Unmasking the Threat to Property Rights: 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 and enforcement. In this paper, I examine the impact of the COVID-19 pandemic on property rights in the context of unauthorized fishing activity. 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, I compile a comprehensive database with weekly, country-level fishing effort data for 146 countries before and after the COVID-19 lockdowns and international fishing access agreements data. I employ Differences in Differences approaches to shed light on the consequences of the pandemic for marine resource governance. The findings indicate that the implementation of restrictions resulted in a decrease in overall fishing efforts; however, unauthorized fishing activity saw an increase. Heterogeneous effects are found when I consider income-country variable, and Ocean Health Index components. This paper offers valuable insights for policymakers and stakeholders aiming to protect and strengthen property rights in the face of unforeseen disruptions.

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

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1 Introduction

The COVID-19 pandemic has generated a global socioeconomic crisis as a result of government responses aimed at containing the health impacts (Gold et al., 2023). Mobility regulations have been the primary public health tool implemented by countries (Nivette et al., 2021), and these regulations have disrupted various economic activities, including those related to monitoring and control, specifically in the maritime sector (Mallik et al., 2022, Nivette et al., 2021). Regulatory entities in the maritime field play a fundamental role in ensuring the property rights delegated to each country within their maritime borders. Therefore, the reduction in monitoring and control activities may have created sufficient incentives for unauthorized vessels to engage in fishing activities that violate the property rights of each country.

Exclusive Economic Zones (EEZs) represent the maritime space owned by each country, which grants them rights of exploration and exploitation over their resources (Englander, 2019). In this article, I 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. Unauthorized fishing activity refers to any fishing activity conducted within a country's Exclusive Economic Zone (EEZ) without the necessary permits.

To investigate this issue, I compile a large number of 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. I employ Difference-in-Differences strategy using a Two-Way Fixed Effect Model and I consider heterogeneous time effects using the estimators proposed by Callaway and Sant'Anna (2021) as a robustness check analysis.

The method used allow me to obtain robust results regarding the effect of lockdown impositions relative to the start date of these regulations. I find that the imposition of restrictions contributed to a decrease in total fishing efforts. However, contrary to the overall fishing dynamics, unauthorized fishing activity showed increases, which may be associated with a decrease in maritime monitoring and control capacities in some regions (Mallik et al., 2022). Similarly, 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).

This article relates to the literature on the effects of the COVID-19 pandemic on economic activity, as well as the literature on property rights and illegal fishing activity. In this regard, the article contributes by providing empirical evidence of the behavior of industrial vessels globally in response to mobility restrictions associated with the COVID-19 pandemic. Additionally, to the best of my knowledge, this article is the first to address the question of the effects of lockdown heterogeneities during the pandemic on maritime compliance through global causal estimations, disaggregated by authorization type, and studying this relationship with weekly data, allowing for control of fishing data dynamics associated with this periodicity.

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 I discuss the empirical model used. Sections 6 present the main results and the robustness checks, distinguishing between authorized and unauthorized fishing. Section 7 present the heterogeneity analysis. Finally, the conclusions are presented in Section 8.

2 Background

Property Rights and Fisheries Management

Exclusive Economic Zones (EEZs) are instruments of property rights that each country has over marine resources, covering approximately 39% of the ocean surface (Figure 1) and accounting for about 95% of global fish catch (Englander, 2019).

The designation of EEZ boundaries is arbitrary, so statistically significant differences in ecosystem productivity-related properties such as depth, surface temperature, and net primary productivity are not expected between both sides of the border (Englander, 2019).

