Unmasking the Threat to Property Rights: Fishermen's Compliance and Unauthorized Fishing Activity during the COVID-19 Pandemic

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Abstract

The global health crisis has disrupted economic activities and posed significant challenges to fisheries management, control, and surveillance. In this paper, we examine the impact of the COVID-19 pandemic on property rights in the context of unauthorized fishing activity providing theoretical and empirical evidences. This study investigates to what extent the pandemic has led to an increase in unauthorized fishing, potentially undermining existing property rights systems. To do so, we compile a comprehensive database with weekly, country-level fishing effort data for 146 countries before and during the COVID-19 lockdowns and international fishing access agreements data. We employ Differences in Differences approaches to shed light on the consequences of the pandemic for marine resource governance. The findings indicate that the stringency of the restrictions led to a decrease in authorized fishing efforts. However, unauthorized fishing hours increased, but we did not find any effects on the number of vessels engaged in unauthorized fishing due to the onset of the lockdowns. The increase in unauthorized fishing hours was higher in low- and middle-income countries, and in areas with a higher biodiversity index. These results inform the design of control policies by understanding the motivations of fishermen in low-monitoring scenarios.

Key words: Property Rights, Unauthorized Fishing, COVID-19 Pandemic, Fisheries Management, Marine Resource Governance.
JEL Classification: Q22, Q58, K42

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1 Introduction

The governance of marine resources is one of the primary challenges in the sector due to the high costs, relative to the benefits, of enforcement (Englander, 2019, Rowlands et al., 2019). Despite the costs associated with enforcement, it is essential for the sustainable management of marine resources (Haas, 2021, Olaniyi et al., 2024). In this context, the level of compliance among fishermen will depend on the wealth and productivity of the ecosystem in conjunction with enforcement efforts. Reduced enforcement may necessarily lead to lower compliance and decreased sustainability of the ecosystem, as it makes avoidance activities less costly or non-existent (Milliman, 1986, Arnason, 2013). This emphasizes the need for understanding the decision-making mechanisms of fishermen in response to changes in enforcement levels. However, studying this relationship among enforcement and no-compliance present a challenge.

This paper addresses this challenge studying the impact of the COVID-19 pandemic on fishermen's compliance through its effects on enforcement. Pandemic generated a global socioeconomic crisis as a result of government responses aimed at containing the health impacts (Gold et al., 2023). COVID-19-related regulations disrupted various economic activities (Nivette et al., 2021, Naseer et al., 2023), including those related to monitoring, control, and surveillance in the context of maritime administration due to the limitations imposed on the operations of on-board observer programs, and in-port and at-sea inspections (OCDE, 2021, Magalhães et al., 2021, UNCTAD, 2022, Mallik et al., 2022, Loveridge et al., 2024), also explained by the reductions in enforcement efforts due to reduced logistical, personnel and financial resources during the COVID-19 outbreak (FAO, 2020, March et al., 2021, Bates et al., 2021, Powlen et al., 2023). Given the lack of spatial and temporal data on monitoring, control, and surveillance operations, the COVID-19 pandemic presents an opportunity as a quasi-experiment to evaluate the relationship between enforcement and compliance.

This paper examines the impact on Exclusive Economic Zones (EEZs), which are one of the most important maritime governance figures, representing the maritime spaces owned by each country and grant them rights of exploration and exploitation over their resources (Englander, 2019). Regulatory entities in the maritime field play a fundamental role in ensuring the property rights delegated to each country by EEZ (Bellanger et al., 2019, Haas, 2021). Thus, a reduction in monitoring, control, and surveillance activities may have created sufficient incentives for non-compliant fishermen to engage in activities that violate these property rights (FAO, 2020, UNCTAD, 2022, Powlen et al., 2023). We define non-compliance activities as unauthorized fishing, referring to any fishing conducted within a country's EEZ without the necessary access agreement.

We provide empirical evidence of the impact of COVID-19-related restrictions on industrial fishing activity in general, and specifically on unauthorized fishing activity at a global level on a weekly basis. To investigate this issue, we compile several sources to create a comprehensive database that encompasses weekly fishing activity for 146 EEZs under the sovereignty of 98 countries during the years 2019-2020. The database also includes information on the characteristics of the fishing activities and the COVID-19-related measures implemented by national governments. It incorporates climate and marine ecosystem quality variables. Based on this database. we employ Difference-in-Differences strategy using a Two-Way Fixed Effect Model and we consider heterogeneous time effects using the estimators proposed by Callaway and Sant'Anna (2021).

The method used allow us to obtain robust results regarding the effect of lockdown impositions relative to the start date of these regulations. we find that the imposition of restrictions contributed to a decrease in total fishing efforts, especially when the stringency's measure was higher. However, we find that unauthorized fishing activity showed increases, which may be associated with a decrease in maritime monitoring, control, and surveillance capacities (OCDE, 2021, March et al., 2021, Loveridge et al., 2024). Also, it is possible that the motivations behind the increase in unauthorized fishing efforts are driven by the economic shock generated by the pandemic, as previous literature has found regarding the sector's sensitivity to economic shocks (Flückiger and Ludwig, 2015, Axbard, 2016); however, further research is needed to explore this. Additionally, the theoretical and empirical results show that unauthorized fishing hours increase, but the number of vessels does not increase due to the onset of lockdowns, primarily due to the risk aversion assumption. The implementation of lockdowns did not impact the overall set of vessels engaged in legal fishing. Instead, it contributed to an increase in fishing hours by non-compliant fishermen who were naturally less risk-averse and already engaged in unauthorized activities, driven by a reduced probability of being caught.

Furthermore, we find that the increase in unauthorized fishing efforts is not immediate. There is an adaptation period for fishermen to the new context, and after 4-5 weeks, the increases are observed. When examining the heterogeneities associated with this increase, we find that there is a greater rise in low- and middle-income countries. Additionally, approaching the idea of income opportunity studied by Axbard (2016) and Flückiger and Ludwig (2015), we find that the increases are higher in regions with a higher biodiversity index.

This article contributes to the literature in several ways. First, it adds to the literature focused on the effects of the COVID-19 pandemic on economic activity, particularly the impacts of economic and social shocks on fishing activity (Doumbouya et al., 2017, Reid, 2021, Gaspar et al., 2020, Gold et al., 2023, Loveridge et al., 2024, Mallik et al., 2022). This body of work demonstrates that the pandemic disrupted the way markets interacted, generating significant economic and social implications. This study presents findings on how illegal fishing activity increased as a consequence of the pandemic's implications.

Second, we contribute to studies related to the empirical and theoretical evidence on the relationship between enforcement activities and the compliance behavior of fishers (Nøstbakken, 2008, Diekert et al., 2021, Bos, 2021). Monitoring, control, and surveillance play a crucial role in fishers' level of compliance. The interactions between regulators and fishers are critical for the good governance of marine resources; disruptions in these interactions consequently affect resource management. This article presents global causal estimates that support the importance of enforcement on the compliance behavior of fishers.

And third, we contribute to the literature on the role of property rights as instruments of marine governance in deterring illegal fishing activity (Englander, 2019). We explore how governance instruments aimed at providing property rights can be affected in scenarios with low monitoring, control, and surveillance capacities. We study this through a quasi-experiment caused by the pandemic, but it can be considered in contexts of low enforcement capacities observed in low and middle-income countries, where, as we find, unauthorized fishing efforts increased significantly.

Most closely related to this study is one paper by March et al. (2021) and another by Englander (2019). The first one maps the changes in fishing and non-fishing maritime activity around the world generated by the pandemic, using AIS data. Although this study uses the same analysis scenario as ours, it differs in important aspects. First, we focus solely on fishing activity to measure the change in fishing activity; second, we analyze the change in fishing activity within exclusive economic zones, which is determined not only by factors associated with the pandemic but also by those related to access agreements and monitoring, control, and surveillance activities, in addition, we focus on distinguishing between authorized and unauthorized fishing activity. Finally, we propose a causal inference analysis to capture a robust measure of the change in fishing activity (authorized and unauthorized) generated by the pandemic. Regarding Englander (2019), we differ in the perspective of the analysis. The author studies the deterrent effect of EEZs on unauthorized fishing activity, whereas we examine how unauthorized fishing activity within EEZs changes in response to shocks such as those caused by the COVID-19 pandemic.

The rest of the article is organized as follows. Section 2 provides a brief discussion of the context of mobility restrictions associated with the COVID-19 pandemic and Exclusive Economic Zones as property rights. Section 3 present theoretical model, and section 4 describes the data source and the process of constructing the database. In Section 5 we discuss the empirical model used. Sections 6 present the main results, distinguishing between authorized and unauthorized fishing. Section 7 present the heterogeneity analysis. Finally, the conclusions are presented in Section 8.

2 Background

Exclusive Economic Zones (EEZs) are one of the most important maritime governance figures, which represent the maritime spaces owned by each country and grant them rights of exploration and exploitation over their resources, covering approximately 39% of the ocean surface (Figure 1) and accounting for about 95% of global fish catch (Englander, 2019).

Legally, EEZs grant full exploitation rights to the country, with coverage extending up to 200 nautical miles from the coast (Lubchenco and Grorud-Colvert, 2015). Each country has the autonomy to prohibit or negotiate access for foreign vessels within its borders, as well as to define the terms under which fishing activity is permitted. Any fishing activity conducted within a country's EEZ without the necessary permits will be considered unauthorized. Certainly, there are difficulties associated with monitoring and enforcing compliance within these areas, mainly due to their vast extent and distance from coastal regions, considering the technological and physical capacity differences among countries for maritime control (Englander, 2019). Thus, enforcement levels represent an important factor in preserving the property rights of each country, as decreases in these capacities could pose risks to oceanic sovereignty and sustainability of marine resources.

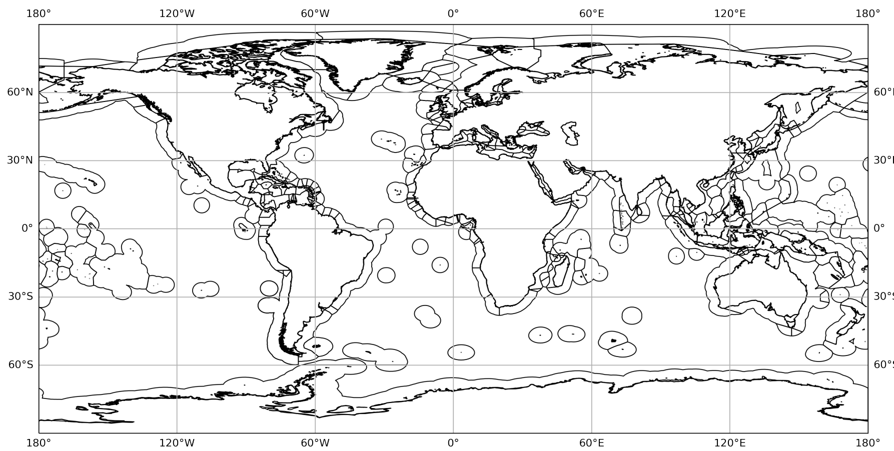


Figure 1: Exclusive Economic Zone Map. Author, using information from Marine Regions Repository.

The COVID-19 pandemic was declared by the World Health Organization on March 11, 2020 (Russo et al., 2021). Since the declaration of the pandemic, countries responded primarily by implementing mobility restrictions (Nivette et al., 2021), including regulations on internal mobility, workplace closures, school closures, and policies such as stay-at-home orders. The implementation of these regulations was effective in containing infection indicators (Chen et al., 2021), but it also led to adverse economic shocks, including disruptions to supply chains and limitations on normal economic activities (Reid, 2021, Gaspar et al., 2020).

The pandemic originated with the spread of the virus worldwide, starting in Wuhan, China[1]. As the number of cases and deaths varied across countries, each nation responded differently with containment measures, such as physical distancing. This led to the closure of non-essential workplaces, schools, shopping centers, and other crowded places. According to

[1]See: WHO: Events as they happen

data from the Oxford COVID-19 Government Response Tracker (OxCGRT), internal mobility regulations included state border closures, where one state restricted entry from other states, as well as restrictions on movement within the state. Workplace closure measures referred to the closure of non-essential workplaces, with the possibility of reopening under sanitary and social distancing requirements, such as operating at reduced capacity (e.g., 30%) or using only outdoor seating. Stay-at-home measures included curfews during specific hours. Unless explicitly stated in a policy, a stay-at-home order should not be interpreted as a restriction on domestic travel, as national travel may still be allowed[2].

