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Universidad del País Vasco
Euskal Herriko Unibertsitatea

ON RISK, DIVERSITY AND FINANCIAL EFFICIENT FRONTIERS:

THE CASE STUDY OF EUROPEAN FISH AND FISHERIES

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Aita eta Ama

Idoia

Mikel

Familia osoa

Eskerrik asko bihotz bihotzez

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Introduction

The concepts of *triple bottom line* (Elkington, 1998) and the three-pillar foundation for ecological, economic and social sustainability are a growing matter in fisheries (Boyer et al., 2016; Hueting & Reijnders, 2004; Kajikawa, 2008; Nielsen et al., 2014). However, it is not clear how fisheries could achieve these three pillars of sustainability, namely economic development, social development and environmental protection (United Nations, 2015), because of the potential negative trade-offs among them. A poor ecological health of a fishery decreases economic benefits for fishers, and a low economic profitability of individual fishers threatens the social objectives of fishing communities (Asche et al., 2018). Likewise, many scholars (Cheung & Sumaila, 2008; Clausen & York, 2008; Douvere, 2008; Grafton et al., 2007; Hilborn, 2007a; Norman & Pascoe, 2011; Walters et al., 2005) argue that the achievement of economic objectives leads to overfishing and deterioration of marine ecosystems. The literature also supports that economic and ecological objectives may not be necessary in conflict if there exist effective management strategies (Birkenbach et al., 2017; Costello et al., 2008; Costello et al., 2016; Essington, 2010).

Following the line of the theory of property rights, the basic foundations of fisheries economics states that individual fishers make privately beneficial decisions that lead to overexploitation of fish stocks that ultimately reduce economic profit (Gordon, 1954; Smith, 1969). To face this, in a seminal paper, Scott (1955) introduced the metaphor of the *sole ownership*, a benevolent social planner that maximises the intertemporal profits of the fishery, internalising the shadow value of the fish stocks. Nevertheless, *sole ownership* would not automatically prevent overfishing, and it may find profitable to lead a fish stock to extinction (Clark, 1973). Two decades later, Arnason (1996) demonstrated that it is theoretically possible to achieve Scott's socially desirable solution by means of a market of fishing rights, where fishers are allowed to freely transfer such rights. After hundreds of papers focusing on the advantages and disadvantages of using the market to overcome the inefficiencies derived from the fact that fish stocks are indeed common pool resources (CPR) (Ostrom, 2000), the need to include social and environmental factors in the discussion started to gain positions, not only in the fisheries economics literature, but also in the real governance of fisheries all over the world. Nowadays, the acceptance that all humanly used natural resources are embedded in complex, social-ecological systems (SES) (Basurto et al., 2013; Charles, 1995; De Young et al., 2018; FAO, 2009; Folke et al., 1998; McGinnis & Ostrom, 2014; Ostrom, 2009, 2010) and the need for an ecosystem-based fisheries management approach are gaining positions towards a new consensus, becoming part of the orthodox thought.

Fisheries need long run strategies and also management tools to achieve required biological and environmental targets (Hilborn, 2007b), and avoid short-run myopic behaviours that can drive to unsustainable harvest levels (Botsford et al., 1997), break-even profits and social disrupts in fisheries dependent communities. This need for management strategies that at the same time account for social, economic and ecological goals have encouraged scholars to call for the ecosystem-based fisheries management as an approach to sustainably develop the fishing activity, targeting both human and ecosystem well-being (Garcia & Cochrane, 2005; Link & Browman, 2017; Long et al., 2015; Pikitch et al., 2004). However, quantifying the impact of fisheries on the environment (biodiversity and habitat degradation) and the impact of the environment on fisheries (natural oscillations and climate change) is not straightforward (Garcia & Cochrane, 2005). In fact, effective management objectives often neglect the ecological and human factors stressed in the academic literature, and besides, there is also a lack of a clear procedure or tool to implement ecosystem-based fisheries management (Arkema et al., 2006). To get a better understanding of the ecosystem functioning (Rosenfeld, 2002) it is necessary to account for fish species interactions (Cochrane, 1985; Marshall et al., 2018; Werner & Gilliam, 1984), to overcome uncertainty and risk related issues (Hoos et al., 2019; Rosenberg & Restrepo, 1994), and to improve forecasting capacity (Farmer et al., 2019; Hobday et al., 2016).

Within this debate, the main objective of this thesis is to explore innovative methods to better understand and asses the governance of fisheries. Although our primary focus is EU fish and fisheries, our methods and results might be easily exported to additional frameworks and aggregation levels. The thesis is structured in this general introduction, three independent chapters, and the final conclusions and discussion section. Each of the three chapters is developed as a self-contained unit, and accordingly, each one has its own introduction, material and methods section, results, conclusions, and references.

In the first chapter, we aim to contribute with additional synthetic and descriptive knowledge so as to guide potential discussions on the future of the European fishing sector. EU is one of the five largest fish producers in the world and becomes one of the main performers in the international fisheries (after China, Norway, Vietnam and Thailand) (FAO, 2018). Fishing activity plays a crucial role for employment and economic activity in certain EU regions and coastal communities (Bailey & Jentoft, 1990; Béné, 2003; Guyader et al., 2013; McGoodwin, 2001) in which the fishing sector accounts for almost half of the local jobs (European Commission, 2018). Analysing the ongoing situation of the European fish and fisheries is crucial to face sustainable solutions (Arlinghaus et al., 2002; Bellido et al., 2011; Linke & Bruckmeier, 2015). However, there exists a gap between the state of the marine environment and existing short and long term policy targets (Fenberg et al., 2012; Liquete et al., 2013; Ward et al., 2002). Therefore, the objective of the first chapter is threefold. Firstly, to describe the Common Fisheries Policy to get a better understanding of the fisheries regulation in the EU. Secondly, to introduce the available figures and data regarding the EU fishing sector in order to provide an overview of the main remarkable points to better understand the challenges of the Common Fisheries Policy (Catchpole et al., 2017; Harte et al., 2019; Symes & Hoefnagel, 2010; Veiga et al., 2016; Villasante et al., 2012). Thirdly, to identify the taxonomy of the EU fishing countries using a set of clustering algorithms (i.e. hierarchical, non-hierarchical and mixed hierarchical-kmeans). Our study reports a set of standard output, input, fleet structure, fleet organisation and profitability indicators at country level. Output indicators include the volume and the value of fish landed in EU fishing countries; input indicators are addressed by the number of vessels, the gross tonnage, the engine power and the number of full-time fishermen; the structure and organisation of the fleets is proxied by the proportion of small-scale artisanal vessels, the proportion of the large industrial vessels, the proportion of the new vessels, the proportion of the quasi amortised vessels; the organisational behaviour is captured by the number of producer's organisation; and the efficiency of the fleets is measured by productivity ratios. Since the variables in the variate are highly correlated, we are using a two-step principal component clustering approach in order to identify potential groups (clusters) of homogeneous EU fishing countries.

In the second chapter, we focus on alternative theoretical and empirical specifications of risk and diversity in the fisheries domain, and the empirical correlation among them. Theoretically, risk and diversity are expected to be negatively correlated. The lower the diversity, the higher the concentration, dominance and dependency of that fishing industry to the evolution of the dominant fish species (del Valle et al., 2017). Therefore, the higher the risk of a potential collapse in the fishing sector.

Firstly, we focus on the species-level risk. Afterwards, based on our species-level risk estimations, and using the catches by species of each EU fishing country as weights, we infer the country-level risk. We suggest using spawning stock biomass as the source of species-level *biological risk*, and catches as the source of species-level *production risk*. The former is a measure of the risk in the natural frame or ocean, while the latter aims to capture the risk inherent to the fishing activity itself. Risk is the concept that best defines precaution (González-Laxe, 2005), since uncertainty exists and the potential danger or harm is more or less predictable. It is a fact that the future of the fish stocks has been endangered due to over-exploitation (Baum et al., 2003; Pauly et al., 2002), and in parallel, there is a growing need to account for interactions among species to find a way of better managing multispecies fisheries and changing environments (Botsford et al., 1997; Edwards et al., 2004; Garcia, 2003; Pikitch et al., 2004). Moreover, it is necessary to predict the vulnerability of fish species before their population collapses (Sala & Knowlton, 2006; Worm et al., 2006). There are some databases, such as FishBase (Froese & Pauly, 2018), and The International Union for Conservation of Nature Red List of Threatened Species (IUCN, 2018) that already include some species-level ecological indicators (i.e. Trophic Level, Vulnerability and Resilience, etc.), but there are many missing species, and besides some of the key indicators are just qualitative. Thus, the lack of reliable quantitative information advocates investigating on fish species vulnerability indicators that might help to better assess the management of fisheries and to set effective conservation strategies.

Quite recent literature suggests financial approaches to be used for ecosystem-based fisheries management (Alvarez et al., 2017; Carmona et al., 2020; Edwards et al., 2004; Jin et al., 2016; Rădulescu et al., 2010; Sanchirico et al., 2008) as a tool for fisheries biodiversity conservation (Pauly et al., 2002; Sylvia et al., 2003), internalising fish species interactions. Nevertheless, it is not clear which is the most appropriate indicator to proxy risk in the fisheries framework. In the field of finances, the financial crises (2008) turned the attention of the practitioners to risk measures based on losses (Almahdi & Yang, 2017; Bali et al., 2009; Hammoudeh et al., 2013; Huang et al., 2012). Although since its adoption by Basel II in 1996 (Basel II, 1996) and the popularisation of J.P. Morgan's RiskMetrics VaR model (Morgan, 1996), Value-at-Risk (VaR) became one of the most widely used risk indicator, VaR does not satisfy coherence property, lacks subadditivity and ignores losses in the far tail of the loss distribution. As a response to these failures, the concept of coherent risk measures was introduced (Artzner, 1997; Artzner et al., 1999). In 2013, Basel III recommended replacing VaR by Expected Shortfall (ES) (also known as Conditional Value-at-Risk (CVaR) (Basel III, 2013). Expected Shortfall is coherent and quantifies tail risk, but it fails the elicitability property deemed essential to backtesting. Accordingly, recent studies have suggested Expectiles as coherent and elicitable alternatives to VaR and CVaR (Bellini & Di Bernardino, 2017; Chen et al., 2018; Waltrup et al., 2015). Thus, there is not a definite theoretical financial risk indicator to measure risk.

In the fisheries framework, there are different ecological indicators which measure the individual vulnerability or risk of the fish species. However, there is lack of consensus on how these indicators should be calculated (Cinner et al., 2013; Methratta & Link, 2006; Shin et al., 2010; Whitfield & Elliott, 2002), and besides, often, there is also a lack of quantitative and accurate data to face this. Due to all these disparities, we will focus on five alternative financial risk indicators, including Value-at-Risk (VaR), Modified Value-at-Risk (MVaR), Expected Shortfall (ES), Modified Expected Shortfall (MES), and Expectiles (EX), in order to explore the one that best fits our fish and fisheries data; so as to quantitatively measure the species-level *biological risk* and *production risk*. We suggest using spawning stock biomass as the source of the species-level *biological risk*, and using catches as the source of the species-level *production risk*.

This way, we contribute to the literature twofold. On the one hand, providing an innovative way of measuring vulnerability of fish species quantitatively, hence complementing the existing ecological indicators. The estimation of species-level biological and production risk may be useful to reduce uncertainty about the status of the fish species, by giving different but additional indicators to the existing conventional vulnerability measures. On the other, our proposed species-level synthetic *biological risk* and *production risk* indicators can be easily inferred to any aggregation level, to measure the overall weighted risk of a country, region, community or fleet. This weighted risk could be useful to compare *biological risk* and/or *production risk* among countries, communities or regions. Specifically, using our own estimations of species-level risk we derive the biological and production risks of each of the EU fishing countries.

The second subsection in Chapter 2 focuses on diversity. We study the country-level bioeconomic diversity in the North-East Atlantic, using conventional diversity indices (i.e. species richness, Berger-Parker index (Berger & Parker, 1970), concentration ratio, Shannon index (Shannon & Weaver, 1998) and Simpson's index (Simpson, 1949). Notice that the same indices are also employed in the economic literature of market concentration (De Bandt & Davis, 2000; Hannah & Kay, 1977), industrial organisation (Finkelstein & Friedberg, 1967; Hildenbrand & Paschen, 1964; Theil, 1967) and corporate diversification (Hoskisson et al., 1993; Jacquemin & Berry, 1979; Palepu, 1985). They have been also used as proxies to measure the degree of bioeconomic diversity (del Valle &

Astorkiza, 2018; del Valle et al., 2017; Lopetegui & del Valle, 2019a, 2019b), and should be understood as inverse measures of concentration, and dependency of ecosystem on dominant species (del Valle & Astorkiza, 2019; Lopetegui & del Valle, 2020). Our point is that synthetic country-based diversity measures may help to get a better understanding of the heterogeneity of the EU fishing sector, and in this sense, might contribute to strengthen fisheries policy.

Biodiversity is widely recognised as a key factor of healthy ecosystems (Kremen, 2005; Worm et al., 2006). The economic activity may negatively impact on biodiversity and obviously the deterioration of the ecosystems has revealed the need for operational indicators of ecosystem health (Costanza, 1992). Most of the studies suggest that biodiversity both enhances and stabilizes ecosystem functioning (Cardinale et al., 2013; Gross et al., 2013; Jiang & Pu, 2009). Greater diversity would imply greater health of the ecosystem and greater ability to adjust and adapt to changes (del Valle & Astorkiza, 2019). Biodiversity is also positively related to productivity, stability and the supply of ecosystem services (Worm et al., 2006). Accordingly, diversity is a measure of variety and heterogeneity on an ecosystem (Baumgärtner, 2006; Jost, 2006; Magurran, 2013) typically synthesized by means of different diversity indices (Magurran, 2013; Pielou, 1975). Neither diversity, nor stability are easy concepts to quantify (Ives & Carpenter, 2007). Not only the economic activity, but also pollution, climate change and habitat degradation (Jackson et al., 2001) affect the biodiversity and abundance of natural resources and the structure of the marine ecosystem (Coll & Libralato, 2012).

Specifically, we study the country-level bioeconomic diversity dynamics of the main commercial fish species in the North-East Atlantic. Hence, each member-state has an individual marine sub-ecosystem comprised by different fish species, which may change over the time. We are using two complementary specifications to generate diversity indices. The former is focused on the volume landed, and the latter in the value of such landings. Thus, we measure four diversity indices to explore how countries diversity patterns change, namely, Berger-Parker index, concentration ratios, Simpson's index and Shannon index. It is advisable to use more than one index because they give similar but not the same information. Besides, we will complement our diversity related findings with ANOVA, Shapiro-Wilk, Levene's, Kruskal-Wallis and TukeyHSD tests to check if significant differences exist on the diversity patterns among EU countries and/or time, in both terms (i.e. landings volume and value).

Once we get EU fishing country-level measures of risk and diversity, we analyse the magnitude and sign of their empirical correlation. A priori, lower species bio-economic diversity levels would mean higher concentration level, dominance and dependency of the fishing activity to the evolution of a dominant species, and similarly, higher risk of a potential collapse (del Valle & Astorkiza, 2019; del Valle et al., 2017). Therefore, concentration and diversity are inversely related concepts that may be well used as cornerstones to discuss of our target multispecies ecosystem's health level. To finish with the second chapter, we will check whether our estimated country-based risk and diversity indicators help to re-cluster the EU fishing countries so as to quantify their structural characteristics and potential taxonomy. In order to do so, we will add the estimated country-level risk and diversity indicators in the variate used in the clustering analysis developed in Chapter 1, and potentially identify a different taxonomy of the EU fishing countries.

In the third chapter, in the framework of the modern portfolio theory (Markowitz, 1952), we provide a new tool for policy makers, which based on species-level risks and returns, explicitly considers the interaction among the different species in the European fisheries ecosystem. It is not new that The Common Fisheries Policy (EU, 2013) calls for an ecosystem-based fisheries management approach; however, there is a lack of consensus on how it should be implemented. Many difficulties, such as monitoring and measuring all the variables, understanding well enough the marine ecosystems, and identifying a more focused set of governance conditions, remain unresolved (Link & Browman, 2017). There is an increasing demand for practical, interdisciplinary and well-tested decision-making methods to assess the management of environmental assets (Guerry et al., 2015), but complex questions arise when researches try to assess and improve decision-making process through sustainability related new forms of risk (Matthies et al., 2019). There also exists increasing literature that suggests financial approaches to be used for fisheries management (Bianchi & Skjoldal, 2008; Gourguet et al., 2014; Pokki et al., 2018; Walters et al., 2002; Yang et al., 2008). Applying modern portfolio theory for fisheries management could be useful to improve decision making and specify optimal policies that account for species interactions in an ecosystem framework (Sanchirico et al., 2008). There is a sounded parallelism between financial assets and fish stocks. Fish stocks can be interpreted as natural assets capable of generating return flows (Alvarez et al., 2017), and fishers must choose which species to target among the diverse and disposable portfolio of harvestable fish species. Fish species interactions are also implicitly considered by the inclusion of species revenues and covariances. Accordingly, modern portfolio theory is consistent with an ecosystem-based fisheries management approach that jointly considers multiple fish stocks, providing a framework for the management of multi-species fisheries by suggesting strategies to maximize returns and/or minimize risks. Following the pioneering paper of Sanchirico et al. (2008), authors such as Alvarez et al. (2017), Rădulescu et al. (2010) Jin et al. (2016), and Carmona et al. (2020) have adapted financial portfolio theory as a methodology for ecosystem-based fishery management accounting for species interdependencies, uncertainty and sustainability constraints.

In response to recent reviews and discussions, we present a complement to the still growing literature on applying modern portfolio theory as a tool to optimize revenues coming from fishing. Besides, we apply it to the North-East Atlantic European fisheries. Using mean-Conditional Value-at-Risk optimization approach, we measure the constrained financial efficient frontier of fish species for the aggregated EU, as well as for each of the nine member-states in the target area. Therefore, the objective of the third chapter of this thesis is twofold: firstly, to apply modern portfolio theory to the fisheries of the North-East Atlantic, by quantifying the inherent risk of the fish portfolios, providing advice to researchers and policy makers to optimize the management of fisheries. And secondly, to demonstrate how returns coming from landings could be increased and risk could be reduced by employing financial efficient frontiers in setting catch limits.

Our empirical measurement of the financial efficient frontier uses the same structure as in finance, but some issues must be considered when applying it to an ecological ecosystem. Natural resources are not unlimited and it is necessary to include some limits/constraints in order to propose sustainable solutions for our ecosystem, and hence, ensure the survival of the fish stocks for future time periods (Sanchirico et al., 2008)). If we are not including such constraints, our recommendation could imply catching up to a level that could cause the collapse of certain fish stocks. These additional restrictions, or constraints, can limit the initial investment and risk preferences (Knoke et al., 2005; Knoke & Wurm, 2006) or even a desired minimum level of diversification (Halpern et al., 2011). Under these circumstances, we present three alternative constrained efficient frontiers. Following Sanchirico et al. (2008), we propose an upper bound as the maximum observed weight to ensure that the proposed weights keep under sustainable solutions. Besides, following Alvarez et al. (2017), we have included a sustainability parameter to compare how increasing or reducing the upper bound could affect the efficient frontier curve. Additionally, we ensure that our recommendation implies catching from each fish species at least the minimum observed proportion to total landings. An alternative upper maximum constraint is also considered, measuring the weight of the total allowable catches as a percentage to total landings. Using this new upper constraint, we can replace the previous maximum observed weight by the total allowable catches weight for the regulated fish species and maintain the previous maximum observed constraint for the non-regulated ones. Adding alternative constraints and comparing three potential efficient frontiers, we can observe how policy makers' decisions would affect the reallocation of landings weights and therefore, it would also imply changes in both return and risk levels.

Once the financial efficient frontiers are measured, alternative efficient portfolios and redistributions of landings weights will be suggested depending on the target return and risk levels. Not only financial practitioners (Gundel & Weber, 2007; Harlow, 1991; Ling et al., 2014; Miller & Reuer, 1996; Zhu et al., 2009) but also when applying portfolio selection models to fisheries, downside risk measures have been suggested as a better and robust alternative when returns do not follow normal distribution (Alvarez et al., 2017), but, is has not been applied yet to fisheries. Therefore our contribution to the literature is innovative in two senses. First, using Conditional Value-at-Risk (Rockafellar, Uryasev et al., 2000; Rockafellar & Uryasev, 2002) as a robust and alternative risk indicator. Second, applying modern portfolio theory for fisheries management aggregately for the EU and also for nine member-states, as an innovative tool to existing models to manage fish stocks sustainably.

Overall, the aim of this thesis is to provide sufficient knowledge about the ongoing situation of the fisheries sector in the EU and suggest potential new tools to be used as innovative, robust and efficient alternatives to account for fish species interactions, understand the biodiversity dynamics of the fish ecosystems and efficiently manage the fishing sector in the EU.

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Chapter 1

On European fish and fisheries

Abstract

There is still a substantial gap between the real state of the marine environment and the existing short and long-term policy targets in the EU. Analysing the ongoing situation of the European fish and fisheries is essential to design effective policies that pursue sustainable outcomes. Therefore, this introductory and descriptive chapter aims to contribute to a better understanding, assessment and provision of the knowledge to guide further discussions on the future of the European fishing sector. Thus, the objective of this chapter is threefold. First, to succinctly describe the institutional framework of the Common Fisheries Policy (CFP). Second, to analyse the current situation of the European fish and fisheries using the standard output and input variables, and, at the same time, introduce the data used in the next two chapters. Third, to identify the taxonomy of the fishing countries in the EU, using a set of hierarchical, non-hierarchical and mixed clustering algorithms. Our variate includes a set of country level input, output, fleets' structure and organisation variables and productivity ratios (i.e. the volume of landings (q), the value of landings (pq), the number of vessels (NV), the gross tonnage (GT), the number of full-time fishermen (FTE), the proportion of the small-scale artisanal vessels ($\leq$12 metres) (ART), industrial vessels ($>$24m) (IND), new vessels ($\leq$10 years), quasi amortised vessels ($>$20y), the number of producer organisations (POs) and productivity ratios (pq/NV, pq/GT and pq/FTE)). Since the variables in our variate are highly correlated, we are applying a two-step principal component-clustering approach in order to identify potential groups of homogeneous fishing countries within a rather heterogeneous European fishing sector. Our results suggest that European fishing

countries may be grouped in four different clusters.

1.1 Introduction

Even the fishing sector in the EU hardly represents around 0.1% of the Gross Domestic Product (GDP) (Lado, 2016), certainly, it highly impacts food security, cultural identity, employment and income (Aranda et al., 2019). Commercial fisheries cover large areas of the European seas, and fishing is considered one of the human activities with the highest impact on the marine environment (FAO, 2016; Micheli et al., 2013). Therefore, the EU is on track towards meeting the objective of spending at least 20% of its budget for 2014-2020 on climate-related measures (such as agriculture, rural development and fisheries) (European Environment Agency, 2020). Fishing activity plays a crucial role for employment and economic activity, especially in certain EU regions, coastal communities where the fishing sector accounts for almost half of the local jobs (European Commission, 2018). The fisheries sector is distributed along the coast of 23 member-states, and EU fleets operate in Western Waters, North Sea, Arctic, Baltic Sea, Mediterranean Sea, as well as some Outermost Regions, third country waters and areas under the domain of Regional Fisheries Management Organisations (RFMOs)[1] (Aranda et al., 2019; Hegland et al., 2012; Le Floch̀ et al., 2015). EU is one of the five largest fish producers in the world (EUMOFA, 2019). Moreover, 80% of fish production in the EU comes from wild fisheries and 20% from aquaculture (EUROSTAT, 2017). Thus, EU becomes one of the main performers in the international fisheries framework (after Norway, Iceland, Japan and Mexico, among others). Since fishing radically depends on the productivity of the marine resources, it is straightforward that long-terms goals are required to maintain fishing resources at sustainable levels.

Therefore, the objective of this chapter is threefold. First, to describe the Common Fisheries Policy (CFP) to get a better understanding of the institutional framework and fisheries regulation in the EU. Second, to introduce the available figures and data regarding the fishing sector in order to provide an overview of the main remarkable points to better understand the ongoing situation of the fishing activity. Third, to identify the taxonomy of the EU fishing countries using a set of hierarchical (i.e. Ward, average and complete linkage), non-hierarchical (i.e. k-means and k-medois) and mixed

[1] Regional Fisheries Management Organisations (RFMOs) are international bodies made up by countries with fishing interests in the same region or in the same group of fisheries. Within these bodies, countries collectively set measures such as catch limits, fishing-effort limitations, technical measures and control obligations to ensure conservation, as well as fair and sustainable management of the shared marine resources (European Commission, 2018).

hierarchical-kmeans algorithms. Our variate $\{\mathbb{X}\}$ includes a set of input, output, fleets' structure and organisation variables and productivity ratios. Variate $\{\mathbb{X}\}$ includes the volume of landings (q) and the value of landings (pq) as output variables. Input variables are represented by the number of vessels (NV), the gross tonnage (GT), and the number of full-time fishers (FTE). The fleet's structure is proxied by the proportion of small-scale artisanal vessels (<12 metres) (ART) to the total fleet, the proportion of the large industrial vessels (24 metres) (IND), the proportion of the *new* vessels (<10 years) (NEW) and the degree of amortisation of the fleets' by the proportion of *old* or quasi amortised vessels (>20 years) to the total fleet (AGED). The trend of organisational behaviour of fishers is captured by the number of producers' organisation (PO). Productivity ratios include the value of landings (pq) per each of the input variables (i.e. pq/NV, pq/GT, pq/FTE). Since the variables in the variate $\{\mathbb{X}\}$ are highly correlated, we are applying a two-step principal component-clustering approach in order to identify potential clusters of homogeneous EU fishing countries.

Data sources and time horizon used in this chapter are summarised in Table 1.1.

Table 1.1: Data sources and time horizon

	Code	Unit	Time	Source	Accessed
Landings$_{ijt}$[2]	TPW	Tonnes product weight	2000-2018	EUROSTAT	07/05/2020
	EUR	Euro[3]	2000-2018	EUROSTAT	07/05/2020
Fleets$_{ijt}$[4]	NV	Number of vessels	2000-2018	EUROSTAT	07/05/2020
	GT	Gross tonnage	2000-2018	EUROSTAT	07/05/2020
	KW	Kilowatts (power)	2000-2018	EUROSTAT	07/05/2020
	LE	NV by length[5]	2000-2018	EUROSTAT	07/05/2020
	AGE	NV by age[6]	2000-2018	EUROSTAT	07/05/2020
Biomass$_{ijt}$[7]	SSB	Tonnes	1992-2016	ICES	19/12/2017
Employment$_{ijt}$[8]	FTE	Number of fishers	2005-2017	OECD	06/02/2020

The remainder of this chapter is organised as follows. After this introduction, Section 1.2 summarises the institutional framework of the EU fishing sector and gives a short overview of the Common Fisheries Policy (CFP). Section 1.3 presents the available data about the sector (including UK) and highlights the outstanding features regarding volume (q) and value of landings (pq), fleets, full time employment in fisheries (FTE),

[2] Total volume and value of the landings by time (t), country (j) and fish species (i).
[3] Value of landings: Landings volume multiplied by first sale prices.
[4] Capacity of the fleets by time (t), country (j) and fish species (i).
[5] 3 length categories: (a) Less than 12 metres, (b) 12 to 24 metres and (c) 24 metres or over
[6] 3 length categories: (a) Less than 10 years, (b) 10 to 20 years and (c) 20 years or over
[7] Spawning stock biomass (SSB) in the North-East Atlantic by time (t) and fish species (i).
[8] Number of full-time employed people (FTE) in the fishing sector by time (t) and country (j)

productivity ratios, producer organisations (POs) and spawning stock biomass (SSB) of key species in the ecosystem. Section 1.4 introduces the clustering algorithms used and the variables included in the analysis, and afterwards, based on a two-step principal component-clustering approach, the taxonomy of the EU fishing countries is addressed. Finally, Section1.5 concludes, adding some discussion points.

1.2 The institutional framework of EU fisheries

Both, fish stocks and fishing fleets in the EU are regulated by the Common Fisheries Policy (CFP), which is designed to manage the common marine biological resources by giving a set of rules to favour the sustainable management of the fishing stocks, fleets and fishing communities. The CFP is applicable to all fishing vessels operating in the waters of the EU, as well as to EU vessels fishing in non-European waters.

The main objectives of the CFP are to ensure the sustainability of fishing and aquaculture environmentally, economically and socially, so as to provide healthy food for the EU citizens. In 2013 the CFP (EU, 2013) included significant changes in order to make fisheries consistent with the so-called ecosystem-based approach and avoid unsustainable exploitation of fishing resources. Moreover, the CFP stipulated that all fish stocks should be exploited at a sustainable level by 2020 at the latest (EC, 2019). Maybe, not only overfishing, but also pollution, has led to the decline in the health of marine ecosystems and to increase vulnerability to changes in the fisheries socio-economy (IPBES, 2019). In the North-East Atlantic Ocean, only the 62.5% of the assessed fish and shellfish stocks have shown signs of recovery, meeting policy targets for fishing mortality and/or reproductive capacity in 2017 (EEA, 2019). This progress seemed to be too slow to achieve the objective of exploiting all EU fish stocks sustainably by 2020 (STECF, 2017).

In order to achieve the objective, a set of CFP rules on catches and fishing effort are applied, including a monitoring system that gives tools to enforce them. The aim of these rules is to eliminate overfishing and overcapacity, to collect necessary data to enable an efficient management of fisheries, to clarify the roles of each of the EU countries and the European Commission, and to ensure that the rules are equally applied to all fishers, so as to control the products throughout all the supply chain. Controls are done in ports, during transport, in factories where fish is processed, and markets in which fish is sold. The EU also works to eliminate the illegal, unreported and unregulated fishing, because this kind of fishing destroys and depletes fish stocks, distorts competition and puts honest fishers at a disadvantageous situation. Therefore, the CFP has tried to set rules to manage fish stocks and fleet capacity. However, the consistency of its the application is discussed in several studies, including, among others, Surís et al. (2003), Gray and Hatchard (2003), Daw and Gray (2005), Hilborn (2007), Del Valle and Astorkiza (2007), Khalilian et al. (2010), Laxe (2010), Symes (2012), del Valle and Astorkiza (2013).

Regarding fisheries management, as already mentioned, the main objective of the CFP is to maintain sustainable long term fish stocks and ensure that the rate of exploitation of marine biological resources allows restoration and maintenance of fish populations of harvested stocks above levels that can produce the maximum sustainable yield (MSY)[9]. If not, collapses might occur and the reproductive capacity of fish stocks could be diminished. One of the key instruments of the CFP is setting total allowable catches (TACs) to make sure that fishing does not harm the reproductive capacity of the fish populations. These TACs are annual catch limits established for most valuable marine commercial fish species, and represent the maximum total amount of tonnes that can be annually caught of each fish species. TACs are annually determined on the basis of estimated Maximum Sustainable Yields (MSY), which represents the maximum annual catch that can be taken from an exploited stock without deteriorating its productivity (Guillén et al., 2016; Mesnil, 2012; Salomon & Holm-Müller, 2013; Ulrich et al., 2017; Voss et al., 2014).

TACs are shared among the EU member-states into quotas assigned to each country and fishing areas. This quota sharing is based on the *relative stability principle* (Hoefnagel et al., 2015; Morin, 2000; Sobrino & Sobrido, 2017; Symes, 2009), which ensures each member-state a certain percentage of the TAC for each species, based on the original allocation in the 1983 quota distributions (EC, 1983). Thus, once the TACs are shared into quotas, each country decides how to distribute their quotas among their fishermen, and how to control and ensure that quotas are not overfished. Regionalisation[10] is also applied for some instruments and measurements, such as multi-annual guidance programmes (MAGPs), landing obligation (LO), establishment of fish stock recovery areas and conservation measures. EU countries, following the objectives of the CFP, submit recommendations to the Commission that can be transformed into EU law applicable to all operators. Countries have to report annually fishing fleet related data so as to ensure the maintenance of a durable balance between the capacity of the fishing

[9] Maximum sustainable yield (MSY) is the maximum catch (in numbers or mass) that, on average, can be removed from a fish population in the long-term. Exploiting fish stocks at or below MSY allow them to maintain and recover to healthy levels, providing food for consumers while contribution to important ecosystem and marine food web functions (European Environment Agency, 2020).

[10] The Common Fisheries Policy (CFP) gives member-states the opportunity to play an active role in designing fisheries conservation measures through the so-called regionalisation (European Commission, 2018).

fleets and the real fishing opportunities. The European Commission prepares guidelines to identify the unbalanced situations, such as overcapacity of the fleets, and the European Council makes decisions to face them.

Multi-annual Guidance Programmes (MAGPs) have been also part of the structural policy of the CFP. MAGPs were generally, 5 to 6 years programmes administered by the European Commission that aimed to restructure the EU fishing fleets and establish equilibrium between the fishing capacity and sustainability of the resources (Lassen et al., 1996). MAGPs guided the progressive structural adjustments to reduce the fleet's capacity to the real biological situation of fish stocks for all EU member states and their fishing fleets. The consecutive regulations of the European Commission concerning both the CFP and MAGPs have been progressively modified since their initial implementation (Cueff, 2007; del Valle & Astorkiza, 2013).

The first MAGP I (1982-1986) included targets for fleet capacity to be achieved by 1986. However, the objective was mainly to balance investments with removals in order to limit the overall capacity at or somewhat below 1982 levels (Cueff, 2007; Hatcher, 2000). The second MAGP II (1987-1991) established for each national fleet a set of objectives including overall reductions of 3% in gross tonnage and 2% in horse-power. The third MAGP III (1992-1996) adopted a new approach to segment fleets and set different effort reduction targets for demersal, benthic and pelagic fish stocks. Moreover, MAGP III managed to achieve the objective of reducing the Community fleet by around 15% (Cueff, 2007). The fourth MAGP IV (1997-2001) aimed to reduce fishing effort by 30% in the case of stocks at risk of depletion, and also to reduce by 20% overfished stocks. Nevertheless, at the end of 2002, MAGP IV was interrupted following the reform of the CFP due to the rather modest results. A new simplified system was established, including an overall ceiling for fishing capacity for national fleets, in order to prevent the expansion of fleets and to verify that member-states follow their obligations under MAGPs. According to the final objectives defined in 2002, fleet reference levels were fixed and any new entry has to be followed by at least an equivalent withdrawal of capacity (entry/exit ratio of 1 to 1). Specifically, a vessel can only enter a fishery when the equivalent capacity has been withdrawn (Tidd et al., 2011).

One of the cornerstones of the last reform of the CFP is the Landing Obligation (LO). Although in 2013 the revised CFP already introduced the LO, it has been gradually implemented from 2015 to 2019 (Article 15 of Council Regulation (EU) No 1380/2013 (EU, 2013)). The LO stipulates the compulsory requirement to bring to land all catches, wanted and unwanted, of regulated fish species with the aim to gradually eliminate discards[11] (Uhlmann et al., 2019). Between 7 and 10 million tonnes of fish is discarded annually in the world (Kelleher, 2005; Zeller et al., 2018). In Europe, the North-East Atlantic and the North Sea have been defined as *discard hotspots,* because there are a number of discard-intensive fisheries in the area (Guillén et al., 2018). Thus, in order to reduce unwanted catches, the new Common Fisheries Policy (CFP) developed and introduced the landing obligation (LO), whereby catches of regulated species in EU waters (or by EU vessels in international waters) have to be kept on board, landed and deducted from applicable quotas. LO has been gradually adopted (between 2015 and 2019) in order to allow fishermen to adapt (EC, 2016; EU, 2013) and reduce unwanted catches through giving incentives for improved selectivity and adaptive measures in the choice of fishing gear and fishing strategies (Bohman, 2019). Additionally, these unwanted species can lead to the under-exploitation of more productive fish stocks, affecting the economy of the fisheries (Baudron & Fernandes, 2015; Ulrich et al., 2011). Consequently, as unwanted catches count against quotas, it creates additional costs for the fishing activity (M. A. Hall et al., 2000; S. J. Hall & Mainprize, 2005). Nevertheless, even bringing in unwanted catches of very low market value will incur additional costs at first, this should incentive fishers to avoid catching them in the first place (Condie et al., 2013).

Certainly, through joint efforts, EU countries have managed to achieve the objective of decreasing fishing pressure in the North-East Atlantic Ocean and the Baltic Sea (European Environment Agency, 2020) and the number of fish stocks being fished at maximum sustainable yield has increased (EEA, 2019). In contrast, still 40% of shark and ray species in European seas show declining populations (Bradai et al., 2012; Nieto et al., 2017), Atlantic cod in the North Atlantic is under threat (Stiasny et al., 2019) and most of the assessed fish stocks in the Mediterranean Sea (94%) and Black Sea (85.7%) were overfished in 2016 (EEA, 2019). To sum up, even 27% of the assessed stocks are in good status, 45% still show signs of overfishing and vulnerability (European Environment Agency, 2020).

Four types of control technologies are also used to monitor fleets effectively (EU, 2011). The first one is the electronic recording and reporting system (ERS)[12] (Article

[11] Discards are defined as the proportion of the total organic material of animal origin in the catch, which is thrown away or dumped at sea, for whatever reason (FAO, 2018).

[12] According to Article 36 of Regulation (EU) No 404/2011 (EU, 2011), 'EU fishing vessel subject to electronic completion and transmission of fishing logbook, transhipment declaration and landing declaration hall not be allowed to leave port without a fully operational electronic recording and reporting system installed on board'.

According to Article 42 of Regulation (EU) No 404/2011 (EU, 2011), 'Member-States shall maintain databases on the functioning of their electronic recording and reporting system'.

36 of Regulation (EU) No 404/2011 (EU, 2011)), which is used to collect data on fishing activity and send the information to the fisheries authorities of each member-states. The second one is the vessel monitoring system (VMS)[13] (Article 9 of Regulation (EU) No 404/2011 (EU, 2011)), a satellite-based fishing vessel system that provides data about the intervals on the location, course and speed of the fishing vessels. The third is the so-called vessel detection system (VDS) (Article 11 of Regulation (EU) No 404/2011 (EU, 2011)), a satellite-based technology, which helps to locate and identify vessels. The fourth, known as the automatic identification system (AIS) (Article 10 of Regulation (EU) No 404/2011 (EU, 2011)) is a vessel identification and monitoring system used for maritime safety and security. Notice that although the policy rules and monitoring systems are agreed in the EU, however they are implemented by the member-states. In order to favour the collaboration among countries, the European Fisheries Control Agency (EFCA) organises monitoring campaigns where national inspectors[14] join and check if they are implementing the rules properly. The credibility of the monitoring system is based on the establishment of sanctions when infringements happen. The EU has listed a series of violations and the countries must include the sanctions in their legislation effectively, proportionately and dissuasively (Garza et al., 2015; Miller et al., 2014; Moutopoulos et al., 2016).

1.3 The EU fisheries in numbers

In this subsection we focus on an input-output descriptive analysis of the EU fishing sector. First, as output variables, we pay attention on the fish catches and landings. Second, we study the distribution of the volume (q) and value of the landings (pq) following a country-based as much as a fish species-based perspective. Third, we consider three input variables; namely, fishing fleet as an approximation of capital (K), direct employment in fisheries (measured in full-time equivalent (FTE)), the number of producer organisations (POs), and the spawning stock biomass (SSB) of the key European leading species as a proxy of the populations of these species.

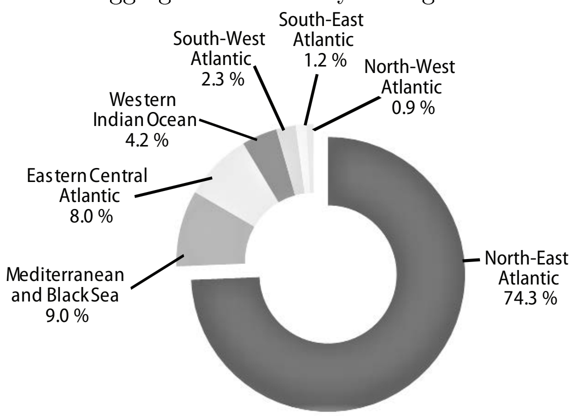
[13] According to Article 9(1) of Regulation (EU) No 404/2011 (EU, 2011), 'Member-States shall operate a satellite-based Vessel Monitoring System for the effective monitoring of fishing activities of their fishing vessels wherever they may be and of fishing activities in their waters. It is appropriate to establish common specifications at the level of the European Union for such a system. Such specifications should set out in particular the characteristics of satellite tracking devices, details on the transmission of position data and rules in the case of a technical failure or non-functioning of satellite tracking devices'.

[14] According to Article 9 of Regulation (EC) No 1005/2008 (EU, 2008), 'an inspection of a fishing vessel shall take place in port or on landing, on the following occasions: routinely subject to a sampling methodology based on a risk-based management; or where it is suspected of failing to comply with the rules of the Common Fisheries Policy'.

1.3.1 Fishing outputs

Fish *catches* (expressed in live weight equivalent of the landings, and measured in metric tons) are derived by the application of conversion factors to the actual landed or product weight. As such, catches exclude all quantities caught but not landed (i.e. discards and fish consumed on board). Production from aquaculture is also omitted from catch statistics. Data on catches (EUROSTAT, 2016) include the aggregated data of fish, crustaceans, molluscs and other aquatic organisms by fishing area for EU countries. Fish catches in the EU (EUROSTAT, 2016) were primarily taken from the North-East Atlantic (74.3%), the Mediterranean and the Black Sea (9%) and Eastern Central Atlantic (8%) (see Figure 1.1). The total amount caught by the EU fleet reached 5,011 thousand tonnes (EUROSTAT, 2016). Spain was the only EU member-state catching significant quantities in all the seven fishing areas, whereas the rest of the EU countries were mostly active in the North-East Atlantic.

Figure 1.1: Aggregated catches by fishing area in the EU



Source: EUROSTAT (2016)

Notes:
Aggregated catches of fish, crustaceans, molluscs and other aquatic organisms by fishing area (in live weight equivalent of the landings).

Landings relates to the total aggregated weight of marine fish species (tonnes) effectively landed in the fishing ports belonging to the EU. Accordingly, discards are explicitly excluded. Overall, the total volume of landings (q) in the EU[15] reached 3,430 thousand tonnes, and the value of such landings (i.e. the total volume (q) multiplied by

[15] For completeness, we are also including United Kingdom in our analysis, even if, it does not belong to the EU nowadays.

Table 1.2: Volume (q) and value (pq) of landings by country

	Volume (q)	%		Value (pq)	%
Spain	851	25%	Spain	2,152	32%
The Netherlands	546	16%	Italy	967	14%
United Kingdom	440	13%	France	926	14%
France	333	10%	United Kingdom	898	13%
Italy	202	6%	The Netherlands	580	9%
Denmark	174	5%	Denmark	310	5%
Portugal	128	4%	Portugal	290	4%
Poland	126	4%	Greece	185	3%
Finland	118	3%	Germany	162	2%
Germany	106	3%	Belgium	64	1%
Sweden	94	3%	Sweden	61	1%
Latvia	74	2%	Croatia	61	1%
Croatia	69	2%	Poland	46	1%
Estonia	64	2%	Finland	30	0.4%
Greece	62	2%	Latvia	20	0.3%
Belgium	15	0.4%	Estonia	15	0.2%
Bulgaria	9	0.2%	Ireland	11	0.2%
Romania	8	0.2%	Bulgaria	8	0.1%
Ireland	5	0.2%	Cyprus	6	0.1%
Lithuania	2	0.1%	Malta	5	0.1%
Cyprus	1	0.04%	Romania	4	0.1%
Malta	1	0.03%	Lithuania	1	0.02%
Slovenia	0.1	0.004%	Slovenia	1	0.01%
EU	3,430	100%	EU	6,803	100%

Source: EUROSTAT (2018)

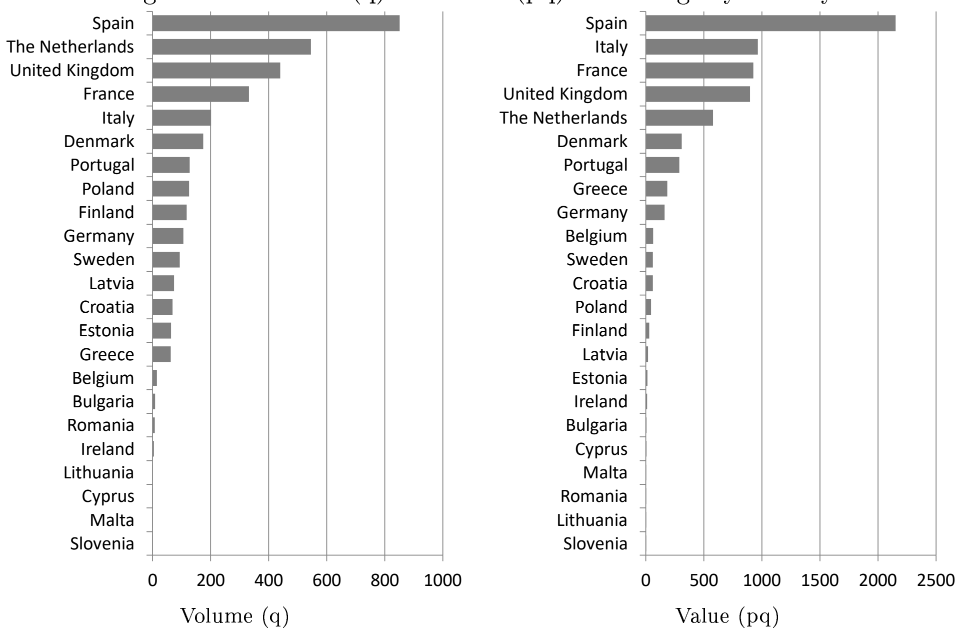
Notes:
Volume (q) in thousand tonnes product weight.
Value (pq) (q multiplied by first sale prices (p)) in million euros.

first sale prices (p), for now on (pq)), reached 6,803 million euros (EUROSTAT, 2018)[16]. Landings, both in volume (q) and value (pq), are heavily concentrated in specific fishing countries. The top five *most fishing countries* in the EU according to q (i.e. Spain (25%), the Netherlands (16%), United Kingdom (13%) and France (10%)) comprised more that 63% of the volume of fish landed in the EU. Equivalently, the top five *most fishing countries* in terms of pq (Spain, Italy, France and United Kingdom) concentrated around 73% of the value of landings. The leading country in terms of volume (q) was Spain (25%), and the value of such landings (pq) represented 32% over the aggregated value (pq). Contrarily, the Netherlands, with the 16% of total volume of landings (q),

[16] Up to date, the latest disposable data regarding the volume and value of landings in Spain is from 2017.

hardly reached the 9% of the total value (pq). United Kingdom, the third country in terms of q (13%) after Spain and the Netherlands, was (with the 13% of the total value of EU landings) in the fourth position. For several member-states, such as Bulgaria, Romania, Ireland, Lithuania, Cyprus, Malta and Slovenia, fishing activity is almost testimonial compared to the above-mentioned core fishing countries. Neither the volume (q), nor the value of their landings (pq) represents the 1% from the total (see Table 1.2 and Figure 1.2).

Figure 1.2: Volume (q) and value (pq) of landings by country



Source: EUROSTAT (2018)

Notes:
Volume (q) in thousand tonnes product weight.
Value (pq) (q multiplied by first sale prices (p)) in million euros.

Official landing records EUROSTAT (2018) show that 1,144 different fish species are landed in the EU fishing ports. Accordingly, to simplify the picture, when following a species-based perspective, we will focus on the ten key species, both in terms of volume (q) and value (pq). It is remarkable that the ten outstanding fish species account for the 57% of the aggregated volume of landings (q) and 37% of the aggregated value (pq) (see Table 1.3 and Figure 1.3). Atlantic herring (with q=565 thousand tonnes) is the leading fish species in terms of quantity (16%), followed by mackerel (7%), blue whiting (6%), pilchard (5%), sprat (5%), skipjack tuna (5%), anchovy (4%), chub mackerel (3%), hake

(3%) and horse mackerel (3%). The species list of the value-based ranking, leaded by hake (pq=359) (5%), consist of yellowfin tuna (4%), mackerel (4%), common sole (4%), great scallop (4%), cod (4%), Norway lobster (3%), anchovy (3%), herring (3%) and bigeye tuna (3%).

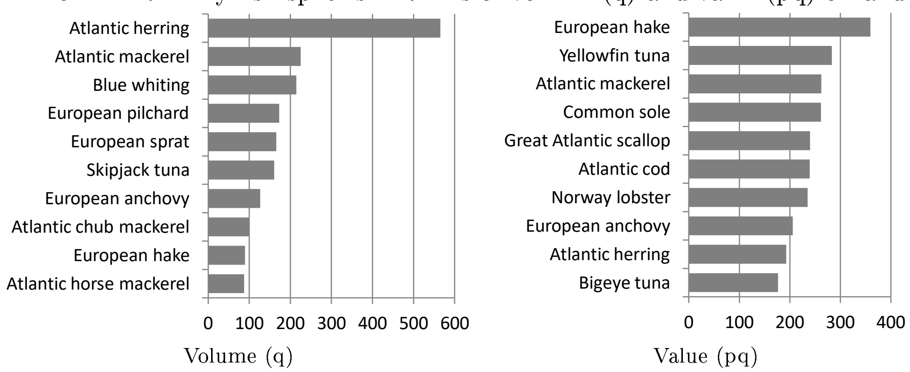
Table 1.3: The ten key fish species in terms of volume (q) and value (pq) of landings

	Volume (q)	%		Value (pq)	%
Atlantic herring	565	16%	European hake	359	5%
Atlantic mackerel	225	7%	Yellowfin tuna	283	4%
Blue whiting	215	6%	Atlantic mackerel	262	4%
European pilchard	173	5%	Common sole	262	4%
European sprat	166	5%	Great Atlant. scallop	240	4%
Skipjack tuna	161	5%	Atlantic cod	239	4%
European anchovy	127	4%	Norway lobster	235	3%
Atlantic chub mackerel	100	3%	European anchovy	206	3%
European hake	89	3%	Atlantic herring	193	3%
Atlant. horse mackerel	87	3%	Bigeye tuna	177	3%
EU	3,430	100%	EU	6,803	100%

Source: EUROSTAT (2018)

Notes:
Volume (q) in thousand tonnes product weight.
Value (pq) (q multiplied by first sale prices (p)) in million euros.

Figure 1.3: The ten key fish species in terms of volume (q) and value (pq) of landings



Source: EUROSTAT (2018)

Notes:
Volume (q) in thousand tonnes product weight.
Value (pq) (q multiplied by first sale prices (p)) in million euros.

Focusing on the country-based species distribution in terms of volume (q), Atlantic herring was primarily landed in the Netherlands (32%) and Finland (18%). The

Netherlands also accounted for the 70% of the total volume of landings for blue whiting and 40% of horse mackerel. Moreover, almost 100% of the volume of skipjack tuna and 62% of chub mackerel was landed in Spain. The volume of landings (q) is more homogeneously distributed for the rest of the key fish species. This is for example the case of pilchard. Croatia (27%), Spain (15%), Italy (15%), France (15%), the Netherlands (11%), Greece (7%), Portugal (6%) and United Kingdom (5%) comprise almost the 100% of the q for pilchard (see Table 1.4 and Figure 1.4).

Table 1.4: The ten key fish species in terms of volume of landings (q) by country (%)

	HER	MAC	WHB	PIL	SPR	SKJ	ANE	VMA	HKE	HOM
ES	-	15%	12%	15%	-	91%	40%	62%	43%	30%
NL	32%	26%	70%	11%	1%	-	0.02%	1%	1%	44%
UK	9%	42%	10%	5%	1%	-	0.4%	-	18%	-
PT	-	0.4%	1%	6%	-	5%	7%	31%	2%	18%
IT	-	0.5%	0.1%	15%	0.1%	3%	29%	1%	8%	3%
FR	1%	4%	3%	15%	0.01%	1%	3%	0.2%	16%	3%
PL	7%	-	-	-	34%	-	-	-	-	-
HR	-	0.02%	0.01%	27%	0.03%	-	10%	2%	1%	0.01%
LV	5%	-	-	-	23%	-	-	-	-	-
EL	-	0.2%	1%	7%	0.01%	-	10%	2%	5%	-
FI	18%	-	-	-	6%	-	-	-	-	-
SE	12%	0.1%	0.01%	-	12%	-	-	-	0.05%	0.01%
EE	6%	-	-	-	17%	-	-	-	-	-
DK	-	10%	-	-	-	-	-	-	6%	1%
DE	10%	1%	3%	0.01%	1%	-	-	-	0.01%	0.1%
IE	-	-	-	-	2%	-	-	-	-	-
BG	-	-	-	-	2%	-	0.04%	-	-	-
LT	0.1%	-	-	-	0.01%	-	-	-	-	-
MT	-	-	-	0.01%	0.02%	0.003%	-	-	-	-
BE	0.01%	-	-	0.01%	-	-	-	-	0.1%	-
RO	-	-	-	-	0.02%	-	0.02%	-	-	-
CY	-	-	-	0.01%	-	0.001%	-	0.01%	0.01%	-
SI	-	-	-	0.01%	-	-	-	-	0.01%	0.01%
EU	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Source: EUROSTAT (2018)

Notes:
Volume of landings (q) of each species (i) in each country (j) (%). i=(Atlantic herring (HER), Atlantic mackerel (MAC), Blue whiting (WHB), European pilchard (PIL), European sprat (SPR), Skipjack tuna (SKJ), European anchovy (ANE), Atlantic chub mackerel (VMA), European hake (HKE), Atlantic horse mackerel (HOM)). j=(Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Malta (MT), Poland (PL), Portugal (PT), Romania (RO), Slovenia (SI), Spain (ES), Sweden (SE), the Netherlands (NL), United Kingdom (UK)).

In terms of value (pq), Spain (46%), Italy (15%), United Kingdom (12%), France (12%), Greece (7%) and Denmark (4%) cover the 96% of hake. Additionally, almost 100% of the value (pq) of yellowfin tuna and bigeye tuna is landed in Spain. The pq for great Atlantic scallop is mainly concentrated in France (69%) and United Kingdom (31%). The value of landings is more homogeneously distributed for fish species such as cod. United Kingdom (27%), Denmark (20%), Spain (17%), Germany (15%), France (9%), Poland (5%) and Portugal (4%) comprise almost the 97% of the aggregated value of landings for cod (see Table 1.5 and Figure 1.5).

Table 1.5: The ten key fish species in terms of value of landings (pq) by country (%)

	HKE	YFT	MAC	SOL	SCE	COD	NEP	ANE	HER	BET
ES	46%	97%	13%	2%	0.1%	17%	5%	43%	-	93%
UK	12%	-	43%	9%	31%	27%	38%	0.3%	11%	-
FR	12%	2%	5%	27%	69%	9%	13%	2%	1%	1%
NL	0.1%	-	24%	37%	0.01%	1%	3%	0.01%	45%	-
IT	15%	1%	2%	9%	-	-	16%	33%	-	0.5%
DK	4%	-	11%	3%	-	20%	15%	-	-	-
DE	0.01%	-	1%	0.03%	-	15%	0.2%	-	10%	-
EL	7%	-	0.5%	2%	0.01%	-	1%	10%	-	-
PT	1%	-	0.4%	2%	-	4%	2%	5%	-	6%
SE	0.05%	-	0.2%	0.05%	-	2%	6%	-	10%	-
PL	-	-	-	-	-	5%	-	-	6%	-
FI	-	-	-	-	-	0.1%	-	-	10%	-
BE	0.03%	-	0.02%	9%	0.4%	0.5%	0.3%	0.01%	0.01%	-
HR	1%	-	0.04%	1%	-	-	1%	6%	-	-
LV	-	-	-	-	-	0.1%	-	-	4%	-
EE	-	-	-	-	-	0.001%	-	-	3%	-
LT	-	-	-	-	-	0.2%	-	-	0.11%	-
MT	-	-	0.1%	-	-	-	0.01%	-	-	-
SI	0.01%	-	0.01%	0.05%	-	-	-	-	-	-
RO	-	-	-	-	-	-	-	0.02%	-	-
CY	0.01%	-	-	-	-	-	-	-	-	-
BG	-	-	-	-	-	-	-	0.01%	-	-
IE	-	-	-	-	-	-	-	-	-	-
EU	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Source: EUROSTAT (2018)

Notes:
Value of landings (pq) of each species (i) in each country (j) (%). i=(European hake (HKE), Yellowfin tuna (YFT), Atlantic Mackerel (MAC), Common sole (SOL), Great Atlantic scallop (SCE), Atlantic cod (COD), Norway lobster (NEP), European anchovy (ANE), Atlantic herring (HER), Bigeye tuna (BET)). j=(Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Malta (MT), Poland (PL), Portugal (PT), Romania (RO), Slovenia (SI), Spain (ES), Sweden (SE), the Netherlands (NL), United Kingdom (UK)).

Figure 1.4: The ten key fish species in terms of volume of landings (q) by country (%)

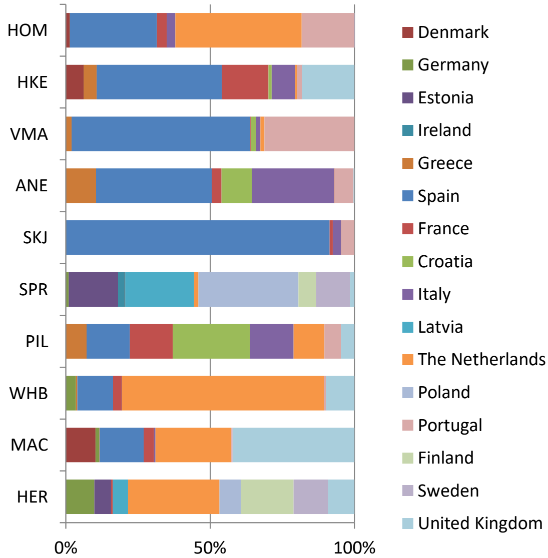
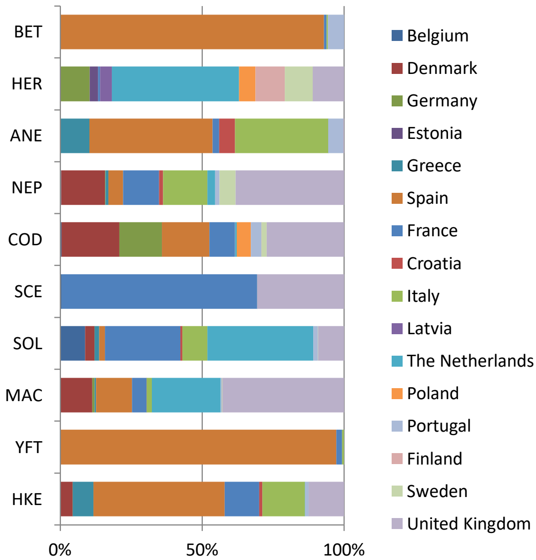


Figure 1.5: The ten key fish species in terms of value of landings (pq) by country (%)



1.3.2 Fishing inputs

The management of the *fleet* capacity has been essential to ensure the sustainability of the fishing sector. In fact, reducing the fleet capacity has been one of the cornerstones of the Common Fisheries Policy (CFP) by means of the so-called Multiannual Guidance Plans (MAGP). In the last two decades the EU fishing capacity has been reduced in terms of number of vessels (NV) by -16.4% (Lagares & Ordaz, 2014; Tingley et al., 2005) and -24% in terms of capacity (GT) (EUROSTAT, 2018). The fishing fleet in the EU (2018) is comprised by 81,860 vessels (NV), a capacity of 1,549,742 gross tonnage (GT)[17], a fishing power of 6,151,200 kilowatts (KW)[18] (EUROSTAT, 2018), and employs 118,322 fishers (OECD, 2017). The average European fishing vessel has 19 GT, 75 KW, 8 metres, a crew of 1.45 full-time fishers and is 23 years old.

The fleet distribution by length (LE)[19] shows the clear dominance of small-scale artisanal vessels ($\leq$12 metres) (see Table 1.6 and Figure 1.6). Specifically, there are 69,842 small-scale fishing vessels in the EU, which represent 85% of the total NV, 11% of the GT and 40% of the KW. Contrarily, only 2,673 of the vessels are 24 metres or over, making up the 3% of the total NV, 65% of the GT and 32% of the KW.

Table 1.6: EU fishing fleet by length

	NV	%	GT	%	KW	%
< 12m	69,842	85%	174,012	11%	2,490,944	40%
12 to 24m	9,345	11%	371,776	24%	1,700,134	28%
> 24m	2,673	3%	1,003,955	65%	1,960,129	32%
Total	81,860	100%	1,549,742	100%	6,151,200	100%

Source: EUROSTAT (2018)

Notes:
NV is the number of vessels, GT the gross tonnage and KW the kilowatts.
The length (LE) categories: less than 12 metres (<12m), 12 to 24 metres (12 to 240m), and >24 metres (>24m).

According to the age of the fishing vessels, most of the fishing units (73%) are 20 years old or over, and amount for the 58% of the total GT and 63% of the KW. Only 7% of the vessels are 10 years or less. These newer vessels constitute the 9% of the total

[17]Gross Tonnage (GT) is defined as a function of the total volume of all enclosed spaces of a ship and it is measured in tonnes.

[18]The engine power (KW) is the total of the maximum continuous power which can be obtained at the flywheel of each engine (whatever by mechanical, electrical, hydraulic or other means) to be applied to vessel the propulsion and it is measured in kilowatts.

[19]Length (LE) is defined as the distance in a straight line between the foremost point of the bow and the aftermost point of the stern and it is measured in metres.

GT and 9% of the KW in the EU (see Table 1.7 and Figure 1.6).

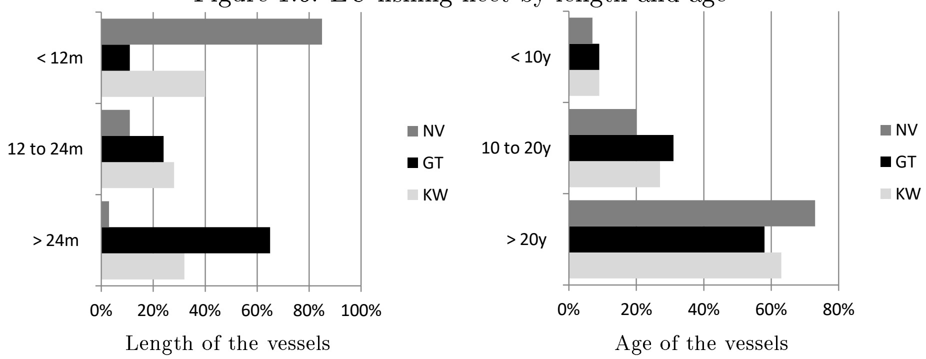
Table 1.7: EU fishing fleet by age

	NV	%	GT	%	KW	%
< 10y	5,860	7%	139,159	9%	539,704	9%
10 to 20y	16,092	20%	481,343	31%	1,688,686	27%
> 20y	59,650	73%	894,067	58%	3,852,864	63%
unk.	258	0%	35,175	2%	69,949	1%
Total	81,860	100%	1,549,742	100%	6,151,200	100%

Source: EUROSTAT (2018)

Notes:
NV is the number of vessels, GT the gross tonnage and KW the kilowatts.
The age categories: (a) less than 10 years (<10y), (b) 10 to 20 years (10 to 20y), (c) 20 years or over (>20y), (d) unknown (unk.).

Figure 1.6: EU fishing fleet by length and age



Source: EUROSTAT (2018)

The distribution of the fishing fleet is rather heterogeneous among member-states. The fishing vessels (NV) are mainly concentrated in the Mediterranean countries (i.e. Greece (18%), Italy (15%), Spain (11%) and Portugal (10%)) (see Table 1.8 and Figure 1.7). Nevertheless, the Greek fleet only represents the 5% of the total GT and 7% of the KW, while the Italian fleet comprises the 9% of the GT and 15% of the KW, patterns that evidence the artisanal (≤12 metres) nature of their fleets. Nevertheless, the Spanish fleet, with 21% of the GT and 13% of the KW, exhibits a mixed artisanal and industrial nature. In the opposite side, the Netherlands is the second country in terms of landed volume (16% from the total volume (q) in the EU). However, the Dutch fleet only accounts for the 1% of the fishing vessels (NV), 8% of the GT and 5% of the KW, figures that give support of the industrial nature of the fishing fleet in the Netherlands.

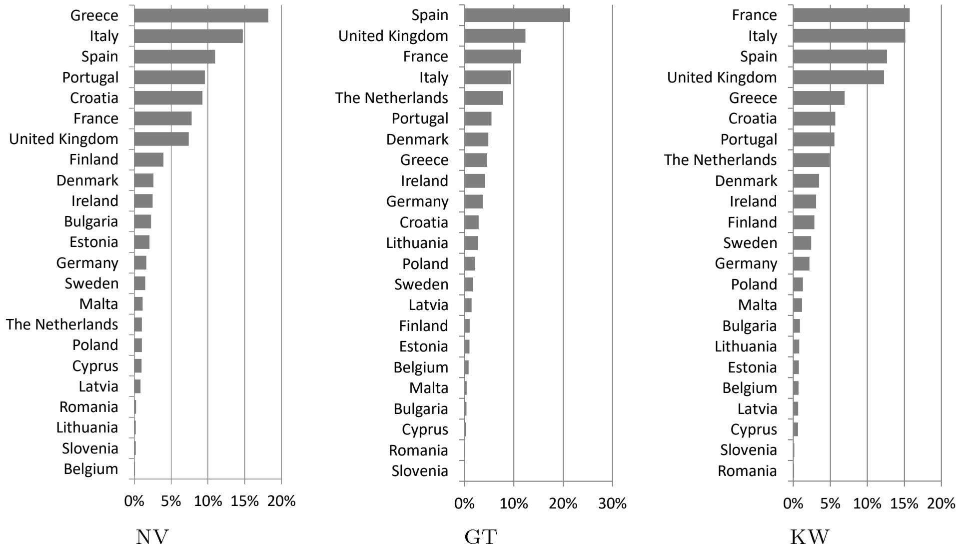
Table 1.8: EU fishing fleet by country

	NV	%	GT	%	KW	%
Greece	14,934	18%	71,104	5%	426,431	7%
Italy	12,059	15%	146,260	9%	930,406	15%
Spain	8,976	11%	331,778	21%	778,914	13%
Portugal	7,851	10%	84,416	5%	341,116	6%
Croatia	7,573	9%	44,286	3%	348,837	6%
France	6,379	8%	177,126	11%	967,643	16%
United Kingdom	6,046	7%	191,439	12%	753,124	12%
Finland	3,245	4%	15,952	1%	174,393	3%
Denmark	2,122	3%	74,426	5%	214,197	3%
Ireland	2,032	2%	64,455	4%	190,015	3%
Bulgaria	1,857	2%	6,086	0.4%	54,491	1%
Estonia	1,663	2%	15,775	1%	46,817	1%
Germany	1,335	2%	58,804	4%	133,232	2%
Sweden	1,215	1%	25,859	2%	148,984	2%
Malta	917	1%	6,496	0.4%	72,487	1%
The Netherlands	833	1%	120,509	8%	304,200	5%
Poland	827	1%	32,350	2%	80,227	1%
Cyprus	807	1%	3,638	0.2%	38,578	1%
Latvia	676	1%	22,325	1%	40,724	1%
Romania	167	0.2%	1,472	0.1%	6,249	0.1%
Lithuania	144	0.2%	41,619	3%	48,844	1%
Slovenia	134	0.2%	669	0.04%	8,621	0.1%
Belgium	68	0.1%	12,898	1%	42,670	1%
EU	81,860	100%	1,549,742	100%	6,151,200	100%

Source: EUROSTAT (2018)

Notes:
NV is the number of vessels, GT the gross tonnage and KW the kilowatts.

