PERSISTENCE AND SUSTAINABILITY OF FISHING GROUNDS FOOTPRINT: EVIDENCE FROM 89 COUNTRIES

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ABSTRACT

This paper focusses on the examination of the fishing ground footprint in a group of 89 countries using fractional integration. The fishing ground footprint is one of the components of the ecological footprint. Nevertheless, it has not been investigated very much from an empirical viewpoint. We contribute to the existing literature on fishing ground footprint by using fractional integration techniques to examine the persistence of the series. Our results are very heterogeneous across countries though we find that most of the series are nonstationary and non-mean reverting, with most of the countries belonging to the upper-middle and high income levels. On the other hand, most of the 14.4% of countries that show a stationary pattern belong to lower-middle and low income countries. One of the implications of the study is that policies aimed at reducing fishing grounds footprint are likely to be effective in most of the investigated countries.

Keywords: Fishing ground footprint; long memory; persistence; fractional integration

JEL Classification: C22; Q56

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1. Introduction

Billions of people around the world - particularly the world's poorest- depend on the fisheries and aquaculture sectors for incomes, jobs, livelihoods and different types of goods and services. Fisheries and aquaculture alone provided about 3.2 billion persons with about one-fifth of their average intake of per capita of animal protein (Food and Agriculture Organization, 2018), assure the livelihoods of 10%-12% of the world's population (WWF Living Planet Report, 2018) and almost 0.2 billion people rely on coral reefs to shield them from waves and storm surges (WWF Living Planet Report, 2018). Nevertheless, some of the important habitats that strengthen ocean productivity and health are experiencing decline. Overfishing as well as plastic pollution are posing threats to the oceans, while habitat destruction and fragmentation have generated disastrous drops in biodiversity of freshwater.

Since 1961 the yearly growth in fish consumption is double the growth of humanity in the globe. The production of fish reached an all-time peak of 171 million tonnes in 2016 and 88% of the production was used for direct human consumption. The production achieved in 2016 translated into a record peak consumption per capita of more than 20 kilograms (Food and Agriculture Organization, 2018). A freshwater living planet index shows an 83% decline since 1970 (WWF Living Planet Report, 2018). To maintain the productivity and health of fisheries, fish stocks must be sustained within biologically sustainable levels. This is because overfishing not only decreases food production, but also harms the functioning of ecosystems and decreases biodiversity, with adverse consequences for the society and economy (United Nations Development Programme, 2019). Overfishing converts an initially stable, efficient and mature ecosystem into one that is stressed and immature. This occurs in numerous ways. By targeting and reducing the abundance of high-value predators, fisheries severely change the trophic chain and the biomass (and energy) flows within the ecosystem. They can also change habitats, particularly by harming and disturbing bottom topography and the related habitats (e.g. seagrass and algal beds, coral reefs) and benthic communities (Food and Agriculture Organisation. 2020)..

Thus, it is essential to employ relevant tools that assess the extent at which humanity's demand exceeds or remains within the bounds of what the water's natural capital can allow, and to identify early warning signs as well as to project the effects of mankind-driven pressures on the water ecosystems (Moldan et. al., 2012). One such tool is the fishing grounds footprint, which is one of the elements of the ecological footprint[1]. The fishing grounds footprint is the demand for inland and marine water ecosystems needed to support aquaculture as well as to restock the harvested seafood. Fishing grounds footprint is related to sustainable development in many ways. Biodiversity (which is an essential component of sustainability) loss is caused by numerous factors including fishing grounds footprint (Bilgili et al., 2020). Besides, the 14th Sustainable Development Goal includes the conservation and sustainable usage of marine resources, oceans, and seas for sustainable development.

Although the fishing grounds footprint is not the most significant part of the ecological footprint but it is showing a rising trend. In 1961-2016, the fishing footprint (in global hectares) increased by more than 80% (Global Footprint Network, 2019). Several features of the fishing grounds footprint are yet to be sufficiently assessed by the existing papers, such as the nonstationarity of the variable.[2] There are many benefits

[1] The other components of the ecological footprint are the grazing land, carbon footprint, cropland, built-up-land and forest products footprints.

[2] Stationarity is a statistical concept. A process is regarded as covariance (or second order) stationary if the mean as well as the variance are not reliant on time, and the covariance between any two points only relies on the distance between them. This is often regarded as a minimum criterion for statistical inference in time series analysis.

associated with knowing whether the fishing grounds footprint is following a stationary pattern or a nonstationary trend.

First, the presence of nonstationarity implies that policy shocks to the fishing grounds footprint resulting from the utilization of technologies and innovations that lower the impact of fishing activities on nature will be permanent (McKitrick, 2007). An example of such technologies is the vessel monitoring system, which has been introduced in several EU countries.[3] Moreover, the Magnuson–Stevens Fishery Conservation and Management Reauthorization Act of 2006[4] in the U.S. which, among other functions, is to ensure conservation of fishery resources and protect essential fish habitats. On the other hand, stationarity of fishing grounds footprint connotes that policy shocks to the series will have temporary effects.

