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Measuring left-tail risk of fish species

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ABSTRACT

The main objective of this paper is to perform a risk analysis for the key commercial fish species in the FAO area 27 by means of a bundle of financial left-tail risk indicators, including Value-at-Risk (VaR), Expected Shortfall (ES) and Expectiles (EX), and panel data of catches (Q_{it}) to measure the *left-tail risk of catches* (LTR_i); an empirical and probabilistic measure of the worst-case reduction of catches resulting from huge negative shocks. LTR_i can be useful, not only to classify the fish species according to their risk level, but also, using the appropriate weights, to infer the risk to any other aggregation level such as fleet, fishing community or fishing country. In this paper, we are employing our species level (LTR_i) estimations to calculate the left-tail risk of catches of the EU fishing countries (LTR_j), a country level proxy variable for the risk inherent to the fishing activity itself.

1. Introduction

Fisheries need long run strategies, management tools and transdisciplinary indicators to achieve required biological and environmental targets (Sainsbury et al., 2000; Hilborn, 2007; Espinoza-Tenorio et al., 2013), and avoid short-run myopic behaviours that can drive to unsustainable harvest levels (Botsford et al., 1997; Larkin et al., 2011), break-even profits and social disrupts in fisheries dependent communities. This need for governance strategies that, at the same time, account for social, economic and ecological goals have encouraged scholars to call for the ecosystem-based fisheries management (EBFM) as an approach to sustainably develop the fishing activity, targeting both, human and ecosystem well-being (Pikitch et al., 2004; Garcia and Cochrane, 2005; Long et al., 2015; Link and Browman, 2017). Undoubtedly, a better understanding of the marine ecosystem functioning (Rosenfeld, 2002; Curtin and Prellezo, 2010) and the dynamics of past collapses could help to detect early warning signs (Jackson et al., 2001; Mullon et al., 2005), to predict the vulnerability of fish species before their population collapses (Worm et al., 2006; Sala and Knowlton, 2006), to improve forecasting capacity (Hobday et al., 2016; Farmer et al., 2019), and to overcome uncertainty and risk related issues (Rosenberg and Restrepo, 1994; Hoos et al., 2019).

Effective decision-making in the framework of fisheries policy is specifically complex due to the uncertainty surrounding the measurement of the abundance of fish stocks, their expected dynamic evolution, and the lack of reliable and synthetic indicators measurable with conventional fisheries data (Pelletier et al., 2005; Claudet et al., 2006). Marine scientists already provide several ecological indicators accessible from different databases, which aim to summarise the status of individual fish species. For instance, FishBase (Froese and Pauly, 2018) includes vulnerability and resilience of fish species, and The Red List of Threatened Species index of the International Union for Conservation of Nature (IUCN) (IUCN, 2018) 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, there are many missing species, and besides, some of the key indicators are just qualitative. The lack of quantitative information, as well as the exclusion of a number of species, advocates investigating on additional indicators that might help to foresight the risk of shocks in particular fishing areas and ecosystems. Moreover, there is an increasing demand for precise scientific information to improve the quantification of risk in order to guide individuals and policy makers' decisions, and help agent's expectations formation (Link et al., 2015; Libralato et al., 2019; Fulton, 2021).

Depending on the specific field, the concept of risk is open to multiple interpretations and formulations. While some disciplines base their definition of risk on probabilities or expected values, other areas conceptualize risk as an undesirable event or danger dealing with uncertainties (Aven, 2012). For the purpose of this paper, we are identifying risk with *a possibility of a bad or undesired outcome happening* (Fox, 1999; Wagner, 2010; Sethi, 2010). Thus, risk involves variability of catches, uncertainty and loss related to the fishing activity itself. More precisely, taking advantage of the domain of finances, risk is defined as the expected loss of benefits from the fish stocks in terms of the returns

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of the catches, which are often used as a proxy variable of the revenues in fisheries (Rosenberg and Restrepo, 1994). Certainly, instead of the volume of catches, we could also use the value of such catches. However, adding prices involves a bundle of supplementary source of risk, because, not only the supply itself, but also many factors influence on fish prices (i.e. environmental change, fish quality, fish size, water pollution, location, days spent on storage, etc.). Besides, to some extent, it is reasonable to assume that local fisheries are price takers (Crona et al., 2016; Rosales et al., 2017).

Regarding the measurement risk, there is not a clear consensus about the most appropriate risk indicator to proxy risk, and frequently, the choice is guided by an empirical perspective. Moreover, designing and quantifying risk presents its own hazards (Barrieu and Scandolo, 2015). In certain cases, financial practitioners measure risk as the probability of shortfall below a benchmark level of return, while in other occasions, they are more concerned with the overall magnitude of the loss (McNeil et al., 2015; Kratz et al., 2018; Novales and Garcia-Jorcano, 2019; Bignozzi et al., 2020). Despite the simple variance of the returns has been widely used as a proxy for risk, the last world financial crises (2008) turned the attention to downside risk measures (Bali et al., 2009; Huang et al., 2012; Hammoudeh et al., 2013; Almahdi and Yang, 2017). Semivariance is one of the most popular downside risk indicator, because, since it measures the dispersion of the observations that fall below the mean or target value of the assets, it is consistent with the intuitive perception of risk for investors. Nevertheless, when investors are especially scared of incurring extreme losses and are averse to deviations below a certain threshold, left-tail risk indicators (henceforth LTRs) constitute a better estimation of risk than variance or semivariance (Miller and Reuer, 1996; Gundel and Weber, 2007; Zhu et al., 2009; Shah and Ando, 2015). LTRs focus on severe downside events, estimating the impact of rare but significant big negative shocks (on catches), that is, the worst-case loss.

Among the LTRs, Value-at-Risk (VaR) (Jorion, 1997, 2001) became the most popular and widely used indicator since its adoption in 1996 by the Basel Committee on Banking Supervision (Basel, 1996). Afterwards, due to the lack of some key properties (such as coherence, subadditivity and the fact that VaR ignores losses in the far tail of the loss distribution (Artzner et al., 1999; Krokhmal, 2007; Chen and Wang, 2008)), in 2013 Basel III (2013) they recommended replacing VaR by the Expected Shortfall (ES) (Rockafellar et al., 2000; Rockafellar and Uryasev, 2002). ES is coherent and quantifies tail risk, but it fails the elicitability property deemed essential to backtesting (Ziegel, 2016) and depends excessively on the extreme tail of the returns distribution (Jadhav et al., 2013). Accordingly, some authors advocate for the use of Expectiles (EX) to measure risk (EX) as a coherent and elicitable alternative to VaR and ES (Waltrup et al., 2015; Bellini and Di Bernardino, 2017; Chen et al., 2018).

In the fisheries framework, LTRs are also more appropriate to measure risk (Charles, 1983; Fock et al., 2011; Alvarez et al., 2017; Lopetegui and del Valle, 2020). Notice that any positive deviation would imply more catches, which, obviously, is not *a bad or undesired outcome,* as we have defined risk. Since there is not a definite theoretical financial risk indicator to measure risk, we will determine the one that best fits our data; to quantitatively measure the left-tail risk of catches (LTR_i) for the key fish species ($i = 1,..,49$) in the target area (FAO area 27). LTR_i measures the worst-case loss on the volume of catches, based on the negative severe reduction on catches occurred in the past. For instance, if species $i = 1$ gets the highest risk level ($LTR_1 = 1$), in the worst case, its catches would be reduced by 100%, or if $LTR_2 = 0$ for species $i = 2$, then, in the worst case the catches of species $i = 2$ would remain constant (0% change). Accordingly, species 1 may be catalogued as a *very high-risk* fish species (since it has already suffered a severe yearly decline on catches in the past), while species 2 would be a *low-risk* fish species (since its catches have always increased or, at least, remained constant in the past).

