10%, **5%, ***1%.

ICCAT, which was excluded from the joint analysis, yields a negative and imprecise coefficient in the first specification, but a large, positive, and very precisely estimated coefficient in the last specification. These findings may be partly due to timing. In the specification in column 4, evidence of a RFMO effect comes from deviations from the trend that the ICCAT fisheries are on pre-establishment. When ICCAT was established in 1969 stock collapses were very rare in all fisheries, and there was probably an increase from the trend after 1969. However, the trend may have been growing slower in ICCAT fisheries to begin with compared to other international fisheries in the Atlantic Ocean. The negative coefficient in column 1 could be a result of such non-parallel trends. Also NAFO yields similarly inconclusive results. The estimates range from positive to negative and are fairly imprecisely estimated.[11]

For CCAMLR the estimates are negative and similar in magnitude across specifications. The estimates in columns 1 through 3 are imprecisely estimated. However, given the very small sample size (16 stocks) this is not surprising. Taking into account the small sample size, the estimate in column 4 (-0.223) can be considered somewhat reliable. This estimate suggests that CCAMLR has reduced the probability of collapse in managed stocks by 22 percentage points, or 38 percent compared to the control group mean. For NEAFC, all coefficients are negative, and the last specification yields a large and statistically significant coefficient (-0.116). For IOTC, the coefficients are negative and of a reasonable magnitude throughout. The estimates are also quite precise, except in the final specification.

The SEAFO estimates are mixed and/or imprecise, and thus not particularly informative. For WCPFC, the problem is again imprecise estimates. The totality of evidence seems to point to no effect of WCPFC management on the probability of collapse. In particular, the final specification yields a coefficient of zero. Finally, the results from the SPRFMO analysis are intriguing. All coefficients are positive, and in the specifications in columns 1 and 4 they are not too imprecisely estimated. These results would suggest that SPRFMO management increases the probability of collapse. Again, as with ICCAT, the timing might be an issue here. SPRFMO was established recently (in 2009), and thus it is feasible that the stocks under SPRFMO's purview were in poor condition

[11] Note that when the area of competence comprises a single FAO area (as in NAFO's case), the FAO area-specific trend is superfluous, since all fisheries belong to the same area. However, we may still control for separate RFMO/non-RFMO trends in the area.

at the time management began. I only have data for five years post-establishment, which makes it likely that no positive effects of management are yet discernible.

The sum of evidence from the eight individual RFMO analyses is somewhat inconclusive. I have most confidence in the analyses of CCAMLR, NEAFC, and IOTC. Here, the results are fairly consistent across specifications and the coefficients are negative (suggesting a benefit from management) and comparatively precisely estimated. It is also noteworthy that CCAMLR, NEAFC, and IOTC are the RFMOs with the highest relative performance scores in the quantitative assessment performed by Cullis-Suzuki and Pauly (2010). This further boosts confidence in my results, since the data and methodology across the two studies are completely different.

Table 2-7. Differences-in-differences estimates of the effect of RFMO management on the probability of collapse

	(1)	(2)	(3)	(4)
ICCAT management	-0.019	0.025	0.028	0.140***
	(0.026)	(0.041)	(0.040)	(0.050)
Fish stocks	450	450	450	450
NAFO management	0.106	-0.040	-	-0.174
	(0.103)	(0.108)		(0.132)
Fish stocks	86	86		86
CCAMLR management	-0.150	-0.172	-0.185	-0.223
	(0.191)	(0.207)	(0.205)	(0.141)
Fish stocks	16	16	16	16
NEAFC management	-0.027	-0.022	-	-0.116***
	(0.047)	(0.054)		(0.042)
Fish stocks	134	134		134
IOTC management	-0.048**	-0.036*	-0.036*	-0.014
	(0.020)	(0.020)	(0.020)	(0.019)
Fish stocks	153	153	153	153
SEAFO management	0.225	0.215	-	-0.075
	(0.134)	(0.156)		(0.146)
Fish stocks	25	25		25
WCPFC management	-0.028	-0.030	-0.028	-0.000
	(0.030)	(0.034)	(0.036)	(0.042)
Fish stocks	195	195	195	195
SPRFMO management	0.099	0.077	0.082	0.055
	(0.070)	(0.071)	(0.072)	(0.041)
Fish stocks	88	88	88	88

Notes: All regressions include fishery and year fixed effects. Column 1 includes no control variables or trends. Column 2 includes species-specific control variables interacted with the year dummies. Column 3 includes control variables and area-specific trends (this specification is omitted in cases where there is only one FAO area). Column 4 includes control variables and specific trends for the RFMO and non-RFMO group, respectively, in each FAO area. Robust standard errors (in parentheses) clustered at the fishery (species-FAO area) level. Significance levels: *10%, **5%, ***1%.

2.6 Conclusion

The proportion of overexploited and collapsed international fisheries has grown during the past decades, leading many to question the effectiveness of RFMOs in conserving international fish stocks. This paper presents some new evidence on the management performance of RFMOs. Using panel data on stocks managed by eight major multi-species RFMOs, together with a differences-in-differences (DD) approach, the paper finds that RFMO management may have reduced the probability of stock collapse in managed fisheries. Whether this holds on average depends on which RFMOs are considered in the analysis, suggesting heterogeneity across RFMO performance. Separate DD analyses for the eight RFMOs confirm this conjecture. Weak evidence is found of a positive impact on stock sustainability for three RFMOs: CCAMLR, NEAFC, and IOTC. Interestingly, an earlier and unrelated evaluation of RFMO performance found these RFMOs to be the most successful. Analysis of what might explain differences across RFMO performance is left for future research.

The analysis and results of this paper are subject to some caveats, some of which can hopefully be addressed in future research. First, many of the individual DD estimates are statistically imprecise, which reduces their reliability. This is at least partly due to the fairly small sample sizes, i.e., low number of stocks, in some of the RFMO case studies. Second, there are indications that the RFMO variable may be endogenously determined. Since currently a good instrumental variable is lacking, this issue is difficult to address at the moment. Third, the use of catch data hinges critically on the assumption that low catches are a result of overexploitation of the stock, and not a RFMO policy prescription. A line of future research is to verify the qualitative findings of this paper using data on stock biomass.

These caveats notwithstanding, this paper provides some new insights to the debate over RFMO performance, and hopefully spurs further inquiries into successes and failures in RFMO management. In spite of tentative positive findings, RFMO management performance can certainly be improved both now and in the future.

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Appendix

Table A-1. Description of the RFMOs currently in operation

Acronym	Full name	Nr. of species	Nr. of signatories	Year established
IPHC	International Pacific Halibut Commission	1	2	1923
IWC	International Whaling Commission	-	88	1946
IATTC	Inter-American Tropical Tuna Commission	16	21	1950
GFCM	General Fisheries Commission for the Mediterranean	51	24	1952
ICCAT	International Commission for the Conservation of Atlantic Tunas	29	50	1969
NAFO	NorthIst Atlantic Fisheries Organization	11	14	1979
CCAMLR	Commission for the Conservation of Antarctic Marine Living Resources	4	25	1982
NEAFC	North East Atlantic Fisheries Commission	46	5	1982
NASCO	North Atlantic Salmon Commission	1	6	1984
PSC	Pacific Salmon Commission	5	2	1985
NPAFC	North Pacific Anadromous Fish Commission	7	5	1993
CCSBT	Commission for the Conservation of Southern Bluefin Tuna	1	5	1994
CCBSP	Convention on the Conservation and Management of the Pollock Resources in the Central Bering Sea	1	6	1995
IOTC	Indian Ocean Tuna Commission	23	32	1996
SEAFO	South East Atlantic Fisheries Organization	17	7	2003
WCPFC	Istern and Central Pacific Fisheries Commission	14	26	2004
SPRFMO	South Pacific Regional Fisheries Management Organization	21	14	2009
SIOFA	South Indian Ocean Fisheries Agreement	-	8	2012

Source: Sea Around Us (2015).