Figure 1.7: EU fishing fleet (NV, GT, KW) by country (%)



Source: EUROSTAT (2018)

Notes:
NV is the number of vessels, GT the gross tonnage and KW the kilowatts.

As mentioned, 85% of the fishing vessels in the EU are below 12 metres, and accordingly may be typified as artisanal. Again, this sub-fleet is not homogeneously distributed along the EU. The small-scale artisanal vessels (<12m) are mainly Greek (NV=14,073, 20% of the EU), Italian (NV=8,644, 12%), Portuguese (NV=7,122, 10%), Croatian (NV=7,017, 10%), Spanish (NV=6567, 9%) and French (NV=5,491, 8%), whereas most of the large-scale industrial vessels (>24m) are from Spain (NV=704, 26%), Italy (NV=318, 12%), the Netherlands (NV=247, 9%) and United Kingdom (NV=227, 8%). Although there are only 68 fishing vessels in Belgium, its fleet distribution by length is quite different from the rest of the countries. There is only one artisanal (<12m) vessel in Belgium, while the rest of the vessels are 12 to 24 metres (NV=33) or large-scale (>24m) (NV=34) (see Table 1.9).

Table 1.9: Country-based number of vessels (NV) by length (LE)

	< 12m	%	12 to 24m	%	> 24m	%	Total	%
Greece	14,073	20%	684	7%	177	7%	14,934	18%
Italy	8,644	12%	3,097	33%	318	12%	12,059	15%
Spain	6,567	9%	1,705	18%	704	26%	8,976	11%
Portugal	7,122	10%	553	6%	176	7%	7,851	10%
Croatia	7,017	10%	446	5%	110	4%	7,573	9%
France	5,491	8%	693	7%	195	7%	6,379	8%
UK	5,144	7%	675	7%	227	8%	6,046	7%
Finland	3,182	5%	43	0%	20	1%	3,245	4%
Denmark	1,772	3%	277	3%	73	3%	2,122	3%
Ireland	1,752	3%	171	2%	109	4%	2,032	2%
Bulgaria	1,762	3%	84	1%	11	0%	1,857	2%
Estonia	1,621	2%	17	0%	25	1%	1,663	2%
Germany	1,053	2%	231	2%	51	2%	1,335	2%
Sweden	1,062	2%	123	1%	30	1%	1,215	1%
Malta	832	1%	66	1%	19	1%	917	1%
Netherlands	343	0%	243	3%	247	9%	833	1%
Poland	665	1%	113	1%	49	2%	827	1%
Cyprus	764	1%	37	0%	6	0%	807	1%
Latvia	612	1%	13	0%	51	2%	676	1%
Romania	143	0%	20	0%	4	0%	167	0%
Lithuania	102	0%	5	0%	37	1%	144	0%
Slovenia	118	0%	16	0%	0	0%	134	0%
Belgium	1	0%	33	0%	34	1%	68	0%
EU	69,842	100%	9,345	100%	2,673	100%	81,860	100%

Source: EUROSTAT (2018)

Notes:
Length categories: (a) less than 12 metres (<12m), (b) 12 to 24 metres (12 to 24m), and (c) 24 metres or over (>24m).

73% of the fishing units in the EU are above 20 years, while the segment of the new vessels (< 10 years) hardy represents 7%. Most of the *new* vessels (<10y) may be found in Italy (NV= 1,137, 19% of the EU), Greece (NV=770, 13%), United Kingdom (NV=688, 12%) and France (NV=606, 10%). Besides, the *old* fishing vessels (>20y) are mainly Greek (NV=11,388, 19% of the EU), Italian (NV=9,241, 15%), Croatian (NV=6,311, 11%) and Spanish (NV=6,050, 10%) (see Table 1.10).

Table 1.10: Country-based number of vessels (NV) by age

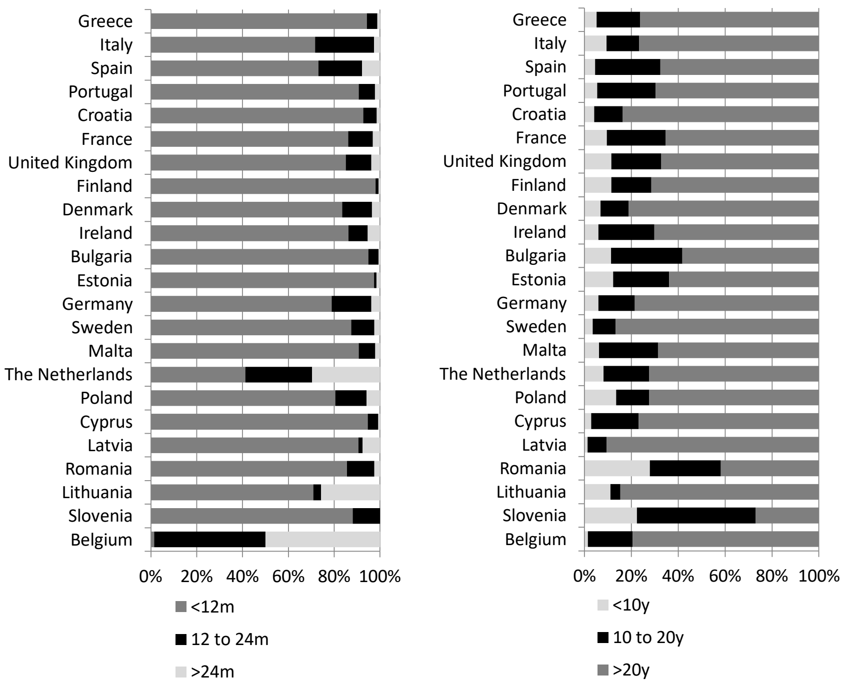
	< 10y	%	10-20y	%	> 20y	%	unk.	%	Total	%
Greece	770	13%	2,776	17%	11,388	19%	0	0%	14,934	18%
Italy	1,137	19%	1,665	10%	9,241	15%	16	6%	12,059	15%
Spain	407	7%	2,490	15%	6,050	10%	29	11%	8,976	11%
Portugal	422	7%	1,949	12%	5,448	9%	32	12%	7,851	10%
Croatia	306	5%	919	6%	6,311	11%	37	14%	7,573	9%
France	606	10%	1,586	10%	4,152	7%	35	14%	6,379	8%
UK	688	12%	1,274	8%	4,039	7%	45	17%	6,046	7%
Finland	368	6%	554	3%	2,306	4%	17	7%	3,245	4%
Denmark	144	2%	251	2%	1,718	3%	9	3%	2,122	3%
Ireland	121	2%	482	3%	1,421	2%	8	3%	2,032	2%
Bulgaria	208	4%	564	4%	1,076	2%	9	3%	1,857	2%
Estonia	203	3%	395	2%	1,061	2%	4	2%	1,663	2%
Germany	79	1%	207	1%	1,047	2%	2	1%	1,335	2%
Sweden	42	1%	118	1%	1,052	2%	3	1%	1,215	1%
Malta	56	1%	231	1%	629	1%	1	0%	917	1%
Netherlands	67	1%	162	1%	601	1%	3	1%	833	1%
Poland	112	2%	116	1%	599	1%	0	0%	827	1%
Cyprus	23	0%	164	1%	620	1%	0	0%	807	1%
Latvia	9	0%	54	0%	611	1%	2	1%	676	1%
Romania	46	1%	50	0%	69	0%	2	1%	167	0%
Lithuania	16	0%	6	0%	122	0%	0	0%	144	0%
Slovenia	29	0%	66	0%	35	0%	4	2%	134	0%
Belgium	1	0%	13	0%	54	0%	0	0%	68	0%
EU	5,860	100%	16,092	100%	59,650	100%	258	100%	81,860	100%

Source: EUROSTAT (2018)

Notes:
Age categories: (a) less than 10 years (<10y), (b) 10 to 20 years (10-20y), (c) 20 years or over (>24y), and (d) unknown (unk.).

According to the proportion (%) of the small-scale artisanal vessels ($\leq$12m) to the total fleet of each country (Figure, 1.8(a)), the highest proportion of artisanal vessels may be found in Finland (98%), followed by Estonia (97%), Bulgaria (95%), Cyprus (95%) and Greece (94%). In the opposite side, the presence of large-scale vessels ($>$24m) is the highest in Belgium (50%), the Netherlands (30%) and Lithuania (26%). Besides, the newest fishing fleet ($<$10y) (28%) is Romanian, followed by Slovenia (22%), Poland (14%) and Estonia (12%). Contrarily, the oldest fishing fleet ($>$20y) (90%) is Latvian, followed by Sweden (87%), Lithuania (85%), Croatia (83%) and Denmark (81%) (see Figure 1.8(b)).

Figure 1.8: Country-based proportion of vessels by length (a) and age (b)



Length of the vessels Age of the vessels

Source: EUROSTAT (2018)

Regarding the *people employed in fisheries*, there were more than 118,000 full-time (FTE)[20] fishers in the EU (2017). The outstanding countries in terms of FTE were Italy (26,146), Greece (22,081), Spain (17,981) and Portugal (17,642). These four

[20]Full-time equivalent (FTE), is a unit to measure employed people in a way that makes them comparable although they may work a different number of hours per week.

Mediterranean countries (Italy (22%), Greece (19%), Spain (15%) and Portugal (15%)) make up around the 71% of the fishermen in the EU. In the opposite side, the rank is closed by countries such as Belgium (FTE=13), Romania (FTE=60) and Slovenia (FTE= 63). Since 2005, all the EU member-states have reduced their FTE fishers, although Belgian (-98%), Polish (-95%) and Latvian (-92%) FTE have been reduced the most (see Table 1.11 and Figure 1.9).

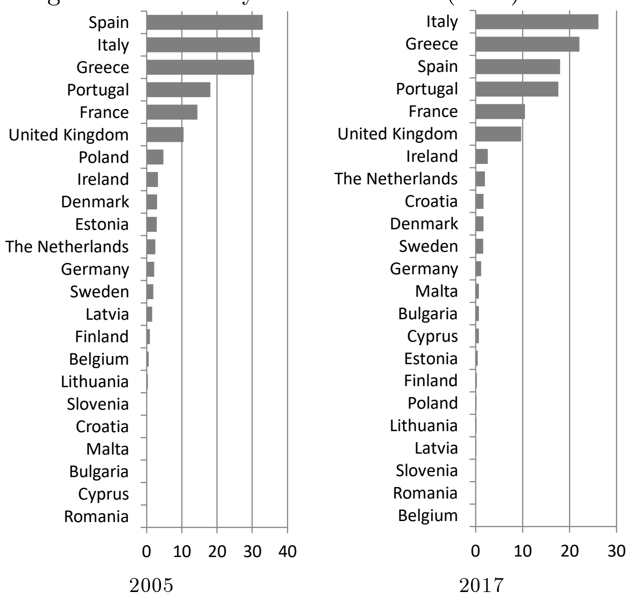
Table 1.11: Country-based full-time (FTE) fishers (2005-2017)

	min	max	mean	st.dev.	2005	%	2017	%
Italy	25,812	32,174	28,433	1,983	32,174	20%	26,146	22%
Greece	22,081	39,705	33,724	4,849	30,502	19%	22,081	19%
Spain	17,981	41,062	28,220	7,823	33,008	20%	17,981	15%
Portugal*	16,402	18,085	17,123	474	18,085	11%	17,642	15%
France	10,469	14,404	11,268	1,087	14,404	9%	10,508	9%
United Kingdom	9,468	10,492	10,085	284	10,492	6%	9,710	8%
Ireland	2,343	3,777	2,916	526	3,170	2%	2,620	2%
The Netherlands*	1,779	2,509	2,118	231	2,509	2%	1,981	2%
Croatia	1,665	2,071	1,868	287	-	-	1,665	1%
Denmark	1,511	2,955	1,857	468	2,955	2%	1,644	1%
Sweden*	1,590	1,902	1,735	112	1,902	1%	1,590	1%
Germany*	1,207	4,917	2,555	1,395	2,184	1%	1,207	1%
Malta	719	959	880	77	-	-	719	1%
Bulgaria	532	716	630	88	-	-	716	1%
Cyprus	689	909	787	112	-	-	689	1%
Estonia	460	2,977	2,557	647	2,872	2%	460	0.4%
Finland	271	924	697	273	889	1%	271	0.2%
Poland	220	4,770	2,274	1,647	4,770	3%	225	0.2%
Lithuania	166	369	278	61	316	0.2%	211	0.2%
Latvia	106	1,549	357	442	1,549	1%	120	0.1%
Slovenia	50	110	80	18	78	0.05%	63	0.1%
Romania	45	60	53	11	-	-	60	0.1%
Belgium	13	571	167	153	571	0.4%	13	0.01%
Total	118,322	166,172	147,722	13,904	162,430	100%	118,322	100%

Source: OECD (2017)

Notes:
FTE is full-time employed fishermen in the period (2005-2017); min is the minimum of the period, max the maximum, mean the average, number of fishermen in the sample period, and stv. dev the standard deviation.
*Total employed fishermen (full-time and part-time) for Portugal, Germany, the Netherlands and Sweden

Figure 1.9: Country-based full-time (FTE) fishers



Source: OECD (2017)

The typology of fishing vessels also differs significantly by member-state. Focusing on the average technical characteristics per vessel (Table 1.12 and Figure 1.10), the vessels with the highest average capacity are from Lithuania (GT=289) and Belgium (GT=190), while the fleets with the lowest average capacity are Bulgarian (GT=3), Slovenian (GT=5), Cypriot (GT=5), Finish (GT=5) and Greek (GT=5). Obviously, due to the high correlation among GT, KW and LE, a similar pattern may be found in the fishing power and length. The most powerful vessels are Belgian (KW=628), followed by the Netherlands (KW=365) and Lithuania (KW=339), whereas the least powerful ones are Estonian (KW=28), Bulgarian (KW=29) and Greek (KW=29). Regarding the average length per vessel, the largest vessels are Belgian (LE=27) and Dutch (LE=20), while the smallest are Estonian (LE=5), Finish (LE=6), Bulgarian (LE=6), Croatian (LE=6) and Cypriot (LE=6). Besides, the newest vessels are Slovenian (AGE=15), Romanian (AGE=17) and Bulgarian (AGE=20), whereas the oldest are Latvian (AGE=26), Belgian (AGE=25), Swedish (AGE=25) and Croatian (AGE=25). The biggest crew (full-time fishers) per vessel may be found in the Netherlands (FTE=2.38), Portugal (FTE=2.25), Italy (FTE=2.17) and Spain (FTE=2), while the smallest crews are Finish (FTE=0.08), Latvian (FTE=0.18) and Belgian (FTE=0.19).

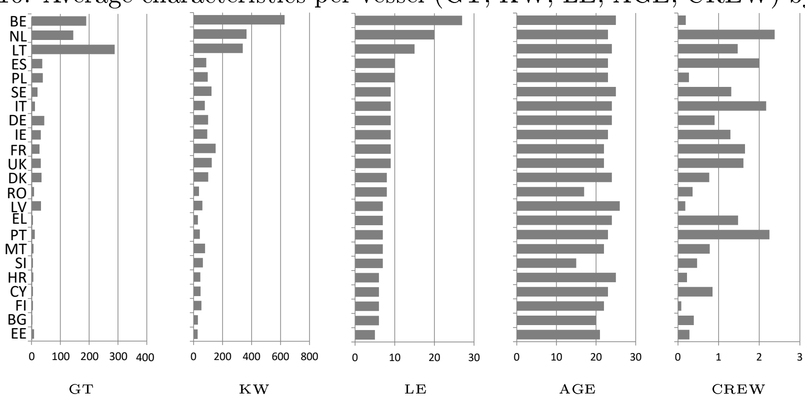
Table 1.12: Average characteristics per vessel (GT, KW, LE, AGE, CREW) by country

	GT	KW	LE	AGE	CREW
Belgium (BE)	190	628	27	25	0.19
The Netherlands (NL)	145	365	20	23	2.38
Lithuania (LT)	289	339	15	24	1.47
Spain (ES)	37	87	10	23	2
Poland (PL)	39	97	10	23	0.27
Italy (IT)	12	77	9	24	2.17
France (FR)	28	152	9	22	1.65
United Kingdom (UK)	32	125	9	22	1.61
Ireland (IE)	32	94	9	23	1.29
Germany (DE)	44	100	9	24	0.9
Sweden (SE)	21	123	9	25	1.31
Denmark (DK)	35	101	8	24	0.77
Romania (RO)	9	37	8	17	0.36
Greece (EL)	5	29	7	24	1.48
Portugal (PT)	11	43	7	23	2.25
Malta (MT)	7	79	7	22	0.78
Latvia (LV)	33	60	7	26	0.18
Slovenia (SI)	5	64	7	15	0.47
Croatia (HR)	6	46	6	25	0.22
Finland (FI)	5	54	6	22	0.08
Bulgaria (BG)	3	29	6	20	0.39
Cyprus (CY)	5	48	6	23	0.85
Estonia (EE)	9	28	5	21	0.28
EU	19	75	8	23	1.45

Source: EUROSTAT (2018)

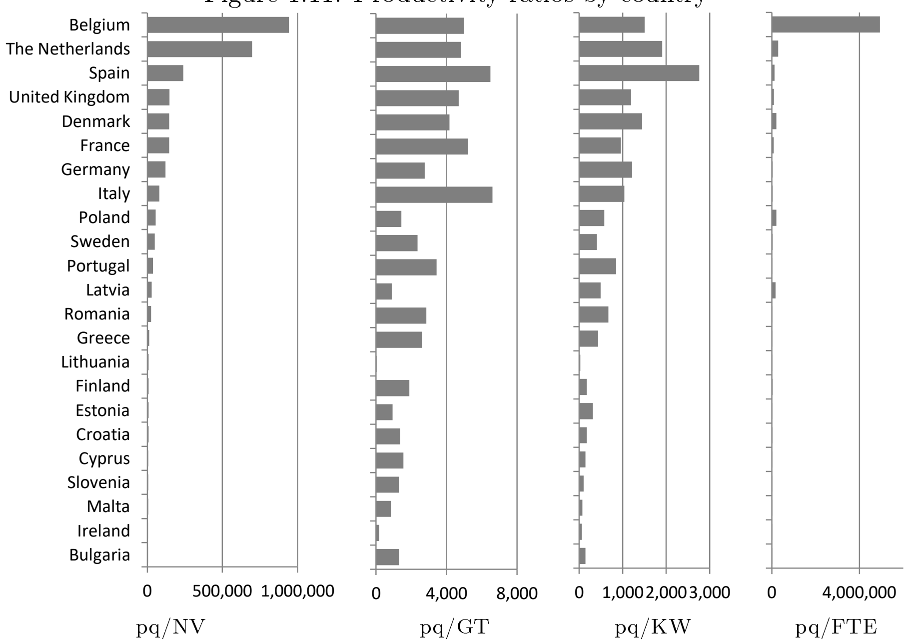
Notes:
GT is the gross tonnage, KW the kilowatts, LE the length, AGE the age and CREW the full-time fishers per vessel.

Figure 1.10: Average characteristics per vessel (GT, KW, LE, AGE, CREW) by country



Productivity ratios may be helpful to evaluate the efficiency of the fishing fleets in the EU (Table 1.13 and Figure 1.11). The most productive countries in terms of total value of landings per vessel (pq/NV) are Belgium (943,299 €/NV), the Netherlands (696,703 €/NV) and Spain (239,753 €/NV). Contrarily, the least productive countries are Bulgaria (4,280 €/NV), Ireland (5,573 €/NV) and Malta (5,981 €/NV). Regarding the pq per gross tonnage (pq/GT), the most productive countries are Italy (6,611 €/GT), Spain (6,486 €/GT) and France (5,228 €/GT), while Lithuania (32 €/GT) and Ireland (176 €/GT) are the least productive ones. According to the engine power employed (pq/KW), the most productive countries are Spain (2,763 €/KW), the Netherlands (1,908 €/KW) and Belgium (1,503 €/KW), whereas Lithuania (28 €/KW), Ireland (60 €/KW) and Malta (76 €/KW) are the least productive ones. In terms of the efficiency of the full-time fishers (pq/FTE), Belgium (4,934,178 €/FTE) and the Netherlands (292,960 €/FTE) are the most productive countries, while Romania (397 €/FTE), Malta (4,209 €/FTE) and Ireland (4,322 €/FTE) are the least productive ones.

Figure 1.11: Productivity ratios by country



Source: EUROSTAT (2018)

Table 1.13: Productivity ratios by country (€)

	pq/NV	pq/GT	pq/KW	pq/FTE
Belgium	943,299	4,973	1,503	4,934,178
The Netherlands	696,703	4,816	1,908	292,960
Spain	239,753	6,486	2,763	119,683
United Kingdom	148,475	4,689	1,192	92,449
Denmark	146,042	4,164	1,447	205,096
France	145,178	5,228	957	88,132
Germany	121,310	2,754	1,216	37,981
Italy	80,182	6,611	1,039	36,981
Poland	56,090	1,434	578	206,161
Sweden	50,075	2,353	408	38,265
Portugal	36,876	3,430	849	16,411
Latvia	29,540	894	490	166,409
Romania	25,182	2,857	673	397
Greece	12,399	2,604	434	8,386
Lithuania	9,375	32	28	6,398
Finland	9,290	1,890	173	35,593
Estonia	8,890	937	316	5,669
Croatia	8,010	1,370	174	25,444
Cyprus	6,989	1,550	146	6,091
Slovenia	6,446	1,291	100	17,275
Malta	5,981	844	76	4,209
Ireland	5,573	176	60	4,322
Bulgaria	4,280	1,306	146	13,704
Average	121,563	2,726	725	276,617

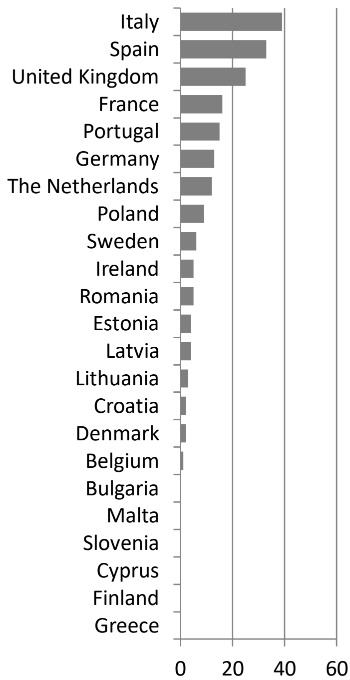
Source: EUROSTAT (2018)

Notes:
Value of landings in euros (pq) per vessel (NV), gross tonnage (GT), kilowatt (KW) and full-time fisher (FTE).

Producer organisations are officially recognised entities in charge of the management of fisheries and play an essential role in guiding producers towards sustainable fishing and supporting their members in creating added value. Producer organisations (POs) also develop production and marketing plans to help their members match supplies with market demands. There are 194 producer organisations in the EU (EC, 2018). Most of the POs are concentrated in Italy (PO=39, 20% of the EU), Spain (PO=33, 17%), United Kingdom (PO=25, 13%), France (PO=16, 8%) and Portugal (PO=15, 8%). Even producer organisations play an essential role in the fishing sector, there are some countries (namely, Greece, Finland, Cyprus, Slovenia, Malta and Bulgaria) in which there are no POs (see Table 1.14).

Table 1.14: Producer organisations

	POs	%
Italy	39	20%
Spain	33	17%
United Kingdom	25	13%
France	16	8%
Portugal	15	8%
Germany	13	7%
The Netherlands	12	6%
Poland	9	5%
Sweden	6	3%
Romania	5	3%
Ireland	5	3%
Latvia	4	2%
Estonia	4	2%
Lithuania	3	2%
Denmark	2	1%
Croatia	2	1%
Belgium	1	1%
Greece	0	0%
Finland	0	0%
Cyprus	0	0%
Slovenia	0	0%
Malta	0	0%
Bulgaria	0	0%
EU	194	100%



Source: EC (2018)

Notes:
Number of producer organisations (PO) in fisheries by country.

In addition to capital and labour, the production process inherent in fisheries requires fish stocks as production inputs. Accordingly, we are paying attention to the *spawning stock biomass* (SSB) of the key commercial fish species in the EU. SSB captures the total weight of the fish in a stock (measured in tonnes) that is old enough to spawn, and it is used as an approximation of the status of the stock and its reproductive capacity. There exists stock assessment for 34 fish species in the North-East Atlantic, which amounted for 30,254 thousand tonnes in 2016. Atlantic herring is the outstanding fish species (9,891 thousand tonnes (33%)), followed by blue whiting (5,032 thousand tonnes (17%)) and Atlantic mackerel (4,958 thousand tonnes (16%)) (see Table 1.15 and Figure 1.12). In the Northern Atlantic and adjacent areas, the number of stocks within safe biological limits has increased almost by 50% from 2003 to 2017 (+2% from 2016) (EC, 2019). Essentially, the overall biomass volume has positively increased by around 41% (2000-2016) (ICES, 2017).

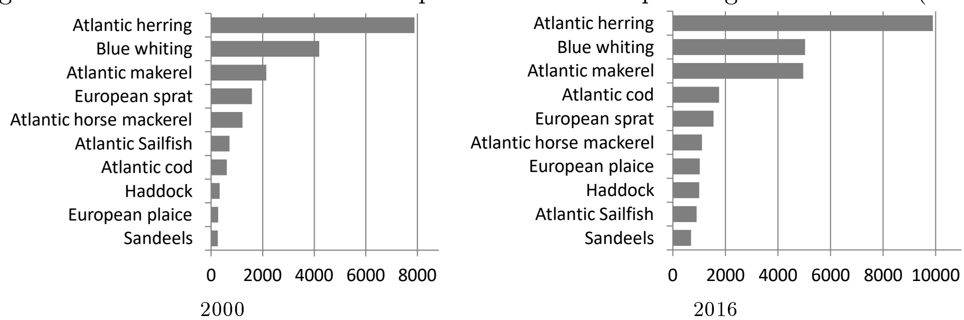
Table 1.15: The ten most abundant fish species in terms of spawning stock biomass (SSB) (2000-2016)

	min	max	mean	st.dev.	2000	%	2016	%
HER	7,694	11,643	9,851	1,229	7,885	37%	9,891	33%
WHB	2,678	6,875	4,499	1,354	4,196	20%	5,032	17%
MAC	1,949	5,304	3,334	1,241	2,141	10%	4,958	16%
COD	612	2,963	1,564	778	612	3%	1,762	6%
SPR	856	1,585	1,223	202	1,585	7%	1,552	5%
HOM	928	1,547	1,242	196	1,217	6%	1,109	4%
PLE	245	1,027	485	239	278	1%	1,027	3%
HAD	335	1,144	809	249	335	2%	1,007	3%
SAI	630	1,121	847	157	713	3%	909	3%
SAN	140	726	387	166	266	1%	693	2%
Total SSB	21,517	30,254	26,458	2,655	21,517	100%	30,254	100%

Source: ICES (2017)

Notes:
The minimum (min), maximum (max) and average (mean) spawning stock biomass (SSB) in the sample period (2000-2016), standard deviation, the SSB in 2000 and the SSB in 2016.
Fish species= Atlantic herring (HER), Blue whiting (WHB), Atlantic mackerel (MAC), Atlantic cod (COD), European sprat (SPR), Atlantic horse mackerel (HOM), European plaice (PLE), haddock (HAD), Atlantic sailfish (SAI) and sandeels (SAN).

Figure 1.12: The ten most abundant species in terms of spawning stock biomass (SSB)



Source: ICES (2017)

1.4 Clustering EU fishing countries

In the previous subsection we have seen that there is a notorious heterogeneity among the different fishing countries in the EU. In this section, taking advantage of the input and output data introduced above, we focus on the taxonomy of the fishing countries related to fishing activity by means of a two-step principal component-clustering approach. In order to do so, we first present the specific clustering algorithms as well as the variables to be incorporated in our variate.

A two-step principal component-clustering is used in order to quantify the structural characteristics of the EU fishing countries. Usual properties such as normality linearity and homoscedasticity are not required in cluster analysis. Nevertheless, other key issues such as representativeness of the sample, presence and treatment of outliers and the potential correlation in the cluster variate should be carefully accounted (del Valle & Astorkiza, 2019; Milligan, 1996). In fact, results coming from cluster analysis entirely depend on the set of variables included in the analysis or variate. Variables should be selected and weighted carefully, and only variables that help to discriminate the countries should be included. Since our clustering process aims to categorise EU fishing countries, output, input, fleets' structure and organisation related variables and productivity ratios will be incorporated in the cluster analysis. Specifically, the variate $\{\mathbb{X}\}$ includes the volume of landings (q) and the value of landings (pq) as output variables. Input variables are represented by the number of vessels (NV), the gross tonnage (GT), and the number of full-time fishermen (FTE). The fleet's structure is proxied by the proportion of small-scale artisanal vessels (<12 metres) (ART) to the total fleet, the proportion of the large industrial vessels (>24 metres) (IND), the proportion of the *new* vessels (<10 years) (NEW) and the degree of amortisation of the fleets' by the proportion of *old* vessels (>20 years) to the total fleet (AGED). The organisational behaviour is captured by the number of producer's organisations (PO). Finally, productivity ratios include the value of landings (pq) per each of the input variables (i.e. pq/NV, pq/GT, pq/FTE).

Although figures and pictures in section 1.3 suggest different groups of fishing countries in the EU, we are checking whether the selected $\{\mathbb{X}\}$ exhibits an underlying clustering structure by means of Hopkins test[21] (Hopkins & Skellam, 1954; Lawson & Jurs, 1990) and a battery of modality tests[22] including Cheng and Hall (1998), Fisher and Marron (2001), P. Hall and York (2001), Hartigan, Hartigan et al. (1985) (Table

[21]The Hopkins statistic tests the spatial randomness of the data by measuring the probability that a given data set is generated by a uniform data distribution. The Hopkins statistic test compares the distances between the data points and the nearest neighbours from a sample of pseudo points and their nearest neighbours. If the data are not distributed in clusters, then both sets of distances should be similar on average.

[22]Multimodality tests initially assume that data is generated from a unimodal distribution (the null) and accordingly the p-value is the probability of observing the given input or a more extremely multimodal input under the null. If only a single mode is present, then the p-value should be large, indicating that the underlying data is deemed not clusterable. By contrast, small p-values make us the question the original assumption of unimodality and instead conclude that multiple modes (and clusters) are present.

1.16). We are using R package *multimode* (Ameijeiras-Alonso et al., 2018) to obtain modality tests. The value of Hopkins statistic is not far from 1, so we can conclude that our dataset is significantly clusterable. Moreover, the multimodality test of Fisher and Marron suggest a multimodal structure with at least 4 modes. However, based on Hartigan, Cheng-Hall, and Hall and York tests, there is no evidence against the dataset is uniformly distributed. Despite this ambiguity, taking into account the small population size of our data set we will accept that our data exhibits a clusterable pattern.

Table 1.16: Testing for clusterability

	$\{\mathbb{X}\}$	
	Statistics	p-value
Hopkins	0.24	-
Hartigan dip test for unimodality[1]	0.02	0.89
Cheng and Hall excess of mass test	0.03	0.41
Hall and York critical bandwidth test	0.56	0.16
Fisher and Marron test[2]	1.59	0.000***
Fisher and Marron test[3]	0.73	0.03**
Fisher and Marron test[4]	0.62	0.002***

Notes:
[1] Alternative hypothesis: non-unimodal, i.e., at least bimodal simulated p-value based on 2000 replicates.
[2] Null hypothesis: unimodality. Alternative hypothesis: at least 2 modes. B=100 bootstrap replicas.
[3] Null hypothesis: 2 modes. Alternative hypothesis: at least 3 modes B=100 bootstrap replicas.
[4] Null hypothesis: 3 modes. Alternative hypothesis: at least 4 modes B=100 bootstrap replicas.

Principal component analysis (PCA) is usually used before clustering to reduce the original variables into a smaller and more parsimonious set of new variables (principal components (PC)), explaining most of the variance in the original variate (Anderson, 1984; Brusco et al., 2017; Raychaudhuri et al., 1999). Since the set of variables in $\{\mathbb{X}\}$ are highly correlated, we are factoring the indicators using principal component analysis (PCA) prior to clustering, and using the resulting factor scores as cluster variables. Before applying PCA, variables in $\{\mathbb{X}\}$ have been typified by subtracting their respective mean and dividing by their standard deviation. Thus, initial variables will be replaced by a limited number of PCs, even all the PC would be required to reproduce the total system variability of the data. Certain number of PC will conform the effective and necessary inputs to compete the clustering (Johnson & Wichern, 1988; Jolliffe & Cadima, 2016). Specially, we are retaining eigenvalues[23]>1 (Kaiser, 1958), and limiting the number of

[23] Eigenvalues are derived for each dimension and measure the variability retained by each principal component.

PC to the number that accounts for at least 85% of the total variance explained, as a common rule of thumb originally suggested by (Kaiser, 1958; Merenda, 1997; Stevens, 2012; Tabachnick & Fidell, 2001). Table 1.17 includes percentages, eigenvalues and cumulative percentages of projected variances for the PCs. The first three PCs (PC1, PC2 and PC3) account for 85% of the total variance of $\{\mathbb{X}\}$, which means that most of the information is retained by the first three PCs. Thus, the variance corresponding to the remaining axes may be considered random noise (Lebart, 1984). Accordingly, we proceed with the cluster analysis using PC1, PC2 and PC3. At this stage we are using the R package *fpc* (Hennig, 2020).

Table 1.17: Clustering EU countries: Principal component analysis (PCA) Eigenvalues and percentages of the projected variances

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Standard deviation	2.31	1.98	1.32	0.98	0.59	0.50	0.43	0.33	0.25	0.19
Prop. of Variance	1.98	0.30	0.13	0.07	0.03	0.02	0.01	0.01	0.00	0.00
Cumulative Prop.	0.41	0.71	0.85	0.92	0.95	0.97	0.98	0.99	0.99	1.00
Eigenvalues	5.34	3.93	1.73	0.97	0.35	0.25	0.18	0.11	0.06	0.04

Notes:
Standard deviation, proportion of variance, cumulative proportion and eigenvalues of projected variance of the variables in variate $\{\mathbb{X}\}$.

Cluster analysis is carried out using the scores of the first three PCs (PC1, PC2 and PC3) and alternative clustering procedures including hierarchical (i.e. Ward, average and complete linkage), non-hierarchical (i.e. k-means and k-medoids (PAM)) and mixed hierarchical-kmeans. In the hierarchical clustering procedures, the clustering algorithm starts out by putting each observation into its own separate cluster. Distances between all the observations/clusters are measured and the closets pairs of clusters are grouped together. This process continues until there is only one unique cluster containing the entire data set. Thus, the result at the earlier stage is always nested with the results at a larger state, creating a dendogram or similarity tree. The most popular agglomerative algorithms are complete[24], average[25] and Ward's[26] linkage methods. There are other

[24]In the *complete linkage* method, the cluster similarity is based on maximum distance between observations in each cluster.

[25]In the *average linkage* procedure similarity of any two clusters is the average similarity of all individuals in one cluster with all individuals in another. Accordingly, average linkage algorithm depends less on outliers and tend to generate clusters with approximately equal within-group variance (Hair et al., 2014).

[26]In the *Ward's* method the similarity between two clusters is not a single measure of similarity, but rather, the sum of squares within the clusters summed over all variables. The selection of which two clusters to combine is based on which combinations of cluster maximises the within-cluster sum of squares across the complete set of separate clusters. The use of a sum of squares measure makes this

non-hierarchical procedures, such as k-means, which do not involve a treelike construction process. Instead, this procedure starts identifying the cluster seeds (starting points) for each cluster and then, based on similarities, assigns each observation to one of the cluster seeds. K-medois procedures, which are less sensitive to noise and outliers, use medois[27] as cluster centres. The most common k-medois clustering method is PAM algorithm (Kaufman & Rousseeuw, 2009). In this case, the sums of the distances between objects within a cluster are constantly recalculated as observations move around, which will probably give a more reliable solution. Clustering algorithms are detailed by (Ball & Hall, 1967; Brusco et al., 2017; Hair et al., 2014; Kassambara, 2017; Romesburg, 2004) among others.

Selecting the optimal number of clusters that best describes our countries is not trivial, due to our limited sample size (n=23). Therefore, we will consider a maximum of no more than 4 clusters (k=4). Some standard internal cluster validation procedures are used in order to select the proper number of clusters: elbow and silhouette methods (Kaufman & Rousseeuw, 2009; Rousseeuw, 1987), a set of additional indices including CH (Calinski & Harabasz, 1974), D (Dunn, 1974), average Pearson gamma (PG) (Halkidi et al., 2001), entropy (Meilă, 2007) and WB ratio. However, the partitions resulted with the two to four cluster solutions, do not conclude about a clear taxonomy for the EU fishing countries (Table 1.18). According to the majority rule, the four-cluster solution (k=4) dominates for $\{\mathbb{X}\}$.

Table 1.18: Internal cluster validation measures for $\{\mathbb{X}\}$

	k=2	k=2	k=2	k=3	k=3	k=3	k=4	k=4	k=4
	km=hkm	pam	hc	km=hkm	pam	hc	km=hkm	pam	hc
between ss	5.98	5.33	5.38	6.07*	4.54	5.55	5.69	4.73	5.32
within ss	148.5	155.8	156.3*	82.9	126.7	85.9	52.8	64.9	57.5
silhouette	0.48	0.41	0.42	0.52	0.24	0.47	0.52*	0.27	0.50
CH	13.25	11.65	11.55	19.19	9.11	18.21	22.72*	17.32	20.34
dunn	0.17	0.11	0.17	0.31	0.06	0.29	0.35*	0.09	0.29
dunn2	1.15	1.55*	1.10	1.06	0.98	0.94	0.83	0.80	0.80
entropy	0.57*	0.57*	0.65	0.74	1.07	0.84	1.01	1.22	1.10
P. gamma	0.66	0.45	0.54	0.74	0.32	0.66	0.77*	0.47	0.69
wb.ratio	0.52	0.59	0.58	0.43	0.62	0.47	0.38*	0.47	0.41

Notes: *optimal cluster choices

method easily distorted by outliers (Hair et al., 2014; Milligan, 1996).

[27] Medois: Object within a cluster for which the average distance between it and all the rest of the members of the cluster is minimal. It coincides with the most centrally located point of the cluster.

Cluster membership related to each of the partitioning hierarchical (ward, average, complete), non-hierarchical (k-means, PAM) and mixed (hkmeans) methods have been reported in Table 1.19. Most of the methods group Belgium and the Netherlands together in one cluster. Belgian and Dutch fleets are mainly industrial and these countries are the most productive ones. Romania and Slovenia are mostly grouped together in one cluster. Even Romanian and Slovenian fleets are small in terms of number of vessels and the least productive ones, their fleets are the newest. France, Italy, Spain and United Kingdom are also grouped together, but, partitions of the EU countries change depending on the algorithms we are applying. Therefore, we are focusing on the partitions related to the non-hierarchical PAM algorithm, since it is a non-parametric alternative of k-means clustering for partitioning a dataset and PAM is less sensitive to outliers (Kaufmann & Rousseeuw, 1990).

Table 1.19: Cluster membership by cluster algorithm for variate $\{\mathbb{X}\}$

	k=4
k-means	{BE NL}{FR IT ES UK}{RO SI}{BG EE FI MT PL HR CY DK DE EL IE LV LT SE PT}
PAM	{BE}{BG EE FI MT PL RO SI}{HR CY DK DE EL IE LV LT SE}{PT FR IT ES UK NL}
Ward.D2	{BE NL}{EL PT FR IT ES UK}{RO SI}{BG EE FI MT PL HR CY DK DE IE LV LT SE}
Average	{BE}{FR IT ES UK}{NL}{BG EE FI MT PL HR CY DK DE IE LV LT SE EL PT RO SI}
Complete	{BE NL}{PT FR IT UK}{ES}{BG EE FI MT PL HR CY DK DE IE LV LT SE RO SI EL}
hkmeans	{BE NL}{FR IT UK ES}{RO SI}{BG EE FI MT PL HR CY DK DE IE LV LT SE EL PT}

Notes:
Cluster membership related to each of the partitioning non-hierarchical (k-means, PAM), hierarchical (Ward.D2, Average, Complete) and the mixed hierarchical-kmeans (hkmeans) algorithms and number of clusters.
Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Malta (MT), Poland (PL), Portugal (PT), Romania (RO), Slovenia (SI), Spain (ES), Sweden (SE), the Netherlands (NL), United Kingdom (UK).

Focusing on the variate $\{\mathbb{X} = \text{q, pq, NV, GT, FTE, ART, IND, NEW, AGED, pq/NV, pq/GT, pq/FTE, PO}\}$, EU fishing countries may be divided in four clusters. According to the k-medoids (or PAM) algorithm, Belgium constitutes cluster 1. Bulgaria, Estonia, Finland, Malta, Poland, Romania and Slovenia make up cluster 2. Croatia, Cyprus, Denmark, Germany, Greece, Ireland, Latvia, Lithuania and Sweden are grouped in cluster 3. France, Italy, Portugal, Spain, the Netherlands and United Kingdom constitute cluster 4. Related taxonomies are revealed in Table 1.20. Belgium (cluster 1) only concentrates 0.4 % (15 thousand tonnes) of the volume (q) and 1% (64 million euros) of the value of the landings (pq) in the EU, with 0.1% of the vessels (NV=68), 1% of the gross tonnage (GT=12,898), and 0.01% of the full-time fishermen (FTE=13).

Besides, the Belgian fleet is mainly industrial (>24m=50%) and the small-scale artisanal vessels (<12m) hardly constitute the 1% of the Belgian fleet. Therefore, the Belgian fishing fleet could be defined as industrial and the most productive in the EU. Bulgaria, Estonia, Finland, Malta, Poland, Romania and Slovenia (cluster 2) only concentrate on average the 1% (46 thousand tonnes) of the of the volume (q) and 0.2% (16 million euros) of the value of the landings (pq) in the EU, with 2% (NV=1,259) of the vessels, 1% (GT=11,257) of the gross tonnage, and 2% (FTE=2,316) of the full-time fishermen. Regarding the fleets' structure, their fleet could be defined as pure artisanal (<12m=91%) and rather new, since the proportion of the new vessels (<10y=15%) is the highest, and the proportion of the quasi amortised old vessels (>20y=57%) the lowest. The productivity ratios referred to countries included in cluster 2 are the lowest and the number of producer organisations is also very low (PO=3). Accordingly, Bulgarian, Estonian, Finish, Maltese, Polish, Romanian and Slovenian fleets are artisanal, new and the least productive ones. Croatia, Cyprus, Denmark, Germany, Greece, Ireland, Latvia, Lithuania and Sweden (cluster 3) only concentrate on average the 2% (65 thousand tonnes) of the of the volume (q) and 1% (91 million euros) of the value of the landings (pq) in the EU, with 4% (NV=3,426) of the vessels, 3% (GT=45,168) of the gross tonnage, and 3% (FTE=3,967) of the full-time fishermen. According to the fleets' structure related variables, their fleet is mainly artisanal (<12m=87%) and the oldest (>20y=81%). Besides, the productivity ratios referred to countries included in cluster 3 are also low (very close to the ones for cluster 2) and the number of producer organisations is very low (PO=4). Therefore, the fleet of the countries included in cluster 3 could be defined as mainly artisanal, quasi amortised and not very productive. France, Italy, Portugal, Spain, the Netherlands and United Kingdom (cluster 4) concentrate 12 % (417 thousand tonnes) of the volume (q) and 14% (969 million euros) of the value of the landings (pq) in the EU, with 9% of the vessels (NV=7,024), 11% of the gross tonnage (GT=175,255), and 12% of the full-time fishermen (FTE=13,995). Regarding the fleets' structure, their fleet could be defined as mixed artisanal and industrial, and the proportion of the new vessels is slightly high (<10y=8%). The productivity ratios reveal that, even the Belgian fleet is the most productive, the productivity per unit of gross tonnage (pq/GT) of the countries included in cluster 4 is very close to the Belgian. Moreover, the number of producer organisations is the highest. Accordingly, France, Italy, Portugal, Spain, the Netherlands and United Kingdom may be catalogued as *the most fishing countries*. They have the largest fleets, their productivity is slightly high and concentrate most of the producer organisations in the EU.

Table 1.20: EU fishing countries taxonomy: average values by cluster

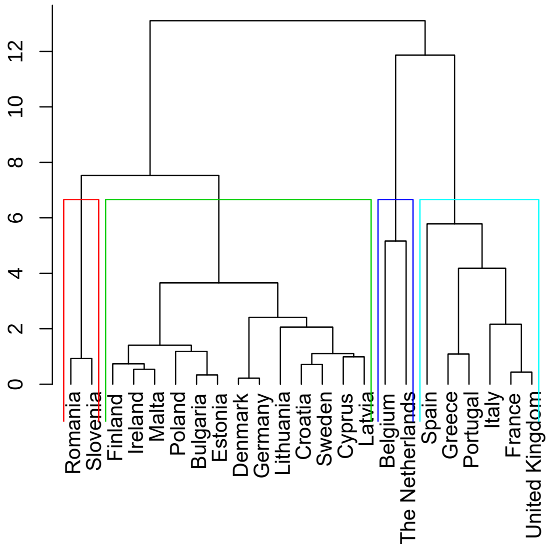
	Clusters			
	1	2	3	4
	{BE}	{BG EE FI MT PL RO SI}	{HR CY DK DE EL IE LV LT SE}	{PT FR IT ES UK NL}
q	15	46	65	417
pq	64	16	91	969
NV	68	1,259	3,426	7,024
GT	12,898	11,257	45,168	175,255
FTE	13	2,316	3,967	13,995
<12m (ART)	1%	91%	87%	75%
>24m (IND)	50%	2%	6%	8%
<10y (NEW)	1%	15%	5%	8%
>20y (AGED)	79%	57%	81%	70%
pq/NV	943,299	16,594	43,257	224,528
pq/GT	4,973	1,508	1,766	5,210
pq/FTE	4,934,178	40,430	55,377	107,769
PO	1	3	4	23

Notes:
Following the non-hierarchical PAM algorithm:
- Cluster 1: {Belgium}
- Cluster 2:{Bulgaria, Estonia, Finland, Malta, Poland, Romania, Slovenia}
- Cluster 3:{Croatia, Cyprus, Denmark, Germany, Ireland, Latvia, Lithuania, Sweden, Greece}
- Cluster 4:{The Netherlands, Portugal, France, Italy, Spain, United Kingdom}.

Average values by cluster membership including:
Volume of landings (q), value of landings (pq), number of vessels (NV), gross tonnage (GT), number of full-time fishermen (FTE), proportion of small-scale artisanal vessels (<12 metres) (ART), proportion of large-scale industrial vessels (>24 metres) (IND), proportion of *new* vessels (<10 years), proportion of *old* vessels (>20 years), productivity ratios (pq/NV, pq/GT, pq/FTE), producer organisations (PO).

The dendogram (Figure 1.13) may be helpful to identify internal specific patterns within clusters.

Figure 1.13: Dendogram



Notes:
Dendogram related to the hierarchical ward method.

1.5 Concluding remarks and discussion

The fishing sector in the EU is rather heterogeneous. Accordingly, it is not straightforward to fix policies that fit perfectly with the particular circumstances of each country and/or fish species. Due to the complexity of the fishing sector, it is not possible to accurately measure the capacity of the environment to absorb the impact of the fishing activity (González-Laxe, 2005), but protective and preventive policies together with responsible acting of the countries could help to reduce the damage on the environment. The fishing activity directly affects the environment, economy and society. Hence, a huge scientific knowledge is needed to improve overall assessment. This chapter gives an overview of the current situation of European fish and fisheries and provides some remarks to get a better understanding of the strengths and weaknesses of the fishing sector in the EU.

Overall, in 2018, the landings in the fishing ports of the EU reached 3,430 thousand tonnes (6,803 million euros) of fish products. According to the volume of landings, the outstanding countries were Spain (25%) and the Netherlands (16%), although their respective percentages in terms of value change to 32% and 9%. In addition to the country-based landings distribution, following a species-based perspective, 1144 different fish species were landed in the EU. Nevertheless, the volume of landings is heavily concentrated on the key 10 leading species, which constituted the 57% of the total landed volume (i.e. Atlantic herring (16%), Atlantic mackerel (7%), blue whiting (6%), European pilchard (5%), European sprat (5%), skipjack tuna (5%), European anchovy (4%), Atlantic chub mackerel (3%), European hake (3%) and Atlantic horse mackerel (3%)) and 37% of the total value of such landings (i.e. European hake (5%), yellowfin tuna (4%), Atlantic mackerel (4%), common sole (4%), great Atlantic scallop (4%), Atlantic cod (4%), Norway lobster (3%), European anchovy (3%), Atlantic herring (3%) and bigeye tuna (3%)). The landings of some of these ten leading species were rather homogeneously distributed among member-states (such as pilchard in Croatia (27%), Spain (15%), France (15%), Italy (15%), the Netherlands (11%), Greece (7%), Portugal (6%) and United Kingdom (5%)), whereas others, such as skipjack tuna and blue whiting are concentrated respectively in Spain (91%) and the Netherlands (70%).

The EU fleet is made up by 81,860 fishing vessels, a capacity of 1,549,742 GT and a fishing power of 6,151,200 KW. The average EU fishing vessel has 19 GT, 75 KW, 8 metres, a crew of 1.45 full-time fishers and is 23 years old. Accordingly, the fleets are mainly comprised by small-scale artisanal ($<$12 metres) (85%) and rather old or quasi amortised vessels ($>$ 20 years) (73%). Greece has the largest fleet (18% of the EU) in terms of the number of vessels, followed by Italy (15%) and Spain (11%). Despite the fact that the Netherlands were the second outstanding country according to the volume of landings (16%), Dutch fleet is only comprised by 833 fishing units (1% of the EU). It is remarkable the fact that the average length per vessel substantially differs among countries. Belgium and the Netherlands have the largest vessels (respectively 27 and 20 meters) and the most productive fleets, while the smallest vessels may be found in Estonia (LE=5m), Cyprus (LE=6m), Bulgaria (LE=6m), Finland (LE=6m) and Croatia (LE=6m). As expected, the proportion of large-scale vessels is the highest in Belgium (50%) and the Netherlands (28%). Following a fairly similar distribution to the fishing fleet, the countries with the highest number of fishers are Italy (26,146, 22% of the EU), Greece (22,081, 19%), Spain (17,981, 15%) and Portugal (17,642, 15%). Additionally, we have analysed the spawning stock biomass (SSB) of the ten most abundant fish species, as an approximation of the status of the fish stocks and their reproductive capacity. The overall biomass volume has positively increased by 41% (2000-2016) (ICES, 2017)), while we can see an species by species asymmetric behaviour (Atlantic herring (+25%), blue whiting (+20%), Atlantic mackerel (+132%), Atlantic cod (+188%), European sprat

(-2%), Atlantic horse mackerel (-9%), European plaice (+269%), haddock (+201%), Atlantic sailfish (+27%), and Sandeels (+161%)).

Under this heterogeneous performance of output (quantity and value of landings) and input (fleets and employment) variables, we have identified the taxonomy of the EU fishing countries based on a two-step principal component-clustering approach. The resulting classification is rather robust to the alternative methods and algorithms we have used, including hierarchical agglomerative (i.e. Ward, average and complete linkage), non-hierarchical (k-means and k-medoids) and the mixed hierarchical-kmeans. Our results support four fishing countries typologies in the EU. Cluster 1 is made up only by Belgium, country with unique characteristics that differentiate it from all the other EU fishing countries. Belgium only concentrates 0.4% of the volume and 1% of the value of the landings in the EU, with 0.1% of the NV, 1% of the GT, and 0.01% of the FTE. Besides, the Belgian fleet is pure industrial and the most productive one. Cluster 2 is comprised by Bulgaria, Estonia, Finland, Malta, Poland, Romania and Slovenia. On average, these countries only concentrate 1% of the volume and 0.2% of the value of the landings in the EU, with 2% of the NV, 1% of the GT, and 2% of the FTE. Moreover, their fleets are pure artisanal, comparatively new and the least productive ones. Croatia, Cyprus, Denmark, Germany, Greece, Ireland, Latvia, Lithuania and Sweden constitute cluster 3. On average, these countries only concentrate 2% of the volume and 1% of the value of the landings in the EU, with 4% of the NV, 3% of the GT, and 3% of the FTE. Besides, their fleets are mainly artisanal, quasi amortised and their productivity is also very low. Cluster 4 is made up by France, Italy, Portugal, Spain, the Netherlands and United Kingdom. On average, these countries are *the most fishing countries*, since they concentrate 12% of the volume and 14% of the value of the landings in the EU, with 9% of the NV, 11% of the GT, and 12% of the FTE. Moreover, their fleets are the largest and most productive, and they exhibit the major associationism in the EU.

As far as measuring the status of exploitation of the resources is not easy, decision-making becomes difficult in this heterogeneous framework. The Common Fisheries Policy (CFP) (EU, 2019), included significant changes in order to make the fishing activity in the EU more in tune with the concept of the Ecosystem-based Fisheries Management (EBFM) (Bohman, 2019). Specifically, the adoption of the landing obligation (EU, 2013) aims to better conserve the marine resources facing discarding, but its future ecological, economic and social impacts will determine if the objectives of the landing obligation have been successfully achieved or not (EU, 2013; Guillén et al., 2018). It is a fact that, overall, the fishing mortality has been reduced in the North-East Atlantic (Aranda et al., 2019), fishing pressure has been decreased and there are signs of recovery of several stocks. However, many fish stocks still remain overexploited (European Environment Agency, 2020; Froese et al., 2018). The ability to adapt and counteract threats will determine the success or failure of the existing policies and consequently, the long-term sustainability of the ecosystem fishing is embedded. The management of the fisheries heavily depends on science to provide enough and accurate knowledge. Nevertheless, the complexity and heterogeneity of the fishing sector and the degree of uncertainty on the states of nature makes fisheries governance challenging. Therefore, new and complementary tools to the conventional ones are needed in order to assess decision-making, increase predictability and ensure future health of the marine environment. In the next two chapters, we are taking advantage of recent risk indicators coming from the field of finance and modern portfolio theory to consider the interaction among fish species within the fisheries ecosystem.

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Chapter 2

Risk and diversity

Abstract

This chapter focuses on alternative empirical specifications of risk and diversity in the fisheries domain, and the potential correlation among them. Firstly, based on financial risk analysis, we estimate the underlying financial risk of each of the 49 key commercial fish species caught in the North-East Atlantic European waters which are subject to analytical stock assessments, and compare our species level financial indicators with the conventional ecological ones (i.e. species vulnerability (V), species resilience (R) and species conservation status (CS)) included in FishBase and the Red List of Threatened Species (RLTS) of the International Union for Conservation of Nature (IUCN). Alternative financial risk indicators will be considered (i.e. Value-at-Risk (VaR), Modified Value-at-Risk (MVaR), Expected Shortfall (ES), Modified Expected Shortfalls (MES) and Expectiles (EX)) using as input data sources, both, the species level spawning stock biomass (SSB) and catches (Q), so as to respectively measure the species-level *biological risk* (BR) and the *production risk* (PR). Afterwards, correlation analysis will be undertaken in order to compare our financial risk indicators with the conventional ecological ones.

The estimation of species level biological (BR) and production risk (PR) may be useful for two main reasons. On the one hand, to reduce uncertainty about the status of the fish species, by giving different but additional indicators to the existing conventional vulnerability measures. On the other, because from the species level BR and PR, using country level average landings as weights, we can infer the weighted biological (wBR) and production risk (wPR) for each of the EU fishing member-states. Thus, our analysis will

help to classify, not only individual fish species, but also EU fishing countries as high/low risk level ones, and accordingly, to find similar patterns among them. Furthermore, our fish species-based synthetic risk indicators, BR and PR, could be also used to infer the risk of any other aggregation level by using the appropriate weights, so as to, for example, estimate the inherent risk level of a fishing community, region or fleet.

Secondly, we study the country-level bioeconomic diversity in the North-East Atlantic, using conventional diversity indices (DIs), namely Berger Parker (BP), Concentration ratios (CR), Simpson's index (SIM) and Shannon index (SHA); and two parallel specification (i.e. the volume of landings (q) and the value of landings (pq)). Notice that each member-state has an individual marine sub-ecosystem (Ω_{jt}) comprised by different fish species, that besides, may change over time. Accordingly, special attention will be paid on checking whether there are potential differences between the diversity patterns of EU fishing countries by means of parametric and not parametric tests such as ANOVA and Kruskal Wallis.

Thirdly, we investigate the correlation between risk and diversity. Risk and diversity are expected to be negatively correlated, that is, the lower the diversity, the higher the concentration, dominance and dependency of the fishing industry to the evolution of the dominant fish species (del Valle & Astorkiza, 2019a; del Valle et al., 2017). However, surprisingly, our results reveal that the country level weighted biological risk (wBR) and the weighted production risk (wPR) and diversity patterns are positively correlated. This is because the risk of a country may be potentially determined not only by the diversity itself, but also by the specific distribution of the landings. Accordingly, it may well happen that it is the fish species risk shares what mainly determines the overall risk of the fishing countries. To finish, a two-step principal component-clustering approach will be applied in order to identify the taxonomy of the EU fishing countries and complement the clustering analysis developed in Chapter 1, after including as well the estimated country level risk and diversity indicators in the variate. Our results suggest that EU fishing countries may be grouped in four different clusters according to their risk, diversity, input, output, fleets' structure and organisation variables, and productivity ratios.

2.1 Approaching fish species vulnerability by means of financial risk indicators

2.1.1 Introduction

Collapses of some fish stocks and the difficulties found to get a sustainable management of certain fisheries have encouraged some scientists to propose portfolio theory as an approach to support decisions-makers optimizing the ecosystem services, and conserve biodiversity, internalising species interaction as a key tool (Alvarez et al., 2017; DuFour et al., 2015; Edwards et al., 2004; Figge, 2004; Jin et al., 2016). Certainly, in certain fisheries the future of the fish stocks has been endangered due to over-exploitation (Baum et al., 2003; Pauly et al., 2002). Besides, there is a growing need to account for interaction between species in order to deal with multispecies fisheries (Edwards et al., 2004). Thus, the latest report from the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (2019) reveals that 33% of marine fish stocks in 2015 were harvested at unsustainable levels. Moreover, industrial fishing is mainly concentrated in the North-East Atlantic, North-West Pacific and upwelling regions off South America and West Africa (Diaz et al., 2019). In fact, North-East and North-West Atlantic, the Mediterranean and the Black Sea have been the areas with the largest number of collapsed fish stocks (Garcia & Grainger, 2005), and some authors have documented the poor state of several fisheries (Pauly & Maclean, 2003). Therefore, effective conservation strategies are needed to plan and manage marine systems accounting for ecosystem effects of fishing activity (Beddington et al., 2007). Undoubtedly, a better understanding of the dynamics of past collapses could help to detect early warning signs (Mullon et al., 2005). This is the main reason to propose precautionary approaches (Garcia, 1994; Hilborn et al., 2001; Lauck et al., 1998). Some marine scientists suggest ecosystem-based fisheries management (EBFM) (Botsford et al., 1997; Pikitch et al., 2004) switching from an individualistic to an ecosystem-based perspective, while others claim the use of marine-protected areas as a tool to avoid the management failure of the fisheries (Hilborn, 2007). However, they all demand that species should not be considered individually, quite the contrary, interactions among species should be also accounted when assessing fish populations and changing environments (Garcia, 2003). The Common Fisheries Policy (CFP) (EU, 2013) also calls for an EBFM approach, however, in the practical arena, it has not been fully implemented, as many difficulties still remain unresolved (Link & Browman, 2017).

The truth is that due to the heterogeneity of the European fishing sector and the peculiarities of the marine ecosystems, it is extremely difficult to fix a governance model that fits perfectly. This may be the reason why a bundle of different management instruments and rules are applied. As far as the precautionary principle is concerned, it has been considered a tool to deal with uncertainty, since it is not possible, neither to measure accurately the capacity of the environment to absorb the impact of the fishing activity, nor to find definite solutions. Some authors define the precautionary approach as the answer to the growing and progressive awareness of scientific uncertainty about environmental deterioration (Boisson de Chazournes, 2002; Garcia, 1994). Others, interpret the concept as a corrective measure to ensure responsible acting and avoid damaging the marine environment (McIntyre & Mosedale, 1997). Precautionary approach should be applied, not only to the threatened resource itself; the potential economic and social impacts should be also considered (Hilborn et al., 2001). Risk is the concept that best defines the precaution (González-Laxe, 2005), since uncertainty exists and the potential danger or harm is more or less predictable. It is necessary to predict vulnerability of fish species before their population collapses (Sala & Knowlton, 2006; Worm et al., 2006). Thus, fish species vulnerability indicators are needed to better assess the management and conservation policies.

Decision-making is rather difficult due to the complexity to measure the status of exploitation of fishing resources and their potential evolution. Therefore, new limits and precautionary reference points are needed. Target reference points are the optimum values of the fishery and they are used to assess parameters such as fishing mortality and spawning stock biomass (González-Laxe, 2005). Marine scientists define and calculate several indicators in order to evaluate the status of the fish species from an ecological point of view, and there are some databases (such as FishBase and the Red List of Threatened Species index of the International Union for Conservation of Nature (IUCN)) in which this information is available. The FishBase on-line database (www.fishbase.se) (Froese & Pauly, 2018) includes some ecological indicators, such as trophic level (TL), vulnerability (V) and resilience (R) for selected fish species, but, unfortunately, many species are not still included in FishBase. The International Union for Conservation of Nature (IUCN) Red List of Threatened Species index (https://www.iucnredlist.org/) (IUCN, 2018) also classifies fish species according to a specific conservation score based on criteria such as the rate of population decline, the population size and distribution, the geographical distribution and the fragmentation degree. However, this database only gives qualitative data. Besides, there are many missing species and issues such as species growth rate, maturity age and life span are ignored.

Different authors suggest financial approaches to be used to face EBFM (Alvarez et al., 2017; Carmona et al., 2020; Edwards et al., 2004; Jin et al., 2016; Rădulescu et al., 2010; Sanchirico et al., 2008) as a tool for fisheries biodiversity conservation and sustainable fisheries management (Pauly et al., 2002; Sylvia et al., 2003). In the framework of finances, the global financial crisis (2008) turned the attention of the practitioners to risk measures based on losses, instead of the conventional variance or covariance risk measures. Several measures have been proposed, including the Value-at-Risk (VaR), which has become the most popular and widely used one since its adoption by Basel II in 1996 (Basel II, 1996). The RiskMetrics model (Morgan, 1996) also collaborated to popularize VaR among financial managers and regulators, mostly due to its conceptual simplicity. However, VaR does not satisfy coherence property, lacks sub-additivity and ignores losses in the far tail of the distribution of losses (Artzner et al., 1999; Emmer et al., 2015). As a response to these failures in desirable properties, the concept of *coherent* risk measure was introduced (Artzner, 1997; Artzner et al., 1999). Although Value-at-Risk (VaR) was one of the most commonly used risk indicators, in 2013 Basel III recommended replacing VaR by the Expected Shortfall (ES) (Basel III, 2013). ES is coherent and quantifies tail risk, but fails the elicitability property deemed essential to backtesting (Bellini & Bignozzi, 2015; Ziegel, 2016). Accordingly, some authors have suggested Expectiles (EX) as coherent and elicitable alternatives to VaR and ES (Bellini & Di Bernardino, 2017; J. M. Chen et al., 2018).

In the fisheries framework there is not a definite way of measuring vulnerability/risk of fish species. Although there are alternative ecological indicators in the literature, such as vulnerability (V), resilience (R) and conservation status (CS), there is not a clear consensus on how these indicators should be calculated. Moreover, there is also a lack of quantitative and accurate estimation of such indicators. Thus, in this subsection we propose an innovative way of quantitatively measuring the vulnerability of fish species that aims to complement the indicators included in FishBase and the Red List of Threatened Species (RLTS). Specifically, we analyse the financial risk indicator that best fits our fish and fisheries, using spawning stock biomass (SSB) and catches (Q) data in the North-East Atlantic in order to measure species-level *biological risk* and *production risk*, from now on (BR) and (PR). The main advantage of using our species level synthetic risk indicators is that they can be inferred to any aggregation level multiplying risk by the weight that each fish species has on the ecosystem, community, region, country, fleet, etc.. Accordingly, this weighted risk could be useful to compare the biological risk and/or production risk among different ecosystems, fleets, countries, communities or regions. Thus, using BR and PR, we will estimate the weighted risk for each EU fishing member-states.

The objective of this subsection is threefold. First, using the financial risk indicator that best fits our objectives and data, we propose two complementary fish species vulnerability measures: *biological risk* (BR) and *production risk* (PR). Second, by means of correlation analysis, we compare our synthetic fish species-level risk indicators to conventional species level ecological ones included in FishBase and the RLTS. Third, from the species level biological (BR) and production risk (PR) and the average individual landing shares of each EU fishing country as weights, we estimate the weighted country-level risk for each EU fishing countries.

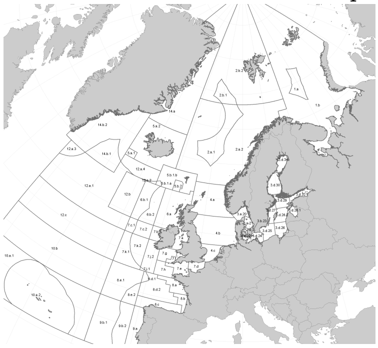
The remainder of this subsection is organised as follows. After this introduction, subsection 2.1.2, analyses the current situation of the key fish species in the North-East Atlantic seas focusing on the spawning stock biomass (SSB) and catches (Q). Then, in the framework of financial portfolio theory, we suggest alternative species risk indicators, namely: Value-at-Risk (VaR), Expected Shortfall (ES) and Expetiles (EX). Afterwards, by means of correlation analysis, we compare them with conventional ecological indicators, such as the trophic level (TL), vulnerability (V), resilience (R) and conservation status (CS). Subsection 2.1.3 summarises the major empirical findings made in this subsection.