This way, we contribute to the literature twofold. On the one hand, providing an innovative way of measuring the risk of fish species quantitatively, deriving the taxonomy of individual fish species, and complementing the existing species level conventional vulnerability indicators. On the other, LTR_i can be easily inferred to any aggregation level by using the appropriate weights, so as to measure the overall left-tail risk of catches of a country, region, community, fleet or fishing area, and to compare their risk patterns. Specifically, using our estimation of species-level risk ($LTR_{i,}$) and the country-level catches as weights (w_{ijt}), we derive the country-based left-tail risk of catches (LTR_{jt}) for each of the ($j = 1, \ldots,15$) EU fishing countries operating in the FAO area 27. This way, if for example, a country ($j = 1$) gets the highest risk level ($LTR_1 = 1$), in the worst case, the catches of such country would be reduced by 100%. Contrarily, if for country ($j = 2$) $LTR_2 = 0$, then, in the worst case the catches of country $j = 2$ would remain constant (0% change).The former ($j = 1$) would be a country operating with a *very high-risk*, while the latter ($j = 2$) will be catalogued as a *low-risk* country. Thus, our analysis will help to classify, not only individual fish species according to their inherent risk, but also EU fishing countries from low to very high risk ones. This may be useful to identify similar risk patterns and potential country specific diversification strategies by means of reducing catches of certain risky fish species and targeting low-risk ones. Additionally, special attention will be paid on checking whether there are potential differences between the LTR patterns of EU fishing countries by means of parametric and not parametric tests such as ANOVA and Kruskal Wallis.

The remainder of this paper is organised as follows. After this introduction, Section 2, focuses on describing the fishing area or ecosystem of the analysis, the data and methods used, including an overview of financial left-tail risk indicators. Section 3 summarises the major empirical findings made in this section, Section 4 adds some discussion points and Section 5 concludes with a summary of the major points made in the paper.

2. Material and methods

2.1. Study area

Our fish species risk analysis focuses on the species subject to stock assessment in the FAO area 27, including North-East Atlantic and adjacent waters (North Sea, Baltic Sea, Skagerrak, Kattegat, West of Scotland Sea, Irish Sea and Celtic Sea) (see Fig. 1), the major fishing ground in the EU with around 75% of the fish catches (EUROSTAT, 2019). Therefore, we proxy our target fishing ecosystem, for now on Ω, as the group of the 49 fish species subject to analytic stock assessments (the full list of the species in the analysis may be found in Table 1).

In order to estimate LTR_i we are using panel data of fish catches (Q_{it}) $\{Q_{it}: i = 1, \ldots,49; t = 2000, \ldots,2018:1\}$ (data accessed from EUROSTAT (2020)).[1] To obtain the aggregated catches of Ω we are summing up the catches of the 15 fishing EU member-states operating in the target area (i.e. Belgium, Denmark, Estonia, Finland, France, Germany, Ireland, Latvia, Lithuania, Poland, Portugal, Spain, Sweden, The Netherlands and United Kingdom[2]). Notice that to get aggregate catches by species in Ω we are not including EU fishing countries such as, Greece, Italy, Malta, Bulgaria, Croatia, Cyprus, Romania or Slovenia, because their fishing grounds are not within our target fishing area.

2.2. Methods

We are following a 3-steps procedure to get country-based left-tail risk estimations (LTR_{jt}) from the species level LTR_i. 1) Firstly, we

[1] Time horizon (2000–2018) is limited to available data, due to the presence of many missing values in 2019.

[2] Even if the UK is no longer part of the EU, it was part of the EU during the period analysed (2000–2018).

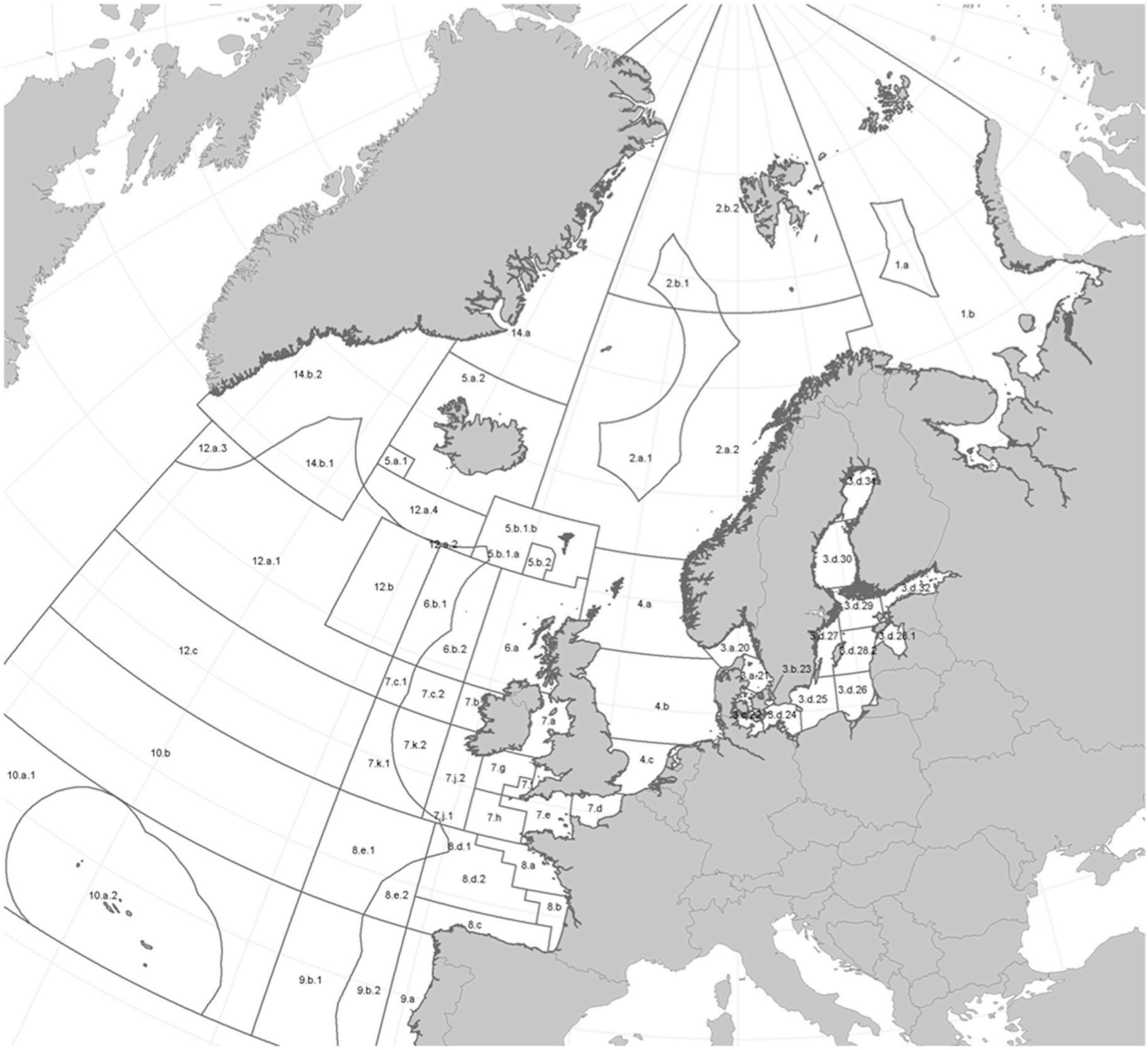

Fig. 1. FAO area 27.
Source: ICES (2019).

Table 1
Shapiro-Wilk normality test: returns (R_{it}).