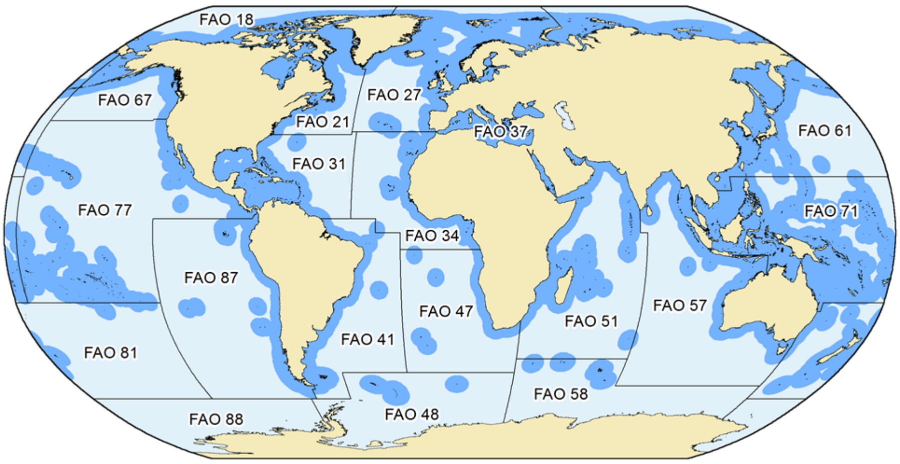

Figure A-1. FAO statistical areas. The darker blue portions are EEZs and the lighter blue portions are the high seas. Source: Sea Around Us (2015).

Table A-2. Criteria used for assigning exploitation status

Exploitation status	Criterion 1: Year	Criterion 2: $Catch/Catch_{Max}$
(1) Underdeveloped	$Year < Year_{MaxCatch}$	< 0.1
(2) Developing	$Year < Year_{MaxCatch}$	$0.1 - 0.5$
(3) Fully exploited	$Year \lesseqgtr Year_{MaxCatch}$	> 0.5
(4) Overexploited	$Year_{MaxCatch} < Year < Year_{Collapsed}$	$0.1 - 0.5$
(5) Collapsed	$Year > Year_{MaxCatch}$	< 0.1
(6) Rebuilding	$Year > Year_{MaxCatch}$	$0.1 - 0.5$

Note: The first criterion establishes whether catch in a given year happened before or after the year of maximum catch. The second criterion establishes the size of the catch in that year relative to the size of maximum catch.

Table A-3. Definitions of the different exploitation/stock categories

Exploitation category	Definition
Underexploited / Underdeveloped	Undeveloped or new fishery. Believed to have a significant potential for expansion in total production.
Moderately exploited / Developing	Exploited with a low level of fishing effort. Believed to have some limited potential for expansion in total production.
Fully exploited	The fishery is operating at or close to an optimal yield level, with no expected room for further expansion.
Overexploited	The fishery is being exploited at above a level which is believed to be sustainable in the long term, with no potential room for further expansion and a higher risk of stock depletion/collapse.
Depleted / Collapsed	Catches are well below historical levels, irrespective of the amount of fishing effort exerted.
Recovering / Rebuilding	Catches are again increasing after having been depleted.

Source: FAO (2018).

Chapter 3

Number of exploiters and ecological outcomes: The case of international fisheries

3.1 Introduction

International fisheries are fisheries that are pursued by more than one fishing nation. These fisheries are often targeted by both coastal states and nations fishing for the stocks in international waters (high seas). Coastal nations are free to harvest international stocks in their respective exclusive economic zones (EEZs). Moreover, as the high seas are essentially open access (e.g., White and Costello, 2014), any fishing nation may participate in international fisheries on the high seas. Over the past decades, many international fisheries have declined and the fraction of overexploited and collapsed stocks has increased (Cullis-Suzuki and Pauly, 2010; Froese et al., 2012; FAO, 2016). It is well-known that the common property fishery is prone to overexploitation (Gordon, 1954), but to what extent ecological outcomes are determined by the total number of harvesting nations is still an under-researched area.

Theory predicts that a higher number of independent users increases the likelihood of poor resource utilization. The fundamental reason for this is that the shadow value each user assigns to the fish stock falls with the number of users, leading the users to increase their fishing effort correspondingly (Arnason, 1990). In the international fisheries setting, similar factors are at work. First, when the number of non-cooperative countries increases, the shadow value of the fish resource to individual countries drops. This leads these countries and their fishers to prefer higher levels of fishing effort. Second, the likelihood of reaching and maintaining a cooperative harvesting agreement is reduced when the number of countries increases (Hannesson, 1997; Pintassilgo et al., 2010). For these reasons, the probability of overharvesting and stock depletion in international fisheries is expected to rise when the number of harvesting countries increases. This paper sets out to empirically test this prediction by studying a large panel of international fisheries.

I follow a common approach in the fisheries literature, in which global catch data are exploited to generate proxies for biological stock status (see e.g., Worm et al., 2006; Costello et al., 2008, 2010; Sakai, 2017; Isaksen and Richter, 2019). The data source is the Sea Around Us (SAU) catch database (Sea Around Us, 2015). SAU is a global fisheries exploitation database with information on year, species, area, fishing country, weight of catch, and landed value of catch. For each species-area combination (i.e., fishery or fish stock), I construct a time series of total yearly catch. I then use the catch record to assign each stock in each year a unique exploitation category: underexploited, moderately exploited, fully exploited, overexploited, or collapsed. My dataset includes approximately 1,300 stocks from major fishing areas in the Atlantic, Pacific, Indian Ocean, and the Mediterranean. To complement the catch dataset, I also compile a smaller dataset on biomass in 142 stocks from the RAM Legacy Stock Assessment Database (Ricard et al., 2011).

I estimate different models in which stock status is a function of the number of exploiting nations. When using the catch data, the dependent variable takes on one of five exploitation categories. I use a random effects ordered probit model, which accounts for the categorical nature of the outcome variable and the panel structure of the data. I control for economic, management, and biological characteristics which may influence exploitation status. In addition, I investigate whether there are fishery characteristics that predispose to overexploitation. That is, are some types of fisheries more negatively affected by an increase in the number of exploiters than others?

When using the biomass data, the dependent variable is either a dummy variable for whether the stock is overexploited (i.e., biomass/fishing mortality is below/above a certain threshold), or simply the total weight of stock biomass. In these cases, I estimate a conditional fixed effects logistic model (for dummy variables) and a linear fixed effects model (for total biomass). Both these models control for all unobserved heterogeneity between fish stocks and the analysis amounts to a within-fishery comparison.

The empirical results provide evidence in support of the hypothesis that more harvesting countries increases the probability of overexploitation. When using the catch data, the results suggest that more harvesting countries is associated with a higher probability that stocks are overexploited or collapsed, and with a lower probability that stocks are under-, moderately, or fully exploited. For a given number of countries, a less even harvesting among countries is also associated with worse outcomes. A plausible mechanism is that more countries and more concentrated harvesting are detrimental to cooperative management. Using subsamples of the data suggests that internationally managed and highly migratory stocks are unaffected by an increase in the number of harvesters. However, this finding may be due to homogeneity (in number of harvesters) across stocks in these subsamples. Using biomass data corroborates the main finding of the paper: the results suggest that an increase in the number of harvesting countries leads to (i) an increase in the odds of overexploitation, and (ii) a reduction in total biomass.

3.1.1 Related literature

This paper's primary contribution is to the empirical literature on common property utilization in international settings. There is a rich tradition of empirically based bioeconomic modeling studies that estimate the economic and ecological effects of competition and cooperation in international fisheries (e.g., Sumaila, 1997; Arnason et al., 2000; Diekert et al., 2010). In addition, a theoretical and applied literature on international fisheries agreements examines how the number of countries and entry of new countries affect the stability of agreements (see Pintassilgo et al., 2015, for an overview). However, there are very few papers that use econometric methods to estimate how the number of countries sharing a resource is related to ecological outcomes.

McWhinnie (2009) is the first paper to use econometric methods to study the impact of sharing in international fisheries. The paper uses a two-period panel to study how different economic and biological variables influence the exploitation status of fish stocks. The paper finds that stocks that are shared among many countries are more likely to be overexploited. Number of countries is defined as the number of EEZs a fish stock is harvested in. Thus, McWhinnie (2009) studies essentially a restricted access setting, in which a fixed number of countries share the stock. I diverge from this approach by considering the total number of countries engaged in harvesting of a fish stock, both in EEZs and on the high seas. Further, my paper complements the work by McWhinnie (2009) in three ways: (i) by analyzing more fish stocks over a longer time period using harvest data, (ii) by studying heterogeneous impacts across different types of stocks, and (iii) by using different measures of stock health constructed from biomass data.