2.1.2 Material and methods

2.1.2.1 Study area

Our fish species vulnerability/risk analysis is focused on the North-East Atlantic European and adjacent waters (North Sea, Baltic Sea, Skagerrak, Kattegat, West of Scotland Sea, Irish Sea and Celtic Sea) (see Figure 2.1), the major fishing ground in the EU with around 75% of the fish caught (EUROSTAT, 2019). In this sense, we define our global EU marine ecosystem (Ω) as the group of the main assessed 49 fish species in the North-East Atlantic. We suggest using spawning stock biomass (SSB) as the source of species-level *biological risk* (BR), and catches (Q) as the source of species-level *production risk* (PR). From now on we will refer them as BR and PR. The former is a measure of the risk in the natural frame or ocean, while the later aims to capture the output risk inherent to the activity of the fishing fleets.

Figure 2.1: ICES Areas: North-East Atlantic Europe and adjacent waters



Source: ICES (2019)

In order to compute BR, we are using ICES data (data accessed, 2017) (ICES, 2017) of spawning stock biomass ($\mathrm{SSB_{it}}$) $\{SSB_{it} : i = 1, ..., 49; t = 1985, ..., 2016 : 1\}$ of the main (analytically) assessed 49 fish species in the North-East Atlantic and adjacent waters (1985-2016). SSB, generally in thousand tonnes, measures the total weight of a fishing stock that is old enough to spawn. Hence, SSB is an indicator of the status of the stock and its reproductive capacity. Overall, based on stock assessment data related to our 49 species, there are on average around 24 million tonnes of fish in the North-East Atlantic. Atlantic herring is the most abundant species (31%), followed by blue whiting (13%), Atlantic mackerel (12%), Atlantic horse mackerel (11%), Atlantic cod (5%) and European sprat (4.7%). On average, the five leading species concentrate the 72% of the biomass of our global ecosystem (Ω). Table 2.1 summarizes the ranking of the 5 leading positions of the key 49 species in (Ω). Atlantic herring is clearly the dominant species for 29 of the 32 years of our sample period. It has been displaced from the outstanding position only twice by Atlantic horse mackerel, and once by Atlantic mackerel. So as for the second, third fourth and fifth positions, there is not a clear dominance.

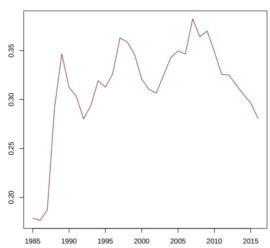
Table 2.1: Species leadership in terms of spawning stock biomass (SSB)

Species ranking	1	2	3	4	5
Atlantic herring (HER)	29	2	1	-	-
Atlantic mackerel (MAC)	1	8	18	4	3
Blue whiting (WHB)	-	13	10	7	2
Atlantic horse mackerel (HOM)	2	9	2	9	3
Atlantic cod (COD)	-	-	1	5	2
European sprat (SPR)	-	-	-	1	10

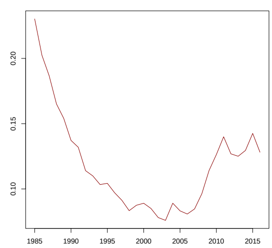
Notes: The first 5 ranking positions of the key species (1985-2016).

Figure 2.2 shows the yearly share of the leading species as a percentage to total SSB including all the 49 species. The time series plots reveal that fish species proportion is rather heterogeneous, and that it fluctuates across the years. Atlantic herring is the leader from 1988 on, and even its percentage fluctuates, it keeps the first position. For its part, Atlantic mackerel's biomass has been reduced considerably from 1985 to 2003, and has recovered its position even if it has not reached previous levels. Besides, blue whiting shows the major variability, reaching the highest values in 2004, but being later reduced to its previous levels. Moreover, European sprat shows a similar pattern reaching the highest values in 1997. Atlantic horse mackerel has suffered a similar reduction on its SSB, but it has never recovered from the declining trend. Last but not least, Atlantic cod has significantly increased its SSB in the last years. Under this heterogeneous performance, our objective is to find a synthetic indicator of *biological risk* (BR) to quantify the risk in the natural frame for each of the 49 fish species, using spawning stock biomass ($\mathrm{SSB}_{\mathrm{it}}$) as input data.

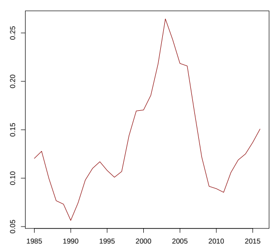
Figure 2.2: Time series plots of the leading species in terms of spawning stock biomass (SSB) (%)



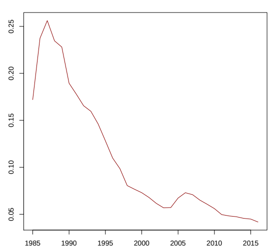
Atlantic herring (HER)



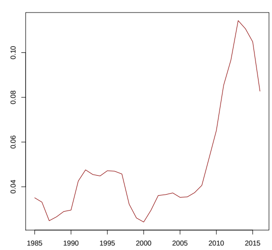
Atlantic mackerel (MAC)



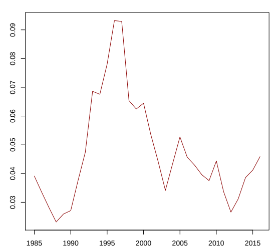
Blue whiting (WHB)



Atlantic horse mackerel (HOM)



Atlantic cod (COD)



European sprat (SPR)

Notes:
Yearly share (%) of the leading fish species in terms of spawning stock biomass (SSB) in the North-East Atlantic European waters (1985-2016).

Our measure of *production risk* (PR) is based on the catches (in thousand tonnes) of the main assessed 49 fish species in the North-East Atlantic and adjacent waters (2000-2016). We are using aggregated catches of the 11 main fishing EU member-states in the target area (i.e. Belgium, Germany, Denmark, Spain, Finland, France, Ireland, the Netherlands, Portugal, Sweden and United Kingdom) as an indicator of the aggregated fishing activity in our ecosystem (Ω). Since we are focusing on the North-East Atlantic, we are not including countries such as Greece and Italy because they mainly catch in the Mediterranean Sea. Thus, aggregated catches ($\mathrm{Q_{it}}$) $\{Q_{it} : i = 1, ..., 49; t = 2000, ..., 2016 : 1\}$ capture the fishing activity in the North-East Atlantic (2000-2016), (data accessed from EUROSTAT (2018)). On average along the sample period, almost 3 million tonnes of fish were caught in the North-East Atlantic by EU fishing countries. Atlantic herring was the most caught species on average (22%), followed by Atlantic mackerel (14%), European sprat (12%), sandeels (11%), blue whiting (8%) and Atlantic horse mackerel (5%). On average, the five leading species concentrate the 67% of the catches on our target ecosystem (Ω). Table 2.2 summarizes the ranking of the first 5 positions of the key 49 species in Ω. Atlantic herring is clearly the dominant species related to catches, leading 15 of the 17 years of our sample period. It has been displaced from the first position only twice by sandeels. So as for the second and third positions, Atlantic mackerel is the second target species, and the European sprat the third one. There is not a clear status for the fourth and fifth position.

Table 2.2: Species leadership in terms of catches (Q)

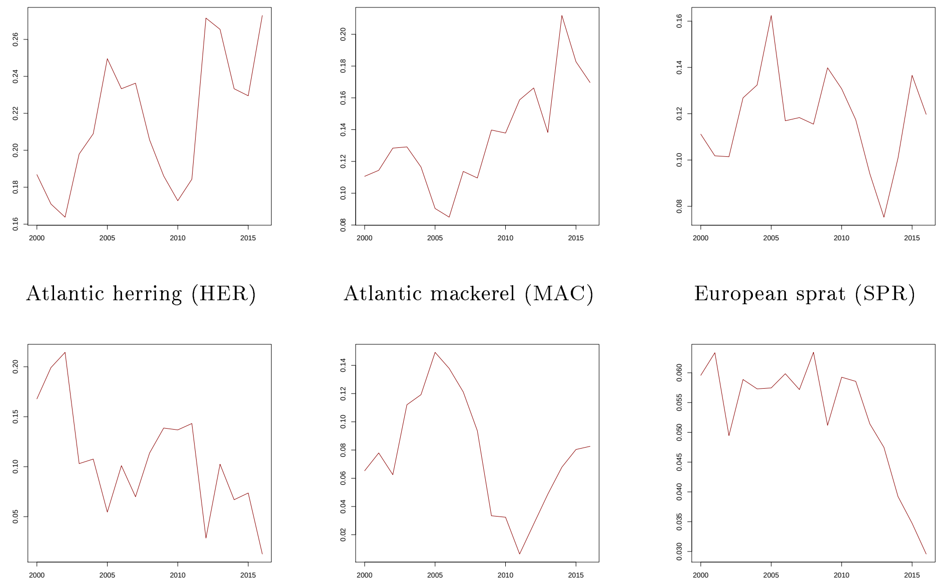
Species ranking	1	2	3	4	5
Atlantic herring (HER)	15	2	-	-	-
Atlantic mackerel (MAC)	-	8	3	5	1
European sprat (SPR)	-	4	8	5	-
Sandeels (SAN)	2	1	4	2	5
Blue whiting (WHB)	-	2	2	4	5
Atlantic horse mackerel (HOM)	-	-	-	-	4

Notes:
The first 5 ranking positions of the key species (2000-2016).

Figure 2.3 illustrates the yearly share of the leading species to total catches. Atlantic herring is the most caught species from 2003 on, and even its proportion varies, it keeps its first position. Atlantic mackerel's catches have increased considerably from 11% to 21% in 2014. European sprat is very heterogeneous, with catches representing the 11% of the total catches in 2000. This percentage increased to 16% in 2005 and reduced to 7.5% in

2013, to finally recover to the starting position in 2016. Sandeels was leading the catches during the period 2001-2002, but its share has been reduced during the full period until it only represents 1.2% in 2016. The performance of blue whiting is also very heterogeneous. It has increased its presence from 6.5% to 15% in 2005, followed by a huge decline to 1% in 2001 and a recovery to the previous catches in 2016. Finally, Atlantic horse mackerel represented the 5% of the total catches until 2010, afterwards, it has reduced significantly its proportion. Under this heterogeneous performance, we aim to estimate a synthetic *production risk* indicator (PR) to quantify the fishing activity/fleet related risk for each of the 49 fish species, using catches (Q_{it}) data. Once our target ecosystem (Ω) has been briefly described, we will focus on alternative financial risk indicators in order to find the one that best captures the *biological* and *production* risk/vulnerability of each of the 49 fish species.

Figure 2.3: Time series plots of the leading species in terms of catches (Q) (%)



Atlantic herring (HER) — Atlantic mackerel (MAC) — European sprat (SPR)

Sandeels (SAN) — Blue whiting (WHB) — Atlantic horse mackerel (HOM)

Notes:
Yearly share (%) of the leading fish species in terms of catches in the North-East Atlantic European waters (2000-2016).

2.1.2.2 Methods

We are taking advantage of the field of finances to estimate the *biological risk* (BR) and *production risk* (PR) of each individual 49 fish species subject to stock assessments, and then, compare our species level risk indicators to the existing ecological ones.

One of the lessons showed by the global financial crises is that there is a need to forecast risk (ρ) the most accurately as possible in order to try to control it appropriately. However, designing and quantifying risk presents its own hazards (Barrieu & Scandolo, 2015). In fact, several financial risk indicators are broadly used to measure the risk of the expected returns or variation of the value of financial assets. For example, the variance, covariance and the standard deviation of the returns are well known risk indicators widely used by financial practitioners.

Returns ($\mathrm{r_t}$) may be defined as the arithmetic rate of return of the assets in the portfolio, $r_t = \frac{P-P_{t-1}}{P_{t-1}}$. Moreover, in order to focus on long-horizon returns, in practice, geometric rate of return ($\mathrm{R_t}$) is used. Thus, $\mathrm{R_t}$ is the logarithm of the arithmetic return $R_t = \ln \frac{P_t}{P_{t-1}} = \ln P_t - \ln P_{t-1}$. Before calculating risk (ρ) is essential to analyse the distribution of the returns ($\mathrm{R_t}$) in order to identify possible fluctuations, non-normal distribution, skewness[1] and/or kurtosis[2] in order to choose the most accurate risk indicators based on the real data of the assets. Notice that, although the above-mentioned conventional risk measures are within the most widely used risk indicators, however, they may not be appropriate when returns are not normally distributed. The literature provides ample empirical evidence that suggests the downside risk measures as a better approximation to measure the risk of returns ($\mathrm{R_t}$) (Ang et al., 2006; Bali et al., 2009; Grootveld & Hallerbach, 1999; Lucas & Klaassen, 1998; Miller & Leiblein, 1996). Downside risk measures punish left-tail deviations below a defined threshold, and therefore, constitute a better estimation of risk, especially when managers are averse to deviation below a certain threshold (Gundel & Weber, 2007; Miller & Reuer, 1996; Shah & Ando, 2015; Zhu et al., 2009). Among the downside measures, Value-at-Risk

[1] Skewness measures symmetry and indicates whether the distribution is symmetric or skewed to one side. Skewness (S) is $S = \frac{E[(x-\bar{x})^3]}{E[(x-\bar{x})^2]^{3/2}} = \frac{m_3}{m_2^{3/2}}$, where m_2 and m_3 are the second and third central moments, $m_3 = \sum(x-\bar{x})^3/n$ and $m_2 = \sum(x-\bar{x})^2/n$. $\bar{x}$ is the mean; n is the sample size; m_2 is the variance, the square of the standard deviation; m_3 is the third moment of the data set. Negative skewness implies that the data distribution is left-skewed. Positive skewness indicates that the data distribution is right-skewed.

[2] Kurtosis measures the shape of the tails of the return distribution and it determines whether the distribution is thin-tailed, fat-tailed or follows normal distribution. Kurtosis (K) is $K = \frac{E[(x-\bar{x})^4]}{E[(x-\bar{x})^2]^2} = \frac{m_4}{m_2^2}$, where m_2 and m_4 are the second and fourth central moments, $m_4 = \sum(x-\bar{x})^4/n$ and $m_2 = \sum(x-\bar{x})^2/n$. Normal distribution has zero kurtosis. Negative kurtosis indicates that the distribution is thin-tailed (platykurtic) and positive kurtosis implies that the distribution is fat-tailed (leptokurtic).

(VaR) (Jorion, 1997, 2001) became the most popular and widely used risk indicator since its adoption in 1996 by the Basel Committee on Banking Supervision (Basel II, 1996). Afterwards, due to the lack of some key properties, in 2013, Basel III (2013) recommended replacing VaR by the Expected Shortfall (ES) (Rockafellar, Uryasev et al., 2000; Rockafellar & Uryasev, 2002). Moreover, recently some authors advocate for the use of Expectiles (EX) to measure risk (Bellini & Di Bernardino, 2017; J. M. Chen et al., 2018) Thus, VaR, ES and EX will be introduced in this subsection as potential financial risk indicators to be used to estimate species level *biological risk* (BR) and *production risk* (PR). Besides, their properties will be compared in order to provide solutions and choose the most appropriate risk indicator to measure BR and production risk PR subject to the empirical characteristics of our real data.

There are some desirable properties (such as coherence, law-invariance, monotonic additivity and elicitability) that a risk indicator should have in order to properly measure risk (J. M. Chen et al., 2018; Z. Chen & Wang, 2008; Emmer et al., 2015; Föllmer & Knispel, 2013; Krokhmal, 2007; Roccioletti, 2015). Following Emmer et al. (2015), let $L_i, i \in \{1, ..., m\}$ be the loss in the i-th position, considering a portfolio of m risky positions. Losses (negative returns) are positive numbers, gains (positive returns) are negative numbers and the portfolio-wide loss is captured by $L = \sum_{i=1}^{m} L_i$. It will be assumed that the loss variable (L) of the portfolio is defined on a probability space $(\Omega, \mathcal{F}, P)$. A risk measure (ρ) will be considered as *coherent* if and only if satisfies all of these four conditions: homogeneity[3], sub-additivity[4], monotonicity[5] and translation invariance[6] (Artzner et al., 1999). As a complement to the sub-additivity property, a risk indicator will be considered as monotonically additive if for any monotonic random variables L_1 and L_2 it holds that $\rho(L_1+L_2) = \rho(L_1)+\rho(L_2)$. Moreover, a risk measure (ρ) will be also considered law-invariant if $P(L_1 \leq \ell) = P(L_2 \leq \ell), \ell \in \mathbb{R} \Rightarrow \rho(L_1) = \rho(L_2)$ Kusuoka (2001). Elicitability is also a key property that provides a natural methodology to perform backtesting (Bellini & Bignozzi, 2015). Accordingly, the functional ν is elicitable relative to $\mathcal{P}$ if, and only if, there is a scoring function[7] S which is strictly

[3] *(Linear) Homogeneity*: Multiplying any position by a positive factor λ, will result in a linear increase in risk. ρ will be *homogeneous* if for all loss variables L and $\lambda > 0$ it holds that $\rho(\lambda L) = \lambda\rho(L)$.

[4] *Sub-additivity*: The risk associated with two positions cannot exceed the total risk associated with either position. ρ will be sub-additive if for all loss variables L_1 and L_2 it holds that $\rho(L_1 + L_2) \leq \rho(L_1) + \rho(L_2)$.

[5] *Monotonicity*: If one position offers higher returns than a second position, then the risk associated to the first position cannot exceed the risk associated with the second one. ρ will be monotonic if for all loss variables L_1 and L_2 it holds that $L_1 \leq L_2 \Rightarrow \rho(L_1) \leq \rho(L_2)$.

[6] *Translation invariance*: Adding a constant return (k) to total return (reducing loss), will lead on a reduction on risk by the same amount. ρ will be translation invariant if for all loss variables L and $k \epsilon \mathbb{R}$ it holds that $\rho(L - k) = \rho(L) - k$.

[7] A *scoring function* is a function $s : \mathbb{R} \times \mathbb{R} \to [0, \infty)$ and $(x, y) \to s(x, y)$ where x and y are the point

consistent[8] for ν relative to $\mathcal{P}$. Elicitability helps determining an optimal forecast, which means that if there is a strictly consistent scoring for a functional ν, optimal forecast[9] $\hat{x}$ for $\nu(P)$.

In this chapter, five potential downside risk indicators will be considered, including Value-at-Risk (VaR), Modified Value-at-Risk (MVaR), Expected Shortfall (ES), Modified Expected Shortfall (MES), and Expectiles (EX). Their properties will be analysed next, which will be useful to afterwards select the most appropriate one(s) subject to the empirical distributional properties of our (species level) returns.

Value-at-Risk (VaR), commonly known as *Historical VaR (HVaR)*, is the most popular downside risk measure. It measures the worst expected loss over a given horizon under normal market conditions at a given level of confidence (Jorion, 2001). VaR became a very popular risk indicator because it brings simplicity, wide applicability and universality (Jorion, 1990, 1997). *VaR* at level $\alpha \in (0,1)$ of a loss variable L is defined as the $\alpha - quantile$ of the loss distribution (Emmer et al., 2015)

$$VaR_\alpha(L) = q_\alpha(L) = \inf\{\ell : P(L \leq \ell) \geq \alpha\} \tag{2.1}$$

The most used confidence level $(1-\alpha)$ in the literature is 99%, which implies that there is only a 1% probability that the return of the portfolio will fall below the VaR value. Moreover, Delta-Normal VaR assumes that returns are normally distributed:

$$VaR_\alpha = \sigma z_\alpha \tag{2.2}$$

where σ represents the standard deviation of the returns and z_α represents the $\alpha - quantile$ standard Gaussian cumulative distribution function.

The so called *Modified VaR (MVaR)* or *Modified Cornish-Fisher VaR* is most appropriate when returns are not normally distributed, because it adjusts the standard deviation to account for skewness and kurtosis in the return distribution (Favre & Galeano, 2002). MVaR uses the Cornish Fisher expansion method to take the higher moments of non-normal distributions (skewness and kurtosis) into account (Cornish &

forecasts and observations respectively. Following Ziegel (2016) procedure, let ν be a functional on a class of probability measures $\mathcal{P}$ on $\mathbb{R}$. $\nu : \mathcal{P} \to 2^{\mathbb{R}},\ P \mapsto \nu(P) \subset \mathbb{R}$,where $2^{\mathbb{R}}$ denotes the power set of $\mathbb{R}$. A *scoring function* $s : \mathbb{R} \times \mathbb{R} \to [0,\infty)$ is *consistent* for the functional ν relative to the class $\mathcal{P}$ if for all $P \in \mathcal{P}, t \in \nu(P)$ and $x \in \mathbb{R}$.

[8] A function will be *strictly consistent* if it is consistent and equality in $E_P[s(t,L)] \leq E_P[s(x,L)]$ implies that $x \in \nu(P)$,$E_P[s(t,L)] = E_P[s(x,L)] \ \Rightarrow \ x \in \nu(P)$.

[9] An optimal forecast is given by $\hat{x} = arg\ \underset{x}{\min} E_P[s(x,L)]$. Point forecasts for a functional ν should be evaluated by means of a scoring function, which is consistent to ν. If not, realistic examples could be constructed where forecasts are ranked worse than using absolute error or the squared error (Ziegel, 2016).

Fisher, 1938). The Cornish Fisher (CF) expansion transforms a standard Gaussian random variable z into a non-Gaussian Z random variable.

$z \approx N(0,1)$ $E(z)=0$ $E(z^2)=1$ $E(z^3)=0$ $E(z^4)=3$

$Z = z + (z^2-1)\frac{S}{6} + (z^3-3z)\frac{K}{24} - (2z^3-5z)\frac{S^2}{36}$

where S is an skewness parameter corresponding to a Gaussian distribution and K corresponds to excess kurtosis parameter. Thus, MVaR for the transformed distribution is:

$$MVaR_\alpha = \sigma z_{CF\alpha} \tag{2.3}$$

where $z_{CF\alpha} = z_\alpha + \frac{(z_\alpha^2-1)S}{6} + \frac{(z_\alpha^3-3z_\alpha)K}{24} - \frac{(2z_\alpha^3-5z_\alpha)S^2}{36}$.

Value-at-Risk (VaR) satisfies homogeneity, monoticity and translation invariance properties. However, it has been criticized because it ignores the severity of losses in the far tail of the loss distribution (Emmer et al., 2015), and it also fails to be sub-additive. Hence, VaR is not a coherent risk indicator (Artzner, 1997). Accordingly, the risk of a portfolio could be higher than the sum of its risk components (Danielsson, 2002), which contradicts the diversification benefit associated with merging portfolios.

Expected Shortfall (ES), commonly known as *Historical ES (HES)*, is a better alternative to VaR, because ES is a coherent risk measure. It also accounts for the tail risk and fulfils the sub-additive property (Artzner et al., 1999). ES, also known as average VaR, Conditional VaR (CVaR), or tail conditional expectation (Rockafellar, Uryasev et al., 2000; Rockafellar & Uryasev, 2002), is calculated by averaging all the returns in the distribution that are worse than VaR. ES at level $\alpha \in (0,1)$ of a loss variable L is defined as (Emmer et al., 2015)

$$\begin{aligned} ES_\alpha(L) &= \frac{1}{1-\alpha}\int_\alpha^1 q_u(L)du \\ &= \mathbb{E}[L|L \geq q_\alpha(L)] + (\mathbb{E}[L|L \geq q_\alpha(L)] - q_\alpha(L))\left(\frac{P[L \geq q_\alpha(L)]}{1-\alpha} - 1\right). \end{aligned} \tag{2.4}$$

if $P[L = q_\alpha(L)] = 0$ (in particular, if L is continuous), $ES_\alpha(L) = \mathbb{E}[L|L \geq q_\alpha(L)]$.

Following the suggestion at Basel III, the most used confidence level $(1-\alpha)$ when calculating ES, is 97.5% (Basel III, 2013). ES is a coherent risk indicator and it is sensitive to the severity of losses in the far tail of the loss distribution; it quantifies tail risk by reporting the mean loss worse than VaR. ES is also continuous with respect to α and the risk measured by ES will not change dramatically when changing the confidence level, as it happens in the case of VaR (Acerbi & Tasche, 2002). ES satisfies law-invariance (Kusuoka, 2001), monotonic additivity (Embrechts et al., 2002) and it is a coherent risk indicator. So, ES fulfils all the conditions that are defined as *spectral* risk measures (Acerbi, 2002). However, it is not elicitable, which is an essential property for robust estimation and backtesting (Ziegel, 2016).

As it is in the case of *Modified VaR*, *Modified Expected Shortfall (MES)* is more appropriate under non-normality of the returns, because it adjusts the standard deviation to account for skewness and kurtosis in the return distribution, through the use of a Cornish-Fisher expansion (Boudt et al., 2008; Jadhav & Ramanathan, 2019). MES is defined as the negative of the expected value of all returns below the Cornish-Fisher quantile Peterson and Boudt (2008).

Expectiles (EX) have been suggested as coherent, sub-additive and elicitable alternative (Bellini & Di Bernardino, 2017; J. M. Chen et al., 2018; Waltrup et al., 2015). The concept of EX, introduced by Newey and Powell (1987), has been suggested by the union of 'expectation' and 'quantiles', and the *τ-Expectile* $e_\tau(L)$ is defined as $e_\tau(L) = \arg\min_{\ell \in \mathbb{R}} E[\tau \max(L-\ell,0)^2 + (1-\tau)\max(\ell-L,0)^2]$. $e_\tau(L)$ is the unique solution ℓ of the equation 2.5 (Emmer et al., 2015) where $\tau \in (0,1)$.

$$\tau E[\max(L-\ell,0)] = (1-\tau)E[\max(\ell-L,0)] \tag{2.5}$$

Using the notation $x_+ := \max\{x,0\}$and $x_- := \max\{-x,0\}$, and considering X a random variable where $X \in L^1$, *τ-Expectile* $e_\tau(X)$ can be also defined as (Bellini et al., 2014)

$$\tau E[(X - e_\tau(X))_+] = (1-\tau)E[(X - e_\tau(X))_-]. \tag{2.6}$$

There is not an official recommendation for considering an acceptable level of gain-loss ratio, but, $\tau = 0.00145$ was proposed by Bellini and Di Bernardino (2017) to make results comparable to VaR and ES. EX is homogeneous and law-invariant, for $0 < \tau < 1$, sub-additive and coherent for $1/2 \leq \tau < 1$, superadditive for $0 < \tau \leq 1/2$, elicitable and not monotonically additive for $1/2 < \tau < 1$ (Bellini et al., 2014).

Table 2.3: Properties of downside risk measures

Property	*VaR*	*ES*	*EX*
Coherence		x	x
Homogeneity	x	x	x
Sub-additivity		x	x [10]
Monotonicity	x	x	x
Invariance	x	x	x
Elicitability	x		x
Monotonic additivity	x	x	x [11]

Source:Adapted from Emmer et al. (2015).

Notes:
VaR is the Value-at-Risk, ES the Expected Shortfall and EX the Expectiles.

Summarising, Expected Shortfall (ES) seems to be the top risk indicator (Emmer et al., 2015) (see Table 2.3). Even ES is not elicitable, backtesting process could be carried out indirectly. Nevertheless, for the purpose of measuring *biological risk* (BR) and *production risk* (PR) at fish species level (as we will see in section 2.1.3), for completeness, we will also compute the Historical Value-at-Risk (HVaR), the Modified Value-at-Risk (MVaR), the Historical Expected Shortfall (HES), the Modified Expected Shortfall (MES) and the Expectiles (EX). Thereafter, depending on the return distribution of spawning stock biomass (SSB) and catches (Q), the best risk indicator will be suggested.

2.1.2.3 Theoretical overview of conventional ecological indicators

It is necessary to predict vulnerability of fish species before their population collapses (Sala & Knowlton, 2006; Worm et al., 2006). Hence, there is a need to forecast risk accurately in order to control and internalise it appropriately in the stocks management and conservation policies. However, the lack of reliable and quantitative information for a broad spectrum of individual fish species suggests the need of a general and consistent approach to be applied to all the spectrum. This way, not only will be possible to compare the inherent risk of each fish species, but also, it may help to assess the management and conservation policies. In order to get a complement to the conventional species-level ecological risk indicators, we aim to estimate the biological (BR) and production risk (PR) of each 49 individual fish species subject to analytical stock assessments.

[10] for $1/2 \leq \tau < 1$
[11] for $0 \leq \tau < 1/2$

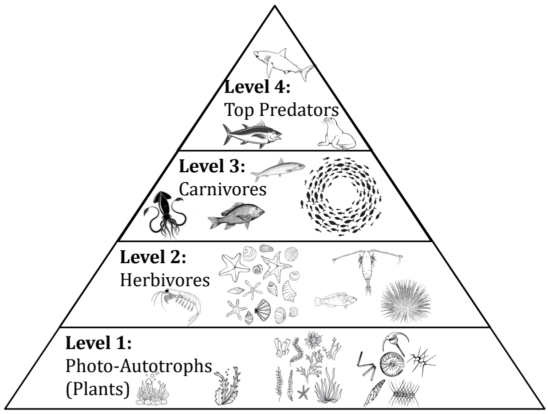
Certainly, there are some key and broadly followed databases (e.g. FishBase and the Red List of Threatened Species (RLTS)), in which species level indicators are available. Specifically, three ecological indicators are included in the mentioned databases as potential indicators for predicting vulnerability of fish species, namely: vulnerability (V), resilience (R) and conservation status (CS) (see Table 2.4). For the purposes of our study, V, R, and the trophic level (TL) were extracted from the FishBase on-line database (Froese & Pauly, 2018). Although not specifically a vulnerability measure, we are also considering TL, because it is a factor conditioning species vulnerability. CS refers to the conservation category stated by the International Union for Conservation of Nature (IUCN) (IUCN, 2018) related to the Red List of Threatened Species (RLTS).

Vulnerability (V) approximates the risk of species extinction (Cheung et al., 2005). V ranges from 0 to 1, and it is calculated on the bases of the species natural life history and their ecological characteristics, which includes maximum length of the first mature age, longevity, Von Bertalanffy growth rate, natural mortality, fertility, spatial behaviour and geographic scale. Accordingly, high vulnerability scores (close to 1) are associated with large sized species that show slow growth rate, long life span and late maturation. In the same way, small species that grow fast will be evaluated as low vulnerability species (close to 0).

Resilience (R) measures the minimum time for doubling the population, i.e. the ability for population to recover after disturbances (such as, for example, overfishing) (Halpern et al., 2012). Resilience ranges from low to high, and it is described by low (4.5 to 14 years), medium (1.4 to 4.4 years) and high (less than 1.3 years). Low values imply a higher ability to recover (high resilience). Contrarily, high values indicate a lower ability to recover (low resilience). Resilience estimations are based on the organism life history, as Von Bertalanffy growth rate, age, maximum age, fecundity, and minimum number of eggs or chicks per year. Nevertheless, the available resilience data give only interval qualitative information about the real status of the fish species, and authors are not confident with the reliability of the current method for obtaining fecundity estimates used for the estimation of resilience (Froese et al., 2000).

Trophic Level (TL) represents the position that each species occupies in the food chain, determined by the number of energy-transfer steps to the basic input of the chain (see Table 2.4). TL ranges from 2.0 (primary consumers) to 4.5 (tertiary consumers) (Pauly & Christensen, 2000; Pauly et al., 1998). Therefore, primary consumers (herbivores), which mainly consume plants, may have values of TL between 2.0 and 2.19. Fish, which are partly herbivore and partly carnivore, consume plants and animals, and may have TL levels between 2.2 and 2.79. Secondary and tertiary consumers (carnivores), mainly consume animals, and may have TL levels equal or greater than 2.8. These values are calculated using a model that describes a numerical ecosystem functioning according to the trophic relationships of the organisms (Christensen & Pauly, 1992; Kline & Pauly, 1998; Mathews, 1993). Following Figure 2.4, we can summarise that larger species have higher TL values and smaller species lower TL values.

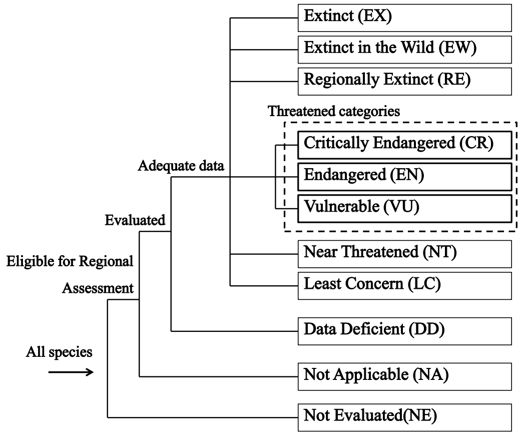
Figure 2.4: Trophic Level (TL)



Notes:
Trophic Level (TL) extracted from the FishBase on-line database (Froese & Pauly, 2018).

Conservation Status (CS) refers to the conservation category stated by the International Union for Conservation of Nature (IUCN) (IUCN, 2018). IUCN Red List of Threatened Species (RLTS) index (see Figure 2.5) evaluates the risk of extinction of species, and classifies them according to a specific conservation score based on criteria such as the rate of population decline, population size and distribution, geographical distribution and fragmentation degree. The species are divided into five categories: least concern (LC), near threatened (NT), vulnerable (VU), data deficient (DD) and not evaluated (NE). However, this database does not include all of our 49 target species, and also ignores issues such as species growth rate, maturity age and life span, which may make our data analysis problematic.

Figure 2.5: Red list categories for conservation status



Source: Packer et al. (2009)

Notes: Conservation Status (CS) categories according to the Red List of Threatened Species (RLTS) of the International Union for Conservation of Nature (IUCN) (IUCN, 2018).

Table 2.4: Conventional ecological indicators

Species	Tr. Level (TL)	Resilience (R)	Vulnerability (V)	Cons. Status (CS)
Angler	4.5	Medium	0.72	LC
Anglerfishes nei	4.1	Low	0.78	NE
Atlantic cod	4.1	Medium	0.65	VU
Atlantic herring	3.4	Medium	0.39	LC
Atlantic horse mackerel	3.7	Medium	0.59	VU
Atlantic mackerel	3.6	Medium	0.44	LC
Beaked redfish	4.1	Very Low	0.58	LC
Blackbellied angler	4.4	Low	0.69	DD
Blackmouth catshark	4.2	Low	0.57	LC
Blonde ray	3.8	Low	0.65	NT
Blue ling	4.5	Low	0.75	NE
Blue whiting	4.1	Medium	0.34	NE
Boarfish	3.1	Low	0.51	LC
Brill	4.4	Medium	0.32	NE
Capelin	3.2	Medium	0.27	NE

Species	Tr. Level (TL)	Resilience (R)	Vulnerability (V)	Cons. Status (CS)
Common dab	3.4	Medium	0.4	LC
Common sole	3.2	Medium	0.36	DD
Cuckoo ray	4.2	Low	0.47	LC
European anchovy	3.1	Medium	0.25	LC
European flounder	3.3	Medium	0.42	LC
European hake	4.4	Medium	0.64	LC
European plaice	3.2	Medium	0.71	LC
European seabass	3.5	Medium	0.69	LC
European sprat	3	Medium	0.33	NE
Four spot megrim	3.7	Medium	0.38	NE
Golden redfish	4	Low	0.71	NE
Greater argentine	3.3	Low	0.51	NE
Greenland halibut	4.4	Low	0.7	NE
Haddock	4	Medium	0.55	VU
Lemon sole	3.2	Medium	0.34	NE
Ling	4.4	Low	0.77	NE
Megrim	4.3	Low	0.62	NE
Megrims nei	4.3	Low	0.62	NE
Northern prawn	NA	NA	NA	NE
Norway lobster	NA	NA	0.14	LC
Norway pout	3.2	Medium	0.26	LC
Nursehound	4	Low	0.67	NT
Rays and skates nei	NA	NA	NA	NA
Saithe	4.3	Medium	0.59	NE
Sandeels	3.1	High	0.23	DD
Sardine	3.1	Medium	0.27	LC
Small spotted catshark	3.8	Low	0.62	LC
Smooth hounds nei	3.8	Very low	0.74	VU
Spotted ray	3.9	Low	0.57	LC
Surmullet	3.5	Medium	0.39	LC
Thornback ray	3.8	Low	0.73	NT
Turbot	4.4	Medium	0.43	NE
Tusk	3.9	Low	0.63	NE
Whiting	4.4	Medium	0.38	LC

2.1.3 Results

From the framework of finances, we suggest two species-level risk indicators, *biological risk* (BR) and *production risk* (PR) as a complement to the above-mentioned conventional ecological indicators. In order to estimate BR and PR, first we measure the returns (R_{it}) for each of the 49 key fish species in our ecosystem (Ω), using spawning stock biomass (SSB) and catches (Q) as data input. BR is based on SSB and captures the risk in the natural frame or ocean. Meanwhile, PR is based on Q, and is a proxy of the output risk related to the EU fleets or fishing activity. Afterwards, based on (R_{it}), we measure the financial risk indicators described in Subsection 2.1.2.2, namely, the Historical Value-at-Risk (HVaR), the Modified Value-at-Risk (MVaR), the Historical Expected Shortfall (HES), the Modified Expected Shortfall (MES) and Expectiles (EX). HVaR (or VaR) measures the worst expected loss (Jorion, 2001). MVaR adjusts the standard deviation to account for skewness and kurtosis in the return distribution when measuring VaR (Favre & Galeano, 2002). HES (or ES) averages all the returns in the distribution that are worse than VaR (Rockafellar & Uryasev, 2002). MES adjusts the standard deviation to account for skewness and kurtosis in the return distribution when measuring ES, and it is more appropriate when returns are not normally distributed (Boudt et al., 2008). EX is defined by the tail expectations rather than tail probabilities (Bellini & Di Bernardino, 2017). To make these five financial risk indicators comparable, following Bellini and Di Bernardino (2017) we are using different confidence levels (i.e. HVaR (99%), MVaR (99%), HES (97.5%), MES (97.5%), EX (99.855%)). Then, after classifying fish species as high/low risk species, by means of correlation analysis we will compare our five risk indicators with the standard ecological ones introduced in Subsection 2.1.2.3, to check potential similarities among financial and ecological measures. Additionally, from our species-level synthetic risk indicators, BR and PR, we will infer a country-based *weighted biological risk* (wBR) and *weighted production risk* (wPR) for each of the EU fishing member-states using the weighted averages of the individual distribution of landings. Hence, we will see that fishing countries with different target fish species distribution will be subject to different underlying risk levels.

2.1.3.1 Biological risk (BR)

Using spawning stock biomass (SSB) we obtain the yearly returns (R_{it}) of the 49 fish species in (Ω) by $R_{it} = \ln \frac{SSB_{it}}{SSB_{it-1}} = \ln SSB_{it} - \ln SSB_{it-1}$. Notice that R_{it} measures the yearly biomass increase or reduction for each fish species in the ecosystem. Figure 2.6 illustrates the box plots of returns (R_{it}) by individual fish species. Species show a quite heterogeneous distribution of $\mathrm{R_{it}}$. Some of them, such as Atlantic cod and common sole, have rather stable SSB, and accordingly, their returns are close to zero; whereas others species, such as Norway pout and beaked redfish, fluctuate significantly from one year to another. Notice that very high and positive returns involve huge yearly increase on SSB. Contrarily, negative returns imply huge SSB reductions. From this first illustration, we can expect that some of the species will be associated to low *biological risk* (stable returns), and others to high *biological risk* (i.e. fluctuating and rather negative returns).

Figure 2.6: Returns ($\mathrm{R_{it}}$) distribution by fish species in terms of spawning stock biomass

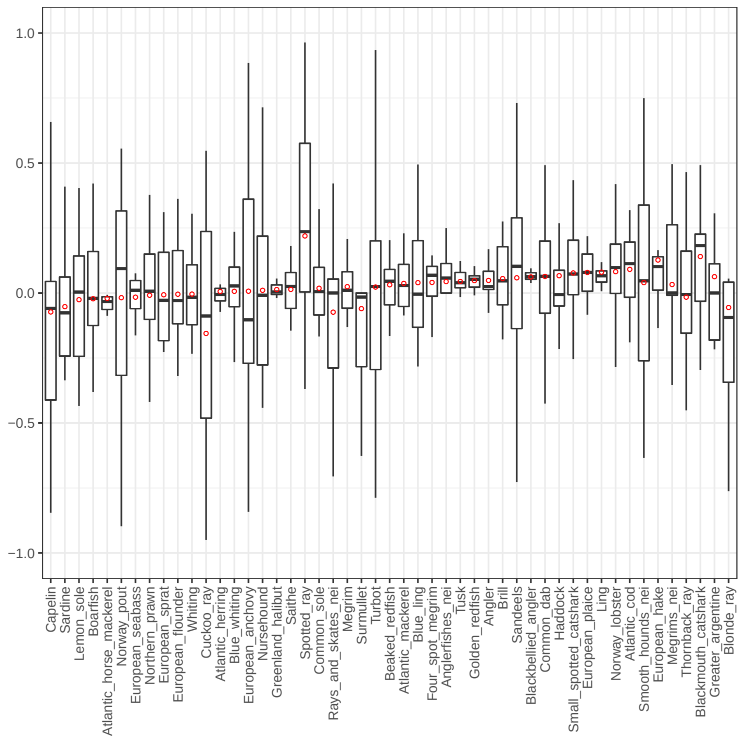


Figure 2.7 shows the density plot of the yearly returns ($\mathrm{R_{it}}$) of the 49 fish species. It can be observed that, although the distribution of $\mathrm{R_{it}}$ is more or less symmetric, it is more peaked than the normal distribution, and that the shape of the tails does not correspond to the normal. As expected, Shapiro-Wilk test (Table 2.6) reveals that the SSB returns are indeed not normally distributed. Accordingly, under these circumstances,

the Modified ES (MES) is more appropriate to measure risk than the Historical Value-at-Risk (HVaR), Modified Value-at-Risk (MVaR), Historical Expected Shortfall (HES) or Expectiles (EX). The reason is that since MES adjusts the standard deviation to account for skewness and kurtosis in the return distribution, it is more appropriate when returns are not normally distributed (Favre & Galeano, 2002). Nevertheless, for completeness, HVaR, MVaR, HES and EX will be also calculated. Notice that, merely considering just one indicator for BR may be misleading, because not all the risk indicators always give the same informative results.

Figure 2.7: Returns ($\mathrm{R_{it}}$) density plot in terms of spawning stock biomass

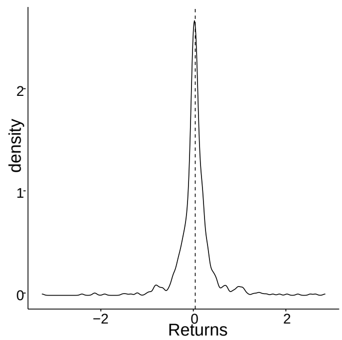


Table 2.6: Shapiro-Wilk normality test: SSB returns

	W	P-value
R_{it}	0.76486	$<$ 2.2e-16

Notes:
Shapiro-Wilk normality test for spawning stock biomass (SSB) yearly returns ($\mathrm{R_{it}}$).
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

Thus, once returns ($\mathrm{R_{it}}$) for each 49 individual fish species have been estimated, we measure the HVaR, MVaR, HES, MES and EX using the returns ($\mathrm{R_{it}}$) of spawning stock biomass (SSB) to proxy the *biological risk* (BR) of each 49 fish species. At this stage, we are using the R package *PerformanceAnalytics* (Peterson & Carl, 2019). Table 2.7 shows the species level biological risk using the above-mentioned financial formulations for BR. BR values range from low (zero) to high (one) risk. At first glance, it can be observed that there are some species (such as turbot, spotted ray and greater Argentine) that can be clearly defined as *high risk* species, whereas others (such as ling, golden redfish and blackbellied angler) could be classified as *low risk* ones. Special attention should be paid on certain species showing an ambiguous behaviour, such as, for example, haddock. Notice that, even HVaR, MVaR, HES and EX values are relatively low for haddock, however MES identifies it as a top high-risk species. As mentioned before, due to the non-normal distribution of the returns, MES is a priori the best approximation to calculate biological risk (BR). MES reflects the effect of not frequent but important disturbances on returns that makes its risk value higher. Accordingly, we have chosen MES as the reference risk indicator to estimate the biological risk (BR) of each of the individual fish species. An additional advantage of MES is that, when compared to HVaR, MVaR, HES and/or EX, helps to easily identify species with huge but not frequent disturbances. This is the case of haddock, which indeed may be catalogued as an *ambiguous* species.

Table 2.7: *Biological risk* indicators (BR)

Species	Code	HVaR		MVaR		HES		**MES**		EX	
Blonde ray	RJH	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Capelin	CAP	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Cuckoo ray	RJN	0.93	Q4	1	Q4	0.95	Q4	1	Q4	0.93	Q4
European anchovy	ANE	0.83	Q4	0.98	Q4	0.84	Q4	1	Q4	0.82	Q4
Greater argentine	ARU	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Haddock	HAD	0.21	Q2	0	Q1	0.22	Q2	1	Q4	0.21	Q2
Norway pout	NOP	0.87	Q4	1	Q4	0.9	Q4	1	Q4	0.88	Q4
Rays and skates nei	RAJ	0.7	Q3	0.68	Q3	0.71	Q3	1	Q4	0.69	Q3
Spotted ray	RJM	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Surmullet	MUR	0.99	Q4	0.66	Q3	1	Q4	1	Q4	0.99	Q4
Turbot	TUR	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Sandeels	SAN	0.72	Q3	0.93	Q4	0.73	Q3	0.94	Q3	0.71	Q3
Smooth hounds nei	SDV	0.62	Q3	0.79	Q4	0.63	Q3	0.94	Q3	0.62	Q3
Thornback ray	RJC	0.78	Q4	0.83	Q4	0.84	Q4	0.93	Q3	0.82	Q4
Boarfish	BOC	0.72	Q3	0.85	Q4	0.78	Q4	0.89	Q3	0.76	Q4
Nursehound	SYT	0.44	Q3	0.58	Q3	0.44	Q3	0.76	Q3	0.43	Q3
Megrims nei	LEZ	0.74	Q4	0.64	Q3	0.81	Q4	0.64	Q3	0.79	Q4
European flounder	FLE	0.53	Q3	0.62	Q3	0.57	Q3	0.62	Q3	0.56	Q3
Northern prawn	PRA	0.48	Q3	0.59	Q3	0.49	Q3	0.59	Q3	0.47	Q3
Average		0.41		0.45		0.42		0.52		0.41	

Species	Code	HVaR		MVaR		HES		**MES**		EX	
Lemon sole	LEM	0.43	Q3	0.56	Q3	0.43	Q3	0.57	Q3	0.43	Q3
Sardine	PIL	0.33	Q3	0.4	Q3	0.34	Q3	0.57	Q3	0.33	Q3
Blackmouth catshark	SHO	0.4	Q3	0.51	Q3	0.42	Q3	0.51	Q3	0.41	Q3
Blue ling	BLI	0.28	Q2	0.36	Q2	0.28	Q2	0.49	Q3	0.28	Q2
Common dab	DAB	0.4	Q3	0.48	Q3	0.43	Q3	0.49	Q3	0.41	Q3
European hake	HKE	0.12	Q1	0.09	Q1	0.14	Q1	0.44	Q2	0.13	Q1
Anglerfishes nei	ANF	0.33	Q3	0.4	Q3	0.34	Q3	0.43	Q2	0.33	Q3
European sprat	SPR	0.23	Q2	0.33	Q2	0.23	Q2	0.4	Q2	0.22	Q2
Atlantic horse mackerel	HOM	0.09	Q1	0.07	Q1	0.09	Q1	0.39	Q2	0.09	Q1
Blue whiting	WHB	0.27	Q2	0.36	Q2	0.27	Q2	0.36	Q2	0.26	Q2
Norway lobster	NEP	0.28	Q2	0.35	Q2	0.29	Q3	0.35	Q2	0.28	Q2
Small spotted catshark	SYC	0.25	Q2	0.34	Q2	0.25	Q2	0.34	Q2	0.25	Q2
Whiting	WHG	0.23	Q2	0.29	Q2	0.23	Q2	0.33	Q2	0.23	Q2
Common sole	SOL	0.16	Q2	0.19	Q2	0.17	Q2	0.26	Q2	0.16	Q2
Atlantic cod	COD	0.18	Q2	0.23	Q2	0.19	Q2	0.23	Q2	0.18	Q2
Brill	BLL	0.17	Q2	0.22	Q2	0.18	Q2	0.23	Q2	0.17	Q2
Atlantic mackerel	MAC	0.09	Q1	0.13	Q1	0.09	Q1	0.22	Q2	0.08	Q1
European seabass	BSS	0.16	Q2	0.21	Q2	0.16	Q2	0.21	Q1	0.16	Q2
Megrim	MEG	0.13	Q1	0.17	Q1	0.13	Q1	0.21	Q1	0.13	Q1
Beaked redfish	REB	0.15	Q2	0.19	Q2	0.16	Q2	0.19	Q1	0.16	Q2
Four spot megrim	LDB	0.16	Q2	0.19	Q2	0.17	Q2	0.19	Q1	0.17	Q2
Saithe	POK	0.14	Q1	0.19	Q2	0.14	Q1	0.19	Q1	0.14	Q1
Ling	LIN	0	Q1	0	Q1	0	Q1	0.17	Q1	0	Q1
Atlantic herring	HER	0.07	Q1	0.08	Q1	0.07	Q1	0.16	Q1	0.07	Q1
Angler	MON	0.07	Q1	0.08	Q1	0.08	Q1	0.12	Q1	0.07	Q1
European plaice	PLE	0.08	Q1	0.11	Q1	0.08	Q1	0.11	Q1	0.08	Q1
Tusk	USK	0.06	Q1	0.08	Q1	0.07	Q1	0.08	Q1	0.07	Q1
Blackbellied angler	ANK	0.01	Q1	0.02	Q1	0.02	Q1	0.05	Q1	0.01	Q1
Greenland halibut	GHL	0.02	Q1	0.02	Q1	0.02	Q1	0.05	Q1	0.02	Q1
Golden redfish	REG	0.01	Q1	0.02	Q1	0.01	Q1	0.02	Q1	0.01	Q1
Average		0.41		0.45		0.42		0.52		0.41	

Notes:

Historical Value-at-Risk (HVaR), Modified Value-at-Risk (MVaR), Historical Expected Shortfall (HES), Modified Expected Shortfall (MES), Expectiles (EX).

Q1: very low risk. Q2: moderate low risk. Q3: moderate high risk. Q4: very high risk.

We have fixed a rule to identify the species showing an ambiguous behaviour. Differences (Δ) between the 5 risk indicators (i.e. MES, HVaR, MVaR, HES, EX) have been calculated, and a confidence interval has been set. Then, species with higher or lower differences over the mean value plus or minus three times standard deviation will be considered as *ambiguous* species according to BR. Following $\mu - 3\sigma \leq diff \leq \mu + 3\sigma$ rule, where μ is the mean value and σ is the standard deviation, we can see that four species show significantly higher or lower differences depending on the risk indicator we are using. The list of ambiguous species, in addition to haddock, is made up by surmullet, boarfish, megrims nei and thornback ray. As mentioned, MES adjusts the standard deviation to account for skewness and kurtosis in the return distribution, reflects the effect of not frequent but important disturbances, and it is more appropriate when returns are not normally distributed. This is the main reason why ES defines these ambiguous species as risky, whereas the rest of the risk indicators classify them as low risk species.

According to BR, the 49 fish species have been divided into four quartiles (Q), namely, species with very low risk (Q1), species with moderate low risk (Q2), species with moderate high risk (Q3) and species with very high risk (Q4). Table 2.7 shows the number of species included in each quartile for the 5 biological risk indicators (HVaR, MVaR, HES, MES and EX). MES is the one that less Q1 (very low risk) species and more Q4 (very high risk) species includes. Under this ambiguity among the indicators, as already mentioned, MES would be our reference indicator, due to the particular distribution of the SSB returns ($\mathrm{R_{it}}$). Moreover, MES helps to identify ambiguous species. Nevertheless, even MES is considered to be the best risk indicator to proxy the biological risk (BR) of the fish species, all the 5 risk indicators will be taken into account for a general and complete analysis.

2.1.3.2 Production risk (PR)

Following the same approach as for the *biological risk* (BR), in this subsection we aim to measure the *production risk* (PR) at fish species level. Using catches (Q) we first measure the yearly returns ($\mathrm{R_{it}}$) of the 49 individual fish species in the global ecosystem by $R_{it} = \ln \frac{Q_{it}}{Q_{it-1}} = \ln Q_{it} - \ln Q_{it-1}$. $\mathrm{R_{it}}$ measures the yearly catches increase or reduction for each fish species (i). Returns will be positive when catches increase, and negative when they decrease. Figure 2.8 shows the catches' returns ($\mathrm{R_{it}}$) by species. $\mathrm{R_{it}}$ exhibits a rather heterogeneous return distribution depending on the species. Some of the species, such as common dab and lemon sole, have very stable catches (close to zero returns), whereas others, such as beaked redfish and Norway pout, are subject to major fluctuations. Notice that very high and positive returns imply that the yearly catches for these species have increased. Contrarily, negative returns involve yearly reduction on the catches. From this first illustration, we can expect that some of the species (such as common sole and Norway lobster) will be associated to *low risk* and others (such as Norway pout and sandeels) to *high risk*.

Figure 2.8: Returns (R_{it}) distribution by fish species in terms of catches

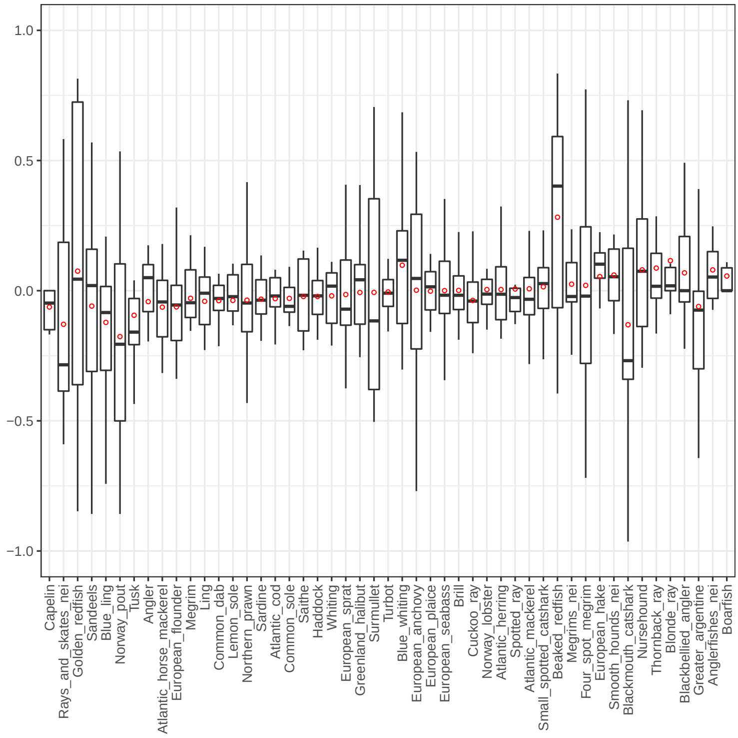


Figure 2.9 shows the density plot for catches' returns (R_{it}) distribution. We can see that although is rather symmetric, it is more peaked than the normal distribution and also that the shape of the tails does not correspond to a normal. Additionally, we have checked by the Shapiro-Wilk test whether our returns are normally distributed. Shapiro-Wilk testing results (Table 2.9) show that the catches returns are indeed not normally distributed. Accordingly, Modified ES (MES) is a priori more appropriate to measure *production risk* (PR), because it adjusts the standard deviation to account for skewness and kurtosis in the distribution of returns (Favre & Galeano, 2002). Nevertheless, for completeness, besides MES, we have also calculated the risk associated to catches of each 49 individual fishing species using the HVaR, MVaR, HES, MES and

EX.

Figure 2.9: Returns (R_{it}) density plot in terms of catches

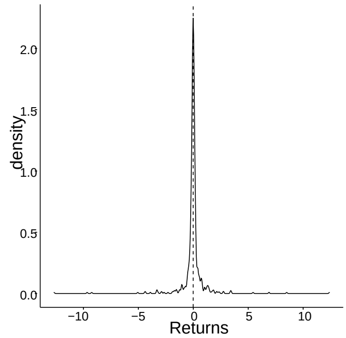


Table 2.9: Shapiro-Wilk normality test: Catches returns

	W	P-value
R_{it}	0.46878	< 2.2e-16

Notes:
Shapiro-Wilk normality test for catches (Q) yearly returns (R_{it}).
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.10 shows the *production risk* (PR) estimates. PR values range from low (zero) to high (one) risk. It is remarkable first that, PR values are higher than the ones obtained in the previous subsection for biological risk (BR). This is comprehensible, because more variables affect catches, including, quotas, stakeholders' individual decisions, market conditions and specific regulations. Special attention should be paid to some species, such as blonde ray and thornback ray, which could be catalogued as *ambiguous* species. Even their HVaR, MVaR, HES and EX values are relatively low, MES catalogues these species as a top *highly risk* species. Notice that MES reflects the effect of not frequent but important disturbances on returns that makes its risk value higher, and accordingly helps to identify ambiguous species. Hence, MES will be also taken as the reference indicator to proxy PR at species level. Following the classification rule already introduced to identify ambiguities for BR, four species exhibit significantly higher or lower differences among the five financial PR measures (i.e. HVaR, MVaR, HES, MES and EX). Specifically, blonde ray, thornback ray, anglerfishes nei and spotted ray would be defined as ambiguous species, since these species show noticeable and significant differences between some of the risk indicators (HVaR, MVaR, HES, MES and EX).

Table 2.10: *Production risk* indicators (PR)

Species	Code	HVaR		MVaR		HES		**MES**		EX	
Angler	MON	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Anglerfishes nei	ANF	0.96	Q3	0.48	Q3	1	Q4	1	Q4	1	Q4
Beaked redfish	REB	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Blackbellied angler	ANK	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Blackmouth catshark	SHO	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Blonde ray	RJH	0.08	Q1	0	Q1	0.09	Q1	1	Q4	0.08	Q1
Blue whiting	WHB	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Boarfish	BOC	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Capelin	CAP	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Cuckoo ray	RJN	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
European anchovy	ANE	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Four spot megrim	LDB	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Golden redfish	REG	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Greater argentine	ARU	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Megrim	MEG	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Norway pout	NOP	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Rays and skates nei	RAJ	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Sandeels	SAN	1	Q4	1	Q4	1	Q4	1	Q4	1	Q4
Surmullet	MUR	0.49	Q3	0.63	Q3	0.5	Q3	0.97	Q3	0.49	Q3
Thornback ray	RJC	0.15	Q1	0.1	Q1	0.16	Q1	0.85	Q3	0.16	Q1
Lemon sole	LEM	0.44	Q3	0.5	Q3	0.49	Q3	0.82	Q3	0.48	Q3
Blue ling	BLI	0.7	Q3	0.79	Q3	0.74	Q3	0.79	Q3	0.73	Q3
European hake	HKE	0.43	Q3	0.48	Q3	0.47	Q3	0.78	Q3	0.46	Q3
Greenland halibut	GHL	0.53	Q3	0.71	Q3	0.54	Q3	0.71	Q3	0.52	Q3
Tusk	USK	0.41	Q2	0.36	Q2	0.44	Q2	0.69	Q2	0.43	Q2
Atlantic mackerel	MAC	0.26	Q2	0.2	Q1	0.28	Q2	0.65	Q2	0.28	Q2
Smooth hounds nei	SDV	0.45	Q3	0.54	Q3	0.5	Q3	0.54	Q2	0.49	Q3
Northern prawn	PRA	0.41	Q2	0.46	Q3	0.43	Q2	0.48	Q2	0.42	Q2
European sprat	SPR	0.36	Q2	0.4	Q2	0.38	Q2	0.47	Q2	0.37	Q2
Average		0.54		0.56		0.55		0.65		0.55	

Species	Code	HVaR		MVaR		HES		**MES**		EX	
Nursehound	SYT	0.29	Q2	0.41	Q2	0.3	Q2	0.46	Q2	0.29	Q2
Ling	LIN	0.38	Q2	0.44	Q2	0.41	Q2	0.45	Q2	0.4	Q2
European seabass	BSS	0.33	Q2	0.4	Q2	0.34	Q2	0.4	Q2	0.34	Q2
Spotted ray	RJM	0.5	Q3	0.4	Q2	0.57	Q3	0.4	Q2	0.55	Q3
European flounder	FLE	0.32	Q2	0.36	Q2	0.34	Q2	0.39	Q2	0.33	Q2
Atlantic horse mackerel	HOM	0.31	Q2	0.37	Q2	0.32	Q2	0.37	Q2	0.31	Q2
Haddock	HAD	0.32	Q2	0.37	Q2	0.34	Q2	0.37	Q2	0.34	Q2
Saithe	POK	0.22	Q1	0.29	Q2	0.23	Q1	0.31	Q1	0.22	Q1
Megrims nei	LEZ	0.23	Q2	0.26	Q1	0.25	Q2	0.3	Q1	0.24	Q2
Small spotted catshark	SYC	0.25	Q2	0.29	Q2	0.26	Q2	0.29	Q1	0.26	Q2
Atlantic herring	HER	0.17	Q1	0.2	Q1	0.18	Q1	0.27	Q1	0.18	Q1
Atlantic cod	COD	0.2	Q1	0.26	Q1	0.21	Q1	0.26	Q1	0.2	Q1
Whiting	WHG	0.2	Q1	0.26	Q1	0.21	Q1	0.26	Q1	0.21	Q1
Sardine	PIL	0.19	Q1	0.24	Q1	0.19	Q1	0.24	Q1	0.19	Q1
Common dab	DAB	0.2	Q1	0.23	Q1	0.21	Q1	0.23	Q1	0.21	Q1
Norway lobster	NEP	0.14	Q1	0.15	Q1	0.15	Q1	0.23	Q1	0.15	Q1
Brill	BLL	0.17	Q1	0.19	Q1	0.19	Q1	0.21	Q1	0.18	Q1
Common sole	SOL	0.13	Q1	0.14	Q1	0.14	Q1	0.2	Q1	0.13	Q1
European plaice	PLE	0.15	Q1	0.19	Q1	0.16	Q1	0.19	Q1	0.15	Q1
Turbot	TUR	0.14	Q1	0.17	Q1	0.16	Q1	0.17	Q1	0.15	Q1
Average		0.54		0.56		0.55		0.65		0.55	

Notes:

Historical Value-at-Risk (HVaR), Modified Value-at-Risk (MVaR), Historical Expected Shortfall (HES), Modified Expected Shortfall (MES), Expectiles (EX).

Q1: very low risk. Q2: moderate low risk. Q3: moderate high risk. Q4: very high risk.

According to PR, the 49 fish species have been divided into four quartiles, namely very low risk (Q1), moderate low risk (Q2), moderate high risk (Q3) and very high risk (Q4). Table 2.10 shows the number of species included in each quartile for the 5 proxies for PR (i.e. HVaR, MVaR, HES, MES and EX). MES is the one that less amount of Q1 species and more Q4 species includes. As for BR, MES is the most appropriate indicator when calculating *production risk* (PR) for two main reasons. On the one hand, due to the non-normality of the distribution of returns based on catches (Q). On the other, because MES is especially helpful to identify ambiguous species.

Summarising, in this subsection we have estimated two risk indicators at fish species level, *biological risk* (BR) (based on SSB) and *production risk* (PR) (based on (Q) using a bundle of 5 financial risk indicators (i.e. HVaR, MVaR, HES, MES and EX). Due to the non-normality of the distribution of returns and the fact that MES reflects the effect of not frequent but important disturbances on returns, helping to identify ambiguities among different indicators, MES will be the reference risk indicator for both, BR and PR (Tables 2.7 and 2.10). According to BR, the average biological risk is 0.52. It means that in the worst case, and due to the risk in the natural frame or ocean, the SSB would be reduced by 52%. Golden redfish ($BR_{REG} = 0.02$) and blackbellied angler ($BR_{ANK} = 0.05$) are the fish species with the lowest BR. Contrarily, turbot ($BR_{TUR} = 1$), surmullet ($BR_{MUR} = 1$) and spotted ray ($BR_{RJM} = 1$) are the fish species with the highest BR. In terms of PR, the average production risk is 0.65. It implies that in the worst case, and due to the risk related to factors influencing the fishing activity of the fleets, the catches in the EU would be reduced by 65%. The fish species with the lowest PR are Turbot ($PR_{TUR} = 0.17$) and European plaice ($PR_{PLE} = 0.19$). On the contrary, sandeels ($PR_{SAN} = 1$), rays and skates ($PR_{RAJ} = 1$) and Norway pout ($PR_{NOP} = 1$) are the fish species with the highest PR.

A specific advantage of our synthetic species level risk indicators, BR and PR, is that they can be used to infer the risk to any aggregation level (i.e. country, port, region or fleet). For example, we could derive our synthetic risk indicators to measure the implicit risk of a community (weighting fish species risk by the weight/proportion of the catches on a community). The underlying idea is that fishing communities showing low risk have higher probability to perform better in the fishing activity.

2.1.3.3 Linking financial risk indicators and ecological indicators through correlation analysis

In the preceding subsections we have concluded that Modified Expected Shortfall (MES) is the most appropriate formulation to proxy species level *biological* (BR) and *production risk* (PR). In this subsection, we proceed to compare BR and PR to the conventional ecological indicators included in FishBase and the Red List of Threatened Species (RLTS)) (i.e. resilience (R), vulnerability (V), trophic level (TL) and Conservation Status (CS)). Using correlation analysis we aim to determine whether our species level risk indicators {BR,PR} and the conventional ones {R,V,TL,CS} are significantly correlated, which to a certain extent, may be understood to be an informal way to validate our main motivation of measuring fish species vulnerability from a financial perspective. In order to do so, we are using the Spearman's ρ statistic,[12] because it is more robust than the widely used Pearson's correlation when variables are not normally distributed or the relationship between the variables is not linear (Hollander et al., 2013). At this stage, we are taking advantage of the R package *Hmisc* (Harrell & Dupont, 2020) and *Corrplot (Wei & Simko, 2017).*

Figure 2.10 illustrates the Spearman's ρ correlation values and signs (the statistics, including p-values are given in Table 2.12). Results show significant correlation between biological risk (BR) and trophic level (TL) and vulnerability (V). BR, which is a proxy of the risk to suffer high negative shocks on biomass in the natural frame or ocean, is significantly and negatively correlated with both TL and V. We can expect higher BR for smaller species (low V), since they live closer to the surface (low TL), and they are expected to be more catchable. On the contrary, BR is lower for larger fish species (higher V) living in deeper waters (higher TL). PR, which is a proxy for the risk to suffer a high negative shock due to fishing activity/fleet related reasons, is significantly and negatively correlated with resilience (R), and indicator that measures the ability to recover after disturbances, specifically after overfishing. This basically means that species with high levels of production risk (PR) tend to show higher ability to recover (low resilience). This surprising result may be biased by the unreliable method for estimating fecundity (used for the estimation of resilience) (Froese et al., 2000) and mainly because resilience in FishBase is just a qualitative indicator. Conservation status (CS) is not significantly correlated with either BR or PR. However, attention should be also paid on the fact that CS just gives qualitative information. Moreover, there are many fish species missing in the database that, to some extent, may bias the results.