A second benefit is that from an econometric viewpoint, the presence of unit roots in fishing grounds footprint series has important consequences for the environmental Kuznets curve (EKC) studies that have employed the fishing grounds footprint as a proxy for environmental degradation. Some EKC studies have assumed that there is trend stationarity in the pollution indicators (Sidneva and Zivot, 2014; Solarin et al., 2019a). Nevertheless, an EKC paper that utilizes a nonstationary fishing grounds footprint series (as the regressand) without differencing it while the explanatory series such as income or output are also nonstationary, is likely to produce spurious and thus invalid results (Granger and Newbold, 1974). In other words, statistical methods such as the ordinary least squares (OLS) method that are premised on the assumption that all the variables under investigation do not contain unit roots could produce spurious regression inferences, if the time series for pollution indices are nonstationary and have a stochastic

[3] The vessel monitoring system (VMS) is a satellite-based device which observes the projection, location and speed of fishing vessels (Jennings et al., 2012).
[4] It was initially introduced in 1976 but has been revised several times over the years.

trend. Thus, the conventional diagnostic tests which are used to interpret the results will indicate a statistically significant relationship among the series in the regression when there is no link in the data-generating processes (Hendry and Juselius, 2000).

Third, distinguishing between difference and trend stationary processes is essential for gauging the prospective long term impact of environmental blueprints, which are dependent on the projection of prospective pollution and assessing the accuracy of these projections. For both stationary and nonstationary series, the long term projections are the inferred deterministic trend. Uncertainty in forecasting a nonstationary series rises as the time horizon of the forecasts rises. On the other hand, series that are stationary are not affected by forecast uncertainty. Thus, the long term effects of a policy are more unambiguous when the variables under investigation are stationary and mean-reverting than when they are nonstationary (Gil-Alana and Solarin, 2018). Fourth, if the series of fishing grounds footprints are difference stationary, there is no chance of convergence between them and thus any suggestion of convergence on the relative fishing grounds footprint is at best weak (Strazicich et al., 2004).

Very few works have been done on the persistence of the fishing grounds footprint (Ulucak and Lin, 2017; Yilanci et al., 2019), whereas the literature is dominated by the papers on the persistence of CO_2 emissions (Christidou et al., 2013; Barros et al., 2016; Belbute and Pereira, 2017) and the ecological footprint (Solarin and Bello, 2018; and Ozcan et al., 2019). The trend that the ecological footprint has followed over the years is quite different from the trend that has been observed for the fishing grounds footprint (Global Footprint Network, 2019). Moreover, the main driver of the ecological footprint is the carbon footprint and not the fishing grounds footprint. Therefore, it might be inaccurate to state that inference made for the aggregate ecological footprint will be applicable for all its components, especially the fishing grounds footprint.

The objective of this research is to add to the literature on the nonstationarity of pollution indices in two distinct ways. It first investigates the stationarity of the fishing grounds footprint in 89 nations, which can potentially provide new information on a series that has been virtually overlooked in the extant literature. Although Ulucak and Lin (2017) and Yilanci et al. (2019) considered the fishing grounds footprint, their emphasis was on the economies of the US as well as the OECD. The characteristics of fishing grounds footprints differ across nations, and thus blueprints that are suitable for the US or the OECD may not essentially be appropriate for other nations. Therefore, the empirical findings from the present paper can potentially serve as direction to several nations on whether their policymakers should introduce new environmental policies aimed at decreasing their fishing grounds footprint or let the domestic dynamics of these nations to automatically tackle any upsurge in the fishing grounds footprint. The other addition to the literature is the utilisation of fractional integration methods which, according to the information available to the authors, has not been adequately utilised in the extant literature to investigate stationarity of the ecological footprint or its components. The only exception is the paper of Solarin et al. (2019a) but this paper focussed on the carbon footprint. Fractional integration is a technique that outperforms other more classical methods like those based on unit roots in the sense that allows for fractional degrees of differentiation, unlike the unit root models where the order of integration is 0 for stationary series and 1 for nonstationary ones. This flexibility allows us to consider nonstationary series where the shocks are still mean reverting though with long lasting effects.

2. Literature review

Numerous papers have investigated the different aspects of the footprints of fishing grounds including their trend (Swartz et al., 2010; Pitcher and Cheung, 2013; Kroodsma et al., 2018). The economic impact of the fishing grounds footprint has been investigated in the existing literature and it has been shown that developing countries are more affected by its consequences (Jennings et al., 2012; Clark and Longo, 2019). The factors affecting fishing grounds footprint have been studied and it has been shown that economic growth and population are the main drivers in the fishing grounds footprint (Clark and Longo, 2019).

However, the investigation of the persistence of fishing grounds footprint is very limited in the literature. Instead, there are studies on the persistence of related environmental indices including CO_2 emissions, the ecological footprint and the carbon footprint.[5] Employing a non-linear test, Christidou et al. (2013) provided support for stationarity of CO_2 emissions in 33 countries for the 1870–2006 period. Yamazaki et al. (2014) used a method that provide for breakpoints to show that CO_2 emissions per capita in OECD countries have unit roots. Barros et al. (2016) utilised a fractional integration approach to examine the stochastic behaviour of CO_2 emissions. The empirical findings signify that the series have orders of integration higher than one. Using a similar method, Belbute and Pereira (2017) stated, however, that CO_2 emissions are mean reverting and stationary.