The impact of international sharing has been studied empirically in other settings than fisheries. Sigman (2002) studies pollution in domestic and international rivers and finds that pollution levels are higher in shared rivers due to free riding. Olmstead and Sigman (2015) study the location of dams and find that dams are more prevalent in border areas where downstream countries bear part of the external costs from damming the river. Smith (2016) is another empirical paper that estimates the effect of sharing of common property resources, although not in an international setting. The paper, which studies the impact of number of users on the productivity of communal irrigation systems in New Mexico, finds that additional users decrease the average production of the systems.

My paper is also related to a handful of other empirical studies that use global fisheries exploitation data.[1] Many of these papers attempt to estimate effects of policies and economic activity on stock outcomes. For example, Sakai (2017) studies the effect of fishery subsidies on resource stocks, Isaksen and Richter (2019) study the impact of property rights on the probability of stock collapse, and Eisenbarth (2018) studies whether exports increase fisheries collapse.

The remainder of the paper is organized as follows. The next section discusses the theoretical framework underlying the empirical analysis of the impact of number of exploiters in international fisheries. Section 3 presents the data, and section 4 describes the empirical models. Section 5 presents and discusses the results. Section 6 concludes.

3.2 Theoretical background

3.2.1 The common fishery problem

A fundamental result in fisheries economics is the tendency of common property fisheries to be overexploited (Gordon, 1954). This result applies to both domestic and international fisheries, where similar factors are at work. A fish stock has potential to yield returns into the indefinite future as long as future harvests are not compromised by harvesting too much today. However, in the absence of property rights, the benefits of maintaining productivity of the fish stock accrue to an indefinite number of exploiters (e.g., Hannesson, 2004). Therefore, from the viewpoint of an individual exploiter, there are few incentives to keep exploitation below the level of biological surplus production, which leads to overfishing and a decline of the fish stock.

Let us consider the behavior of competitive (non-cooperative) exploiters. The exploiters maximize their utility by choosing fishing effort, while assuming that the other exploiters do the same thing. A Nash-Cournot equilibrium is reached when no exploiter finds it desirable to change its level of effort. The individual exploiter determines

[1] Costello et al. (2008, 2010), Sakai (2017), Eisenbarth (2018), Erhardt (2018), Isaksen and Richter (2019), and Noack and Costello (2019).

its fishing effort by equating marginal benefits (evaluated at market price less shadow value of biomass) with marginal costs. The shadow value of biomass is the value given to an additional unit of biomass. The more non-cooperative exploiters that are involved in the fishery, the less is the shadow value of biomass going to be for the individual exploiter. Consequently, as the number of exploiters increases, the exploiters are going to prefer higher levels of fishing effort.[2]

3.2.2 Number of countries and the prospect of cooperation

The solution to the common fishery problem is related to who is the exploiter of the stock. In domestic fisheries the exploiters are the fishing firms (the national fishing fleet), which may be controlled by the fishing country. In international fisheries it is convenient to regard fishing countries as the exploiters, since management often takes the form of negotiations between countries. The countries make decisions on the level of fishing effort or harvesting, which is then carried out by the national fishing fleets.[3]

The solution to the common fishery problem in international fisheries is cooperative management which restricts total harvests. There are essentially two main mechanisms through which an increase in the number of countries negatively affects management. First, through a lower probability that cooperative management is attempted or initiated in the first place (e.g., a RFMO is established).[4] Second, through a lower probability that management is successful (i.e., restrictive harvesting is implemented). Thus, ex ante, we may expect more harvesting countries to lead to worse ecological outcomes in both managed and unmanaged fisheries.

The role of number of exploiters in international management has been studied using theoretical models. Hannesson (1997) analyzes the likelihood of cooperation as a function of number of harvesters in a repeated game framework. When the total number of harvesters increases, the individual harvester's benefit from cooperation necessarily decreases, which increases the incentive to act non-cooperatively. Pintassilgo et al. (2010) reach the same conclusion when analyzing the stability of cooperation in a par-

[2]See Arnason (1990) for a formal exposition of the fundamental fisheries problem in terms of shadow value of biomass, and its relation to socially optimal and individually rational fishing effort.

[3]This is the approach typically taken in the strand of literature that uses game theory and bioeconomic modeling to study performance in international fisheries (see e.g., Kaitala and Munro, 1993; Arnason et al., 2000; Bjørndal and Lindroos, 2004).

[4]Regional Fisheries Management Organizations (RFMOs) are the most prominent management bodies for international fisheries worldwide.

tition function game framework: the more fishing states that compete for a common resource, the less likely is a stable coalition. Reality, however, may be far less straightforward. Agreements may be bound by legal regimes and there may be other reasons than direct benefits form the fishery that induce cooperation among countries.

3.2.3 Number of countries and the ecological outcome

Lastly, let us briefly consider the specific relationship between an increase in number of countries and the change in the ecological state of the stock. The theory outlined above suggests that effort increases faster than the number of countries, since exploiters prefer higher levels of effort the more exploiters there are. This might lead us to expect an increasing rate of decline in the stock as number of countries goes up. On the other hand, the quantity of harvest goes down as the size of the stock gets smaller, which slows the rate of decline. There are likely more important factors playing in as well. When a large number of countries is already participating in the fishery, the impact of a single additional country on the behavior of existing countries is probably quite small. With few countries, on the other hand, an additional country is more likely going to gain the attention of the current exploiters and have an impact on harvesting behavior. In the forthcoming empirical analysis, the econometric specifications take into account that the marginal effect of number of countries on ecological outcomes decreases as the number of countries increases. Specifically, I use a log-transformation of number of harvesters to capture the nonlinear relationship between number of exploiters and overexploitation.[5]

3.3 Data

3.3.1 Dependent variables

The dependent variables in my empirical models measure the ecological status of international fish stocks. Both catch and biomass data are used to construct the dependent variables.

[5] McWhinnie (2009) takes the same approach, but models it differently. Whereas I use a log-transformation of number of countries, McWhinnie (2009) includes a squared term to essentially achieve the same thing.

3.3.1.1 Catch data

When using catch data, each fish stock is given a unique exploitation status in each year based on catch relative to maximum catch. This method of assigning exploitation status relies on using catch as a proxy for biomass. The criteria for assigning exploitation status, developed in Froese and Kesner-Reyes (2002) and Froese et al. (2012), are outlined in Table 3-1. As an example, consider the exploitation status Collapsed. A fishery is collapsed in the current year if catch is less than 10 percent of the all-time maximum catch (criterion 2), and this maximum catch occurred prior to the current year (criterion 1). Definitions of all the exploitation categories are provided in Table 3-2.[6]

There has been a long ongoing debate on the appropriateness of using catch data as a source of information on fish stock status (see e.g., Branch et al., 2011; Froese et al., 2012; Pauly et al., 2013). A review of all the arguments for and against are beyond the scope of this paper. The main criticisms are that (i) catches can be low for a variety of reasons besides a low level of biomass, and (ii) the recorded maximum catch may be a poor reference point, since this may have occurred during a period of non-sustainable open access harvesting. The defense argues that (i) in many stocks biomass trends are consistent with the trends derived from the analysis of catch data, and (ii) maximum recorded catch is often correlated with a stock's maximum sustainable yield. I argue that in my case using these two sources of data jointly provide a stronger argument than using only one or the other. First, biomass data on international stocks is very limited and would shrink the sample two only a few dozen stocks. Second, since I also have access to stock data for a subset of the stocks under study, I can corroborate some of my findings using these more reliable data.

The data on catch are retrieved from the Sea Around Us database (SAU), which holds information on country-specific marine catches at different spatial scales. From these data, and applying the method described above, I construct a panel dataset containing stock status in 1,292 international fisheries around the globe for the period 1980–2014. A *stock* is defined as a unique *species*-area combination, where the areas are the FAO major fishing areas (see e.g., Sea Around Us, 2015). I identify international fish stocks in the database in two principal ways. First, I include all species that are managed

[6]There is a sixth category, Rebuilding, which is omitted from the analysis because it lacks a natural ordering among the other categories.

Table 3-1. Criteria used for assigning exploitation status

Exploitation status	Criterion 1: Year	Criterion 2: Catch/Catch$_{Max}$
Underexploited	Year $<$ Year$_{MaxCatch}$	< 0.1
Moderately exploited	Year $<$ Year$_{MaxCatch}$	$0.1-0.5$
Fully exploited	Year $\lesseqgtr$ Year$_{MaxCatch}$	> 0.5
Overexploited	Year$_{MaxCatch}$ $<$ Year $<$ Year$_{Collapsed}$	$0.1-0.5$
Collapsed	Year $>$ Year$_{MaxCatch}$	< 0.1

Note: The first criterion establishes whether catch in a given year happened before or after the year of maximum catch. The second criterion establishes the size of the catch in that year relative to the size of maximum catch.