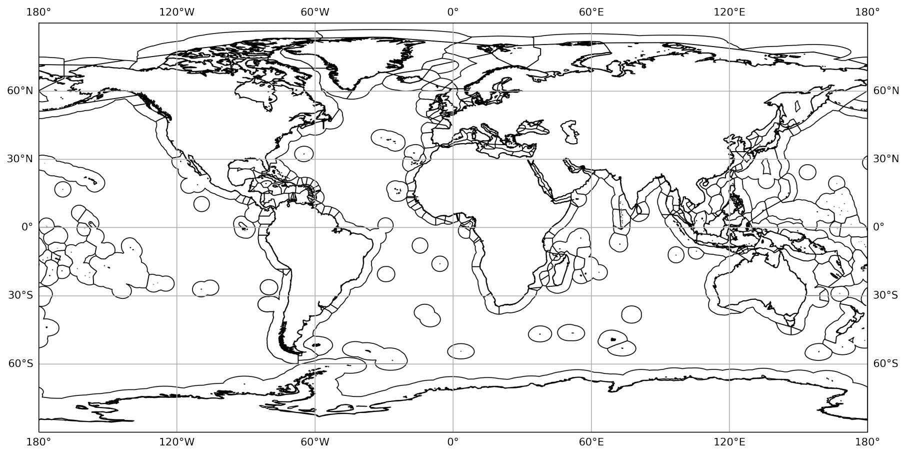


Figure 1: Exclusive Economic Zone Map. Author, using information from Marine Regions Repository.

Legally, EEZs grant full exploitation rights to the country, with coverage extending up to 200 nautical miles from the coast. 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 Exclusive Economic Zone (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.

COVID-19 Pandemic and its Impact on Fisheries

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 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 maritime 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 de-

[1]See: WHO: Events as they happen
[2]See: OxCGRT Coding Interpretation Guide
[3]See: Lockdown allowed illegal fishing to spike in Philippines, satellite data suggest at Mongabay newspaper

creased 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 and control activities (Mallik et al., 2022), 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), 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. The main hypothesis for the change in unauthorized fishing activity will be understood as the change in monitoring and control capacities; however, it is possible that this may not be the only one, as just discussed.

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, March et al., 2021, Loveridge et al., 2024).

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:

$$\max_{x_I, x_L, A} p(q_L x_L B + q_I x_I B) - (c_L x_L^2 + c_I x_I^2 + c_A A^2) - (\alpha x_I + \beta x_I^2) - \left(\frac{(1 - \gamma A)E}{1 + L} x_I \right) \tag{7}$$

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:

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

$$2c_L x_L = pq_L B \tag{8b}$$

$$x_I \frac{\gamma E}{1 + L} = 2c_A A \tag{8c}$$

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.

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

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:

$$\theta pq_I B - \frac{pq_L B}{2c_L} > \theta E \tag{9}$$

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

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

Fishing Efforts To assess fishing efforts, I use the Global Fishing Watch (GFW) database, which allows me to identify fishing activity of industrial vessels in pixels of approximately 0.01 x 0.01 degrees, equivalent to approximately 1x1 km on a daily basis, providing global coverage. To homogenize the different sources of information, I aggregate the data on a weekly basis for the years 2019 and 2020. This aggregation allows me 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, I 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, I 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 efforts 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. Using this data, I 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 during a specific week.

Exclusive Economic Zones To identify the EEZs, I utilize 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, I 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, I first construct a 100 km buffer from the EEZ boundaries towards open sea. This allows me 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, I 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, I 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, I develop a web scraping algorithm to collect the details of agreements for each of the 282 countries. Through this algorithm, I am able to compile a database with information for 249 countries on agreements negotiated from 1950 to 2020. Using this data, I 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, I utilize 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. I 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, I consider the first positive change in the stringency index, indicating the

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

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, I consider information from various data sources. For the construction of time-varying covariates, I 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, sea level pressure, station pressure, visibility, wind speed, maximum and minimum temperature, maximum sustained wind speed, maximum gust, precipitation, snow depth, and weather indicators.

To characterize the quality of the marine ecosystem, I utilize information from the Ocean 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.