Lockdowns resulted in significant decreases in both artisanal and commercial fishing activity (Russo et al., 2021, March et al., 2021). Although there have been anecdotal reports of increased illegal fishing activity[3], highlighting the importance of mobility restrictions in terms of control capacity and the economic shocks generated. In other sectors, lockdowns have been found to increase maritime crimes, such as piracy (Gold et al., 2023), and have had an impact on crime rates in cities (Nivette et al., 2021).

In the commercial context, the effects of COVID-19-related mobility restrictions on illegal activity and fishing in general are ambiguous. On one hand, shocks to supply chains and decreased demand for seafood products have affected the sector's economic performance (Russo et al., 2021). On the other hand, the implementation of lockdown and mobility restrictions has changed the way various activities are carried out, including monitoring, control, and surveillance due to the limitations imposed on the operations of on-board observer programs, and in-port and at-sea inspections (OCDE, 2021, Magalhães et al., 2021, Mallik et al., 2022, Loveridge et al., 2024), also due to reduced logistical, personnel and financial resources during the COVID-19 outbreak (March et al., 2021, Bates et al., 2021, Powlen et al., 2023), potentially creating incentives for increased illegal fishing.

Broadly speaking, global fishing activity during the pandemic may or may not have complied with mobility regulations. However, the negative economic shock could have generated sufficient incentives to comply for a certain period and then disregard the regulations to engage in fishing as a means of livelihood (Gold et al., 2023, Nivette et al., 2021). According to economic models of crime (Becker, 1968, Ehrlich, 1973) and those related to illegal fishing (Charles et al., 1999, Nøstbakken, 2008), vessels will choose to engage in illegal fishing if the net benefits of fishing illegally (e.g., entering unauthorized areas or fishing during prohibited times) are positive and considering risk aversion of the fishers. The main hypothesis for the change in unauthorized fishing activity will be understood as the change in monitoring, control, and surveillance capacities; however, it is possible that this may not be the only one, as just discussed.

[2]See: OxCGRT Coding Interpretation Guide

[3]See: Lockdown allowed illegal fishing to spike in Philippines, satellite data suggest at Mongabay newspaper

3 Theoretical model

This model studies the decision-making of fishermen under the scenario of imperfectly enforced input control, such as fishing in an unauthorized area. Based on the model by Charles et al. (1999), we explore how industrial fishermen make decisions about where to fish in response to changes in enforcement, monitoring, control, and surveillance levels. We assume that when fishermen decide to engage in any illegal, unauthorized, or unreported activity, they face a probability of being caught (P_c) that is a function of the enforcement capabilities of the control entities (E). Considering the context of the pandemic, we integrate the effect of the level of stringency (L) of control measures implemented by countries during the pandemic on the probability of capture:

$$P_C = \frac{E}{1+L} \tag{1}$$

Following this equation, the probability of capture will be higher as enforcement and monitoring measures increase, while the probability will decrease as stringency increases. Regarding the stringency of the measures, two considerations must be made: 1) Higher stringency was associated with a greater interest of governments in reducing the infection rate, both in countries where it was already high and in countries where it was low, to prevent an increase (Violato et al., 2021). This explains why stringency was considerably high in most countries from the beginning of the pandemic and remained high throughout much of 2020 (Figure B4); and 2) Increased stringency was associated with a reduced capacity for monitoring, control, and surveillance in the context of maritime administration due to the limitations imposed on the operations of on-board observer programs, and in-port and at-sea inspections (OCDE, 2021, Magalhães et al., 2021, UNCTAD, 2022, Mallik et al., 2022, Loveridge et al., 2024), also by reduced logistical, personnel and financial resources during the COVID-19 outbreak (FAO, 2020, March et al., 2021, Bates et al., 2021, Powlen et al., 2023).

3.1 Production Function

The fishermen's production function is explained by the level of catches h, which in the short term is given by:

$$h = h(x_L, x_I, A; K, B) \tag{2}$$

Where x_L and x_I represent the number of legal and illegal fishing hours that fishermen decide to undertake, respectively; A indicates the escape activities performed by the vessels when they decide to engage in illegal fishing ($A = 0$ if $x_I = 0$). K indicates the vessel's capital stock and B is the biomass of fish available in the ecosystem. h will be increasing in x_L, x_I, K, and B, while it will be decreasing in A, assuming that escape activities reduce the available fishing time. However, we assume that $h_A = 0$ and account for it in the costs, so the production function is expressed as follows:

$$h = q_L x_L B + q_I x_I B \tag{3}$$

3.2 Fishing Costs

For simplicity, it is assumed that costs are expressed as the sum of all costs incurred by the vessel for each type of choice, and a quadratic specification is assumed due to the characteristic of increasing marginal costs:

$$C = c_L x_L^2 + c_I x_I^2 + c_A A^2 \tag{4}$$

3.3 Penalties for Illegal Fishing

Given the option of illegal fishing assumed by the fishermen, they will face a probability of being caught P_c as described above. If the vessel is caught, it must assume a fine F, which may be constant or increasing according to the level of illegal fishing x_I, but less than the vessel's capital stock K.

Additionally, it is assumed that the probability of capture may decrease as vessels develop greater evasion activities. We have:

$$P_c F = \frac{(1 - \gamma A)E}{1 + L} x_I \tag{5}$$

Where γ is a constant. The expected value of the fine will increase with the level of illegal activity and enforcement, while it will decrease with greater evasion activities and higher stringency.

3.4 Fisher Optimization

Each year, fishermen are assumed to decide the strategies they will use. Fishermen will decide on the number of legal and illegal fishing hours, along with the total evasion activities they will undertake. It is assumed that fishermen make their decisions following a level of risk aversion expressed by the following equation:

$$R = \alpha x_I + \beta x_I^2 \tag{6}$$

This equation models risk under the assumption of convexity, indicating that the marginal risk cost increases with more illegal activity. Thus, the function that characterizes the fishermen's decision is as follows:

$$\max_{x_I,x_L,A} p(q_Lx_LB + q_Ix_IB) - (c_Lx_L^2 + c_Ix_I^2 + c_AA^2) - (\alpha x_I + \beta x_I^2) - \left(\frac{(1-\gamma A)E}{1+L}x_I\right) \quad (7)$$

Where p is a price indicator per unit of the product, in this case, fish.

3.5 Profit-Maximizing Decision Making

When evaluating fishermen's decisions, for the case where fishermen are risk-averse ($\alpha, \beta \neq 0$), we find the following results:

$$x_I(2\beta + 2c_I) = pq_IB - \left(\alpha + \frac{(1+\gamma A)E}{(1+L)}\right) \quad \text{(8a)}$$

$$2c_Lx_L = pq_LB \quad \text{(8b)}$$

$$x_I\frac{\gamma E}{1+L} = 2c_AA \quad \text{(8c)}$$

As sustained in the theory of crime and punishment (Becker, 1968), illegal fishing will occur whenever the benefits of illegal fishing outweigh the costs, in this case, associated with the probability of capture and fishermen's risk aversion. Risk aversion reduces the incentives for illegal fishing, even if the probability of capture decreases due to increased stringency, for example; if there are fishermen with sufficiently high risk aversion, they will have no incentive to engage in illegal fishing, while risk-loving fishermen will decide to increase their illegal fishing hours.

Proposition 1: It is expected that with the decrease in the probability of capture P_c, only risk-loving fishermen will increase the number of illegal fishing hours, but due to the risk aversion of a proportion of fishermen, the number of vessels will not increase.

The fishing sector exemplifies the presence of fishermen with high risk aversion, given the high costs of being caught, ranging from heavy fines to the loss of fishing licenses, which can render the activity unviable in subsequent periods.

$$x_I = \frac{(1+L)2c_A[(1+L)(pq_IB - \alpha) - E]}{(1+L)^2 2c_A(2\beta + 2c_I) - \gamma^2E^2} \quad (8)$$

Additionally, note that illegal fishing hours will be greater than legal fishing hours ($x_I > x_L$), as long as the benefits of illegal fishing are greater than legal fishing, and this difference is greater than the levels of enforcement, which would increase if the probability of capture decreases due to factors associated with increased stringency during the pandemic:

$$\theta pq_IB - \frac{pq_LB}{2c_L} > \theta E \quad (9)$$

Where $\theta = \frac{2c_A}{4c_I(1+L)-1}$. Given the model structure and the context of the relationship between stringency and the probability of capture, note that higher stringency decreases monitoring, control, and surveillance activities, contributing to the increase in unauthorized fishing hours.

4 Data

Description and Sources

Our analysis examines the relationship between lockdown measures, internal fishing access agreements, and fishing efforts. Below, we describe the data and the measurement of each variable:

Fishing Efforts To assess fishing efforts, we use the Global Fishing Watch (GFW) database, which allows us to identify fishing activity of industrial vessels in pixels of approximately 0.01 degrees, equivalent to approximately 1 km on a daily basis, providing global coverage (Kroodsma et al., 2018). To homogenize the different sources of information, we aggregate the data on a weekly basis for the years 2019 and 2020. This aggregation allows us to control for different fishing patterns, which exhibit seasonality according to the time of year and fishing regions. The database provides various characteristics for evaluation, such as the type of fishing, which has its own particularities as it determines the targeted fish species and the type of fishing operation conducted. Additionally, we have information on the country of origin of the vessel, obtained through the cross-referencing of data from the Automatic Identification System (AIS), Vessel Monitoring System (VMS), and public vessel registries. It is possible that the origin of the vessel may not be detected for the entire population of detected vessels. Therefore, we restrict the sample to those vessels for which the origin can be detected, which corresponds to approximately 135 countries. This allows for validation of whether the vessel is authorized to fish in a specific location. However, it should be noted that the estimated effect in the econometric analysis would represent a lower bound due to this restriction.

The unit of measurement for fishing effort is hours. This means that the number of fishing hours performed by a vessel in a given pixel on a specific date can be determined. The quantification of the number of hours is obtained from a prediction process using machine learning techniques (Kroodsma et al., 2018). Using this data, we identify the fishing locations based on Exclusive Economic Zones (EEZs) and aggregate the measurement of fishing efforts as the total and average hours conducted in a given EEZ per week.

Exclusive Economic Zones To identify the EEZs, we use information from the Marine Regions Repository, which provides data on the geographic boundaries of EEZs for 146 coastal countries. In cases where the sovereignty of an EEZ is not determined by the country itself, we identify countries that have sovereignty over the EEZs of other countries, resulting in a sample of 98 countries that have property rights over the exploitation of the 146 analyzed EEZs.

To intersect this information with the fishing efforts data, we first construct a 100 km buffer from the EEZ boundaries towards open sea. This allows us to select the fishing pixels that are both within the EEZ and the buffer, creating a variable indicating whether the fishing efforts take place inside or outside the EEZ. By merging the two datasets, we determine whether the fishing is conducted by a domestic or foreign vessel by validating the vessel's origin and the country of the EEZ and the country with sovereignty over the EEZ.

Internal Fishing Access Agreements Considering that EEZs represent property rights of countries for the management and exploitation of these areas, countries can negotiate with other countries regarding access to and the terms of exploitation. To validate this information, we obtain data from the Sea Around Us, which is publicly available on their website.[4] Since the information is not compiled into a single database but rather disaggregated by countries, we develop a web scraping algorithm to collect the details of agreements for each of the 282 countries. Through this algorithm, we are able to compile a database with information for 249 countries on agreements negotiated from 1950 to 2020. Using this data, we create a variable indicating whether the fishing conducted by a vessel from one country in another country in a given year is authorized or unauthorized, taking into account the year of agreement termination.

Lockdown Measures To obtain information related to COVID-19 pandemic measures, we use data from the "Oxford COVID-19 Government Response Tracker" (OxCGRT), which provides daily records of COVID-19-related restrictions for each country. This database includes information on various lockdown measures implemented by countries, such as school closures, workplace restrictions, travel limitations, public gathering bans, and more. we use a government stringency index for each country, which ranges from 0 to 100, with 0 indicating lower stringency and 100 representing the highest level of government response. For identification purposes, we also consider the first positive change in the stringency index, indicating the onset of COVID-19-related restrictions.

Furthermore, the OxCGRT database contains information on other government response measures during the pandemic, including the economic support index, containment health index, government response index, and other indicators.

Additional Data To enhance the robustness of the analysis, we consider information from various data sources. For the construction of time-varying covariates, we compile data from the National Oceanic and Atmospheric Administration (NOAA) obtained from the USAF Climatology Center. These data include daily mean values of weather variables such as temperature, dew point temperature, wind speed, and precipitation.