Table 3-2. Definitions of the different exploitation categories

Exploitation status	Definition
Underexploited	Undeveloped or new fishery. Believed to have a significant potential for expansion in total production.
Moderately exploited	Exploited with a low level of fishing effort. Believed to have some limited potential for expansion in total production.
Fully exploited	The fishery is operating at or close to an optimal yield level, with no expected room for further expansion.
Overexploited	The fishery is being exploited at above a level which is believed to be sustainable in the long term, with no potential room for further expansion and a higher risk of stock collapse.
Collapsed	Catches are well below historical levels, irrespective of the amount of fishing effort exerted.

Source: FAO (2018).

by a Regional Fisheries Management Organisation (RFMO) somewhere in the world. These represent typical "international species", such as straddling and highly migratory species, which due to their wide geographical distribution are typically targeted by multiple countries.[7] Second, I include non-RFMO species as long as the respective stocks are harvested by multiple countries and annual catches are not negligible.

3.3.1.2 Biomass data

I retrieve biomass data on 142 multinational stocks for the period 1990–2014 from the RAM Legacy Stock Assessment Database (RAM). The primary dependent variable when using the stock data is an indicator variable for whether the stock is overexploited. I apply different definitions for overexploitation. The first definition is that

[7] Straddling species are found in both EEZs and on the high seas. Highly migratory species are a subset of straddling species, which include, for example, species of tuna and shark.

total biomass is less than 50 percent of the amount corresponding to maximum sustainable yield (MSY) ($B/B_{MSY} < 0.5$). This is a definition used by, for example, the governments of Australia and the United States (Hilborn and Stokes, 2010). Because the frequency of overexploitation is quite small in the sample (0.088) when applying this definition, I use a second definition which allows more stocks to be included in the analysis.[8] In this definition, overexploitation is defined as total biomass less than 75 percent of the amount corresponding to MSY ($B/B_{MSY} < 0.75$). Basically, one could claim that any stock level below MSY is a sign of overexploitation. However, most fisheries management agencies define overexploitation as biomass levels well below MSY because (i) catches corresponding to MSY are possible for a wide range of biomass levels around B_{MSY}, and (ii) natural fluctuations prevent the stock from staying exactly at B_{MSY} (Hilborn and Stokes, 2010). I also apply two definitions of overexploitation based on fishing mortality (U). The first is that mortality is larger than the level corresponding to MSY ($U/U_{MSY} > 1$). The second is the ratio of mortality to the MSY reference when $U/U_{MSY} > 1$. That is, an increase in the ratio unambiguously indicates a higher degree of overexploitation.

The other dependent variable when using the stock data is the weight of biomass. Specifically, the dependent variable is biomass when $B/B_{MSY} < 2$. Thus, I do not consider instances when biomass is over twice as large as the amount corresponding to MSY. It could appear that excluding high biomass levels excludes cases of good resource management. However, it is unlikely that using this qualifier excludes biomass levels commonly associated with good management, such as MEY (maximum economic yield) or OY (optimum yield). Although MEY and OY typically imply biomass levels above MSY (FAO, 1995; Froese et al., 2011; Grafton et al., 2012), these are likely less than twice the size of MSY.[9] Instead, the qualifier excludes instances when the stocks are still in an underexploited phase and biomass well above management targets. Reduction in biomass which is significantly above a given management target cannot be considered a sign of poor resource management. As I am interested in how number of exploiters is linked to the intensity of overexploitation, I limit the analysis

[8] Stock collapse, defined as $B/B_{MSY} < 0.2$ (see Branch et al., 2011) is too infrequent in the sample to be used as a dependent variable.

[9] Grafton et al. (2012) note that biomass levels that are 15–30 percent above B_{MSY} often correspond to B_{MEY}.

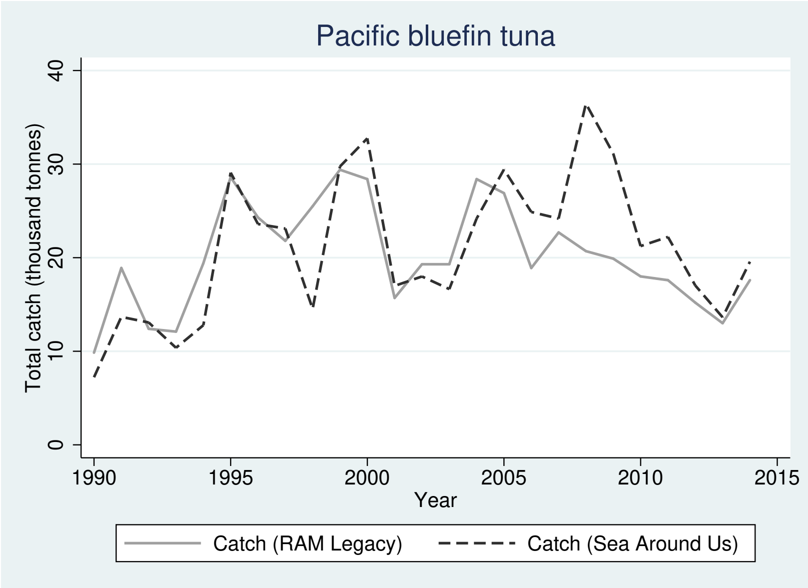

Figure 3-1. Comparison of RAM Legacy and Sea Around Us catch data on Pacific bluefin tuna. Source: Data from Ricard et al. (2011) and Sea Around Us (2015).

to situations where a reduction in the dependent variable is, to some extent, unambiguously a sign of poor resource management. As a last specification, I use the ratio of biomass to the MSY target with the qualifier that biomass is below double the MSY level.

A limitation when using the RAM data in the present context is that it does not include information on harvesting countries. This means that I have to combine the RAM biomass data with SAU harvester data. The RAM data consist of actual stocks, whereas the SAU data consist of data on species at different spatial scales. Thus, with the SAU data I have to define the stocks myself by choosing certain species-area combinations, such as, species-EEZ, species-FAO area, or species-RFMO area. Matching the SAU data with the RAM data works differently well depending on the stock. I may check how well the RAM and SAU stocks correspond to each other by comparing total catches from the RAM stock with the "constructed" SAU stock. As an example, Figure 3-1 shows a comparison of total catch of Pacific bluefin tuna obtained from the RAM and SAU databases, respectively. In this case, although the trends appear fairly similar, there are also clear discrepancies between the SAU and RAM catches. SAU and RAM catches that do not match well could mean that the data on number of harvesters (from SAU) are a poor representation of the RAM fishery. If the number of harvesters variable is subject to measurement error, then the estimate of interest may be attenuated.

3.3.2 Independent variables

The main explanatory variable in all models is the number of countries harvesting in a fishery in a given year. The data on number of harvesting countries come from SAU.

I also include additional explanatory variables which, apart from number of exploiters, may influence the ecological status of fish stocks. The first variable is the average landings price over the course of the time period (in 2005 US dollars). The average landings price is a measure of the commercial value of the fish stock.[10] Economic value may be correlated with both the number of exploiters a fish stock attracts and its ecological status. Using average price instead of time-varying price alleviates concerns about price being endogenously determined (the dependent variable being a function of catch and the volume of catch a determinant of price).

The set of countries participating in a given fishery may influence ecological outcomes if some countries are more predisposed toward conservation than others. To capture heterogeneity across the set of countries targeting given stocks, I include a time-varying variable on the average number of signed international environmental agreements (IEAs) among the countries.[11] This variable controls for heterogeneity in environmental awareness across the set of countries participating in different fisheries.

A channel through which number of countries may affect stock outcomes is the probability of cooperative management. Therefore, I also attempt to control for other factors that may affect the prospect of successful management. The average number of signed IEAs among harvesting countries is one such factor. Another factor is uniformity in fishing capacity across countries. Intuitively, uniformity between harvesting countries may seem conducive to cooperative management, and thus better for sustainability. I include a time-varying Herfindahl index (HHI) calculated based on the shares of the total catch that the individual countries have landed. The HHI formula is

$$\mathrm{HHI} = \sum_{l=1}^{n} s_l^2 \tag{3.1}$$

where s_l is country l's share of the total catch, and n is the total number of countries. The HHI attains a low value when catches are evenly distributed across harvesting countries.