Lastly, I employ data from the "Google COVID-19 Community Mobility Reports," which provide information on the percentage changes in mobility compared to a baseline year for various locations, such as residences, workplaces, parks, and others. With this dataset, I assess possible heterogeneities among countries associated with the general public's compliance with government regulations. Additionally, I 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 population mobility indicators, 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.

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 high-income regions where the fishing sector is generally more advanced. 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.

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.

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: Total MMSI								
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: Total MMSI								
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.

5 Empirical Model

I begin this analysis by evaluating the relationship between total fishing efforts and the strengthening of COVID-19-related restrictions. Figure B4 shows that, on average, countries started imposing lockdowns from the first week of 2020. However, it is not until weeks 4 and 11 that the majority of countries declared some form of lockdown. For this first point, the following Two-Way Fixed Effects (TWFE) Model is estimated:

$$Y_{ijzt} = \beta SI_{zt} + \gamma X_{it} + \alpha_z + \tau_t + \epsilon_{ijzt} \tag{10}$$

Where Y_{ijzt} is the outcome variable, which represents the total number of fishing hours or the number of vessels conducting fishing 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. 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, I decompose the effect by examining the correlation between fishing and lockdown measures separately for authorized and unauthorized fishing activities. The following model is estimated:

$$Y_{ijzt} = \tau D_{zt} + \gamma_z + \gamma_t + \gamma_{ijt} + \epsilon_{ijzt} \tag{11}$$

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. The outcome variable in Panel A is the total fishing efforts, while the number

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

of fishing vessels is presented in Panel B. 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.

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. Total Fishing Efforts										
Stringency index	-5.55**	-6.56**	-0.10	0.30	-0.29	-0.44	0.16	-0.18	-22.44***	-22.7***
	(2.22)	(2.65)	(0.29)	(0.28)	(0.76)	(0.80)	(1.10)	(1.21)	(7.45)	(8.43)
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	103,258	95,566	25,989	22,479	27,103	25,549	25,366	22,999	24,800	24,539
Panel B. Total MMSI										
Stringency index	-7.5**	-9.15**	-0.04	0.32	0.22	-0.09	-0.14	-0.88	-30.1**	-31.01**
	(3.81)	(4.54)	(0.36)	(0.41)	(0.90)	(0.94)	(1.61)	(1.78)	(13.8)	(14.2)
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	103,258	95,566	25,989	22,479	27,103	25,549	25,366	22,999	24,800	24,539

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

The results suggest that strengthening restrictions led to reductions in the total hours of industrial fishing by -6.56 hours per week and a decrease of approximately 9 fishing vessels. This means that the implementation of lockdowns contributed to a decrease in fishing activity by 9 vessels, whether authorized or unauthorized, in a given week. Furthermore, it is observed that this effect is particularly concentrated among countries in the right tail of the stringency index distribution.

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 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. Total MMSI				
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 total MMSI 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.

Robustness check

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?

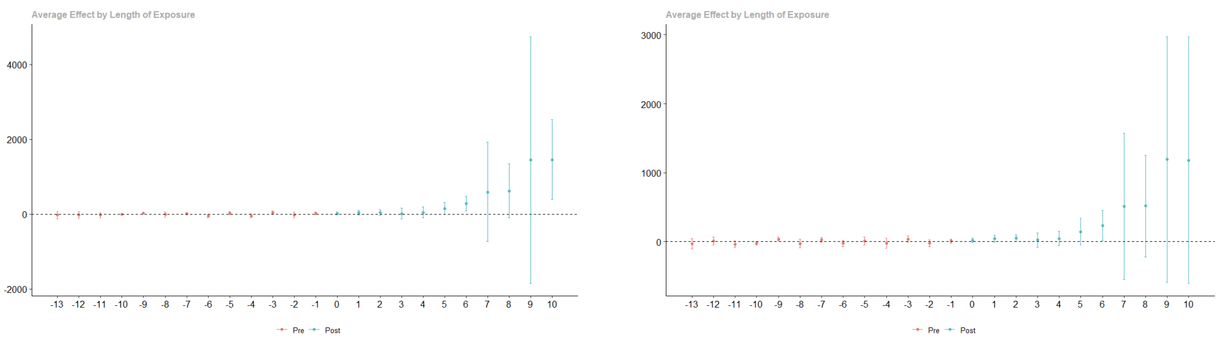
Estimating equation To address the question of this section, I employ the DiD estimator proposed by Callaway and Sant'Anna (2021), which follows the following specification of the dynamic Two-Way Fixed Effects (TWFE) model:

$$Y_{ijzt} = \sum_{\varphi=-S}^{T_{-1}} \gamma_j D_{z,\varphi} + \sum_{\varphi=T_{+1}}^{M} \delta_\varphi D_{z,\varphi} + \lambda_i + \lambda_t + \epsilon_{zt} \quad (12)$$

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)** Total MMSI*

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 total MMSI 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. However, Table B3 shows the Average Treatment Effect on Treated (ATT) by regions, and it is found that in the North America region, the number of unauthorized vessels increased by approximately 3.5. 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, which I will discuss it in the heterogeneity analysis section.

7 Heterogeneity Analysis

In this section, I conducted an analysis of potential heterogeneities associated with unauthorized fishing activity. I evaluated the results obtained based on income-country variable, economic support index variable and the distribution of the Ocean Health Index.

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. These results are consistent with the hypothesis that countries with lower incomes (developing countries, for example) have lower monitoring and control capacities.

Table 5: *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. Total MMSI				
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 total MMSI 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. Figure 3 presents estimates of the effect of the onset of mobility restrictions on unauthorized fishing efforts. 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 relative to the results of other components of the Ocean Health Index. Economies, Fisheries and Food Provision dimensions shows a no statistically significant effect.

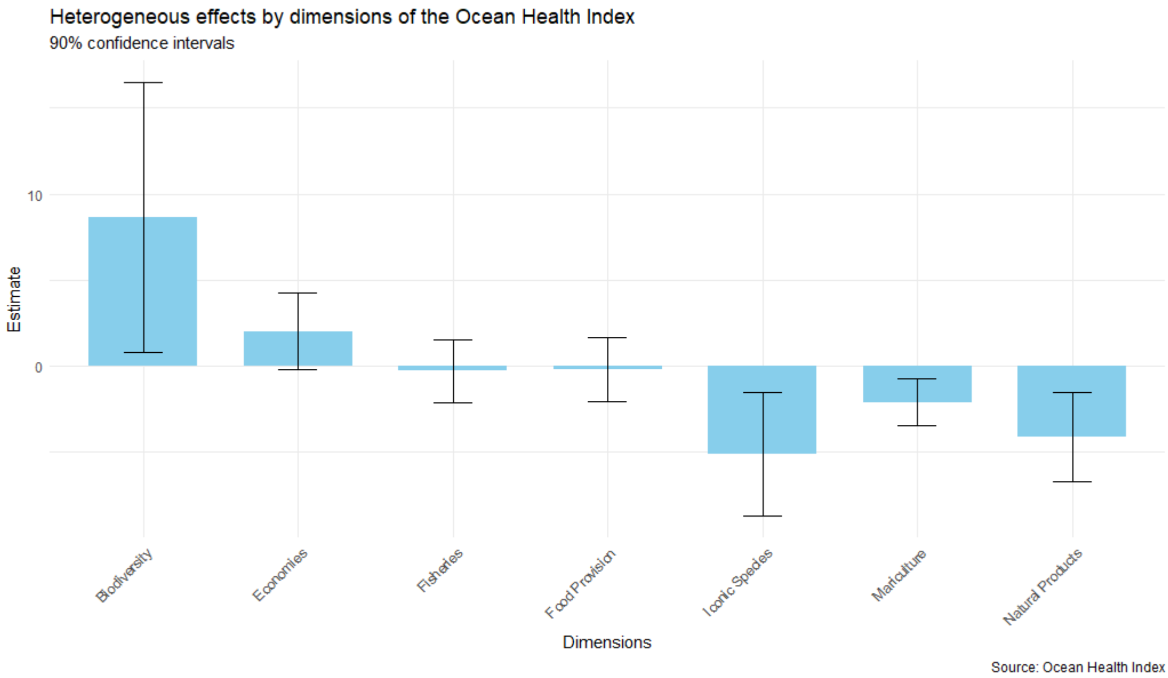


Figure 3: Unauthorized fishing change during COVID-19 pandemic by Ocean Health Index Components. Note: figure shows estimates from TWFE model with a 90% confidence interval (black line).

8 Conclusion

In this article, I studied the impact of COVID-19 pandemic-related restrictions on industrial fishing activity in general and specifically evaluated the impact on unauthorized fishing activity globally. The literature has documented that lockdowns disrupted economic activities, including fishing. Additionally, the monitoring and control capacities were reduced, which could have created incentives, along with the economic shock caused by the pandemic, for engaging in unauthorized activities, such as fishing in prohibited areas or at unauthorized times.

The findings of this study indicate that while overall fishing efforts decreased with the imposition of restrictions, unauthorized fishing activity increased following the onset of COVID-