To characterize the quality of the marine ecosystem, we use information from the Ocean

[4] https://www.seaaroundus.org

Health Index (OHI). The OHI is a framework for assessing ocean health based on the sustainable provisioning of benefits and services that people expect from healthy oceans, including food, cultural and social value, and job opportunities. The global OHI measures the status of key societal goals, such as artisanal fishing opportunity, biodiversity, carbon storage, clean waters, coastal livelihoods and economies, coastal protection, food provision, natural products, sense of place, and tourism and recreation (Halpern et al., 2012). Additionally, we identify regions and economic types based on World Bank definitions.

Summary of the Data

The resulting database comprises weekly fishing activity for 146 EEZs under the sovereignty of 98 countries during the years 2019-2020. It also includes information on the characteristics of the fishing types conducted, along with the COVID-19-related measures implemented by national governments. The database incorporates climate variables, and marine ecosystem quality variables.

Descriptive statistics are presented in Tables 1 and 2. Table 1 provides the distribution of the database according to the authorization of fishing activity. On average, globally, the majority of fishing hours were conducted with authorization, primarily within national borders (see also Table B1). However, unauthorized fishing, on average, is not far behind the levels of legal activity carried out by foreign vessels. Regarding the number of vessels engaged in unauthorized fishing, it can be observed that the regions with the highest activity are East Asia and the Pacific (136.4) and Europe and Central Asia (132.3). However, when evaluating the average hours of unauthorized fishing conducted by each vessel, the South Asian region (5.7), the Middle East and North Africa (3.7), and Latin America and the Caribbean (3.5) have the highest incidence. Figure B3 presents the total amount of unauthorized fishing by regions. It is observed that unauthorized fishing activity increased in 2020 relative to 2019 in the regions of the Middle East and North Africa, Latin America and the Caribbean, and South Asia.

For the studied years (Table 2), on average, unauthorized fishing efforts decreased from 2019 to 2020, both in terms of the total number of fishing hours and the number of vessels involved. However, in terms of average hours per vessel, the efforts remained unchanged at 2.5 hours per vessel. Analyzing the regions, Latin America and the Caribbean, along with the Middle East and North Africa, were the only two regions where the total number of unauthorized fishing hours increased.

Overall, unauthorized fishing activity tends to occur mainly in middle-income regions where the fishing sector is generally more prominent. In Figure B1, the evolution of total and unauthorized fishing efforts can be observed for each week in 2019 and 2020. Similarly, Figure B2 presents fishing efforts according to the global evolution of the average stringency index.

Table 1: *Descriptive Statistics: Summary of Baseline Data by Internal Fishing Access Agreements*

	Internal Fishing Access Agreements							
	Authorized Fishing				Unauthorized Fishing			
	Mean	Standard deviation	Min	Max	Mean	Standard deviation	Min	Max
Panel A: Total Fishing								
Vessel Nationality								
National Fishing	1,009.4	9,226	0.5	436,404	-	-	-	-
Foreign Fishing	169.6	493	0.5	7,263.1	125.8	379.2	0.5	9,780.0
Vessel in Sovereign	231.8	476.3	0.5	3,161.2	-	-	-	-
World Bank Regions								
East Asia & Pacific	1,789.2	15,355.2	0.5	436,402	194.2	531.7	0.5	9,779.9
Europe & Central Asia	532.9	2,071.1	0.5	32,445	149.1	370.4	0.5	4,445.2
Latin America & Caribbean	364.6	1,140.1	0.5	11,695	48.7	126.7	0.5	2,048.8
Middle East & North Africa	202.8	480.8	0.5	3,505	23.4	43	0.5	410.4
North America	576.3	1,612.9	0.5	17,847	65.8	116	0.5	1,722.6
South Asia	339.3	564.5	0.5	4,059	68.9	81.9	0.5	439.6
Sub-Saharan Africa	210.8	418.6	0.5	3,688	106.5	479.5	0.5	7,797.6
World Bank Income Groups								
High Income	510.5	1,808.8	0.5	32,445	134.4	370.7	0.5	9,780
Low income	239.9	493.2	0.5	3,498	52.9	84.4	0.5	508.1
Middle Income	1,172	12,151.8	0.5	436,402	119.4	423.1	0.5	7,798
Panel B: Fishing Average								
Vessel Nationality								
National Fishing	2.9	3.9	0.5	121.6	-	-	-	-
Foreign Fishing	2.4	4.0	0.5	115.1	2.5	4.8	0.5	215.4
Vessel in Sovereign	1.6	1.7	0.5	23.1	-	-	-	-
World Bank Regions								
East Asia & Pacific	3.1	4.1	0.5	92.1	2.6	4.0	0.5	64.4
Europe & Central Asia	2.3	3.4	0.5	91.7	2.3	3.4	0.5	79.8
Latin America & Caribbean	2.8	5.1	0.5	115.1	3.5	8.0	0.5	147
Middle East & North Africa	3.4	4.0	0.5	28.5	3.7	5.3	0.5	38.7
North America	2.7	3.8	0.5	121.6	2.8	8.6	0.5	215.4
South Asia	4.0	3.2	0.5	23.9	5.7	4.1	0.5	23.8
Sub-Saharan Africa	2.5	3.4	0.5	48.3	1.8	2.7	0.5	55.7
World Bank Income Groups								
High Income	2.5	3.6	0.5	121.6	2.4	4.7	0.5	215.4
Low income	2.5	3.7	0.5	48.3	1.7	3.0	0.5	52.3
Middle Income	3.0	4.2	0.5	103.3	2.7	5.2	0.5	147.0
Panel C: Number of fishing vessels								
Vessel Nationality								
National Fishing	1,302	17,066	1	911,097	-	-	-	-
Foreign Fishing	150.4	545.6	1	9,439	100.3	326.1	1	6,855
Vessel in Sovereign	283.4	605.9	1	4,361	-	-	-	-
World Bank Regions								
East Asia & Pacific	2,325.3	28,502	1	911,097	136.4	379	1	6,855
Europe & Central Asia	774.6	3,545	1	64,835	132.3	382.4	1	5,630
Latin America & Caribbean	480.2	2,550.8	1	39,644	26.8	71	1	1,377
Middle East & North Africa	120.9	372	1	4,256	12.78	23.86	1	170
North America	453.3	1,505	1	19,700	47.07	87.37	1	1,147
South Asia	134.4	303.6	1	2,939	15.18	18.58	1	88
Sub-Saharan Africa	182.4	465.5	1	4,278	77.5	313.1	1	4,801
World Bank Income Groups								
High Income	622	2,876.2	1	64,835	112.6	350.4	1	6855
Low income	201	482.4	1	3,642	40.4	72.2	1	675
Middle Income	1,534.1	22,559	1	911,097	84.7	295.1	1	4,801

Source: Author. Note: Panel A presents a summary of descriptive statistics for the total sum of fishing efforts by EEZ. Panel B presents descriptive statistics for the average fishing efforts per vessel by EEZ. Panel C presents the results for the total number of fishing vessels by EEZ.

Table 2: *Descriptive Statistics: Summary of Unauthorized Fishing by Year*

	Unauthorized Fishing							
	2019				2020			
	Mean	Standard deviation	Min	Max	Mean	Standard deviation	Min	Max
				Panel A: Total Fishing				
Vessel Nationality								
Foreign Fishing	126.7	379.2	0.5	9,780	106.5	354.5	0.5	14,264
World Bank Regions								
East Asia & Pacific	194.2	531.7	0.5	9,780	114.8	292.6	0.5	4,649.2
Europe & Central Asia	149.1	370.4	0.5	4,445	131.4	339.2	0.5	4,480.3
Latin America & Caribbean	48.7	126.7	0.5	2,049	94.4	707.5	0.5	14,264
Middle East & North Africa	23.4	43.0	0.5	410	79.4	205.7	0.5	2,095.7
North America	65.8	115.9	0.5	1,723	47.1	75.4	0.5	535.0
South Asia	68.9	81.9	0.6	439.6	31.2	38.3	0.5	193.3
Sub-Saharan Africa	106.5	479.5	0.5	7,798	77.8	209.5	0.5	3,604.8
World Bank Income Groups								
High Income	134.4	370.6	0.5	9,780	113.5	311.7	0.5	4649.2
Low income	52.6	84.4	0.5	508	92.5	280.2	0.5	2825.6
Middle Income	119.4	423.1	0.5	7,798	96.0	416.7	0.5	14264
				Panel B: Fishing Average				
Vessel Nationality								
Foreign Fishing	2.5	4.9	0.5	215.5	2.5	4.9	0.5	115
World Bank Regions								
East Asia & Pacific	2.6	4	0.5	64.4	2.9	5.2	0.5	91.7
Europe & Central Asia	2.3	3.4	0.5	79.8	2.2	3.7	0.5	115
Latin America & Caribbean	3.5	8	0.5	147	3.8	9	0.5	98
Middle East & North Africa	3.7	5.3	0.5	38.7	3.7	5.3	0.5	66.3
North America	2.8	8.6	0.5	215.5	2	3.1	0.5	60.3
South Asia	5.7	4.1	0.6	23.9	5.5	5	0.5	29.9
Sub-Saharan Africa	1.8	2.7	0.5	55.7	2.1	4.2	0.5	84.2
World Bank Income Groups								
High Income	2.4	4.7	0.5	215.4	2.3	4.2	0.5	115
Low income	1.7	3	0.5	52.3	2.3	3.8	0.5	63.3
Middle Income	2.7	5.2	0.5	147	2.9	6	0.5	98
				Panel C: Number of fishing vessels				
Vessel Nationality								
Foreign Fishing	100.3	326.1	1	6,855	98.1	381.1	1	10,076
World Bank Regions								
East Asia & Pacific	136.4	378.8	1	6,855	82.5	244.4	1	4,172
Europe & Central Asia	132.3	382.4	1	5,630	141.8	477.4	1	8,624
Latin America & Caribbean	26.8	71	1	1,377	81	532.1	1	10,076
Middle East & North Africa	12.8	23.9	1	170	50.3	167.3	1	2,733
North America	47.1	87.4	1	1,147	40.2	67.9	1	588
South Asia	15.2	18.6	1	88	9	15.1	1	80
Sub-Saharan Africa	77.5	313.1	1	4,801	64.9	176.8	1	3,117
World Bank Income Groups								
High Income	112.6	350.4	1	6,855	116.8	420.9	1	8,624
Low income	40.4	72.2	1	675	61.8	204.2	1	2,354
Middle Income	84.7	295.1	1	4,801	76.4	325.6	1	10,076

Source: Author. Note: Panel A presents the summary of descriptive statistics for the total sum of unauthorized fishing efforts by EEZ. Panel B presents the descriptive statistics for the average of unauthorized fishing efforts per vessel by EEZ. Panel C presents the results for the total sum of unauthorized fishing vessels by EEZ.

Figure B4 shows the weekly evolution in 2020 of the stringency index and the number of countries declaring some form of lockdown. It can be observed that starting from weeks 8-10, the stringency index begins to rapidly increase, along with the cumulative number of countries with lockdown measures. In total, 105 countries implemented some form of lockdown, with the last country declaring restrictions in week 34. Figure B5 displays the distribution of the stringency index, which is concentrated in measures between 60 and 80 points, where 0 represents countries without any restrictions and 100 represents countries with very strict measures for pandemic management. Table B2 presents additional descriptive statistics and the data sources for the different variables analyzed in this research.

5 Empirical Model

To assess the effect of the implications generated by the restrictions associated with the pandemic on total and unauthorized fishing activity, we estimate the change in fishing efforts carried out by vessels before and after the declaration of restrictions. Taking advantage of the heterogeneity in the start of the declaration of restrictions, we propose the following model:

$$Y_{ijzt} = \beta SI_{zt} + \gamma X_{it} + \alpha_z + \tau_t + \epsilon_{ijzt} \tag{1}$$

Where Y_{ijzt} is the outcome variable, which represents the total number of fishing hours or the number of vessels conducting fishing from country i, of type j, within an EEZ z or its influence area[5] in week t. SI_{zt} is the treatment variable representing the stringency index, X_{it} is a vector of observable time-varying covariates such as temperature, wind speed, and precipitation. α_z and τ_t are fixed effects for EEZ/country and week, respectively. ϵ_{ijzt} represents the error term with robust standard errors.