The studies that have been dedicated exclusively to the persistence of the ecological footprint include Solarin and Bello (2018) that focussed on 128 countries for the period 1961–2013. Using both linear and nonlinear approaches, the overall results

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[5] There are also studies that have focused on the convergence of these series. A detailed literature survey on the CO_2 emissions convergence has been conducted by Acar et al., (2018). Moreover, Bilgili and Ulucak, (2018). Ulucak and Apergis (2018), Haider and Akram (2019) and Solarin et al. (2019b) have considered the convergence of either ecological footprint.

show evidence of nonstationarity in 81% of the sample of 96 countries. Conversely, Ozcan et al. (2019) used different tests including the Sequential Panel Selection Method (SPSM) to examine the nonstationarity of the series in 113 countries over the 1961-2013 period. The results show that there is stationarity (nonstationarity) in high-income countries (lower middle-income economies) and mixed results for the other income groups. In the sole study on the persistence of the carbon footprint that is noted in the literature, Solarin et al. (2019a) concentrated on a group of 92 countries. Using fractional integration, the empirical findings suggest that only 27% of the countries have mean reverting carbon footprint and most of these countries fall under low-income and lower middle income categories.

Among the few studies that have included fishing grounds footprint in their work we can mention Ulucak and Lin (2017) who focused on the time series properties of the ecological footprints and its components inclusive of the fishing grounds footprint in the US. Utilising Fourier unit root tests, they observe that the ecological footprint, as well as the fishing grounds footprint are nonstationary. Yilanci et al. (2019) used a panel stationary test with both smooth and sharp breaks to examine the time series properties of the ecological footprint and its six components in 25 OECD economies for the 1961–2013 period. The empirical findings suggest that the footprint of fishing grounds is nonstationary.

3. Methodology

3.1 Fishing footprint and dataset

The fishing grounds footprint is computed by normalising the quantity of primary production consumed by species in the aquatic ecosystem during its lifetime by an estimate of the harvestable primary production per hectare of marine area. The harvestable primary production is calculated based on a worldwide estimate of the sustainable catch of numerous species in the aquatic ecosystem. These sustainable catch figures are converted into primary production equivalents, and divided by the entire area of continental shelf. (Global Footprint Network, 2019). The four categories of activities included in the computation of fishing grounds footprint are marine capture (which is related to the fishing activities in oceans and seas of the world but landed in a country), inland capture (which is related to fishing operations taking place in freshwater), fish in livestock (fish meal used in livestock feed mixes), and commodities (trade in many derived fish products). The fishing grounds footprint includes all wild caught fish and production through aquaculture. [6] [7]

The fishing grounds footprint of consumption of a country, symbolised by EF_C in equation (1) can be computed by respectively subtracting and adding exports and imports of fishing grounds footprint from a country's primary fishing grounds footprint of production as follows:

$$EF_c = EF_p + (EF_m - EF_x). \tag{1}$$

where EF_p is the fishing grounds footprint of production, which include all marine and inland fish species that are landed in the country. The total footprint of production is calculated by summing only the footprint of production of primary products (marine and inland captures only) in order to circumvent double counting. EF_M represents fishing grounds footprint of imports of both fish in livestock and commodities EF_X stand for

[6] In the Global Footprint Network (2019), about 1,941 marine and freshwater species including invertebrates, fish, aquatic plants and mammals production are tracked.

[7] The yields for fish catches are computed by estimating the quantity of primary production needed, given the trophic level. This computation incorporates only the raw primary production that is available to feed marine consumers, and not the dynamics of specific marine species stocks. This approach might overvalue the existing biocapacity of fisheries each year if certain fisheries stocks are eroding or degrading over time at the species level. (Global Footprint Network, 2019).

ecological footprint of exports of both fish in livestock and commodities. The latter captures footprint of products that are produced domestically but exported while the former is embodied in locally consumed but imported products. In order to calculate the fishing grounds footprint of production, the following equation has been used:

$$EF_P = \frac{Q \times Y_F \times EY_F \times IY}{Y_N}, \tag{2}$$

where Q is all marine and inland fish species that are landed in the country in metric tonnes per year; Y_N is the yield from fishing extraction measured in metric tonnes on national average hectares per year; Y_F is the yield factor for fishing grounds in national-average hectares; EY_F is the equivalence yield factor of a fishing grounds measured in global hectares of World average hectares; IY is the intertemporal yield factor for fishing grounds.

$$EF_M = \frac{M}{Y_W}, \tag{3}$$

where M is imports and Y_W is the yield from fishing extraction measured in metric tonnes on world average hectares per year.

$$EF_X = \frac{X}{Y_N} \tag{4}$$

where X is exports.

EF_C is finally divided by the country's population to obtain the fishing grounds footprint per capita that is used in the econometric analysis.

We extracted the yearly dataset of fishing grounds footprints in per capita global hectares from the website of the Global Footprint Network (2019). We have considered 89 nations and the world-level dataset for the 1961 to 2016 period as they are the countries with available datasets for the whole period. Table 1 contains the abbreviation of the countries' names.