19-related mobility measures. Interestingly, this increase was more pronounced in low and middle-income countries compared to high-income countries. These results are consistent with the hypothesis that countries with lower incomes (developing countries, for example) have lower monitoring and control capacities. The motivations behind the increase in unauthorized fishing efforts may be driven by the economic shock caused by the pandemic, as previous studies have found regarding the sector's sensitivity to economic shocks (Flückiger and Ludwig, 2015, Axbard, 2016).

Furthermore, ecosystems with better biodiversity indicators exhibited higher increases in unauthorized activity, likely due to the enhanced likelihood of fish capture in these regions. Conversely, ecosystems with superior indicators for iconic species and natural products experienced decreases in unauthorized activity. Similar trends were observed in mariculture-rich regions, where unauthorized fishing efforts declined relative to other components of the Ocean Health Index. To deepen our understanding of these findings, further research is needed to explore the underlying mechanisms driving the observed patterns.

These results have three main policy implications. Firstly, it is observed that command and control policies can be useful in reducing fishing pressure overall. However, deficiencies in economic support can undermine the sector's compliance capacity, motivating the development of unauthorized activities. Secondly, the results suggest that fishing vessels are sensitive to economic incentives associated with economic activity, considering the potential impact of economic shocks on the sector. The challenge in managing marine resources would primarily involve strengthening the economic and insurance capacities of the sector, as well as innovating in monitoring and control methods. Finally, the mariculture might be an alternative to traditional fishing activity as a mechanism to control or decrease of IUU fishing.

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Appendix A. Additional Data Details

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.

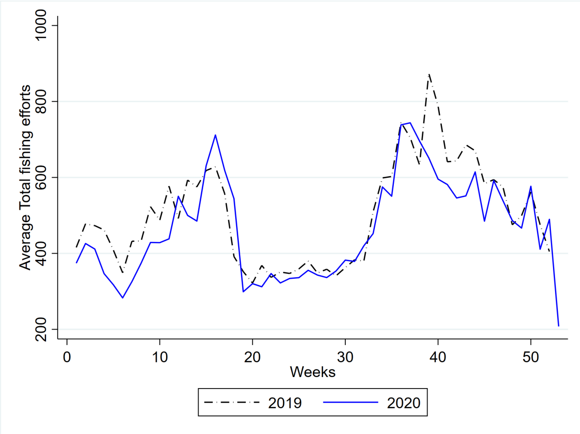
For the categorization of fishing authorization type for each recorded fishing data in the database, as explained in the main document, it was necessary to consolidate a database of fishing access agreements by countries compiled by Sea Around Us (SAU) following FAO guidelines. SAU collects information from 282 countries, from which I 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, I 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*