[10] Since SAU reports landed value, I obtain an estimate for landings price by dividing the landed value with the catch.

[11] Information on how many IEAs a country has signed is available from the International Environmental Agreements database (Mitchell, 2018).

The HHI attains a high value when catch is concentrated. When there is only one country the HHI equals 1.

Finally, I include time-invariant dummy variables for RFMO-managed stocks, highly migratory stocks, tropical and subtropical stocks, and stocks with low and very low biological resilience. RFMO-managed stocks are generally targeted by a large number of countries, and RFMO stocks may be prone to poor stock outcomes due to characteristics of these stocks. Highly migratory stocks are to a larger extent than other shared stocks harvested on the high seas, which may be a factor influencing stock status beyond the fact that high seas stocks are often harvested by many countries.[12] However, it is ambiguous whether high seas stocks are generally in better or worse shape than other shared stocks. The fact that a large share of the harvesting takes place beyond EEZs and national jurisdictions may exacerbate the degree of overexploitation. On the other hand, the distance from shore and the migratory trait of high seas species may provide these stocks with a certain natural protection.[13]

Geographical location may be linked to biological and socio-economic characteristics influencing exploitation status. A dummy variable is used to differentiate between tropical/subtropical and temperate fish stocks. Biological resilience is another factor which may influence exploitation status. In this case, resilience is measured based on how long it takes for a stock to double its biomass. A doubling time of 4.5–14 years indicates low resilience, whereas a doubling time of over 14 years indicates very low resilience. Information on these biological variables is obtained from the FishBase databank (FishBase, 2018).[14]

3.3.3 Summary of data

Data characteristics are presented in Table 3-3. The table shows mean, standard deviation, and minimum and maximum values of dependent and independent variables. The SAU dataset is presented on the left hand side. The sample comprises 562 species and 1,292 stocks. The average number of countries participating in a fishery is 7 and

[12] The highly migratory species are listed in Annex I of the United Nations Convention on the Law of the Sea (UNCLOS).

[13] McWhinnie (2009) finds that high seas stocks are associated with better stock status than other shared stocks.

[14] The indicator variables for (sub)tropical species and species with (very) low resilience are not coded for every single species in the sample because of lack of data.

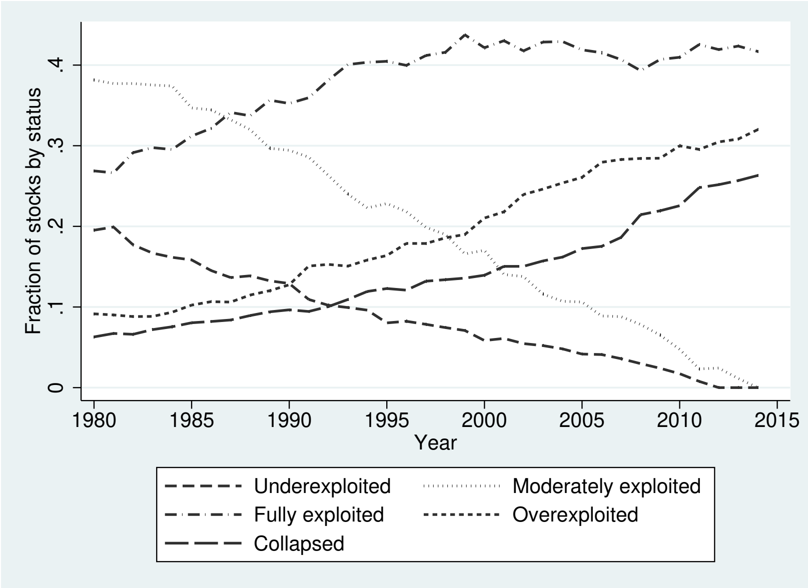

Figure 3-2. The fraction of stocks in each exploitation category over time. Source: Data from Sea Around Us (2015).

the maximum number of countries measured in the sample is 53. The dependent variable, Stock status, takes on one of five exploitation categories. Figure 3-2 shows how the stocks in the sample are distributed in the different exploitation categories over the course of the study period. The general trend is clear: the fraction of underexploited and moderately exploited stocks has decreased, and the fraction of overexploited and collapsed stocks has increased. The fraction of fully exploited stocks increased until the mid-1990s, after which it has remained fairly constant.

The RAM dataset is presented on the right hand side of Table 3-3. This dataset contains information on, among other things, biomass and the ratio of biomass and fishing mortality to management targets in 142 stocks (96 species). The frequencies of overexploitation based on $B/B_{MSY} < 0.5$, $B/B_{MSY} < 0.75$, and $U/U_{MSY} > 1$ in the sample are 11, 19, and 53 percent, respectively. The mean of B/B_{MSY} is 1.4, which indicates a mean stock level above MSY in the sample. The mean of U/U_{MSY} is 1.5, which indicates overexploitation. The average number of countries is 18, which is over two and a half times as many as in the SAU dataset. This is because a large portion of biologically assessed international stocks are highly migratory (tunas in particular), which are often targeted by many countries. As an example, Figure 3-3 shows the evolution of total biomass and number of harvesting countries in four tuna fisheries from different oceans around the world. In these four fisheries, there generally appears

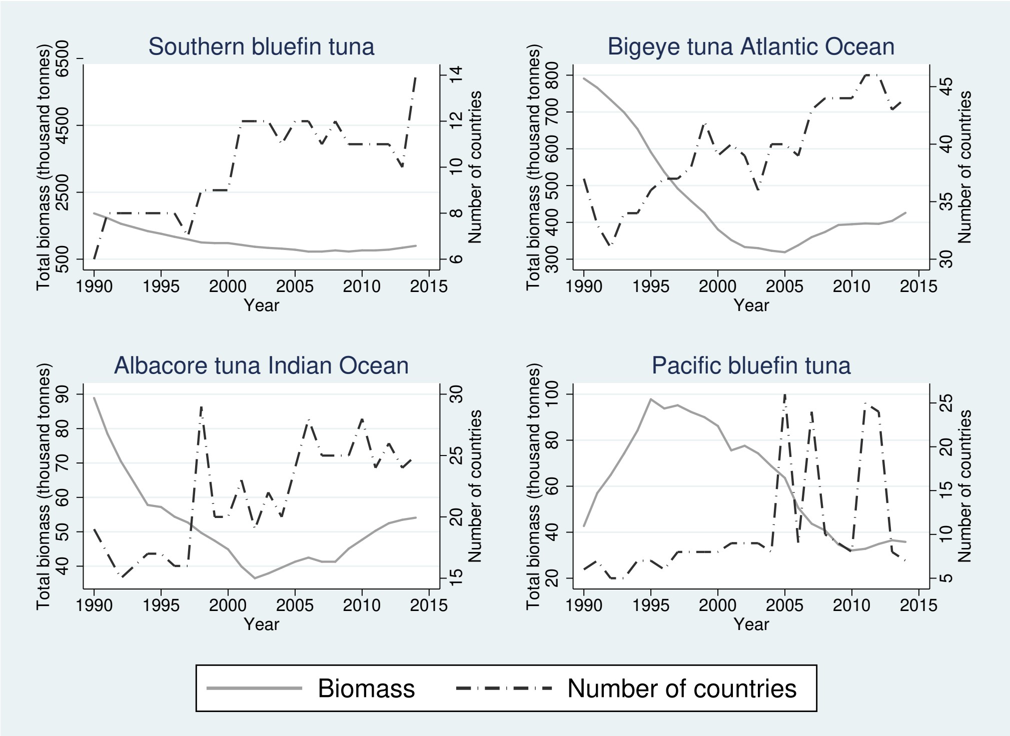

Figure 3-3. Biomass and number of harvesting countries in four tuna fisheries. Source: Data from Ricard et al. (2011) and Sea Around Us (2015).

to be an inverse relationship between biomass and the number of harvesting countries.