3.2 Method

We examine the statistical properties of the series and, in particular, its stationary/nonstationary behaviour by using a long memory model based on fractional integration. Thus, the number of differences required in the series to become I(0) stationary is a real value and may include fractional numbers.[8] For the empirical application, we consider the following regression model,

$$y_t = \alpha + \beta t + x_t, \quad (1-B)^d x_t = u_t, \quad t = 1, 2, ..., \tag{5}$$

where α and β are coefficients referring respectively to a constant and a linear time trend; the detrended series x_t is integrated of order d, i.e., I(d), and u_t is I(0) described in terms of an i.i.d. error term with zero mean and constant variance. Thus, α and β will indicate if there is a deterministic trend in the data, while the differencing parameter d will support a stochastic trend if d = 1, but also other alternatives for different values of d, such as stationary long memory (if $0 < d < 0.5$); nonstationary mean reverting behaviour ($0.5 \le d < 1$) or explosive patterns (if $d > 1$). Fractional integration was introduced in the early 80s by Granger (1980, 1981), Granger and Joyeux (1980) and Hosking (1981) though it has been only during the last twenty years when it has been widely implemented in the analysis of time series in many disciplines including energy and environmental studies (Elder and Serletis, 2008; Apergis and Tsoumas, 2011; Gil-Alana et al., 2017; Barassi et al., 2018; etc.). Note that our objective is not forecast the series but estimate the degree of persistence by means of its differencing parameter d. For this purpose, we use a version

[8] For a review of theoretical and empirical works on fractional integration, see Gil-Alana and Hualde (2009).

of the tests of Robinson (1994) widely employed in numerous empirical applications (see, Gil-Alana and Robinson, 1997; Gil-Alana and Moreno, 2012; Solarin et al., 2019a; etc.).

[TABLE 1 ABOUT HERE]

4. Empirical results

We start this section by estimating the differencing parameter d and their associated 95% confidence bands in the model given by equation (5) under the three classical assumptions of i) with no terms, ii) with an intercept, and iii) with an intercept and a linear time trend, choosing the most appropriate model by looking at the t-values of these deterministic terms in the d-differenced processes. Table 2 displays the estimated coefficients for each country.

[TABLE 2 ABOUT HERE]

According to the results displayed in Table 2 we observe that the time trend is found to be statistically significant in 29 out of the 90 countries examined. Within this group, 23 countries display positive coefficients for the time trend and only six display negative ones: Jordan, Burundi, France, Belgium, Angola and Japan. On the other hand, most of the countries that show a significant positive trend are countries with low or medium low income levels, while three out of the six countries with a negative time trend belong to high level income countries.

Dealing with the differencing parameter, we observe a large degree of heterogeneity across the countries. Table 3 classifies the countries in five categories: 1) I(0) or short memory behaviour; 2) stationarity with long memory (i.e., $0 < d < 0.5$); 3) nonstationary mean reversion ($0.5 \leq d < 1$); 4) I(1) or unit roots, and 5) explosive patterns ($d > 1$). Note that this classification is not based on the estimated values of d for each case but on the confidence band of the non-rejection values of d. Thus, for example, a series may belong to the I(1) category even if the estimated value of d is smaller than 1 if the interval includes that value.

[TABLE 3 HERE]

We observe in Table 3 that there is a single country belonging to the short memory category 1) which is Barbados. Twelve countries (13.33%) display a long memory stationary pattern (category 2), and seventeen (18.88%) are nonstationary though with a mean reverting pattern; most countries (61.11%) belong to the I(1) category 4) and finally five countries (5.55%), namely China, Myanmar, Paraguay, Canada and Rwanda display orders of integration strictly higher than 1.

[TABLE 4 ABOUT HERE]

Table 4 displays once more the degree of integration of each country, looking at the same time at their income levels and continental location. We observe that most of the countries showing nonstationarity though mean reverting patterns ($0.5 \leq d < 1$) belong to the category of upper-middle income countries. Finally, most of non-mean reverting series ($d \geq 1$) are European high level income countries, though there is also a large number of countries in this group which are African with low income levels. Thus, results are a bit unclear in terms of income and geographical location.

In any case, as a general conclusion, we can say that most African countries, with low income levels belong to the stationary mean reverting group ($d < 0.5$) or to the I(1) case, and the main feature for the European countries (high level countries) is that the fishing ground series are I(1) and thus non-mean reverting. Thus, shocks in the high income level countries will have permanent effects, while those affecting low income countries will be mean reverting with the effect of the shocks disappearing in the long run.

5. Discussion

The results are consistent with the empirical findings of Yilanci et al. (2019), which observed that the fishing grounds footprint is nonstationary in OECD countries (Table 5). Also, in line with Ulucak et al. (2017), we support the nonstationarity of the US series, though we found evidence of mean reverting behaviour since the order of integration is found to be significantly below 1 (Table 5). The results are also consistent with the suggestions of Hsu et al. (2008) that stipulates that bigger series are more likely to be more nonstationary. Shocks will generate a stronger deviation from the long-run equilibrium path for countries with larger fishing grounds footprint, and it might be harder for them to swiftly move the series to long-run equilibrium (Hsu et al., 2008). We note that the countries with the largest fishing footprint per capita (Global Footprint Network, 2019) also have nonstationary fishing footprint per capita.