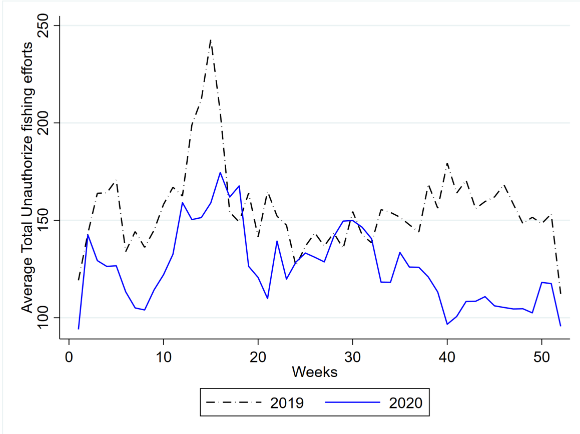
Countries	Country Code	Misleading count
Ascension Isl. (UK)	-	-
Belize	BLZ	0
Bosnia & Herzegovina	BIH	27
Cambodia	KHM	0
Canada (Arctic)	-	-
Chagos Archipelago (UK)	IOT	0
Comoros Isl.	COM	0
Curaçao (Netherlands)	CUW	0
Desventuradas Isl. (Chile)	-	-
Egypt (Red Sea)	EGY	99
Gabon	GAB	330
Gaza Strip	-	-
Guatemala (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.

Appendix B. Additional Figures and Tables

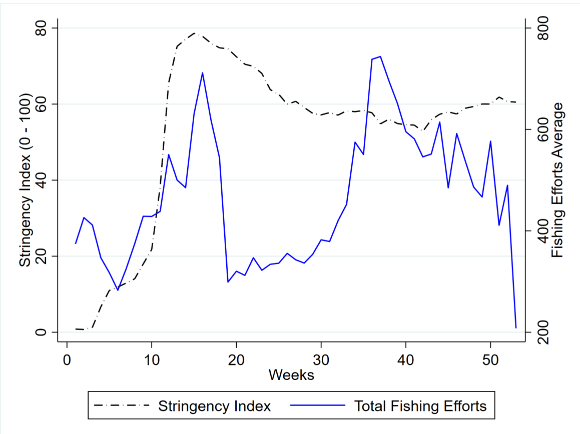


(a)

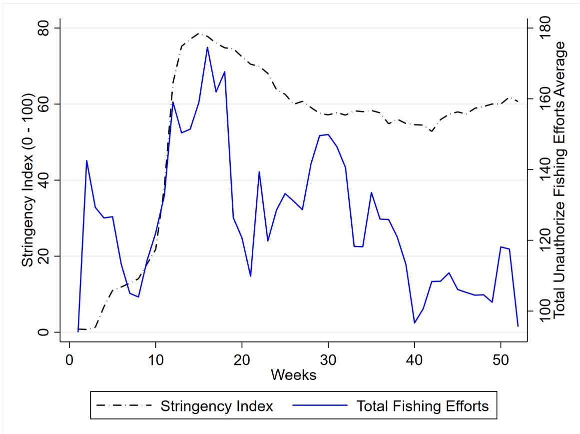


(b)

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.