The stringency index serves to express the marginal effect of the evolution of lockdown policies; However, due to its composition, it complicates the understanding of the effect of lockdowns on fishing activity. Additionally, during the pandemic, the stringency of lockdown measures in many countries fluctuated, rising and falling at different times. This variation complicates the accurate identification of the lockdown effects, as a second increase in stringency does not have the same implications as the first, due to the learning effect among fishermen. Therefore, a second exercise is carried out, in which the first positive change in the stringency index is considered as an approximation of the onset of lockdown measures during the COVID-19 pandemic. Additionally, we decompose the effect by examining the correlation between fishing and lockdown measures separately for authorized and unauthorized fishing activities. The following model is estimated:

[5]The influence area is defined as the 100km buffer created from the EEZ's border towards open sea.

$$Y_{ijzt} = \tau D_{zt} + \gamma_z + \gamma_t + \gamma_{ijt} + \epsilon_{ijzt} \quad (2)$$

Where Y_{ijzt} indicates the fishing activity variable for authorized and unauthorized vessels from country i, of type j, in EEZ z in week t. D_{zt} is an indicative variable that takes the value of 1 when the stringency index becomes positive and 0 otherwise. ϵ_{ijzt} represents the error term with robust standard errors. The parameter of interest is the coefficient τ, which captures the relationship between the onset of lockdown measures during the COVID-19 pandemic and the fishing activity.

6 Results

Main findings

Table 3 presents the results of equation (1). The first two columns show the results for the entire sample. Panel A presents the results for the authorized fishing activity, and Panel B presents the results for unauthorized fishing activity. In both cases, the results are presented for both the number of fishing hours and the number of fishing vessels. Columns (3) - (10) present the results for quintiles of the stringency index distribution, allowing us to observe heterogeneities based on the intensity of the restrictions imposed by countries.

The results indicate that as the stringency of measures implemented during the pandemic increased, a decrease in authorized fishing activity was observed. Given the compliance expected from this segment, it is anticipated that fishermen would lack the capacity to reach their vessels and engage in fishing activities due to mobility restrictions and other constraints imposed by the countries. Conversely, when the stringency was still low, unauthorized fishing activity increased. It is noteworthy that the lowest levels of stringency were reported at the beginning of the pandemic (Figure B4), suggesting the importance of evaluating the impact on unauthorized fishing activity starting from the onset of pandemic-related restrictions, rather than over the entire set of weeks analyzed here.

Table 4 shows the results of equation (2). Panel A present the result using total fishing efforts as outcome variable while panel B presents results to when number of vessel is used. The estimates for authorized segment are presented in columns (1) - (3), and columns (4) - (6) present estimates for unauthorized segment. Controls and fixed effects are considered. According to the results, when we focus on the first change of stringency index, that is the onset of COVID-19-related mobility measures, the unauthorized fishing activity increase. Any statistical significant effect is founded neither for authorized segment nor total number of vessel.

Table 3: *TWFE Model: Stringency index and industrial fishing activity*

	All		Quintiles							
			1st		2nd		3rd		4th	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Panel A. Authorized Fishing										
I. Total Fishing Efforts										
Stringency index	-0.21	-0.43	0.86	0.87	-50.11**	-65.26***	2.33***	2.34***	-282***	-337***
	(60.78)	(61.18)	(2.17)	(2.15)	(20.39)	(20.67)	(0.86)	(0.86)	(71.09)	(87.6)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14.010	14.010	2.919	2.919	2.328	2.328	1.459	1.459	1.599	1.599
II. Number of fishing vessels										
Stringency index	12.22	10.32	5.06	5.16	-77.32**	-97.15**	0.01	0.01	-411.9***	-524.1***
	(110.4)	(111.2)	(4.27)	(4.29)	(37.5)	(39.3)	(1.22)	(1.22)	(135.4)	(169.4)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14.010	14.010	2.919	2.919	2.328	2.328	1.459	1.459	1.599	1.599
Panel B. Unauthorized Fishing										
I. Total Fishing Efforts										
Stringency index	0.88**	0.84**	4.33**	3.41**	-0.03	0.35	0.19	0.24	0.14	0.14
	(0.35)	(0.36)	(1.67)	(1.67)	(1.07)	(1.13)	(1.09)	(1.11)	(0.29)	(0.29)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18.427	18.427	1.607	1.607	2.562	2.562	5.175	5.175	1.046	1.046
II. Number of fishing vessels										
Stringency index	0.77**	0.77**	3.22***	2.74**	0.93	1.22	-0.30	-0.07	-0.06	-0.05
	(0.38)	(0.39)	(1.20)	(1.22)	(1.83)	(1.87)	(1.22)	(1.25)	(0.18)	(0.19)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18.427	18.427	1.607	1.607	2.562	2.562	5.175	5.175	1.046	1.046

Note: * p<.10, * p<.05, ** p<.01. Results of the Two-Way Fixed Effects Model were estimated using the ‘reghdfe‘ command in Stata. Clustered errors are reported in parentheses. Control variables include temperature, wind speed, and precipitation.

Table 4: *TWFE model: First change of stringency index and commercial fishing activity*

	Authorized		**Unauthorized**	
	(1)	*(2)*	*(3)*	*(4)*
Panel A. Total Fishing Efforts				
1. Stringency index	-1.608	-1.690	74.8	77.92*
	(2.873)	(2.897)	(45.6)	(45.7)
Controls	No	Yes	No	Yes
FE	z, t, ijt	z, t, ijt	z, t, ijt	z, t, ijt
Observations	9.928	9.928	9.164	9.164
Panel B. Number of fishing vessels				
1. Stringency index	-3.275	-3.400	25.9	27.7
	(4.862)	(4.907)	(46.7)	(46.6)
Controls	No	Yes	No	Yes
FE	z, t, ijt	z, t, ijt	z, t, ijt	z, t, ijt
Observations	9.928	9.928	9.164	9.164

Note: * p<.10, * p<.05, ** p<.01. The dependent variable is fishing activity in Panel A, and Number of fishing vessels in Panel B. Each column presents the results of an TWFE estimate. Controls and fixed effects by date, eez, flag and gear type are included. Clustered errors in parentheses. Control variables include temperature, wind speed, and precipitation.

To further explore the idea that the number of vessels did not increase, we evaluated whether there was any effect on vessels originating from regions that did not engage in fishing within the EEZs prior to the pandemic. This analysis serves as a means to assess whether there was any impact on vessels that did not typically fish in certain regions. Table 5 presents the results, indicating that there was no significant effect on vessels from non-frequent origins.

Table 5: *TWFE model: First change of stringency index and Unfrequented flag probability*

	Unfrequented flag	
	(1)	*(2)*
1. Stringency index	-0.001	-0.001
	(0.02)	(0.02)
Controls	No	Yes
FE	z,t,ijt	z,t,ijt
Observations	9.164	9.164

Note: * p<.10, * p<.05, ** p<.01. The dependent variable is the probability of being a unfrequented flag. Each column presents the results of an TWFE estimate. Controls and fixed effects by date, eez, flag and gear type are included. Clustered errors in parentheses. Control variables include temperature, wind speed, and precipitation.

Event Study

The use of the difference-in-differences (DiD) model is motivated by the heterogeneity in the timing of treatment declaration across countries. In addition to the analysis provided by the Two-Way Fixed Effect Model, the staggered DiD model allows for the evaluation of the effect over the weeks relative to the date of the lockdown, rather than solely focusing on the weeks close to the cutoff date in a partial way as TWFE model. Thus, the DiD model provides a broader analysis of the effect over time, addressing the question: What is the effect several weeks after the start of the lockdown declarations?

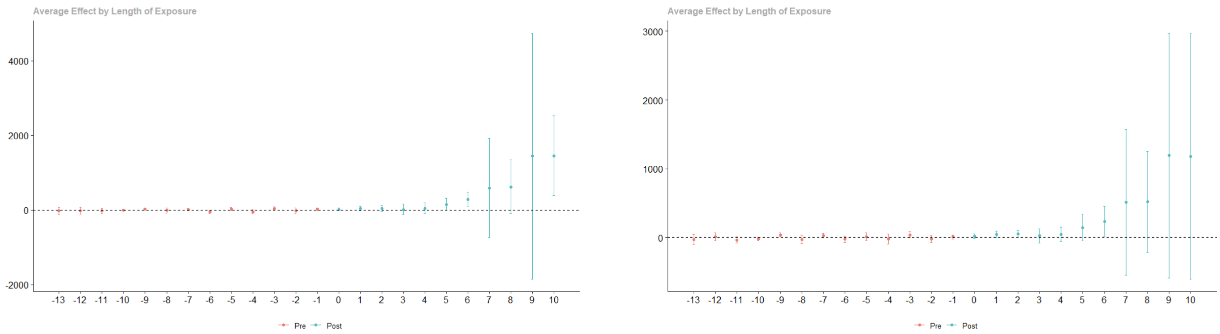
Estimating equation To address the question of this section, we employ the DiD estimator proposed by Callaway and Sant'Anna (2021), which follows the following specification of the dynamic Two-Way Fixed Effects (TWFE) model:

$$Y_{ijzt} = \sum_{\varphi=-S}^{T_{-1}} \gamma_j D_{z,\varphi} + \sum_{\varphi=T_{+1}}^{M} \delta_\varphi D_{z,\varphi} + \lambda_i + \lambda_t + \epsilon_{zt} \tag{3}$$

Where Y_{ijzt} refers to the outcome variables previously used. T indicates the treatment timing in weeks. S refers to the periods t before the treatment, and M to the periods t after the treatment. In contrast to the estimation performed by this specification, Callaway and Sant'Anna (2021) suggest a series of modifications to the δ_φ estimator to ensure its unbiasedness. Initially, the control group must be established. In this case, countries that had not yet implemented lockdowns in period t are used as controls, compared to countries that had already started implementing them in period t. The estimation is performed using the Double-Robust estimator, and the reference period is t_{-1}.

In this proposed dynamic DiD model, the estimator eliminates potential biases in post-treatment comparisons between countries that had already started implementing lockdowns and those that had not, by accounting for pre-existing differences in pre-treatment periods.

Results Figure 2 displays the estimation results for each week relative to the start date of the lockdowns. Similarly to TWFE model results, There is no significant evidence of an increase in the number of vessel of unauthorized fishing activity (Panel B), while it is found that the number of fishing hours engaging in unauthorized activity in the EEZs of other countries significantly increases from week 8 onward since the start of the lockdowns (Panel A).



(a) Total Fishing Efforts *(b) Number of fishing vessels*

Figure 2: Covid-19 lockdowns and unauthorized industrial fishing activity - Difference-in-Differences Model. Note: Panel (a) shows the average total unauthorized fishing efforts, and panel (b) shows the average Number of fishing unauthorized vessels.

Figure B6 and Figure B7 present the dynamic results of the DiD model by regions. In the disaggregated analysis, no significant effects are found for either of the two outcome variables evaluated. Table B4 displays the results for different stringency alternatives. The patterns of the effects remain consistent, although no significance is found, except for the estimates obtained using the economic support index variable.

7 Heterogeneity Analysis

In this section, we conducted an analysis of potential heterogeneities associated with unauthorized fishing activity. We evaluated the results obtained based on country-level incomes variable, and the distribution of the Ocean Health Index using the equation 2 and interaction with country-level incomes group and OHI variables.

When considering the income level of countries, it is found that unauthorized fishing efforts increased by 131.1 hours per week more for low and middle-income countries compared to unauthorized fishing efforts in high-income countries (Table 6). These results are consistent with the hypothesis that countries with lower incomes (developing countries, for example) have lower monitoring and surveillance capacities. This could allow for a more significant increase in unauthorized activity in response to further reductions in monitoring and surveillance capabilities.

Table 6: *TWFE model: First change of stringency index and commercial fishing activity by income levels*

	Authorized		Unauthorized	
	(1)	*(2)*	*(3)*	*(4)*
Panel A. Total Fishing Efforts				
1. Stringency index	-1.829	-1.872	16.1	17.5
	(1.766)	(1.797)	(59.9)	(60.3)
1.Stringency index * Low and Middle Income	1.511	1.920	123.7**	131.1**
	(2.987)	(2.994)	(59.9)	(62.1)
Controls	No	Yes	No	Yes
FE	*z, t, ijt*	*z, t, ijt*	*z, t, ijt*	*z, t, ijt*
Observations	9.174	9.174	7.048	7.048
Panel B. Number of fishing vessels				
1. Stringency index	-2.845	-2.972	-10.6	-8.33
	(3.071)	(3.138)	(74.1)	(74.5)
1.Stringency index * Low and Middle Income	759	1.670	94.2	94.1
	(4.978)	(4.958)	(63.5)	(64.9)
Controls	No	Yes	No	Yes
FE	*z, t, ijt*	*z, t, ijt*	*z, t, ijt*	*z, t, ijt*
Observations	9.174	9.174	7.048	7.048

Note: * p<.10, * p<.05, ** p<.01. The dependent variable is fishing activity in Panel A, and Number of fishing vessels in Panel B. Each column presents the results of an TWFE estimate. Controls and fixed effects by date, eez, flag and gear type are included. Robust standard errors in parentheses. Control variables include temperature, wind speed, and precipitation.