Table 3-3. Summary statistics of the two datasets used in the study

	Sea Around Us				RAM Legacy			
	Mean	Sd	Min	Max	Mean	Sd	Min	Max
Stock status	3.094	1.127	1	5				
Underexploited	0.083	0.267	0	1				
Moderately expl.	0.205	0.404	0	1				
Fully expl.	0.383	0.486	0	1				
Overexploited	0.191	0.393	0	1				
Collapsed	0.137	0.344	0	1				
Total biomass (thousand tonnes)					745.9	1348.5	0	11800
B/B_{MSY}					1.399	1.418	0.040	10.725
U/U_{MSY}					1.486	1.146	0	11.706
$B/B_{MSY} < 0.5$					0.109	0.312	0	1
$B/B_{MSY} < 0.75$					0.192	0.394	0	1
$U/U_{MSY} > 1$					0.533	0.499	0	1
Number of countries	7	7	1	53	18	12	1	56
Average number of agreements	93.0	50.1	13	288				
Herfindahl index	0.623	0.284	0.064	1				
Average price (2005 US $/tonne)	2173.0	1898.4	258.7	20913.1				
RFMO managed	0.281	0.450	0	1				
Highly migratory	0.196	0.397	0	1				
(Sub)tropical	0.323	0.468	0	1				
(Very) low resilience (Doubl. time>4.5 yrs)	0.176	0.380	0	1				
Time period	1980–2014				1990–2014			
N species	562				96			
N stocks	1,292				142			
N observations	41,413				3,004			

Notes: Mean, standard deviation (Sd), and minimum and maximum values of dependent and independent variables. Stock status is an ordered variable (1–5); binary indicators for overexploitation (in RAM Legacy); RFMO managed, highly migratory, (sub)tropical, and (very) low resilience are binary variables.

3.4 Empirical models

In this section, I introduce the econometric models to be estimated. The first model takes the following general form

$$y_{i,t} = \beta_1 \log(COUNTRIES)_{i,t} + \beta_2 X_i + \beta_3 W_{i,t} + \tau_t + \varepsilon_{i,t} \tag{3.2}$$

where $y_{i,t}$ takes on one of five exploitation categories in each fish stock i in each year t. $COUNTRIES_{i,t}$ is the main explanatory variable, and measures the number of countries harvesting a fish stock in a given year. The log specification means that a given percentage increase in number of countries yields a constant marginal effect on the outcome variable. That is, the impact of one more country is greater the fewer countries are participating in the fishery. X_i is a vector of time-invariant stock- or species-specific explanatory variables, $W_{i,t}$ is a vector of time-varying stock-specific variables, τ_t is a full set of year dummies, and $\varepsilon_{i,t}$ is an error term. In particular, the error term is specified as $\varepsilon_{i,t} = \alpha_i + u_{i,t}$, where α_i is a fishery-specific random component and $u_{i,t}$ is an idiosyncratic component. Because the random effect is part of the error term, these are consequently correlated across periods. A random effects model produces efficient estimates given this structure of the error component. Further, when the dependent variable is ordered the use of an ordered dependent variable model is warranted. Therefore, equation 3.2 takes the form of a random effects ordered probit model which is estimated by the use of maximum likelihood methods.[15]

For the random effects model to yield unbiased and consistent results the fishery-specific effect, α_i, needs to be uncorrelated with the explanatory variables. By including species- and stock-specific control variables, such as commercial value and whether a stock is highly migratory, I attempt to control for some of the determinants of stock status which may be correlated with the main explanatory variable, i.e., number of harvesting countries. Another potential concern for consistency is simultaneity bias; namely, that the status of the fish stock is a determinant of the number of harvesting countries. In this case, deterioration of the fish stock results in fewer countries participating in the fishery. Thus, this is a cause of concern primarily if the model in equation 3.2 outputs

[15] Examples of papers that use this kind of model include McWhinnie (2009) and Langpap and Kerkvliet (2010, 2012).

counterintuitive results, such as that more harvesting countries is associated with lower probability of overexploitation. It turns out that this is not the case here.

The next model to be estimated is

$$\Pr(y_{i,t} = 1 \mid X_{i,t}, \alpha_i, \tau_t) = \frac{\exp(\beta_1 X_{i,t} + \alpha_i + \tau_t)}{1 + \exp(\beta_1 X_{i,t} + \alpha_i + \tau_t)} \tag{3.3}$$

where $y_{i,t}$ is a dummy variable which takes on the value 1 if fishery i is overexploited in year t, and 0 otherwise. $X_{i,t}$ is the explanatory variable (log number of harvesting countries), α_i is the unobserved fishery-specific effect, and τ_t is the year effect. The model in equation 3.3 is known as conditional logit, and it consistently estimates parameters of binary choice models in a fixed effects setting (see Chamberlain, 1980). As with the random effects probit model discussed above, this model can be estimated using maximum likelihood methods.

The final model is specified as

$$\log y_{i,t} = \beta_1 \log(COUNTRIES)_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t} \tag{3.4}$$

where $y_{i,t}$ is the dependent variable (biomass or ratio of biomass/fishing mortality to MSY targets) of fish stock i in year t. $COUNTRIES_{i,t}$ is again the main explanatory variable. Since the dependent variable is measured in logs, the coefficient on countries represents an elasticity with respect to number of exploiters. A coefficient below one indicates that the impact on the outcome variable from one more country is greater the fewer countries are participating in the fishery. In this model the fishery-specific effect, α_i, is treated as a parameter to be estimated, as opposed to a random effect as in equation 3.2. International fish stocks may vary in terms of a range of unobserved characteristics which could be related to the number of harvesting countries and have an influence on biological stock status. Treating α_i as a parameter to be estimated controls for all time-invariant differences between fish stocks (including those added to the random effects model) by focusing on variation within fish stocks over time. The year fixed effects, τ_t, again control for time-varying shocks that affect all fisheries.

3.5 Empirical results

This section presents the results from estimating the empirical models. In all econometric models the statistical inference is based on standard errors that are heteroskedasticity-consistent and clustered at the fishery level to account for time series correlation (if not indicated otherwise).

3.5.1 Catch data

3.5.1.1 Main results

Table 3-4 presents coefficients and marginal effects from the ordered dependent variable model.[16] The numerical values of the coefficients do not have a meaningful interpretation, but their sign and statistical significance are of interest. Specifically, we are interested in whether an explanatory variable is associated with generally better or worse stock status and whether this effect is statistically significant. A positive coefficient implies that an explanatory variable has a negative impact on stock status, whereas a negative coefficient implies the opposite. In addition, we would want to know how the explanatory variables affect the probability that a fish stock is in any given exploitation category. For this we need to look at the marginal effects. These tell us how an incremental increase in an explanatory variable changes the probability that a fish stock has a certain exploitation status.

The coefficient on number of countries is statistically significant at the 1 percent level and has a positive sign, i.e., a higher number of countries is associated with poorer stock status.[17] As the number of harvesting countries goes up, the probability that a stock is overexploited or collapsed goes up, as evidenced by the positive marginal effects for these two categories. Correspondingly, as the number of countries goes up the probability that a stock is under-, moderately, or fully exploited goes down. These results are in line with the theory outlined above, which predicts that the degree of overexploitation increases as the shadow value of the fish stock to the exploiters decreases.

[16] Using a random effects ordered logit model yields qualitatively similar results.

[17] Using number of countries in levels with a squared term yields the same qualitative result as using the log specification. The coefficient on the main term is positive and the coefficient on the squared term is negative. Both coefficients are significantly different from zero at conventional levels.

Let us consider the magnitude of the estimated marginal effects of number of countries.[18] Let us begin with the poorest stock status: a one unit increase in number of countries is associated with an increase in the probability that a stock is collapsed by 0.017. As we are dealing with the log of number of countries, a one unit increase corresponds to the explanatory variable being multiplied by $e = 2.718$, i.e., an increase of approximately 172 percent. If the number of countries at baseline is, say, one, then a one unit increase strictly means that there are now 2.7 countries. If the number of countries at baseline is 10, then a one unit increase means that there are 27 countries. Since the mean of stock collapse in the sample is 0.137, increasing the number of countries by one unit corresponds to a 12 percent ($\frac{0.017}{0.137} = 0.124$) increase in the probability that a stock is collapsed. Similarly, a one unit increase in number of countries is associated with a 15 percent increase in the probability that a stock is overexploited. On the other hand, a one unit increase in number of countries is associated with a 4 percent decrease in the probability that a stock is fully exploited. The corresponding reductions in the probability for moderately exploited and underexploited as number of countries is increased by one unit are 13 and 5 percent, respectively.[19]

Let us consider the rest of the explanatory variables. The coefficient on average number of signed agreements is positive and statistically significant at the 1 percent level. More signed agreements is thus generally associated with poorer stock status: stocks are more likely overexploited or collapsed, and less likely under-, moderately, or fully exploited. This result could suggest that overexploitation has been more common in the developed world, where presumably countries have signed more agreements. The coefficient on the Herfindahl index is also positive and statistically significant. Interestingly, this suggests that, conditional on the number of countries, stocks are more likely overexploited and collapsed when harvesting is concentrated to few countries. A possible explanation is that it is more difficult sustain cooperative harvesting when countries have very unequal shares in the fishery. The coefficient on average landings price, which measures commercial value of the stock, is positive and statistically signif-

[18] I present average marginal effects throughout, where the values of the explanatory variables are left as they are observed. Using conditional marginal effects, where the values of the explanatory variables are fixed at their means, yields similar results.