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

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

measure individual fish species returns (R_{it}) using each species catches (Q_{it}) as input data, and analyse the distributional properties of such returns in order to empirically preselect the LTR that best fits our real data. 2) Secondly, we measure LTR_i of each fish species using alternative LTRs. 3) Thirdly, using the proportion of the catches of each individual fish species (i) in each country (j) and year (t) as weights (w_{ijt}), from the species-level risk measure (LTR_i), we infer the country-level risk (LTR_{jt}) of the EU fishing countries operating in Ω.

2.2.1. *Step 1: estimating species returns (R_{it})*

Firstly, using the geometric rate of the catches (Q_{it}) we measure the returns (R_{it}) of each (i = 1, …,49) species in Ω (1). R_{it} measures the yearly catches increase or reduction for each fish species. Returns will be positive ($R_{it}>0$) when catches increase, and negative ($R_{it}<0$) when they decrease. Fishers, following their expectations about future gains (positive returns) or losses (negative returns) and their related risk,[3] decide whether to target or not a specific species.

$$R_{it} = \ln\frac{Q_{it}}{Q_{it-1}} = \ln Q_{it} - \ln Q_{it-1} \tag{1}$$

where Q_{it} are the yearly (t) aggregated catches of the i fish species in Ω.

A common practice before calculating the risk of the returns is to analyse the distribution of R_{it} in order to identify possible fluctuations, non-normal distribution, skewness and/or kurtosis that might bias the risk measure (Rachev et al., 2005; Bali et al., 2008; You and Daigler, 2010). Hence, the best strategy is to choose the most accurate risk indicators based on the real data of the particular fishing area.

2.2.2. *Step 2: estimating species-level risk*

Secondly, we measure the risk of R_{it} using five alternative LTRs, namely, Value-at-Risk (VaR) (2), the Modified Value-at-Risk (MVaR) (a robust version of VaR) (3), the Expected Shortfall (ES) (4), the Modified

[3] In general, there is a negative tradeoff between the expected returns and the risk of the assets. Higher expected returns assume more risk, and, contrarily, lower expected returns are associated with lower risk.

Expected Shortfall (MES) (a robust version of ES) (5) and the Expectiles (EX) (6). Depending on the distribution of R_{it}, the most appropriate risk indicator will be proposed so as to proxy the left-tail risk of catches (LTR_i). Special attention will be paid on the potential ambiguities among the different risk measures in order to select, joint with the empirical distributional properties of R_{it}, the best financial risk formulation to proxy LTR_i, and derive the taxonomy of individual fish species based on their estimated risk.

Value-at-Risk (VaR)[4] (2) is the most popular LTR, mainly because it brings simplicity, wide applicability and universality (Jorion, 1997). VaR measures the worst expected loss over a given horizon under normal conditions at a given level of confidence (Jorion, 2001), that is to say, the worst-case loss or negative return ($R_{it}<0$).

$$VaR_{\alpha}(R_{it}) = -q_{\alpha}(R_{it}) \tag{2}$$

where α is the confidence level $\alpha\varepsilon(0,1)$ and q_α is the α-quantile of the return (R_{it}) distribution (Emmer et al., 2015). The so called *Modified VaR (MVaR)* (3), a robust version of VaR, is more appropriate when returns are not normally distributed, because it adjusts the standard deviation to account for skewness and kurtosis in the return distribution (Favre and Galeano, 2002) using the Cornish Fisher expansion method (Cornish and Fisher, 1938) by

$$MVaR_{\alpha}(R_{it}) = \mu(R_{it}) + \sigma(R_{it})q_{CF,\alpha} \tag{3}$$

where α is the confidence level of the MVaR, μ is the potential rate of drift of returns (R_{it}), σ is the standard deviation and $q_{CF,\alpha}$[5] is the Cornish Fisher approximation of the α quantile of the distribution.

Expected Shortfall (ES) (4) (Rockafellar and Uryasev, 2000; Rockafellar and Uryasev, 2002)[6] is the mean worst-case loss beyond VaR, that is to say, the average worst-case loss (Emmer et al., 2015), and it is calculated by averaging all the returns in the distribution that are worse than VaR.

$$ES_{\alpha}(R_{it}) = -E[R_{it} | -R_{it} \geq VaR_{\alpha}(R_{it})] \tag{4}$$

where α is the confidence level and R_{it} the returns. ES is a better alternative to VaR, because it is sensitive to the severity of losses (negative returns ($R_{it}<0$)) in the far tail of the R_{it} distribution. 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 and Tasche, 2002). As it is in the case of Modified VaR, *Modified Expected Shortfall (MES)* (5) is suggested as a robust version of ES. MES is the mean loss (negative return ($R_{it}<0$)) between the VaR at α-quantile and the α(1-α^a)-quantile of the worst cases of R_{it}, eliminating the non-frequent and exceptionally very negative returns above the α(1-α^a)-quantile by

$$MES_{(\alpha,a)}(R_{it}) = -E[R_{it} | -q_{\alpha(1-\alpha^a)}(R_{it}) \geq -R_{it} \geq VaR_{\alpha}(R_{it})] \tag{5}$$

where α is the confidence level, R_{it} the returns, and $a\geq 0$ is a specified number. 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 (Boudt et al., 2008; Jadhav et al., 2013; Jadhav and Ramanathan, 2019).

Expectiles (EX) (6) were introduced by Newey and Powell (1987) and have been suggested by the union of 'expectation' and 'quantiles' (Emmer et al., 2015). EX is similar to quantiles but is determined by tail expectations rather than tail probabilities.

$$EX_{\tau}(R_{it}) = \underset{R\varepsilon\mathbb{R}}{\operatorname{argmin}}\,\tau\mathbb{E}\left[(R_{it}-q)_{+}^{2} + (1-\tau)\mathbb{E}(R_{it}-q)_{-}^{2}\right] \tag{6}$$

where $q_+ = \max(q,0)$ and $q_- = \max(-q,0)$ are the left and right quantiles, R_{it} the returns and $\tau\varepsilon(0,1)$ is the asymmetry parameter as an *index of prudentiality* (Kuan et al., 2009). EX weight negative deviations by (1-τ) and positive deviations by τ, providing information about the symmetry of the distribution of R_{it}. When $\tau = 0.5$, $EX_\tau = [\ R_{it}]$, therefore, EX can be interpreted as an asymmetric generalisation of the mean.

We use R_{it} (1) coming from the previous step to measure the LTR_i of each of the (i) fish species in Ω, employing the above-mentioned five LTRs. In order to make the five risk indicators comparable, in the case of $VaR_\alpha(R_{it})$ it is usual to choose 99% confidence level ($\alpha = 0.01$) (Basel, 1996); the latest revisions of the Basel III (2013) suggests $\alpha = 0.025$ for $ES_\alpha(R_{it})$; and asymmetry parameter $\tau = 0.00145$ is suggested for $EX_\tau(R_{it})$ (Bellini and Di Bernardino, 2017). The underlying idea is to compare alternative risk indicators without changing the resulting value of the left-tail risk (worst-case loss ($R_{it}<0$)), thus, following Bellini and Di Bernardino (2017), $VaR_{0.01}(R_{it}) \simeq MVaR_{0.01}(R_{it}) \simeq ES_{0.025}(R_{it}) \simeq MES_{0.025}(R_{it}) \simeq EX_{0.00145}(R_{it})$.

All of our five risk indicators (VaR, MVaR, ES, MES and EX) range from 0 to 1. Accordingly, the lowest left-tail risk of catches ($LTR_i = 0$) would imply that, in the worst case, R_{it} (i.e. the yearly change on Q_{it} of the fish species (i)) would be zero. That is to say, catches (Q_{it}) would remain constant. An intermediate left-tail risk of catches level ($LTR_i = 0.5$) would indicate that in the worst case, the Q_{it} of the fish species (i) would be reduced by 50%. The highest left-tail risk of catches ($LTR_i = 1$) implies that in the worst case, the Q_{it} would be reduced by 100%.