One of the reasons for the foregoing results is the existence of persistence (mean-reverting) in macroeconomic data of developed countries, especially the GDP datasets. Persistence in GDP is also likely to lead too persistence in the environmental indicators of a country including the fishing grounds footprint, since economic activity in a country is associated with the pollution of the country (Solarin et al., 2019b). According to Hendry and Juselius (2000), a variable associated with another variable which is nonstatonary will absorb such nonstationarity, and disseminate it to numerous other variables in an economy. Rapach (2002) observed that GDP is nonstationary in developed countries, while Chang et al. (2008) and Ying et al. (2014) observed that GDP is stationary in many developing countries.

Another reason that can be attributed to the foregoing results is that policy effectiveness is more prevalent in high-income countries relative to the low-income countries. Hence, any policy shock that has been introduced to reduce the growth of fishing grounds footprint per capita have been more effective in the high –income countries.

6. Conclusions

In this paper we have examined the degree of persistence in the fishing ground footprint for a group of 89 countries using fractional integration. This methodology is very appropriate to detect the nature of shocks in a very flexible way permitting, for example, for nonstationary mean reverting behaviour with series having transitory though long-lasting effects. The application of fractional integration methods in this work is an important methodological contribution in the sense that it outperforms the standard methods based on integer degrees of differentiation, allowing for a higher flexibility in the modelization of the series.

The results suggest an enormous degree of heterogeneity in the countries examined. Nevertheless, some conclusions can be inferred from our results. We find 17 countries where the order of integration is constrained between 0.5 and 1, implying nonstationarity though mean reversion. Thus, the no applicability of the appropriate differentation before conducting Granger causality test or ordinary least squares (OLS), may cause erroneous conclusions in the results. Moreover, the conventional diagnostic statistics which are utilised to evaluate OLS estimates will suggest a statistically significant relationship between the series when there is no relationship and ultimately the procedure may yield inappropriate policy actions. Moreover, 77 out of the 90 series investigated (85.5%) display a nonstationary pattern and more than half of them belong to the upper-middle- and high-income levels. This is in line with the results provided in Yilanci et al. (2019). On the other hand, 14.4% of the series appear to be stationary (with an order of integration below 0.5), and most of the them belong to lower-middle- and low-income countries.

A policy implication of the results is that there is a path dependence or hysteresis in the fishing grounds footprint of the upper-middle- and high-income levels and therefore shocks resulting from policies implemented to stem the fishing grounds footprint per capita will have long lasting impacts on their growth, suggesting that policies aimed at changing the path of the fishing grounds footprint will be effective. On the other hand, the policies aimed at ensuring conservation of fishery resources and protecting essential fish habitats, especially the fishing grounds footprint per capita in the lower-middle- and low-income countries might not be effective. Policies that can protect fishing habitats include regulating or prohibiting trawling and other forms of destructive fishing in countries where these activities are common. There is also a need to improve institutional arrangements for fisheries management in order to reduce fishing grounds footprint. Co-management or authorities partnering with stakeholders in the fishery industry for managing fisheries is an important management tool in this direction, if rightly implemented.

One of the practical significances of this work is that it can provide guide to firms (engaged in providing fishing grounds footprint technologies) on which countries they should focus their activities on. It is recommended that firms that provide products or services such as artificial intelligence, big data, block chain, drones, smart weighing at sea, smartphones for monitoring, radio-frequency identification (RFID), on-board cameras innovation, machine learning and common ship tracking technologies aimed at reducing fishing gear and destructive fishing practices, and should focus more on countries with nonstationarity fishing grounds footprint. This is because interventions to reduce fishing grounds footprint will be more successful in these countries and as a results such firms' products or services are likely to more needed in these countries. Further work is required to find a clear relationship between the fishing grounds footprint and levels of income. Thus, a following-up step in this direction should be to examine the possibility of a long run equilibrium relationship between fishing grounds footprint and real GDP using, for example, the recent developed fractionally cointegrated VAR (FCVAR) approach by Johansen and Nielsen (2010, 2012). In addition, noting that fractional integration is very much related with potential breaks in the data (Diebold and Inoue, 2001; Granger and Hyung, 2004; Ohanissian et al., 2008; Aue and Horváth, 2013; etc.), the presence of non-linearities and/or structural breaks is another relevant issue that deserves to be investigated. Work in this direction is now in progress.

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Table 1: Countries and abbrevations