The state of ecosystems plays a significant role in determining the incidence of illegal fishing activity. There is a great dependence between fishing activity and the health of ecosystems (Halpern et al., 2012). A healthier ecosystem contributes to greater biomass production that encourages fishing activity, generating an income opportunity for fishermen (Flückiger and Ludwig, 2015, Axbard, 2016).

Figure 3 presents estimates of the effect of the onset of mobility restrictions on unauthorized fishing efforts by each dimension in OHI. It is found that ecosystems with better biodiversity indicators show higher increases in unauthorized activity, which can be explained by the higher probability of fish capture in these regions. On the other hand, ecosystems with better indicators in terms of iconic species and natural products show decreases in unauthorized activity. Similarly, this occurs with mariculture indicators; regions where there is a greater development of mariculture activities show decreases in unauthorized fishing efforts, This could be explained because mariculture represents a substitute for wild-caught fisheries. Economies, Fisheries and Food Provision dimensions shows a no statistically significant effect.

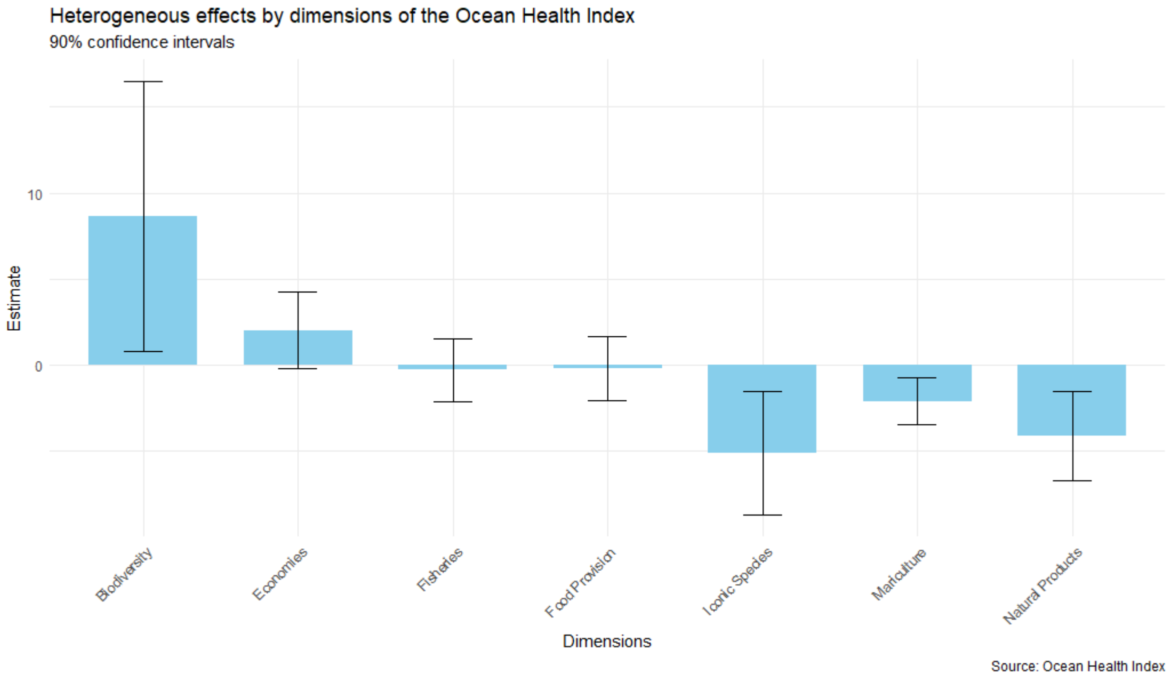


Figure 3: Unauthorized fishing change during COVID-19 pandemic by Ocean Health Index Components. Note: figure shows estimates from TWFE model with a 90% confidence interval (black line).

8 Conclusion

This paper examines the impact of COVID-19 pandemic-related restrictions on industrial fishing activity in general, and specifically evaluates the impact on unauthorized fishing activity globally. To this end, we differentiate between authorized and unauthorized fishing activity using information from fishing access agreements between nations. We propose a causal inference model, leveraging the heterogeneity in the implementation of pandemic-related restrictions across countries. Using this model, we estimate the impact of restrictions by employing the stringency measure, which provides reliable and comparable information across countries through a real-time monitoring system, on both authorized and unauthorized fishing activities.

Our results suggest that higher stringency of the measures had a significant effect on the total fishing activity, especially in the segment of authorized fishing, while unauthorized fishing increased following the implementation of restrictions, approximately 4-5 weeks later. The greatest increase in unauthorized activity occurred in low and middle-income countries, likely due to their limited resources and personnel for monitoring compared to high-income countries. Additionally, the highest increase was observed in regions with a higher biodiversity index, supporting the income opportunities hypothesis (Flückiger and Ludwig, 2015, Axbard, 2016).

Furthermore, the increase in unauthorized activity was observed in the number of fishing hours, with no significant effect on the number of vessels. The implementation of lockdowns did not impact the overall set of vessels engaged in illegal fishing. Instead, it contributed to an increase in fishing hours by non-compliant fishermen who were naturally less risk-averse and already engaged in unauthorized activities, driven by a reduced probability of being caught. This has significant policy implications, indicating that policies should focus on the segment of non-compliant vessels, as they are the most sensitive to changes in enforcement levels. By improving targeting within this group, compliance levels could be significantly enhanced.

Empirical evidence has shown that EEZs have been effective in deterring unauthorized fishing, with significant heterogeneities driven by differences in monitoring and enforcement capacities of countries, as well as variations in ecosystem productivity and health (Englander, 2019). Based on the results obtained, we now understand that the deterrent effect of EEZs can be compromised by changes in enforcement capacities, particularly when these capacities were already low and if the ecosystem productivity is high.

A limitation of this study is the explanation of the mechanisms behind the observed results. We assume that the impact on unauthorized fishing activity is explained by the pandemic's effect on monitoring, control, and surveillance activities, which were affected by the limitations imposed on the operations of on-board observer programs, and in-port and at-sea inspections (OCDE, 2021, Magalhães et al., 2021, Mallik et al., 2022, Loveridge et al., 2024), and by reduced logistical, personnel, and financial resources (March et al., 2021, Bates et al., 2021, Powlen et al., 2023). However, we lack data to validate this mechanism directly. Given the relationship between compliance and enforcement (Nøstbakken, 2008, Diekert et al., 2021), we infer that this is one of the main factors mediating the observed effect, Similarly, given the lack of availability of information about control, monitoring and surveillance operations at a global level, we use the COVID-19 pandemic and the implemented measures as a quasi-experiment that allows us to approximate the relationship between compliance and changes in monitoring, control, and surveillance capacities. Another limitations is related to the measurement of the fishing effort variable, which is reported by GFW as a prediction and therefore serves as a measure of the apparent number of fishing hours, and related to fishing vessels detection. We only use vessels that can be publicly tracked via the Automatic Identification System (AIS), allowing for the identification and origin of the vessels to be determined. Consequently, the results obtained here represent a lower bound of the estimation, as it is possible that vessels may turn off their transmitters and locators to avoid detection when engaging in unauthorized activities (Paolo et al., 2024). Finally, it is important to note that this study focuses on unauthorized fishing, and we cannot make any claims regarding the impact on IUU fishing in general.

In general, we know that the pandemic was an unprecedented shock to humanity. Despite this, we observe that only non-compliant vessels experienced significant changes in their levels of activity, intensifying their non-compliance. The results of this article suggest that compliance levels are sensitive to reductions in monitoring, control, and surveillance capacities, not in the total population of fishers, but specifically among the segment of less risk-averse individuals. Therefore, understanding motivations and decision-making processes of fishermen is crucial for achieving sustainable management of marine resources and proper governance of national territories. This insight underscores the importance of targeted enforcement strategies and the need for tailored policy interventions to address the unique behaviors of non-compliant actors in the fisheries sector.

References

Arnason, R. (2013). On optimal dynamic fisheries enforcement. *Marine Resource Economics*, 28(4):361–377.

Axbard, S. (2016). Income opportunities and sea piracy in indonesia: Evidence from satellite data. *American Economic Journal: Applied Economics*, 8(2):154–94.

Bates, A. E., Primack, R. B., et al, and Duarte, C. M. (2021). Global covid-19 lockdown highlights humans as both threats and custodians of the environment. *Biological Conservation*, 263:109175.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2):169–217.

Bellanger, M., Holland, D. S., Anderson, C. M., and Guyader, O. (2019). Incentive effect of joint and several liability in fishery cooperatives on regulatory compliance. *Fish and Fisheries*, 20(4):715–728.

Bos, B. (2021). Fishing under the radar: Estimating compliance with fishing bans. Available at SSRN: https://ssrn.com/abstract=3871993 or http://dx.doi.org/10.2139/ssrn.3871993.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Charles, A. T., Mazany, R. L., and Cross, M. L. (1999). The economics of illegal fishing: A behavioral model. *Marine Resource Economics*, 14(2):95–110.

Chen, J., Vullikanti, A., Santos, J., Venkatramanan, S., Hoops, S., Mortveit, H., Lewis, B., You, W., Eubank, S., Marathe, M., Barrett, C., and Marathe, A. (2021). Epidemiological and economic impact of covid-19 in the us. *Scientific Reports*, 11:20451.

Dang, H.-A. H. and Trinh, T.-A. (2021). Does the covid-19 lockdown improve global air quality? new cross-national evidence on its unintended consequences. *Journal of Environmental Economics and Management*, 105:102401.

Diekert, F., Nøstbakken, L., and Richter, A. (2021). Control activities and compliance behavior—survey evidence from norway. *Marine Policy*, 125:104381.

Doumbouya, A., Camara, O. T., Mamie, J., Intchama, J. F., Jarra, A., Ceesay, S., Guèye, A., Ndiaye, D., Beibou, E., Padilla, A., and Belhabib, D. (2017). Assessing the effectiveness of monitoring control and surveillance of illegal fishing: The case of west africa. *Frontiers in Marine Science*, 4.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy*, 81(3):521–565.

Englander, G. (2019). Property rights and the protection of global marine resources. *Nature Sustainability*, 2.

FAO (2020). How is covid-19 affecting the fisheries and aquaculture food systems? Technical report, FAO.

Flückiger, M. and Ludwig, M. (2015). Economic shocks in the fisheries sector and maritime piracy. *Journal of Development Economics*, 114:107–125.

Gaspar, D.-D.-C., Garcia, G., and Santos, C. (2020). The impact of covid-19 on the eu-27 fishing fleet.

Gold, A., Phayal, A., and Prins, B. (2023). The unexpected consequences of the covid-19 pandemic on maritime crime: Evidence from indonesia and nigeria. *International Area Studies Review*, 26:7–23.

Haas, P. (2021). Evaluating the effectiveness of marine governance. In *Epistemic Communities, Constructivism, and International Environmental Politics*. Routledge.

Halpern, B. S., Longo, C., Hardy, D., et al. (2012). An index to assess the health and benefits of the global ocean. *Nature*, 488:615–620.

Kroodsma, D. A., Mayorga, J., Hochberg, T., Miller, N. A., Boerder, K., Ferretti, F., Wilson, A., Bergman, B., White, T. D., Block, B. A., Woods, P., Sullivan, B., Costello, C., and Worm, B. (2018). Tracking the global footprint of fisheries. *Science*, 359(6378):904–908.

Loveridge, A., Elvidge, C. D., Kroodsma, D. A., White, T. D., Evans, K., Kato, A., Ropert-Coudert, Y., Sommerfeld, J., Takahashi, A., Patchett, R., Robira, B., Rutz, C., and Sims, D. W. (2024). Context-dependent changes in maritime traffic activity during the first year of the covid-19 pandemic. *Global Environmental Change*, 84:102773.

Lubchenco, J. and Grorud-Colvert, K. (2015). Making waves: The science and politics of ocean protection. *Science*, 350(6259):382–383.

Magalhães, K. M., de Souza Barros, K. V., de Lima, M. C. S., de Almeida Rocha-Barreira, C., Rosa Filho, J. S., and de Oliveira Soares, M. (2021). Oil spill + covid-19: A disastrous year for brazilian seagrass conservation. *Science of The Total Environment*, 764:142872.