Risk measures may be ambiguous depending on the formulation of the risk indicator used. Although all the five risk indicators we are focusing on (i.e. VaR (2), MVaR (3), ES (4), MES (5) and EX (6)) are theoretically consistent, however, as we will show later in subsection 3.1, MES will be found to be the most accurate and preventive risk indicator based on the specific distributional characteristics of our returns (1). Since MES reflects the effect of not frequent but important disturbances on returns (R_{it}), it helps to identify ambiguities among different indicators. Therefore, even we are measuring the five left-tail risk indicators, MES will be the reference one to proxy LTR_i, and to infer the country-level risk.

2.2.3. Step 3: From species-level risk to country-level risk

So as to get the country-level left-tail risk of catches (LTR_{jt}) for each of the 15 EU fishing countries (j = Belgium, Denmark, Estonia, Finland, France, Germany, Ireland, Latvia, Lithuania, Poland, Portugal, Spain, Sweden, The Netherlands and United Kingdom), first, we calculate the weights (w_{ijt}). w_{ijt} measure the proportion of each (i) fish species' volume of catches to the total catches of the (j) country; Afterwards, using w_{ijt}, we infer the country-level left-tail risk of catches (LTR_{jt}), multiplying the corresponding w_{ijt} by the individual species-level left-tail risk of catches (LTR_i). Accordingly, the resulting LTR_{jt} would be: $LTR_{jt} = \sum w_{ijt} LTR_i$ ($i = 1,\ldots,49; j = 1,\ldots,15;\ t = 2000,\ldots,2018$). Notice that, our procedure could be easily carried out using data coming from other fishing areas.

3. Results

3.1. Species-level risk indicators

Catches' returns (R_{it}) exhibit a rather heterogeneous return distribution depending on the species. Some of the species, such as common dab and lemon sole, exhibit very stable catches in the period of analysis (close to zero R_{it}), whereas others, such as beaked redfish and Norway pout, are subject to major fluctuations. Notice that very high and positive R_{it} imply that the yearly catches for these species have increased, while contrarily, negative R_{it} involve yearly reduction on the catches. We can expect that some of the species (such as common sole and

[4] VaR is commonly known as Historical VaR (HVaR).

[5] $q_{CF,\alpha} = q_\alpha + \frac{1}{6}(q_\alpha^2 - 1)S(R_{it}) + \frac{1}{24}(q_\alpha^3 - 3q_\alpha)K(R_{it}) - \frac{1}{36}(2q_\alpha^3 - 5q_\alpha)S^2(R_{it})$ where q_α is the α quantile of a standard normal distribution, S (R_{it}) is the standardized skewness of the returns (R_{it}) and K(R_{it}) is the excess kurtosis of R_{it}.

[6] ES is commonly known as Historical ES, average VaR, Conditional VaR (CVaR), or tail conditional expectation.

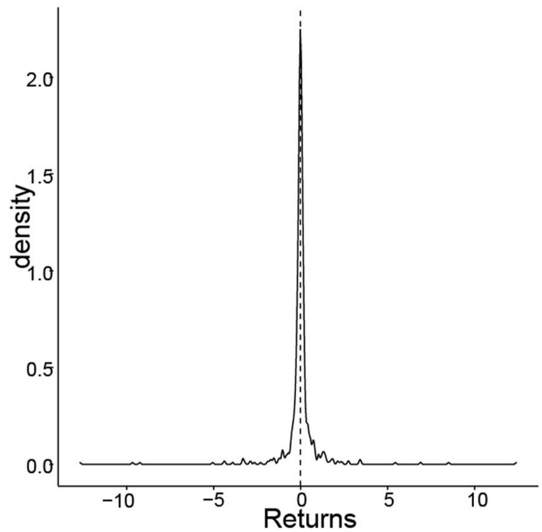

Fig. 2. Returns (R_{it}) density plot.

Norway lobster) will be associated to *low left-tail risk of catches* and others (such as Norway pout and sandeels) to *very high left-tail risk of catches*. Fig. 2 shows the density plot for R_{it} distribution. We can observe that although is rather symmetric, it is more peaked than the normal distribution and the shape of the tails does not correspond to a normal. Additionally, we have checked by the Shapiro-Wilk test whether our R_{it} are normally distributed. Shapiro-Wilk testing results (Table 1) show that the R_{it} are indeed not normally distributed.

We are taking advantage of the R package *PerformanceAnalytics* (Peterson and Carl, 2019) and *expectreg* (Sobotka et al., 2014) to estimate VaR (2), MVaR (3), ES (4), MES (5) and EX (6) so as to proxy LTR_i of each i species based on R_{it} (1). Table 2 shows the left-tail risk of catches (LTR_i) estimates for each species (i = 1, …,49) in Ω. According to MES, the average left-tail risk of catches of the species in the fishing area Ω is 0.65. This means that, in the worst case, and due to the risk related to factors influencing the fishing activity, the catches in Ω would be reduced by 65%. Even that the resulting overall classification of the fish species is rather stable, there are however some noticeable particularities. Special attention should be paid on some species, such as blonde ray, thornback ray and anglerfishes nei, which could be catalogued as *ambiguous* species. Even their VaR, MVaR, ES and EX values are relatively low, MES catalogues these species as *very high-risk* species.

These results support that it is always recommendable to measure different risk measures to afterwards, based on the empirical distributions of the returns and potential ambiguities among alternative indicators, choose the reference risk indicator to be used in each case study. For the purpose of this paper, there are several reasons to focus on MES to proxy species-level left-tail risk of catches (LTR_i). On the one hand, (the same as MVaR) MES is more appropriate under non-normality of returns. Besides, MES reflects the effect of not frequent but important disturbances on returns that makes its risk value higher. Additionally, MES is capable of appropriately measuring the risk of the fish species showing an *ambiguous* behaviour. In fact, for some species (i.e. blonde ray, European hake and Atlantic mackerel for example), MES values are significantly higher than the rest of the risk indicators, because such indicators (i.e. VaR, MVaR, ES and EX) may miscommunicate the actual risk when the returns exhibit huge breakdowns. That is the main reason why in the field of finances MES is often proposed as the best robust and coherent risk indicator, which is also able to account for these huge breakdowns and consequently, quantify the authentic risk (Jadhav et al., 2013). Hence, based on our empirical findings, we focus on MES to proxy species-level left-tail risk of catches as a measure of the average worst-case loss (severe reduction) on catches. Based on MES, the *low-risk* fish species (lowest LTR_i) are Turbot ($LTR_{TUR} = 0.17$) and European plaice ($LTR_{PLE} = 0.19$). On the contrary, European anchovy ($LTR_{ANE} = 1$), blackbellied angler ($LTR_{ANF} = 1$) and sandeels ($LTR_{SAN} = 1$), are some of the *very high-risk* fish species (highest LTR_i).

Table 2
Left-tail risk of catches (LTR_i).