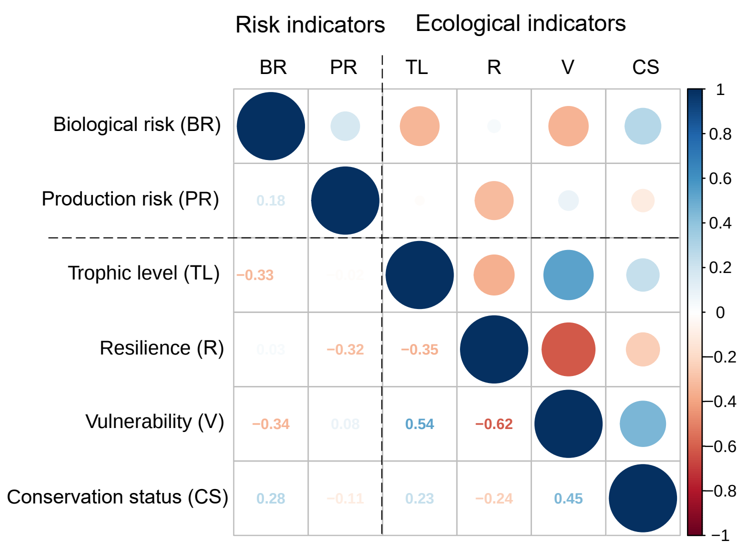
[12] Spearman's ρ correlation between the rank of variables x and y is $\rho = \frac{\sum(x'-m_{x'})(y'_i-m_{y'})}{\sqrt{\sum(x'-m_{x'})^2\sum(y'-m_{y'})^2}}$ where m_x and m_y are the means of x and y respectively, $x' = rank(x)$ and $y' = rank(y)$.

Table 2.12: Spearman's ρ correlation between risk indicators and conventional ecological indicators

	Risk indicators		Ecological indicators			
	BR	PR	TL	R	V	CS
Biological risk (BR)	-	0.18	-0.33**	0.03	-0.34**	0.28
		(0.22)	(0.02)	(0.82)	(0.02)	(0.13)
Production risk (PR)		-	-0.02	-0.32**	0.08	-0.11
			(0.91)	(0.03)	(0.57)	(0.56)
Trophic level (TL)			-	-0.35**	0.54***	0.23
				(0.02)	(0)	(0.23)
Resilience (R)				-	-0.62***	-0.24
					(0)	(0.21)
Vulnerability (V)					-	0.45***
						(0.01)
Conservation status (CS)						-

Notes:
Spearman's ρ correlation values and p-values between risk indicators (BR and PR) and conventional ecological indicators (TL, R, V, and CS).
*** significant at 1%
** significant at 5%
* significant at 10%

Figure 2.10: Spearman's ρ correlation between risk indicators and conventional ecological indicators



2.1.3.4 From species level to country level financial risk indicators

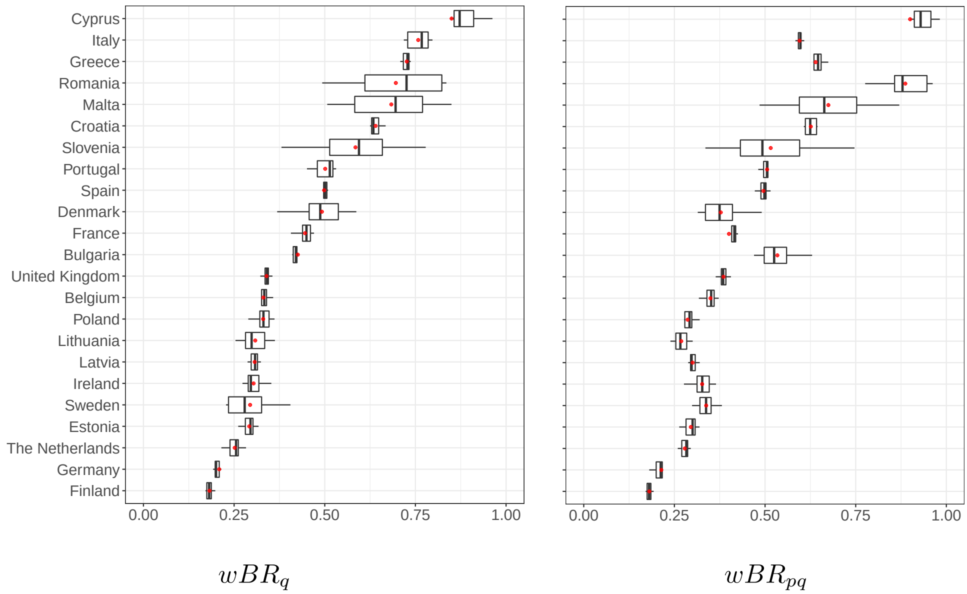
Obtaining primary species level risk indicators such as BR and PR is essential to later infer it to any aggregation level (i.e. country, port, community or fleet). In this section we aim to measure the country level biological (wBR) and production risk (wPR). In order to do so, we are weighting the risk of each fish species by the proportion of the landings of each individual fish species on that country and year ($\mathrm{w_{ijt}}$). Accordingly, countries with different target fish species will suffer from different underlying risk.

So as to get the *weighted biological risk* (wBR) and the *weighted production risk* (wPR) for each of the 23 EU fishing countries (i.e. Belgium, Denmark, Germany, Estonia, Ireland, Spain, France, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Finland, Sweden, United Kingdom, Greece, Bulgaria, Croatia, Cyprus, Malta, Romania and Slovenia) first we calculate the proportion ($w_{ijt} = \frac{Landingsijt}{\sum Landingsijt}$) of the landings of each fish species (i), in country (j) and year (t). This way we can infer the weighted risk for each country, multiplying the weights ($\mathrm{w_{ijt}}$) by the individual species level biological risk (BR) and production risk (PR) ($wBR_{jt} = \sum w_{ijt} * BR_i$ and $wPR_{jt} = \sum w_{ijt} * PR_i$). When calculating the weights, for completeness, we are using both, the volume of landings ($\mathrm{q_{ijt}}$) (tonnes) and the value of the landings ($\mathrm{p_{ijt}}$*$\mathrm{q_{ijt}}$) (where $\mathrm{p_{ijt}}$ are first sale prices (€)) (see Table 2.13). This way, using the value of landing, via prices, we are directly incorporating the market side in the analysis. Thus, based on our species-level risk indicators (BR) and (PR), and using as weights the proportion of the landings of each country to the total landings (both in volume and the value), we can infer the weighted biological and production risk for the 23 EU fishing countries.

Figure 2.11 illustrates two separate box plots in which the weighted biological risk (wBR) is plotted for each country according to the weighting scheme of the volume of landings (q) and value of landings (pq). The left-hand box plot in Figure 2.11 shows the biological risk ($\mathrm{wBR_q}$) (risk to suffer high negative shocks on biomass in the natural frame or ocean) for each country (volume-based). The average q based biological risk (wBRq) is 0.45. Cyprus, Italy, Greece, Romania, Malta and Croatia are the countries with the highest mean wBRq. It implies that, in the worst case, due to natural/biological reasons, the SSB of the species targeted by Cyprus, Italy, Greece, Romania, Malta and Croatia would be reduced respectively by 85% ($wBR_{q,Cyprus} = 0.85$), 76% ($wBR_{q,Italy} = 0.76$), 73% ($wBR_{q,Greece} = 0.73$), 70% ($wBR_{q,Romania} = 0.70$), 68% ($wBR_{q,Malta} = 0.68$) and 64% ($wBR_{q,Croatia} = 0.64$). Contrarily, Finland and Germany are the countries with the lowest biological risk ($wBR_{q,Finland} = 0.18$) and ($wBR_{q,Germany} = 0.21$). Notice that the landings' distribution for Finland is almost totally comprised by Atlantic Herring

(HER), which is a very low risk species ($BR_{HER} = 0.16$). The right-hand box plot in Figure 2.11 shows the weighted biological risk ($\mathrm{wBR_{pq}}$) for each country (value-based (pq)). The risk distribution according to the value of landings ($\mathrm{wBR_{pq}}$), hardly changes compared to the volume-based biological risk ($\mathrm{wBR_q}$). The average pq based biological risk is 0.45. The countries with the highest $\mathrm{wBR_{pq}}$ are Cyprus (90%), Romania (89%), Malta (67%), Greece (64%), Croatia (63%) and Italy (60%), and the ones with the lowest $\mathrm{wBR_{pq}}$ are Finland (18%) and Germany (21%). Thus, $\mathrm{wBR_{pq}}$ seems to be barely affected by the market (via prices).

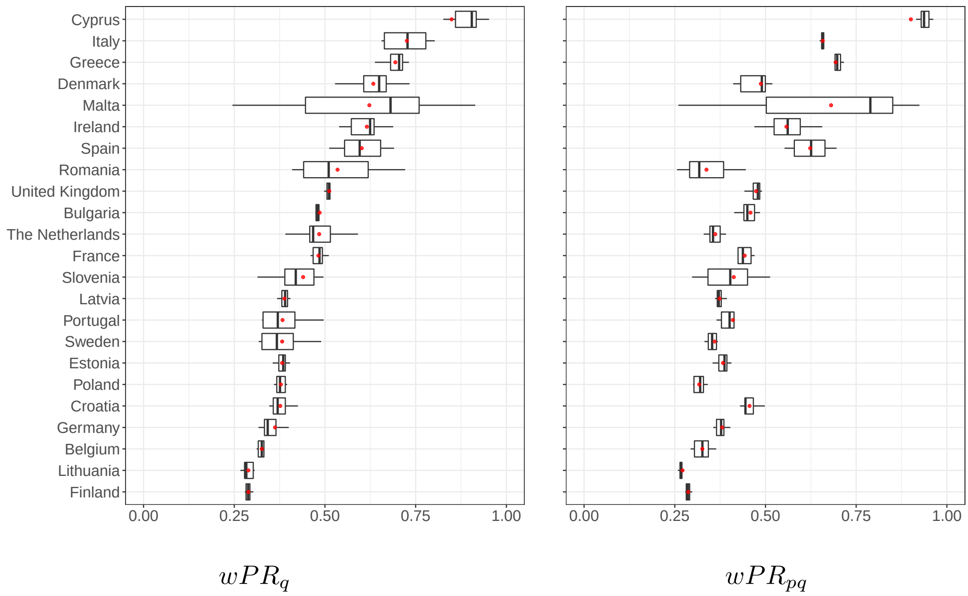
Figure 2.11: Weighted *biological risk* (wBR)



Notes:
The red points are the mean risk and the black lines capture the median.

The left-hand box plot in Figure 2.12 shows the weighted production risk wPR (risk to suffer a high negative shock due to fishing activity/fleet related reasons) for each country (volume-based) ($\mathrm{wPR_q}$). The average volume (q) based production risk (wPRq) is 0.49. Cyprus, Italy, Greece and Denmark are the countries with the highest weighted production risk ($\mathrm{wPR_q}$). Accordingly, in the worst case, the landed volume would be reduced by 85% in Cyprus, 73% in Italy, 69% in Greece and 63% in Denmark. Contrarily, Finland and Lithuania have the lowest production risk ($wPR_{q,Finland} = 0.29$, $wPR_{q,Lithuania} = 0.29$). It is remarkable that the distribution of value-based (pq) production risk ($\mathrm{wPR_{pq}}$) is slightly different to the volume-based one ($\mathrm{wPR_q}$) (see right-hand box plot in figure 2.12). The average pq based production risk is 0.46. The countries with the highest $\mathrm{wPR_{pq}}$ are Cyprus (90%), Greece (69%), Malta (68%) and Italy (66%). This apparent and first sight asymmetric behaviour of $\mathrm{wPR_q}$ and $\mathrm{wPR_{pq}}$ suggests that the market side is also conditioning the results.

Figure 2.12: Weighted *production risk* (wPR)



Notes:
The red points are the mean risk and the black lines capture the median.

We have divided the $\mathrm{wBR_q}$, the $\mathrm{wBR_{pq}}$, the $\mathrm{wPR_q}$ and the $\mathrm{wPR_{pq}}$ into four quartiles to classify EU fishing countries suffering from very high risk (Q4) to very low risk (Q1) (see Table 2.13). The countries facing more risk (Q4) are Cyprus, Italy, Greece, Romania, Malta and Croatia. Croatia is also classified as Q4 according to the biological risk (BR), even the Croatian classification varies to Q2 when production risk (wPRq) is considered. The countries with a moderate high risk (Q3) are Slovenia, Portugal, Spain, Denmark, France, Bulgaria and the United Kingdom. Belgium, Poland, Lithuania, Latvia and Ireland are mostly classified as moderate low risk (Q2) countries, although Ireland is considered Q4 according to wPRq. Sweden and Estonia could be identified as moderate to low risk countries, since most of the risk indicators classify them as Q2 or Q1. Finally, The Netherlands, Germany and Finland are the countries with the lowest risk (Q1).

Table 2.13: Average *weighted biological risk* (wBR) and *weighted production risk* (wPR) by country

	wBR_q		wBR_{pq}		wPR_q		wPR_{pq}	
Cyprus	0.85	Q4	0.90	Q4	0.85	Q4	0.90	Q4
Italy	0.76	Q4	0.60	Q4	0.73	Q4	0.66	Q4
Greece	0.73	Q4	0.64	Q4	0.69	Q4	0.69	Q4
Romania	0.70	Q4	0.89	Q4	0.53	Q3	0.34	Q1
Malta	0.68	Q4	0.67	Q4	0.62	Q4	0.68	Q4
Croatia	0.64	Q4	0.63	Q4	0.38	Q2	0.46	Q3
Slovenia	0.58	Q3	0.52	Q3	0.44	Q2	0.41	Q3
Portugal	0.50	Q3	0.51	Q3	0.38	Q2	0.41	Q3
Spain	0.50	Q3	0.50	Q3	0.60	Q3	0.62	Q4
Denmark	0.49	Q3	0.38	Q2	0.63	Q4	0.49	Q3
France	0.45	Q3	0.40	Q3	0.48	Q3	0.44	Q3
Bulgaria	0.43	Q3	0.53	Q3	0.49	Q3	0.46	Q3
United Kingdom	0.34	Q2	0.39	Q3	0.51	Q3	0.47	Q3
Belgium	0.33	Q2	0.35	Q2	0.33	Q1	0.33	Q1
Poland	0.33	Q2	0.29	Q1	0.38	Q2	0.32	Q1
Lithuania	0.31	Q2	0.27	Q1	0.29	Q1	0.27	Q1
Latvia	0.31	Q2	0.30	Q2	0.39	Q2	0.37	Q2
Ireland	0.30	Q1	0.33	Q2	0.62	Q4	0.56	Q4
Sweden	0.29	Q1	0.34	Q2	0.38	Q2	0.36	Q2
Estonia	0.29	Q1	0.30	Q2	0.38	Q2	0.38	Q2
The Netherlands	0.25	Q1	0.28	Q1	0.48	Q3	0.36	Q2
Germany	0.21	Q1	0.21	Q1	0.36	Q1	0.38	Q2
Finland	0.18	Q1	0.18	Q1	0.29	Q1	0.29	Q1
Average risk	0.45		0.45		0.49		0.46	

Notes:
Weighted biological risk (wBR):

- wBR_q in terms of q: $wBR_{jt} = \sum \frac{q_{ijt}}{\sum q_{ijt}} * BR_i$
- wBR_{pq} in terms of pq:$wBR_{jt} = \sum \frac{p_{ijt} * q_{ijt}}{\sum p_{ijt} * q_{ijt}} * BR_i$

Weighted production risk (wPR):

- wPR_q in terms of q: $wPR_{jt} = \sum \frac{q_{ijt}}{\sum q_{ijt}} * PR_i$
- wPR_{pq} in terms of pq: $wPR_{jt} = \sum \frac{p_{ijt} * q_{ijt}}{\sum p_{ijt} * q_{ijt}} * PR_i$

Q1: very low risk. Q2: moderate low risk. Q3: moderate high risk. Q4: very high risk.

2.2 Exploring country level diversity in the EU fishing sector

2.2.1 Introduction

The structure of the fishing sector in the EU is rather heterogeneous, which obviously adds complexity when setting effective policies to manage EU fishing fleets and conserve fish stocks sustainably (Dintheer et al., 1995; McClanahan & Castilla, 2008; Pope, 1997; Urquhart et al., 2011). Moreover, interactions between species do exist due to complex relationships within different ecosystems. Accordingly, neither diversity, nor stability of marine ecosystems are trivial concepts to be quantified (Ives & Carpenter, 2007). Not only the economic activity, but also pollution, climate change and habitat degradation (Jackson et al., 2001) affect the biodiversity and abundance of natural resources and the structure of the marine ecosystem (Coll & Libralato, 2012). Still 37,5% of the assessed fish and shellfish stocks in the North-East Atlantic European waters are not meeting policy targets for fishing mortality and/or reproductive capacity (EEA, 2019). This biodiversity loss implies an enormous challenge for the EU (Freyhof & Brooks, 2017).

Thus, analysing how biodiversity contributes to ecosystem functioning is crucial to get a better understanding of how biodiversity offers services to society, so as to give useful scientific advice for policy makers to set effective conservation tools and strategies. Biodiversity is widely recognised as a key factor of healthy ecosystems (Kremen, 2005; Worm et al., 2006). The economic activity may negatively impact biodiversity, and accordingly the deterioration of the ecosystems has revealed the need for operational indicators of ecosystem health (Costanza, 1992). Greater diversity would imply greater health of the ecosystem and greater ability to adjust and adapt to changes (del Valle & Astorkiza, 2019a). Most of the studies analysing the link between biodiversity and the health of ecosystems, suggest that biodiversity both enhances and stabilizes ecosystem functioning (Cardinale et al., 2013; Gross et al., 2013; Jiang & Pu, 2009). Biodiversity is also positively related to productivity, stability and the supply of ecosystem services (Worm et al., 2006). Accordingly, diversity is a measure of variety and heterogeneity on an ecosystem (Baumgärtner, 2006; Jost, 2006; Magurran, 2013), which is typically synthesized by the so-called diversity indices (DIs) (del Valle & Astorkiza, 2019a; Magurran, 2013; Pielou, 1975). The most popular and widely used ecological diversity measures are Species Richness (SR), Berger-Parker index (BP)(Berger & Parker, 1970), Concentration Ratios (CR), Shannon index (SHA) (Pielou, 1966) and Simpson's index (SIM) (Simpson, 1949). These DIs are also broadly employed in the economic literature of market concentration (De Bandt & Davis, 2000; Hannah & Kay, 1977), industrial organisation (Finkelstein & Friedberg, 1967; Hildenbrand & Paschen, 1964; Theil, 1967) and corporate diversification (Hoskisson et al., 1993; Jacquemin & Berry, 1979; Palepu, 1985). DIs are used as proxies to measure the degree of diversification, and should be understood, depending on the application, as inverse measures of concentration, industrial organisation, corporate diversification or dependency of ecosystems. These bio-economic diversity indices are also useful to discuss about the risk of survival of the fishing activity within an ecosystem (del Valle & Astorkiza, 2018; del Valle & Astorkiza, 2019a).

In this subsection, we study the EU fishing country level bioeconomic diversity in the North-East Atlantic. We consider that each member-state has an individual marine sub-ecosystem comprised by its different target fish species, which may change over time in the institutional framework of TACs and quotas. Therefore, we define an individual dynamic sub-ecosystem for each EU fishing country (2007-2017) in terms of both, the volume of landings (q) and the value of landings (pq) as data sources to get the diversity indices. Considering only quantities (q) would be poor, because it would underestimate expensive fish species, and similarly, considering only the landings' values (pq) would also underestimate cheap but abundant ones. We measure four diversity indices (DIs) to explore EU fishing countries diversity patterns, namely Berger-Parker index ($\mathrm{BP_{jt}}$), Concentration Ratios ($\mathrm{CR_{kjt}}$), Simpson's index ($\mathrm{SIM_{jt}}$) and Shannon index ($\mathrm{SHA_{jt}}$). It is convenient to use more than one index because they give similar but not exactly the same information, mainly because they use different weighting schemes. Species Richness (SR), for example, measures the amount of species included in the ecosystem, ignoring the abundance of the species. On the contrary, BP measures the relative abundance of the leading species ignoring the rest. SIM and SHA account for both the amount and the relative abundance of species. SIM is weighted towards the most abundant species (Sanders, 1968; Whittaker, 1972), whereas SHA weights all species equally (Keylock, 2005). After calculating the above-mentioned DIs (both in terms of q and pq), we will check if significant differences exist on the diversity patterns among EU countries and/or time, by means of ANOVA, Kruskal-Wallis and TukeyHSD tests.

The remainder of this subsection is organised as follows. After this introduction, Subsection 2.2.2 describes the material and methods. We specify the data used to define each individual country-based marine sub-ecosystem, and give a broader overview of the diversity indices (DIs). Subsection 2.2.3 summarises the major empirical findings made in this subsection and focuses on checking whether significant differences exist on the diversity patterns among EU coastal fishing countries. Finally, Section 2.5 summarises the major points made in the chapter and concludes with a short discussion.

2.2.2 Material and methods

2.2.2.1 Data and sub-ecosystem definition (Ω_{jt})

The main objective of this subsection is to measure the diversity of landings of each of the fishing countries in the EU, and explore the potential different patterns and particularities among different EU fishing countries. For this purpose, we are taking advantage of the conventional diversity indices (DIs), using the volume of landings (q) and the value of such landings (pq) as inputs. We define our global marine ecosystem (Ω_t) as the group of fish species (s_{ijt}) landed[13]in the EU from 2007 to 2017. Notice that, our analysis is focused at country level, and accordingly each member-state has a sub-ecosystem (Ω_{jt}). We are using species level (i) yearly landings data for the period 2007-2017 (t) for each 23 EU fishing countries (j), including Belgium, Denmark, Germany, Estonia, Ireland, Spain, France, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Finland, Sweden, United Kingdom, Greece, Bulgaria, Croatia, Cyprus, Malta, Romania and Slovenia.

As mentioned, we are working with two complementary specifications to generate diversity indices. The former is focused on the volume landed (q), and the later in the value of such landings (pq), where q measures the volume (tonnes product weight) landed in EU fishing ports (q_{ijt}) $\{q_{ijt} : i = 1, ..., 1144; j = BE, ..., SI; t = 2007, ..., 2017 : 1\}$ for 1144 fish species (i) in country j[14] and pq is the result of multiplying country level volume landed (q_{ijt}) by its country level first sale price (q_{ijt}) (€) ($p_{ijt}q_{ijt}$) $\{p_{ijt}q_{ijt} : i = 1, ..., 1123; j = BE, ..., SI; t = 2007, ..., 2017 : 1\}$ for 1123 fish species[15] and countries (j) (EUROSTAT, 2018). Prices have been deflated by the Harmonised Index of Consumer Prices (HICP) for Fish and Seafood (EUROSTAT, 2018) to the year 2015 to get constant value of landings ($p_{ijt}q_{ijt}$) [€ 2015=100].

Overall, on average along the full sample period (2007-2017), around 4.4 million tonnes of fish was landed in the EU. The most outstanding fish species (% over total landed volume) were Atlantic herring (HER) (15%), European sprat (SPR) (11%), Atlantic mackerel (MAC) (7%), blue whiting (WHB) 6% and sandeels (SAN) (5%).

[13]All countries are required to include data for all fish products landed by Community and European Free Trade Association (EFTA) fishing vessels in ports of that country under the terms of Council Regulation no 2104/93 (EEC, 1993).

[14]j=Belgium (BE), Germany (DE), Denmark (DK), Greece (EL), Spain (ES), Finland (FI), France (FR), Ireland (IE), Italy (IT), the Netherlands (NL), Portugal (PL), Sweden (SE), United Kingdom (UK), Estonia (EE), Latvia (LV), Lithuania (LT), Poland (PL), Bulgaria (BG), Croatia (HR), Cyprus (CY), Malta (MT), Romania (RO), Slovenia (SI).

[15]There exists available data for 1144 fish species in terms of volume of landings, although 21 of these species lack of quantitative data in terms of value of landings.

The ranking of the key leading species changes when we focus on the landed value. The average value of such landings reached 7,511 million €. The value of landings was led by hake (HKE) (5%) and Atlantic mackerel (MAC) (5%), followed by Norway lobster (NEP) (4%), Atlantic herring (HER) (4%) and common sole (SOL) (4%). This apparent and first sight asymmetric behaviour on species leadership depending on volume (q) or value (pq), reinforces the need to incorporate the market side in the sub-ecosystem via first sale prices.

2.2.2.2 Diversity indices (DIs)

For our purpose, we are considering four diversity indices (DIs): Berger Parker (BP) Concentration ratios ($\mathrm{CR_k}$), Simpson's index (SIM) and Shannon index (SHA) to analyse the diversity of fish landings (using both $\mathrm{q_{ijt}}$ and $\mathrm{p_{ijt}q_{ijt}}$) on our target 23 sub-ecosystems (Ω_{jt}). We define each fish species absolute abundance as (s_{ijt}) $\{s_{ijt} : i = 1, ..., n; t = 2007, ..., 2017 : 1\}$ where the subscripts represent species (i), country (j) and year (t) (in thousand tonnes or euros (€), depending on the specification we are using (volume or value). Species richness ($\mathrm{SR_{jt}}$) captures the number of species at time t and country j, $SR_{jt} = \sum_{i=1}^{n} s_{ijt}$. In our empirical setting, $\mathrm{w_{ijt}}$ denotes the relative abundance (weight) of each species i to the entire countries sub-ecosystem (Ω_{jt}) during period t, $w_{ijt} = \frac{s_{ijt}}{\sum_{i=1}^{n} s_{ijt}}$. By construction, $0 \leq w_{ijt} \leq 1$, where $w_{ijt} = 0$ means that the species i would be absent from the sub-ecosystem (Ω_{jt}) and $w_{ijt} = 1$ would mean that the species i is the only existing species in the ecosystem.

Berger Parker ($\mathrm{BP_{jt}}$) index, measures the relative abundance of the most abundant species z at time t,

$$BP_{jt} = s_{zjt}^{max} / \sum_{i=1}^{n} s_{ijt} = w_{jt} \tag{2.7}$$

Accordingly, $\mathrm{BP_{jt}}$ is a dominance measure (Berger & Parker, 1970) ranging from 0 to 1. A high BP_{jt} value means that the ecosystem is highly dominated by the most abundant species.

Concentration ratios ($\mathrm{CR_{kjt}}$) capture the relative abundance of the k most abundant species.

$$CR_{kjt} = \sum_{i=1}^{k} w_{ijt}(k < n) \tag{2.8}$$

There is no rule for determining the value of k, so it is an arbitrary decision. In our case, we define $k = 5$ and $k = 10$, which implies considering the five and ten leading species in each Ω_{jt}. $\mathrm{CR_{kjt}}$ ranges from 0 to 1, and following the same understanding as $\mathrm{BP_{jt}}$, high values of $\mathrm{CR_{kjt}}$ indicate that the ecosystem is highly dominated by the k leading species.

Simpson's index ($\mathrm{SIM_{jt}}$) can be interpreted as the probability that two species randomly selected from a sample will belong to different species (Simpson, 1949). It uses the relative abundances ($\mathrm{w_{ijt}}$) when calculating the dominance or relevance of the species,

$$SIM_{jt} = \sum w_{ijt}^2 \tag{2.9}$$

Notice that $\mathrm{SIM_{jt}}$ weights the proportion of the principal species more heavily than the secondary ones (Jost, 2007; Keylock, 2005; Tsallis, 2001). $\mathrm{SIM_{jt}}$ varies positively with the degree of concentration, reaching its lowest value ($SIM_{jt} = 1/SR_t$) when concentration is minimum (maximum diversity). Contrarily, at its maximum ($SIM_{jt} = 1$), the species diversity would be minimum, and accordingly, Ω_{jt} would be just comprised by a single fish species.

Shannon index (or Entropy) ($\mathrm{SHA_{jt}}$) (Pielou, 1966), weights all species equally without favouring any species, and varies inversely with the degree of concentration,

$$SHA_{jt} = -\sum_{i=1}^{n} w_{ijt} \ln w_{ijt} \tag{2.10}$$

$\mathrm{SHA_{jt}}$ reaches the lowest value ($SHA_{jt} = 0$) as concentration of species increases (diversity decreases), and reaches its highest value ($SHA_{jt} = \ln SR_t$) when shares of all the fish species are equal. Further details on diversity indices may be found in (Baumgärtner, 2006; del Valle & Astorkiza, 2018; del Valle & Astorkiza, 2019a; Gross et al., 2013; Johnston et al., 2010; Jost, 2006; Magurran, 2013).

2.2.3 Results

In this subsection the diversity of country level 23 sub-ecosystems (Ω_{jt}) is measured using two different specifications, landings volume ($\mathrm{q_{ijt}}$) and value ($\mathrm{p_{ijt}q_{ijt}}$). As mentioned, it is advisable to use more than one index because they give similar but not the same information. Thus, five diversity indices (DIs), namely Berger Parker (BP), Concentration ratio (5) ($\mathrm{CR_5}$), Concentration ratio (10) ($\mathrm{CR_{10}}$), Simpson's index (SIM), and Shannon index (SHA) have been measured, from now on referred as $\mathrm{q_{ijt}}$ based $\{BP_q, CR_{q,5}, CR_{q,10}, SIM_q, SHA_q\}$ and $\mathrm{p_{ijt}q_{ijt}}$ based $\{BP_{pq}, CR_{pq,5}, CR_{pq,10}, SIM_{pq}, SHA_{pq}\}$. At this stage, we are using the R package *BiodiversityR* (Kindt & Coe, 2005).

Table 2.14 summarises the average volume-based $\{BP_q, CR_{q,5}, CR_{q,10}, SIM_q, SHA_q\}$ for each of the 23 countries, as well as the global DIs for EU. Overall, according to the volume of landings (q_{ijt}), a total of 1144 fish species are landed in the EU. The most outstanding fish species, Atlantic herring (HER), constitutes on average the 15% ($\overline{BP}_{q,EU} = 0.15$) of the total volume of fish landed in the EU. Moreover, the CRs reveal that the top five and ten most abundant fish species, concentrate respectively the 45% ($\overline{CR}_{q,EU,k=5} = 0.45$) and 60% ($\overline{CR}_{q,EU,k=10} = 0.60$) of the total volume of fish landed. Therefore, we can point that the diversity in the EU is rather high, and accordingly, the dominance and concentration of the global EU fishing ecosystem low. At individual country level, the highest diversity (i.e. lowest concentration/dominance) corresponds to France ($\overline{BP_{q,FR}} = 0.11$, $\overline{CR_{q,FR,k=5}} = 0.34$, $\overline{SIM_{q,FR}} = 0.04$) and Spain ($\overline{BP_{q,ES}} = 0.15$, $\overline{CR_{q,ES,k=5}} = 0.39$, $\overline{SIM_{q,ES}} = 0.05$). In fact, the diversity of these two countries is higher than the average diversity of the EU ($\overline{BP_{q,EU}} = 0.15$, $\overline{CR_{q,EU,k=5}} = 0.45$, $\overline{SIM_{q,EU}} = 0.06$). Contrarily, according to BP and SIM, the countries with the lowest diversity are Finland ($\overline{BP_{q,FI}} = 0.87$, $\overline{SIM_{q,FI}} = 0.77$) and Croatia ($\overline{BP_{q,HR}} = 0.68$, $\overline{SIM_{q,HR}} = 0.50$). Based on CR_5 and CR_{10}, Estonia and Latvia exhibit the strongest concentration and dependency (i.e. lowest diversity). As a reference, the most abundant ten species compose the 100% of the total volume of fish landed in Estonia and Latvia.

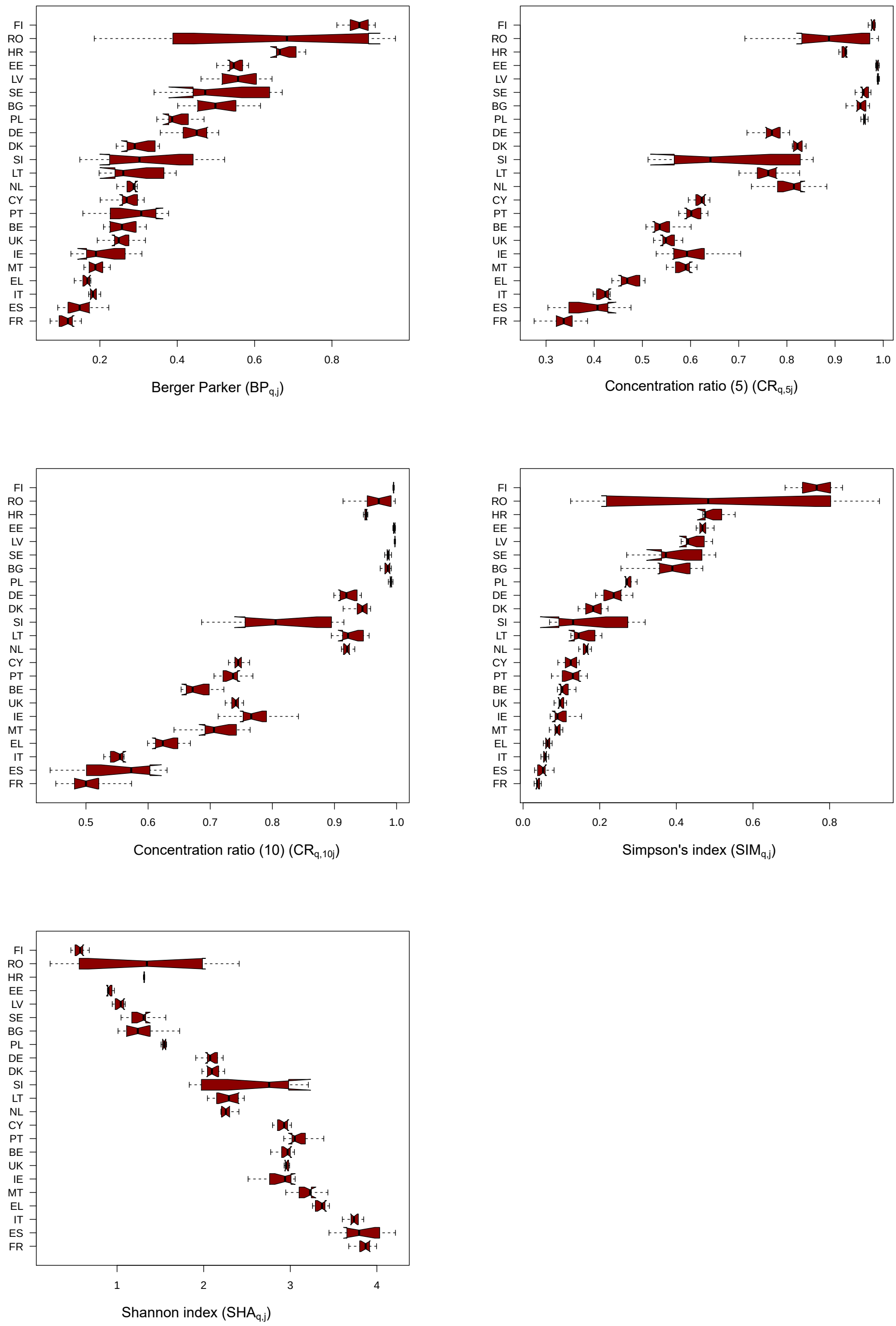
Table 2.14: Average diversity indices based on the volume of landings (q)

Country	BP_q		$CR_{q,5}$		$CR_{q,10}$		SIM_q		SHA_q		*Leader*
France (FR)	0.11	Q4	0.34	Q4	0.5	Q4	0.04	Q4	3.86	Q4	LQD
Spain (ES)	0.15	Q4	0.39	Q4	0.55	Q4	0.05	Q4	3.85	Q4	SKJ
Greece (EL)	0.16	Q4	0.47	Q4	0.63	Q4	0.06	Q4	3.35	Q4	ANE
Italy (IT)	0.18	Q4	0.43	Q4	0.56	Q4	0.06	Q4	3.73	Q4	ANE
Malta (MT)	0.19	Q4	0.58	Q3	0.71	Q4	0.09	Q4	3.18	Q4	VMA
Ireland (IE)	0.21	Q4	0.6	Q3	0.77	Q3	0.1	Q4	2.88	Q4	MAC
United Kingdom (UK)	0.25	Q3	0.56	Q4	0.74	Q4	0.1	Q4	2.95	Q3	MAC
Belgium (BE)	0.26	Q3	0.54	Q4	0.68	Q4	0.11	Q3	2.95	Q3	PLE
Portugal (PT)	0.28	Q3	0.6	Q3	0.73	Q3	0.12	Q3	3.1	Q3	HOM
Cyprus (CY)	0.27	Q3	0.62	Q3	0.74	Q3	0.12	Q3	2.91	Q3	FIN
The Netherlands (NL)	0.28	Q3	0.81	Q2	0.92	Q2	0.17	Q3	2.24	Q3	HER
Lithuania (LT)	0.31	Q2	0.76	Q3	0.93	Q3	0.17	Q3	2.24	Q3	COD
Denmark (DK)	0.3	Q3	0.81	Q2	0.94	Q2	0.18	Q2	2.12	Q3	SPR
Slovenia (SI)	0.33	Q2	0.69	Q3	0.82	Q3	0.18	Q2	2.52	Q2	WHG
Germany (DE)	0.44	Q2	0.77	Q2	0.92	Q2	0.24	Q2	2.09	Q2	HER
Poland (PL)	0.4	Q2	0.96	Q1	0.99	Q1	0.27	Q2	1.56	Q2	SPR
Bulgaria (BG)	0.5	Q2	0.95	Q1	0.98	Q1	0.39	Q2	1.26	Q2	RPN
Sweden (SE)	0.52	Q1	0.96	Q1	0.99	Q1	0.4	Q1	1.27	Q1	HER
Latvia (LV)	0.56	Q1	0.99	Q1	1	Q1	0.45	Q1	1.03	Q1	SPR
Estonia (EE)	0.56	Q1	0.99	Q1	1	Q1	0.47	Q1	0.91	Q1	HER
Croatia (HR)	0.68	Q1	0.92	Q2	0.95	Q2	0.5	Q1	1.31	Q1	PIL
Romania (RO)	0.63	Q1	0.88	Q2	0.97	Q2	0.5	Q1	1.32	Q1	RPW
Finland (FI)	0.87	Q1	0.98	Q1	0.99	Q1	0.77	Q1	0.57	Q1	HER
EU	0.15		0.45		0.60		0.06		3.78		HER

Notes:
Berger Parker (BP), Concentration ratio (5) (CR_5), Concentration ratio (10) (CR_{10}), Simpson's index (SIM), Shannon index (SHA) and the leading species (Leader).
Q1: very low diversity. Q2: moderate low diversity. Q3: moderate high diversity. Q4: very high diversity.
Leading species: Atlantic chub mackerel (VMA), Atlantic horse mackerel (HOM), Atlantic cod (COD), Atlantic herring (HER), Atlantic mackerel (MAC), European anchovy (ANE), European plaice (PLE), European sprat (SPR), Finfishes nei (FIN), Sardine (PIL), Sea snails (RPN), Skipjack tuna (SKJ), Tangle (LQD), Thomas' rapa whelk (RPW), Whiting(WHG).

Figure 2.13 shows notched box plots for $\{BP_q, CR_{q,5}, CR_{q,10}, SIM_q, SHA_q\}$. If two boxes' notches do not overlap there is *strong evidence* (95% confidence level) that their medians differ (Chambers, 2018). Spain (ES) and France (FR) exhibit overlapping box plots, which means that the diversity of Spain and France is not significantly different. Therefore, the diversity of the sub-ecosystems (Ω_{jt}) in both countries is homogeneous, and as mentioned, rather high. Portugal (PT) and Cyprus (CY) also show overlapping box plots. In this case, the diversity in PT and CY is homogeneous and moderate. Latvia (LV) and Estonia (EE) also show similar low diversity patterns in their sub-ecosystems.

Figure 2.13: Notched box plots for diversity indices based on the volume of landings (q)



Additionally, we have divided the BP_q,$CR_{q,5}$,$CR_{q,10}$,SIM_q and SHA_q into four quartiles, from very high diversity (Q4) to very low diversity (Q1) (see Table 2.14). Based on the volume of landings (q), the countries with the most diverse sub-ecosystems (Q4) are France, Spain, Greece, Italy, Malta, Ireland and the United Kingdom. Followed by countries with moderate high diversity (Q3) (i.e. Belgium, Cyprus, Portugal, Lithuania and the Netherlands). Denmark, Slovenia, Germany, Poland and Bulgaria have a moderate low diversity (Q2). Finally, Sweden, Latvia, Estonia, Croatia, Romania and Finland are the countries with the lowest diversity (Q1).

Table 2.15 summarises the average value-based $\{BP_{pq}, CR_{pq,5}, CR_{pq,10}, SIM_{pq}, SHA_{pq}\}$ for each of the 23 countries, including the global ones for the EU. Globally for the EU, when the value of landings instead the volume is considered, the estimated diversity is higher. The leading species, Atlantic herring (HER), constitutes on average the 6% ($\overline{BP_{pq,EU}} = 0.15$) of the total value of fish landed in the EU. In addition, the concentration ratios reveal that the top five and ten most abundant fish species, concentrate respectively the 23% ($\overline{CR_{pq,EU,k=5}} = 0.23$) and 37% ($\overline{CR_{pq,EU,k=10}} = 0.37$) of the total value. Similarly, SIM and SHA reveal that the diversity in the EU is rather high. Low Simpson's index ($\overline{SIM_{pq,EU}} = 0.02$) and high Shannon index $\overline{(SHA_{pq,EU}} = 4.5)$ involve rather high diversity, low dominance and accordingly, low concentration in the EU fishing ecosystem (Ω_{jt}). The highest diversity at country level corresponds to Italy ($\overline{BP_{q,IT}} = 0.06$, $\overline{CR_{q,IT,k=5}} = 0.28$, $\overline{SIM_{q,FR}} = 0.03$), Spain ($\overline{BP_{q,ES}} = 0.10$, $\overline{CR_{q,ES,k=5}} = 0.31$, $\overline{SIM_{q,ES}} = 0.03$) and France ($\overline{BP_{q,FR}} = 0.09$, $\overline{CR_{q,FR,k=5}} = 0.36$, $\overline{SIM_{q,FR}} = 0.04$). On the opposite side, Finland ($\overline{BP_{pq,FI}} = 0.59$, $\overline{SIM_{pq,FI}} = 0.38$) and Romania ($\overline{BP_{pq,RO}} = 0.58$, $\overline{SIM_{pq,RO}} = 0.40$) together with Estonia ($\overline{CR_{pq,EE,k=5}} = 0.96$, $\overline{CR_{pq,EE,k=10}} = 0.99$) and Latvia ($\overline{CR_{pq,LV,k=5}} = 0.98$, $\overline{CR_{pq,LV,k=10}} = 0.99$) show the lowest diversity (i.e. the highest concentration/dominance).

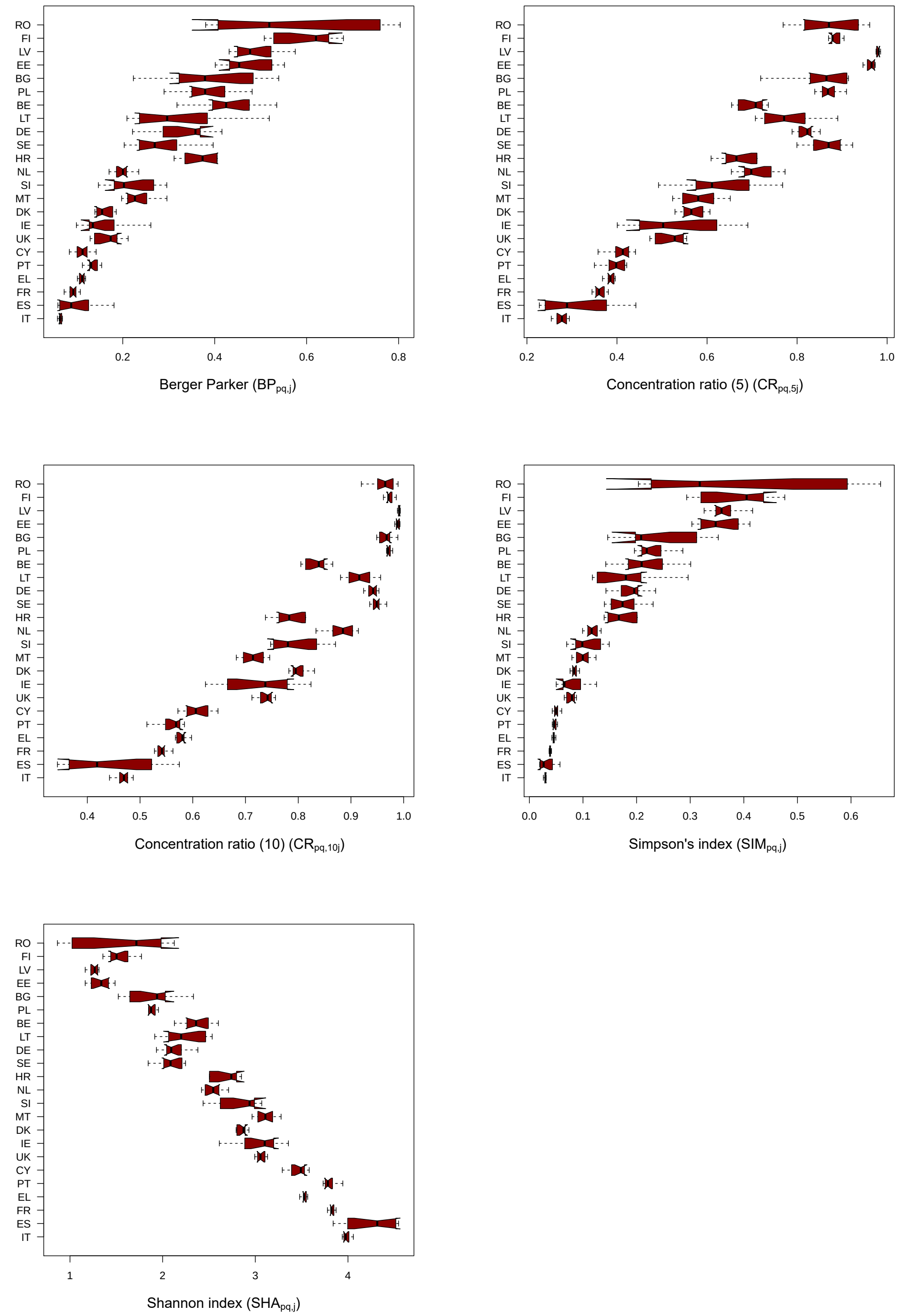
Figure 2.14 illustrates notched box plots for $\{BP_{pq}, CR_{pq,5}, CR_{pq,10}, SIM_{pq}, SHA_{pq}\}$. Overlapping box plots (this is, for example, the case of Italy (IT) and Spain (ES)) reveal that the diversity of Italy and Spain is not different, thus, the value-based diversity of the sub-ecosystems (Ω_{jt}) in IT and ES is homogeneous, and besides rather high. Again, Finland is the country with the highest concentration and dependency (i.e. lowest diversity), together with Romania, Latvia and Estonia. Contrarily, Spain, France, Greece, Italy and Portugal are the countries with the most diverse landings in terms of value.

Table 2.15: Average diversity indices based on the value of landings (pq)

Country	BP_{pq}		$CR_{pq,5}$		$CR_{pq,10}$		SIM_{pq}		SHA_{pq}		*Leader*
Spain (ES)	0.1	Q4	0.31	Q4	0.45	Q4	0.03	Q4	4.24	Q4	YFT
Italy (IT)	0.06	Q4	0.28	Q4	0.47	Q4	0.03	Q4	3.99	Q4	ANE
France (FR)	0.09	Q4	0.36	Q4	0.54	Q4	0.04	Q4	3.83	Q4	SCE
Greece (EL)	0.11	Q4	0.39	Q4	0.57	Q4	0.05	Q4	3.54	Q4	HKE
Portugal (PT)	0.13	Q4	0.4	Q4	0.56	Q4	0.05	Q4	3.8	Q4	OCC
Cyprus (CY)	0.11	Q4	0.41	Q4	0.61	Q4	0.05	Q4	3.46	Q4	ALB
Denmark (DK)	0.16	Q3	0.57	Q3	0.8	Q3	0.08	Q3	2.86	Q3	HER
Ireland (IE)	0.17	Q3	0.5	Q3	0.67	Q3	0.08	Q3	3.05	Q3	MAC
United Kingdom (UK)	0.17	Q3	0.52	Q3	0.74	Q3	0.08	Q3	3.06	Q3	MAC
Malta (MT)	0.24	Q3	0.58	Q3	0.71	Q3	0.1	Q3	3.11	Q3	SWO
Slovenia (SI)	0.22	Q3	0.63	Q3	0.79	Q3	0.11	Q3	2.83	Q3	SBG
The Netherlands (NL)	0.2	Q3	0.71	Q2	0.88	Q2	0.12	Q3	2.55	Q3	SOL
Croatia (HR)	0.37	Q2	0.67	Q3	0.79	Q3	0.17	Q2	2.66	Q2	PIL
Sweden (SE)	0.29	Q2	0.86	Q2	0.95	Q2	0.18	Q2	2.07	Q2	PRA
Germany (DE)	0.33	Q2	0.82	Q2	0.94	Q2	0.19	Q2	2.12	Q2	CSH
Lithuania (LT)	0.35	Q2	0.78	Q2	0.92	Q2	0.2	Q2	2.19	Q2	COD
Belgium (BE)	0.44	Q1	0.7	Q2	0.83	Q2	0.22	Q2	2.36	Q2	SOL
Poland (PL)	0.38	Q2	0.87	Q1	0.97	Q1	0.23	Q1	1.86	Q1	COD
Bulgaria (BG)	0.39	Q1	0.86	Q2	0.96	Q1	0.24	Q1	1.86	Q1	CLS
Estonia (EE)	0.47	Q1	0.96	Q1	0.99	Q1	0.35	Q1	1.33	Q1	HER
Latvia (LV)	0.49	Q1	0.98	Q1	0.99	Q1	0.37	Q1	1.25	Q1	SPR
Finland (FI)	0.59	Q1	0.88	Q1	0.97	Q1	0.38	Q1	1.53	Q1	HER
Romania (RO)	0.58	Q1	0.87	Q1	0.96	Q1	0.4	Q1	1.54	Q1	RPW
EU	0.06		0.23		0.37		0.02		4.50		HER

Notes:
Berger Parker (BP), Concentration ratio (5) (CR_5), Concentration ratio (10) (CR_{10}), Simpson's index (SIM), Shannon index (SHA) and the leading species (Leader).
Q1: very low diversity. Q2: moderate low diversity. Q3: moderate high diversity. Q4: very high diversity.
Leading species: Albacore (ALB), Atlantic cod (COD), Atlantic herring (HER), Atlantic mackerel (MAC), Common octopus (OCC), Common shrimp (CSH), Common sole (SOL), European anchovy (ANE), European hake (HKE), European sprat (SPR), Gilthead seabream (SBG), Great Atlantic scallop (SCE), Northern prawn (PRA), Sardine (PIL), Soft clam (CLS), Swordfish (SWO), Thomas' rapa whelk (RPW), Yellowfin tuna (YFT).

Figure 2.14: Notched box plots for diversity indices based on the value of landings (pq)



Additionally, we have divided the BP_{pq},$CR_{pq,5}$,$CR_{pq,10}$,SIM_{pq} and SHA_{pq} into four quartiles from very high diversity (Q4) to very low diversity (Q1) (Table 2.15). Based on the value of landings (pq), the countries with the most diverse sub-ecosystems (Q4) are Italy, Spain, France, Cyprus, Greece and Portugal. Followed by countries with moderate high diversity (Q3) (i.e. Denmark, Ireland, United Kingdom, Malta, Slovenia and the Netherlands). Croatia, Sweden, Germany, Lithuania and Belgium have a moderate low diversity (Q2). Finally, Poland, Bulgaria, Estonia, Latvia, Finland and Romania are the countries with the lowest diversity (Q1).

We have tested if these apparent differences among countries and/or time are significant through one-way analysis of variance (ANOVA)[16]. However, attention should be paid on the fact that these results may be biased, because ANOVA assumes that the data follows a normal distribution and has a common variance. Therefore, we have checked by the Shapiro-Wilk test whether our landings data are normally distributed, and by Levene's test whether the variance across countries is significantly different. Shapiro-Wilk testing results (Table 2.16) show that the diversity of landings data is indeed not normally distributed in both approximations used, volume (q) and value (pq). Besides, Levene's test results (Table 2.17) reveal that the variance across countries is significantly different for the concerned DIs. Consequently, ANOVA results may not be consistent since both normality and homogeneity of variances assumptions are violated. Therefore, Kruskal-Wallis rank sum test (i.e. non-parametric alternative to ANOVA test) may be a better approximation to check whether these apparent differences on diversity between countries and/or time are significant.

ANOVA results (Table 2.18) show that there are significant differences in the mean diversity among the countries, no matter the approximation used to calculate diversity (volume or value). Contrarily, these differences do not change significantly over time for none of the DIs. Kruskal-Wallis rank sum test results (Table 2.18) corroborate the ANOVA ones. Thus, it can definitely be concluded that q and pq based diversity is significantly different between EU fishing countries, but, diversity does not significantly change over time.

[16]The one-way analysis of variance (ANOVA) compares mean values in situations where there are more than two groups. It is used to test if means of different groups are the same through the measurement first of the variance within samples (S^2_{within}) and second the variance between samples ($S^2_{between}$). Therefore, the ANOVA test produces the F-statistic as a ratio of $S^2_{between}/S^2_{within}$. If P-value is less than the significance level 0.05, it can be concluded that there are significant differences between groups.

Table 2.16: Shapiro-Wilk normality test: results by country and year

COUNTRY		q		pq	
	DIs	W	P-value	W	P-value
	BP	0.88021	3.51E-14	0.90432	1.69E-12
	SIM	0.6742	$<$ 2.2e-16	0.76832	$<$ 2.2e-16
	SHA	0.81155	$<$ 2.2e-16	0.93633	9.43E-10
	CR_5	0.87584	1.85E-14	0.84127	$<$ 2.2e-16
	CR_{10}	0.86944	7.41E-15	0.50354	$<$ 2.2e-16
YEAR		q		pq	
	DIs	W	P-value	W	P-value
	BP	0.90763	3.02E-12	0.94017	2.29E-09
	SIM	0.8342	$<$ 2.2e-16	0.87902	2.94E-14
	SHA	0.97145	1.82E-05	0.98091	0.0007195
	CR_5	0.9343	5.97E-10	0.9574	2.03E-07
	CR_{10}	0.85842	1.65E-15	0.89941	7.29E-13

Notes: Shapiro-Wilk normality test for landings volume (q_{ijt}) based and value ($p_{ijt}q_{ijt}$) based diversity indices (DIs): Berger Parker (BP), Simpson's index (SIM), Shannon index (SHA), Concentration ratio (5) (CR_5) and Concentration ratio (10) (CR_{10}), by country and year.
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.17: Levene's test: results by country and year

COUNTRY		q		pq	
	DIs	F-value	P-value	F-value	P-value
	BP	12.595	$<$ 2.2e-16***	6.221	1.247E-15***
	SIM	24.29	$<$ 2.2e-16***	9.0949	$<$ 2.2e-16***
	SHA	17.219	$<$ 2.2e-16***	7.9054	$<$ 2.2e-16***
	CR_5	11.66	$<$ 2.2e-16***	5.9964	5.635E-15***
	CR_{10}	10.949	$<$ 2.2e-16***	3.5641	1.185E-07***
YEAR		q		pq	
	DIs	F-value	P-value	F-value	P-value
	BP	0.1651	0.9983	0.0373	1
	SIM	0.109	1	0.0736	1
	SHA	0.0306	1	0.0408	1
	CR_5	0.0286	1	0.0725	1
	CR_{10}	0.0237	1	0.1322	0.9994

Notes: Levene's homogeneity of variances test for landings volume (q_{ijt}) based and value ($p_{ijt}q_{ijt}$) based diversity indices (DIs): Berger Parker (BP), Simpson's index (SIM), Shannon index (SHA), Concentration ratio (5) (CR_5) and Concentration ratio (10) (CR_{10}), by country and year.
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.18: ANOVA and Kruskal-Wallis tests: results by country and year

	ANOVA		Kruskal-Wallis	
COUNTRY	q	pq	q	pq
DIs	F-value	F-value	χ^2	χ^2
BP	53.98	58.59	236.6	256.62
	(<2e-16)***	(<2e-16)***	(<2e-16)***	(<2e-16)***
SIM	67.4	52.31	257.9	266.6
	(<2e-16)***	(<2e-16)***	(<2e-16)***	(<2e-16)***
SHA	184	252.2	265.9	274.85
	(<2e-16)***	(<2e-16)***	(<2e-16)***	(<2e-16)***
CR_5	218.5	184.6	267.6	271.16
	(<2e-16)***	(<2e-16)***	(<2e-16)***	(<2e-16)***
CR_{10}	356.9	130.5	273.7	275.42
	(<2e-16)***	(<2e-16)***	(<2e-16)***	(<2e-16)***
YEAR	q	pq	q	pq
DIs	F-value	F-value	χ^2	χ^2
BP	0.022	0.013	0.318	0.402
	(1)	(1)	(1)	(1)
SIM	0.06	0.031	0.150	0.266
	(1)	(1)	(1)	(1)
SHA	0.016	0.013	0.212	0.169
	(1)	(1)	(1)	(1)
CR_5	0.021	0.049	0.477	0.377
	(1)	(1)	(1)	(1)
CR_{10}	0.019	0.077	0.390	0.434
	(1)	(1)	(1)	(1)

Notes:
One-way analysis of variance (ANOVA) for landings volume (q_{ijt}) based and value ($p_{ijt}q_{ijt}$) based diversity indices (DIs): Berger Parker (BP), Simpson's index (SIM), Shannon index (SHA), Concentration ratio (5) (CR_5) and Concentration ratio (10) (CR_{10}), by country and year.
Kruskal-Wallis rank sum test (non-parametric alternative to ANOVA test) for landings volume (q_{ijt}) based and value ($p_{ijt}q_{ijt}$) based diversity indices (DIs): Berger Parker (BP), Simpson's index (SIM), Shannon index (SHA), Concentration ratio (5) (CR_5) and Concentration ratio (10) (CR_{10}), by country and year.
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

We have complemented the guess coming from the notched boxes with Tukey HSD[17]

[17] Tukey HSD (Tukey Honest Significant Differences) multiple pairwise-comparisons between the means of countries takes the fitted ANOVA as an argument and with 95% family-wise confidence level and calculates the difference between means of the two countries.

test to analyse pairings between similar countries (Table 2.19). Tukey results confirm that the diversity (q) is similar in Spain, France and Italy, countries with the highest diversity. The diversity of the sub-ecosystems is moderately high and rather homogenous in United Kingdom, Ireland, Cyprus, Malta, Portugal and Belgium. The Netherlands, Denmark, Germany and Lithuania have medium and homogeneous diversity. The countries with a moderately low diversity are Latvia, Estonia, Bulgaria and Sweden. Finally, the diversity in Romania and Croatia is homogeneous and very low.

Table 2.19: Tukey multiple pairwise-comparisons test: results by country (q)

	BE	BG	CY	DE	DK	EE	EL	ES	FI	FR	HR	IE	IS	IT	LT	LV	MT	NL	NO	PL	PT	RO	SE	SI	TR
BG	*** *** *** ***	- - - -																							
CY	 ** 	*** *** *** ***	- - - -																						
DE	*** *** ** ***	 *** *** ***	*** *** * ***	- - - -																					
DK	 *** ***	*** *** *** ***	 *** ***	** 	- - - -																				
EE	*** *** *** ***	 *	*** *** *** ***	 *** *** ***	*** *** *** ***	- - - -																			
EL	 * **	*** *** *** ***	 *** ***	*** *** *** ***	** *** ** ***	*** *** *** ***	- - - -																		
ES	 *** ***	*** *** *** ***	 *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	 *** ***	- - - -																	
FI	*** *** *** ***	*** *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	*** *** *	*** *** *** ***	*** *** *** ***	- - - -																
FR	** *** ***	*** *** *** ***	*** *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	 *** ***	 	*** *** *** ***	- - - -															
HR	*** *** *** ***	*** 	*** *** *** ***	*** *** *** ***	*** *** *** ***	 * **	*** *** *** ***	*** *** *** ***	*** *** ***	*** *** *** ***	- - - -														
IE	 	*** *** *** ***	 	*** *** *** ***	 *** ***	*** *** *** ***	 *** ***	 *** ***	*** *** *** ***	 *** ***	*** *** *** ***	- - - -													
IS	 *** ***	*** *** *** ***	 *** ***	*** 	 	*** *** *** ***	 *** ***	 *** ***	*** *** *** ***	** *** ***	*** *** *** ***	 *** ***	- - - -												
IT	 *** ***	*** *** *** ***	 *** ***	*** *** *** ***	 *** ** ***	*** *** *** ***	 **	 	*** *** *** ***	 *** 	*** *** *** ***	 *** ***	 *** ***	- - - -											
LT	 *** ***	*** *** *** ***	 *** ***	** 	 	*** *** *** ***	** *** ***	*** *** ** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	 *** ***	 	* *** * ***	- - - -										
LV	*** *** *** ***	 	*** *** *** ***	 *** *** ***	*** *** *** ***	 	*** *** *** ***	*** *** *** ***	*** *** ***	*** *** *** ***	* * 	*** *** *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	- - - -									
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NO	 *** ***	*** *** *** ***	 *** ***	 	 	*** *** *** ***	*** *** ** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	 *** ***	 	** *** ** ***	 	*** *** *** ***	* *** ***	 	- - - -						
PL	** *** *** ***	 ** 	* *** *** ***	 *** ***	 *** ***	*** *** ***	*** *** *** ***	*** *** *** ***	*** *** ***	*** *** *** ***	*** *** 	*** *** *** ***	** *** ** ***	*** *** *** ***	 *** ***	*** *** ***	*** *** *** ***	 *** ***	 *** ***	- - - -					
PT	 	*** *** *** ***	 	*** *** * ***	 *** ***	*** *** *** ***	 *** 	** *** ***	*** *** *** ***	 *** ***	*** *** *** ***	 	 *** ***	 *** ***	 *** ***	*** *** *** ***	 	 *** ***	 *** ***	 *** *** ***	- - - -				
RO	*** *** *** ***	* ** * 	*** *** *** ***	*** *** *** ***	*** * *** ***	 *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	 	*** *** *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	 *** 	*** *** *** ***	*** ** *** ***	*** ** *** ***	*** *** *** 	*** *** *** ***	- - - -			
SE	*** *** *** ***	 	*** *** *** ***	 *** *** ***	*** *** *** ***	 *	*** *** *** ***	*** *** *** ***	*** *** ***	*** *** *** ***	*** 	*** *** *** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	 	*** *** *** ***	*** *** *** ***	*** *** *** ***	* ** 	*** *** *** ***	 *** 	- - - -		
SI	 *** ***	*** *** *** ***	 * **	 *** ***	 *** **	*** *** *** ***	*** *** * ***	*** *** ** ***	*** *** *** ***	*** *** *** ***	*** *** *** ***	 *** *	 *** 	*** *** ** ***	 ** 	*** *** *** ***	** *** ***	 *** 	 *** **	 *** ***	 *** ***	*** *** *** ***	*** *** *** ***	- - - -	
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UK	 	*** *** *** ***	 	*** *** *** ***	 *** ***	*** *** *** ***	 *** **	 *** ***	*** *** *** ***	** *** ***	*** *** *** ***	 	 *** ***	 *** ***	 *** ***	*** *** *** ***	 	 *** ***	 *** ***	** *** *** ***	 	*** *** *** ***	*** *** *** ***	 *** ***	 *** ***

Notes:
Each box containing four results are ordered by the first pairwise-comparison for BP_q, $CR_{q,5}$, SIM_q and SHA_q. Grey shadow means not statistically significant differences, *** significant at 1%, ** significant at 5% and * significant at 10%.