Mallik, A., Chakraborty, P., Bhushan, S., and Nayak, B. B. (2022). Impact of covid-19 lockdown on aquatic environment and fishing community: Boon or bane? *Marine Policy*, 141:105088.

March, D., Metcalfe, K., Tintoré, J., and Godley, B. J. (2021). Tracking the global reduction of marine traffic during the covid-19 pandemic. *Nature Communications*, 12:2415.

Milliman, S. R. (1986). Optimal fishery management in the presence of illegal activity. *Journal of Environmental Economics and Management*, 13(4):363–381.

Naseer, S., Khalid, S., Parveen, S., Abbass, K., Song, H., and Achim, M. V. (2023). Covid-19 outbreak: Impact on global economy. *Frontiers in Public Health*, 10.

Nivette, A. E., Zahnow, R., Aguilar, R., Ahven, A., Amram, S., Ariel, B., Burbano, M. J. A., Astolfi, R., Baier, D., Bark, H.-M., Beijers, J. E. H., Bergman, M., Breetzke, G., Concha-Eastman, I. A., Curtis-Ham, S., Davenport, R., Díaz, C., Fleitas, D., Gerell, M., Jang, K.-H., Kääriäinen, J., Lappi-Seppälä, T., Lim, W.-S., Revilla, R. L., Mazerolle, L., Meško, G., Pereda, N., Peres, M. F. T., Poblete-Cazenave, R., Rose, S., Svensson, R., Trajtenberg, N., van der Lippe, T., Veldkamp, J., Perdomo, C. J. V., and Eisner, M. P. (2021). A global analysis of the impact of covid-19 stay-at-home restrictions on crime. *Nature Human Behaviour*, 5:868–877.

Nøstbakken, L. (2008). Fisheries law enforcement—a survey of the economic literature. *Marine Policy*, 32(3):293–300.

OCDE (2021). Covid-19 and multilateral fisheries management. Report, National Bureau of Economic Research.

Olaniyi, E. O., Solarte-Vasquez, M. C., and Inkinen, T. (2024). Smart regulations in maritime governance: Efficacy, gaps, and stakeholder perspectives. *Marine Pollution Bulletin*, 202:116341.

Paolo, F. S., Kroodsma, D., Raynor, J., Hochberg, T., Davis, P., Cleary, J., Marsaglia, L., Orofino, S., Thomas, C., and Halpin, P. (2024). Satellite mapping reveals extensive industrial activity at sea. *Nature*, 625(7993):85–91.

Powlen, K. A., Jones, K. W., Moreno, E. I. B., Cordero, M. A. O., Solomon, J. N., and Gavin, M. C. (2023). Perceived impacts of the covid-19 pandemic on protected area management and conservation outcomes in mexico. *Oryx*, 57(6):736–746.

Reid, L. J. (2021). The economic effect of the covid-19 lockdown in the united states: Was the cure worse than the disease? *SSRN Electronic Journal*.

Rowlands, G., Brown, J., Soule, B., Boluda, P. T., and Rogers, A. D. (2019). Satellite surveillance of fishing vessel activity in the ascension island exclusive economic zone and marine protected area. *Marine Policy*, 101:39–50.

Russo, E., Monti, M. A., Toninato, G., Silvestri, C., Raffaetà, A., and Pranovi, F. (2021). Lockdown: How the covid-19 pandemic affected the fishing activities in the adriatic sea (central mediterranean sea). *Frontiers in Marine Science*, 8.

UNCTAD (2022). Impact and implications of covid-19 for the ocean economy and trade strategy: Case studies from barbados, belize and costa rica. Unctad/ditc/ted/2021/4, United Nations.

Violato, C., Violato, E. M., and Violato, E. M. (2021). Impact of the stringency of lockdown measures on covid-19: A theoretical model of a pandemic. *PLOS ONE*, 16(10):1–14.

Appendix A. Additional Data Details

COVID-19-related measures

In the OxCGRT database, the stringency index variable is used as a treatment, representing the level of government response to the COVID-19 pandemic in 2020. This indicator synthesizes the response in different dimensions, as presented in Table A1. Each component of the index is measured on an ordinal scale (e.g., 0-no measure, 1-recommended closing, 2-require partial closing, 3-require closing all levels) capturing the level of strengthening of the measures per component. The index is calculated as the simple average after rescaling the components based on their maximum values.

Table A1: *Stringency index components*

Number	Components	Description
1	School closing	Record closing of schools and universities
2	Workplace closing	Record closing of workplaces
3	Cancel public events	Record canceling public events
4	Restrictions on gathering	Record the cut-off size for bans on private gatherings
5	Close public transport	Record closing of public transport
6	Stay at home requirement	Record orders to "shelter-in-place" and otherwise confine to home
7	Restrictions on internal movement	Record restrictions on internal movements
8	International travel controls	Record restrictions on international travel
9	Public info campaigns	Record presence of public info campaigns

Source: Dang and Trinh (2021). Note: Each component is measured on an ordinal scale (e.g., 0-no measure, 1-recommended closing, 2-require partial closing, 3-require closing all levels). It is then rescaled by the maximum value to create a score between 0 and 100. These scores are then averaged to obtain the stringency index. The stringency index is measured by the OxCGRT team as a simple average of individual component indicators.

For the categorization of fishing authorization type for each recorded fishing data in the database, as explained in the main document, it was necessary to consolidate a database of fishing access agreements by countries compiled by Sea Around Us (SAU) following FAO guidelines. SAU collects information from 282 countries, from which we managed to gather information using a web scraping algorithm for 249 countries. Table A2 presents the countries for which information on agreements could not be obtained. Out of these countries, only 75 had valid relationships between 2019 and 2020, representing only 26.6%. Therefore, we assume that the foreign fishing activity detected in the database for the countries listed in Table A2 will be considered unauthorized, implying a probability of 73.4% for unauthorized fishing. Column 3 of Table A2 shows the total foreign fishing activity detected for these countries not found in the SAU database. In total, 9.7% of the total observations of unauthorized fishing in the database are assumed to be unauthorized. The remaining observations of unauthorized fishing in the database were correctly characterized based on the data captured from SAU. Finally, all country code information was assigned according to the alpha code 3 digits from the "country-codes" database in the BigQuery Public Data repository.

Table A2: *Countries not found*

Countries	**Country Code**	**Misleading count**
Ascension Isl. (UK)	-	-
Belize	BLZ	0
Bosnia & Herzegovina	BIH	27
Cambodia	KHM	0
Canada (Arctic)	-	-
Chagos Archipelago (UK)	IOT	0
Comoros Isl.	COM	0
Curaçao (Netherlands)	CUW	0
Desventuradas Isl. (Chile)	-	-
Egypt (Red Sea)	EGY	99
Gabon	GAB	330
Gaza Strip	-	-
Guatemala (Caribbean)	GTM	79
Honduras (Pacific)	HND	0
India (mainland)	IND	193
Indonesia (Central)	IDN	361
Iraq	IRQ	0
Israel (Mediterranean)	ISR	0
Israel (Red Sea)	ISR	0
Jordan	JOR	0
Kiribati (Line Islands)	KIR	0
Mauritania	MRT	1,661
Mauritius	MUS	561
Russia (Laptev to Chukchi Sea)	RUS	0
Saint Lucia	LCA	0
Saudi Arabia (Red Sea)	SAU	42
Slovenia	SVN	181
St Barthelemy (France)	BLM	0
St Martin (France)	MAF	0
Timor Leste	TLS	14
Tonga	TON	318
United Arab Emirates	ARE	396
Wake Isl. (USA)	-	-
Total		4,262

Note: Countries without data in the table indicate that no information regarding the country code was found.

Ocean Health Index

To consider a standardized, quantitative, transparent, and scalable measure of marine ecosystem conditions across countries, we use the Ocean Health Index proposed by Halpern et al. (2012). This index measures the overall health of marine ecosystems, treating nature and people as integrated parts of a healthy system.

The index is composed of 10 goals with 8 sub-goals (Figure A1). Each goal is scored on the delivery of specific benefits with respect to a sustainable target. A goal is given a score of 100 if its benefits are maximized without compromising the ocean's ability to deliver those benefits in the future. Lower scores indicate that more benefits could be gained or that current methods are harming the delivery of future benefits.[6]

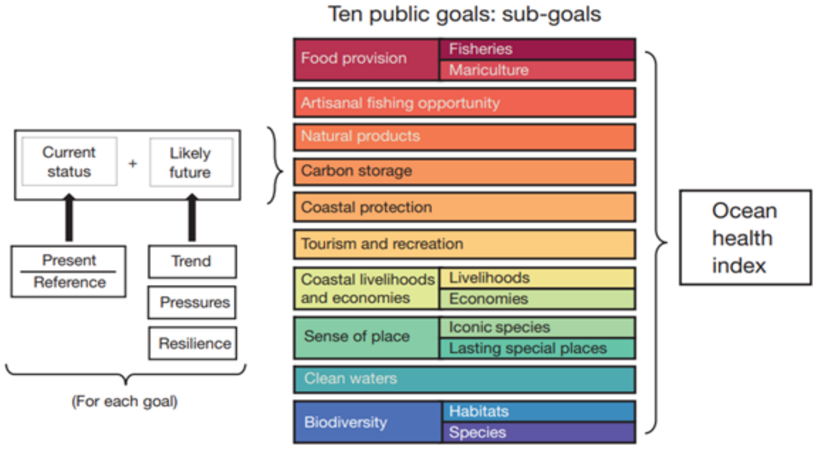


Figure A1: Conceptual framework for calculating the index. Note: Each dimension (status, trend, pressures and resilience) is derived from a wide range of data. Dimensions combine to indicate the current status and likely future condition for each of ten goals. Taken from Halpern et al. (2012)

The biodiversity indicator measures the effectiveness of efforts to maintain the richness and diversity of marine life globally. The economies indicator captures the economic value associated with various marine industries, including revenue from sectors such as commercial fishing, mariculture, tourism and recreation, shipping and transportation, whale watching, ports and harbors, ship and boat building, and renewable energy production. The food provision indicator generally assesses the sustainable harvest of seafood for human consumption, encompassing both mariculture and wild-caught fisheries (commercial, artisanal, and recreational). Specifically, it evaluates the ability to sustainably optimize wild-caught fisheries and farm-raised marine food production. The iconic species indicator measures the conservation status of marine species that hold unique significance to humans through traditional activities, ethnic or religious practices, existence value, or recognized aesthetic value. Finally, the

[6]See https://oceanhealthindex.org/methodology/

natural products indicator assesses how effectively countries are maximizing the sustainable harvest of non-food marine resources.[7]

To calculate each Goal Score, the Present Status and Likely Future Status are considered. The Present Status reflects the goal's current value compared to its reference point, resulting in a score from 0 to 100. The Likely Future Status is the predicted status score five years into the future, also on a scale from 0 to 100. This is estimated by adjusting the current status score using three variables: Trend, Pressures, and Resilience. The weighted average of these scores captures the Goal Score for each goal.

Figure A2 presents the correlation between the dimensions considered in the analysis shown in Figure 3 for the period from 2012 to 2022. Figure A3 shows the average score of each goal in the index by the income group of the countries. It is observed that there are no significant differences between the groups, with the exception of Mariculture, which is higher in high-income countries.

	Biodiversity	Economies	Fisheries	Food provision	Iconic species	Mariculture	Natural products
Biodiversity	1.00						
Economies	-0.64	1.00					
Fisheries	0.67	0.09	1.00				
Food provision	0.45	0.35	0.95	1.00			
Iconic species	0.69	-0.11	0.65	0.54	1.00		
Mariculture	-0.84	0.32	-0.69	-0.54	-0.94	1.00	
Natural products	0.88	-0.31	0.86	0.71	0.76	-0.83	1.00

Figure A2: Ocean Health Index Components Correlations. Author, using information from Halpern et al. (2012). Note: Correlation were calculated using available years from 2012 to 2022.