	Left-tail risk of catches (LTR_i)						Left-tail risk of catches (LTR_i)				
Species	VaR	MVaR	ES	**MES**	EX	Species	VaR	MVaR	ES	**MES**	EX
European anchovy	1	1	1	1	1	Atlantic mackerel	0.26	0.2	0.28	0.65	0.28
Anglerfishes nei	0.96	0.48	1	1	1	Smooth hounds nei	0.45	0.54	0.5	0.54	0.49
Blackbellied angler	1	1	1	1	1	Northern prawn	0.41	0.46	0.43	0.48	0.42
Greater argentine	1	1	1	1	1	European sprat	0.36	0.4	0.38	0.47	0.37
Boarfish	1	1	1	1	1	Nursehound	0.29	0.41	0.3	0.46	0.29
Capelin	1	1	1	1	1	Ling	0.38	0.44	0.41	0.45	0.4
Four spot megrim	1	1	1	1	1	European seabass	0.33	0.4	0.34	0.4	0.34
Megrim	1	1	1	1	1	Spotted ray	0.5	0.4	0.57	0.4	0.55
Angler	1	1	1	1	1	European flounder	0.32	0.36	0.34	0.39	0.33
Norway pout	1	1	1	1	1	Haddock	0.32	0.37	0.34	0.37	0.34
Rays and skates nei	1	1	1	1	1	Atlantic horse mackerel	0.31	0.37	0.32	0.37	0.31
Beaked redfish	1	1	1	1	1	Saithe	0.22	0.29	0.23	0.31	0.22
Golden redfish	1	1	1	1	1	Megrims nei	0.23	0.26	0.25	0.3	0.24
Blonde ray	0.08	0	0.09	1	0.08	Small spotted catshark	0.25	0.29	0.26	0.29	0.26
Cuckoo ray	1	1	1	1	1	Atlantic herring	0.17	0.2	0.18	0.27	0.18
Sandeels	1	1	1	1	1	Atlantic cod	0.2	0.26	0.21	0.26	0.2
Blackmouth catshark	1	1	1	1	1	Whiting	0.2	0.26	0.21	0.26	0.21
Blue whiting	1	1	1	1	1	Sardine	0.19	0.24	0.19	0.24	0.19
Surmullet	0.49	0.63	0.5	0.97	0.49	Common dab	0.2	0.23	0.21	0.23	0.21
Thornback ray	0.15	0.1	0.16	0.85	0.16	Norway lobster	0.14	0.15	0.15	0.23	0.15
Lemon sole	0.44	0.5	0.49	0.82	0.48	Brill	0.17	0.19	0.19	0.21	0.18
Blue ling	0.7	0.79	0.74	0.79	0.73	Common sole	0.13	0.14	0.14	0.2	0.13
European hake	0.43	0.48	0.47	0.78	0.46	European plaice	0.15	0.19	0.16	0.19	0.15
Greenland halibut	0.53	0.71	0.54	0.71	0.52	Turbot	0.14	0.17	0.16	0.17	0.15
Tusk	0.41	0.36	0.44	0.69	0.43	Average risk	0.54	0.56	0.55	**0.65**	0.55

Notes.
Value-at-Risk (VaR), Modified Value-at-Risk (MVaR), Expected Shortfall (ES), Modified Expected Shortfall (MES), Expectiles (EX). LTR_i values range from low (zero) to very high (one) risk. The lowest left-tail risk of catches ($LTR_i = 0$) denotes that in the worst case, the catches of the species (i) would keep constant. On the contrary, the maximum left-tail risk of catches ($LTR_i = 1$) implies that in the worst case, the catches of the fish species (i), would be reduced by 100%.

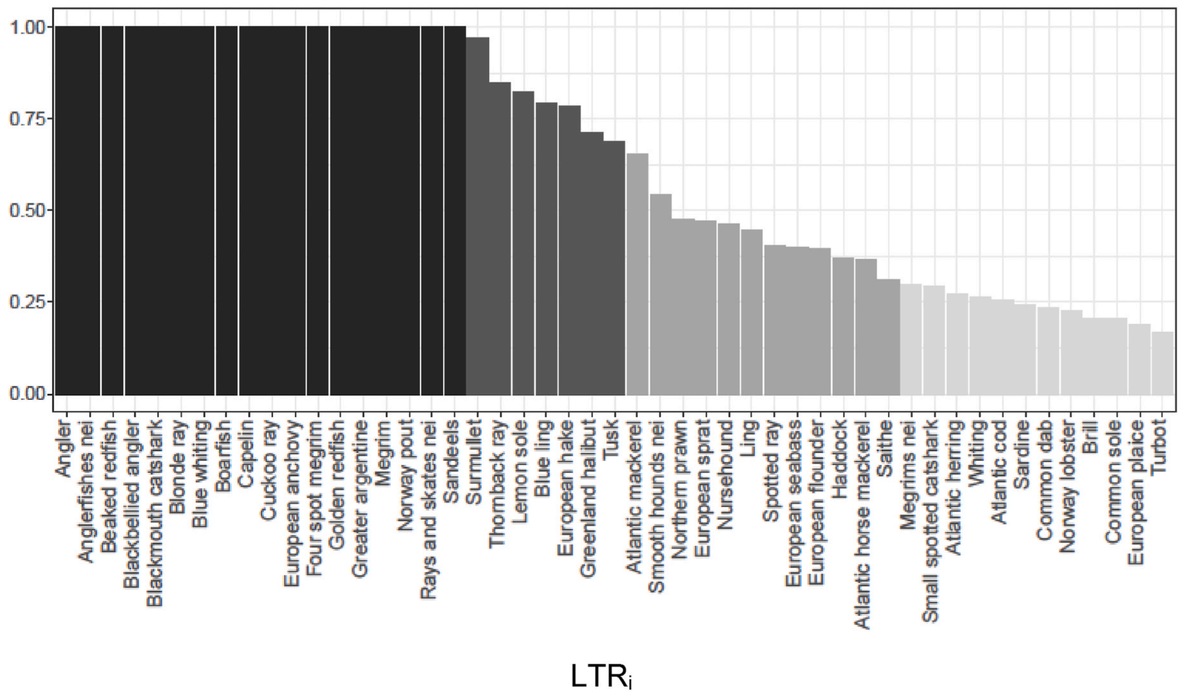

Fig. 3. Bar plot for the left-tail risk of catches by fish species (LTR_i).
Notes.Bar plot for the left-tail risk of catches by fish species (LTR_i) according to MES (Table 2). Bars are displayed from the highest risk ($LTR_i = 1$) to the lowest ($LTR_i = 0.17$). Colours represent quartiles: very high risk (Q4) in black, moderate high risk (Q3) in dark grey, moderate low risk (Q2) in grey, low risk (Q1) in light grey.

Summarising, we have estimated the left-tail risk of catches (LTR_i) (based on Q_{it}) at fish species level, using a bundle of five left-tail financial risk indicators (i.e. VaR, MVaR, ES, MES and EX). Due to the non-normality of the distribution of returns (R_{it}) 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 LTR_i (Table 2 and Fig. 3).

3.2. From species-level to country-level financial risk indicators

Based on our species-level risk indicator (LTR_i), and using the proportion of the catches of each country to the total catches as weights (w_{ijt}), we have inferred the country-based left-tail risk of catches (LTR_{jt}) for the 15 EU fishing countries operating in the target area Ω. We have divided the resulting LTR_{jt} into four quartiles to classify the EU fishing countries as *low-risk* (Q1), *moderate-risk* (Q2), *high-risk* (Q3), and *very high-risk* (Q4) (Table 3 and Fig. 4). Even our results[7] have a panel structure containing the country-based risk for each of the countries and years, due to space limitations, Table 3 only shows the average risks by country, as well as the standard deviation (σ), the coefficient of variation (CV) and the quartile (Q). Additionally, we are showing the multi-panel graphs and the notched box plots for the country-based left-tail risk of catches (LTR_{jt}) for the concerned period (t) and country (j) in Figs. 5 and 6.

The average country level left-tail risk of catches (LTR_j) is 0.45; this means that in the worst case, the catches would be reduced by 45%. Denmark, Spain, Ireland and United Kingdom are the countries with the highest average country-based LTR_j. Accordingly, in the worst case, the volume of catches would be reduced by 64% in Denmark, 62% in Spain, 56% in Ireland and 51% in United Kingdom. Contrarily, Belgium and Finland are lowest-risk countries ($LTR_{Belgium} = 0.31$, $LTR_{Finland} = 0.30$).