Abbrev.	Country	Abbrev.	Country	Abbrev.	Country
ALB	Albania	GAM	Gambia	NOR	Norway
AFG	Afghanistan	GER	Germany	PAK	Pakistan
ANG	Angola	GHA	Ghana	PAN	Panama
ARG	Argentina	GRE	Greece	PAR	Paraguay
AUS	Australia	GUA	Guadeloupe	PER	Peru
AUST	Austria	GUI	Guinea	PHI	Philippines
BAR	Barbados	GUY	Guyana	POL	Poland
BEL	Belgium	HAI	Haiti	POR	Portugal
BEN	Benin	IND	India	ROM	Romania
BOL	Bolivia	INDO	Indonesia	RWA	Rwanda
BRA	Brazil	ISR	Israel	SAI	Saint Lucia
BUR	Burkina Faso	ITA	Italy	SIE	Sierra Leone
BURU	Burundi	JAP	Japan	SOM	Somalia
CAD	Côte d'Ivoire	JOR	Jordan	SPA	Spain
CAM	Cameroon	KEN	Kenya	SRI	Sri Lanka
CAN	Canada	KOR	North Korea	SWE	Sweden
CEN	Central Af. Rep.	KORE	South Korea	SWI	Switzerland
COL	Colombia	LEB	Lebanon	SYR	Syrian Arab R.
CONGO	Congo	LUX	Luxembourg	THA	Thailand
CONGOD	Congo Dem. R.	LAO	Lao People R.	TOG	Togo
COS	Costa Rica	MAD	Madagascar	TUN	Tunisia
CUB	Cuba	MAL	Malaysia	TUR	Turkey
CHA	Chad	MALI	Mali	UGA	Uganda
CHI	Chile	MEX	Mexico	UNI	United Kingdom
CHIN	China	MOZ	Mozambique	UNIT	U. S. A.
DEN	Denmark	MYA	Myanmar	VEN	Venezuela,
DOM	Dominican R.	NET	Netherlands	VIE	Viet Nam
ELS	El Salvador	NIC	Nicaragua	WORLD	World
FIJ	Fiji	NIG	Niger	YEM	Yemen
FRA	FRANCE	NIGE	Nigeria	ZIM	Zimbabwe

Table 2: Estimated coefficients for each country

Country	d	Intercept	Time trend
ALB	**1.03 (0.90, 1.21)**	**0.00261 (2.24)**	**0.00060 (1.93)**
AFG	**0.41 (0.28, 0.60)**	**0.00005 (1.83)**	**0.000002 (44.4)**
ANG	**0.75 (0.64, 0.89)**	**0.25162 (9.37)**	**-0.00293 (-1.87)**
ARG	0.88 (0.69, 1.17)	0.02497 (1.90)	---
AUS	0.97 (0.80, 1.26)	0.05054 (5.44)	---
AUST	0.71 (0.57, 0.94)	0.06882 (16.90)	---
BAR	0.13 (-0.06, 0.39)	0.25257 (21.75)	---
BEL	**0.65 (0.39, 1.06)**	**0.18915 (16.36)**	**-0.00152 (-2.93)**
BEN	**1.01 (0.89, 1.19)**	**0.03591 (6.55)**	**0.00125 (1.65)**
BOL	0.71 (0.52, 0.98)	0.00650 (4.37)	---
BRA	0.75 (0.56, 1.05)	0.02843 (10.11)	---
BUR	**1.12 (1.00, 1.32)**	**0.00263 (1.62)**	**0.00057 (1.72)**
BURU	**0.43 (0.10, 0.81)**	**0.02894 (65.17)**	**-0.00048 (-2.75)**
CAD	0.76 (0.61, 0.99)	0.17153 (15.33)	---
CAM	0.93 (0.78, 1.13)	0.04020 (4.10)	---
CAN	1.31 (1,11, 1.56)	0.61843 (16.82)	---
CEN	1.08 (0.95, 1.28)	0.00465 (4.70)	---
COL	0.71 (0.57, 0.90)	0.03435 (7.90)	---
CONGO	0.93 (0.75, 1.19)	0.04840 (4.19)	---
CONGOD	0.73 (0.55, 0.99)	0.02669 (8.75)	---
COS	0.68 (0.34, 1.12)	0.01666 (2.06)	---
CUB	0.88 (0.77, 1.03)	0.07710 (3.09)	---
CHA	0.89 (0.73, 1.18)	0.02454 (10.30)	---
CHI	1.04 (0.90, 1.25)	0.15821 (1.90)	---
CHIN	1.16 (1.02, 1.37)	0.02376 (9.22)	---
DEN	0.83 (0.68, 1.04)	0.60153 (2.81)	---
DOM	0.67 (0.38, 1.18)	0.03435 (8.35)	---
ELS	**0.72 (0.63, 0.85)**	**-0.00198 (-2.13)**	**0.00228 (2.92)**
FIJ	**0.57 (0.35, 0.87)**	**0.15909 (2.42)**	**0.01174 (2.77)**
FRA	**0.75 (0.46, 1.09)**	**0.26111 (25.60)**	**-0.00118 (-1.98)**

(cont.)