[7] See https://oceanhealthindex.org/goals/

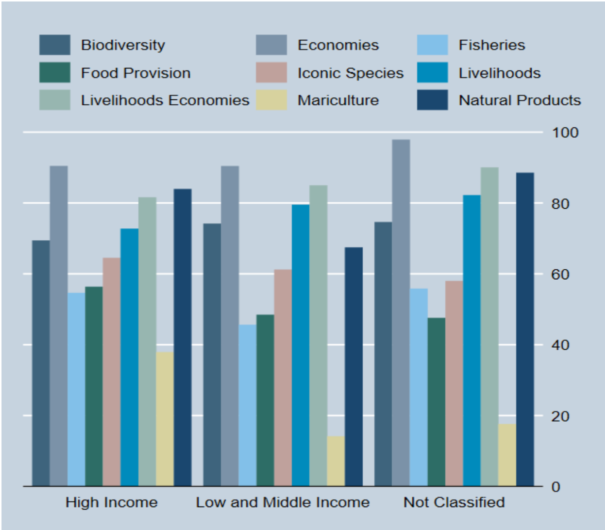
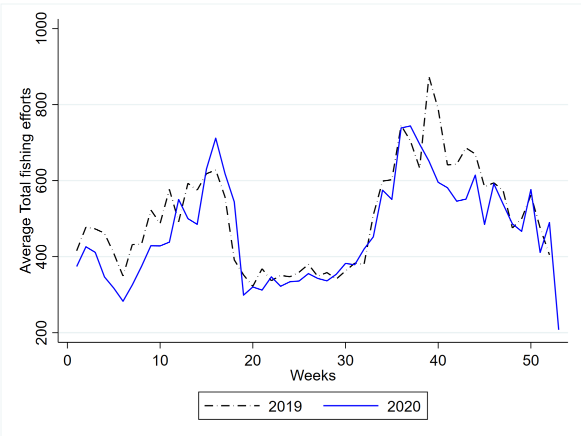
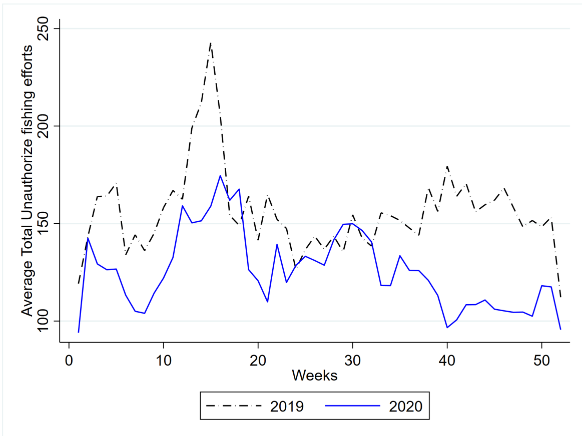


Figure A3: Ocean Health Index Components and income level of countries. Author, using information from Halpern et al. (2012).

Appendix B. Additional Figures and Tables

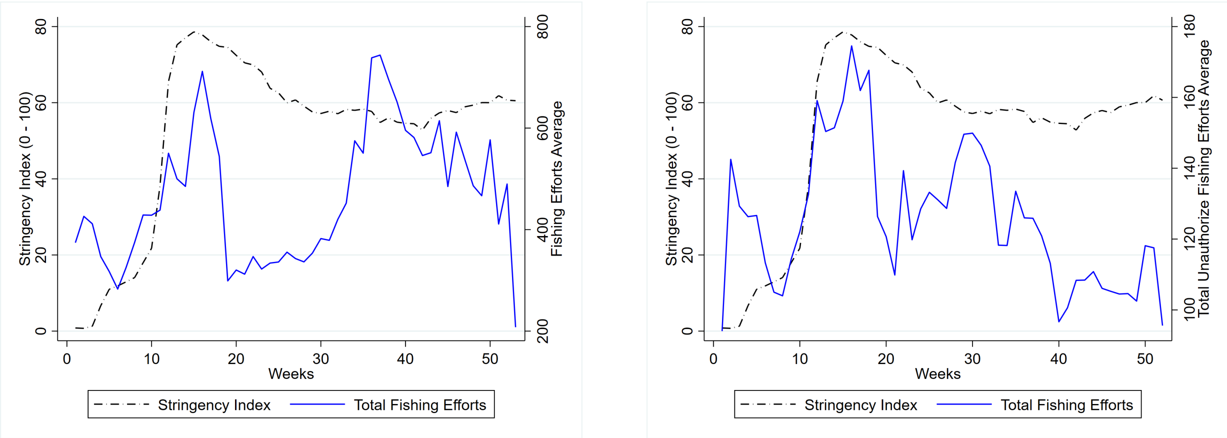


(a)



(b)

Figure B1: Average fishing efforts, 2019 - 2020. Author, using information from GFW. Note: The figure displays the average fishing efforts for 2019 as a black dashed line and the average for 2020 as a blue solid line. Panel A represents the total average fishing efforts, and Panel B represents the total unauthorized fishing efforts.



(a) *(b)*

Figure B2: Average fishing efforts and stringency index, 2020. Author, using information from GFW and OxCGRT. Note: The figure displays the average stringency index as a black dashed line and the average fishing efforts for 2020 as a blue solid line. Panel A represents the stringency index with total fishing efforts, and Panel B represents the stringency index with total unauthorized fishing efforts.

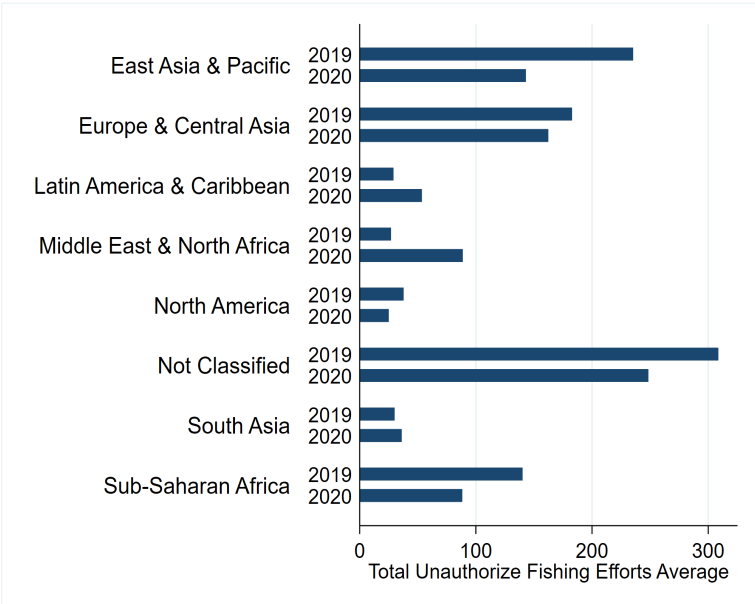


Figure B3: Total unauthorized fishing efforts by year and regions. Author, using information from GFW and Sea Around Us. Note: The figure displays the cumulative number of countries that introduced lockdowns as a black dashed line and the average stringency index for 2020 as a blue solid line.

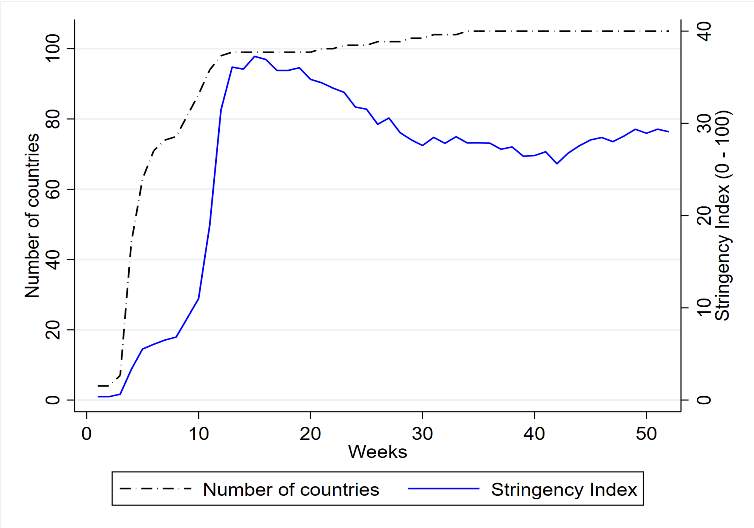


Figure B4: Cumulative number of countries that introduced lockdowns and average stringency index. Author, using information from OxCGRT. Note: The figure displays the cumulative number of countries that introduced lockdowns as a black dashed line and the average stringency index for 2020 as a blue solid line.

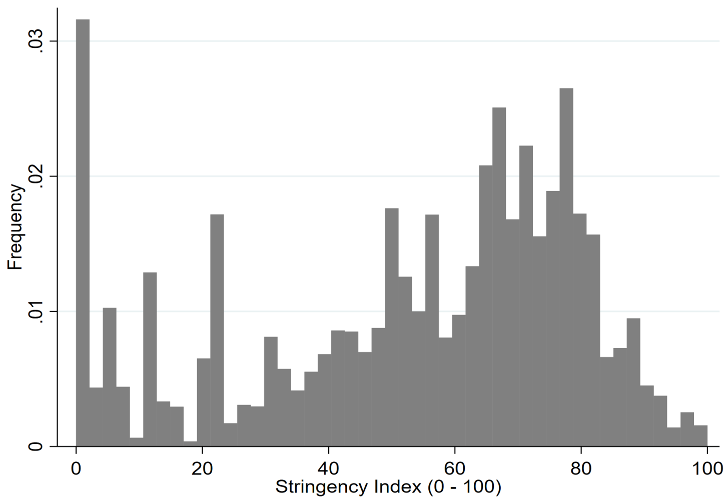
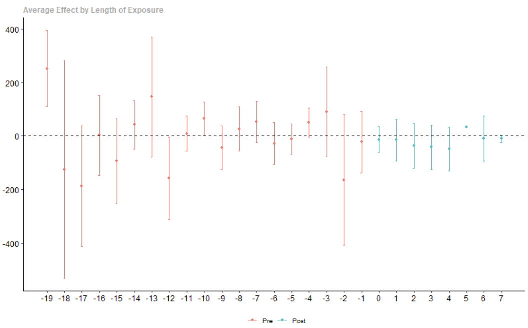
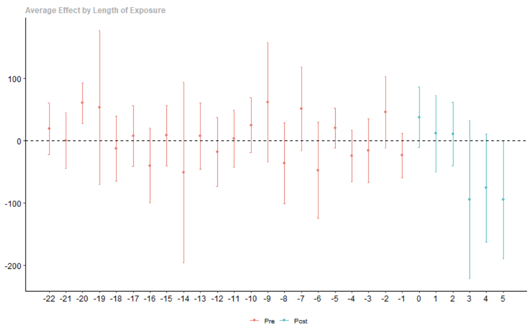


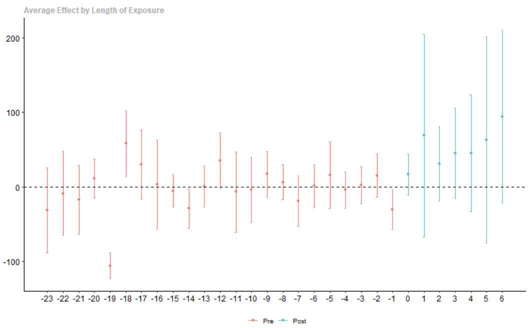
Figure B5: Stringency index distribution, 2020. Note: The figure shows a histogram with bin=47, start=0, width=2.1276596



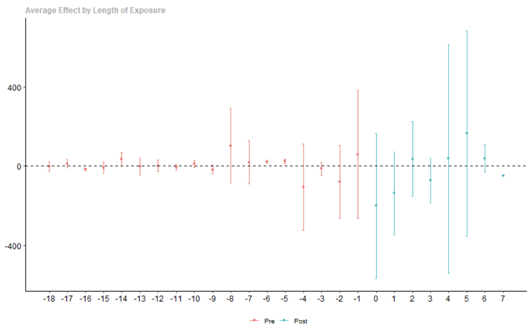
(a)



(b)



(c)



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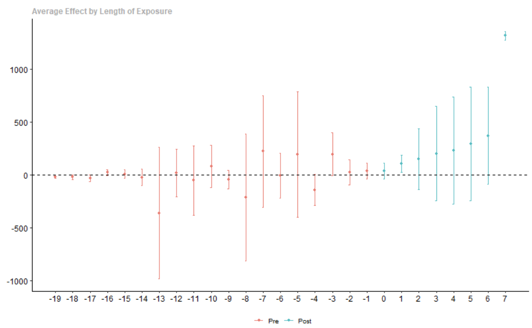
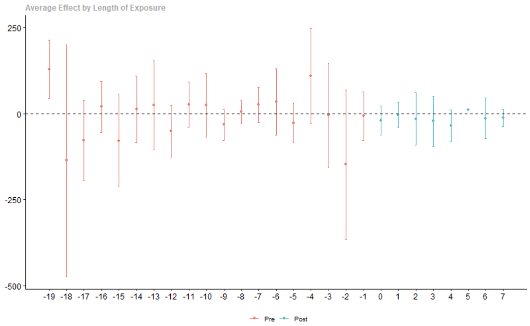
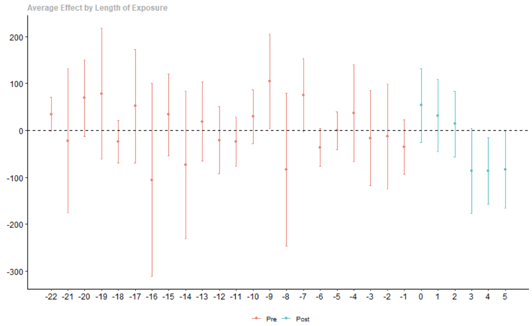


(e)

Figure B6: Covid-19 lockdowns and authorized industrial fishing efforts by region. Note: Panel A shows the results for East Asia & Pacific, Panel B for Europe & Central Asia, Panel C for Latin America & Caribbean, Panel D for Middle East & North Africa, and Panel E for South Asia.