EU fishing countries operating in Ω exhibit rather heterogeneous left-tail risk of catches patterns (see panel graphs for the estimated risk in Fig. 5). In fact, Denmark ($LTR_{Denmark} = 0.64$) and Spain ($LTR_{Spain} = 0.62$) are the countries facing the highest average left-tail risk of catches. Nevertheless, focusing on the temporal path, whereas the Spanish LTR_{jt} is rather stable oscillating between 0.58 and 0.68, the Danish LTR_{jt} presents much more variability. The LTR_{jt} in Denmark reached the highest value (0.77) in 2002 and declined several times over the period until it reached 0.49 the last year. The case of Portugal is also remarkable, since it is the country facing the highest increasing trend, from 0.31 to 0.56. The Portuguese LTR_{jt} evolution implies that Portugal is

Table 3
Average country-based left-tail risk of catches (LTR_j).

	LTR_j	Q	σ	CV
Denmark	0.64	Q4	0.08	13%
Spain	0.62	Q4	0.04	6%
Ireland	0.56	Q4	0.04	7%
United Kingdom	0.51	Q4	0.02	4%
The Netherlands	0.47	Q3	0.05	10%
France	0.46	Q3	0.03	6%
Lithuania	0.46	Q3	0.05	11%
Germany	0.45	Q2	0.03	6%
Sweden	0.44	Q2	0.06	13%
Poland	0.40	Q2	0.02	4%
Latvia	0.39	Q2	0.01	4%
Estonia	0.39	Q1	0.01	4%
Portugal	0.37	Q1	0.07	20%
Belgium	0.31	Q1	0.04	13%
Finland	0.30	Q1	0.01	4%
Average risk	0.45			

Notes.
Average country-based left-tail risk of catches (LTR_j).
Quartiles (Q) = Q1: low-risk, Q2: moderate-risk, Q3: high-risk, Q4: very high-risk.
σ is the standard deviation and CV is the coefficient of variation.

[7] Detailed panel data including yearly LTR_{jt} results available upon request.

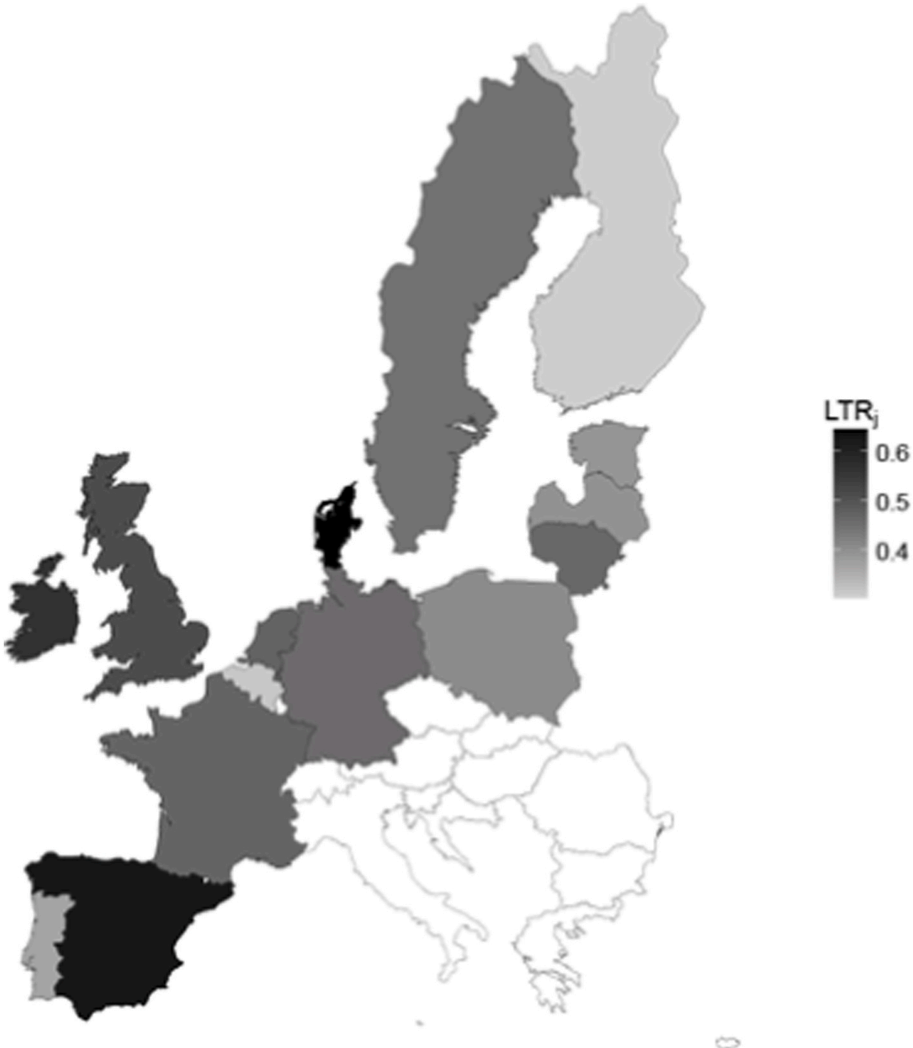

Fig. 4. Mapped country-based left-tail risk of catches (LTR_j).
Notes.Mapped average left-tail risk of catches by EU countries (LTR_j) (Table 3). Colours represent the LTR_j from the highest risk ($LTR_{Denmark} = 0.64$) in black to the lowest risk ($LTR_{Finland} = 0.30$) in light grey.

targeting more risky fish species than in the past.[8] Contrarily, Latvia, Poland, Finland and Estonia are the countries with the most stable LTR_{jt}. Accordingly, not only the average risk but also the variability of the left-tail risk of catches (LTR_{jt}) matters.

Summarising, the EU fishing countries facing *very high-risk* (Q4) are Denmark, Spain, Ireland and United Kingdom. Even the LTR_{jt} of Denmark and Spain is significantly different (not overlapping box plots) and higher to the Irish and British ones (see Fig. 6). The *high-risk* countries (Q3) are The Netherlands, France and Lithuania. Germany, Sweden, Poland and Latvia are *moderate-risk* (Q2) countries, although differences between Q3 and Q2 countries are not clearly noticeable. Finally, Estonia, Portugal, Belgium and Finland are *low-risk* countries (Q1).

For completeness, we have also tested if these apparent differences among countries and/or time are significant through one-way analysis of variance (ANOVA)[9] using the *plm* package in R (Croissant and Millo, 2018). 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 left-tail risk of catches (LTR_{jt}) is normally distributed, and by Levene's test whether the variance across countries/time is significantly different. Shapiro-Wilk testing results (Table 4) show that the LTR_{jt} is indeed not normally distributed. Besides, Levene's test results (Table 4) reveal that the variance across countries is significantly different for their concerned risk. 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

[8] In 2000, it was sardine the most caught fish species in Portugal, which has a relatively low risk ($LTR_{PIL} = 0.24$), followed by Atlantic horse mackerel ($LTR_{HOM} = 0.37$) and Atlantic cod ($LTR_{PIL} = 0.26$). However, the distribution of the catches in Portugal changed over the time. Atlantic horse mackerel became the most caught fish species in 2017 and 2018, followed by sardine and European anchovy ($LTR_{ANE} = 1$), which is one of the most risky fish species in the target area Ω.

[9] 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 implies that there are significant differences between groups.