Table 2.20: Tukey multiple pairwise-comparisons test: results by country (pq)

	BE	BG	CY	DE	DK	EE	EL	ES	FI	FR	HR	IE	IS	IT	LT	LV	MT	NL	NO	PL	PT	RO	SE	SI	TR
BG	ns / *** / ns / ***	- / - / - / -																							
CY	*** / *** / *** / ***	*** / *** / *** / ***	- / - / - / -																						
DE	* / *** / ns / ns	ns / ns / ns / *	*** / *** / *** / ***	- / - / - / -																					
DK	*** / *** / *** / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	- / - / - / -																				
EE	ns / *** / *** / ***	ns / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	- / - / - / -																			
EL	*** / *** / *** / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	- / - / - / -																		
ES	*** / *** / *** / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / ns / ns / ***	- / - / - / -																	
FI	*** / *** / *** / ***	*** / ns / *** / ***	*** / *** / *** / ***	*** / ns / *** / ***	*** / *** / *** / ***	*** / * / ns / ns	*** / *** / *** / ***	*** / *** / *** / ***	- / - / - / -																
FR	*** / *** / *** / ***	*** / *** / *** / ***	ns / ns / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / ns / ns / **	ns / ns / ns / ***	*** / *** / *** / ***	- / - / - / -															
HR	ns / ns / ns / **	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / ** / ns	** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	- / - / - / -														
IE	*** / *** / *** / ***	*** / *** / *** / ***	ns / ** / ns / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / *** / ns / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / ** / ***	- / - / - / -													
IS	*** / ns / ns / ns	*** / *** / ** / ***	*** / *** / *** / ***	ns / ** / ns / ns	** / *** / ns / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	* / ns / ns / ***	ns / *** / ns / ***	- / - / - / -												
IT	*** / *** / *** / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / ** / ns / ns	*** / *** / *** / ***	** / *** / ns / ***	*** / *** / *** / ***	- / - / - / -											
LT	ns / ** / ns / ns	ns / * / ns / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	- / - / - / -										
LV	ns / *** / *** / ***	* / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	*** / *** / *** / ***	** / *** / ns / **	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	- / - / - / -									
MT	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / ns / ***	ns / *** / ** / ***	ns / ns / ns / ns	*** / *** / *** / ***	*** / *** / ns / ***	*** / *** / ns / ***	*** / *** / *** / ***	*** / *** / ns / ***	*** / ** / ns / ***	ns / ** / ns / ns	ns / *** / ns / ***	*** / *** / ns / ***	** / *** / *** / ***	*** / *** / *** / ***	- / - / - / -								
NL	*** / ns / *** / ns	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / ns / ***	ns / *** / ns / **	*** / *** / *** / ***	ns / *** / ns / ***	* / *** / ** / ***	*** / *** / *** / ***	** / *** / * / ***	*** / ns / ns / ns	ns / *** / ns / ***	ns / ns / ns / *	*** / *** / ** / ***	*** / ns / ** / ***	*** / *** / *** / ***	ns / *** / ns / ***	- / - / - / -							
NO	*** / *** / ns / ns	ns / ns / ns / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / ** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / ** / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / *** / ns / ***	** / ** / ns / *	- / - / - / -						
PL	ns / *** / ns / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / ns / *** / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	*** / *** / ns / ***	*** / *** / *** / ***	ns / ** / ns / ***	** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	ns / * / ns / ns	- / - / - / -					
PT	*** / *** / *** / ***	*** / *** / *** / ***	ns / ns / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / ns / ns / ns	ns / ** / ns / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ns	*** / *** / *** / ***	*** / *** / *** / ***	* / *** / ns / ***	ns / *** / ns / ***	*** / *** / *** / ***	*** / *** / *** / ***	- / - / - / -				
RO	*** / *** / *** / ***	*** / ns / *** / ***	*** / *** / *** / ***	*** / ns / *** / ***	*** / *** / *** / ***	* / ** / ns / ns	*** / *** / *** / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	ns / *** / ns / **	*** / *** / *** / ***	*** / *** / *** / ***	*** / ** / *** / ***	*** / ns / *** / ***	*** / *** / *** / ***	- / - / - / -			
SE	*** / *** / ns / **	* / ns / ns / ns	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / *** / ***	*** / ns / *** / ***	*** / *** / *** / ***	ns / *** / ns / ***	** / *** / *** / ***	ns / *** / ns / ns	*** / *** / *** / ***	ns / ** / ns / ns	*** / *** / *** / ***	ns / *** / ** / ***	ns / *** / ns / ***	ns / ns / ns / ns	ns / ns / ns / ns	*** / *** / *** / ***	*** / ns / *** / ***	- / - / - / -		
SI	*** / ns / *** / ***	*** / *** / *** / ***	** / *** / ns / ***	** / *** / * / ***	ns / ns / ns / ns	*** / *** / *** / ***	** / *** / ns / ***	*** / *** / ns / ***	*** / *** / *** / ***	*** / *** / ns / ***	*** / ns / ns / ns	ns / *** / ns / ns	ns / *** / ns / ***	*** / *** / ns / ***	*** / *** / *** / ***	*** / *** / *** / ***	ns / ns / ns / **	ns / * / ns / *	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	- / - / - / -	
TR	*** / *** / *** / ***	*** / *** / *** / ***	*** / *** / ns / ***	ns / *** / ** / ***	ns / ns / ns / ns	*** / *** / *** / ***	*** / *** / ns / ***	*** / *** / ns / ***	*** / *** / *** / ***	*** / *** / ns / ***	*** / *** / ns / ns	ns / * / ns / ns	ns / *** / ns / ***	*** / *** / ns / ***	* / *** / *** / ***	*** / *** / *** / ***	ns / ns / ns / ns	ns / *** / ns / ***	ns / *** / ns / ***	*** / *** / *** / ***	** / *** / ns / ***	*** / *** / *** / ***	ns / *** / * / ***	ns / ns / ns / ns	- / - / - / -
UK	*** / *** / *** / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / ns / ns / ns	*** / *** / *** / ***	ns / *** / ns / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	ns / ns / ns / ns	* / *** / * / ***	* / *** / ns / ***	*** / *** / *** / ***	*** / *** / *** / ***	ns / ns / ns / ns	ns / *** / ns / ***	*** / *** / ** / ***	*** / *** / *** / ***	ns / *** / ns / ***	*** / *** / *** / ***	*** / *** / *** / ***	ns / *** / ns / ns	ns / ns / ns / ns

Notes:
Each box containing four results are ordered by the first pairwise-comparison for BP_{pq}, $CR_{pq,5}$, SIM_{pq} and SHA_{pq}. Grey shadow means not statistically significant differences, *** significant at 1%, ** significant at 5% and * significant at 10%.

Tukey results confirm that the diversity (pq) is similar and rather high in Spain and Italy (Table 2.20). The diversity of the sub-ecosystems is moderately high in France, Portugal, Greece and Cyprus. United Kingdom, Ireland, Denmark, Malta and Slovenia have medium diversity. The countries with a moderately low diversity are Germany, Lithuania, Sweden, Poland and Bulgaria. Finally, the diversity in Latvia, Estonia, Romania and Croatia is homogeneous and very low.

2.3 Correlation between risk and diversity

In this section, we aim to analyse the sign and magnitude of the correlation between the risk and diversity indicators estimated in the two previous subsections of this chapter. Diversity indices (DIs) are useful tools to evaluate the risk of survival of the fishing activity within each sub-ecosystem (del Valle & Astorkiza, 2019a). Following the same ideas as in a financial portfolio, the lower the diversity, the higher the concentration and dependency of the fishing activity to the evolution of the dominant fish species and, therefore, the greater the risk of a potential collapse for the fishing activity (del Valle et al., 2017). Risk, understood as volatility, is directly linked with the degree of variation from an expected value, price or model (Engle, 1982). Accordingly, as the literature suggests, biodiversity both reinforces and stabilizes ecosystem functioning (Cardinale et al., 2013; Gross et al., 2013; Jiang & Pu, 2009), and it is positively related to productivity, stability and the supply of ecosystem services. Therefore, our diversity indices (DIs) may be interpreted as inverse measures of the risk of a survival of the fishing activity (del Valle & Astorkiza, 2018). Thus, one could expect our country-based *weighted biological risk* (wBR) (risk in the natural frame or ocean) and *weighted production risk* (wPR) (risk related to the EU fleets or fishing activity) to be negatively correlated with Shannon Index (SHA) (high SHA reveals high diversity on the ecosystem), and positively correlated with Berger Parker (BP), Concentration ratios ($\mathrm{CR_k}$) and Simpson's index (SIM) (high BP, $\mathrm{CR_k}$ and SIM imply high concentration and low diversity on the ecosystem).

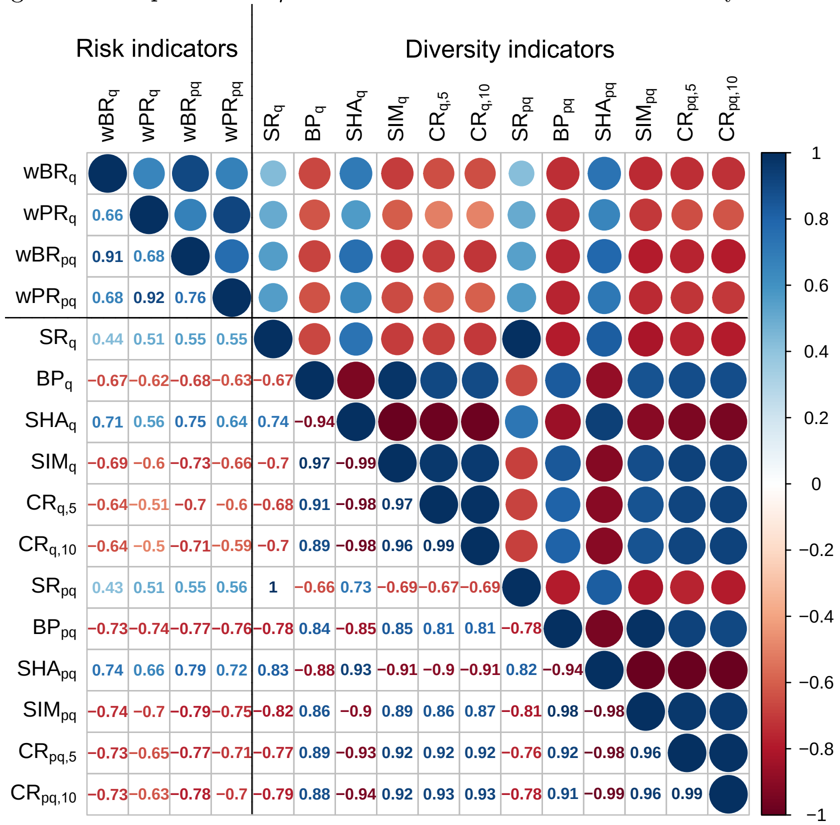
Table 2.21 and Figure 2.15 show Spearman's correlation between our risk and diversity indicators. At this stage, we are using the R package *Hmisc* (Harrell & Dupont, 2020) and *Corrplot* (Wei & Simko, 2017). Surprisingly and contrarily to what we expected, *weighted biological risk* (wBR) and *weighted production risk* (wPR) are significantly and positively correlated with Shannon index (SHA) and negatively correlated with Berger Parker (BP), Concentration Ratios ($\mathrm{CR_5}$ and $\mathrm{CR_{10}}$) and Simpson's index (SIM) (no matter whether the volume ($\mathrm{q_{ijt}}$) or value of landings ($\mathrm{p_{ijt}q_{ijt}}$) is used).

Table 2.21: Spearman's ρ correlation between risk and diversity indicators

	Diversity indicators														
	q	pq		q						pq					
	wPR_q	wBR_{pq}	wPR_{pq}	SR_q	BP_q	SHA_q	SIM_q	$CR_{q,5}$	$CR_{q,10}$	SR_{pq}	BP_{pq}	SHA_{pq}	SIM_{pq}	$CR_{pq,5}$	$CR_{pq,10}$
wBR_q	0.66	0.91	0.68	0.44	-0.67	0.71	-0.69	-0.64	-0.64	0.43	-0.73	0.74	-0.74	-0.73	-0.73
wPR_q	-	0.68	0.92	0.51	-0.62	0.56	-0.6	-0.51	-0.5	0.51	-0.74	0.66	-0.7	-0.65	-0.63
wBR_{pq}		-	0.76	0.55	-0.68	0.75	-0.73	-0.7	-0.71	0.55	-0.77	0.79	-0.79	-0.77	-0.78
wPR_{pq}			-	0.55	-0.63	0.64	-0.66	-0.6	-0.59	0.56	-0.76	0.72	-0.75	-0.71	-0.7
SR_q				-	-0.67	0.74	-0.7	-0.68	-0.7	1	-0.78	0.83	-0.82	-0.77	-0.79
BP_q					-	-0.94	0.97	0.91	0.89	-0.66	0.84	-0.88	0.86	0.89	0.88
SHA_q						-	-0.99	-0.98	-0.98	0.73	-0.85	0.93	-0.9	-0.93	-0.94
SIM_q							-	0.97	0.96	-0.69	0.85	-0.91	0.89	0.92	0.92
$CR_{q,5}$								-	0.99	-0.67	0.81	-0.9	0.86	0.92	0.93
$CR_{q,10}$									-	-0.69	0.81	-0.91	0.87	0.92	0.93
SR_{pq}										-	-0.78	0.82	-0.81	-0.76	-0.78
BP_{pq}											-	-0.94	0.98	0.92	0.91
SHA_{pq}												-	-0.98	-0.98	-0.99
SIM_{pq}													-	0.96	0.96
$CR_{pq,5}$														-	0.99
$CR_{pq,10}$															-

Notes:
All of them are significant at 1%.

Figure 2.15: Spearman's ρ correlation between risk and diversity indicators



Correlation values suggest that as far as the diversity of the ecosystem increases the risk also increases. Although this unexpected result may be well due to different reasons, our guess is that it is mainly related to the combination of the species distribution and certain species leadership. The case of Finland is illustrative. In Finland the concentration of the marine sub-ecosystem is very high, that is to say, the diversity is very low and the landed volume (q) almost totally corresponds to Atlantic herring (HER) (89% on average). Due to its low diversity, the landings distribution of herring could be defined as potentially risky to collapse because it mainly depends on the landings of just one fish species. Nevertheless, Atlantic herring exhibits the lowest risk level for both *biological* (BR) and *production risk* (PR). Notice that Atlantic herring is the most abundant species in the EU waters, and neither spawning stock biomass nor catches or quotas fluctuate so much compared to other fish species. Accordingly, even the diversity of a country could determine the potential risk of it, it is the share and type of targeted fish species what in fact determines, the *weighted biological risk* (wBR) and *weighted production risk* (wPR) of each of the countries.

2.4 Re-clustering fishing countries in the EU

Finally, we aim to check whether our estimated risk and diversity indicators help to re-cluster the EU fishing countries so as to quantify their structural characteristics and potential taxonomy. Taking advantage of our country-level estimations of risk and diversity, we return back to the discussion of the taxonomy of the EU fishing countries initiated in Chapter 1. For this purpose, two potential variates, $\{\mathbb{Y}\}$ and $\{\mathbb{Z}\}$, will be considered. Variate $\{\mathbb{Y}\}$ includes country-based risk and diversity indicators estimated in the preceding subsections, while variate $\{\mathbb{Z} = \mathbb{X} + \mathbb{Y}\}$, also incorporates the output, input, fleet's structure, fleet organisation and productivity ratios in $\{\mathbb{X}\}$, the variate used in the clustering analysis carried out in Chapter 1.

Regarding the methods, as in Chapter 1, a two-step principal component-clustering approach will be followed. Notice that, the usual properties such as normality linearity and homoscedasticity are not required on cluster analysis. Nevertheless, other key issues such as representativeness of the sample, presence and treatment of outliers and the potential correlation in the cluster variate should be carefully accounted (del Valle & Astorkiza, 2019b; Milligan, 1996). In fact, results coming from cluster analysis entirely depend on the set of variables included in the analysis or variate. Since our clustering process aims to categorise EU coastal fishing countries, just fisheries related indicators will be incorporated in the analysis.

As above mentioned, we are working with two separate variates, $\{\mathbb{Y}\}$ and $\{\mathbb{Z}\}$. Specifically, variate $\{\mathbb{Y}\}$ includes country-based risk and diversity indicators in terms of landings volume (q) and landings value (pq). Risk is captured by the *weighted biological risk* (wBR) and the *weighted production risk* (wPR). We are employing the Modified Expected Shortfall (MES) (Peterson & Boudt, 2008) to measure risk, since MES adjusts the standard deviation to account for skewness and kurtosis in the return distribution, reflects the effect of not frequent but important disturbances, and it is more appropriate when returns are not normally distributed (Boudt et al., 2008; Jadhav & Ramanathan, 2019), as it is in our case. Accordingly, using MES and spawning stock biomass (SSB), biological risk (BR) is proxied as a source of risk in the natural frame or ocean. Similarly, using catches, production risk (PR) is measured, as a source of risk related to the fishing activity of the EU fishing fleets. Moreover, based on our species-level risk indicators BR and PR, and using as weights the proportion of the landings of each country to the total landings (both in volume and the value), we have inferred the weighted biological and production risk for the 23 EU fishing countries (Subsection2.1.3.4). In addition, we are using two diversity indices, Berger Parker (BP) and Shannon index (SHA). BP is a pure single species diversity index, and, accordingly, with its inclusion we intend to discriminate fishing countries based on their dependency towards their dominant species. Although SHA is often used in ecological studies (Mouillot et al., 2005; Patil & Taillie, 1982; Townsend et al., 2003), however it is far from clear which is the most appropriate multispecies diversity indicator. In some studies SHA is considered more robust than SIM (Magnussen & Boyle, 1995), while others have found SHA to be the most appropriate multispecies diversity measure (Boydstun et al., 2014; Grunewald & Schubert, 2007; Stocker et al., 1985). SIM is weighted toward the abundance of the most common species (Risser & Rice, 1971; Sanders, 1968; Whittaker, 1972), while SHA weighs all species by their frequency, without favouring either common or rare species (Keylock, 2005; Tsallis, 2001). This balance of the of latter is often understood as an advantage of SHA, occasionally categorized as the fairest index (Jost, 2007; Melo, 2008). However, it is also reasonable that the multispecies diversity index choice could be more influenced by the specific objectives pursued, rather than by its inherent mathematical properties. Thus, since with the inclusion of BP we are already paying special attention on the dependency of the countries toward the leading species, to avoid a potential extra bias in favour of the dominant species that the inclusion of SIM might imply, and besides, bearing in mind the high correlation between both the indices, we have decided to include SHA.

Taking advantage from the variate $\{\mathbb{X}\}$ already introduced in Chapter 1, variate $\{\mathbb{Z} = \mathbb{X} + \mathbb{Y}\}$ together with risk and diversity indicators in $\{\mathbb{Y}\}$, includes the *output variables* [the volume of landings (q), the value of landings (pq)], the *input variables* [number of vessels (NV), the gross tonnage (GT), the number of full-time fishermen (FTE)], the *fishing fleet's structure and organisation variables* [the proportion of small-scale artisanal vessels (ART), the proportion of the large industrial vessels (>24 metres) (IND), the proportion of the new vessels (<10 years) (NEW), the degree of amortisation of the fleets' by the proportion of old or quasi amortised vessels (>20 years) to the total fleet (AGED), the number of producer organisations (POs)] and *productivity ratios* [pq/NV, pq/GT, pq/FTE] that made up variate $\{\mathbb{X}\}$. Summarising, the indicators included in variate, $\mathbb{Y}$ and $\mathbb{Z}$ will be as follows:

$\{\mathbb{Y} = \mathrm{wBR_q}, \mathrm{wPR_q}, \mathrm{wBR_{pq}}, \mathrm{wPR_{pq}}, \mathrm{BP_q}, \mathrm{SHA_q}, \mathrm{BP_{pq}}, \mathrm{SHA_{pq}}\}$

$\{\mathbb{Z} = \mathrm{q, pq, NV, GT, FTE, PO, ART, IND, NEW, AGED, pq/NV, pq/GT, pq/FTE}, \mathrm{wBR_q}, \mathrm{wPR_q}, \mathrm{wBR_{pq}}, \mathrm{wPR_{pq}}, \mathrm{BP_q}, \mathrm{SHA_q}, \mathrm{BP_{pq}}, \mathrm{SHA_{pq}}\}$.

Although the inquiries in subsection 2.1.3.4 and section 2.2.3 suggest different groups of fishing countries within the EU, we are formally checking whether the variates $\{\mathbb{Y}\}$ and $\{\mathbb{Z}\}$ exhibit an underlying clustering structure by means of Hopkins test[18] (Hopkins & Skellam, 1954; Lawson & Jurs, 1990) and a battery of modality tests[19] including Cheng and Hall (1998), Fisher and Marron (2001), Hall and York (2001), Hartigan, Hartigan et al. (1985) (Table 2.22). We are using R package *multimode* (Ameijeiras-Alonso et al., 2018) to obtain modality tests. The values of Hopkins statistics are not far from 1, so we can conclude that our datasets are significantly clusterable. However, based on Hartigan, Cheng-Hall, Hall and York, and Fisher and Marron tests, there is no evidence against that the $\{\mathbb{Y}\}$ dataset is uniformly distributed. Despite this ambiguity, taking into account the small population size of our data set, we will accept that $\{\mathbb{Y}\}$ exhibits a clusterable pattern. Moreover, the multimodality test of Fisher and Marron suggest a multimodal structure with at least 4 modes for variate $\{\mathbb{Z}\}$.

Table 2.22: Testing for clusterability

	$\{\mathbb{Y}\}$		$\{\mathbb{Z}\}$	
	Statistics	p-value	Statistics	p-value
Hopkins	0.32	-	0.29	-
Hartigan dip test for unimodality[1]	0.02	1	0.01	0.98
Cheng and Hall excess of mass test	0.03	0.90	0.02	0.59
Hall and York critical bandwidth test	0.25	0.65	0.52	0.14
Fisher and Marron test[2]	0.11	0.75	1.12	0.01***
Fisher and Marron test[3]	0.10	0.94	0.47	0.07*
Fisher and Marron test[4]	0.09	0.94	0.39	0.00***

Notes:
[1] Alternative hypothesis: non-unimodal, i.e., at least bimodal simulated p-value based on 2000 replicates.
[2] Null hypothesis: unimodality. Alternative hypothesis: at least 2 modes. B=100 bootstrap replicas.
[3] Null hypothesis: 2 modes. Alternative hypothesis: at least 3 modes B=100 bootstrap replicas.
[4] Null hypothesis: 3 modes. Alternative hypothesis: at least 4 modes B=100 bootstrap replicas.

Some of the variables in the set of output, input, fleet structure and organisation,

[18] The Hopkins statistic tests the spatial randomness of the data by measuring the probability that a given data set is generated by a uniform data distribution. The Hopkins statistic test compares the distances between the data points and the nearest neighbours from a sample of pseudo points and their nearest neighbours. If the data are not distributed in clusters, then both sets of distances should be similar on average.

[19] Multimodality tests initially assume that data is generated from a unimodal distribution (the null) and accordingly the p-value is the probability of observing the given input or a more extremely multimodal input under the null. If only a single mode is present, then the p-value should be large, indicating that the underlying data is deemed not clusterable. By contrast, small p-values make us the question the original assumption of unimodality and instead conclude that multiple modes (and clusters) are present.

productivity, risk and diversity indicators in $\{\mathbb{Y}\}$ and $\{\mathbb{Z}\}$ are highly correlated. Therefore, we are factoring the variables using principal component analysis (PCA) prior to clustering and using the resulting factor scores as cluster indicators. Before applying PCA, variables in variates $\{\mathbb{Y}\}$ and $\{\mathbb{Z}\}$ have been typified by subtracting their respective mean and dividing by their standard deviation. PCA is usually used before clustering to reduce the original variables into smaller and more parsimonious set of new principal components (PC) explaining most of the variance in the original variates (Anderson, 1984; Brusco et al., 2017; del Valle & Astorkiza, 2019b; Raychaudhuri et al., 1999). Thus, initial indicators will be replaced by a limited number of PCs even all the PCs would be required to reproduce the total system variability of the data. Certain number of PC will conform the effective and necessary inputs to compete the clustering (Johnson & Wichern, 1988; Jolliffe & Cadima, 2016). As a rule of thumb, we are retaining eigenvalues[20]>1 and limiting the number of PCs to the number that accounts for at least 85% of the total variance explained (Kaiser, 1958; Merenda, 1997; Stevens, 2012; Tabachnick & Fidell, 2001). Table 2.23 includes percentages, eigenvalues and cumulative percentages of projected variances for the first five PCs. The first two factors (PC1 and PC2) account for 89% of the total variance of $\{\mathbb{Y}\}$ and the first five factors (PC1, PC2, PC3, PC4 and PC5) account for 89% of the total variance of $\{\mathbb{Z}\}$. Thus, the variance corresponding to the remaining axes may be considered random noise (Lebart, 1984). Accordingly, we proceed with the cluster analysis using PC1 and PC2 for the variate $\{\mathbb{Y}\}$ and PC1, PC2, PC3, PC4 and PC5 for variate $\{\mathbb{Z}\}$. At this stage, we are taking advantage of the R packages *fpc* (Hennig, 2020) and *factoextra* (Kassambara & Mundt, 2017).

Table 2.23: Principal component analysis (PCA)
Eigenvalues and percentages of the projected variances

	$\{\mathbb{Y}\}$				$\{\mathbb{Z}\}$					
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC5	PC6
Standard deviation	2.33	1.30	0.66	0.48	2.86	2.21	1.65	1.38	1.05	0.89
Prop. of variance	0.68	0.21	0.05	0.03	0.39	0.23	0.13	0.09	0.05	0.04
Cumulative prop.	0.68	0.89	0.94	0.97	0.39	0.62	0.75	0.84	0.89	0.93
Eigenvalues	5.41	1.70	0.43	0.23	8.17	4.87	2.72	1.90	1.10	0.79

Notes:
Standard deviation, proportion of variance, cumulative proportion and eigenvalues of projected variance of the indicators in variates $\{\mathbb{Y}\}$ and $\{\mathbb{Z}\}$.

[20] Eigenvalues are derived for each dimension and measure the variability retained by each principal component.

Cluster analysis is carried out using the scores of the first two PCs for variate $\{\mathbb{Y}\}$ and the first five PCs for variate $\{\mathbb{Z}\}$, using alternative clustering procedures including hierarchical (i.e. Ward, average and complete linkage), non-hierarchical (i.e. k-means and k-medoids (PAM)) and mixed hierarchical-kmeans. In the hierarchical clustering procedures, the clustering algorithm starts out by putting each observation into its own separate cluster. Distances between all the observations/clusters are measured and the closets pairs of clusters are grouped together. This process continues until there is only one unique cluster containing the entire data set. Thus, the result at the earlier stage is always nested with the results at a larger state, creating a dendogram or similarity tree. The most popular agglomerative algorithms are complete[21], average[22] and Ward's[23] linkage methods. There are other non-hierarchical procedures, such as k-means, which do not involve a treelike construction process. Instead, this procedure starts identifying the cluster seeds (starting points) for each cluster and then, based on similarities, assigns each observation to one of the cluster seeds. K-medois procedures, which are less sensitive to noise and outliers, use medois[24] as cluster centres. The most common k-medois clustering method is PAM algorithm (Kaufman & Rousseeuw, 2009). In this case, the sums of the distances between objects within a cluster are constantly recalculated as observations move around, which will probably give a more reliable solution. Clustering algorithms are detailed by (Ball & Hall, 1967; Brusco et al., 2017; Hair et al., 2014; Kassambara, 2017; Romesburg, 2004) among others.

Selecting the optimal number of clusters that best describes our countries is not trivial. Due to our limited population size (n=23), we will consider a maximum of no more than 4 cluster (k=4). Some standard internal cluster validation procedures are used in order to select the proper number of clusters: elbow and silhouette methods (Kaufman & Rousseeuw, 2009; Rousseeuw, 1987), a set of additional indices including CH (Calinski & Harabasz, 1974), D (Dunn, 1974), average Pearson gamma (Halkidi et al., 2001), entropy (Meilă, 2007) and WB ratio (Table 2.24). The two-cluster solution (k=2) dominates for

[21]In the *complete linkage* method, the cluster similarity is based on maximum distance between observations in each cluster.

[22]In the *average linkage* procedure similarity of any two clusters is the average similarity of all individuals in one cluster with all individuals in another. Accordingly, average linkage algorithm depends less on outliers and tend to generate clusters with approximately equal within-group variance (Hair et al., 2014).

[23]In the *Ward's* method the similarity between two clusters is not a single measure of similarity, but rather, the sum of squares within the clusters summed over all variables. The selection of which two clusters to combine is based on which combinations of cluster maximises the within-cluster sum of squares across the complete set of separate clusters. The use of a sum of squares measure makes this method easily distorted by outliers (Hair et al., 2014; Milligan, 1996).

[24]Medois: Object within a cluster for which the average distance between it and all the rest of the members of the cluster is minimal. It coincides with the most centrally located point of the cluster.

$\{\mathbb{Y}\}$. Nevertheless, although the k=2 solution may be highly informative, does not help to conclude about a clear taxonomy for the EU fishing countries. Accordingly, four clusters have been ultimately determined after balancing the performance of the cluster statistics and the informative capacity of the resulting partitions. For completeness, 2 clusters related taxonomies are also discussed (see Table 2.25).

Table 2.24: Internal cluster validation measures for $\{\mathbb{Y}\}$

	k=2	k=2	k=3	k=3	k=4	k=4
	km=hc=hkm	pam	km=pam=hkm	hc	km=pam=hkm	hc
between ss	4.34*	4.30	4.07	4.12	3.93	3.96
within ss	67.71	70.51*	44.40	46.33	28.06	29.18
silhouette	0.47*	0.45	0.41	0.43	0.45	0.45
CH	27.51	25.58	25.22	23.76	28.96*	27.61
dunn	0.25	0.11	0.14	0.26	0.18	0.29*
dunn2	1.92*	1.81	1.47	1.39	1.61	1.83
entropy	0.69*	0.69	1.05	1.01	1.33	1.30
P. gamma	0.59	0.57	0.58	0.58	0.59	0.60*
wb ratio	0.52	0.53	0.45	0.45	0.39*	0.39

Notes: *optimal cluster choices

Cluster membership related to each of the partitioning hierarchical (ward, average, complete), non-hierarchical (k-means, PAM) and mixed (hkmeans) methods have been reported in Table 2.25. Results are rather robust to the algorithm used. The most noticeable differences are the cluster membership of the Netherlands (NL) and Spain (ES). The hierarchical algorithms include NL in the first cluster, while the non-hierarchical and mixed algorithms include NL in the fourth cluster. Besides, the hierarchical algorithms include ES in the fourth cluster, while the non-hierarchical and mixed algorithms include ES in the third cluster. When concluding about cluster membership we are paying preferable attention to the partitions (k=4) resulting from the non-hierarchical PAM algorithm, since such algorithm is less sensitive to outliers (Kaufmann & Rousseeuw, 1990).

Focusing merely on the risk and diversity indicators included in variate $\mathbb{Y}=\{wBR_q, wPR_q, wBR_{pq}, wPR_{pq}, BP_q, SHA_q, BP_{pq}, SHA_{pq}\}$, EU fishing countries may be partitioned in four clusters. Following the outcomes of the non-hierarchical and mixed algorithms {Belgium, Estonia, Finland, Germany, Latvia, Lithuania, Poland, Sweden} constitute cluster 1. {Bulgaria, Croatia, Romania} make up cluster 2. No matter the algorithm we are using in the clustering process, these three countries

Table 2.25: Cluster membership by cluster algorithm for variate $\{\mathbb{Y}\}$

	k=2
k-means	{BE EE FI DE LV LT PL SE BG HR RO NL}{CY EL IT MT ES DK FR IE PT SI UK}
PAM	{BE EE FI DE LV LT PL SE BG HR RO}{NL CY EL IT MT ES DK FR IE PT SI UK}
Ward.D2	{BE EE FI DE LV LT PL SE BG HR RO NL}{CY EL IT MT ES DK FR IE PT SI UK}
Average	{BE EE FI DE LV LT PL SE BG HR RO NL}{CY EL IT MT ES DK FR IE PT SI UK}
Complete	{BE EE FI DE LV LT PL SE BG HR RO NL}{CY EL IT MT ES DK FR IE PT SI UK}
hkmeans	{BE EE FI DE LV LT PL SE BG HR RO NL}{CY EL IT MT ES DK FR IE PT SI UK}

	k=4
k-means	{BE EE FI DE LV LT PL SE}{BG HR RO}{CY EL IT MT ES}{DK FR IE PT SI NL UK}
PAM	{BE EE FI DE LV LT PL SE}{BG HR RO}{CY EL IT MT ES}{DK FR IE PT SI NL UK}
Ward.D2	{BE EE FI DE LV LT PL SE NL}{BG HR RO}{CY EL IT MT}{ES DK FR IE PT SI UK}
Average	{BE EE FI DE LV LT PL SE NL}{BG HR RO}{CY EL IT MT}{ES DK FR IE PT SI UK}
Complete	{BE EE FI DE LV LT PL SE NL}{BG HR RO}{CY EL IT MT}{ES DK FR IE PT SI UK}
hkmeans	{BE EE FI DE LV LT PL SE}{BG HR RO}{CY EL IT MT ES}{NL DK FR IE PT SI UK}

Notes:
Cluster membership related to each of the partitioning non-hierarchical (k-means, PAM), hierarchical (Ward.D2, Average, Complete) and the mixed hierarchical-kmeans (hkmeans) algorithms and number of clusters.
Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Malta (MT), Poland (PL), Portugal (PT), Romania (RO), Slovenia (SI), Spain (ES), Sweden (SE), the Netherlands (NL), United Kingdom (UK).

constitute a single differentiated group. {Cyprus, Greece, Italy, Malta, Spain} are grouped in cluster 3. {Denmark, France, Ireland, Portugal, Slovenia, the Netherlands, United Kingdom} constitute cluster 4. Related taxonomies are illustrated in Table 2.26. Countries in cluster 1 {Belgium, Estonia, Finland, Germany, Latvia, Lithuania, Poland, Sweden} are the countries with the lowest *weighted biological risk* ($\mathrm{wBR_q}$=0.28, $\mathrm{wBR_{pq}}$=0.28) and *weighted production risk* ($\mathrm{wPR_q}$=0.35, $\mathrm{wPR_{pq}}$=0.34) (for both the volume-based (q) and the value-based (pq) landings). Besides, the dominance of the most abundant species ($\mathrm{BP_q}$=0.49, $\mathrm{BP_{pq}}$=42) in these countries, is moderately high and the diversity ($\mathrm{SHA_q}$=1.58, $\mathrm{SHA_{pq}}$=1.84) rather low. Therefore, Belgium, Estonia, Finland, Germany, Latvia, Lithuania, Poland and Sweden (cluster 1) are the countries with the lowest weighted biological and production risks, high dominance and low diversity in their sub-ecosystems (Ω_j). Countries in cluster 2 {Bulgaria, Croatia, Romania} show a rather high *weighted biological risk* ($\mathrm{wBR_q}$=0.59, $\mathrm{wBR_{pq}}$=0.68) and an intermediate *weighted production risk* ($\mathrm{wPR_q}$=0.47, $\mathrm{wPR_{pq}}$=0.42) (for both the

Table 2.26: EU fishing countries taxonomy $\{\mathbb{Y}\}$: average values by cluster

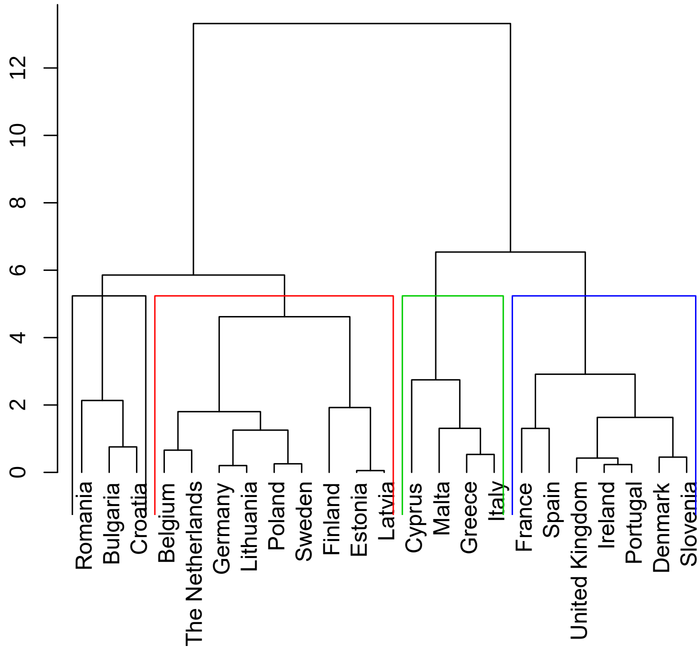
		Cluster			
		1	2	3	4
		{BE EE FI DE LV LT PL SE}	{BG HR RO}	{CY EL IT MT ES}	{DK FR IE PT SI NL UK}
Risk indicators	$\mathrm{wBR_q}$	0.28	0.59	0.70	0.42
	$\mathrm{wPR_q}$	0.35	0.47	0.70	0.51
	$\mathrm{wBR_{pq}}$	0.28	0.68	0.66	0.40
	$\mathrm{wPR_{pq}}$	0.34	0.42	0.71	0.45
Diversity indicators	$\mathrm{BP_q}$	0.49	0.60	0.19	0.25
	$\mathrm{SHA_q}$	1.58	1.30	3.40	2.81
	$\mathrm{BP_{pq}}$	0.42	0.44	0.12	0.16
	$\mathrm{SHA_{pq}}$	1.84	2.02	3.67	3.14

Notes:
Following the non-hierarchical PAM algorithm, Cluster 1: {Belgium, Estonia, Finland, Germany, Latvia, Lithuania, Poland, Sweden}; Cluster 2: {Bulgaria, Croatia, Romania}; Cluster 3: {Cyprus, Greece, Italy, Malta, Spain}; Cluster 4: {Denmark, France, Ireland, Portugal, Slovenia, the Netherlands, United Kingdom}
Average values by cluster membership including:
(a) Risk indicators:
- Landings volume-based: *weighted biological risk* ($\mathrm{wBR_q}$) and *weighted production risk* ($\mathrm{wPR_q}$)
- Landings value-based: *weighted biological risk* ($\mathrm{wBR_{pq}}$) and *weighted production risk* ($\mathrm{wPR_{pq}}$)
(b) Diversity indicators:
- Landings volume-based: Berger Parker ($\mathrm{BP_q}$), Shannon index ($\mathrm{SHA_q}$)
- Landings value-based: Berger Parker ($\mathrm{BP_{pq}}$), Shannon index ($\mathrm{SHA_{pq}}$)

volume-based (q) and the value-based (pq) landings). Additionally, the dominance of the most abundant species ($\mathrm{BP_q}$=0.60, $\mathrm{BP_{pq}}$=44) in cluster 2, is the highest and the diversity ($\mathrm{SHA_q}$=1.30, $\mathrm{SHA_{pq}}$=2.02) the lowest. Accordingly, Bulgaria, Croatia and Romania (cluster 2) exhibit a rather high risk, highest dominance and the lowest diversity in their sub-ecosystems (Ω_j). Countries in cluster 3 {Cyprus, Greece, Italy, Malta, Spain} show the highest *weighted biological risk* ($\mathrm{wBR_q}$=0.70, $\mathrm{wBR_{pq}}$=0.66), the highest *weighted production risk* ($\mathrm{wPR_q}$=0.70, $\mathrm{wPR_{pq}}$=0.71), the lowest dominance ($\mathrm{BP_q}$=0.19, $\mathrm{BP_{pq}}$=12), and the highest diversity ($\mathrm{SHA_q}$=3.40, $\mathrm{SHA_{pq}}$=3.67). Finally, countries in cluster 4 {Denmark, France, Ireland, Portugal, Slovenia, the Netherlands, United Kingdom} exhibit intermediate risk ($\mathrm{wBR_q}$=0.42, $\mathrm{wBR_{pq}}$=0.40, $\mathrm{wPR_q}$=0.51, $\mathrm{wPR_{pq}}$=0.45), rather low dominance ($\mathrm{BP_q}$=0.25, $\mathrm{BP_{pq}}$=0.16), and the highest diversity ($\mathrm{SHA_q}$=2.81, $\mathrm{SHA_{pq}}$=3.14).

The dendogram related to the hierarchical algorithms (Figure 2.16) is helpful to identify internal specific patterns within clusters.

Figure 2.16: Dendogram $\{\mathbb{Y}\}$



Notes:
Dendogram related to the hierarchical (ward, average and complete) methods.

Regarding the partitions resulting from variate $\{\mathbb{Z}\}$, which is comprised by risk and diversity indicators of the EU coastal fishing countries in $\{\mathbb{Y}\}$ together with input, output, fishing fleet's structure and organisation variables and productivity ratios, coming from Chapter 1, the four clusters have been ultimately determined after balancing the performance of the cluster statistics and the informative capacity of the resulting partitions (Table 2.27). However, for completeness, 2 and 3 clusters related taxonomies are also discussed. Cluster membership related to each of the partitioning hierarchical (ward, average, complete), non-hierarchical (k-means, PAM) and mixed (hkmeans) methods have been reported in Table 2.28. Although partitions change slightly depending on the algorithm used, the hard core of the groups is rather stable. Most of the algorithms (specifically, PAM, ward, average and complete) isolate Belgium in one single cluster, the country with the largest and most productive vessels, while others (specifically, k-means and hkmeans), group Belgium together with the Netherlands, the second country with the largest and most productive vessels. Most of the algorithms (k-means, PAM, ward, complete and hkmeans), group {France, Italy, United Kingdom, Spain} together. These four countries belong to the group of *the most fishing countries*, showing the largest fleets and the highest diversity on their sub-ecosystems (Ω_j). However, the average algorithm, isolates Spain and Italy in a single cluster. Spain and Italy are two of *the most fishing countries* in terms of value (pq), they exhibit the major trend toward associationism, concentrating most of the producer organizations in the EU, they are the most productive countries in terms of gross tonnage (pq/GT), and their diversity in terms of value of landings (pq) is the highest. Taking into account these ambiguities, we are paying special attention on the partitions (k=4) that the non-hierarchical PAM algorithm defines, basically because PAM is less sensitive to outliers (Kaufmann & Rousseeuw, 1990). The dendogram related to the hierarchical complete clustering algorithm (Figure 2.17) may be also helpful to identify internal specific patterns within clusters.

Table 2.27: Internal cluster validation measures for $\{\mathbb{Z}\}$

	k=2	k=2	k=2	k=3	k=3	k=3	k=4	k=4	k=4
	km=hkm	pam	hc	km=hkm	pam	hc	km=hkm	pam	hc
between ss	6.79	6.51	6.72	6.95	6.35	7.04*	6.5	6.5	6.4
within ss	281.2	284.6	285.6*	204.2	226.0	211.6	147.2	152.8	159.5
silhouette	0.30	0.27	0.29	0.34*	0.25	0.32	0.3	0.3	0.3
CH	9.80	9.44	9.33	10.20	8.25	9.50	11.4*	10.8	10.0
dunn	0.19	0.24	0.19	0.22	0.19	0.23	0.4*	0.3	0.3
dunn2	1.44*	1.38	1.40	1.09	1.27	1.43	0.9	1.3	1.1
entropy	0.61*	0.68	0.61	0.88	1.02	0.78	1.2	1.2	1.2
P. gamma	0.43	0.38	0.41	0.61*	0.40	0.59	0.6	0.6	0.5
wb ratio	0.69	0.72	0.70	0.62	0.66	0.61	0.6	0.6*	0.6

Notes:
*optimal cluster choices

Focusing on the full variate $\{\mathbb{Z}\}$ and using the partitions derived from PAM as the reference algorithm, EU fishing countries may be divided in four clusters. {Belgium} constitutes cluster 1. {Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden, Slovenia} make up cluster 2. {Cyprus, Denmark, Greece, Ireland, Malta} are grouped in cluster 3. {Spain, France, Italy, The Netherlands, Portugal, United Kingdom} constitute cluster 4. Related taxonomies are revealed in Table 2.29. On average, Belgium (cluster 1) is *the least fishing country* in terms of volume (q) (q=15, 0.4% of the EU), it has the smallest fleet with 0.1% of the vessels (NV=68), 1% of the gross tonnage (GT=12,898), 0.01% of the full-time fishermen (FTE=13), and only one producer organisation (PO=1). Nevertheless, the nature of the Belgian fleet is industrial (>24m=50%), and, besides, the Belgian fleet is the most productive one. Belgian weighted biological and production risks are the lowest

(wBR_q=0.33, wBR_{pq}=0.35, wPR_q=0.33, wPR_{pq}=0.33), the dominance of the leading species (common sole) in terms of value (pq) is the highest (BP_{pq}=0.44), but the overall diversity is intermediate (SHA_q=2.95, SHA_{pq}=2.36). Countries in cluster 2 {Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden, Slovenia} are *the least fishing countries* in terms of value (pq) (pq=37, 0.5% of the EU), their fleets are the newest ($<$10y=11%), but the least productive ones. On average, their weighted biological and production risks are rather low, the dominance of the leading species is the highest (BP_q=0.53) and the diversity the lowest (SHA_q=1.46, SHA_{pq}=1.93). The nature of the fleets in cluster 3 {Cyprus, Denmark, Greece, Ireland, Malta} is pure artisanal ($<$12m=90%), the productivity is rather low and they only have one producer organisation (PO). Besides, the weighted biological and production risks are the highest (wBR_q=0.61, wBR_{pq}=0.58, wPR_q=0.68, wPR_{pq}=0.66) and the diversity is rather high (SHA_q=2.89, SHA_{pq}=3.20). The countries in cluster 4 {Spain, France, Italy, The Netherlands, Portugal, United Kingdom} are *the most fishing countries* in terms of q (q=417, 12% of the EU) and pq (pq=969, 14%). On average, they have the largest fleets with 9% of the vessels (NV=7,024), 11% of the gross tonnage (GT=175,255), 12% of the full-time fishermen (FTE=13,995), and they exhibit the major trend toward associationism concentrating most of the producer organisations in the EU (PO=23, 12%). Their weighted biological and production risks are rather high (wBR_q=0.47, wBR_{pq}=0.44, wPR_q=0.53, wPR_{pq}=0.49), dominance of the leading species is the lowest (BP_q=0.21, BP_{pq}=0.13) and the diversity on their sub-ecosystems is the highest (SHA_q=3.29, SHA_{pq}=3.58).

Table 2.28: Cluster membership by cluster algorithm for variate $\{\mathbb{Z}\}$

	k=2
k-means	{BE NL BG EE FI DE LV LT PL SE RO SI HR DK IE MT}{CY EL PT IT FR UK ES}
PAM	{BE NL BG EE FI DE LV LT PL SE RO SI HR}{DK IE MT CY EL PT IT FR UK ES}
Ward.D2	{BE BG EE FI DE LV LT PL SE RO SI HR DK IE MT CY}{NL EL PT IT FR UK ES}
Average	{BE}{BG EE FI DE LV LT PL SE RO SI HR DK IE MT CY NL EL PT IT FR UK ES}
Complete	{BE BG EE FI DE LV LT PL SE RO SI}{HR DK IE MT CY NL EL PT IT FR UK ES}
hkmeans	{BE BG EE FI DE LV LT PL SE RO SI HR DK IE MT NL}{CY EL PT IT FR UK ES}
	k=3
k-means	{BE NL}{BG EE FI DE LV LT PL SE RO SI HR DK IE MT}{CY EL PT IT FR UK ES}
PAM	{BG EE FI DE LV LT PL SE RO SI HR BE}{DK IE MT CY EL}{PT IT FR UK ES NL}
Ward.D2	{BE}{BG EE FI DE LV LT PL SE RO SI HR DK IE MT CY}{EL PT IT FR UK ES NL}
Average	{BE}{BG EE FI DE LV LT PL SE RO SI HR DK IE MT CY EL PT FR UK NL}{IT ES}
Complete	{BE}{BG EE FI DE LV LT PL SE RO SI}{HR DK IE MT CY EL PT FR UK NL IT ES}
hkmeans	{BE NL}{BG EE FI DE LV LT PL SE RO SI HR DK IE MT}{CY EL PT FR UK IT ES}
	k=4
k-means	{BE NL}{BG HR EE FI DE LV LT PL RO SI SE}{CY DK EL IE MT PT}{FR IT ES UK}
PAM	{BE}{BG HR EE FI DE LV LT PL RO SI SE}{CY DK EL IE MT}{NL PT FR IT ES UK}
Ward.D2	{BE}{BG HR EE FI DE LV LT PL SE}{RO SI CY DK IE MT}{EL NL PT FR IT ES UK}
Average	{BE}{BG HR EE FI DE LV LT PL SE CY DK IE MT EL NL PT FR UK}{IT ES}{RO SI}
Complete	{BE}{BG EE FI DE LV LT PL SE RO SI}{HR CY DK IE MT EL IT}{NL PT FR UK ES}
hkmeans	{BE NL}{BG EE FI DE LV LT PL SE RO SI HR}{CY DK IE MT EL PT}{IT FR UK ES}

Notes: Cluster membership related to each of the partitioning non-hierarchical (k-means, PAM), hierarchical (Ward.D2, Average, Complete) and the mixed hierarchical-kmeans (hkmeans) algorithms and number of clusters.
Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Malta (MT), Poland (PL), Portugal (PT), Romania (RO), Slovenia (SI), Spain (ES), Sweden (SE), the Netherlands (NL), United Kingdom (UK).

If we compare the clusters determined in Chapter 1 using variate $\{\mathbb{X}\}$ with the ones resulting from $\{\mathbb{Z}\}$, even the hard core of the groups is rather stable, it can be definitely concluded that risk and diversity matter to characterise European fishing countries. Cluster 1 {Belgium} and cluster 4 {Spain, France, Italy, The Netherlands, Portugal, United Kingdom} keep constant. However, substantial changes occur in cluster 2 {Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden, Slovenia} and cluster 3 {Cyprus, Denmark, Greece, Ireland, Malta} (compared to the classification coming from Chapter 1). Malta switches to cluster 3, since risk and diversity are rather high. Besides, {Germany, Croatia, Lithuania, Latvia, Sweden} change to cluster 2, because their weighted biological and production risks are rather low, the dominance of the leading species is the highest and the diversity the lowest.

Table 2.29: EU fishing countries taxonomy {$\mathbb{Z}$}: average values by cluster

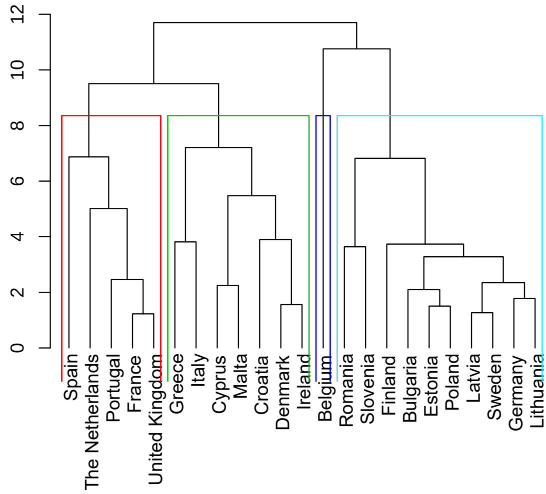
		Cluster			
		1 {BE}	2 {BG HR EE FI DE LV LT PL RO SI SE}	3 {CY DK EL IE MT}	4 {NL PT FR IT ES UK}
Output variables	q	15	61	49	417
	pq	64	37	104	969
Input variables	NV	68	1,712	4,162	7,024
	GT	12,898	24,109	44,024	175,255
	FTE	13	2,134	5,688	13,995
Fleets' structure and organisation variables	<12m (ART)	1%	88%	90%	75%
	>24m (IND)	50%	5%	3%	8%
	<10y (NEW)	1%	11%	5%	8%
	>20y (AGED)	79%	69%	75%	70%
	PO	1	4	1	23
Productivity ratios	pq/NV	943,299	29,863	35,397	224,528
	pq/GT	4,973	1,556	1,868	5,210
	pq/FTE	4,934,178	50,300	45,621	107,769
Risk indicators	wBR_q	0.33	0.39	0.61	0.47
	wPR_q	0.33	0.39	0.68	0.53
	wBR_{pq}	0.35	0.40	0.58	0.44
	wPR_{pq}	0.33	0.37	0.66	0.49
Diversity indicators	BP_q	0.26	0.53	0.23	0.21
	SHA_q	2.95	1.46	2.89	3.29
	BP_{pq}	0.44	0.41	0.16	0.13
	SHA_{pq}	2.36	1.93	3.20	3.58

Notes:
Following the non-hierarchical PAM algorithm, Cluster 1: {Belgium}; Cluster 2: {Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden, Slovenia}; Cluster 3: {Cyprus, Denmark, Greece, Ireland, Malta}; Cluster 4: {Spain, France, Italy, The Netherlands, Portugal, United Kingdom}.
Average values by cluster membership including:
(a) Variables coming from variate {$\mathbb{X}$} (Chapter 1):
- Output variables: volume of landings (q) and the value of landings (pq).
- Input variables: the number of vessels (NV), the gross tonnage (GT), and the number of full-time fishermen (FTE).
- Fleet's structure and organisation variables: the proportion of small-scale artisanal vessels (<12 metres) to the total fleet (ART), the proportion of the large industrial vessels (>24 metres) (IND), the proportion of the *new* vessels (<10 years) (NEW) and the degree of amortisation of the fleets' by the proportion of *old* vessels (>20 years) (AGED), the organisational behaviour is captured by the number of producer's organisations (PO).
-Productivity ratios: pq/NV, pq/GT, pq/FTE.

(b) Risk indicators:
- Landings volume-based: *weighted biological risk* (wBR_q) and *weighted production risk* (wPR_q).
- Landings value-based: *weighted biological risk* (wBR_{pq}) and *weighted production risk* (wPR_{pq}).

(c) Diversity indicators:
- Landings volume-based: Berger Parker (BP_q) and Shannon index (SHA_p).
- Landings value-based: Berger Parker (BP_{pq}) and Shannon index (SHA_{pq}).

Figure 2.17: Dendogram $\{\mathbb{Z}\}$



Notes:
Dendogram related to the hierarchical complete method.

2.5 Concluding remarks and discussion

Fisheries management can be controversial when the conservation objectives and vulnerability of fish species are not well defined. The information given by conventional ecological vulnerability indicators is limited. Some of them, such as resilience (R) and vulnerability (V) (FishBase, Froese and Pauly (2018)) and conservation status (CS) (Red List of Threatened Species (RLTS), IUCN (2018)), are in essence qualitative indicators. There also exist many missing values, and, besides, some species are not included. Thus, there is a need of vulnerability indices to help to conserve fish stocks sustainably and set effective conservation policies. Our approach gives an innovative perspective of measuring fish vulnerabilities through the application of financial risk indicators. We have been able not only to measure risks, but also to observe how risk values can be ambiguous depending on the formulation of the indicators used. Even the five risk indicators considered (i.e. Historical Value-at-Risk (HVaR), Modified Value-at-Risk (MVaR), Historical Expected

Shortfall (HES), Modified Expected Shortfall (MES) and Expectiles (EX)) are consistent and relevant, Modified Expected Shortfall (MES) is the most accurate and preventive risk indicator based on the distributional characteristics of our data. Therefore, using MES and spawning stock biomass (SSB), *biological risk* (BR) is proxied as a source of risk in the natural frame or ocean. Similarly, using catches, *production risk* (PR) is measured, as a source of risk related to the fishing activity of the EU fishing fleets.

According to the biological risk (BR), the riskiest species (BR=1) are turbot, surmullet, spotted ray, rays and skates, Norway pout, haddock, greater Argentine, European anchovy, cuckoo ray, capelin and blonde ray. Contrarily, the species with the lowest BR are golden redfish (BR=0.02), blackbellied angler (BR=0.05), Greenland halibut (BR=0.05), tusk (BR=0.08) and European plaice (BR=0.11). In terms of production risk (PR), the species with the highest risk (PR=1) are sandeels, rays and skates, Norway pout, megrim, greater Argentine, golden redfish, four spot megrim, European anchovy, cuckoo ray, capelin, boarfish, blue whiting and blonde ray. The species with the lowest PR are turbot (PR=0.17), European plaice (PR=0.19), common sole (PR=0.20), brill (PR=0.21), common dab (PR=0.23) and Norway lobster (PR=0.23). Since more variables affect catches, including quotas, stakeholders' individual decisions, market conditions and specific regulations, the average production risk (0.65) is 25% higher than the average biological risk (0.52).

Obtaining a classification of the fish species based on their inherent risk, is beneficial for two reasons. First, to reduce uncertainty of fisheries and apply them to prediction models. Expectations could be generated through these models and fishermen could also improve their economic activity. Moreover, these two proposed new synthetic risk indicators could be also included in the existing vulnerability databases, such as FishBase (Froese & Pauly, 2018) and IUCN (IUCN, 2018) as a complementary new risk sources at fish species level, giving different but additional information compared to the existing ecological indicators. Second, from our fish species-based biological risk (BR) and production risk (PR) alternative synthetic risk indicators can be inferred to any aggregation level (i.e. country, port, region, community or fleet). Thus, obtaining primarily species-level risk indicators is essential to latter infer to whatever the aggregation level, weighting species by the proportion each fish species has on that country, region or community.

Based on our species-level risk indicators (BR) and (PR), and using as weights the proportion of the landings of each country to the total landings (both in volume and the value), we have inferred the *weighted biological risk* (wBR) and the *weighted production risk* (wPR) for the 23 EU fishing countries. Our results reveal that the countries with the highest wBR (Q4) are Cyprus, Italy, Greece, Romania, Malta and Croatia. The countries with a moderate high risk (Q3) are Slovenia, Portugal, Spain, Denmark, France, Bulgaria and the United Kingdom. Belgium, Poland, Lithuania, Latvia, Ireland, Sweden and Estonia are classified as moderate low risk (Q2). The lowest wBR countries (Q1) are Finland, Germany and the Netherlands. It is remarkable that the volume-based biological risk distribution, does not change compared to the value-based biological risk, and therefore, wBR (risk to suffer high negative shocks on biomass in the natural frame or ocean) is not affected by the market side. According to the wPR, the ranking of the risky countries hardly changes. Nevertheless, our results suggest that the market side is slightly conditioning the wPR (risk to suffer a high negative shock due to fishing activity/fleet related reasons). Undoubtedly, the fishing activity is directly related with prices while the biomass itself is not.

As it is in a portfolio, the lowest the fish species diversity, the higher the concentration, dominance and dependency of the fishing industry to the evolution of the dominant species, and higher the risk of a potential collapse in the sector (del Valle & Astorkiza, 2019a). Accordingly, in addition to the country-based risk indicators, we have given an overview of the diversity at country-based sub-ecosystems (Ω_{jt}) comprised by the commercial fish species in the EU using two specifications: volume of landings (q) and value of landings (pq). We have quantified the diversity of each sub-ecosystem (Ω_{jt}) related to the EU fishing member-states. There are some studies, such as del Valle et al. (2017), Kasulo and Perrings (2006), which suggest focusing on the value of the landings instead of quantities to get diversity indicators. Nevertheless, we found out more convincing analysing both perspectives and comparing them. Even diversity results do not change so much when we use landed volume or landed value, we have been able to capture an asymmetric behaviour on species leadership and therefore, we have decided to incorporate also the market side in the ecosystem, via prices. Considering only quantities would be poor because it would underestimate expensive fish species and similarly, considering only landings values would also underestimate cheap but abundant fish species.

Overall, the aggregate species richness for EU is rather high. A total of 1144 fish species are landed in the EU. The most outstanding fish species (Atlantic herring (HER)) accounts for 15% of the total volume of fish landed. Nevertheless, the five leading fish species accumulate a large share (45%) of the total volume landed in the EU. Diversity results change considerably when the value of landings is considered. Atlantic Herring comprises the 6% of the total landed value and the five leading fish species constitute the 23% of the total landed value in the EU. Moreover, results suggest that countries sub-ecosystems are very highly concentrated and dependent on just few species. As a reference, the five-leading species (concentration ratio (5) (CR_5)) surpass the 60% of the overall landed volume for 19 of the 23 countries. Only France (34%), Spain (39%), Italy (43%), Greece (47%), Belgium (54%), United Kingdom (56%) and Malta (58%) are below the above mentioned $\overline{CR}_{5j} < 60\%$. Results change little when landed value is considered. 15 countries out of 23 still are very dependent on their key five species: Latvia (98%), Estonia (96%), Finland (88%), Poland (87%), Romania (87%), Sweden (86%), Bulgaria (86%), Germany (82%), Lithuania (78%), the Netherlands (71%), Belgium (70%), Croatia (67%) and Slovenia (63%). Managers should be aware of these particularities when setting policies. Therefore, the potential application of the modern portfolio theory (MPT) for fisheries management will be explored on the next chapter, as a tool to optimize resources and complement to the existing models.

As it is well known from the framework in which biodiversity is conceptualized as a portfolio of natural assets (Koellner & Schmitz, 2006; Schläpfer et al., 2002; Weitzman, 2000), higher biodiversity may contribute with natural risk insurance. In fact, diverse composition of landings brings higher and more stable returns from fisheries. Some countries, such as Finland and Romania, are heavily dependent on one or a few species, and therefore, they may potentially assume higher risk levels than others due to their high concentration level. Nevertheless, we have unexpectedly found that our risk and diversity measures are positively correlated. Countries risk level is potentially defined by their quota and landings/catches distribution, but it is the fish species risk share what mainly determines the overall risk level of the countries.

Our clustering results support four types of fishing countries in the EU. Belgium (cluster 1) is isolated alone in one cluster, which basically means that is different from the rest of the EU fishing countries. Belgium is *the least fishing country* (q=15), with the smallest fleet (NV=68, GT=12,898, FTE=13, PO=1), but, at the same time, the most productive one. Besides, the weighted biological and production risks are the lowest in Belgium (wBRq=0.33, wPRq=0.33), the dominance of the leading species (common sole) in terms of value (pq) is the highest (BPpq=0.44), but the overall diversity is intermediate (SHAq=2.95, SHApq=2.36). Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden and Slovenia (cluster 2) are *the least fishing countries* in terms of pq (q=37), their fleets are the newest (<10y=11%), but the less productive ones. On average, their weighted biological and production risks are rather low, the dominance of the leading species is the highest (BP_q=0.53) and the diversity the lowest (SHA_q=1.46, SHA_{pq}=1.93). Cypriot, Danish, Greek, Irish and Maltese (cluster 3) fleets are pure artisanal (<12m=90%), their productivity is rather low and their behaviour toward associationism the lowest. Besides, the weighted biological and production risks are the highest (wBR_q=0.61, wPR_q=0.68) and the diversity is rather high (SHA_q=2.89). Spain, France, Italy, The Netherlands, Portugal and United Kingdom (cluster 4) are *the most fishing countries* in terms of volume (q) (q=417, 12% of the EU) and pq (pq=969, 14%). On average, they have the largest fleets (NV=7,024, GT=175,255, FTE=13,995) and they concentrate most of the producer organisations in the EU (PO=23, 12%). Their weighted biological and production risks are rather high (wBR_q=0.47, wPR_q=0.53), dominance of the leading species is the lowest (BP_q=0.21) and the diversity on their sub-ecosystems is the highest (SHA_q=3.29).

Summarising, the most remarkable characteristics of each of the four clusters are as follows: Belgium (cluster 1) is *the least fishing country* in terms of volume fished (q), it has the smallest but the most productive fleet, the weighted biological and production risks are the lowest, and the overall diversity is intermediate. Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden and Slovenia (cluster 2) are *the least fishing countries* in terms of the value of fish landed (pq), their fleets are the newest but the least productive ones, their weighted biological and production risks are rather low, and the diversity in their sub-ecosystems is the lowest. The fleets in Cyprus, Denmark, Greece, Ireland and Malta (cluster 3) are pure artisanal, the productivity is rather low, the weighted biological and production risks are the highest and the diversity in their sub-ecosystems is rather high. Spain, France, Italy, The Netherlands, Portugal and United Kingdom (cluster 4) are *the most fishing countries* in the EU, they have the largest fleets and they concentrate most of the producer organisations in the EU. Their weighted biological and production risks are rather high and the diversity on their sub-ecosystems is the highest.

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Chapter 3

An efficient portfolio approach towards ecosystem-based fisheries governance in the EU

Abstract

In the framework of ecosystem-based approach to multispecies fisheries governance, the main objective of this chapter is to apply modern portfolio theory (MPT) to the North-East Atlantic European fisheries, including all the 28 key fish species subject to total allowable catches (TAC) and quota regimes within the EU. This is done, first, quantifying the inherent return and risk of the potential fish portfolios and, secondly, estimating both, a global constrained financial efficient frontier (FEF) for all EU, as well as an individual FEF for each fishing country in the target area. Unlike previous studies in the field of financial fisheries economics, and due to its major robustness under non-normality and the presence of fat tails, we are using Conditional Value-at-Risk (CVaR) instead of the conventional mean-variance optimization (MVO) as the method to solve the inherent optimization problem of minimizing risk under a set of alternative constraints so as to obtain the respective FEFs. Our results show that changing the species portfolio distribution, it would be possible to improve efficiency, that is to say, to get increasing returns and decreasing risk levels. Moreover, this efficiency gain would be compatible with specific quota transfers among fishing countries.

3.1 Introduction

The lack of effective sustainable strategies to plan and manage fisheries have encouraged some specialists to propose an ecosystem-based fisheries management (EBFM) approach (Beddington et al., 2007; Botsford et al., 1997; Pikitch et al., 2004), switching from an individual species based to an ecosystem-based perspective that explicitly puts the species' interactions in the centre of the debate. Hence, according to the EBFM, species should not be considered in isolation. Quite the contrary, interactions among species are essential to accomplish the tripe bottom line of sustainability in fisheries (Asche et al., 2018). Therefore, these interactions should be also accounted when assessing the inherent risk of fish populations and changing environments. Interaction among fish species take for granted that risk related to catching different species are correlated and, accordingly, considering all the species together in the ecosystem can be beneficial to promote a sustainable use of marine resources (Essington et al., 2006).

The Common Fisheries Policy (CFP) (EU, 2013) also calls for an ecosystem-based fisheries management (EBFM) approach to govern EU fisheries sustainably. However, there is a lack of consensus on how EBFM should be implemented. Different interrelated difficulties, such as understanding well enough the marine ecosystem itself, measuring and monitoring all the relevant variables, and identifying a more accurate set of governance conditions still remain unsolved (Link & Browman, 2017). Undoubtedly, there is an increasing demand for practical, interdisciplinary and well-tested decision-making methods and tools to assess the management of the environment and natural resources (Guerry et al., 2015), but the fact is that complex questions arise when researches try to evaluate and improve the decision-making process through new sustainability related forms of risk (Matthies et al., 2019). There is also a growing branch in the literature that suggests financial approaches to be used in fisheries management (Bianchi & Skjoldal, 2008; Gourguet et al., 2014; Pokki et al., 2018; Walters et al., 2002; Yang et al., 2008). In fact, economic and environmental researchers have recently advocated using the modern portfolio theory (MPT) to improve the guidance and decision making process of natural resources, including agriculture (Knoke et al., 2015; Matthies et al., 2019; Paut et al., 2019), landscape conservation under climate change (Ando & Mallory, 2012a; Shah & Ando, 2015), forestry (Knoke & Wurm, 2006; Matthies et al., 2015; Reeves & Haight, 2000), energy (Bazilian & Roques, 2009), biodiversity conservation and crop diversification (Figge, 2004; Fraser & Figge, 2005; Paut et al., 2019), and last, but not least, fisheries (Alvarez et al., 2017; Carmona et al., 2020; Edwards et al., 2004; Jin et al., 2016; Rădulescu et al., 2010; Sanchirico et al., 2008).

Modern portfolio theory (MPT) is based on a standard microeconomic model where an investor chooses from a variety of available financial assets with varying rates of return (Markowitz, 1952). Assets are combined, creating this way a financial portfolio with the aim to get the highest expected return at the lowest risk (either variance or covariance) level. Therefore, it is possible to observe the effect of the asset diversification by reducing the global risk of a portfolio (Kolm et al., 2014). Hence, MPT proposes diversifying investment options to optimize the portfolio of risky assets using a mean-variance optimization (MVO) model. Thus, for a given level of return, one can derive the minimum risk by minimizing the variance of a portfolio, and find the financial efficient portfolio frontier (FEF) where different efficient portfolios can be selected. Portfolios below the efficient frontier are inefficient, as a better performance can be achieved at the same risk level, or the same performance at a lower risk level. Based on the FEFs, alternative efficient portfolios may be proposed depending on the target return and risk levels. For example, the minimum risk portfolio (MRP) could be suggested in order to achieve the lowest possible risk level, or the tangency portfolio (TP) could be also recommended to achieve the optimum portfolio with the highest reward, where the risk/return ratio (also known as Sharpe Ratio (SR)), is maximized.