Table 2: Estimated coefficients for each country

Country	d	Intercept	Time trend
GAM	**0.59 (0.45, 0.79)**	**0.03796 (3.05)**	**0.00118 (2.42)**
GER	1.10 (0.94, 1.35)	0.18622 (18.59)	---
GHA	**0.67 (0.45, 0.96)**	**0.10369 (4.76)**	**0.00190 (1.85)**
GRE	0.64 (0.51, 0.84)	0.08753 (9.89)	---
GUA	0.66 (0.47, 0.93)	0.23926 (14.27)	---
GUI	**0.64 (0.39, 0.98)**	**0.00959 (2.16)**	**0.0062 (3.23)**
GUY	**0.65 (0.54, 0.80)**	**0.00989 (1.95)**	**0.00078 (1.67)**
HAI	**0.71 (0.56, 0.93)**	**0.00711 (4.76)**	**0.00014 (1.88)**
IND	**0.73 (0.52, 1.04)**	**0.01043 (10.63)**	**0.00012 (2.32)**
INDO	**0.91 (0.79, 1.09)**	**0.03799 (5.97)**	**0.00338 (5.48)**
ISR	0.61 (0.41, 1.09)	0.09367 (9.03)	---
ITA	**0.83 (0.63, 1.08)**	**0.05936 (10.32)**	**0.00141 (3.31)**
JAP	**0.76 (0.60, 0.99)**	**0.58391 (24.56)**	**-0.00487 (-3.41)**
JOR	**0.68 (0.55, 0.84)**	**0.04644 (12.96)**	**-0.00034 (-2.00)**
KEN	1.03 (0.88, 1.28)	0.00483 (2.33)	---
KOR	0.90 (0.77, 1.10)	0.04425 (5.61)	---
KORE	**0.82 (0.67, 1.05)**	**0.07112 (2.25)**	**0.00727 (3.20)**
LEB	0.89 (0.75, 1.09)	0.04677 (12.31)	---
LUX	**0.88 (0.77, 1.04)**	**0.02849 (3.31)**	**0.00212 (2.82)**
LAO	1.12 (0.89, 1.38)	0.01053 (9.37)	---
MAD	0.49 (0.25, 0.88)	0.02466 (6.32)	---
MAL	**0.78 (0.56, 1.13)**	**0.11309 (5.03)**	**0.00527 (3.68)**
MALI	0.84 (0.68, 1.07)	0.11309 (5.03)	---
MEX	**0.69 (0.54, 0.94)**	**0.01653 (2.44)**	**0.00118 (3.54)**
MOZ	1.09 (0.97, 1.30)	0.00841 (4.23)	---
MYA	1.17 (1.04, 1.38)	0.02739 (15.28)	---
NET	0.77 (0.52, 1.08)	0.07432 (3.39)	---
NIC	0.63 (0.46, 0.99)	0.00469 (1.69)	---
NIG	0.82 (0.66, 1.11)	0.00292 (2.87)	---
NIGE	0.90 (0.70, 1.20)	0.04575 (4.79)	---

(cont.)

Table 2: Estimated coefficients for each country

Country	d	Intercept	Time trend
NOR	1.02 (0.85, 1.33)	3.28337 (7.79)	---
PAK	0.74 (0.51, 1.03)	0.00949 (2.51)	---
PAN	0.85 (0.64, 1.13)	0.01118 (2.14)	---
PAR	1.17 (1.01, 1.39)	0.00118 (1.79)	---
PER	0.69 (0.56, 0.88)	0.70819 (8.28)	---
PHI	0.81 (0.66, 0.99)	0.15835 (8.85)	---
POL	1.10 (0.93, 1.39)	0.06709 (3.42)	---
POR	1.04 (0.89, 1.25)	0.04800 (14.54)	---
ROM	0.92 (0.78, 1.10)	0.02388 (3.75)	---
RWA	1.60 (1.40, 1.91)	0.00066 (2.13)	---
SAO	**0.81 (0.67, 0.99)**	**0.04447 (2.48)**	**0.00411 (3.26)**
SIE	0.89 (0.75, 1.12)	0.03251 (3.18)	---
SOM	**0.60 (0.47, 0.79)**	**0.00075 (2.47)**	**0.00007 (3.69)**
SPA	1.03 (0.85, 1.25)	0.36801 (12.58)	---
SRI	**0.80 (0.61, 1.06)**	**0.04580 (2.31)**	**0.00425 (3.16)**
SWE	1.05 (0.87, 1.30)	0.34210 (18.27)	---
SWI	1.00 (0.88, 1.17)	0.14796 (20.16)	---
SYR	0.90 (0.71, 1.14)	0.01187 (7.07)	---
THA	1.10 (0.93, 1.38)	0.00808 (2.36)	---
TOG	0.79 (0.57, 1.13)	0.074f82 (7.93)	---
TUN	**0.66 (0.45, 0.93)**	**0.01611 (4.31)**	**0.00106 (6.19)**
TUR	0.63 (0.42, 0.93)	0.04638 (4.30)	---
UGA	0.84 (0.71, 1.03)	0.11378 (4.43)	---
UNI	1.14 (0.98, 1.39)	0.39474 (27.65)	---
UNIT	**0.70 (0.51, 0.98)**	**0.09768 (16.63)**	**0.00061 (2.04)**
VEN	1.00 (0.87, 1.18)	0.08145 (6.43)	---
VIE	1.04 (0.90, 1.26)	0.02022 (6.61)	---
WORLD	1.14 (0.92, 1.45)	0.09471 (38.73)	---
YEM	0.67 (0.47, 1.01)	0.01777 (1.99)	---
ZIM	1.11 (0.87, 1.41)	0.00424 (3.10)	---