[19] These marginal effects are similar in magnitude to those reported by McWhinnie (2009). In that paper, a stock shared by two countries is associated with a 14 and 7 percent increase in being collapsed and overexploited, respectively, compared to a sole owned stock (i.e., an increase by 100 percent in number of countries).

Table 3-4. The impact of number of countries on exploitation status

Explanatory variable	Coefficients	Marginal effects				
		Under	Moderately	Fully	Over	Collapsed
Model: RE ordered probit						
log(Number of countries)	0.179*** (0.061)	-0.004	-0.027	-0.014	0.028	0.017
log(Average number of agreements)	0.321*** (0.091)	-0.008	-0.049	-0.025	0.051	0.031
log(Herfindahl index)	0.128** (0.058)	-0.003	-0.019	-0.01	0.020	0.012
log(Average landings price)	0.211*** (0.081)	-0.005	-0.032	-0.017	0.034	0.020
RFMO managed	0.058 (0.135)	-0.001	-0.009	-0.005	0.009	0.005
Highly migratory	0.252 (0.173)	-0.005	-0.037	-0.024	0.039	0.026
(Sub)tropical	-0.343** (0.143)	0.009	0.054	0.022	-0.055	-0.031
(Very) low resilience	-0.059 (0.160)	0.001	0.009	0.004	-0.009	-0.005

Notes: The dependent variable takes on one of five exploitation categories. The model includes a full set of year dummies. Standard errors (in parentheses) are robust to clustering at the fishery (species-FAO area) level. The sample size is 41,404. ***, **, * indicate statistically different from zero at the 1%, 5%, and 10% significance levels.

icant. Everything else equal, more valuable stocks are more likely to be overexploited or collapsed than less valuable stocks.

The coefficient on RFMO managed stocks is small and not significantly different from zero. Thus, there appears to be no difference in the exploitation status between managed and unmanaged stocks. The coefficient on highly migratory stocks is positive, but not significantly different from zero. This suggests that highly migratory stocks are no more overexploited than other international stocks when holding constant, among other things, stock value and number of exploiters.[20] The coefficient on tropical and subtropical stocks is negative and statistically significant. That is, stocks in tropical and subtropical regions are generally associated with better status than stocks in temperate regions. Finally, the coefficient on stocks with low and very low resilience is negative, which is a somewhat counterintuitive result as this means that stocks with low resilience are generally associated with better stock status. However, the coefficient on low resilience is small and not significantly different from zero.

[20] A high number of exploiters and high economic value are reasons why one might expect highly migratory stocks to be prone to overexploitation.

3.5.1.2 Heterogeneous effects

To shed some more light on plausible mechanisms through which number of exploiters affects stock status, I explore heterogeneous effects. Number of countries is interacted with the other explanatory variables to elicit whether some stocks are more responsive to an increase in the number of exploiters than others. I add all interactions into the ordered probit model in equation 3.2, and thus estimate each heterogeneous effect conditional on the others. The result from this estimation is shown in Table 3-5. Both the main effects and interactions are reported, but only the latter are of interest in this case. Only coefficients (i.e., no marginal effects) are shown to save space. Number of countries is interacted with both continuous and dummy variables. Coefficients on three interactions turn out to be substantive and significantly different from zero. The positive coefficient on the countries and Herfindahl interaction suggests that the negative impact from more countries is greater the more concentrated harvesting is in the fishery. This makes sense if both more countries and more concentrated harvesting are inconducive to successful management. Next, in line with intuition, it seems that stocks with low resilience are more negatively affected by an increase in the number of harvesting countries than stocks with normal or high resilience. The result is opposite for (sub)tropical stocks. Highly migratory and RFMO-managed stocks do not appear to be differentially affected by more harvesting countries compared to their non-RFMO and non-migratory counterparts.

For the binary explanatory variables, I also estimate separate versions of equation 3.2 using subsamples including only RFMO stocks and no RFMO stocks, only highly migratory stocks and no highly migratory stocks, etc. These estimations may reveal heterogeneous effects in levels, even when no effects were found in relative terms. The results for the RFMO and highly migratory variables are shown in Table 3-6 and for the (sub)tropical and (very) low resilience variables in Table 3-7. The coefficient on number of countries is small and not significantly different from zero when confining the sample to only RFMO stocks. However, for unmanaged stocks the coefficient is substantially positive and statistically significant. Correspondingly, the impact from number of countries seems to driven by other than highly migratory stocks. Thus, these findings are different from when using interactions, which showed no differences between the groups. An explanation could be that most fisheries in the RFMO and highly migratory subsamples are likely to have a high number of participating countries. This may make it difficult to find a relationship between number of exploiters and stock outcomes, as this is essentially a cross-fishery comparison. In non-RFMO and non-highly migratory fisheries there is probably more variation in participation across fisheries.

In managed (RFMO) stocks the Herfindahl index is not associated with stock status, whereas in unmanaged fisheries more concentration is associated with worse stock status. If this result is driven by similar levels of (low) concentration across RFMO fisheries, then this could suggest that equal harvest shares are conducive to fisheries being managed.[21] A linear regression (not reported) of the log Herfindahl index on a RFMO dummy and other covariates reveals that RFMO fisheries are indeed less concentrated than non-RFMO fisheries. On the other hand, perhaps harvesting is more even, i.e., less concentrated, in managed fisheries because harvesting levels and shares are results of negotiations between countries.

Confining the sample to only (sub)tropical stocks yields a small coefficient on number of countries, which is not significantly different from zero. However, in temperate stocks, more countries is again associated with more overexploitation. For the (very) low resilience variable, there is no qualitative difference between the subsamples, although the coefficient is larger in the subsample comprising only stocks with low or very low resilience.

3.5.2 Biomass data

Results from estimations using the biomass data are shown in Table 3-8. In all models, unobserved heterogeneity is controlled for by the inclusion of fishery fixed effects. In contrast to the cross-fishery comparison above, the following analysis amounts to a within-fishery comparison.

3.5.2.1 Conditional fixed effects logistic model

In columns 1 through 3, the dependent variable is an indicator for whether a stock is overexploited. Note that these columns report odds ratios instead of coefficients. The

[21] Whether management improves ecological outcomes is a another question. The conditional comparison in Table 3-4 showed no difference in stock status across managed and unmanged stocks.

Table 3-5. Heterogeneous effects with interactions

Explanatory variable	Main effect	Explanatory variable (*continued*)	Interaction
Model: RE ordered probit			
log(Number of countries)	0.571 (0.354)		
log(Average number of agreements)	0.270** (0.134)	Agreements×countries	-0.047 (0.078)
log(Herfindahl index)	-0.584*** (0.142)	Herfindahl×countries	0.328*** (0.060)
log(Average landings price)	0.364** (0.156)	Price×countries	-0.000 (0.000)
RFMO managed	-0.077 (0.270)	RFMO×countries	0.115 (0.132)
Highly migratory	0.381 (0.337)	Migratory×countries	-0.029 (0.150)
(Sub)tropical	0.340 (0.295)	Tropical×countries	-0.409*** (0.143)
(Very) low resilience	-0.670 (0.304)	Resilience×countries	0.333** (0.136)

Notes: The dependent variable takes on one of five exploitation categories. The model includes a full set of year dummies. Standard errors (in parentheses) are robust to clustering at the fishery (species-FAO area) level. The sample size is 41,385. ***, **, * indicate statistically different from zero at the 1%, 5%, and 10% significance levels.

odds ratios on number of countries are significant at the 1 percent level in all columns. The odds ratio in column 1 suggests that the odds of a stock being overexploited (according to the definition $B/B_{MSY} < 0.5$) are 20 times larger for each one unit increase in the log number of countries. This increase in number of countries corresponds again to an increase of roughly 172 percent. In column 2, the odds of a stock being overexploited (according to the definition $B/B_{MSY} < 0.75$) are 57 times larger for each one unit increase in the log number of countries. Recall that there are about twice as many instances of the second type overexploitation in the sample. In column 3, the dependent variable is a dummy variable for whether the fishing mortality is above the level corresponding to MSY ($U/U_{MSY} > 1$). The odds of overexploitation are 4 times larger for each one unit increase in the log number of countries. The odds ratios reported here are qualitatively in line with the theory and appear quite large in magnitude. However, it is good to acknowledge the fairly small sample sizes (a few dozen stocks) and treat the effects as directional.