However, using conventional measures such as variances and covariances to proxy risk involves taking the assumption that returns are normally distributed or that investors have a quadratic utility function (Harlow, 1991). There is huge empirical evidence to admit that the distribution of many financial returns is non-normal (Boothe & Glassman, 1987; Fama & Roll, 1968; Sheikh & Qiao, 2009), and that returns are usually fat tailed (Jansen & De Vries, 1991). Additionally, using variance or covariance also involves that gains and losses are equally penalized, and accordingly, neither variance nor covariance would be appropriate risk indicators when portfolio managers are loss averse (Kahneman et al., 1990; Lusk & Coble, 2008). Moreover, mean-variance optimization (MVO) fails to identify strategies that minimize risk. As far as investors are more concerned about potential losses from extreme shocks, practitioners pay more attention to downside risks (Wan et al., 2015). Therefore, following Rockafellar, Uryasev et al. (2000), Rockafellar and Uryasev (2002), Alexander and Baptista (2004) and Salahi et al. (2013), instead of using variance or covariance, we propose a mean-CVaR portfolio selection model as a non-parametric method to optimize and estimate the financial efficient frontiers (FEF).

Applying modern portfolio theory (MPT) to fisheries management is useful to improve decision making and help to specify optimal policies that account for species interactions in an EBFM framework in which fish stocks can be view as natural assets capable of generating return flows (Alvarez et al., 2017; Sanchirico et al., 2008). These returns can be monetary or monetized depending on the nature of the assets or harvestable resources. If, for example, we consider fish landings, these assets could be measured in tonnes or monetized multiplying the volume of the landings by the corresponding market values (i.e. prices) as if they were financial assets. Notice also that fishers choose their target species among the diverse and disposable portfolio of harvestable fish species. So, there exists a sound parallelism between financial assets and fish stocks. Moreover, modern portfolio theory (MPT) is consistent with an ecosystem-based fisheries management (EBFM) approach that jointly considers multiple fish stocks. Fish species interactions are also implicitly considered by the inclusion of species related revenues and covariances. Therefore, MPT provides an attractive framework to face the management of multi-stock population dynamics by suggesting strategies to maximize returns and/or minimize risks.

Although the estimation of FEFs in the fisheries domain follows the same structure as in finance, specific restrictions must be considered when applying financial efficient frontiers to fisheries. Since fish stocks are not unlimited, it is necessary to include some constraints in order to propose sustainable solutions that ensure the survival of the fish stocks in the future (Sanchirico et al., 2008). If we are not including such constraints, our recommendations might even imply catching up to a level that could cause the fish stock to collapse. These additional restrictions in the optimization model are defined as constraints that can limit the initial investment and risk preferences (Knoke et al., 2005; Knoke & Wurm, 2006), a desired minimum level of diversification (Halpern et al., 2011) or, in the field of fisheries, a TAC based regulation (Carmona et al., 2020). For the purpose of our study, we will focus on three alternative constrained financial efficient frontiers (FEF), from now on, EF_{MAX}, EF_{MINMAX} and EF_{MINTAC}. Following Sanchirico et al. (2008), the EF_{MAX} frontier includes an upper box constraint as the maximum observed weight to ensure that the proposed weights keep under sustainable solutions. Besides, following Alvarez et al. (2017), we are also including a sustainability parameter (γ) to compare how increasing or reducing the upper bound could affect the efficient frontier. This sustainability parameter indicates the proportion of the maximum observed landings weight which is allowed, and therefore, γ helps to observe how policy makers decisions would affect the potential reallocation of weights, and how portfolio's risk and return levels would change. EF_{MINMAX} implies adding a minimum box constraint to the model. Certainly, there are some fish species whose mean return is negative, and accordingly, their risk level is very high. Nevertheless, it would not be feasible to recommend zero catches of these risky fish species, because it would directly imply the closure of these fisheries, which might not be socio-economically sustainable.

Thus, we ensure that our recommendation implies catching from each fish species at least the minimum observed proportion to total landings. Finally, following Carmona et al. (2020), the EF_{MINTAC} frontier includes an upper maximum constraint that measures the weight of the total allowable catches (TACs) as a percentage to total landings. With this constraint, we have replaced the maximum observed weight by the TAC weight for the regulated fish species, and maintained the previous maximum observed constraint for the non-regulated ones. A priori EF_{MINTAC} is the preferred one among the three efficiency models, because it is the one that best fits reality, keeps under regulatory limits, and reveals a feasible reallocation of landings weights to achieve the efficient portfolio that minimizes risk for a certain desired level of return. However, comparing these three potential financial efficient frontiers (EF_{MAX}, EF_{MINMAX} and EF_{MINTAC}) is useful to observe how policy makers' decisions would affect the reallocation of landings weights, implying changes in both return and risk levels.

This marriage between financial and fisheries economics literature is still rather recent. Sanchirico et al. (2008) adapted financial portfolio theory as a pioneering methodology for EBFM, accounting for species interdependencies, uncertainty and sustainability constraints, applying MPT to the Chesapeake Bay (USA); and demonstrating that there were benefits from considering variances and covariances of gross fishing revenues in setting species TACs. In addition, Rădulescu et al. (2010) present a multi-objective programming model to manage fisheries of the Galati county (Romania). Aiming to obtain optimal fishing plans that minimize the risk, they maximize the expected return and solve the optimal trade-off problem, modelling parameters such as the minimum expected return, the sum invested in the portfolio and the target return, so as to determine the minimum risk scenarios. Jin et al. (2016) propose a measure of excessive risk taking and conduct portfolio assessment of historical commercial fishing performance in a large marine ecosystem (New England (USA)) and fishing ports in the north-eastern USA. They found that using portfolio analysis could improve management, not only at large marine ecosystems, but also at community level, suggesting that excessive risk taking is associated with overfishing. Alvarez et al. (2017) use landings data from the Colombian Pacific to establish catch limits in fisheries at ecosystem level, simulating potential policy options regarding sustainability and social equity by developing a set of alternative constraints. They propose efficient catch portfolios to optimize the flow of provisioning ecosystem services from their target area. Finally, Carmona et al. (2020) adapt MPT to the Basque local inshore fleet by constructing two financial efficient frontiers, namely the ecosystem efficient frontier considering stock interactions, and the stock efficient frontier considering individual stock variances. Their results reveal that taking the single-stock approach as the benchmark, it is possible to obtain the same historical revenue while reducing risk, and alternatively, maintain the same level of risk by increasing revenues.

Table 3.1: Empirical fish portfolios in the literature

Study	Fish data	Measure of returns	Measure of risk
Sanchirico et al. (2008)	Yearly catches USA [1976-2003]	Expected revenues assuming that prices are exogenous, i.e. unresponsive to changes in the catch levels	Variance
Rădulescu et al. (2010)	Yearly fish farm Galati county (Romania) [2000-2008]	Expected return of the market prices/kg	The first partial lower moment
Jin et al. (2016)	Yearly landings North-Eastern USA [1964-2012]	Expected return of the value of landings in dollars	Standard deviation
Alvarez et al. (2017)	Yearly landings Colombian Pacific Coast [1950-2010]	Expected return of the value of landings, assuming same price for all the species	Variance
Carmona et al. (2020)	Daily landings Basque country (Spain) [2001-2015]	Expected annual revenues of the value of landings	Standard deviation

In the framework of the above-mentioned financial fisheries economics literature, we are adding a new contribution to this growing branch within fisheries economics, which, based on the modern portfolio theory (MPT) aims to provide new tools for policy makers so as to optimize revenues coming from fishing activity accounting for species interactions. The main objective of this chapter is to apply modern portfolio theory (MPT) to the North-East Atlantic EU waters using, Conditional Value-at-Risk (CVaR), a novel measure in the financial fisheries economics literature. The use of downside risk measures, such as CVaR, is broadly recommended by financial practitioners (Gundel & Weber, 2007; Harlow, 1991; Ling et al., 2014; Miller & Reuer, 1996; Zhu et al., 2009) when returns do not follow a normal distribution, and we are concerned with big negative shocks; but is has not been applied yet to fisheries. Furthermore, quantifying the inherent risk of the fish portfolios and using the estimated financial efficient frontiers, we aim to show how returns coming from fish landings could be increased and, at the same time, risk decreased. This way, we are providing a new tool for policy makers to improve multispecies fisheries management in the EU. Therefore, our main contribution to the literature is innovative twofold. Firstly, using Conditional Value-at-Risk (CVaR) (Rockafellar, Uryasev et al., 2000; Rockafellar & Uryasev, 2002) as a robust and alternative risk indicator, not employed before in the financial fisheries economics literature. Secondly, applying modern portfolio theory (MPT) in a large ecosystem comprised by the major fishing ground in the EU. In order to do so, using the mean-CVaR optimization approach, we estimate an aggregate-level financial efficient frontier (FEF) for the overall EU ($\mathrm{FEF_{EU}}$) and also individual-level FEFs for the nine EU fishing countries operating in the North-East Atlantic (i.e. Belgium, Germany, Denmark, Spain, France, Ireland, the Netherlands, Portugal and United Kingdom). This way we are able to propose a redistribution of fish species weights and suggest how individual countries should increase or reduce landings of some fish species in order to perform better.

The returns of each fish species (asset) can be defined in two ways: using volume of landings (tonnes) or value of landings (€). Undoubtedly, fish prices also give relevant information about the food-related ecosystem services generated by a multispecies fishery (Alvarez et al., 2017). Certainly, we use value of landings (pq) as a measurement for returns in order to estimate global $\mathrm{FEF_{EU}}$. Nevertheless, although pq seems to be more related to the financial arena, in the case of individual $\mathrm{FEF_j}$ we have decided to use landed volume (q) instead of landed value (pq) for two main reasons. Firstly, local fisheries are often price takers, that is, they do not control prices because local catches are too small, relative to total market supply (Sethi, 2010). Secondly, quotas for individual fish stocks limit the maximum allowed catches for the key fish species, which are also measured in tonnes live weight. Thus, the maximum allowed quantity (quotas) will determine our recommended redistribution for the volume of landings. Consequently, our country-based efficient portfolio proposal also will be focused on the potential reallocation of landed volume, specifying which species should be targeted to land more or less according to our findings. From the viewpoint of the fisheries management, the objective is to land the largest amount of fish with the lowest possible risk, regardless of prices and under sustainable limits.

The remainder of this chapter is organised as follows. After this introduction, Section 3.2 describes the material and methods used in the chapter, the data used and the theoretical framework, giving a broader overview of the modern portfolio theory (MPT) and its adaptation to fisheries. Returns are defined, CVaR is suggested as the best risk indicator for our particular case studies and constraints are also detailed for the estimation of the constrained financial efficient frontiers. Section 3.3 summarises the major empirical findings made in this chapter, both aggregately (for the overall EU) and for the nine individual fishing countries operating in the North-West Atlantic. Finally, Section 3.4 concludes, adding some discussion points, such as the potential quota transfers within the ecosystem-based fisheries management (EBFM) framework.

3.2 Material and methods

3.2.1 Theoretical framework

From a pure financial point of view, portfolio theory (PT) is based on a model where an investor chooses from a variety of available financial assets with varying rates of return. Financial assets are usually contractual agreements that generate liquidity to one of the parties involved and equity or liability to the other. Due to the agreement, both parties are binding to some positive or negative payoffs, which could be guaranteed or not. There are various types of financial assets in the market, such as bonds, stocks, derivatives, futures, options and swaps (see, among many others, Cvitanić and Zapatero (2004)), in which portfolio managers invest, following their expectations about future values of the financial assets. *Returns* are the payoff from each asset, generally in the form of dividends and market valorisation. Managers usually focus on the annual rate of return considering the cost of acquiring the asset at the beginning of the year, the value of the asset at the end of the year, and any dividends paid throughout the year. Based on the past performance of the returns, managers generate expectations of the potential future valorisation of the financial assets. Employing historical price data of these assets, returns (r_{it}) are generally defined as the arithmetic rate of return of the assets in the portfolio, and are given by $r_{it} = \frac{P_{it}-P_{it-1}}{P_{it-1}}$. Prices of singles assets (i) vary over the time and hence, r_{it} represents the price difference or production gain/loss across the period of interest (Elton et al., 2009). Moreover, in order to focus on long-horizon returns, usually the continuously compounded rate of return is used, which is the logarithm of the arithmetic return:

$$R_{it} = \ln \frac{P_{it}}{P_{it-1}} = \ln P_{it} - \ln P_{it-1}. \tag{3.1}$$

In addition to the portfolio theory (PT), modern portfolio theory (MPT) suggests combining assets and considering correlations across assets, reducing risk for a given level of return (Markowitz, 1952). Assets, are combined to get the highest possible return at the lowest risk level (Roy, 1952). Therefore, it is possible to observe the effect of the asset diversification reducing the global risk of a portfolio (Kolm et al., 2014). According to their expected rate of return and variation of the value of the assets, financial assets are combined trying to maximize benefits, assuming a tolerable risk level. A financial portfolio is created through the combination of assets, to get the most desirable rate of return at a defined risk level. Managers, acting on their own or for other individuals, choose the $(n \times 1)$ vector of assets weights $w(t)$ for the i assets at time t, which expresses the portion of the total investment allocated to each asset. Expected returns $\mu(t)$ are expressed as a $(n \times 1)$ vector for the i assets at time t. For its part, the expected return of the portfolio, $E(R_p) = w(t)'\mu(t)$ reflects the weighted or proportional average returns of all assets included in the portfolio.

Additionally, not only returns, but also *risk* is also considered by managers. There are different risk measures, such as variance, covariance and downside risk measures, among others. The most commonly used risk measure is the variance of returns (σ^2)[1], mainly because it is easy to use, broadly understandable and widely implemented. Taking advantage of the $(n \times n)$ matrix of covariances[2] $\sum(t)'$ at time t, $V_p = w(t)'\sum(t)w(t)$ measures the variance of the portfolio.

Modern portfolio theory (MPT) proposes diversifying investment options to optimize the portfolio of risky assets employing a mean-variance optimization (MVO) model (Markowitz, 1952). Therefore, for a given level of return, one can derive the minimum risk by minimizing the variance of a portfolio, and find the financial efficient portfolio frontier (FEF) where different efficient portfolios can be selected. The financial efficient frontier or minimum risk set of portfolios can be found solving the next dynamic programming problem

$$\begin{aligned} &\min w(t)'\textstyle\sum(t)w(t) \\ &s.t. \;\; w(t)'\mu(t) \geq M(t) \end{aligned} \tag{3.2}$$

where $w(t)$ are weights of the assets, $\mu(t)$ are the expected returns and $M(t)$ is the minimum expected target return of the portfolio for the period t. So, problem 3.2 minimizes the risk of the portfolio, finding the efficient return weights for the given level of expected return. Thus, any point at the financial efficient frontier (FEF) gives an efficient combination of asset weights to get the minimum risk for a certain level of

[1] The variance of a random variable X is $\sigma^2(X) := \mathbb{E}[(X - \mathbb{E}[X])^2]$.

[2] The covariance of two random variables X_1 and X_2 is $Cov(X_1, X_2) := \mathbb{E}[(X_1 - E[X_1])(X_2 - E[X_2])]$.

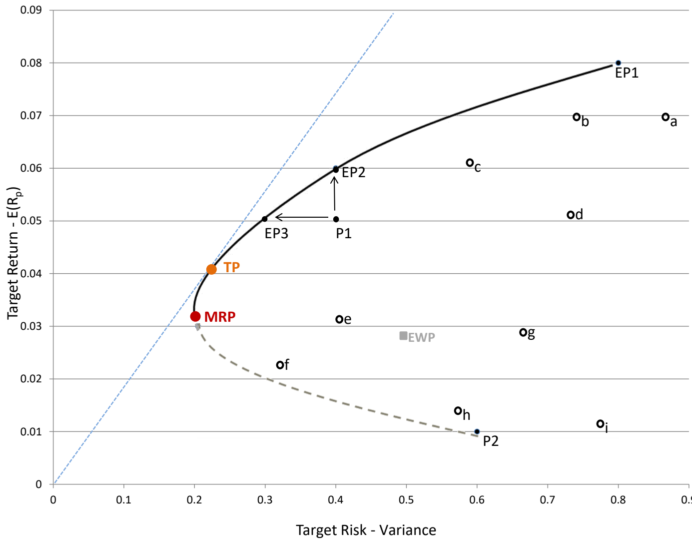
return. Depending on the manager's attitude towards risk or risk tolerance and target return, different points on the FEF can be selected. One useful way to pick and compare efficient points is calculating the Sharpe Ratio (SR) (Sharpe, 1994). SR measures the average return earned per unit of risk on a portfolio, and is usually used to compare, discriminate and rank alternative portfolios. Hence, the portfolio with the highest Sharpe Ratio (SR) would be the optimal or efficient portfolio, because it has the highest reward for a unit of risk. $SR = \frac{R-R_F}{\sqrt{\sigma^2}}$, where R is the return of the portfolio, R_F is the risk-free rate of return ($R_F = 0$ in our particular case) and σ^2 is the variance of returns.

Figure 3.1 illustrates an example of a financial efficient frontier (FEF) curve of a mean-variance portfolio, the solution of the problem 3.2. Single assets' (such as a,b,c,d,e,f,g,h,i) risk vs. return points are shown. The target return is on the vertical axis and risk (variance) is captured along the horizontal axis. In a portfolio assets are combined, and due to the effect of diversification, the FEF curve is measured. The concave black curve is the FEF, where different efficient portfolios can be selected. Any point at the FEF gives a combination of asset weights to get the minimum risk for a certain level of return. Portfolios which are not on the FEF, as for example P1, are inefficient. Accordingly, reallocating single asset's weights, it will be possible to achieve a better risk-return performance. For instance, the same rate of return could be achieved by reducing considerably the risk level to the efficient portfolio (EP3). Alternatively, the rate of return could be also increased to an efficient portfolio (EP2) maintaining the same risk level. Similarly, the Equally Weighted Portfolio (EWP), which is a portfolio where assets are weighted equally, is also an inefficient portfolio. The lowest point at the financial efficient frontier (red dot) is the minimum risk portfolio (MRP). This portfolio shows the combination of assets that leads to the lowest possible risk level. The convex and grey lower part of the curve is the inefficient frontier. Any point at this inefficient frontier (such as P2) has a respective efficient point that gives a higher level of return for the same risk level. The blue tangency line starts from the zero risk-free rate and touches the financial efficient frontier curve at the orange tangency portfolio (TP) point. The TP is the optimum portfolio with the highest reward, where the risk/return ratio, also known as Sharpe Ratio (SR), is maximized.

Restrictions on the amount of assets may be specified to make the problem solutions more realistic. These additional limitations are defined as constraints that can limit the initial investment and risk preferences (Knoke et al., 2005; Knoke & Wurm, 2006), or even a desired minimum level of diversification (Halpern et al., 2011). For example, in situations where no short sales of assets are allowed, the constraint $w(t) \geq 0$ should be added to bound weights by zero and make investment weights be non-negative (Mallory

& Ando, 2014). Similarly, any other individual or group constraints can be included in the problem 3.2 to limit weights to certain minimum or maximum levels.

Figure 3.1: Theoretical financial efficient frontier (FEF)



3.2.2 Adapting modern portfolio theory (MPT) to fisheries

We often assume that the managers of natural resources act on behalf of the society, trying to maximize monetary returns, even their motivation might not always be profit based. For example, they may pursue additional socio-economic objectives such as maintaining employment and settlement along a geographic area. Policy makers' decisions affect the ecosystem's biomass, yields and resilience, but also social equity, employment, fishers' capacity to adapt and other variables related to the fishing activity. Employing fish landings data, each fish species (i) is considered as an asset that has an economic value that changes over the time (t) (with positive or negative returns). Thus, fish species are considered assets because their management can yield returns to individuals or in general to society. Moreover, fishers must choose their target species among the diverse and disposable portfolio of catchable fish species, which have varying risk and return levels. So, there exists a parallelism between financial assets and fish stocks. In the role of returns (R_{ijt}) (3.1) we can use the volume of landings (thousand tonnes) or the value of the landings (€) across the concerned period. Thus, when the landings volume and/or value increase we would get a positive return, while when they decrease, the return will be negative.

As mentioned in subsection 3.2.1, mean-variance optimization (MVO) is widely used to identify diversified portfolios of environmental investments to reduce uncertainty in the expected value of the returns. However, natural resource returns are not usually normally distributed (Ando & Mallory, 2012b; Dunkel & Weber, 2012). Besides, the decision-makers tend to be averse to deviations below a benchmark return. Under these circumstances, mean variance-covariance would not be an appropriate risk measure. Therefore, alternative risk indicators should be used, such as the so-called downside risk indicators (Boudt et al., 2008; Harlow, 1991; Miller & Reuer, 1996; Zhu et al., 2009). Specifically, we are using the Conditional Value-at-Risk (CVaR), because (as we will see later) it is the most appropriate risk indicator subject to the empirical distribution of our returns. This choice requires a further explanation.

There exists empirical evidence in the literature that points downside risk measures as a better approximation of risk than the conventional variance or semi-variance. Downside risk measures punish deviations below a defined threshold more than valuing options above this threshold, and therefore, they are more appropriate risk measures, especially when managers are averse to deviations below a certain threshold (Shah & Ando, 2015).

Since its adoption by Basel II in 1996 (Basel II, 1996), *Value-at-Risk (VaR)* became the most popular and widely used downside risk measure. Besides, it brings simplicity, wide applicability and universality (Jorion, 1990, 1997). In fact, VaR is also one of the key downside risk measures in environmental planning (Bird et al., 2016; Estrada et al., 2012; Hahn et al., 2014). VaR (3.3) measures the worst expected loss over a given horizon under normal market conditions at a given level of confidence (Jorion, 2001), defined as the $\alpha - quantile$ of the loss distribution (Emmer et al., 2015). However, under non-normally distributed returns VaR lacks essential properties for portfolio selection such as subadditivity, homogeneity and monotonicity (Artzner et al., 1999), and accordingly, it may not be adequate to capture the benefits of diversification (Dunkel & Weber, 2012).

$$VaR_\alpha(L) = q_\alpha(L) = \inf\{\ell : P(L \leq \ell) \geq \alpha\} \tag{3.3}$$

Conditional Value-at-Risk (CVaR) (Rockafellar, Uryasev et al., 2000; Rockafellar & Uryasev, 2002) has been recently proposed to overcome the above-mentioned shortcomings, because it satisfies law-invariance (Kusuoka, 2001), monotonic additivity (Embrechts et al., 2002), and it is a coherent risk measure (Krokhmal et al., 2002; Pflug, 2000). Hence CVaR fulfils all the conditions for spectral risk measures (Acerbi, 2002). $CVaR_\alpha$ is defined as the conditional expectation of losses exceeding VaR at a specified confidence level (α) (3.4). Following the Basel Committee, the most widely used confidence level is 97.5% (Basel III, 2013). $CVaR_\alpha$ is calculated by averaging all the returns in the distribution worse than VaR. Besides, CVaR can capture all non-linearities and asymmetries of the distribution of returns.

$$CVaR_\alpha(w) = \frac{1}{1-\alpha} \int_{f(w,r) \leq VaR_\alpha(w)} f(w,r)p(r)dr \tag{3.4}$$

where w is the portfolio vector of weights, vector r captures the random events and $f(w,r)$ denotes the loss function when the portfolio W is chosen from a set of X feasible portfolios (Würtz et al., 2009). It is assumed that the random vector r has a probability density function denoted by $p(r)$. Hence, for a fixed decision vector w, the cumulative distribution function of the loss associated with that vector r is $\Psi(w,\gamma) = \int_{f(w,r) \leq \gamma} p(r)dr$. CVaR is a more appropriate proxy for risk than the conventional variance or VaR for an optimal portfolio selection model which minimises risk. The mean-CVaR approach is more robust to the non-normality of asset returns, and it can reduce more risk than the traditional mean-variance optimization (MVO) approach (Wan et al., 2015). Recently, environmental researchers have also highlighted that variance may not be an appropriate risk measure, and call for further research accounting for downside risks (such as CVaR) (Matthies et al., 2019).

Returning back to the efficient frontier model (3.2) aiming to minimize risk of the fish portfolio for a given level of expected return, then substituting variance by CVaR, the optimization problem to find the financial efficient frontier (FEF) can be rewritten as follows (3.5):

$$\begin{aligned} &\min_{w} CVaR_\alpha(w,r) \\ &s.t.\ \ w(t)'\hat{\mu}(t) \geq M(t) \end{aligned} \tag{3.5}$$

where w are the portfolio weights, vector r captures the random events, vector $w(t)$ denotes the individual proportion or weights, $\hat{\mu}(t)$ are the expected returns of the fish species and $M(t)$ is the minimum expected target return of the fish portfolio for the period t. Problem 3.5 finds the return weights that minimize the total risk of the fish portfolio. Through this programming problem we find the financial efficient frontier (Rockafellar, Uryasev et al., 2000). Therefore, different efficient points or feasible portfolio distributions can be allocated depending on manager's objectives and risk tolerance. Thus, for example, a risk averse manager would choose the efficient point with the lowest risk level, minimum risk portfolio (MRP). On the contrary, a manager that aims to optimize resources would choose the efficient point with the highest risk/reward ratio, tangency portfolio (TP). Sharpe Ratio (SR) can also be reformulated to Conditional Sharpe Ratio (CVaRSR), which replaces the variance by CVaR as a risk measure, $CVaRSR = \frac{R-R_F}{CVaR_\alpha(R)}$.

Once the returns (R_{it}) and risk ($CVaR_\alpha$) have been calculated, we design the mean-CVaR portfolio selection model (3.5) to estimate the financial efficient frontier (FEF) and optimize the portfolios of harvestable fish species, following both, a global EU and an individual country-based perspective. In the former perspective, one could identify EU with the entire and large ecosystem in which different fish species are effectively landed, and where there may be different potential efficient strategies to achieve the optimal distribution of landings. In the later, individual fishing countries act as individual entities within their particular sub-ecosystem. Accordingly, these country-based individual frontiers may help to make each country's particular fish portfolios achieve an efficient reallocation of landings. Hence, we firstly estimate a global FEF for the EU (for now on $\mathrm{FEF_{EU}}$), including the aggregated EU landings of Belgium, Denmark, Finland, France, Germany, Ireland, the Netherlands, Portugal, Spain, Sweden and United Kingdom as a whole. For this purpose, we consider the EU countries fishing in the North-East Atlantic and included in the EU15, prior to the accession of other candidate countries. We could have also incorporated other EU countries (such as Poland, Romania, Hungary, Malta, Cyprus, Estonia and Lithuania), but since their data of volume and value of fish landed exhibit many missing values, these countries were excluded. Secondly, we estimate individual FEFs for each of the nine EU fishing countries operating in the target area (i.e. North-East Atlantic), namely Belgium, Germany, Denmark, Spain, France, Ireland, the Netherlands, Portugal and United Kingdom (for now on $\mathrm{FEF_{BE}}$, $\mathrm{FEF_{DE}}$, $\mathrm{FEF_{DK}}$, $\mathrm{FEF_{ES}}$, $\mathrm{FEF_{FR}}$, $\mathrm{FEF_{IE}}$, $\mathrm{FEF_{NL}}$, $\mathrm{FEF_{PT}}$, $\mathrm{FEF_{UK}}$). We are excluding Finland and Sweden, because their main fishing area is the Baltic Sea. Thus, for any feasible target return ($\bar{R}$) and solving problem 3.5, we can find the weights of the landings returns that minimize the total risk of each portfolio for the aggregated EU and for each individual country. Based on the estimated financial efficient frontiers (FEF), different efficient points or feasible portfolio distributions can be allocated depending on manager's objectives and risk tolerance. But, some additional issues must be considered when applying modern portfolio theory (MPT) to fisheries. Notice that fishing resources are finite, and accordingly, we need to include additional constraints to make the solutions feasible and sustainable.

We have considered three alternative FEFs depending on the sustainability constraints we include, for now on EF_{MAX}, EF_{MINMAX} and EF_{MINTAC} (see Table 3.2). The comparison of the three constrained financial efficient frontiers is useful to explore the effect of the inclusion of additional constraints in our optimal solutions, and observe how policy makers' decisions could affect the reallocation of landings weights. In financial analysis, managers can have the possibility to borrow money to purchase the targeted assets. However, in natural resources there is no ecological mechanism for borrowing to invest on a certain asset at the level implied by the efficient frontier. Therefore, we add a 'long-only' constraint $w_i(t) \geq 0$ to problem 3.5, to force return weights to be non-negative. Moreover, we need to adapt the model to ensure that the efficient weights are sustainable solutions for our ecosystem, and ensure the survival of the fish stocks in the future (Sanchirico et al., 2008). Since our fish stocks are not infinite, we need to include maximum constraints to make the recommended weight for landings be sustainable. If not, our recommendation could imply catching up to a level that could cause the collapse of the fish stocks. Some authors treat the maximum sustainability constraint as an exogenous choice to the ecosystem manager, and define it as the maximum observed level of catches (Sanchirico et al., 2008), while others (Alvarez et al., 2017) identify the maximum sustainable yield (MSY) parameter as the maximum level of harvest, and include a sustainability parameter (γ) to compare how increasing or reducing MSY could affect the financial efficient frontier curve.

The EF_{MAX} frontier includes an upper maximum constraint as $w_i(t) \leq \gamma * w_i^{max}(t)$ as the maximum observed landings weight (w_i^{max}) in our period. Moreover, we have also added a sustainability parameter (γ) that indicates which proportion of the maximum observed landings weights for each species (i) is allowed when calculating the efficient portfolio. We have considered 3 different values for γ, $\{\gamma = 1, \gamma = 0.75\ , \gamma = 1.25\}$ in order to simulate three potential policies when setting the maximum catch limits. If $\gamma = 1$, we ensure that only weights below the maximum observed landings are allowed. While $\gamma = 1.25$ and $\gamma = 0.75$ imply that the proportion of the observed maximum levels could be respectively increased by 25% and reduced by 25%. Through the comparison of these three potential scenarios we can observe how policy makers' decisions could affect the reallocation of landings, and therefore, the resulting changes in both returns and risks.

In addition to the upper maximum constraint, the EF_{MINMAX} frontier also includes a minimum constraint. If we were not including such minimum constraint, our solutions could involve prohibiting the landings for some species ($w_i(t) = 0$), which would be unrealistic and unsustainable form the socio-economic point of view, because fishers are very dependent to the catches of particular fish species. Therefore, we have calculated the minimum observed landings for each fish species and added to our EF_{MAX} model as a minimum landings level that should be attained by the constraint $w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{max}(t)$ to make our solutions feasible and sustainable.

When defining EF_{MINTAC}, following Carmona et al. (2020) we have substituted the maximum constraint by TAC/quota[3] constraints. Thus, we have measured the proportion of the quotas as a percentage to total landings ($\sum q_{it}$) and included it as maximum allowed weights. By this new formulation of the maximum constraint, we have limited our efficient frontier to sustainability levels already set by quotas by $w_i(t) \leq w_i^{TAC}(t)$.

$$w_i^{TAC} = \begin{cases} \max \frac{quota_{kt}}{\sum q_{it}} & (k)\ fish\ stocks\ regulated\ by\ quota\ regime \\ \max \frac{q_{it}}{\sum q_{it}} & (N-k)\ non-regulated\ fish\ stocks \end{cases} \tag{3.6}$$

Therefore, for the TAC based (k) fish species, we have replaced the maximum observed constraint by the quota constraint, whereas for the non-regulated $(N-k)$ fish species we have maintained the maximum observed constraint.

Table 3.2: Constrained financial efficient frontiers: optimization problems to be solved

EF_{MAX} :
$\min_w CVaR_\alpha(w,r)$ $s.t.\ w(t)'\hat{\mu}(t) \geq M(t)$ $0 \leq w_i(t) \leq \gamma * w_i^{max}(t)$
EF_{MINMAX} :
$\min_w CVaR_\alpha(w,r)$ $s.t.\ w(t)'\hat{\mu}(t) \geq M(t)$ $w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{max}(t)$
EF_{MINTAC} :
$\min_w CVaR_\alpha(w,r)$ $s.t.\ w(t)'\hat{\mu}(t) \geq M(t)$ $w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{TAC}(t)$

[3] In the EU, the management of fisheries is ruled by the Common Fisheries Policy (CFP) which sets rules for managing European fishing fleets and for conserving fish stocks. These policies are yearly updated and enable to control the long term sustainability of fishing environmentally, economically and socially so as to provide healthy food for the EU citizens. One of the instruments of the CFP to achieve the main objectives is setting total allowable catches (TACs). These TACs are annual catch limits set mostly for commercial fish species, and constitute the maximum total amount of tonnes that can be caught for each fish species. TACs are shared between the EU members into quotas assigned to each country. Once the TACs are shared into quotas, each country decides how to distribute them among their fishers and how to control and ensure that quotas are not overfished.

3.2.3 Data

3.2.3.1 Global EU ecosystem

In order to estimate the global financial efficient frontier (FEF_{EU}) we are using EU level aggregated data of the value of the fish landed in the EU during the period $\{t = 2006, ..., 2016\}$ (EUROSTAT, 2018). Our particular global marine ecosystem is comprised by the group of the key assessed 28 fish species[4] in the North-East Atlantic and adjacent waters (i.e. North Sea, Baltic Sea, Skagerrak, Kattegat, West of Scotland Sea, Irish Sea and Celtic Sea), including the fish landed in Belgium, Denmark, Finland, France, Germany, Ireland, the Netherlands, Portugal, Spain, Sweden and United Kingdom. To obtain the value of the landings, the yearly volume of landings (q_{it}) $\{i = 1, ..., 28\}$ $\{t = 2006, ..., 2016\}$ of these 28 fish species (i) (in thousand tonnes product weight) have been multiplied by the first sale prices (p_{it}) (€) ($p_{it} * q_{it}$) and deflated by the Harmonised Index of Consumer Prices (HICP) for Fish and Seafood (EUROSTAT, 2018) to the year 2015 to get constant value of landings (pq) [€ 2015=100]. Notice that fish species may be catalogued as assets, since each fish species has an economic value that changes over the time, and they provide returns to individuals and/or society. We could use returns (r_{it}) as landings value gain or loss across the period (Elton et al., 2009) but in order to focus on the long-horizon returns, the geometric rate of return (R_{it}) will be used (3.1).

Before measuring risk (ρ) it is essential to analyse the distributional properties of the returns in order to identify possible fluctuations, non-normal distribution, skewness[5] and/or kurtosis[6]. This is essential to empirically choose the risk indicator that best fits to our particular data. Table 3.3 summarises the distribution of returns by fish species

[4]Fish species (i) = European anchovy (ANE), anglerfishes nei (ANF), brill (BLL), European seabass (BSS), Atlantic cod (COD), Greenland halibut (GHL), haddock (HAD), Atlantic herring (HER), European hake (HKE), Atlantic horse mackerel (HOM), lemon sole (LEM), megrims nei (LEZ), ling (LIN), Atlantic mackerel (MAC), megrim (MEG), angler (MON), surmullet (MUR), Norway lobster (NEP), European sardine (PIL), European plaice (PLE), saithe (POK), northern prawn (PRA), sandeels (SAN), common sole (SOL), European sprat (SPR), turbot (TUR), blue whiting (WHB) and whiting (WHG).

[5]Skewness measures the symmetry at it indicates whether the distribution is symmetric or skewed to one side. Skewness (S) is $S = \frac{E[(x-\bar{x})^3]}{E[(x-\bar{x})^2]^{3/2}} = \frac{m_3}{m_2^{3/2}}$, where m_2 and m_3 are the second and third central moments, $m_3 = \sum(x - \bar{x})^3/n$ and $m_2 = \sum(x - \bar{x})^2/n$. $\bar{x}$ is the mean; n is the sample size; m_2 is the variance, the square of the standard deviation; m_3 is the third moment of the data set. Negative skewness implies that the data distribution is left-skewed. Positive skewness indicates that the data distribution is right-skewed.

[6]Kurtosis measures the shape of the tails of the distribution of returns and it determines whether the distribution is thin-tailed, fat-tailed or follows normal distribution. Kurtosis (K) is $K = \frac{E[(x-\bar{x})^4]}{E[(x-\bar{x})^2]^2} = \frac{m_4}{m_2^2}$, where m_2 and m_4 are the second and fourth central moments, $m_4 = \sum(x - \bar{x})^4/n$ and $m_2 = \sum(x - \bar{x})^2/n$. Normal distribution has zero kurtosis. Negative kurtosis indicates that the distribution is thin-tailed (platykurtic) and positive kurtosis implies that the distribution is fat-tailed (leptokurtic).

(R_{it}), providing species level descriptive statistics, including minimum and maximum returns, mean, variance, standard deviation, skewness and kurtosis. Additionally, figure 3.2 captures the mean returns, standard deviation, skewness and kurtosis for the above mentioned 28 fish species in the global ecosystem.

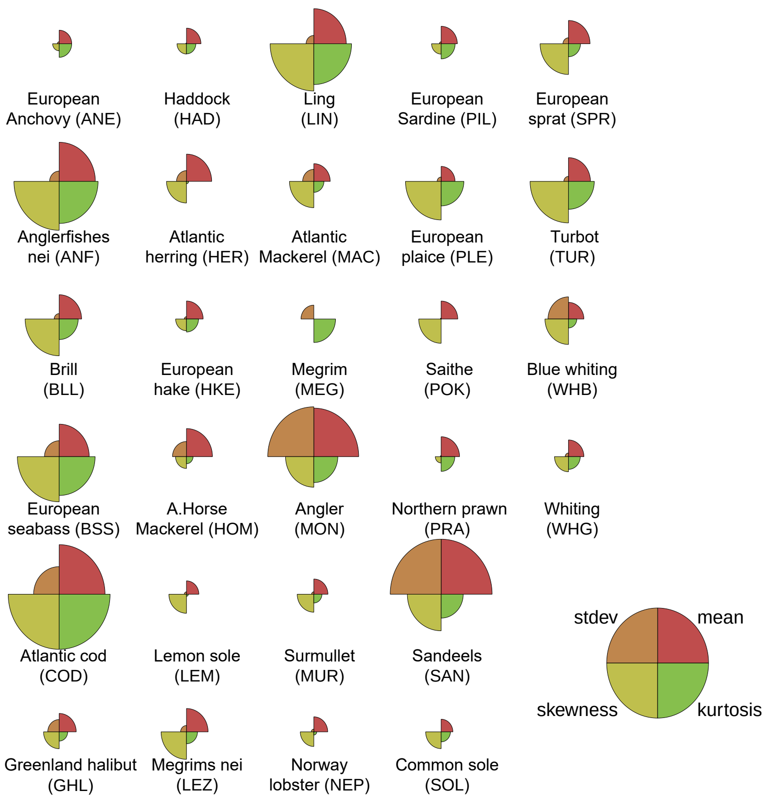
Table 3.3: Descriptive statistics of the value of landings by species (R_{it})

Fish species	Min	Max	Mean	Variance	St.dev.	Skewness	Kurtosis	CVaR
European anchovy	-33.1	10.6	-4.4	195.4	14.0	-0.8	-0.7	0.33
Anglerfishes nei	-12.7	111.2	16.0	1295.7	36.0	1.8	2.0	0.13
Brill	-21.3	56.5	4.2	527.5	23.0	1.0	0.0	0.21
European seabass	-50.7	141.6	10.7	2568.2	50.7	1.5	1.7	0.51
Atlantic cod	-25.7	253.4	24.4	6687.7	81.8	2.1	3.2	0.26
Greenland halibut	-77.3	54.3	-0.5	1703.0	41.3	-0.2	-1.1	0.77
Haddock	-24.0	8.2	-2.7	114.5	10.7	-0.6	-1.0	0.24
Atlantic herring	-41.2	59.7	6.5	1381.3	37.2	0.1	-1.7	0.41
European hake	-27.3	22.2	-0.8	220.2	14.8	-0.6	-0.7	0.27
A. horse mackerel	-77.2	63.4	7.2	2372.9	48.7	-0.5	-1.3	0.77
Lemon sole	-27.3	12.9	-4.5	223.0	14.9	-0.1	-1.7	0.27
Megrims nei	-37.2	48.2	3.4	650.8	25.5	0.4	-0.8	0.37
Ling (LIN)	-12.2	93.5	12.8	946.3	30.8	1.7	1.9	0.12
Atlantic mackerel	-56.8	78.6	-1.1	1651.3	40.6	0.4	-0.9	0.57
Megrim	-121.2	17.1	-15.2	2060.4	45.4	-1.3	0.2	1
Angler	-221.8	338.2	23.5	19761.3	140.6	0.6	0.5	1
Surmullet	-28.5	20.4	-3.0	227.6	15.1	-0.2	-1.1	0.28
Norway lobster	-26.1	15.2	-3.2	254.1	15.9	-0.4	-1.6	0.26
Sardine	-30.1	17.4	-1.2	193.1	13.9	-0.6	-0.5	0.30
European plaice	-26.9	44.3	-3.2	407.9	20.2	1.1	0.3	0.27
Saithe	-11.9	14.7	-0.9	121.1	11.0	0.2	-1.9	0.12
Northern prawn	-23.3	12.3	0.7	126.1	11.2	-0.9	-0.6	0.23
Sandeels nei	-155.8	387.3	28.7	23856.9	154.5	1.0	0.3	1
Common sole	-21.4	7.3	-5.1	75.4	8.7	-0.2	-1.0	0.21
European sprat	-26.0	53.2	3.4	599.1	24.5	0.6	-0.7	0.26
Turbot	-17.1	57.1	3.7	483.7	22.0	1.3	0.7	0.17
Blue whiting	-96.7	123.2	-1.9	4527.1	67.3	0.3	-1.1	0.97
Whiting	-34.5	28.7	-1.9	331.8	18.2	-0.3	-0.8	0.35

Figure 3.2 shows that the distribution of the returns of the 28 key fish species is rather heterogeneous. Some species (i.e. European pilchard (PIL), saithe (POK) and whiting (WHG) have rather stable returns, whereas other, such as angler (MON) and sandeels (SAN), suffer large fluctuations. The shape of the distribution of returns is not

symmetric. Some species, such as megrim (MEG), are highly left-skewed, while other species (i.e. Atlantic cod (COD), ling (LIN) and turbot (TUR)) are highly right skewed. In addition, from the kurtosis values we can see that the distribution of the returns is more peaked than the normal distribution for some species, and that the shape of the tails does not correspond to a normal distribution. For instance, saithe (POK), Norway lobster (NEP) and lemon sole (LEM) have a thin-tailed distribution of returns (platykurtic), whereas ling (LIN), Atlantic cod (COD) and anglerfishes nei (ANF) show a fat-tailed distribution (leptokurtik). As expected, Shapiro-Wilk test (Table 3.4) reveals that the returns (R_{it}) are indeed not normally distributed.

Figure 3.2: Returns (R_{it}) mean, standard deviation, skewness and kurtosis



Notes:
Segment plots displaying four distributional sample estimates from the 28 fish species landings returns (R_{it}) including the mean, standard deviation, skewness and kurtosis.

Table 3.4: Shapiro-Wilk normality test

	W	P-value
R_{it}	0.6754	$<$ 2.2e-16

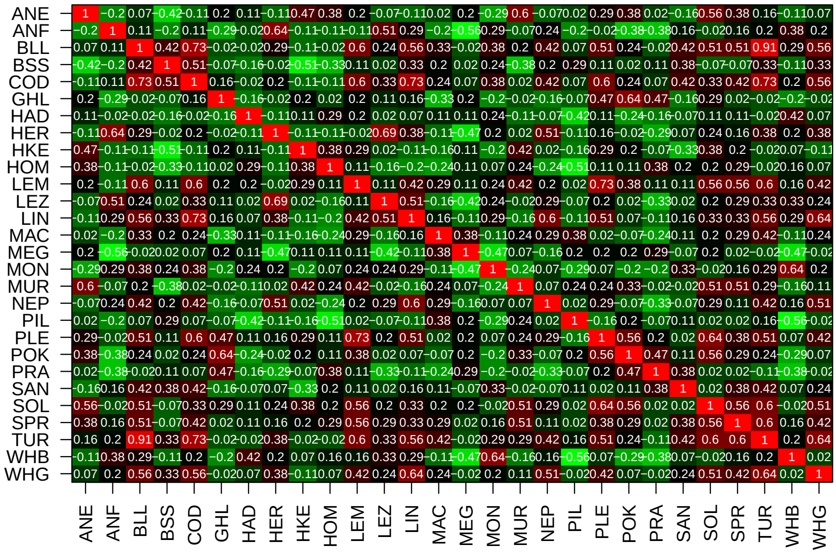
Notes:
Shapiro-Wilk normality test for yearly landings returns (R_{it}).
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

We have also analysed the correlation between fish species in order to identify potential common patters among them. The correlation between assets (fish species) is a key factor when measuring covariances, because the correlation directly affects portfolio's variances, and accordingly, the diversification process itself. The lowest correlation between asset returns on a portfolio, the lowest variance (volatility) of the portfolio we get. Although Pearson's correlation coefficient is the most widely used when calculating correlation between variables, we have used Kendall's tau[7] statistic because it is more reliable when variables are not normally distributed (Kendall, 1938, 1945). It is robust, less sensitive to outliers and more accurate with smaller sample sizes (Bonett & Wright, 2000; Croux & Dehon, 2010; Morgenthaler, 2007).

Figure 3.3 shows Kendall's pairwise correlations among the returns (R_{it}) of the fish species. The maximum positive correlation is between turbot (TUR) and brill (BLL), which implies that both species have a similar behavioural pattern, and accordingly might be considered substitutes. Contrarily, other paired fish species, such as megrim (MEG) and anglerfishes nei (ANF) or sardine (PIL) and blue whiting (WHB), are highly and negatively correlated. These pairs of fish species have an inverse behavioural pattern, that is to say, when one of the species increases its returns, the other species reduces them. These correlation patterns may be essential when a certain species suffers a collapse.

[7]Kendall's tau statistic is a rank-based correlation coefficient and measures the correspondence between the ranking of x and y variables (Kendall, 1975). The total number of possible pairings of x with y observations is $n(n-1)/2$, where n is the size of x and y. Variables are ordered by the x values. If x and y are correlated, then they would have the same relative rank orders. The number of concordant pairs n_c and the number of discordant pairs n_d are calculated and as result, the Kendall's rank correlation coefficient between two random variables with n observations is calculated $tau = \frac{n_c - n_d}{\frac{1}{2}n(n-1)}$.

Figure 3.3: Kendall's correlation coefficient of the landings returns (R_{it})



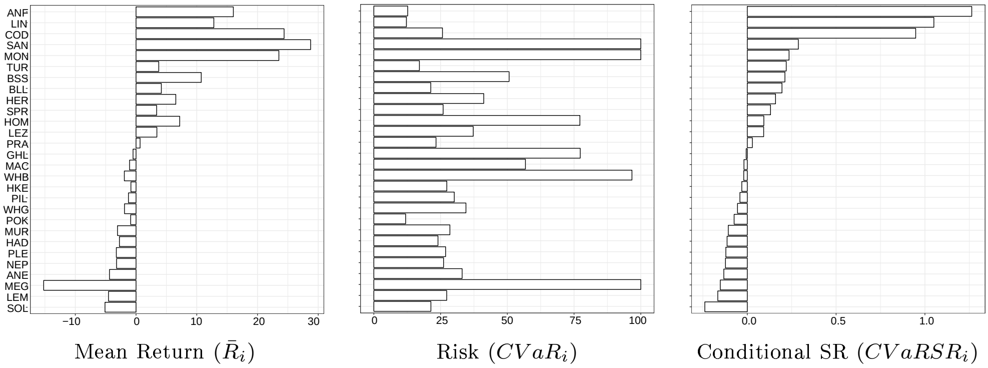
Notes:
The figure shows a symmetric coloured image and numbers show values for Kendall's correlation coefficient.

Figure 3.4 shows the histogram of the mean returns (R_i), risk ($CVaR_i$) and Conditional Sharpe Ratio ($CVaRSR_i$) at the species level in our global ecosystem. Additionally, Table 3.5 includes the exact values for returns (R_i), risk ($CVaR_i$) and Conditional Sharpe Ratio ($CVaRSR_i$). As mentioned, the distribution of the returns is far from the usual shape of the normal, and accordingly using CVaR is the best and more robust strategy. Some species, such as anglerfishes nei (ANF), have high and positive mean return ($\bar{R}_{ANF} = 16$) and low risk ($CVaR_{ANF} = 0.13$). This implies that the average increase of the landed value is 16% and that in the worst case, the landed value of anglerfishes nei would be only reduced by 13%. High positive returns and low risk levels make Conditional Sharpe Ratio (CVaRSR) be quite high and positive. Therefore, these species should be targeted due to their capacity to generate high returns at a low risk level. On the contrary, there are some other species (such as megrim (MEG)), which have negative mean returns ($\bar{R}_{MEG} = -15.2$), high risk ($CVaR_{MEG} = 1$), and therefore a negative Conditional Sharpe Ratio (CVaRSR). The value of their landings has been considerably reduced along the time, and therefore, their mean return is negative. These species should be avoided, if possible, because they contribute with loses (negative returns) and high risk to our portfolio.

Table 3.5: Fish species mean return, risk and Conditional Sharpe Ratio

Fish species	$\bar{R}_i$	$CVaR_i$	$CVaRSR_i$
Anglerfishes nei (ANF)	16.02	12.68	1.26
Ling (LIN)	12.81	12.19	1.05
Atlantic cod (COD)	24.38	25.71	0.95
Sandeels nei (SAN)	28.74	100	0.29
Angler (MON)	23.52	100	0.24
Turbot (TUR)	3.74	17.07	0.22
European seabass (BSS)	10.74	50.67	0.21
Brill (BLL)	4.17	21.33	0.20
Atlantic herring (HER)	6.55	41.17	0.16
European sprat (SPR)	3.39	25.95	0.13
Atlantic horse mackerel (HOM)	7.19	77.20	0.09
Megrims nei (LEZ)	3.43	37.23	0.09
Northern prawn (PRA)	0.67	23.29	0.03
Greenland halibut (GHL)	-0.49	77.32	-0.01
Atlantic mackerel (MAC)	-1.06	56.80	-0.02
Blue whiting (WHB)	-1.93	96.70	-0.02
European hake (HKE)	-0.84	27.33	-0.03
Sardine (PIL)	-1.25	30.12	-0.04
Whiting (WHG)	-1.90	34.51	-0.06
Saithe (POK)	-0.88	11.91	-0.07
Surmullet (MUR)	-3.05	28.50	-0.11
Haddock (HAD)	-2.73	24.03	-0.11
European plaice (PLE)	-3.24	26.88	-0.12
Norway lobster (NEP)	-3.21	26.12	-0.12
European anchovy (ANE)	-4.37	33.07	-0.13
Megrim (MEG)	-15.21	100	-0.15
Lemon sole (LEM)	-4.53	27.29	-0.17
Common sole (SOL)	-5.11	21.38	-0.24

Figure 3.4: Fish species returns, risk and Conditional Sharpe Ratio



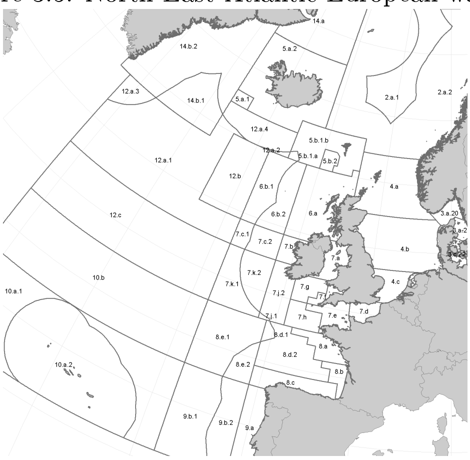
Notes:
Common sole (SOL), lemon sole (LEM), megrim (MEG), European anchovy (ANE), Norway lobster (NEP) European plaice (PLE), haddock (HAD), surmullet (MUR), saithe (POK), whiting (WHG), European sardine (PIL), European hake (HKE), blue whiting (WHB), Atlantic mackerel (MAC), Greenland halibut (GHL), northern prawn (PRA), megrims nei (LEZ), Atlantic horse mackerel (HOM), European sprat (SPR), Atlantic herring (HER), brill (BLL), European seabass (BSS), turbot (TUR), angler (MON), sandeels (SAN), Atlantic cod (COD), ling (LIN) and anglerfishes nei (ANF).

3.2.3.2 Individual EU fishing countries

In order to estimate the individual financial frontiers for FEF_{BE}, FEF_{DE}, FEF_{DK}, FEF_{ES}, FEF_{FR}, FEF_{IE}, FEF_{NL}, FEF_{PT}, FEF_{UK}, we define the country-based fish portfolios as the group of the main assessed fish species in the North-East Atlantic from 2007 to 2017 (see Figure 3.5). We focus on the yearly landings (q_{ijt}) $\{t = 2007, ..., 2017\}$ of the main assessed fish species $\{i = 1, ..., N'\}$ (thousand tonnes), in each of the $\{j = 1, ..., 9\}$ EU countries. Data comes from EUROSTAT (2018). There are some outstanding asymmetries among countries relative to their species richness (N) that conditioned the species selection and inclusion approach. Some countries, such as Spain ($N_{ES} = 858$) and France ($N_{FR} = 393$), land a huge amount of species, while others, as for example Belgium ($N_{BE} = 70$), concentrate their landings in just a few species. The concentration of landings is very high in Germany, where the dominant species, Atlantic herring (HER), represents on average 44% of the total fish landed. The landings of other countries are much more diverse. This is for example the case of France and Spain, where their respective key species barely amount for the 11% and 15%. Under this asymmetric distribution of landings across countries, and in order to operate with a computationally tractable optimisation problem (3.5), we need to establish a species inclusion criterion.

Our inclusion criterion satisfies two conditions. Firstly, the aggregated sum of the species included should represent at least 80% of the total landings of the country. Secondly, in order to be included, the species should individually represent at least 1% of the landings of the country. Thus, following both the criteria, we have removed redundant species that add nothing, but made impossible to run effective calculations to obtain the FEFs. Table 3.6 summarises the coverage level of the included species (N_j') to the total number of species landed in each of the 9 countries.

Figure 3.5: North-East Atlantic European waters



Source: ICES (2019)

Table 3.6: Fish species selection by country

country	Original sample (N_j)	Selected sample (N_j')	Coverage
Belgium (BE)	70	23	90%
Germany (DE)	106	9	88%
Denmark (DK)	125	10	92%
Spain (ES)	858	42	83%
France (FR)	393	44	87%
Ireland (IE)	206	20	90%
Netherlands (NL)	225	9	89%
Portugal (PT)	403	26	86%
United Kingdom (UK)	214	21	90%

Notes:
Coverage level of the included species (N'_j) to the total number of species (N_j) landed in each country. N_j is the number of species landed, N_j' is the number of species included in the optimisation problem (3.5).

Undoubtedly, fish prices also give relevant information about the food-related ecosystem services created by a multispecies fishery (Alvarez et al., 2017). Hence, landed quantity by species and by country (q_{ijt}) could be reconstructed multiplying such landings by species and country level prices (p_{ijt}) to obtain the species and country level value of the landings ($q_{ijt} * p_{ijt}$). Certainly, we could use landed value as a measurement for returns (R_{ij}) in order to estimate the individual FEFs, as we did to obtain the global $\mathrm{FEF_{EU}}$. Nevertheless, in the case of individual $\mathrm{FEF_j}$ we have decided to use landed volume (tonnes) instead of landed value (€) for two main reasons. Firstly, local fisheries are often price takers, that is, they do not control prices because local catches are too small, relative to total market supply (Sethi, 2010). Secondly, Total Allowable Catches (TACs) and quotas for individual fish stocks limit the maximum allowed catches for the key fish species, which are also measured in tonnes live weight (EU, 2017). Thus, the maximum allowed quantity (quotas) will determine our recommended redistribution for landed quantities. Consequently, our country-based efficient portfolio proposal also will be focused on the potential reallocation of landed volume, specifying which species should be targeted to land more or less according to our findings.

The general strategy to model the constrained efficient frontiers is as follows: firstly, using the fish landing (in tonnes) we measure the returns (R_{ij}). Secondly, distributional properties of the returns will be checked, paying special attention on normality. If, as expected, we confirm that returns do not follow a normal distribution, Conditional Value-at-Risk ($CVaR_{ij}$) will be selected as the best risk indicator for the financial efficient frontier estimation ($\mathrm{FEF_j}$). Once return and risk are defined, we will derive mean-CVaR portfolio selection model to estimate the constrained financial efficient frontier for each country.

3.3 Results

3.3.1 Constrained financial efficient frontiers for the aggregate EU

In this subsection, using the aggregated value of the landings (€) to measure the species returns (R_{ij}) we estimate the unconstrained global financial efficient frontier (EF_{EUU}) as well as the above mentioned constrained efficient frontiers (i.e. EF_{EUMAX}, $EF_{EUMINMAX}$, $EF_{EUMINTAC}$) and Conditional Sharpe Ratio (CVaRSR) for the overall ecosystem. We are applying the mean-CVaR portfolio selection model using the EU aggregated value of the landings (€) related to the key 28 fish species for the period

2006- 2016. Based on the estimated financial frontiers, we will find the optimum weights of the landed value of fish species, or to put in another words, the optimal fish portfolio. Afterwards, alternative reweighting strategies will be recommended so as to improve the efficiency of the global ecosystem. At this stage, we are taking advantage of *fPortfolio* package from R software (R Core Team, 2018; Wuertz et al., 2017). Figures 3.6-3.9 show the minimum Conditional Value-at-Risk (CVaR) locus and the efficient frontier for 28 equidistant return points according to the value of landings. Each of the four figures show the solutions for the unconstrained financial efficient frontier (EF_{EUU}), EF_{EUMAX}, $EF_{EUMINMAX}$ and $EF_{EUMINTAC}$.

Coloured circles in Figures 3.6-3.9 show the risk-return points for each of the individual 28 fish species. For example, Atlantic cod (COD) is one of the fish species with the highest mean return and lowest risk level. Contrarily, megrim (MEG) has a negative mean return, and comparatively, a high risk level. The curved lines constitute the financial efficient frontiers, the convex grey points amount to the inefficient portfolios, and the concave black points capture the efficient ones. The lowest point at each efficient frontier (red dot) is the minimum risk portfolio (MRP). Thus, this portfolio shows the efficient combination of species that leads to the lowest possible risk level. The blue tangency line starts from the zero risk-free rate and touches the efficient frontier curve at the tangency portfolio (TP), where the Conditional Sharpe Ratio (CVaRSR) is maximized. This combination of species at the tangency portfolio (TP) would lead to the optimum scenario where the maximum risk-reward ratio is obtained in the ecosystem.

Figure 3.6: Unconstrained efficient frontier (EF_{EUU})

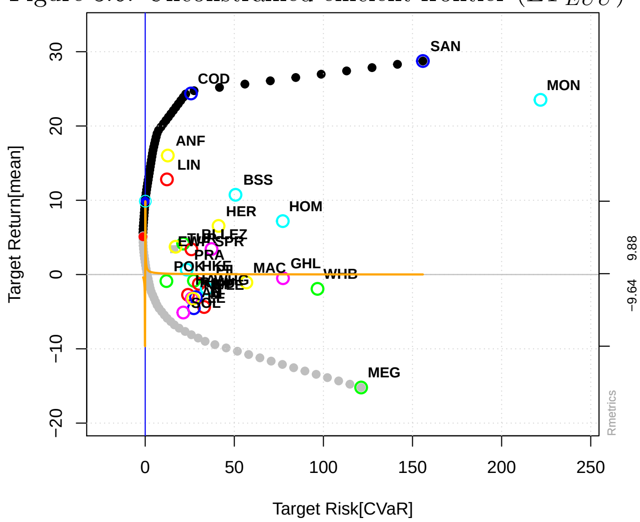
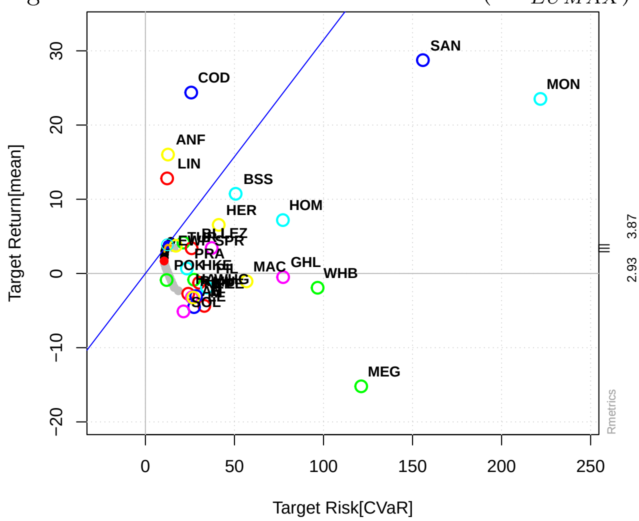


Figure 3.6 illustrates the unconstrained financial efficient frontier (EF_{EUU}). Although it certainly shows just a theoretical solution, it is not feasible, because natural resources are not unlimited and there exist sustainable limits that must be considered. Under these circumstances, three alternative constrained efficient frontiers have been estimated (namely EF_{EUMAX}, $EF_{EUMINMAX}$ and $EF_{EUMINTAC}$). We consider that the $EF_{EUMINTAC}$ might be the most appropriate because it includes a maximum and a minimum observed constraint, together with a TAC upper constraint. Thus, $EF_{EUMINTAC}$ is the efficient frontier that best fits reality, keeps under regulatory limits, and will reveal a feasible reallocation of landings weights. Accordingly, $EF_{EUMINTAC}$ will be our reference frontier.

The EF_{EUMAX} in Figure 3.7 includes an upper maximum constraint ($w_i^{max}(t)$) as the maximum observed landings weight for each fish species. Due to the upper constraint, the efficient frontier curve and also the slope of the tangency line have changed comparing to EF_{EUU}. The black points are the EF_{EUMAX} curve, where different efficient portfolios can be selected. Moreover, any point at the EF_{EUMAX} gives a combination of species weights to get the minimum risk for a certain level of return. In the illustration we are assuming that sustainability parameter $\gamma = 1$, which implies that the species allocation is constrained by the 100% of the observed maximum landings value for our period.

Figure 3.7: Constrained efficient frontier (EF_{EUMAX})



In order to minimise risk, the minimum risk portfolio (MRP) (red dot) would be suggested to achieve a $\overline{R}_{MRP} = 1.68$ rate of return and $CVaR_{MRP} = 10.53$ risk level.

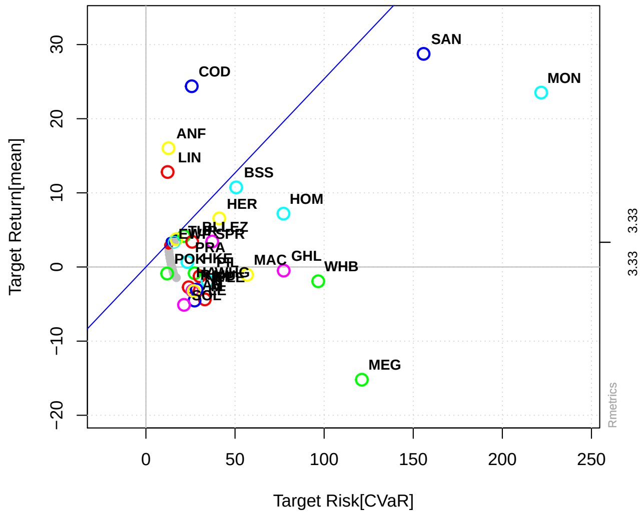
This implies that the mean increase of the value of landings in the EU would be 1.68% and, in the worst case, returns would be reduced by 10.53%. Besides, if the objective was to optimize the returns, the tangency (TP) would be suggested. TP is the point in which the blue tangency line touches the efficient frontier curve and implies an optimum scenario in which the Conditional Shape Ratio (CVaRSR) is maximized. By reallocating landings' weights, we could achieve a $\overline{R}_{TP} = 3.87$ rate of return, $CVaR_{TP} = 12.28$ risk level and $CVaRSR_{TP} = 0.31$. Additionally, we could simulate complementary policies by changing the value of the sustainability parameter (see Table 3.7). Thus, $\gamma = 1.25$ would imply that the proportions of the observed maximum values of landings have been increased by 25%. Contrarily, $\gamma = 0.75$ would imply reducing them by 25%. Analysing these three possible scenarios ($\gamma = 1$, $\gamma = 1.25$ and $\gamma = 0.75$) is helpful to quantify how policy makers' decisions would affect the reallocation of landings weights as well as the effects on return and risk levels. For example, to minimise risk (MRP), increasing the maximum constraint by 25% ($\gamma = 1.25$) would imply increasing the rate of return to $\overline{R}_{MRP} = 2.25$ (+34%) and reducing risk to $CVaR_{MRP} = 7.62$ (-28%). Similarly, to optimize returns (TP), increasing the maximum constraint by 25% ($\gamma = 1.25$) would imply increasing the rate of return to $\overline{R}_{TP} = 5.06$ (+31%) and reducing risk to $CVaR_{TP} = 9.09$ (-26%).

Table 3.7: Constrained efficient frontier (EF_{EUMAX}): key points

Constraint	γ	FrontierPoint	meanReturn	CVaR	CVaRSR
$w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 1$	MRP	1.68	10.53	0.16
$w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 1$	TP	3.87	12.28	0.31
$w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 1.25$	MRP	2.25	7.62	0.30
$w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 1.25$	TP	5.06	9.09	0.56
$w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 0.75$	MRP	2.20	17.05	0.129
$w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 0.75$	TP	2.35	17.63	0.133

$EF_{EUMINMAX}$ in Figure 3.8 includes a lower minimum constraint ($w_i^{min}(t)$) as the minimum observed landings weights. Due to the maximum weight constraints, and the inclusion of the minimum weight constraints, the efficient frontier curve and also the slope of the tangency line have changed compared to EF_{EUMAX}. The EF_{MINMAX} curve has been shortened, or to put in another words, there are less efficient and feasible portfolios to be selected. Depending on the targeted objectives, since the combination of assets is more limited, less efficient solutions are feasible under these constraints. If we were not including such a minimum constraint, our solutions could involve unrealistically and unfeasibly, prohibiting the landings for some of the species ($w_i(t) = 0$). Since solutions in EF_{MINMAX} are more reasonable, the previous EF_{MAX} would be rejected. In the illustration, we are assuming that sustainability parameter $\gamma = 1$, which implies that the species allocation is constrained by the 100% of the observed maximum landings value for our period.