Table 3: Classification of countries according to the order of integration

I(0)	0 < d < 0.5	0.5 ≤d < 1	I(1)	d >1
BAR (0.13)	AFG (0.41) BURU (0.43) MAD (0.49) FIJ (0.57) GAM (0.59) SOM (0.60) NIC (0.63) TUR (0.63) GUI (0.64) GUA (0.66) TUN (0.66) GHA (0.67)	GRE (0.64) GUY (0.65) JOR (0.68) MEX (0.69) PER (0.69) UNIT (0.70) AUST (0.71) BOL (0.71) COL (0.71) HAI (0.71) ELS (0.72) ANG (0.75) CAD (0.76) JAP (0.76) CONGOD (0.73) PHI (0.81) SAI (0.81)	ISR (0.61) BEL (0.65) DOM - YEM (0.67) COS (0.68) IND (0.73) PAK (0.74) BRA - FRA (0.75) NET (0.77) MAL (0.78) TOG (0.79) SRI (0.80) KORE - NIG (0.82) DEN - ITA (0.83) MALI - UGA (0.84) PAN (0.85) ARG – CUB - LUX (0.88) CHA – LEB - SIE (0.89) KOR – NIGE - SYR (0.90) INDO (0.91) ROM (0.92) CAM - CONGO (0.93) AUS (0.97) SWI - VEN (1.00) BEN (1.01) NOR (1.02) ALB - KEN - SPA (1.03) CHI - POR - VIE (1.04) SWE (1.05) CEN (1.08) MOZ (1.09) GER - POL - THA (1.10) ZIM (1.11) BUR - LAO (1.12) UNI - WORLD (1.14)	CHIN (1.16) MYA (1.17) PAR (1.17) CAN (1.31) RWA (1.60)
I(0)	0<d<0.5	0.5≤ d < 1	I(1)	d>1
1	12	17	55	5
1.11%	13.33%	18.88%	61.11%	5.55%

Table 4: Countries according to d, the income level and the continent

Country	d	Income Level	Continent
ALB	1.03	2	4
AFG	0.41	4	3
ANG	0.75	3	1
ARG	0.88	2	2
AUS	0.97	1	5
AUST	0.71	1	4
BAR	0.13	1	2
BEL	0.65	1	4
BEN	1.01	4	1
BOL	0.71	3	2
BRA	0.75	2	2
BUR	1.12	4	1
BURU	0.43	4	1
CAD	0.76	3	1
CAM	0.93	3	1
CAN	1.31	1	2
CEN	1.08	4	1
COL	0.71	2	2
CONGO	0.93	3	1
CONGOD	0.73	4	1
COS	0.68	2	2
CUB	0.88	2	2
CHA	0.89	4	1
CHI	1.04	1	2
CHIN	1.16	2	3
DEN	0.83	1	4
DOM	0.67	2	2
ELS	0.72	3	2
FIJ	0.57	2	5
FRA	0.75	1	4
GAM	0.59	4	1

GER	1.10	1	4
GHA	0.67	3	1
GRE	0.64	1	4
GUA	0.66	1	2
GUI	0.64	4	1
GUY	0.65	2	2
HAI	0.71	4	2
IND	0.73	3	3
INDO	0.91	3	3
ISR	0.61	1	3
ITA	0.83	1	4
JAP	0.76	1	3
JOR	0.68	3	3
KEN	1.03	3	1
KOR	0.90	4	3
KORE	0.82	1	3
LEB	0.89	2	3
LUX	0.88	1	4
LAO	1.12	3	3
MAD	0.49	4	1
MAL	0.78	2	3
MALI	0.84	4	1
MEX	0.69	2	2
MOZ	1.09	4	1
MYA	1.17	3	3
NET	0.77	1	4
NIC	0.63	3	2
NIG	0.82	4	1
NIGE	0.90	3	1
NOR	1.02	1	4
PAK	0.74	3	3
PAN	0.85	2	2
PAR	1.17	2	2
PER	0.69	2	2
PHI	0.81	3	3

POL	1.10	1	4
POR	1.04	1	4
ROM	0.92	2	4
RWA	1.60	4	1
SAI	0.81	2	2
SIE	0.89	4	1
SOM	0.60	4	1
SPA	1.03	1	4
SRI	0.80	3	3
SWE	1.05	1	4
SWI	1.00	1	4
SYR	0.90	3	3
THA	1.10	2	3
TOG	0.79	4	1
TUN	0.66	3	1
TUR	0.63	2	4
UGA	0.84	4	1
UNI	1.14	1	4
UNIT	0.70	1	2
VEN	1.00	2	2
VIE	1.04	3	3
YEM	0.67	3	3
ZIM	1.11	4	1
		INCOME LEVEL: High income 1 Upper-middle 2 Lower-middle 3 Low income 4	CONTINENT: Africa 1 América 2 Asia 3 Europe 4 Oceania 5
WORLD	1.14	Countries High-income 25 Upper-middle 20 Lower-middle 24 Low-income 20	Countries Africa 27 America 22 Asia 19 Europe 19 Oceania 2

Table 5: Comparison of the results of fishing grounds footprint

Authors	Dataset	Period	Method	Results
Ulucak and Lin (2017)	U.S.	1961–2013	Fourier unit root tests	Nonstationary
Yilanci et al. (2019)	25 OECD countries	1961–2013	Panel stationary tests	Nonstationary
Current paper	90 countries	1961–2016	Fractional integration techniques	Nonstationary