(a)



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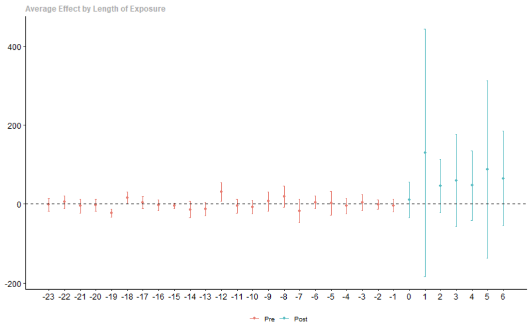
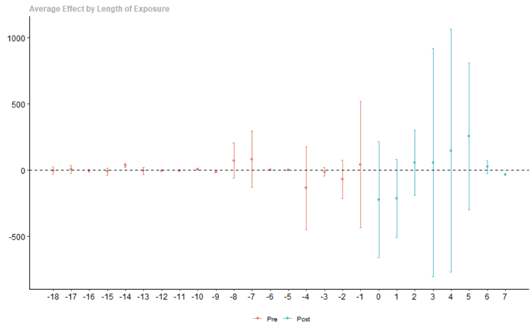


(c)



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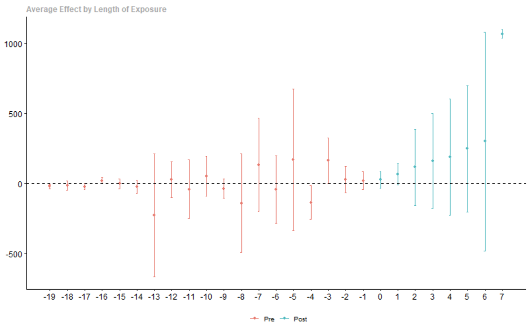

(e)

Figure B7: Covid-19 lockdowns and unauthorized industrial fishing efforts by region. Note: Panel A shows the results for East Asia & Pacific, Panel B for Europe & Central Asia, Panel C for Latin America & Caribbean, Panel D for Middle East & North Africa, and Panel E for South Asia.

Table B1: *Descriptive Statistics: Summary by fishing location*

	Location							
	Inside EEZ				Outside EEZ			
	Mean	Standard deviation	Min	Max	Mean	Standard deviation	Min	Max
Panel A: Total Fishing								
Vessel Nationality								
National Fishing	1,343.7	10,697	0.5	436,402	53.0	133.2	0.5	2,803.6
Foreign Fishing	157.2	428.8	0.5	9,780	111.5	401.1	0.5	7,263
Vessel in Sovereign	316.2	537.6	0.5	3,161.2	13.5	17.3	0.5	142.8
World Bank Regions								
East Asia & Pacific	1,906.3	15,725	0.5	436,402	105.7	296.1	0.5	4,050.9
Europe & Central Asia	511.5	1,910.8	0.5	32,446	49.0	138.4	0.5	1,655.7
Latin America & Caribbean	294.9	1,039.7	0.5	11,695	205.3	778.6	0.5	7,263
Middle East & North Africa	165.8	433.1	0.5	3,505.2	7.6	11.8	0.5	84.4
North America	693.9	1,803.2	0.5	17,847	91.7	182.6	0.5	2,803.6
South Asia	347.1	600.5	0.6	4,058.7	144.0	211.5	0.5	1,234.2
Sub-Saharan Africa	218.7	515.7	0.5	7,797.6	56.8	129.3	0.5	1,262.1
World Bank Income Groups								
High Income	516.8	1,754.4	0.5	32,446	60.0	148.3	0.5	2,803.6
Low income	262.4	520.0	0.5	3,497.8	62.5	114.3	0.5	798.3
Middle Income	1,112.8	11,854	0.5	436,402	137.1	511.4	0.5	7,263
Panel B: Fishing Average								
Vessel Nationality								
National Fishing	2.5	2.8	0.5	103.3	4.0	5.8	0.5	121.6
Foreign Fishing	2.4	3.9	0.5	147.0	2.5	5.4	0.5	215.4
Vessel in Sovereign	1.3	0.9	0.5	11.8	2.5	2.6	0.5	23.1
World Bank Regions								
East Asia & Pacific	2.8	3.6	0.5	87.5	3.4	5.1	0.5	92.1
Europe & Central Asia	1.9	2.2	0.5	79.8	3.1	5.2	0.5	91.7
Latin America & Caribbean	3.2	6.9	0.5	147.0	2.8	5.0	0.5	89.2
Middle East & North Africa	3.3	3.2	0.5	38.7	6.0	8.2	0.5	38.3
North America	2.6	2.3	0.5	23.8	2.9	8.1	0.5	215.4
South Asia	4.0	3.0	0.6	23.9	5.1	4.1	0.5	23.9
Sub-Saharan Africa	2.4	3.1	0.5	55.7	1.9	3.3	0.5	51.4
World Bank Income Groups								
High Income	2.2	2.6	0.5	115.1	3.1	6.0	0.5	215.4
Low income	2.6	4.0	0.5	52.3	1.7	2.0	0.5	22.1
Middle Income	2.9	4.4	0.5	147.0	3.0	5.0	0.5	92.1
Panel C: Number of fishing vessels								
Vessel Nationality								
National Fishing	1,740	19,807	1	911,097.0	46.9	164.2	1	3,114
Foreign Fishing	136.7	453.4	1	9,439	81.1	318.0	1	8,371
Vessel in Sovereign	389.1	684.8	1	4,361	9.9	18.1	1	176
World Bank Regions								
East Asia & Pacific	2,457	29,196	1	911,097	82.6	231.1	1	3,114
Europe & Central Asia	706.0	3,258.7	1	64,835	45.5	195.0	1	5,263
Latin America & Caribbean	454.6	2,648.1	1	39,644	139.1	592.0	1	8,371
Middle East & North Africa	98.6	333.3	1	4,256	3.2	3.8	1	22
North America	542.8	1,687.4	1	19,700	71.7	167.8	1	2,278
South Asia	142.5	326.9	1	2,939	39.7	67.6	1	522
Sub-Saharan Africa	185.1	486.5	1	4,801	40.4	94.6	1	1,110
World Bank Income Groups								
High Income	613.1	2,776.2	1	64,835	50.3	175.7	1	5,263
Low income	223.8	510.6	1	3,642	40.6	75.4	1	618
Middle Income	1,458.1	22,007	1	911,097	97.2	389.3	1	8,371

Source: Author. Note: Panel A presents the summary of descriptive statistics for the total sum of fishing efforts by EEZ. Panel B presents the descriptive statistics for the average fishing efforts per vessel by EEZ. Panel C presents the results for the total number of fishing vessels by EEZ. "Outside EEZ" indicates observations that are located outside the EEZ but within a 100km buffer from the EEZ border towards open sea.

Table B2: *Data sources and summary statistics*

Sources/Variable	Description	2020				2019			
		Mean	**Standard deviation**	**Min**	**Max**	**Mean**	**Standard deviation**	**Min**	**Max**
Global Fishing Watch									
Total Fishing Efforts	Sum of fishing efforts by EEZ	465.4	5,156.8	0.5	323,988	503.4	5,976.2	0.5	436,402
Fishing Average	Average fishing efforts per vessel/EEZ	2.7	4.6	0.5	143.1	2.6	4.2	0.5	215.5
Number of fishing vessels	Sum of vessels by EEZ	567.3	8,906.7	1	617,320	612.7	11,030	1	911,097
Oxford covid-19 government response tracker (OxCGRT)									
Stringency index	Total government responses to COVID-19 (Score between 0-100)	53.07	26.7	0	100	-	-	-	-
Government response index	Government responses to COVID-19 (Score between 0-100)	49.99	22.69	0	89.84	-	-	-	-
Containment and health index	Containment and health measures related to COVID-19 (Score between 0-100)	50.7	34.25	0	100	-	-	-	-
Economic support index	Economic support related to COVID-19 (Score between 0-100)	49.91	22.53	0	91.96	-	-	-	-
Sea Around Us									
Internal Fishing Access Agreements	Categorization of the validity of access agreements	0.54	0.5	0	1	0.61	0.49	0	1
Ocean Health Index (OHI)									
Index	Total Ocean Health Index	68.45	5.44	48.44	82.97	69.25	5.49	47.29	83.21
Biodiversity	Ocean Health Index related to biodiversity	71.38	5.59	51.01	91.16	71.94	6.19	51.58	91.32
Economies	Ocean Health Index related to economies	91.39	14.92	0.05	100	89.71	17.55	18.57	100
Fisheries	Ocean Health Index related to fisheries	49.6	16.28	10.89	83.93	51.39	17.18	10.91	85.39
Food Provision	Ocean Health Index related to food provision	51.4	16.84	14.82	83.9	53.21	17.31	14.89	85.38
Iconic Species	Ocean Health Index related to iconic species	62.58	7.86	48.07	92.52	63.71	7.63	53.04	92.57
Livelihoods	Ocean Health Index related to livelihoods	76.39	18.01	35.15	100	76.22	18.74	3.34	100
Livelihoods and Economies	Ocean Health Index related to livelihoods and economies	83.89	11.76	27.48	100	82.96	13.48	12.8	100
Mariculture	Ocean Health Index related to mariculture	30.82	35.86	0	88.47	28.84	35.33	0	88.38
Natural Products	Ocean Health Index related to natural products	79.13	17.2	0	100	77.36	18.65	0	100
NOAA									
Temperature (Celsius)	Mean temperature for the day in degrees Celsius to tenths	19.89	9.44	-26.9	37.92	20.21	9.62	-24.6	37.19
Wind speed	Mean wind speed for the day in knots to tenths	54.52	120.2	0.44	632.6	54.85	116.5	0.49	566.3
Precipitation (inches)	Total precipitation (rain and/or melted snow) reported during the day in inches and hundredths	9.81	15.48	0	95.23	9.31	14.3	0	95.23

Table B3: *DiD Model: Stringency change and unauthorized industrial fishing activity by regions*

	Total Fishing		Number of fishing vessels	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
Panel A. East Asia & Pacific				
Stringency change	42.99	70.63	14.48	52.67
Obs	1,404	1,404	1,404	1,404
Panel B. Europe & Central Asia				
Stringency change	-33.22	21.18	-71.07	37.2
Obs	3,854	3,854	3,854	3,854
Panel C. Latin America & Caribbean				
Stringency change	9.69	15.17	24.91	27.17
Obs	740	740	740	740
Panel D. Middle East & North Africa				
Stringency change	-52.81	60.29	-34.02	44.4
Obs	656	656	656	656
Panel E. North America				
Stringency change	1.36	11.65	3.5*	0.74
Obs	221	221	221	221
Panel F. South Asia				
Stringency change	-298.2	221.8	-152.9	190.4
Obs	1,674	1,674	1,674	1,674

Note: Signif. codes: '*' confidence band does not cover 0. Control Group: Not Yet Treated, Anticipation Periods: 0. Estimation Method: Doubly Robust. All estimates were calculated using the estimator proposed by Callaway and Sant'Anna (2021).

Table B4: *DiD Model: Stringency change and unauthorized industrial fishing activity - Alternative stringency indexes*

	Total Fishing		**Number of fishing vessels**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
Panel A. Goverment response index				
Stringency change	37.74	46.53	49.73	39.57
Panel B. Containment and health index				
Stringency change	-138.2	88.16	-82.89	52.93
Panel C. Economic suport index				
Stringency change	-227.16*	102.5	-163.9*	71.33
Obs	10.841	10.841	10.841	10.841

Note: Signif. codes: '*' confidence band does not cover 0. Control Group: Not Yet Treated, Anticipation Periods: 0. Estimation Method: Doubly Robust. All estimates were calculated using the estimator proposed by Callaway and Sant'Anna (2021). Errors are clustered by region.