Figure 3.8: Constrained efficient frontier ($EF_{EUMINMAX}$)



In order to minimise risk, the minimum risk portfolio (MRP) (red dot) would be suggested to achieve a $\overline{R}_{MRP} = 2.93$ rate of return and $CVaR_{MRP} = 12.68$ risk level. This implies that the mean increase of the value of landings in the EU would be 2.93%, and in the worst case, returns would be reduced by 12.68%. Besides, if the objective was to optimize the returns, the tangency (TP) would be suggested to achieve a $\overline{R}_{TP} = 3.46$ rate of return, $CVaR_{TP} = 13.63$ risk level and $CVaRSR_{TP} = 0.25$. Additionally, we could simulate complementary policies by changing the value of the sustainability parameter (see Table 3.8). For example, to minimise risk (MRP), increasing the maximum constraint by 25% ($\gamma = 1.25$) would imply reducing the rate of return to $\overline{R}_{MRP} = 2.33$ (-20%) and reducing risk to $CVaR_{MRP} = 11.12$ (-12%). Similarly, to optimize returns (TP), increasing the maximum constraint by 25% ($\gamma = 1.25$) would imply increasing the rate of return to $\overline{R}_{TP} = 4.30$ (+24%) and reducing risk to $CVaR_{TP} = 12.75$ (-6%).

Table 3.8: Constrained efficient frontier ($EF_{EUMINMAX}$): key points

Constraint	γ	FrontierPoint	meanReturn	CVaR	CVaRSR
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 1$	MRP	2.93	12.68	0.23
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 1$	TP	3.46	13.63	0.25
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 1.25$	MRP	2.33	11.12	0.21
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 1.25$	TP	4.30	12.75	0.34
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 0.75$	MRP	2.19	17.20	0.127
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{max}(t)$	$\gamma = 0.75$	TP	2.34	17.84	0.131

$EF_{EUMINTAC}$ in Figure 3.9, replaces the maximum constraint by TAC constraint (w_i^{TAC}) for the regulated species, to limit upper bounds to sustainability levels already set by TAC. Accordingly, the $EF_{EUMINTAC}$ curve is wider than $EF_{EUMINMAX}$ and EF_{EUMAX}. This implies that even it is feasible to land more of some fish species, historically, their landings have never reached the maximum 'allowed level'. Therefore, our $EF_{EUMINTAC}$ model is the one that best fits reality, and covers all the possible scenarios to suggest a redistribution of landings to reach the efficient portfolio that minimizes risk for a certain desired level of return.

Figure 3.9: Constrained efficient frontier ($EF_{EUMINTAC}$)

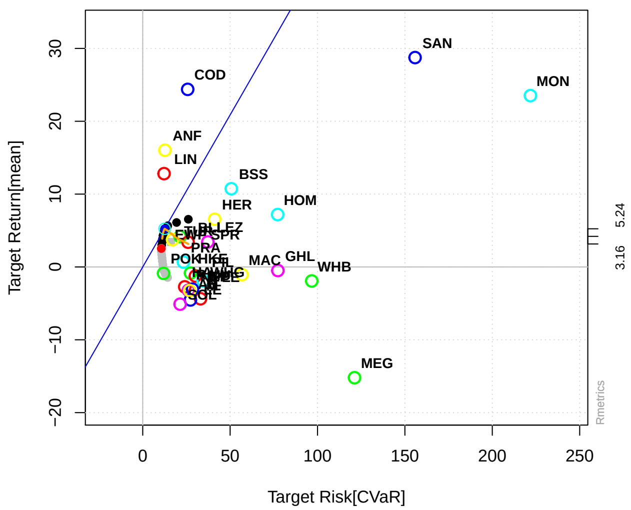


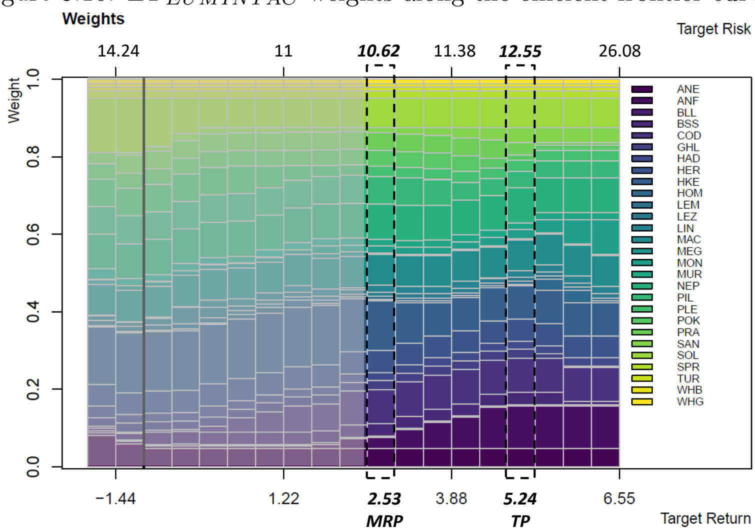
Table 3.9 summarises the two representative points at the $EF_{EUMINTAC}$ (the minimum risk portfolio (MRP) and tangency portfolio (TP)) for sustainability parameter $\gamma = 1$ and $\gamma = 1.25$. In this case, we are not including $\gamma = 0.75$ because there is not a feasible and efficient solution for this potential policy.

Table 3.9: Constrained efficient frontier ($EF_{EUMINTAC}$): key points

Constraint	γ	FrontierPoint	meanReturn	CVaR	CVaRSR
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{TAC}(t)$	$\gamma = 1$	**MRP**	**2.53**	**10.62**	**0.24**
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{TAC}(t)$	$\gamma = 1$	**TP**	**5.24**	**12.55**	**0.42**
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{TAC}(t)$	$\gamma = 1.25$	MRP	3.35	10.20	0.33
$w_i^{min}(t) \leq w_i(t) \leq \gamma * w_i^{TAC}(t)$	$\gamma = 1.25$	TP	6.02	12.99	0.46

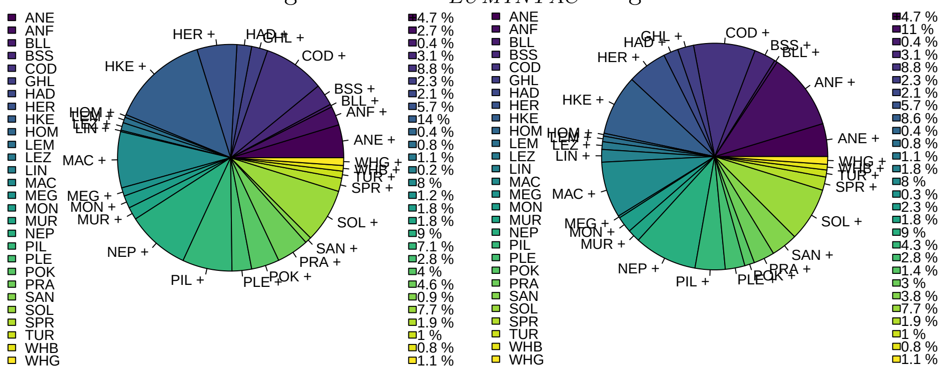
Since the $EF_{EUMINTAC}$ best fits reality, keeps under regulatory limits and reveals a feasible reallocation of landings weights, for now on we will focus on $EF_{EUMINTAC}$. Figure 3.10 illustrates the species weights along the $EF_{EUMINTAC}$ (from Figure 3.9) in detail. The upper axis labels the target risk (CVaR), the lower axis labels the target return, and the legend to the right shows the species names. Therefore, each bar captures an efficient portfolio in the $EF_{EUMINTAC}$ curve and the colours illustrate the proportion (weight) that each individual fish species should represent to achieve this risk and return values. The grey coloured bars are inefficient portfolios on the convex lower part of the curve, and the resulting ones are the efficient portfolios. Note that since any of the coloured bars show an efficient fish species landings distribution, any of these distributions could be suggested. Depending on the objectives and the attitude towards risk, one or the others might be selected.

Figure 3.10: $EF_{EUMINTAC}$ weights along the efficient frontier curve



The first highlighted bar is the minimum risk portfolio (MRP). That is to say, the efficient combination of fish species that leads to the lowest possible risk level. MRP implies that the mean increase of the value of landings in the EU would be 2.53% ($\overline{R}_{MRP} = 2.53$), and in the worst case, returns would be reduced by 10.62% ($CVaR_{MRP} = 10.62$). The second highlighted bar is the tangency portfolio (TP), this is the optimum combination of landings weights to obtain the maximum risk-reward ratio ($CVaRSR_{TP} = 0.42$). TP increases mean return ($\overline{R}_{TP} = 5.24$) but also risk ($CVaR_{TP} = 12.55$). It can be observed how recommendations would change depending on the target return and affordable risk level.

Figure 3.11: $EF_{EUMINTAC}$ weights



Minimum risk portfolio (MRP) | Tangency portfolio (TP)

Figure 3.11 illustrates and quantifies the recommendation if the target was to minimise risk (MRP) or maximise returns (TP). For both, MRP and TP, the recommendation is to catch the minimum observed landing of anchovies (ANE) (4.7%). As mentioned before, anchovy fishery has suffered a collapse in the past, and therefore, it is a risky species that also has a negative mean return. Contrarily, the weight recommendation for other species changes depending on the objectives. Anglerfishes nei (ANF) for example, is not an interesting species to minimise risk, and therefore, its landings should only amount for the 2.7% of the total value of landings if we aim to minimise risk. If the objective was to maximise returns, the recommended weight for ANF rises to 11%. European hake (HKE) seems an interesting species in order to minimize risk (MRP). The recommendation would be to make more effort to land HKE until it reaches the 14% of the total landed value of fish. However, if the objective was to maximise returns (TP), HKE should only amount for the 8.6% of the total landed value of fish. Table 3.10 gives a detailed overview of the minimum, maximum and TAC constraints, the observed weights in 2016, and the recommended weights for minimum risk portfolio

(MRP) and tangency portfolio (TP). Moreover, it also includes the weighted returns, weighted Conditional Value-at-Risk (CVaR) and Conditional Sharpe Ratio (CVaRSR) for the mentioned fish species distributions.

Table 3.10: Observed and proposed landings weights (%)

	Constraints			Observed	$EF_{EUMINTAC}$	
Fish species	w_i^{min}(%)	w_i^{max}(%)	w_i^{TAC}(%)	**2016(%)**	**MRP**	**TP**
European anchovy (ANE)	4.7%	8.1%	8.1%	5.2%	4.7%	4.7%
Anglerfishes nei (ANF)	0.7%	3.5%	11.0%	3.5%	2.7%	11.0%
Brill (BLL)*	0.4%	0.7%	-	0.6%	0.4%	0.4%
European seabass (BSS)*	0.7%	3.1%	-	1.9%	3.1%	3.1%
Atlantic cod (COD)	0.5%	6.9%	8.8%	5.9%	8.8%	8.8%
Greenland halibut (GHL)	0.4%	1.3%	2.3%	1.1%	2.3%	2.3%
Haddock (HAD)	2.1%	2.9%	5.4%	2.2%	2.1%	2.1%
Atlantic herring (HER)	5.7%	13.0%	10.4%	13.0%	5.7%	5.7%
European hake (HKE)	8.6%	13.6%	15.4%	12.3%	14.0%	8.6%
Atl. horse mackerel (HOM)	0.4%	2.5%	15.7%	2.5%	0.4%	0.4%
Lemon sole (LEM)*	0.8%	1.3%	-	0.8%	0.8%	0.8%
Megrims nei (LEZ)	1.1%	1.8%	4.3%	1.6%	1.1%	1.1%
Ling (LIN)	0.2%	0.8%	1.8%	0.8%	0.2%	1.8%
Atl.c mackerel (MAC)	8.0%	17.2%	21.3%	8.0%	8.0%	8.0%
Megrim (MEG)*	0.3%	1.2%	-	0.3%	1.2%	0.3%
Angler (MON)	0.1%	2.6%	12.9%	1.0%	1.8%	2.3%
Surmullet (MUR)*	1.8%	2.7%	-	1.9%	1.8%	1.8%
Norway lobster (NEP)	9.0%	14.2%	27.0%	10.2%	9.0%	9.0%
Sardine (PIL)*	4.3%	7.1%	-	4.3%	7.1%	4.3%
European plaice (PLE)	2.8%	5.1%	7.1%	3.6%	2.8%	2.8%
Saithe (POK)	1.4%	2.2%	4.0%	1.7%	4.0%	1.4%
Northern prawn (PRA)	0.6%	1.1%	4.6%	0.9%	4.6%	3.0%
Sandeels nei (SAN)	0.0%	2.8%	3.8%	0.4%	0.9%	3.8%
Common sole (SOL)	7.7%	13.0%	14.1%	7.7%	7.7%	7.7%
European sprat (SPR)	1.9%	3.3%	2.2%	2.9%	1.9%	1.9%
Turbot (TUR)	1.0%	1.6%	2.0%	1.5%	1.0%	1.0%
Blue whiting (WHB)	0.8%	5.7%	5.0%	2.9%	0.8%	0.8%
Whiting (WHG)	1.1%	1.7%	2.7%	1.4%	1.1%	1.1%
			weighted Returns (R)	**2.33**	**2.53**	**5.24**
			$\triangle Return$	-	(+9%)	(+125%)
			weighted Risk (CVaR)	**35.75**	**10.62**	**12.55**
			$\triangledown Risk$	-	(-70%)	(-65%)
			Conditional Sharpe Ratio (CVaRSR)	0.07	0.24	0.42
			$\triangle CVaRSR$	-	(+243%)	(+500%)

* Fish species without an official TAC limitation.

Summarising, there are potential efficiency gains by moving from the observed portfolio of landings in 2016 to the efficient minimum risk portfolio (MRP) or tangency portfolio (TP). If the objective is to minimise risk (MRP), then, we would be able to achieve a fish species portfolio that increases mean return by 9%, and also reduces risk by 70%. Contrarily, if the aim is to maximize fish landings returns, then TP would be recommended, where the maximum risk reward of the portfolio is obtained. Accordingly, the mean return would be increased by 125% and risk reduced by 65%. It is remarkable the exponential increase on the Conditional Sharpe Ratio (CVaRSR), which increases by 500% compared to the one for the observed landings in 2016.

3.3.2 Constrained financial efficient frontiers for individual countries

In this subsection, we estimate the individual country-based constrained $EF_{MINTACj}$ efficient frontiers for each of the nine EU fishing countries operating in the North-East Atlantic (i.e. Belgium, Germany, Denmark, Spain, France, Ireland, the Netherlands, Portugal and the United Kingdom). As already mentioned in subsection 3.3.1, $EF_{MINTACj}$ will be our reference frontier, since it includes a TAC upper constraint, it is the one that, keeping the weights under regulatory limits, best fits reality. Unlike the global frontier (subsection 3.3.1), in the individual $\mathrm{FEF_j}$ we are using the landed volume (tonnes) instead of landed value (€) to measure returns. This is because local fisheries are often price takers, that is, they do not control prices because local catches are too small, relative to total market supply (Sethi, 2010). Besides, Total Allowable Catches (TACs) and quotas for individual fish stocks limit the maximum allowed catches for the key fish species, which are also measured in tonnes live weight (EU, 2017).

Based on the regulation framework of The Common Fisheries Policy (CFP), fishing quotas are individually assigned to member-states. Accordingly, each country targets different species, and obviously, lands different quantities. There are important asymmetries among countries relative to the diversity of species landed. Moreover, in some countries the species richness is so high that the constrained optimisation problem (3.5) is not computationally tractable. Accordingly, we established a species inclusion criterion based on two conditions. Firstly, the species included must represent at least 90% of the total landings of the country. Secondly, to be included in the analysis the species should represent at least 1% of the landings of the country (country specific coverages are summarised in Table 3.6).

Based on our country-based estimated $EF_{MINTACj}$, we will be able to analyse whether the actual fish portfolios of each country are financially efficient or not, and, potentially, recommend an efficient reallocation of landings for each individual country that result in the lowest level of risk for a given expected level of return. In order to do so, first, following equation 3.1, we measure the returns (R_{ijt}), in this case using the volume of (species-based) landings (in tonnes) as data source. Second, in order to guide the choice of the most appropriate risk indicator to be used in the optimization model summarised in Table 3.2, we will analyse the distribution of the returns (R_{ijt}), paying special attention to check whether they follow a normal distribution. If, as expected, returns are not normally distributed, then Conditional Value-at-Risk ($CVaR_{ij}$) (equation 3.4) will be selected as the most appropriate risk indicator for the ($EF_{MINTACj}$) financial efficient frontier estimation. Thirdly, once returns and risk are properly measured, we will derive mean-CVaR portfolio selection model to estimate the constrained financial ($EF_{MINTACj}$) efficient frontier for each individual country (see Table 3.2). At this stage we are taking advantage of the *fPortfolio* package from R software (R Core Team, 2018; Wuertz et al., 2017).

Figure 3.12: Country-based histograms of the mean returns of landings ($\bar{R}_{ij}$)

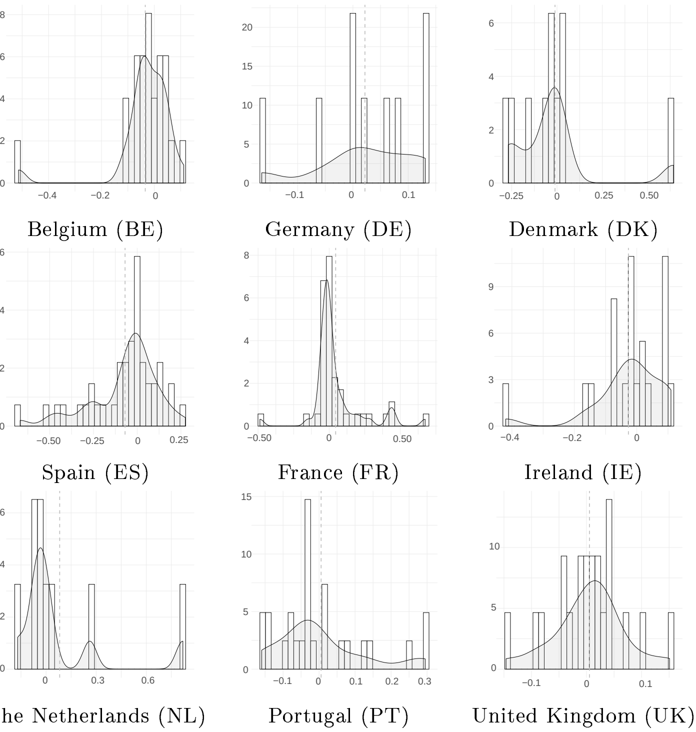


Figure 3.12 illustrates the distribution of the mean rate of returns ($\bar{R}_{ij}$) for each individual country, that is to say, the average increase (positive rate of return) or reduction (negative rate of return) of the volume of fish landed. Two major points should be highlighted. First, it can be observed a quite heterogeneous distribution of the returns among countries. Second, as expected, the returns do not follow a normal distribution (see Shapiro-Wilks normality tests results in Table 3.11). Accordingly, neither the conventional variance nor Value-at-Risk (VaR) would be appropriate risk indicators, because they both assume that returns follow a normal distribution. Therefore, Conditional Value-at-Risk (CVaR) is selected as the most appropriate and robust risk indicator for our empirical case studies.

Table 3.11: Shapiro-Wilk normality test

	W	P-value
Belgium	0.80776	3.838e-16
Germany	0.59175	1.936e-14
Denmark	0.67442	1.422e-13
Spain	0.76288	$<$ 2.2e-16
France	0.68985	$<$ 2.2e-16
Ireland	0.60323	$<$ 2.2e-16
The Netherlands	0.76362	1.009e-10
Portugal	0.8303	3.554e-16
United Kingdom	0.81703	5.584e-15

Notes:
Shapiro-Wilk normality test for yearly landings returns (R_{ijt}) by country (j).
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

3.5 optimisation problem, including quota constraint for the TAC-based regulated species and maximum and minimum constraint for the resulting non-regulated species, yields the constrained efficient frontier (EF_{MINTAC}) (see Table 3.2). The EF_{MINTAC} curve for each individual country includes the mean target return ($\bar{R}_{ij}$) on the vertical axis, and risk ($CVaR_{ij}$) on the horizontal axis. Thus, each curved line constitutes the EF_{MINTAC}, where the convex grey points are inefficient portfolios, and the concave black points efficient ones. Each efficient portfolio in the curve is an efficient combination of fish species weights (%) to get the minimum risk for a certain level of return. The lowest point (red dot) at the EF_{MINTAC}, is the minimum risk portfolio (MRP), which shows the efficient combination of species that leads to the lowest possible risk (CVaR) level. The blue points capture the Conditional Sharpe Ratio (CVaRSR) all along the EF_{MINTAC}, with its maximum coinciding with the tangency portfolio (TP), where

CVaRSR is maximized. This combination of species would lead to the optimum scenario where the highest risk-reward ratio is obtained.

Each of the country-based EF_{MINTAC} figures also include the portfolio for observed landings weights in 2017 (black box), and our optimum efficient portfolio proposal (green point). This proposal is regarded as an efficient and feasible reallocation of fish landings, where new weighting scheme is recommended. These proposals refer to the weight (%) that each fish species should have to achieve target risk and return levels. Broadly speaking, there are two types of efficient portfolio proposals depending on the particularities of each individual country. On the one hand, tangency portfolio (TP) will be suggested for the countries in which the efficient portfolio tangency exists and, at least, reaches the observed (2017) return level. On the other, if the TP does not exist, a second-best strategy will be suggested. Namely, the efficient portfolio that at least reaches the observed (2017) portfolio return.

As well as the respective efficient frontier curves ($\mathrm{FEF_j}$), using bar plots the observed and suggested portfolios for each individual country will be described. Each of the country-based bar plots includes six bar plots. The first three belong to the portfolio for observed landings weights in 2017. Specifically, the first bar plot describes the weight (w_{ij}) (%) each species had in 2017; the second bar plot captures the weighted mean return contribution ($w_{ij} * \bar{R}_{ij}$) to the total mean return in 2017; and the third bar plot indicates the weighted risk (CVaR) contribution to total risk in 2017. Similarly, the next three bar plots are related to our efficient portfolio proposal. Thus, the fourth bar plot describes the suggested (w_{ij}) weight (%) each species should have; the fifth bar plot illustrates the weighted mean return contribution ($w_{ij} * \bar{R}_{ij}$) to the portfolio; and the sixth bar plot captures the weighted risk (CVaR) contribution to total risk of the portfolio.

Table 3.12 summarises the key efficiency gains for each of the nine EU member-states. Following our suggested reallocation of landings weights, countries could achieve an efficient distribution of fish landings that increases or, at the worst, maintains constant the observed return, and significantly reduces the risk level.

Table 3.12: Summary of the observed portfolio and the efficient portfolio proposal

		Return ($\overline{R}$)	*Risk* ($CVaR$)	$\triangle$*Return*	$\triangledown$*Risk*
Belgium	Observed	0.001	0.101	-	-
	Proposal	0.003	0.067	+181%	-34.02%
Germany	Observed	0.056	1	-	
	Proposal	0.056	0.91	const.	-8.42%
Denmark	Observed	0.014	0.47	-	-
	Proposal	0.014	0.32	const.	-33.41%
Spain	Observed	0.051	0.38	-	-
	Proposal	0.051	0.23	const.	-39.65%
France	Observed	0.07	0.107	-	-
	Proposal	0.07	0.002	const.	-97.98%
Ireland	Observed	0.033	0.62	-	-
	Proposal	0.050	0.06	+52.10%	-90.39%
Netherlands	Observed	0.015	0.71	-	-
	Proposal	0.051	0.28	+239.51%	-61.22%
Portugal	Observed	0.015	0.24	-	-
	Proposal	0.017	0.10	+11.92%	-57.13%
United Kingdom	Observed	0.003	0.11	-	-
	Proposal	0.003	0.07	const.	-40.28%

Notes:
$\overline{R}$ is the total mean return of the fish portfolio, $CVaR$ is the total risk, $\triangle Return$ is the increase over the observed return (R), $\triangledown Risk$ is the risk reduction over the observed level of risk (CVaR).

Next, the findings for each individual country will be explained.

Belgium

Table 3.13 gives a general overview of the 23 species ($N'_{BE} = 23$) that satisfy the species inclusion criteria above mentioned. The most outstanding fish species (European plaice (PLE)) constitutes on average the 26% of the total volume of fish landed, and the five dominant fish species, concentrate the 54%. The leading species (European plaice (PLE)) was at least 23% and as much 35% from the total landed volume. Moreover, PLE has a low but positive mean return ($\bar{R}_{PLE,BE} = 0.02$), low risk level ($CVaR_{PLE,BE} = 0.15$) and potential to increase its landings weight up to 46%, as maximum allowed weight by quota regulation. Nevertheless, our suggestion implies reducing its proportion to 29.9%, because of its low contribution to returns. Contrarily, anglerfishes nei (ANF) has historically never been less than 2% and more than 3% from the total fish landings.

Anglerfishes nei (ANF) also has a positive mean return ($\bar{R}_{ANF,BE} = 0.02$), but and higher risk level ($CVaR_{ANF,BE} = 0.47$). In addition, its quota constraint enables to increase its proportion up to 20%. Therefore, even ANF is riskier, we recommend increasing landed volume to 7.1%, due to the benefit derived by risk diversification.

Table 3.13: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for Belgium

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
PLE	0.02	0.15	23%	35%	46%	34%	29.9%
SOL	-0.05	0.21	12%	22%	23%	12%	12.2%
COD	-0.07	0.88	3%	6%	8%	3%	2.8%
LEM	-0.03	0.36	3%	5%	-	3%	3.1%
CTC	-0.05	0.98	2%	7%	-	5%	1.9%
GUU	0.05	0.23	2%	7%	-	7%	6.9%
CNZ	0.11	0.00	1%	4%	-	4%	3.9%
DGZ	0.01	0.00	2%	3%	-	3%	3.3%
RJC	-0.03	0.38	2%	4%	-	2%	2.2%
SCE	-0.06	0.22	2%	4%	-	2%	2.1%
SCL	-0.11	1	1%	4%	-	1%	1.0%
ANF	0.02	0.47	2%	3%	20%	3%	7.1%
SYC	0.04	0.00	2%	4%	-	4%	3.5%
RJH	0.04	0.18	2%	3%	-	3%	3.3%
CSH	0.00	0.47	1%	3%	-	2%	3.2%
TUR	0.03	0.14	2%	3%	2%	3%	2.1%
BIB	-0.05	0.31	1%	3%	-	2%	2.2%
SKA	-0.51	1	0%	9%	-	0%	0.1%
DAB	-0.10	0.46	1%	3%	-	1%	0.9%
LEZ	0.06	1	1%	3%	3%	2%	3.2%
BLL	-0.03	0.15	1%	2%	-	2%	1.3%
GUR	-0.02	0.47	1%	2%	-	2%	2.0%
FLE	-0.05	0.71	1%	2%	-	1%	2.0%
					weighted Returns ($\overline{R}_{ij}$)	**0.001**	**0.003**
					$\triangle Return$	-	(+181%)
					weighted Risk ($CVaR_{ij}$)	**0.101**	**0.067**
					$\bigtriangledown Risk$	-	(-34.02%)

Notes:
Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

Notice that most of the fish species in Table 3.13 have quite low or even negative mean returns ($\bar{R}_{ij}$), which considerably reduces the efficient frontier curve (EF_{MINTAC}) shown in Figure 3.13. As far as there is no tangency portfolio (TP), we recommend the minimum risk portfolio (MRP) as the second-best strategy. Our efficient portfolio proposal (green point) implies the reallocation of fish species weights to achieve an efficient portfolio composition at higher return (+181%) and lower risk level (-34.02%), compared to the portfolio for observed landings weights in 2017 (black box).

Figure 3.13: Constrained EF_{MINTAC} efficient frontier for Belgium

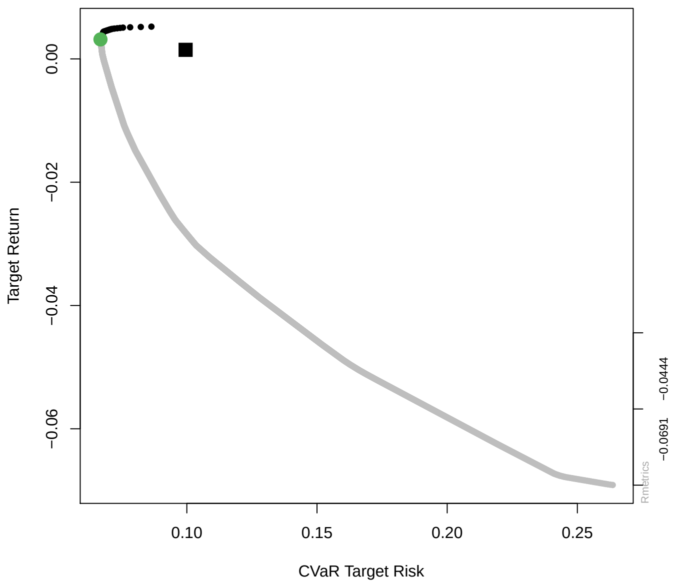
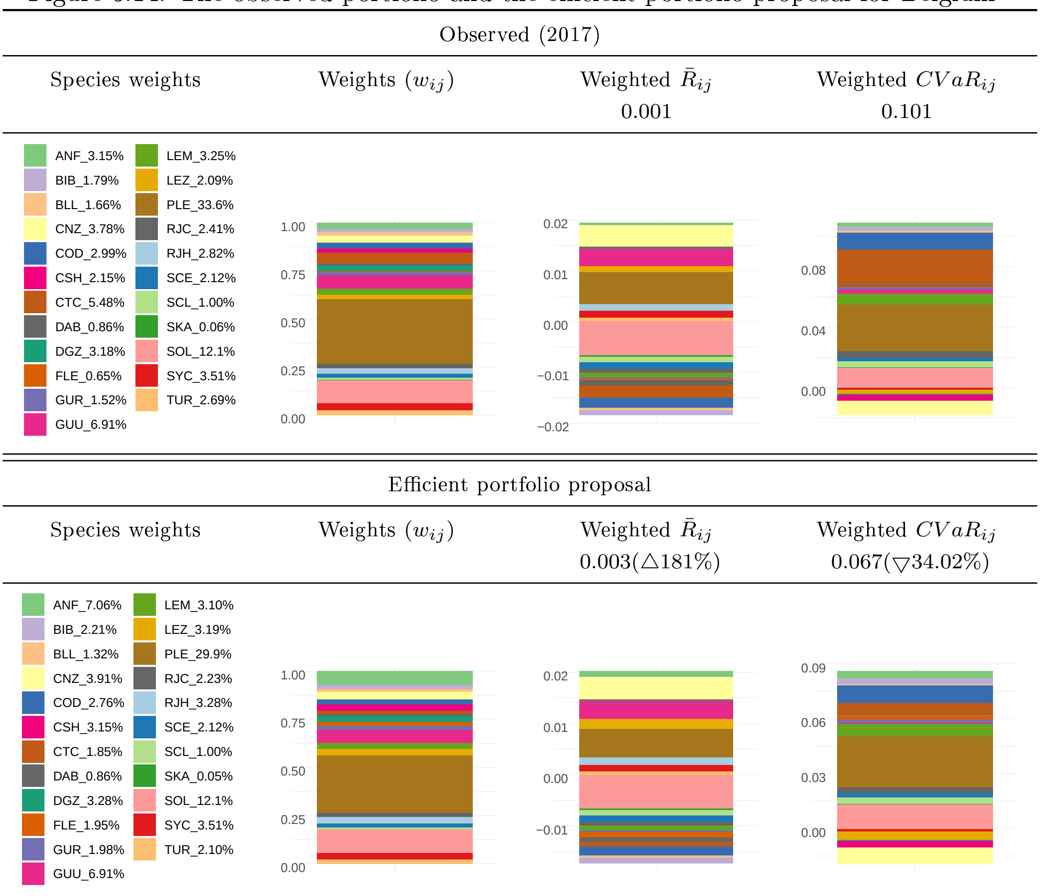


Figure 3.14 shows that the weighting composition does not change so much. The first bar plot illustrates the weight that each species had in 2017. Clearly European plaice (PLE) stands out as the key landed species, representing the 33.6% from the total volume of fish landed. The second bar plot illustrates the weighted returns for each species, that is, the contribution of each species to the portfolio return in 2017. It can be observed that the resulting 2017 portfolio mean return is quite low ($\sum(w_{ij} * \bar{R}_{ij}) = 0.001$) and close to zero. It implies that the mean increase of the landed volume would be hardly 0.1%. Similarly, the third bar plot captures the weighted risk (CVaR) for each species, that is, the contribution of each species to the portfolio risk in 2017. The resulting portfolio risk is also quite low ($CVaR = 0.101$). Hence, in the worst case, returns of the fish landings in Belgium would be reduced by 10.1% on average.

According to our proposal, the fourth illustration in Figure 3.14 shows the weight that each fish species should have in order to achieve the target return and risk levels. It is remarkable that the proportion of the key species, i.e. European plaice (PLE), should be reduced from the observed 33.6% to the recommended 29.9%. Contrarily, anglerfishes nei (ANF) represented 3.15% from total landings, and our second-best optimal strategy suggests increasing its proportion up to 7.06%. Due to the reallocation of the weighting scheme in Belgium, we suggest an efficient portfolio in which the mean return would be increased by 181% and risk reduced by 34.02%. Thus, we are able to propose a feasible and efficient distribution of fish landings in Belgium. Accordingly, the volume of fish landed would increase by 3% ($\overline{R}_{BE} = 0.003$), and in the worst case, returns would only be reduced by 6.7% ($CVaR_{BE} = 0.067$).

Figure 3.14: The observed portfolio and the efficient portfolio proposal for Belgium



Germany

In the case of Germany only 9 fish species ($N'_{DE} = 9$) satisfy the inclusion criteria. Table 3.14 gives a general overview of this species. The most outstanding fish species (Atlantic herring (HER)) constitutes on average the 44% of the total volume of fish landed, and the five most landed fish species, concentrate the 77%. It can be observed for example, that Greenland halibut (GHL) has historically been 1% as minimum and 3% as maximum from the total volume of fish landed. Nevertheless, we suggest increasing the landed volume of GHL up to 9.2%, as maximum allowed weight by quota regulation. Contrarily, our suggestion also involves reducing the weight of Atlantic mackerel (MAC) to 6.3%. Notice that the mean return is quite low ($\bar{R}_{MAC,DE} = 0.06$), and risk is very high ($CVaR_{MAC,DE} = 1$), which does not make MAC attractive at all from a financial point of view.

Table 3.14: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for Germany

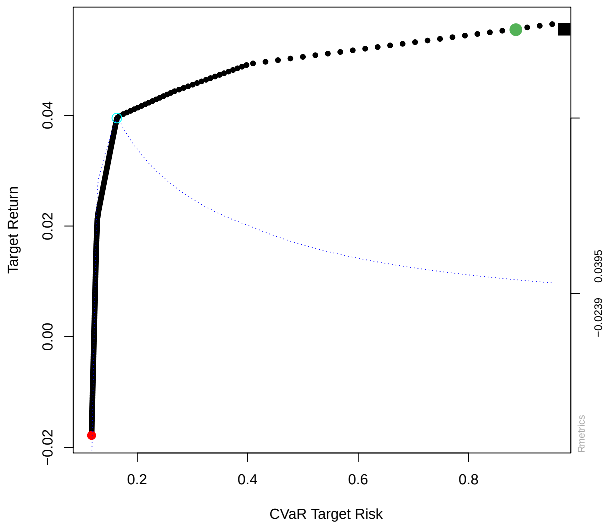
Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
HER	0.02	0.24	41%	55%	48%	41%	41.1%
CSH	-0.06	0.62	4%	19%	-	4%	4.2%
MUS	0.13	0.86	4%	18%	-	13%	17.5%
HOM	0.00	0.00	4%	9%	-	4%	4.2%
COD	-0.16	1	1%	10%	14%	1%	0.9%
MAC	0.06	1	0%	12%	30%	12%	6.3%
WHB	0.13	1	0%	21%	15%	21%	14.4%
SAA	0.00	0.00	2%	4%	-	2%	2.1%
GHL	0.08	0.30	1%	3%	9.2%	2%	9.2%
					weighted Returns ($\overline{R}_{ij}$)	**0.056**	**0.056**
					$\triangle Return$	-	(const.)
					weighted Risk ($CVaR_{ij}$)	**1**	**0.91**
					$\nabla Risk$	-	(-8.42%)

Notes:
Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

The constrained financial efficient frontier (EF_{MINTAC}) for Germany (Figure 3.15) is completely different to the one for Belgium. Due to the risk and return particularities of the fish species landed in Germany, there are much more efficient portfolios to be selected than in the Belgian case study. Nevertheless, the portfolio for the observed landings in

2017 (black square) has a considerably high mean return. Therefore, we suggest the efficient portfolio that maintains the return level constant, but reduces risk by 8.42% (green point).

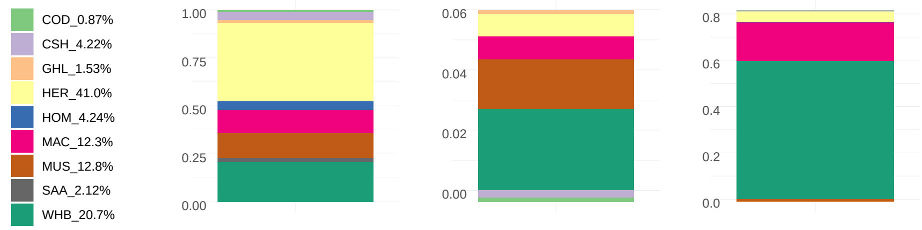
Figure 3.15: Constrained EF_{MINTAC} efficient frontier for Germany



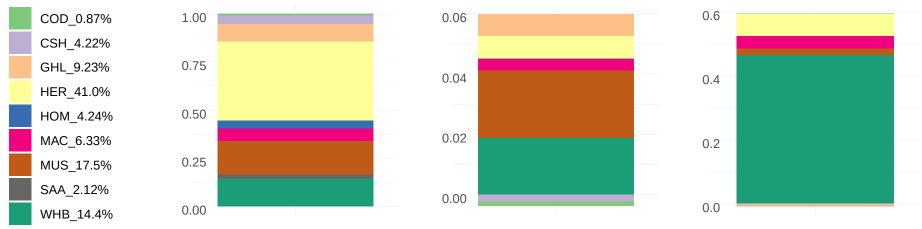
Both the portfolio for the observed landings in 2017 and our proposal for Germany are detailed in Figure 3.16. It can be observed that the weighting composition does not change so much. The first bar plot shows the weights that each fish species had in 2017. Clearly Atlantic herring (HER) is the leading species in Germany, representing the 41% from the total volume of fish landed. Atlantic herring is followed by blue whiting (WHB) (20.7%), blue mussel (MUS) (12.8%) and Atlantic mackerel (MAC) (12.3%). The second and the third bar plots illustrate respectively the contribution to weighted return and risk. Notice that the return contribution of Atlantic herring (HER) is low. It is blue whiting (WHB) the species that more positively contributes to the portfolio of the observed landing, but also the species that more risk generates. Due to the observed weighting scheme, the portfolio belonging to the observed landings has a positive and high weighted mean return ($\sum(w_{ij} * \bar{R}_{ij}) = 0.056$). This implies that the landed volume in Germany would increase by 5.6% on average. However, the portfolio also has a very high weighted risk ($CVaR = 1$), which means that in the worst case, returns would have been reduced by 100%.

Figure 3.16: The observed portfolio and the efficient portfolio proposal for Germany

Observed (2017)			
Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$ 0.056	Weighted $CVaR_{ij}$ 1



Efficient portfolio proposal			
Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$ 0.056(*const.*)	Weighted $CVaR_{ij}$ 0.91($\bigtriangledown$8.42%)



According to our reweighting, the fourth illustration in Figure 3.16 shows the suggested reallocation of weights for each fish species in order to get the target return and risk levels. Our proposal for Germany keeps constant the proportion of Atlantic herring (HER) (41%), increases Greenland halibut (GHL) to 9.23% and blue mussel (MUS) to 17.5%. Contrarily, our suggestion also implies reducing Atlantic mackerel (MAC) to 6.33% and blue whiting (WHB) to 14.4%. Following this redistribution of landings in Germany, we are able to suggest an efficient portfolio in which the mean return would be constant (with respect to the observed in 2017), but risk would be reduced by 8.42%.

Denmark

10 fish species ($N'_{DK} = 10$) satisfy the inclusion criteria in Denmark. The leading fish species (European sprat (SPR)) constitutes on average the 30% of the total volume, and the leading fish species, concentrate the 81%. Additionally, Table 3.15 gives a general overview of the fish species included in the analysis for Denmark. For example, sandeels (SAN) has a negative mean return ($\overline{R}_{SAN,DK} = -0.15$) and a quite high risk ($CVaR_{SAN,DK} = 1$). However, our proposal implies increasing its weight up to 17%, because other low risk species (i.e. European sprat (SPR) (positive mean return and low risk) and Atlantic herring (HER) (negative but low mean return and also low risk level)) have already reached the maximum allowed weights respectively, 30.5% and 23.1%. This implies targeting species such as sandeels, that might not be attractive from the financial point of view, but enable diversifying the portfolio and reducing the weighted risk (-33.41%).

Table 3.15: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for Denmark

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
SPR	0.02	0.38	22%	39%	30%	39%	30.5%
SAN	-0.15	1	5%	39%	62%	5%	17.0%
HER	-0.02	0.24	13%	23%	23%	22%	23.1%
WHB	-0.01	1	0%	19%	7%	19%	6.0%
MUS	-0.06	0.76	3%	7%	-	5%	7.3%
NOP	0.64	1	0%	7%	22%	4%	7.0%
CAP	-0.27	1	0%	6%	1%	0%	0.3%
BOR	-0.26	1	0%	8%	4%	0%	0.0%
COD	-0.03	0.27	2%	4%	4%	2%	4.4%
PLE	0.03	0.10	2%	4%	4%	3%	4.4%
					weighted Returns ($\overline{R}_{ij}$)	**0.014**	**0.014**
					$\triangle Return$	-	(const.)
					weighted Risk ($CVaR_{ij}$)	**0.47**	**0.32**
					$\triangledown Risk$	-	(-33.41%)

Notes:
Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

Figure 3.17 shows the EF_{MINTAC} for Denmark. The tangency portfolio (green point) is suggested as the best strategy to efficiently redistribute the landings weights. Our proposal keeps the return level constant, but reduces risk by 33.41%, compared to the portfolio for the observed landings weights (black box).

Figure 3.17: Constrained EF_{MINTAC} efficient frontier for Denmark

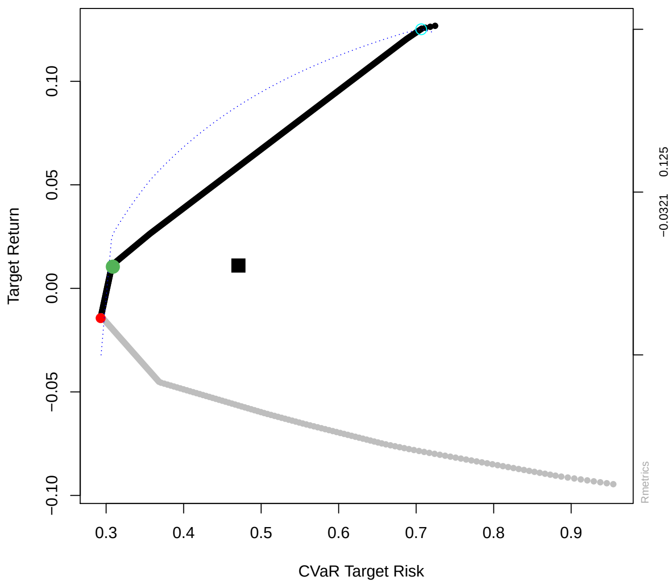
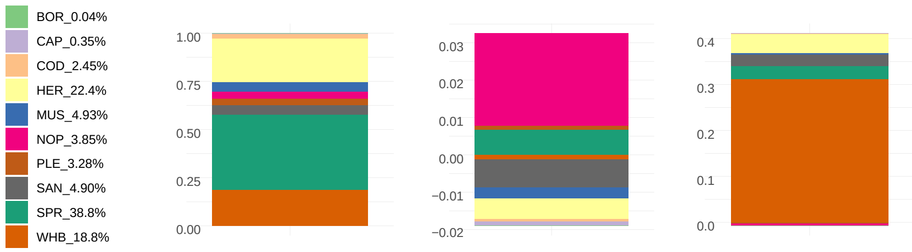


Figure 3.18 details the composition of the observed and suggested portfolios for Denmark. Based on our results, the most noticeable species that should change weights are sandeels (SAN) and blue whiting (WHB). SAN should increase its proportion from the observed 4.9% to the recommended 16.9%, while WHB should reduce from the observed 18.8% to the suggested 6.03%. As a result of the changes on the landings distribution, we can achieve an efficient portfolio that keeps the return level ($\sum(w_{ij} * \bar{R}_{ij}) = 0.014$), but reduces risk (from $CVaR = 0.47$ to $CVaR = 0.32$). Accordingly, the Danish landings average increase would be 1.4%, and in the worst case, fish landings would be reduced by 32%.

Figure 3.18: The observed portfolio and the efficient portfolio proposal for Denmark

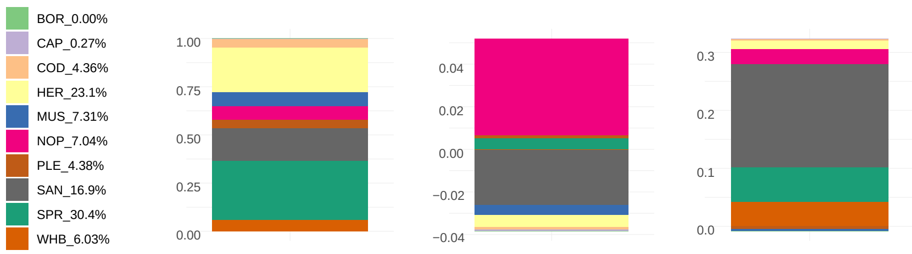
Observed (2017)

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$	Weighted $CVaR_{ij}$
		0.014	0.47



Efficient portfolio proposal

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$	Weighted $CVaR_{ij}$
		0.014(*const.*)	0.32($\bigtriangledown$33.41%)



Spain

The number of species satisfying the inclusion criteria in Spain reaches 42 ($N'_{ES} = 42$). The leading species (skipjack tuna (SKJ)) constitutes on average the 15% of the total volume of fish, and the five leading fish species, concentrate the 39%. Additionally, Table 3.16 gives a general overview of the 42 species included in the analysis. The key species, i.e. skipjack tuna (SKJ), has a positive mean return ($\overline{R}_{SKJ,ES} = 0.03$), but a very high risk level ($CVaR_{SKJ,ES} = 1$). Nevertheless, we suggest increasing its weight up to 25.1%. Notice that SKJ is not regulated by TAC and therefore, we recommend catching up to the maximum observed level in our sample period. Similarly, the second key species, i.e. yellowfin tuna (YFT), has also a quite high risk, but its mean return is negative. Therefore, as YFT is not an attractive fish species from a financial point of view, we suggest reducing its proportion to the minimum observed weight (1.1%).

Table 3.16: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for Spain

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
SKJ	0.03	1	1%	25%	-	20%	25.1%
YFT	-0.01	1	1%	15%	-	9%	1.1%
PIL	-0.10	0.69	4%	16%	-	4%	3.5%
HKE	0.06	0.45	3%	7%	5%	5%	5.4%
VMA	0.08	0.06	3%	8%	-	8%	8.4%
JAX	-0.09	0.79	2%	8%	10%	2%	1.6%
ANE	0.19	0.08	1%	7%	6%	7%	5.7%
SAA	-0.25	1	0%	10%	-	1%	0.4%
MAC	0.03	0.31	2%	5%	6%	5%	6.4%
HOM	0.01	0.22	2%	4%	-	4%	4.3%
BSH	0.12	0.29	1%	5%	-	5%	5.2%
SWO	0.04	0.22	2%	4%	2%	3%	2.5%
WHB	-0.03	0.98	1%	5%	11%	4%	0.8%
BET	0.28	0.68	0%	6%	3%	6%	3.4%
HKP	0.12	1	0%	4%	-	4%	4.0%
COD	0.10	0.27	1%	3%	3%	2%	2.8%
ALB	0.00	0.44	1%	2%	4%	2%	4.2%
MAZ	-0.26	1	0%	8%	-	1%	0.0%
PEL	-0.06	1	0%	8%	-	0%	0.0%
SQA	-0.01	1	0%	3%	-	1%	1.0%
GRO	-0.51	1	0%	3%	-	0%	0.0%
OCC	-0.04	0.36	1%	1%	-	1%	0.6%
FIN	-0.23	0.84	0%	2%	-	0%	0.2%
PAT	0.13	1	0%	2%	-	1%	1.7%
BOG	0.19	0.58	0%	2%	-	1%	2.0%
OCT	-0.46	1	0%	2%	-	0%	0.0%
PRC	-0.18	1	0%	3%	-	0%	0.0%
RED	-0.12	1	0%	2%	1%	0%	0.2%
LEZ	-0.02	0.27	1%	1%	2%	1%	1.7%
NOX	-0.04	1	0%	2%	-	1%	0.3%
TUN	-0.29	1	0%	3%	-	0%	0.1%

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
SQP	0.06	1	0%	1%	-	1%	0.0%
ANF	0.00	0.11	1%	1%	1%	1%	1.0%
GHL	-0.01	0.45	0%	1%	1%	1%	0.9%
POA	-0.41	1	0%	2%	-	0%	0.0%
MNZ	-0.33	1	0%	2%	1%	0%	0.0%
COE	-0.08	0.56	0%	1%	-	0%	0.2%
GAD	-0.08	1	0%	3%	-	0%	3.2%
HKX	-0.67	1	0%	2%	-	0%	0.0%
SKA	-0.09	0.70	0%	1%	1%	0%	0.3%
SQI	0.01	1	0%	1%	-	0%	0.8%
GRM	0.00	1	0%	1%	-	0%	0.9%
					weighted Returns ($\overline{R}_{ij}$)	**0.051**	**0.051**
					$\triangle Return$	-	(const.)
					weighted Risk ($CVaR_{ij}$)	**0.38**	**0.23**
					$\triangledown Risk$	-	(-39.65%)

Notes:

Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

Figure 3.19 illustrates the EF_{MINTAC} for Spain. The pattern and the shape of the constrained financial efficient frontier (EF_{MINTAC}) curve is slightly similar to the one for Denmark, although the observed portfolio of landings in 2017 (black square) and our proposal (green point) are radically different. The portfolio for observed landings weights has a high return level ($\sum(w_{ij} * \bar{R}_{ij}) = 0.051$). Accordingly, we suggest an efficient distribution of landings (green point) that maintains the mean return constant (compared to the portfolio for the observed landings weights), but reduces risk by 39.65%.

Figure 3.19: Constrained EF_{MINTAC} efficient frontier for Spain

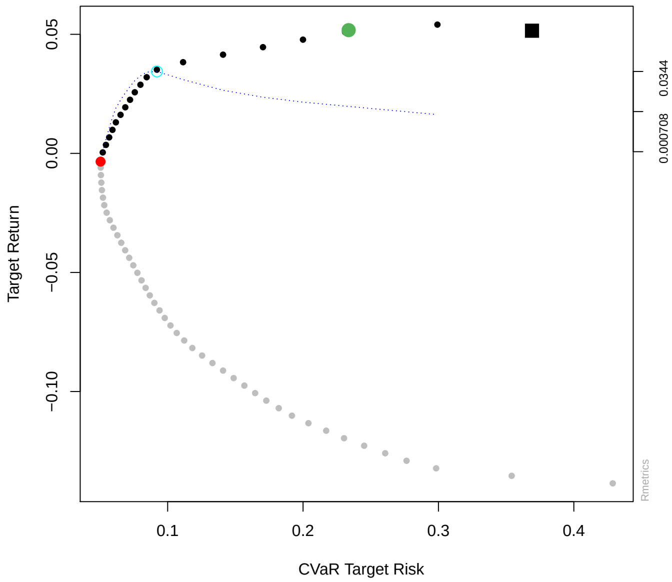
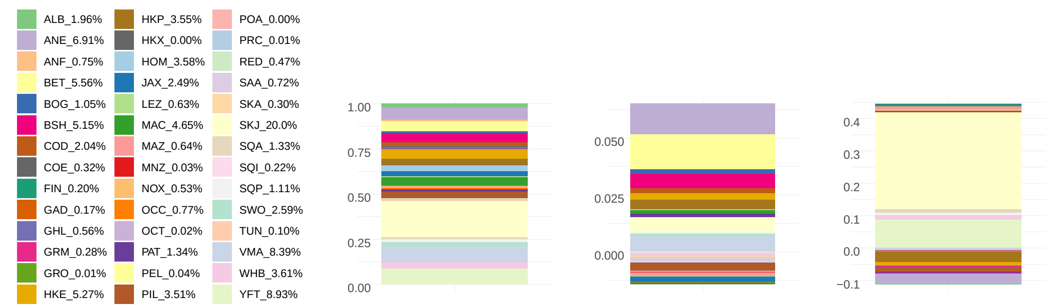


Figure 3.20 shows the observed portfolio in 2017 and our proposal in detail. It is remarkable, that the leading species (i.e. skipjack tuna (SKJ)) was 20% of the total volume of fish landed in Spain. Moreover, we recommend increasing its landed volume until it reaches the 25.1%. Contrariwise, we suggest reducing yellowfin tuna (YFT) from observed 8.93% to 1.06%. Due to the redistribution of landings, the weighted risk has been considerably reduced to $CVaR = 0.23$. These results indicate that the mean increase of landings in Spain would be 5.1%, and in the worst case, returns would be reduced by 23%.

Figure 3.20: The observed portfolio and the efficient portfolio proposal for Spain

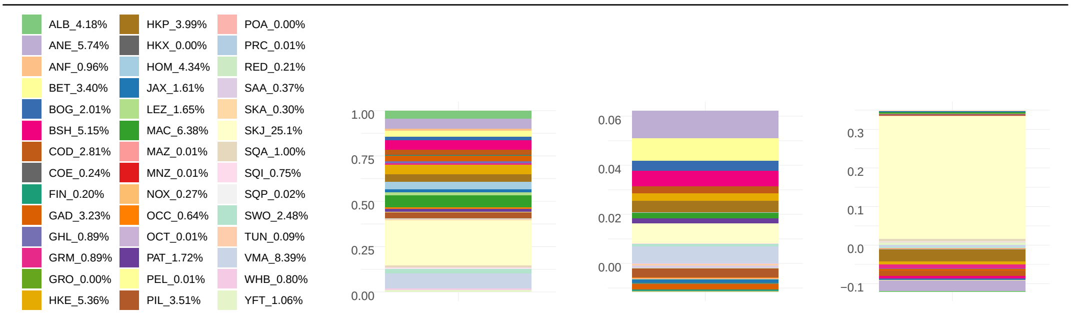
Observed (2017)

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$	Weighted $CVaR_{ij}$
		0.051	0.38



Efficient portfolio proposal

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$	Weighted $CVaR_{ij}$
		0.051(*const.*)	0.23($\triangledown$39.65%)



France

The number of fish species satisfying the inclusion criteria in France is 44 ($N'_{FR} = 44$). The leading species (Tangle (LQD) constitutes on average the 15% of the total volume of fish landed, and the five most outstanding fish species, concentrate the 39%. Moreover, Table 3.18 gives a more detailed information about the species included in France. Historically, European hake (HKE) has never exceeded the 6% of the total volume of fish landed in France. However, HKE has potential to reach the maximum allowed level of 22.7%. In addition, HKE has a positive mean return ($\bar{R}_{HKE,FR} = 0.08$) and a quite low risk level ($CVaR_{HKE,FR} = 0.19$), which makes it an interesting species from the financial point of view. Thus, our proposal implies increasing HKE until it reaches the maximum level established by the quota regime (22.7%). On the contrary, European sardine (PIL) has a negative mean return ($\bar{R}_{PIL,FR} = -0.04$) and high risk ($CVaR_{PIL,FR} = 0.73$). Accordingly, our proposal implies reducing PIL to the historically observed minimum level (5.7%).

Table 3.18: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for France

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
LQD	0.28	0.97	1%	17%	-	10%	4.6%
PIL	-0.04	0.73	6%	14%	-	8%	5.7%
SCE	0.02	0.33	6%	9%	-	9%	6.1%
MON	-0.01	0.12	3%	6%	-	4%	6.2%
HKE	0.08	0.19	3%	6%	23%	5%	22.7%
MNZ	0.03	0.15	4%	5%	16%	5%	3.5%
WHE	0.09	0.32	2%	5%	-	5%	2.1%
MAC	-0.03	0.26	2%	4%	11%	3%	2.5%
WHG	-0.01	0.27	3%	4%	9%	3%	2.7%
LAH	0.18	1	1%	11%	-	3%	3.9%
WHB	-0.04	0.61	1%	5%	16%	3%	5.1%
CTC	0.67	0.32	0%	4%	-	3%	2.5%
HOM	-0.01	1	1%	15%	-	1%	0.8%
POK	-0.15	0.70	1%	6%	26%	1%	0.8%
COD	0.02	0.91	1%	3%	6%	3%	1.3%
SOL	-0.04	0.28	1%	3%	5%	2%	1.4%
HAD	0.00	0.37	1%	3%	7%	1%	1.1%
ANE	0.00	0.57	1%	3%	1%	2%	1.2%
CRE	0.00	0.33	1%	2%	-	1%	1.1%
SQC	-0.01	0.15	1%	2%	-	2%	2.2%
SQZ	0.45	0.36	0%	2%	-	2%	2.0%
SYC	-0.04	0.63	1%	2%	-	1%	1.0%
BSS	-0.06	0.42	1%	2%	-	1%	0.7%
COE	-0.03	0.65	1%	2%	-	1%	1.0%
SCR	0.10	0.17	1%	2%	-	2%	2.2%
BIB	-0.02	0.27	1%	2%	-	1%	0.8%
HER	-0.01	0.92	1%	2%	17%	1%	0.8%

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
YFT	0.14	1	0%	11%	-	1%	0.0%
NEP	-0.03	0.68	1%	2%	6%	1%	0.8%
ALB	0.03	0.68	0%	2%	4%	1%	0.4%
SKJ	0.44	1	0%	10%	-	1%	1.5%
GKL	-0.01	1	0%	2%	-	1%	0.4%
BRB	-0.07	0.52	1%	2%	-	1%	0.6%
POL	-0.06	0.41	1%	1%	8%	1%	0.6%
GUR	0.05	0.33	0%	1%	-	1%	1.3%
QSC	-0.01	1	0%	2%	-	2%	2.2%
SWX	0.05	1	0%	3%	-	1%	1.4%
SDV	0.00	0.42	1%	1%	-	1%	0.7%
LIN	-0.06	0.84	0%	1%	2%	0%	0.4%
PLE	-0.01	0.30	1%	1%	2%	1%	0.6%
RJN	-0.02	0.20	1%	1%	-	1%	0.6%
CTL	-0.49	1	0%	6%	-	0%	0.0%
MUR	0.42	0.55	0%	2%	-	1%	1.5%
MEG	0.22	0.13	0%	1%	-	1%	1.0%
					weighted Returns ($\overline{R}_{ij}$)	**0.07**	**0.07**
					$\triangle Return$	-	(const.)
					weighted Risk ($CVaR_{ij}$)	**0.107**	**0.002**
					$\triangledown Risk$	-	(-97.98%)

Notes:

Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

Figure 3.21 illustrates the EF_{MINTAC} for France. The efficient frontier curve is somewhat similar to the Spanish one, but both, the observed and proposed portfolios, change for France. The portfolio for the observed landings weights in 2017 (black square) has a high return level ($\sum(w_{ij} * \bar{R}_{ij}) = 0.07$). Consequently, as a second-best strategy, we suggest an efficient portfolio (green point) that keeps the observed mean return level constant, but considerably reduces the risk (-97.98%).

Figure 3.21: Constrained EF_{MINTAC} efficient frontier for France

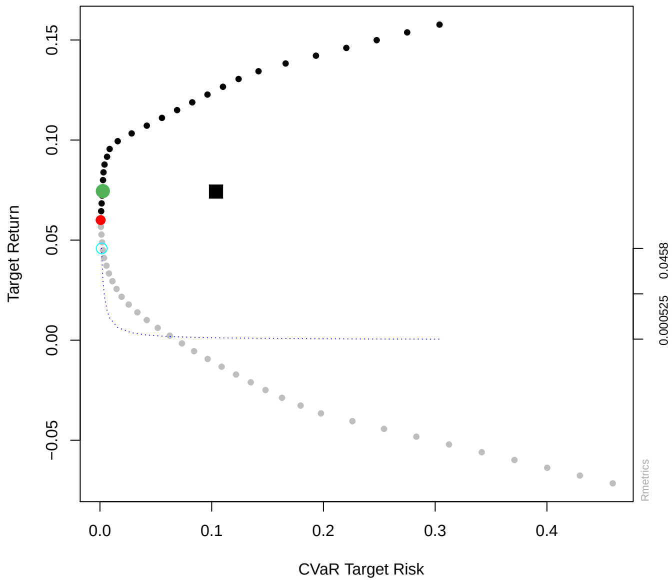
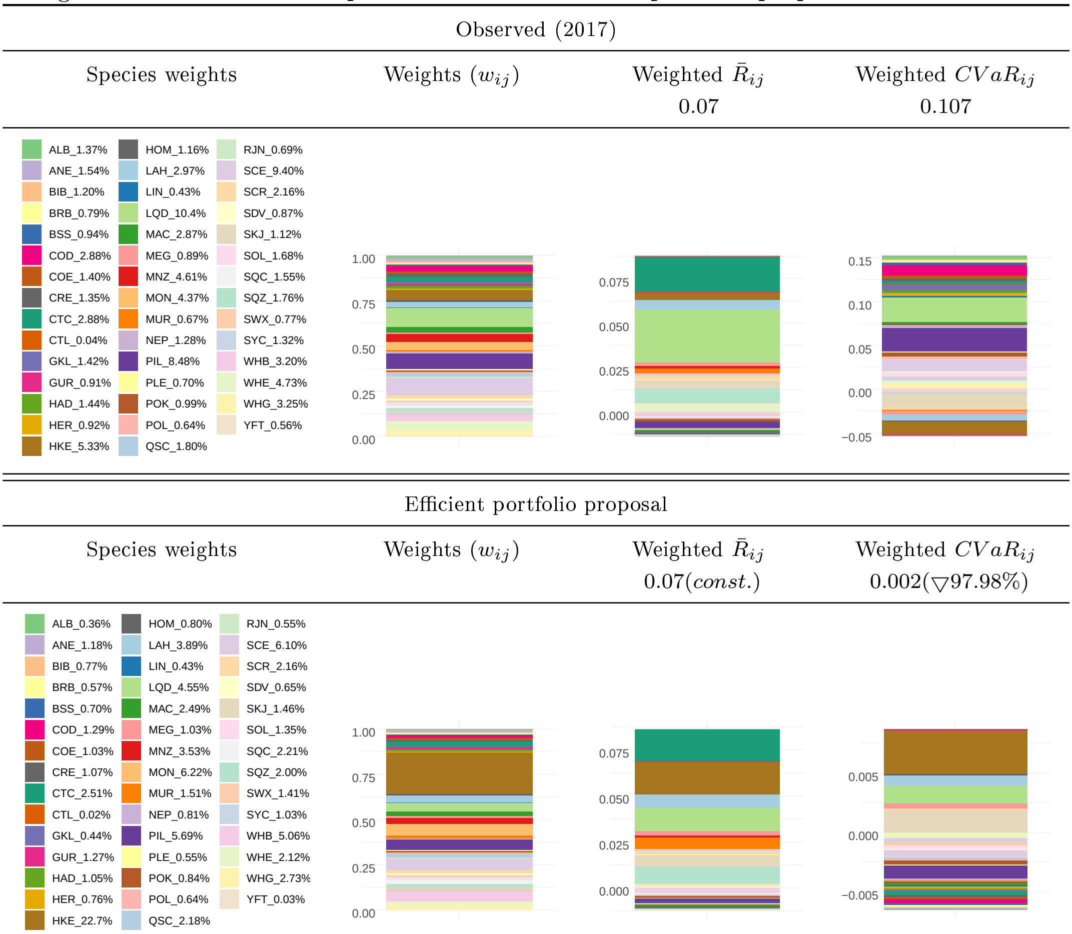


Figure 3.22 gives detailed information about the observed and proposed distribution of fish landings for France. The principal changes imply increasing European hake (HKE) from the observed 5% to the recommended 22.7%, which is the maximum allowed proportion given by quota regulation. Besides, we suggest reducing tangle (LQD) from 10% to 4.6%. Following our redistribution of landings in France, we propose an efficient portfolio in which the mean increase of landings would be 7%, and in the worst case, the volume of fish landed would be only reduced by 0.2%. Notice that this result is quite close to zero, implying that we are able to suggest an efficient portfolio for France with almost zero risk.

Figure 3.22: The observed portfolio and the efficient portfolio proposal for France



Ireland

The number of species fulfilling the inclusion criteria in Ireland is 20 ($N'_{IE} = 20$). The most outstanding species (Atlantic mackerel (MAC)) constitutes on average the 21% of the total volume of fish landed, and the five more outstanding species, concentrate the 60%. Additionally, Table 3.20 gives a more detailed description about the distribution of landings and the weighting scheme in Ireland. Atlantic mackerel (MAC), which is the principal species, was 31% from the total volume of fish landed in 2017. We suggest increasing MAC to 41.2%, which corresponds to the maximum allowed weight by quota regulation. Conversely, blue whiting (WHB) has positive but low mean return

($\bar{R}_{WHB,IE} = 0.03$) and a very high risk level ($CVaR_{WHB,IE} = 1$). Therefore, our proposal implies reducing WHB until the minimum observed weight (1.4%).