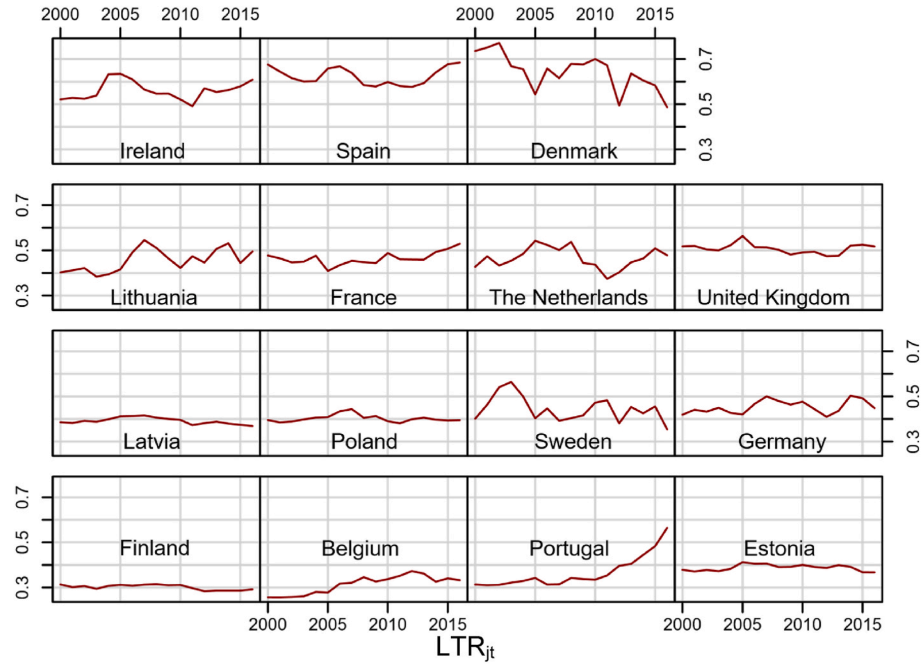

Fig. 5. Multi-panel graph for the country-based left-tail risk of catches (LTR_{jt}). Notes.Country-based left-tail risk of catches (LTR_{jt}) by country (j) and year (t).

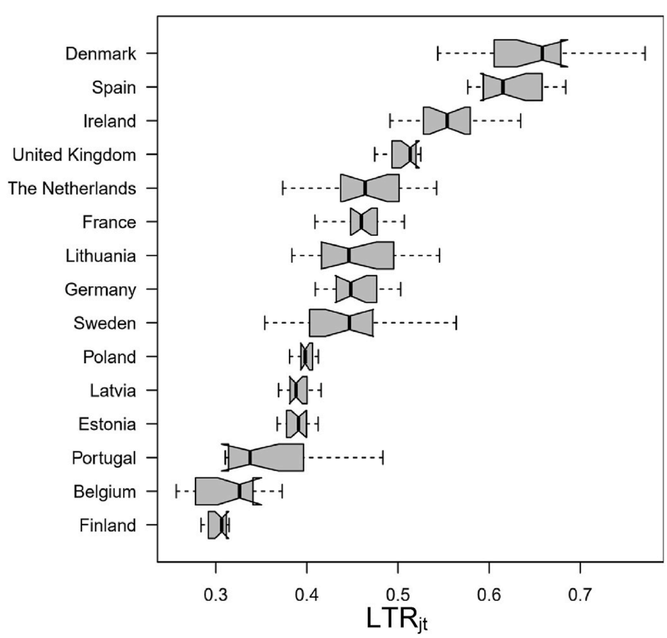

Fig. 6. Notched box plots for the country-based left-tail risk of catches (LTR_{jt}). Notes.Notched box plots for the country-based left-tail risk of catches (LTR_{jt}). Notched box plots display a confidence interval around the median (McGill et al., 1978) and are useful to compare groups of countries. If the notches of two boxes do not overlap this is 'strong evidence' their medians differ (Chambers, 2018).

approximation to check whether these apparent differences on LTR_{jt} between countries and/or time are significant.

ANOVA results (Table 5) show that there are significant differences in the mean LTR_{jt} among the countries, while, these differences do not change significantly over time. Kruskal-Wallis rank sum test results (Table 5) corroborate the ANOVA ones. Thus, it can be definitely concluded that EU fishing countries operating in Ω are facing significantly different risk levels, but their risk does not significantly change over time.

Table 4
Shapiro-Wilk normality and Levene's tests.

	Shapiro-Wilk		Levene's	
	W	P-value	F-value	P-value
Country	0.9579	8.992E-07	5.0777	2.524 E−08***
Year	0.97141	5.366E-05	0.3227	0.9943

Notes.
Shapiro-Wilk normality test and Levene's homogeneity of variances test for the left-tail risk of catches (LTR_{jt}) by country and year.
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 5
ANOVA and Kruskal-Wallis tests.

	ANOVA		Kruskal-Wallis	
	F-value	P-value	χ 2	P-value
Country	94	(<2e-16)***	214.69	(<2.2e-16)***
Year	0.274	0.601	3.9737	0.9989

Notes.
One-way analysis of variance (ANOVA) and Kruskal-Wallis rank sum test (non-parametric alternative to ANOVA test) for the left-tail risk of catches (LTR_{jt}) by country and year.
P-values: *** significant at 1%, ** significant at 5%, * significant at 10%.

We have complemented the guess coming from the notched box plots with Tukey HSD[10] test to analyse pairings between similar countries (Table 6). Tukey results confirm that Spain and Denmark comprise the group of the two *highest risk* countries. Ireland and the United Kingdom are also *very high-risk* countries, but their risk patterns are completely different from the rest of the countries. The group of the five *moderately*

[10] 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.

Table 6
Tukey multiple pairwise-comparisons test.

	DK	ES	IE	UK	NL	FR	LT	DE	SE	PL	LV	EE	PT	BE
Denmark (DK)														
Spain (ES)	***													
Ireland (IE)														
United Kingdom (UK)														
The Netherlands (NL)														
France (FR)					***									
Lithuania (LT)					***	***								
Germany (DE)					***	***	***							
Sweden (SE)					**	**	***	***						
Poland (PL)														
Latvia (LV)										***				
Estonia (EE)										***	***			
Portugal (PT)											*	**		
Belgium (BE)														
Finland (FI)														***

Notes.
Pairwise-comparison for the left-tail risk of catches (LTR_{jt}). Blank means there are statistically significant differences between the left-tail risk of catches of the countries, *** not significant differences at 99%, ** not significant differences at 95% and * not significant differences at 90%.

high-risk countries is comprised by The Netherlands, France, Lithuania, Germany and Sweden. Poland, Latvia and Estonia constitute the group of the three *moderately low-risk* countries. Portuguese risk level is *low* and rather similar to the Estonian and Latvian one. Finally, Belgium and Finland constitute the group of the two *lowest-risk* countries.

4. Discussion

The difficulties to design effective conservation strategies to manage fish stocks sustainably encourages an increasing demand for indicators and methods to get a better understanding of the vulnerability of fish species and ecosystems, so as to program preventive actions to increase their resilience. Fisheries management may be controversial when the conservation goals and the vulnerability of fish species are not properly defined. Certainly, due to the complexity to measure vulnerability of fish species and the difficulties to provide quantitative scores, the information given by conventional ecological indicators is to some extent limited. Some of these indicators, such as resilience and vulnerability (FishBase, Froese and Pauly (2018)) or conservation status (Red List of Threatened Species (RLTS), IUCN (2018)), are in essence qualitative indicators, and besides, many species are not still included.