Table 3-6. Heterogeneous effects with subsamples

	(1) Only RFMO stocks	(2) No RFMO stocks	(3) Only migratory stocks	(4) No migratory stocks
log(Number of countries)	0.049	0.251***	-0.047	0.227***
	(0.101)	(0.077)	(0.117)	(0.070)
log(Average number of agreements)	0.347**	0.291	0.083	0.353***
	(0.176)	(0.107)	(0.158)	(0.107)
log(Herfindahl index)	0.037	0.184**	0.475***	-0.005
	(0.096)	(0.073)	(0.108)	(0.072)
log(Average landings price)	0.417***	0.157	0.962***	0.104
	(0.141)	(0.100)	(0.240)	(0.087)
RFMO managed	-	-	-0.264	0.136
			(0.298)	(0.157)
Highly migratory	0.084	0.439	-	-
	(0.241)	(0.267)		
(Sub)tropical	-0.253	-0.445**	-0.036	-0.365**
	(0.262)	(0.175)	(0.522)	(0.147)
(Very) low resilience	-246	0.066	-0.159	-0.037
	(0.237)	(0.225)	(0.280)	(0.202)
Fish stocks	369	923	262	1,030
Observations	11,666	29,723	8,124	33,290

Notes: The dependent variable takes on one of five exploitation categories. The model includes a full set of year dummies. Standard errors (in parentheses) are robust to clustering at the fishery (species-FAO area) level. ***, **, * indicate statistically different from zero at the 1%, 5%, and 10% significance levels.

Table 3-7. Heterogeneous effects with subsamples (*continued*)

	(1) Only tropical stocks	(2) No tropical stocks	(3) Only low resilience stocks	(4) No low resilience stocks
log(Number of countries)	0.048	0.257***	0.294**	0.141**
	(0.097)	(0.078)	(0.124)	(0.071)
log(Average number of agreements)	0.073 (0.141)	0.392*** (0.115)	-0.131 (0.179)	0.441*** (0.104)
log(Herfindahl index)	0.264***	0.022	0.305**	0.103
	(0.097)	(0.076)	(0.131)	(0.066)
log(Average landings price)	0.417*** (0.134)	0.114 (0.103)	0.616*** (0.232)	0.115 (0.086)
RFMO managed	-0.060	-0.102	-0.506*	0.055
	(0.184)	(0.202)	(0.294)	(0.156)
Highly migratory	0.320*	0.200	0.694**	0.038
	(0.179)	(0.483)	(0.299)	(0.207)
(Sub)tropical	-	-	-1.799**	0.077
			(0.368)	(0.145)
(Very) low resilience	-0.717***	0.722**	-	-
	(0.186)	(0.283)		
Fish stocks	418	874	224	1,068
Observations	13,372	28,023	7,269	34,135

Notes: The dependent variable takes on one of five exploitation categories. The model includes a full set of year dummies. Standard errors (in parentheses) are robust to clustering at the fishery (species-FAO area) level. ***, **, * indicate statistically different from zero at the 1%, 5%, and 10% significance levels.

3.5.2.2 *Linear fixed effects model*

Columns 4 through 6 represent linear fixed effects models where the dependent variable is continuous instead of binary. In column 4, the dependent variable is the log ratio of fishing mortality to the MSY target (U/U_{MSY}) when $U/U_{MSY} > 1$. The coefficient on number of countries (0.177) is positive, albeit somewhat imprecise. A positive coefficient in this specification suggests that the degree of overexploitation increases when the number of countries rises. Further, a coefficient below one suggests that the marginal impact gets smaller as the number of countries increases. In column 5, the dependent variable is the log of total biomass when $B/B_{MSY} < 2$. The coefficient on number of countries (-0.294) is negative and statistically significant at the 5 percent level. The obtained point estimate indicates that a one percent increase in number of harvesting countries is associated with a reduction in total biomass by 0.294 percent. Let us again assume an increase in number of countries by 172 percent (e.g., from 1 to approximately 3 countries): this would imply a decrease in biomass by 25 percent $((2.72^{-0.294}) - 1)$.

Lastly, in column 6, the dependent variable is the log ratio of biomass to the MSY target (B/B_{MSY}) when $B/B_{MSY} < 2$. The coefficient on number of countries is negative and statistically significant at the 5 percent level. This means that biomass is reduced when the number of countries increases. Taken together, the results in Table 3-8 are in line with the hypothesis that the degree of overexploitation increases when there is a rise in the number of non-cooperative exploiters.

The qualifier, $B/B_{MSY} < 2$, excludes instances when the stock size is well above conventional management targets, i.e., the stock is underexploited. The results are not sensitive to the specific value of the qualifier. However, omitting the qualifier altogether yields an imprecise coefficient with opposite sign in column 5, and an imprecise coefficient (the sign unaffected) in column 6. This suggests that the relationship between number of countries and biomass is ambiguous when the fishery is underexploited. There could be different explanations for this.[22] There may be a surge in number of countries participating in the unexploited fishery and the stock is initially insensitive to the increase in number of exploiters. Or a stock may initially be fished mainly as by-catch by a relatively large number of countries, and biomass remains at a high level.

[22] Recall that in this model we are comparing outcomes within individual fisheries over time.

Table 3-8. The impact of number of countries on ecological outcomes

	(1) FE logit	(2) FE logit	(3) FE logit	(4) OLS-FE	(5) OLS-FE	(6) OLS-FE
Dep. var.:	$B/B_{MSY} < 0.5$	$B/B_{MSY} < 0.75$	$U/U_{MSY} > 1$	$\log(U/U_{MSY})$	$\log(B)$	$\log(B/B_{MSY})$
log(Number of countries)	20.36***	57.17***	3.88***	0.177	-0.294**	-0.347**
	(3.42)	(5.12)	(2.76)	(0.135)	(0.120)	(0.152)
Log likelihood	-155.814	-238.544	-513.723			
Fish stocks	18	28	52	63	54	56
Observations	434	680	1,256	864	1,132	1,197

Notes: All regressions include fishery and year fixed effects. Odds ratios and Z statistics (in parentheses) reported in columns 1–3. Coefficients and robust standard errors adjusted for clustering at the fishery level (in parentheses) reported in columns 4–6. ***, **, * indicate statistically different from zero at the 1%, 5%, and 10% significance levels.

At a later point, a market is created for the fishery, but with fewer countries than before participating initially. As the fishery develops from here, more countries join and biomass begins to decline.

3.6 Conclusion

A fundamental theoretical result in fisheries economics is that the common property fishery is prone to overexploitation. The international fishery is a type of common property resource where the resource users are sovereign countries. The international fishery has been a study object in fisheries economics since the late 1970s, when game theoretical methods were introduced to study strategic interactions between exploiters. In addition to purely theoretical work, there are many empirical case studies that combine bioeconomic modeling and game theoretical concepts. These studies conclusively demonstrate the harmful economic and biological effects of non-cooperative harvesting. However, very little statistical and econometric work has been done in the realm of international fisheries. This paper aims to contribute in filling this research gap in the literature. Using different data sources and a range of econometric models, this paper presents evidence that more harvesting countries increases the probability of overexploitation.

Using subsamples of the data, I find clear impacts from a rise in number of countries on stock outcomes in unmanaged and non-highly migratory stocks, but not in managed and highly migratory stocks. At first blush, this could be interpreted as tentative evidence for a beneficial impact of RFMO management. Perhaps RFMOs have succeeded in accommodating new harvesting countries and getting them to comply with regulations. However, these heterogeneous effects could also be driven by the similarity of RFMO and highly migratory stocks. That is, in these subsamples the random effects (cross-fishery) model compares stocks which all have a fairly high number of participating countries. When studying heterogeneous effects using interactions, I find no differences across the aforementioned stocks.

The ex ante conjecture in this paper is that the prospect of cooperation is a key channel through which more exploiters affects stock outcomes. An avenue for future research is to further explore the causal links between number of countries, cooperative management (whether it takes place/is effective), and ecological outcomes. Also the tentative finding that less concentrated harvesting is associated with better sustainability warrants more research. Specifically, are some fisheries ecologically better off because uniformity across countries contributes to success in international management?

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