Table 3.20: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for Ireland

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
MAC	0.09	0.19	12%	31%	41%	31%	41.2%
JAX	-0.02	1	2%	18%	22%	8%	2.5%
WHB	0.03	1	1%	23%	23%	19%	1.4%
HER	-0.07	0.37	5%	11%	17%	5%	5.3%
FIN	-0.42	1	0%	19%	-	0%	0.1%
HKE	0.08	1	1%	10%	10%	7%	9.7%
HOM	0.11	1	1%	10%	-	2%	8.4%
BOC	-0.02	0.16	3%	6%	-	3%	5.6%
CRE	-0.16	1	2%	12%	-	2%	1.7%
MOL	-0.15	0.99	1%	7%	-	2%	1.4%
MON	-0.07	0.73	2%	5%	-	2%	1.6%
NEP	0.01	0.36	2%	4%	4%	2%	4.3%
BOR	-0.07	1	0%	7%	29%	3%	0.5%
ANF	0.09	0.00	1%	4%	4%	4%	3.8%
WHG	0.01	0.69	1%	3%	3%	2%	1.4%
SPR	-0.04	0.78	1%	4%	-	1%	2.0%
HAD	-0.01	0.44	1%	2%	2%	1%	1.0%
MNZ	0.00	0.93	1%	4%	4%	2%	3.7%
LEZ	0.09	0.11	1%	3%	3%	2%	2.5%
WHE	-0.03	0.25	1%	2%	-	1%	1.8%
					weighted Returns ($\overline{R}_{ij}$)	**0.033**	**0.050**
					$\triangle Return$	-	(+52.10%)
					weighted Risk ($CVaR_{ij}$)	**0.62**	**0.06**
					$\triangledown Risk$	-	(-90.39%)

Notes:
Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

Figure 3.23 illustrates the EF_{MINTAC} for Ireland. Although the shape and the slope of the Irish efficient frontier curve is quite similar to the Belgian, however, the observed and proposed portfolios change considerably. In the case of Ireland, the portfolio for the observed landings weights in 2017 (black square) has higher risk level but lower mean return. Therefore, we suggest the tangency portfolio (TP) as the efficient portfolio proposal (green point). Consequently, based on to the optimal reallocation of the distribution of landings, we are able to suggest an efficient portfolio for Ireland that increases the return (+52.10%) and reduces risk (-90.39%), compared to the observed risk and return levels.

Figure 3.23: Constrained EF_{MINTAC} efficient frontier for Ireland

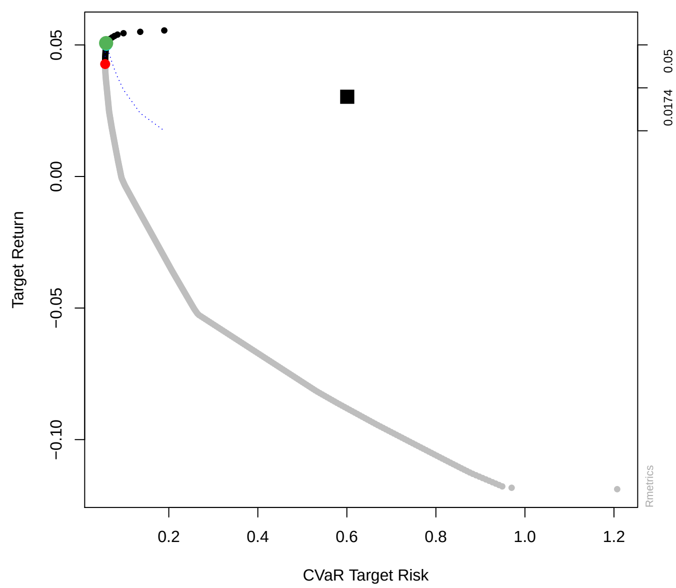
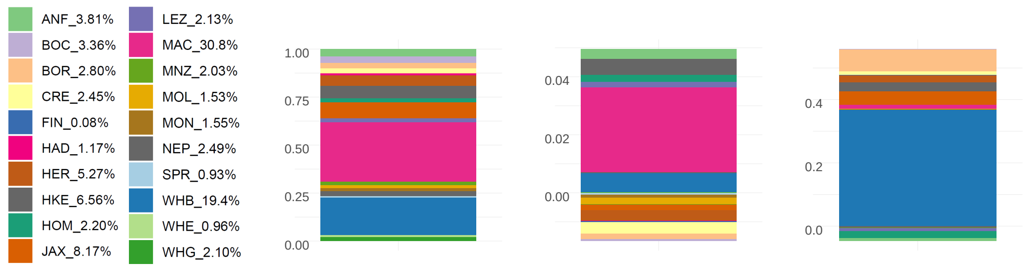


Figure 3.24 includes six bar plots explaining how weights, return and risk change, from the observed to the proposed efficient portfolio. The major changes imply increasing Atlantic Mackerel (MAC) from the observed 30.8% to recommended 41.2%, and reducing blue whiting (WHB) from 19.4% to 1.42%. Due to the proposed redistribution of landings in Ireland, we are able to suggest an efficient portfolio that increases the weighted return to $\sum(w_{ij} * \bar{R}_{ij}) = 0.05$ (mostly contributed by MAC), and reduces risk to $CVaR = 0.06$ (mostly diminished by the reduction of WHB). Our results imply that the mean increase of landings in Ireland would be 5%, and in the worst case, fish landings would be only reduced by 6%.

Figure 3.24: The observed portfolio and the efficient portfolio proposal for Ireland

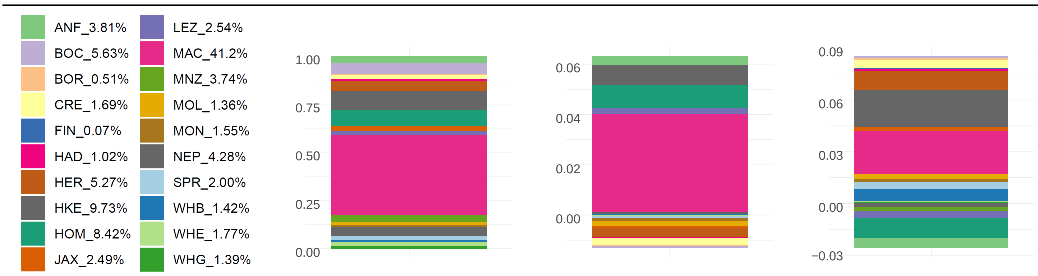
Observed (2017)

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$ 0.033	Weighted $CVaR_{ij}$ 0.62



Efficient portfolio proposal

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$ 0.050($\triangle$52.10%)	Weighted $CVaR_{ij}$ 0.06($\triangledown$90.39%)



The Netherlands

Only 9 species satisfy the inclusion criteria for the Netherlands ($N'_{NL} = 9$). The leading species (Atlantic herring (HER)) constitutes on average the 28% of the total volume of fish landed, and the five most landed fish species, concentrate the 81%. Additionally, Table 3.21 gives a general overview of the landings in the Netherlands. For example, common shrimp (CSH) has a low but positive mean return ($\overline{R}_{CSH,NL} = 0.03$) and a slightly low risk ($CVaR_{CSH,NL} = 0.31$), therefore, we suggest increasing its weight to 7.5%, coinciding with the maximum observed weight. Contrarily, we propose reducing Atlantic mackerel (MAC) to the minimum observed 7.6%, since MAC has a negative mean return ($\overline{R}_{MAC,NL} = -0.04$) and high risk ($CVaR_{MAC,NL} = 0.76$).

Table 3.21: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for the Netherlands

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
HER	-0.06	1	22%	36%	27%	32%	26.0%
WHB	-0.08	1	1%	33%	12%	26%	3.7%
JAX	-0.17	1	1%	33%	21%	3%	20.7%
MAC	-0.04	0.76	8%	21%	12%	15%	7.6%
PLE	0.00	0.35	4%	13%	11%	7%	11.4%
CSH	0.03	0.31	1%	7%	-	3%	7.5%
HOM	0.82	0.23	0%	10%	-	6%	10.2%
PIL	0.26	1	0%	9%	-	6%	9.0%
SOL	-0.02	0.15	1%	4%	4%	2%	3.9%
					weighted Returns ($\overline{R}_{ij}$)	**0.015**	**0.051**
					$\triangle Return$	-	(+239.51%)
					weighted Risk ($CVaR_{ij}$)	**0.71**	**0.28**
					$\triangledown Risk$	-	(-61.22%)

Notes:
Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

Figure 3.25 illustrates the EF_{MINTAC} for the Netherlands. Its shape is similar to the Irish efficient frontier. The main difference comes from the portfolio of the observed landings weights in 2017 (black square), which has a high risk and low return level. Thus, our proposal (green point) is the minimum risk portfolio (MRP), where the return is increased by 239.51% and risk reduced by 61.22% (compared to the portfolio of the observed landings in 2017).

Figure 3.25: Constrained EF_{MINTAC} efficient frontier for the Netherlands

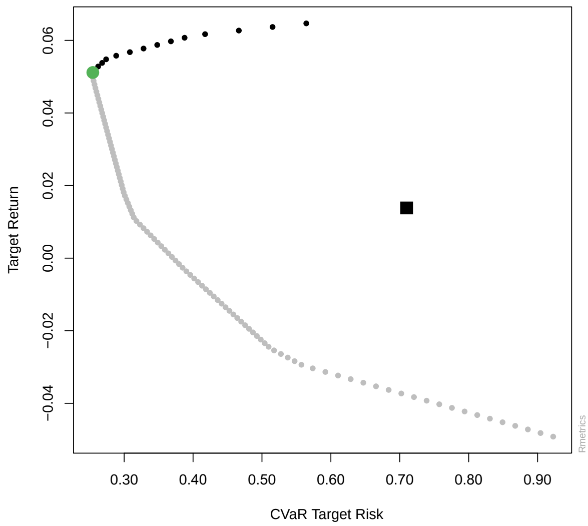
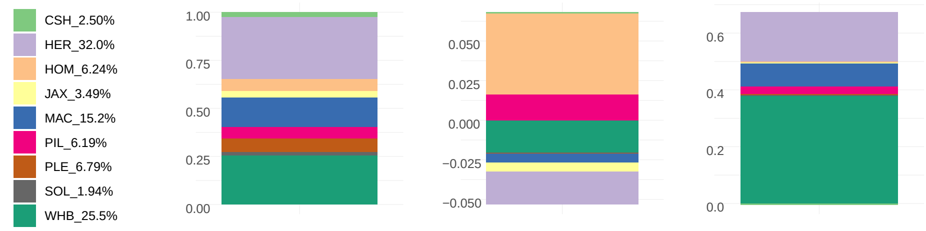


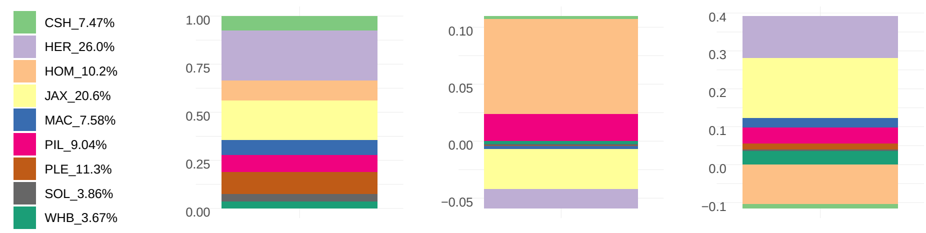
Figure 3.26 gives a more detailed information about the observed and proposed portfolios in the Netherlands. The first bar plot shows that Atlantic herring (HER) is the leading species in the Netherlands. HER was 32% of the total volume of fish landings in 2017, and HER was followed by blue whiting (WHB) (25.5%). Our efficient portfolio proposal suggests reducing WHB to 3.67% and HER to 26%, mainly because both species have a negative mean return and both are risky species. Contrarily, we recommend increasing Atlantic horse mackerel (HOM) from 6.24% to 10.2%, jack and horse mackerels (JAX) from 3.49% to 20.6% and European plaice (PLE) from 6.79% to 11.3%. Due to the redistribution of landings weights, the return of the proposed portfolio is considerably increased (+239.51%) and risk reduced (-61.22%). Therefore, the mean increase of the landings in the Netherlands would be 5.1%, and in the worst case, landings would be reduced by 28%.

Figure 3.26: The observed portfolio and the efficient portfolio proposal for the Netherlands

Observed (2017)			
Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$ 0.015	Weighted $CVaR_{ij}$ 0.71



Efficient portfolio proposal			
Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$ 0.051(△239.51%)	Weighted $CVaR_{ij}$ 0.28(▽61.22%)



Portugal

In Portugal the number of species satisfying the inclusion criteria is 26 ($N'_{PT} = 26$). The outstanding fish species (Atlantic horse mackerel (HOM)) constitutes on average the 28% of the total volume of fish landed, and the five most landed fish species, concentrate the 60%. As Table 3.22 shows, European sardine (PIL) and Atlantic chub mackerel (VMA) have negative mean returns ($\bar{R}_{PIL,PT} = -0.15$ and $\bar{R}_{VMA,PT} = -0.01$) and rather high risks ($CVaR_{PIL,PT} = 0.57$ and $CVaR_{VMA,PT} = 0.51$). Accordingly, our proposal implies reducing their proportion to the minimum observed level (respectively 11.4% and 10.1%). Contrariwise, Atlantic horse mackerel (HOM) has positive mean return ($\bar{R}_{HOM,PT} = 0.07$) and low risk level ($CVaR_{HOM,PT} = 0.14$). Thus, our proposal suggests increasing its landings to the maximum observed weight (18.6%).

Table 3.22: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for Portugal

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs. (%)**	**Proposal (%)**
PIL	-0.15	0.57	11%	44%	-	14%	11.4%
VMA	-0.01	0.51	10%	36%	-	17%	10.1%
HOM	0.07	0.14	5%	19%	-	18%	18.6%
OCC	0.01	0.60	2%	7%	-	4%	7.4%
BSF	-0.03	0.14	3%	4%	-	4%	4.2%
RED	-0.10	1	1%	6%	8%	3%	4.0%
BET	-0.03	0.54	1%	5%	5%	3%	5.2%
JAA	0.01	0.43	2%	4%	-	4%	4.4%
COD	0.01	0.46	2%	6%	7%	3%	6.9%
SKJ	-0.16	1	1%	7%	-	2%	0.7%
BSH	-0.14	1	1%	4%	-	1%	0.6%
ANE	0.25	1	0%	9%	4%	9%	4.4%
HKE	-0.03	0.28	1%	2%	5%	1%	4.7%
COC	0.14	0.77	1%	4%		4%	3.6%
WHB	-0.08	0.71	0%	2%	8%	2%	0.4%
BIB	-0.03	0.23	1%	2%	-	2%	1.8%
COE	-0.03	0.14	1%	1%	-	1%	1.5%
GHL	-0.06	1	0%	1%	2%	1%	0.4%
ALB	0.29	1	0%	2%	4%	2%	3.9%
CTC	-0.04	0.29	1%	1%		1%	1.0%
SWO	-0.16	1	0%	2%	2%	1%	0.5%
REB	0.29	1	0%	1%	-	1%	1.2%
SBR	-0.08	0.40	0%	1%	-	1%	0.5%
ULO	0.12	0.29	0%	1%	-	1%	1.3%
SBA	-0.04	0.40	0%	1%	-	0%	0.8%
RJC	0.08	0.16	0%	1%	-	1%	0.8%
					weighted Returns ($\overline{R}_{ij}$)	**0.015**	**0.017**
					$\triangle Return$	-	(+11.92%)
					weighted Risk ($CVaR_{ij}$)	**0.24**	**0.10**
					$\triangledown Risk$	-	(-57.13%)

Notes:
Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

Figure 3.27 illustrates the EF_{MINTAC} for Portugal. Its shape is slightly similar to the Spanish efficient frontier plot. The main difference is the efficient portfolio proposal (green point). We suggest tangency portfolio (TP) for Portugal, as the best strategy to achieve a higher return (+11.92%) at a lower risk level (-57.13%), compared to the portfolio for the observed landings' weights in 2017 (black square).

Figure 3.27: Constrained EF_{MINTAC} efficient frontier for Portugal

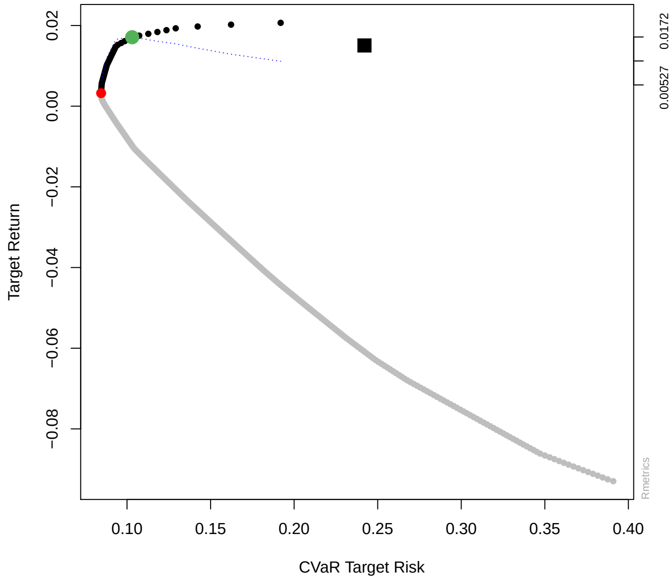
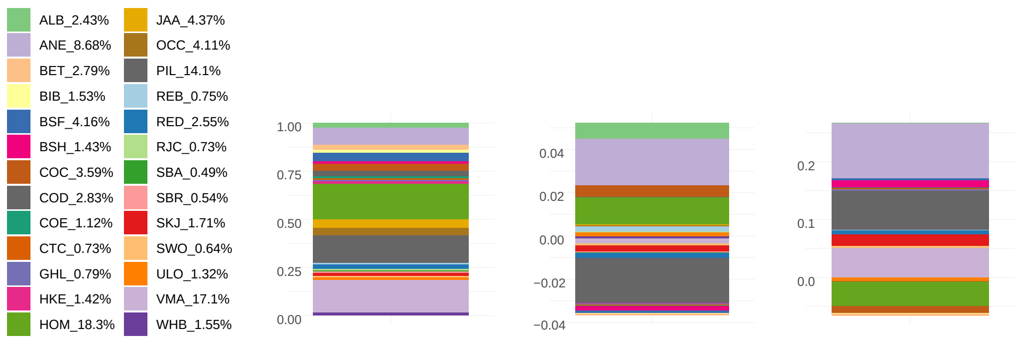


Figure 3.28 captures more detailed information about the observed and proposed portfolios in Portugal. The first bar plot shows that Atlantic horse mackerel (HOM) was the outstanding species in 2017 (18.3%), closely followed by Atlantic chub mackerel (VMA) (17.1%). Our efficient portfolio proposal implies practically maintaining the proportion of HOM (18.6%), but reducing VMA to 10.1%. Due to the redistribution of landings, we can recommend an efficient portfolio that has a positive return ($\sum(w_{ij} * \bar{R}_{ij}) = 0.017$) and considerably low risk level ($CVaR = 0.10$), mainly due to the reduction of VMA. Hence, the mean increase of the landings in Portugal would be 1.7% and, in the worst case, the volume of fish landed would be reduced by 10%.

Figure 3.28: The observed portfolio and the efficient portfolio proposal for Portugal

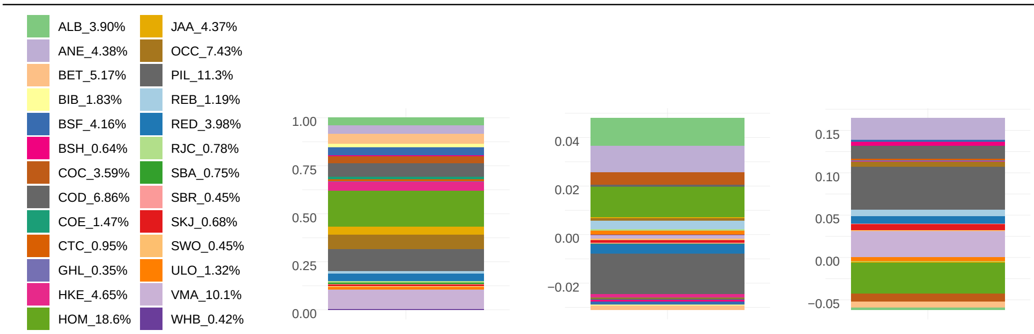
Observed (2017)

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$ 0.015	Weighted $CVaR_{ij}$ 0.24



Efficient portfolio proposal

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$ 0.017($\triangle$11.92%)	Weighted $CVaR_{ij}$ 0.10($\triangledown$57.13%)



United Kingdom

The number of species fulfilling the species inclusion criteria in the UK is 21 ($N'_{UK} = 21$). The leading species (Atlantic mackerel (MAC)) constitutes on average the 25% of the total volume of fish landed in the UK, and the five outstanding species concentrate the 56%. Additionally, Table 3.23 gives a general overview of the 21 species included in the analysis for the UK. Both, Atlantic mackerel (MAC) and Atlantic herring (HER), have negative mean returns and quite high level of risk. This is the main reason why our proposal suggests reducing their proportion to the minimum observed weight. On the contrary, European plaice (PLE) has a positive mean return ($\bar{R}_{PLE,UK} = 0.04$) and a low risk level ($CVaR_{PLE,UK} = 0.12$). Hence, it is suggested to increase its proportion up to 9%, established by quota regime.

Table 3.23: Landings (q_{ijt}) mean returns ($\bar{R}_{ij}$), risk ($CVaR_{ij}$) and weights (%) for the United Kingdom

Species	$\bar{R}_{ij}$	$CVaR_{ij}$	$w_{ij}^{min}(\%)$	$w_{ij}^{max}(\%)$	$w_{ij}^{TAC}(\%)$	**Obs.(%)**	**Proposal (%)**
MAC	-0.01	0.40	22%	34%	62%	27%	21.6%
HER	-0.04	0.33	10%	16%	24%	12%	9.7%
HAD	0.00	0.12	7%	9%	11%	8%	6.6%
SCE	0.03	0.11	4%	8%	-	6%	4.5%
CRE	0.02	0.13	5%	7%	-	7%	5.0%
NEP	-0.04	0.19	4%	7%	12%	5%	4.1%
WHB	-0.09	1	1%	12%	15%	3%	3.0%
WHE	0.00	0.53	3%	5%	-	3%	3.1%
POK	0.01	0.13	3%	4%	4%	3%	3.9%
COD	0.04	0.27	2%	4%	7%	4%	7.0%
HKE	0.15	0.07	1%	5%	2%	5%	2.5%
QSC	-0.01	0.75	1%	6%	-	1%	4.9%
WHG	-0.03	0.15	2%	3%	3%	2%	2.1%
ANF	0.03	0.54	2%	3%	4%	3%	3.9%
COC	-0.08	1	0%	3%	-	1%	3.2%
JAX	-0.15	1	0%	4%	5%	0%	0.4%
LIN	0.07	0.05	1%	2%	2%	2%	1.3%
SPR	0.02	0.33	1%	2%	3%	1%	0.7%
CTL	0.05	0.48	1%	2%	-	2%	1.8%
PIL	0.10	0.15	1%	2%	-	2%	1.9%
PLE	0.04	0.12	1%	1%	9%	1%	9.0%
					weighted Returns ($\overline{R}_{ij}$)	**0.003**	**0.003**
					$\triangle Return$	-	(const.)
					weighted Risk ($CVaR_{ij}$)	**0.11**	**0.07**
					$\triangledown Risk$	-	(-40.28%)

Notes:
Landings mean returns ($\overline{R}_{ij}$), risk ($CVaR_{ij}$), minimum observed weight constraint ($w_i^{min}(\%)$), maximum observed weight constraint ($w_{ij}^{max}(\%)$), maximum allowed weight by quota constraint ($w_{ij}^{TAC}(\%)$), observed weight in 2017 (Observed (%)), and our proposed weight (Proposal (%)).

Figure 3.29 shows the EF_{MINTAC} for United Kingdom. Although it is similar to the Belgian and Irish frontiers, it has some noticeable differences. The return of the minimum risk portfolio (MRP) (red point) is below the return of the portfolio for the observed landings in 2017 (black square). Therefore, we suggest the efficient portfolio (green point) that keeps the return level constant (to the observed portfolio in 2017) and reduces risk by 40.28%.

Figure 3.29: Constrained EF_{MINTAC} efficient frontier for the United Kingdom

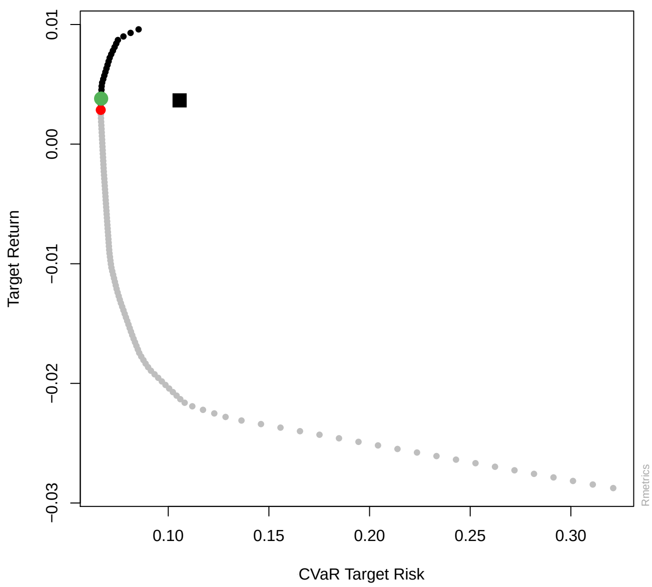
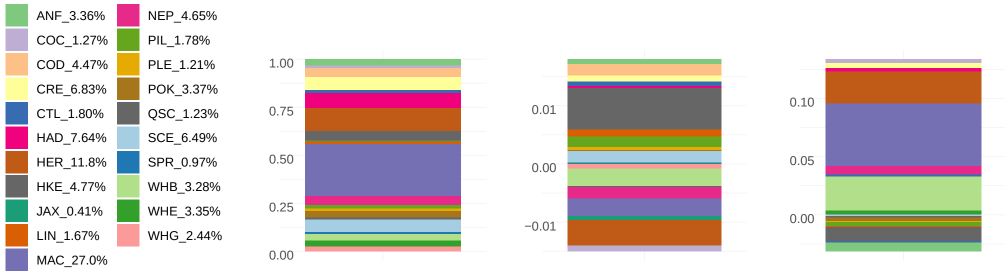


Figure 3.30 shows the observed and proposed portfolios for the UK. In the first bar plot it can be seen that Atlantic mackerel (MAC) (27%) and Atlantic herring (HER) (11.8%) were the most landed fish species in 2017. Our proposal implies reducing their weight respectively to 21.5% and 9.72%, because both species (MAC and HER) have negative mean returns. Conversely, we recommend increasing the landed volume of European plaice (PLE) from 1.21% to 9.04%, since PLE has a positive mean return and low risk level. As a result of the suggested redistribution of landings for the United Kingdom, the return level ($\sum(w_{ij} * \bar{R}_{ij}) = 0.003$) is kept, but the risk has been reduced to $CVaR = 0.07$. Under these circumstances, the mean increase of the volume of fish landed would be 0.3%, and in the worst case, landings would be reduced by 7% .

Figure 3.30: The observed portfolio and the efficient portfolio proposal for the United Kingdom

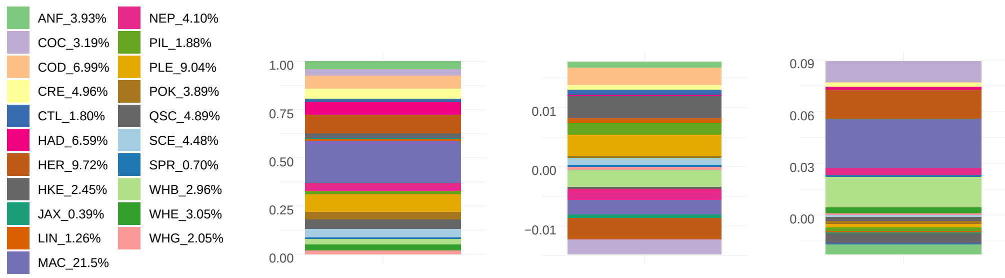
Observed (2017)

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$	Weighted $CVaR_{ij}$
		0.003	0.11



Efficient portfolio proposal

Species weights	Weights (w_{ij})	Weighted $\bar{R}_{ij}$	Weighted $CVaR_{ij}$
		0.003($const.$)	0.07($\bigtriangledown$40.28%)



3.4 Concluding remarks and discussion

Modern portfolio theory (MPT) gives a flexible tool to manage fisheries sustainably and efficiently. Efficient portfolio selection modelling for fisheries management in the EU enables us to observe how countries have performed in the past, and how they could perform better in the future by reallocating their fish landings. It is possible to suggest an efficient portfolio distribution for each country in order to make them increase or at least maintain the observed return levels, and also, reduce risk. Policy makers could use this modelling as a complementary tool to improve their decision making and stock assessments. Moreover, additional and different constraints could be included in the model in order to observe how strategies would change. Besides, excluding the minimum observed weight as a minimum constraint would imply, for example, suggesting to close some fisheries due to their low return and high risk.

There is and increasing attention in the financial literature to consider the left-tail risk indicators (Matthies et al., 2019), because they are more appropriate for natural resource management. We have contributed to the literature developing a feasible approach to manage downside uncertainty in fisheries management outcomes by the inclusion of a robust risk indicator, the Conditional Value-at-Risk (CVaR). Up to date, to the best of our knowledge, this is the first paper using CVaR in fisheries. Considering the optimization problem including a minimum constraint and a maximum constraint (i.e. the maximum allowed weights by TAC regulation), we have estimated an efficient financial frontier, and based on it, we have recommended an efficient reallocation of landing weights for the aggregate EU, and also individually for Belgium, Germany, Denmark, Spain, France, Ireland, the Netherlands, Portugal and the United Kingdom. Our efficient portfolio proposals are based on historical volume and value of landings data, which incorporates changing ecological economic and regulatory factors. Therefore, our approach is able to detect excessive landings of some species and excessive risk taking (Jin et al., 2016).

Our major finding is that countries could benefit by adopting mean-CVaR optimization approach as a tool to manage fisheries efficiently and account for species interactions. Countries could considerably reduce risk and also increase, or at least maintain previous return levels by reallocating their landings. Our approach is flexible and could be adapted to any other particular case study. Second, additional constraints may be added to the model in order to analyse how different strategies or limitations would affect the overall efficiency of the fish portfolios. Comparing different scenarios could be helpful to quantify changes on portfolio's risk and return levels, and observe how different decisions would affect the reallocation of our recommended weights. There are also potential scenarios to be explored by the inclusion of the sustainability parameter (γ). It would be useful to simulate possible policies and observe how these decisions would affect the reallocation of landings. And third, there are potential gains from transferring quota rights between countries that would increase return and reduce risk and help their fish landings be more efficient.

Member-states are responsible for ensuring that fish species are not overfished above quota limitations. Whenever a country reaches the allowed quota, the European Commission allows them to manage and transfer quota limits during the year (EU, 2017). Some authors suggest that improving transferability of quota rights could be a feasible solution to reduce overcapacity and generate resource rents in the fishery (Arnason, 1996;

Asche et al., 2008; Branch, 2009; Weninger, 1998). Hence, special attention deserves the fact that countries would not only transfer catching rights, but also return and above all, risk. Therefore, these potential quota exchanges could be also considered when portfolio selection model is optimized. Furthermore, our proposal could imply different strategies depending on the country. There are some fish species catalogued as low return and high risk for some countries, and inversely catalogued as high return and low risk for others, depending on their temporal performance. For instance, according to our efficient portfolio reweighting proposals, Spain and Portugal should increase their landed volume of albacore (ALB), while France should reduce it. Therefore, there would exist potential quota transfer interests among these countries, which would benefit the three of them in financial terms. Something similar happens with bigeye tuna (BET). While Spain is suggested to reduce BET, the piece of advice to Portugal is to increase its weight. The recommendation for France and Belgium is to reduce their volume of Atlantic cod (COD) landed. Contrarily, Portugal, United Kingdom, Denmark and Spain, should increase its weight. In addition, blue whiting (WHB) is considered a risky species for all the countries except for France. Therefore, our suggestion is to increase the proportion of WHB for France, and to reduce it for the rest of the countries. Thus, countries should consider the possibility of transferring WHB catching rights to France, in order to make their fish portfolio efficient.

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Overall concluding remarks and discussion

The main objective of this thesis has been to provide a better understanding of the marine ecosystem functioning, accounting for the interactions among different fish species, overcoming uncertainty and risk related issues, and improving foresighting capacity to develop effective and sustainable management tools to steer the implementation of ecosystem-based fisheries management, so as to specifically asses the fisheries governance in the EU.

The ***first chapter*** aimed to provide knowledge to focus, and potentially guide, the discussions on the future of the European fishing sector. Fishing directly affects the three pillars of sustainability, that is to say, the environment, the economy and the society. Thus, a great scientific knowledge is needed to improve the assessment and governance of fisheries. However, as far as the measuring of the status of exploitation of the resources is not easy, decision-making becomes rather complex. The Common Fisheries Policy has already included significant changes in order to make the European fishing activity more alienated with the ecosystem-based fisheries management (EBFM). For example, the adoption of the landing obligation aimed to improve the conservation of marine resources, but the future ecological, economic and social impacts of such measure will determine if its objectives have been successfully achieved or not. To a large extent, the ability to adapt and counteract threats will determine the success or failure of the existing fishing policies, and consequently, the long-term sustainability of the full ecosystem. Therefore, the governance of the fisheries heavily depends on science to provide enough and accurate knowledge. Nevertheless, the heterogeneity and the complexity of the fishing sector, as well as the degree of uncertainty on the states of nature makes its management challenging. Hence, new and complementary tools are needed in order to assess decision-making, increase predictability and ensure the future health of the marine ecosystem.

Specifically, the first chapter gives a synthetic picture of the EU fishing sector by means of a set of standard country-based output, input, fleet structure, fleet organisation and profitability indicators. Output indicators include the volume and the value of fish landed in EU fishing countries; input indicators are addressed by the number of vessels, the gross tonnage, the engine power and the number of full-time equivalent fishers; the structure of the fleets is proxied by the respective proportions of small-scale artisanal vessels, large industrial vessels, new vessels, and quasi amortised vessels; the organisational behaviour is captured by the number of producer's organisation; and, finally, the efficiency of the fleets is measured by productivity ratios. Additionally, based on a variate exclusively comprised by fishing related variables and a set of alternative clustering algorithms, the taxonomy of the EU fishing countries has been identified. This descriptive analysis highlights the heterogeneity of the European fishing sector, which has a direct impact on the establishment and implementation of policies that should fit the particular circumstances of each country and/or fishery.

The landings of fish products in the EU fishing ports reached 3,430 thousand tonnes and 6,803 million euros in 2018. In terms of the volume of fish landed, the most outstanding country was Spain (25%), followed by the Netherlands (16%), United Kingdom (13%), France (10%), Italy (6%) and Denmark (5%). Unsurprisingly, the same countries, namely, Spain (32%), Italy (14%), France (14%), United Kingdom (13%), the Netherlands (9%) and Denmark (5%) leaded the raking in terms of the value of fish landed. Following a species-based perspective, although more than 1000 varieties of fish were officially landed in the EU (2018), nevertheless, the volume of such landings was heavily concentrated on ten key species (i.e. Atlantic herring (16%), Atlantic mackerel (7%), blue whiting (6%), European pilchard (5%), European sprat (5%), skipjack tuna (5%), European anchovy (4%), Atlantic chub mackerel (3%), European hake (3%) and Atlantic horse mackerel (3%)). The distribution of these species by individual countries was rather asymmetric. While the landings of species such as Atlantic herring or European pilchard were rather homogeneously distributed among member-states, other species, such as skipjack tuna and blue whiting were mainly landed in specific countries (i.e. Spain and the Netherlands).

The EU fishing fleet was made up by 81,860 fishing vessels in 2018, a capacity of 1,549,742 gross tonnage, a fishing power of 6,151,200 kilowatts, and around 118,000 fishers were directly involved in the European fishing sector. The average EU fishing vessel has a capacity of 19 gross tonnages, an engine power of 75 kilowatts, a length of 8 metres, a crew of 1.45 full time equivalent fishers, and it is 23 years old. The fleet is mainly comprised by small-scale artisanal (<12 metres) (85%) and rather quasi amortised vessels (> 20 years) (73%). Only 3% of the vessels are 24 metres or over, and the quasi new vessels (<10 years) hardly amount for 7% of the total EU fleet.

It is not straightforward to identify *the most fishing countries* in the EU. The immediate answer depends on the input and/or the output choice. In the reference year (2018), Greece had the largest fleet in terms of the number of vessels (18%), followed by Italy (15%), Spain (11%), Portugal (10%), Croatia (9%) and France (8%). Despite the fact that the Netherlands was the second outstanding country according to the volume of landings (16%), Dutch fleet, comprised by 833 units, hardly represented 1% of the total amount of EU fishing vessels. However, with a capacity of 120,509 gross tonnages and a fishing power of 304,200 kilowatts, Dutch fleet respectively agglutinated 8% and 5% of the of the total EU capacity and fishing power. It is also remarkable the fact that the average length per vessel differs significantly among countries. Belgium and the Netherlands had the largest vessels (respectively 27 and 20 meters on average), while the smallest units may be found in Estonia (5 metres), Cyprus, Bulgaria, Finland and Croatia, where the average length of the fishing vessels was around 6 metres. As expected, the proportion of large-scale vessels (> 24 metres) was the highest in Belgium (50%) and the Netherlands (28%). Following a fairly similar distribution to the fishing fleet, the countries with the larger number of fishers were Italy (26,146 full time equivalent, 22% of the EU), Greece (22,081 full time equivalent, 19% of the EU), Spain (17,981 full time equivalent, 15% of the EU) and Portugal (17,642 full time equivalent, 15% of the EU).

This sounded heterogeneity constituted a perfect breeding ground to analyse the taxonomy of the EU fishing countries. Based on a two-step principal component clustering approach, our results hold that European fishing countries may be partitioned in four clusters: [Cluster 1= {Belgium}, Cluster 2={Bulgaria, Estonia, Finland, Malta, Poland, Romania, Slovenia}, Cluster 3={Croatia, Cyprus, Denmark, Germany, Greece, Ireland, Latvia, Lithuania, Sweden}, Cluster 4={France, Italy, Portugal, Spain, the Netherlands, United Kingdom}].

Belgium, isolated alone, constitutes a differentiated group with unique characteristics. Belgium only concentrates 0.4% of the volume and 1% of the value of the landings in the EU, with 0.1% of the vessels, 1% of the gross tonnage, and 0.01% of the full-time fishers. Besides, the Belgian fleet is pure industrial and the most productive one. The seven countries in Cluster 2 {Bulgaria, Estonia, Finland, Malta, Poland, Romania, Slovenia} hardly concentrate an average of 1% of the volume, and 0.2% of the value of the landings in the EU, around 2% of the vessels, 1% of the gross tonnage, and 2% of the fishers. Moreover, their fleets are pure artisanal, relatively new, and the least productive ones in the EU. On average, the nine countries in Cluster 3 {Croatia, Cyprus, Denmark, Germany, Greece, Ireland, Latvia, Lithuania, Sweden}, represent 2% of the volume and 1% of the value of the landings in the EU, 4% of the vessels, 3% of the gross tonnage, and 3% of the fishers. Besides, their fleets are mainly artisanal, quasi amortised and their productivity is also rather low. Cluster 4, made up by {France, Italy, Portugal, Spain, the Netherlands, United Kingdom} may be catalogued as the club of *the most fishing countries*. On average, they concentrate 12% of the volume and 14% of the value of the landings in the EU, 9% of the vessels, 11% of the gross tonnage, and 12% of the fishers. Moreover, their fleets are the largest and also the most productive ones (with the only exception of Belgium). Additionally the club of *the most fishing countries* exhibit the foremost associationism behaviour in the EU fishing sector.

In the ***second chapter*** we aimed to measure the risk and diversity inherent in the EU fishing countries. For that purpose, we focus on alternative theoretical and empirical specifications of risk and diversity, and also the potential correlation among them. Notice that, risk and diversity are expected to be negatively correlated. The lower the diversity, the higher the concentration, dominance and dependency of the fishing industry to the evolution of the dominant fish species. Therefore, the higher might be the risk of a potential collapse in the fishing sector. Moreover, we analyse whether the inclusion of risk and diversity in the former cluster analysis makes the difference in the taxonomy of EU fishing countries.

The estimation of risk for each of the EU fishing countries is inferred from a previous species-level risk analysis, using country specific catches by species as individual weights. Our approach to estimate species-level risk contributes to the literature providing an innovative perspective of measuring fish vulnerabilities through the application of downside financial risk indicators, including Historical Value-at-Risk, Modified Value-at-Risk, Historical Expected Shortfall, Modified Expected Shortfall, and Expectiles. Using spawning stock biomass and catches (both, in volume and value) as data, the species-level *biological risk (BR)* and species-level *production risk (PR)* have been quantified. The former, is a proxy of the species-level risk in the natural frame or ocean, while the latter proxies the risk related to the fishing itself.

We have been able not only to measure the risk of each individual species, but also to detect how risk measures may be ambiguous depending on the formulation of the risk indicator used. Although all five risk indicators we focus on are theoretically consistent, however, Modified Expected Shortfall (MES) was found to be the most accurate and preventive risk indicator based on the specific distributional characteristics of our data. We have found that species show rather distinctive and heterogeneous risk patterns. The average species-level *biological risk (BR)* is 0.52. The riskiest species are turbot (BR=1), surmullet (BR=1) and spotted ray (BR=1). Contrarily, the species with the lowest BR are golden redfish (BR=0.02), blackbellied angler (BR=0.05) and Greenland halibut (BR=0.05). For its part, the average *production risk (PR)* is 0.65. The fish species with the highest PR are sandeels (PR=1), Norway pout (PR=1) and megrim (PR=1), while the ones with the lowest PR are turbot (PR=0.17), European plaice (PR=0.19) and common sole (PR=0.20). Moreover, species-level average *production risk* (PR=0.65) is 25% higher than the average *biological risk* (BR=0.52). This may be well due to the fact that, compared to SSB, catches are directly influenced by additional variables such as quotas, stakeholders' individual decisions, market conditions and specific regulations, hence increasing the overall risk. Even that the resulting overall classification of the fish species according to BR and is rather similar and stable, there are however some noticeable anomalies. While some of the fish species are catalogued as low risk species (quartile 1) according to BR (namely, golden redfish, blackbellied angler, four spot megrim, angler, beaked redfish and megrim), however PR identifies these species as highly risk species (quartile 4). As mentioned, even the biomass of these fish species may be rather stable (i.e. low BR), their catches, and accordingly their PR may have been influenced by additional variables. Therefore, since PR is able to capture the shocks negatively affecting catches, even the *biological risk* of such species is low, nevertheless, their *production risk* is rather high.

Based on our species-level *biological risk (BR)* and *production risk (PR)* estimations, we have inferred the country-level biological risk (wBR) and production risk (wPR), both in volume and value, weighting the risk of each fish species by their specific proportion in the landings of each of the 23 EU fishing countries. Notice that our estimated species-based synthetic risk indicators, BR and PR, may be also employed to infer the risk of any other aggregation level by choosing the appropriate weights, so as to, for example, to estimate the inherent risk level of a fishing community, fishing region or fleet segment. Our country-level risk estimations reveal that the EU fishing countries subject to the highest weighted biological risk (wBR) (quartile 4) are Cyprus, Italy, Greece, Romania, Malta and Croatia, while the ones with the lowest wBR (quartile 1) are Finland, Germany and the Netherlands. It is remarkable that the volume-based biological risk distribution does not change compared to the value-based biological risk. Therefore, wBR (i.e. the risk of EU fishing country to suffer negative shocks on biomass in the natural frame or ocean) seems not to be affected by the market side. On another hand, the ranking and distribution of the countries according to the volume-based production risk (wPR) is similar to the classification obtained from wBR. The EU fishing countries subject to the highest volume-based weighted production risk (wPR) (quartile 4) are Cyprus, Italy, Greece, Denmark Malta and Ireland, while the ones with the lowest volume-based wPR (quartile 1) are Finland, Lithuania, Belgium and Germany. Nevertheless, our results suggest that the market side is slightly conditioning the wPR (i.e. the risk of each EU fishing country to suffer a high negative shock due to fishing activity/fleet related reasons). According to the value-based weighted production risk (wPR), Denmark moves from the highest risk quartile (Q4) to a moderate one (quartile 3), and Romania changes from the moderate risk (quartile 3) to the lowest quartile (Q1).

Besides risk, in chapter 2 we also explore the bio-economic diversity patterns of each of the 23 EU fishing countries. Thus, each member-state is considered to have an individual marine sub-ecosystem comprised by its different target fish species, which, besides, may change over time. Therefore, we define an individual dynamic sub-ecosystem (2007-2017) in terms of both, the volume of landings (q) and the value of landings (pq) as data sources. We use a bundle of diversity indices, namely Berger-Parker index (BP), Concentration Ratios (CR_k), Simpson's index (SIM) and Shannon index (SHA). It is convenient to use more than one index, because since each index has its own weighting schemes, they all give similar but not exactly the same information.

Overall, with 1144 landed fish species, the aggregate EU species richness may be considered high. However, the outstanding fish species (Atlantic Herring (HER)) accounts for 15% of the total landed volume, and the five leading fish species accumulate a share of 45% of the total landed volume in the EU. These results change considerably when the value of landings is considered. Atlantic Herring comprises the 6% of the total landed value, and the five leading fish species constitute the 23% of the total value of landings in the EU. Moreover, results suggest that most of the country based sub-ecosystems are very highly concentrated and dependent on just a few species. As a reference, the 5 leading species surpass the 60% of the overall landed volume for 19 of the 26 countries. Only France (34%), Spain (39%), Italy (43%), Greece (47%), Belgium (54%), United Kingdom (56%) and Malta (58%) are below the above mentioned CR5<60%. Results hardly change when landed value is considered. 15 countries out of 26 still are very dependent on five species (i.e. Latvia (98%), Estonia (96%), Finland (88%), Poland (87%), Romania (87%), Sweden (86%), Bulgaria (86%), Germany (82%), Lithuania (78%), the Netherlands (71%), Belgium (70%), Croatia (67%) and Slovenia (63%)).

Special attention should be paid on countries with extremely low diversity such as Finland, Estonia, Latvia, Bulgaria and Romania. These countries are heavily dependent on one or few fish species, and therefore, they may potentially assume higher risk levels than others due to their high level of species concentration. However, correlation analysis paradoxically suggests that as far as the diversity of the fishing country increases, the country-level risk also increases. Although this unexpected result may be well due to different reasons, our guess is that it is mainly related to the combination of the species distribution and certain species leadership. Accordingly, even the diversity of a country could determine its potential risk, it is the share and the type of targeted fish species what in fact determines the weighted biological and production risk.

Risk and diversity matter to draw the taxonomy of EU fishing countries. Or to put in another words, the estimated country-based risk and diversity measures condition the partitions obtained in Chapter 1. Our re-clustering process, conducted by adding our risk and diversity measures to the variate already used in Chapter 1) supports four clusters (C'): [Cluster 1'= {Belgium}, Cluster 2'={Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden, Slovenia}, Cluster 3'={Cyprus, Denmark, Greece, Ireland, Malta}, Cluster 4'={Spain, France, Italy, The Netherlands, Portugal, United Kingdom}]. {Belgium} is maintained alone in Cluster 1'. It is the least fishing country in terms of volume fished, it has the smallest but the most productive fleet, the weighted biological and production risks are the lowest, and the overall diversity is intermediate. The eleven countries in Cluster 2' {Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden, Slovenia} are the least fishing countries in terms of the value of fish landed, their fleets are the newest but the less productive ones, their weighted biological and production risks are rather low, and the diversity in their sub-ecosystems is the lowest. The fleets in Cluster 3' {Cyprus, Denmark, Greece, Ireland, Malta} are mainly pure artisanal, the productivity is rather low, the weighted biological and production risks are the highest, and the diversity in their sub-ecosystems is rather high. Finally, the six countries in Cluster 4' {Spain, France, Italy, The Netherlands, Portugal, United Kingdom} are kept together in the club of *the most fishing countries*. Notice that they have the largest fleets, and they concentrate most of the producer organisations in the EU. Their weighted biological and production risks are rather high and the diversity on their sub-ecosystems is the highest. When comparing the clusters determined in Chapter 1 (C) with the ones resulting from Chapter 2 (C'), despite the hard core of the EU fishing countries is rather stable, (Cluster 1 = Cluster 1' {Belgium} Cluster 4= Cluster 4' {Spain, France, Italy, The Netherlands, Portugal, United Kingdom} keep constant), however, substantial changes occur in Cluster 2' {Bulgaria, Germany, Estonia, Finland, Croatia, Lithuania, Latvia, Poland, Romania, Sweden, Slovenia} and Cluster 3' {Cyprus, Denmark, Greece, Ireland, Malta}. Malta, a country with rather high risk and diversity switches to Cluster 3', and

{Germany, Croatia, Lithuania, Latvia, Sweden} change to Cluster 2'. Notice that the weighted biological and production risks of the latter are rather low, the dominance of the leading species is the highest and the diversity the lowest compared to the countries that already remain in the same cluster.

In the ***third chapter*** we provide a rather innovative tool to EU fishing policy makers so as to potentially redirect multispecies fisheries management. Taking advantage of the modern portfolio theory, we estimate a constrained global financial efficient frontier for the aggregated EU, as well as the respective constrained individual efficient frontier for each EU fishing country operating in the Atlantic Northeast (i.e. Belgium, Germany, Denmark, Spain, France, Ireland, the Netherlands, Portugal and the United Kingdom). Based on the related frontiers, we suggest an efficient reallocation of landings weights in order to increase returns and/or reduce risk coming from landings.

We have developed a feasible approach to manage downside uncertainty in fisheries management outcomes by the inclusion of a robust risk indicator, Conditional Value-at-Risk (CVaR). Up to date, to the best of our knowledge, this is the first study using CVaR in the financial fisheries economics literature. Our efficient portfolio proposals are based on historical landings data which incorporates changing ecological, economic, and regulatory factors. For the purpose of our study, we focus on three alternative constrained financial efficient frontiers (FEFs), namely, $\mathrm{EF}_{\mathrm{MAX}}$, $\mathrm{EF}_{\mathrm{MINMAX}}$ and $\mathrm{EF}_{\mathrm{MINTAC}}$. $\mathrm{EF}_{\mathrm{MAX}}$ includes an upper box constraint as the maximum observed weight to ensure that the proposed weights keep under sustainable solutions. Besides we are also including a sustainability parameter to observe how policy makers decisions would affect the potential reallocation of weights, and how portfolio's risk and return levels would change. $\mathrm{EF}_{\mathrm{MINMAX}}$ implies adding a minimum box constraint to the $\mathrm{EF}_{\mathrm{MAX}}$ model. Certainly, there are some fish species whose mean return may be negative, and accordingly, their risk level very high. Nevertheless, it would not be feasible to recommend zero catches of these risky fish species, because it would directly imply the closure of these fisheries, which might not be socio-economically sustainable. Thus, we ensure that our recommendation implies catching from each fish species at least the minimum observed proportion to total landings. Finally, the $\mathrm{EF}_{\mathrm{MINTAC}}$ frontier includes a new upper maximum constraint that measures the weight of the total allowable catches (TACs) as a percentage to total landings. With this new constraint, we have replaced the maximum observed weight by the TAC weight for the regulated fish species, and maintained the previous maximum observed constraint for the non-regulated ones. A priori the $\mathrm{EF}_{\mathrm{MINTAC}}$ will be our reference constrained financial efficient frontier, since the $\mathrm{EF}_{\mathrm{MINTAC}}$ best fits reality, keeps under regulatory limits and reveals a feasible reallocation of landings weights. However, comparing these three potential financial efficient frontiers ($\mathrm{EF}_{\mathrm{MAX}}$, $\mathrm{EF}_{\mathrm{MINMAX}}$ and $\mathrm{EF}_{\mathrm{MINTAC}}$) may be useful to observe how policy makers' decisions would affect the reallocation of landings weights, implying changes in both return and risk levels.

In order to do so, using the mean-CVaR optimization approach, we estimate an aggregate-level constrained financial efficient frontier (FEF) for the overall EU ($\mathrm{FEF}_{\mathrm{EU}}$) and also individual-level FEFs for the nine EU fishing countries operating in the North-East Atlantic. So as for the aggregate EU, depending on the managers' target return and risk tolerance, there are potential efficiency gains by moving from the observed portfolio of landings to the efficient minimum risk portfolio (MRP) or tangency portfolio (TP). If the objective is to minimise risk, then, we would suggest the minimum risk portfolio (MRP) to achieve a fish species distribution that increases mean return by +9%, and also reduces risk by -70%. Contrarily, if the aim is to maximize fish landings returns, then the tangency portfolio (TP) would be recommended, to achieve the maximum risk to reward of the portfolio. Accordingly, the overall EU mean return would be increased by +125% and risk reduced by -65%.

Regarding the individual country-based constrained efficient frontiers, we suggest an individualized reallocation of landings weights for each of the nine EU countries. This way, countries could achieve an efficient distribution of fish landings that increases or, at the worst, maintains constant the observed return, and significantly reduces the risk level. This way we are able to propose a redistribution of fish species weights and suggest how individual countries should increase or reduce landings of some fish species, under sustainable limits, in order to perform better. Following our proposals, Belgium could achieve a higher return (+181%) at a lower risk level (-34.02%), compared to the portfolio for the last observed landings weights. Ireland could increase return by +52.10% and reduce risk by -90.39%. The Netherlands could increase return by +240% and reduce risk by -61%. In the case of Portugal, it could be possible to achieve a higher return level (+11.92%) at a lower risk level (-57.13%). As a second-best strategy, we suggest maintaining the return level constant, but considerably reducing risk for Germany (-8.42%), Denmark (-33.41%), Spain (-39.65%), France (-97.98%) and United Kingdom (-40.28%). Summarising, all the countries could benefit by adopting mean-CVaR optimization approach as a tool to manage fisheries efficiently and account for species interactions.

Moreover, there may be potential gains from transferring quota rights between countries that would increase return and reduce risk, and thus increase the financial efficiency of fishing quotas. EU member-states are responsible of ensuring that fish species are not overfished above quota limitations. Whenever a country reaches the allowed quota, the European Commission allows them to manage and transfer quota limits during the year. Hence, special attention deserves the fact that countries would not only transfer catching rights, but also returns and risk. Therefore, these potential quota exchanges could be also considered when portfolio selection model is optimized. Furthermore, our proposal could imply different strategies depending on the country. There are some fish species catalogued as low return and high risk for some countries, which depending on their temporary performance are inversely catalogued as high return and low risk for others. That is the case of blue whiting, which is classified as a very high risk for all the countries except for France. Therefore, our suggestion implies increasing the proportion of the landed volume of blue whiting for France, while we recommend reducing it for Germany, Denmark, Spain, Ireland, the Netherlands and United Kingdom. Similarly, according to our efficient portfolio reweighting proposals, Spain and Portugal should increase their landed volume of albacore, while France should reduce it.

Overall, we have been able to achieve the objectives of this thesis. We have provided additional knowledge about the ongoing situation of the fisheries sector in the EU, and suggest new tools to be used as innovative, robust and efficient alternatives to account for fish species interactions, understand the biodiversity dynamics of the fish ecosystems and efficiently manage the fishing sector in the EU. However, this, we guess, is not more than a starting point. There are several ideas, topics and methods that are still to be explored in the future. Specifically, our future work is expected to turn in the next three directions.

(1) Using Modified Expected Shortfall (MES) and spawning stock biomass (SSB) as data, we have proxied the *biological risk (BR)* as a source of risk in the natural frame or ocean. Similarly, using MES and catches, we have measured the *production risk (PR)*, as a source of risk related to the fishing activity of the EU fishing fleets. We are conscious that selecting one risk indicator is not a trivial exercise since results may entirely depend on the choice. In this thesis the Modified Expected Shortfall has been selected as the most appropriate proxy for risk, since it is more robust to the non-normality of asset returns. Nevertheless, alternative risk indicators, such as Expectiles, may be a better approximation of risk (Abdous & Remillard, 1995; Newey & Powell, 1987; Waltrup et al., 2015). Indeed, Expectiles are suggested as the only elicitable, law-invariant and coherent risk measures (Bellini & Bignozzi, 2015; Chen et al., 2018; Ziegel, 2016). Besides, inference on Expectiles is much easier than the inference on quantiles, the available data is more efficiently used to make estimations and Expectiles are more sensitive to the magnitude of infrequent catastrophic losses (Daouia et al., 2018; Martin, 2014).

Accordingly, we intend to reformulate the constrained financial efficient frontier using Expectiles, which will require further software developments.

(2) Regarding the results coming from the Chapter 2, we have found that as far as the diversity of the ecosystem increases the risk also increases. This unexpected and paradoxical result is related to the combination of the country based targeted fish species distribution and certain species leadership, and of course, to the weighting scheme we are using to infer country based risk from the species level risk. The use of composite indicators could help to reduce these potential bias and ambiguities. Composite indicators (CIs) are increasingly being used to make comparisons among countries' performance in specific areas such as competitiveness, globalisation or innovation (see, for example, Bollen and Bauldry, 2011; Cherchye et al., 2007; Freudenberg, 2003; Grupp and Mogee, 2004; Saltelli, 2007). Rather than using a disaggregated set of individual indicators, CIs are constructed when individual indicators are arranged into a single index on the basis of an underlying model (Joint Research Centre et al., 2008). Composite indicators are useful to measure multi-dimensional concepts which hardly can be captured by a single indicator, to summarise complex realities, and to reduce the magnitude of a set of indicators (Saisana & Tarantola, 2002). Besides, CIs are easier to interpret and could be helpful to compare effectively the performance across member-states and their progress over the time. In fact, the use of composite indicators may help to better measure the weighted risk of each of the 23 EU fishing countries, which may affect our previous and unexpected positive correlation among risk and diversity.

(3) The adaptation of the modern portfolio theory and the efficient portfolio selection modelling for fisheries management in the EU has enabled us to observe how member-states have performed in the past, and how they could perform better in the future by reallocating their fish landings. We have suggested an efficient portfolio redistribution for each country in order to make them increase, or at least maintain, the observed return levels, and also, reduce risk. Similarly, these procedures could be applied to increase the efficiency of the aquaculture production in the EU. Aquaculture is here to stay. Aquaculture produced approximately 1.4 million tonnes (5.1 billion euros), it employed around 60,000 fishers (EUROSTAT, 2017), and it is a key factor of the Common Fisheries Policy (CFP) and the Blue Growth Agenda towards a sustainable growth in the sector (Hadjimichael, 2018; Lillebø et al., 2017). The aquaculture production volume represented 20% of the total output of the European fisheries, and about 40% of the value of the total production of fishery products in the EU (EUROSTAT, 2017). The major producer was Spain (23% of the EU), followed by the United Kingdom (16.4%), France (13.8%), Italy (11.4%) and Greece (9.2%). A sustainable management

in aquaculture should find reciprocity between food security, employment opportunities and the environmental costs of production (Radulescu et al., 2011). Accordingly, modern portfolio theory could give a wide branch of potential applications for aquaculture management, in order to make fish production more efficient by reallocating the target fish species, and achieve higher return at a lower risk level. Following Rădulescu et al. (2010), who applied the minimum risk portfolio model for a fish farm in Romania to obtain optimal fishing plans for six fish species, we could adapt the constrained financial efficient frontier to any particular EU fish farm or fish producing countries. This procedure could lead to an efficient advice on how should EU countries reallocate their production efforts in different fish species, and accordingly, favour the achievement of an efficient management of the aquaculture production.

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Appendix

Table 3.24: List of countries

Code	Country
BE	Belgium
DE	Germany
DK	Denmark
EL	Greece
ES	Spain
FI	Finland
FR	France
IE	Ireland
IT	Italy
NL	The Netherlands
PT	Portugal
SE	Sweden
UK	United Kingdom
EE	Estonia
LV	Latvia
LT	Lithuania
PL	Poland
BG	Bulgaria
HR	Croatia
CY	Cyprus
MT	Malta
RO	Romania
SI	Slovenia

Table 3.25: List of acronyms, abbreviations and units of measure

AIS	Automatic identification system
ANOVA	One-way analysis of variance
BP	Berger Parker
BR	Biological risk
CEF	Constrained Efficient Frontier
CFP	Common Fisheries Policy
CR	Concentration Ratio
CVaR	Conditional Value-at-Risk
CVaRSR	Conditional Sharpe Ratio
DIs	Diversity Indices
EBFM	Ecosystem-based fisheries management
EC	European Commission
EEA	European Environment Agency
EF	Efficient Frontier
EFCA	European Fisheries Control Agency
ERS	Electronic recording and reporting system
ES	Expected Shortfall
EUMOFA	EU Market Observatory for Fisheries and Aquaculture Products
EUROSTAT	European Statistical Office
EWP	Equally Weighted Portfolio
EX	Expectiles
FAO	Food & Agriculture Organization of the United Nations
FEF	Financial efficient frontier
FTE	Full-time equivalent
GDP	Gross Domestic Product
GT	Gross Tonnage
HC	Hierarchical Clustering
ICES	International Council for the Exploration of the Sea
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IUCN	International Union for Conservation of Nature
LO	Landing Obligation
MAGP	Multi-annual Guidance Programme
MPT	Modern Portfolio Theory

MRP	Minimum Risk Portfolio
MSY	Maximum Sustainable Yield
MVO	Mean-Variance Optimization
OECD	Organisation for Economic Co-operation and Development
PCA	Principal component analysis
PR	Production risk
PT	Portfolio Theory
RFMO	Regional Fisheries Management Organisation
RLTS	Red List of Threatened Species
SHA	Shannon Index
SIM	Simpson's Index
SR	Sharpe Ratio
SSB	Spawning Stock Biomass
STECF	Scientific, Technical and Economic Committee for Fisheries
TAC	Total Allowable Catch
TP	Tangency Portfolio
Tukey HSD	Tukey Honest Significant Differences
VaR	Value-at-Risk
VDS	Vessel detection system
VMS	Vessel monitoring system

Table 3.27: Fish species (English and scientific names)

CODE	Common Name	Scientific Name
ALB	Albacore	Thunnus alalung
ANE	European anchovy	Engraulis encrasicolu
ANF	Anglerfishes nei	Lophiida
BET	Bigeye tuna	Thunnus obesu
BIB	Pouting (Bib)	Trisopterus luscu
BLL	Brill	Scophthalmus rhombu
BOC	Boarfish	Capros ape
BOG	Bogue	Boops boop
BOR	Boarfishes nei	Caproida
BRB	Black seabream	Spondyliosoma cantharu
BSF	Black scabbardfish	Aphanopus carb

CODE	Common Name	Scientific Name
BSH	Blue shark	Prionace glauc
BSS	European seabass	Dicentrarchus labra
CAP	Capelin	Mallotus villous
CNZ	Crangon shrimps nei	Crangon sp
COC	Common edible cockle	Cerastoderma edul
COD	Atlantic cod	Gadus morhu
COE	European conger	Conger conge
CRE	Edible crab	Cancer paguru
CSH	Common shrimp	Crangon crango
CTC	Common cuttlefish	Sepia officinali
CTL	Cuttlefish, Bobtail squids, nei	Sepiidae, Sepiolidae
DAB	Common dab	Limanda limand
DGZ	Dogfishes nei	Squalus sp
FIN	Finfishes nei	Osteichthye
FLE	European flounder	Platichthys flesu
GAD	Gadiformes nei	Gadiforme
GHL	Greenland halibut	Reinhardtius hippoglossoide
GKL	Common European bittersweet	Glycymeris glycymeri
GRM	Patagonian grenadier	Macruronus magellanicu
GRO	Groundfishes nei	Osteichthye
GUR	Red gurnard	Chelidonichthys cuculu
GUU	Tub gurnard	Chelidonichthys lucern
HAD	Haddock	Melanogrammus aeglefinu
HER	Atlantic herring	Clupea harengu
HKE	European hake	Merluccius merlucciu
HKP	Argentine hake	Merluccius hubbs
HKX	Hakes nei	Merluccius sp
HOM	Atlantic horse mackerel	Trachurus trachuru
JAA	Blue jack mackerel	Trachurus picturatu
JAX	Jack and horse mackerels nei	Trachurus sp
LAH	North European kelp	Laminaria hyperbore
LEM	Lemon sole	Microstomus kit
LEZ	Megrims nei	Lepidorhombus sp
LIN	Ling	Molva molv
LQD	Tangle	Laminaria digitat

CODE	Common Name	Scientific Name
MAC	Atlantic mackerel	Scomber scombru
MAZ	Scomber mackerels nei	Scomber sp
MEG	Megrim	Lepidorhombus whiffiagoni
MNZ	Monkfishes nei	Lophius sp
MOL	Marine molluscs nei	Mollusc
MON	Angler (Monk)	Lophius piscatoriu
MUR	Surmullet	Mullus surmuletu
MUS	Blue mussel	Mytilus eduli
NEP	Norway lobster	Nephrops norvegicu
NOP	Norway pout	Trisopterus esmarki
NOX	Antarctic rockcods,Noties, nei	Nototheniidae
OCC	Common octopus	Octopus vulgari
OCT	Octopuses etc, nei	Octopodidae
PAT	Longtail Southern cod	Patagonotothen ramsay
PEL	Pelagic fishes nei	Osteichthye
PIL	European pilchard (Sardine)	Sardina pilchardu
PLE	European plaice	Pleuronectes platess
POA	Atlantic pomfret	Brama bram
POK	Saithe (Pollock)	Pollachius viren
POL	Pollack	Pollachius pollachiu
PRC	Percoids nei	Percoide
QSC	Queen scallop	Chlamys operculari
REB	Beaked redfish	Sebastes mentell
RED	Atlantic redfishes nei	Sebastes sp
RJC	Thornback ray	Raja clavat
RJH	Blonde ray	Raja brachyur
RJN	Cuckoo ray	Raja naevu
SAA	Round sardinella	Sardinella aurit
SAN	Sandeels (Sandlances) nei	Ammodytes sp
SBA	Axillary seabream	Pagellus acarn
SBR	Blackspot(red) seabream	Pagellus bogarave
SCE	Great Atlantic scallop	Pecten maximu
SCL	Catsharks,Nursehounds, nei	Scyliorhinus spp
SCR	Spinous spider crab	Maja squinad
SDV	Smooth-hounds nei	Mustelus sp

CODE	Common Name	Scientific Name
SKA	Raja rays nei	Raja sp
SKJ	Skipjack tuna	Katsuwonus pelami
SOL	Common sole	Solea sole
SPR	European sprat	Sprattus sprattu
SQA	Argentine shortfin squid	Illex argentinu
SQC	Common squids nei	Loligo sp
SQI	Northern shortfin squid	Illex illecebrosu
SQP	Patagonian squid	Loligo gah
SQZ	Inshore squids nei	Loliginida
SWO	Swordfish	Xiphias gladiu
SWX	Seaweeds nei	Alga
SYC	Small-spotted catshark	Scyliorhinus canicul
TUN	Tunas nei	Thunnin
TUR	Turbot	Psetta maxim
ULO	Solid surf clam	Spisula solid
VMA	Atlantic chub mackerel	Scomber colia
WHB	Blue whiting (Poutassou)	Micromesistius poutasso
WHE	Whelk	Buccinum undatu
WHG	Whiting	Merlangius merlangu
YFT	Yellowfin tuna	Thunnus albacare