Thus, there is a global need of vulnerability indices to improve foresighting capacity to develop effective and sustainable management tools to steer the implementation of ecosystem-based fisheries management. Obtaining a classification of the fish species based on their inherent risk is beneficial to reduce uncertainty of fisheries and, potentially, apply them to prediction models. Moreover, expectations could be generated through these models, which could also favour the improvement of fisher's outcomes. Therefore, inspired by the field of finances, we propose a new species-level synthetic vulnerability indicator, namely the left-tail risk of catches. This indicator aims to complement the species level vulnerability measures in FishBase (Froese and Pauly, 2018) and IUCN (IUCN, 2018), and could be used to infer the overall vulnerability of different ecosystems. Specifically, based on the left-tail risk of catches of the species in the FAO area 27 (Ω) we measure the left-tail risk of the EU fishing countries operating in the target area.

The paper provides managers and decision-makers with a tool that can be used to evaluate the inherent risk of the fish species, and accordingly measure the weighted risk of a fishing country, region, fleet or any other concerned aggregation level. Our results could facilitate the design of the establishment of quotas and, even, generate relevant information for the fishing companies themselves, which could evaluate their basket of catches in the same way that a financial investor builds its optimal portfolio of securities. Notice that, whenever policy makers establish fishing quotas, they are not only deciding catching rights but also assigning a certain level of risk. This way, based on our species' left-tail risk of catches (LTR_i) we could derive the risk of the fishing TAC and quotas, and accordingly, the risk of the overall portfolio of the quotas for each of the EU fishing countries. Thus, any change in quotas can be directly measured in terms of risk. This direct and immediate method for deriving the risk to any aggregation level opens up a wide range of opportunities to measure the policy implications affecting, first, the risk of the countries/regions/fleets/companies; second the risk changes over the time; and third, the inherent risk of potential quota transfers among countries.

There are three major considerations in analysing and interpreting our results. First, we are conscious that selecting one risk indicator is not a trivial exercise, since results may entirely depend on the choice. In this paper, the Modified Expected Shortfall (MES) has been selected as the most appropriate proxy for risk, since it is more robust to the non-normality of returns. Nevertheless, alternative risk indicators, such as Expectiles, may be a better approximation of risk (Newey and Powell, 1987; Abdous and Remillard, 1995; Waltrup et al., 2015). Indeed, Expectiles are suggested as the only elicitable, law-invariant and coherent risk measures (Bellini and Bignozzi, 2015; Ziegel, 2016; Chen et al., 2018). Besides, inference on Expectiles is much easier than the inference on quantiles, the use of available data is more efficient to make estimations and Expectiles are more sensitive to the magnitude of infrequent catastrophic losses (Martin, 2014; Daouia et al., 2018). Alternative selection of different but appropriate indicators as a proxy for risk could be useful to highlight how the selection of the risk indicator affects the classification of the fish species and fishing countries.

Second, risk is a concept that entirely depends on the time horizon of the analysis, which may significantly condition the taxonomy of species. For example, we found that Atlantic herring is a low-risk fish species ($LTR_{HER} = 0.27$). In fact, Atlantic herring represents the 19% of the total catches in the EU on average (EUROSTAT, 2020), which have been relatively stable during the last two decades. Nevertheless, Atlantic herring stocks in the FAO area 27 collapsed in the 70s and the volume of catches declined from 2 million tons in 1966 to 20 thousand tons in 1971 (Sigurdsson, 2006). A change in the time horizon from the period (2000–2018) to (1970–2018) would surely imply different results. Certainly, it is commonly reiterated in the literature that extending the time period increases robustness (Pesaran and Timmermann, 1995; De Nicolao et al., 1996; Malagon et al., 2015). Nevertheless, this may not necessarily hold when measuring the risk of the fish species, because capturing severe but remote shocks might not be currently realistic. Therefore, the inclusion of a decay factor could be useful to adjust the presence of these improbable and negative events in the distant past by giving more emphasis to recent negative shocks.

Third, results also depend on the data availability. This case study focuses on the period 2000–2018, since previous data regarding catches is not available on Eurostat. Selecting the optimal period would be a different but complementary case study. If previous data were available, we could address a multi-horizon approach to observe how risk patterns may change over different time periods. In fact, this methodology could be easily replicated using previous or different data. This extension would be important because risk measures related to past collapses may be certainly different depending on the period within the time horizon. This way, species such as Atlantic herring, which is considered a low-risk fish species nowadays, would be probably identified as very-high risk in previous periods. After all, the procedure of measuring risk could be carried out selecting different and/or longer periods in order to observe how the selection of the time horizon affects the taxonomy of species in terms of their left-tail risk.

5. Concluding remarks

Our approach to estimate fish species-level risk contributes to the literature providing an innovative perspective of measuring fish vulnerabilities through the application of five left-tail financial risk indicators, including the Value-at-Risk, Modified Value-at-Risk, Expected Shortfall, Modified Expected Shortfall, and Expectiles. Using catches (Q_{it}) as data, the species-level left-tail risk of catches (LTR_i) is a proxy for the risk related to the fishing activity itself, that is to say, the worst-case loss/reduction on the volume of fish caught based on negative severe reduction on catches in the past. 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 the five risk indicators we focus on are theoretically consistent, however, Modified Expected Shortfall (MES) was the most accurate and preventive risk indicator based on the specific distributional characteristics of our data.

Obtaining primarily species-level risk indicators is essential to classify fish species and later infer to whatever the aggregation level and fishing area. Based on the period (2000–2018) the average left tail risk of the catches in the FAO area 27 is 0.65. This means that in the worst-case, the catches would be reduced by 65%. The riskiest fish species are European anchovy ($LTR_{ANE} = 1$), blackbellied angler ($LTR_{ANF} = 1$) and blue whiting ($LTR_{WHB} = 1$), while the low-risk ones (lowest LTR_i) are turbot ($LTR_{TUR} = 0.17$), European plaice ($LTR_{PLE} = 0.19$) and common sole ($LTR_{SOL} = 0.20$). Additionally, our species level synthetic risk indicators may be also employed to infer the risk of any other aggregation level by choosing the appropriate weights (following step 3 in subsection 2.2.), so as to, for example, estimate the inherent risk level of a fishing community, fishing region or fleet segment. We have estimated the risk for each of the 15 EU fishing countries inferring from the previous species-level risk analysis and using country specific catches by species as individual weights.

The country-level risk estimations reveal that the EU fishing countries subject to the highest country-based left-tail risk of catches (quartile 4), are Denmark, Spain, Ireland and United Kingdom, the high-risk ones (quartile 3) are The Netherlands, France and Lithuania; the countries facing a moderate-risk (quartile 2) are Germany, Sweden, Poland and Latvia; while the low-risk ones (quartile 1) are Estonia, Portugal, Belgium and Finland. In fact, based on ANOVA and Kruskal-Wallis tests, the left-tail risk of fish catches is significantly different among EU fishing countries whereas their risk does not significantly change over time. These significant differences among countries entirely depend on the risk of the key leading fish species. Certainly, there are some countries such as Spain, in which the most captured fish species are risky fish species (i.e. European anchovy ($LTR_{ANE} = 1$), European hake ($LTR_{HKE} = 0.78$) and Atlantic mackerel ($LTR_{MAC} = 0.65$)). Whereas in other countries such as Finland, the catches are heavily concentrated (around 90%) in just one very-low risk fish species (i.e. Atlantic herring ($LTR_{HER} = 0.27$)). Therefore, not only the risk of individual fish species matters, but also the distribution of the catches on each of the countries will definitely determine the overall risk on these countries.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Itsaso Lopetegui reports a relationship with Dpto. de Educación, Política Lingüística y Cultura del Gobierno Vasco through Beca Predoctoral de Formación de Personal Investigador no Doctor and research grant EGONLABUR from the same department that includes: funding grants. Ikerne del Valle reports a relationship with Spanish Ministry of Economics and Competitiveness. Project Ref RTI2018-099225-B-I00 that includes: funding grants.

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