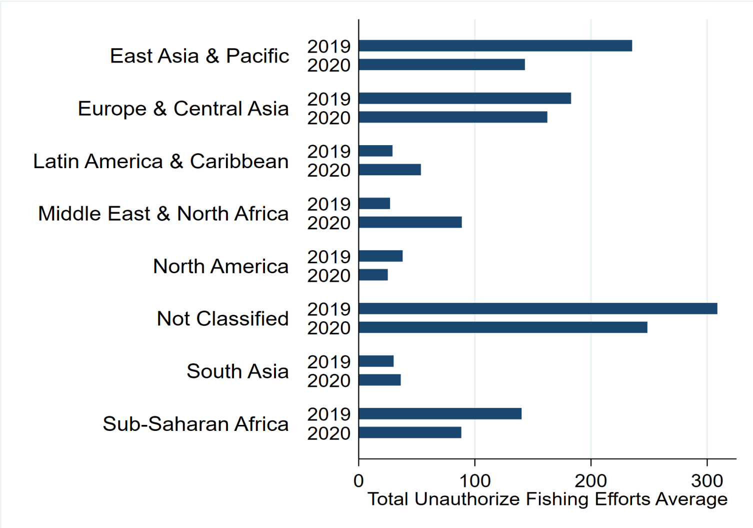


Figure B3: Total unauthorized fishing efforts by year and regions. Author, using information from GFW and Sea Around Us. Note: The figure displays the cumulative number of countries that introduced lockdowns as a black dashed line and the average stringency index for 2020 as a blue solid line.

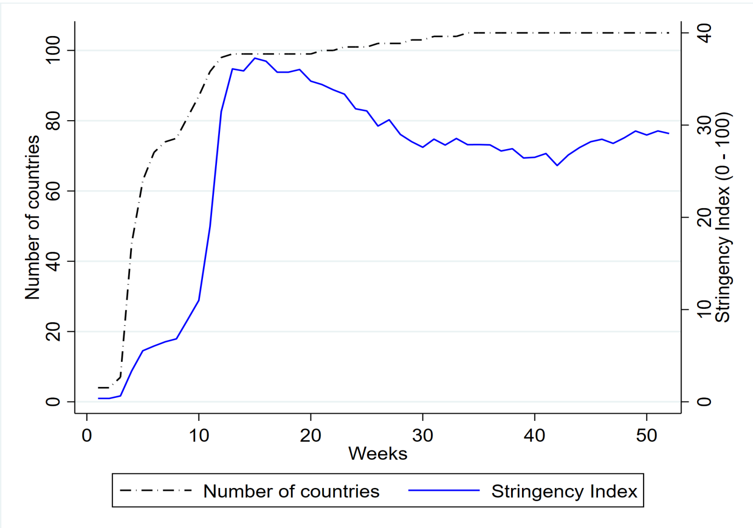


Figure B4: Cumulative number of countries that introduced lockdowns and average stringency index. Author, using information from OxCGRT. Note: The figure displays the cumulative number of countries that introduced lockdowns as a black dashed line and the average stringency index for 2020 as a blue solid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

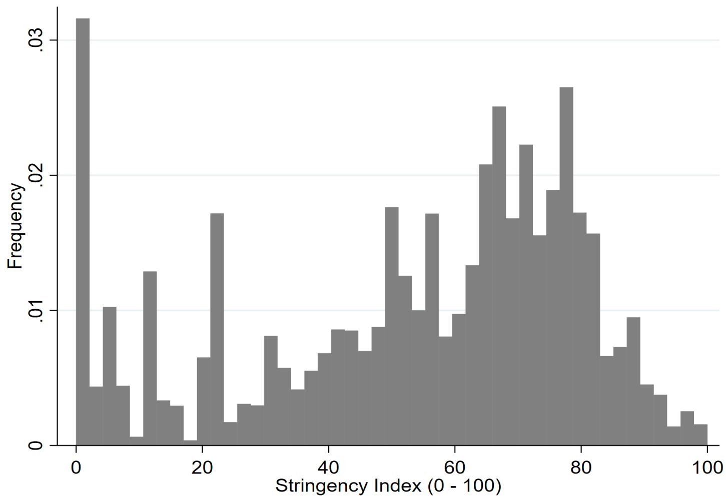


Figure B5: Stringency index distribution, 2020. Note: The figure shows a histogram with bin=47, start=0, width=2.1276596

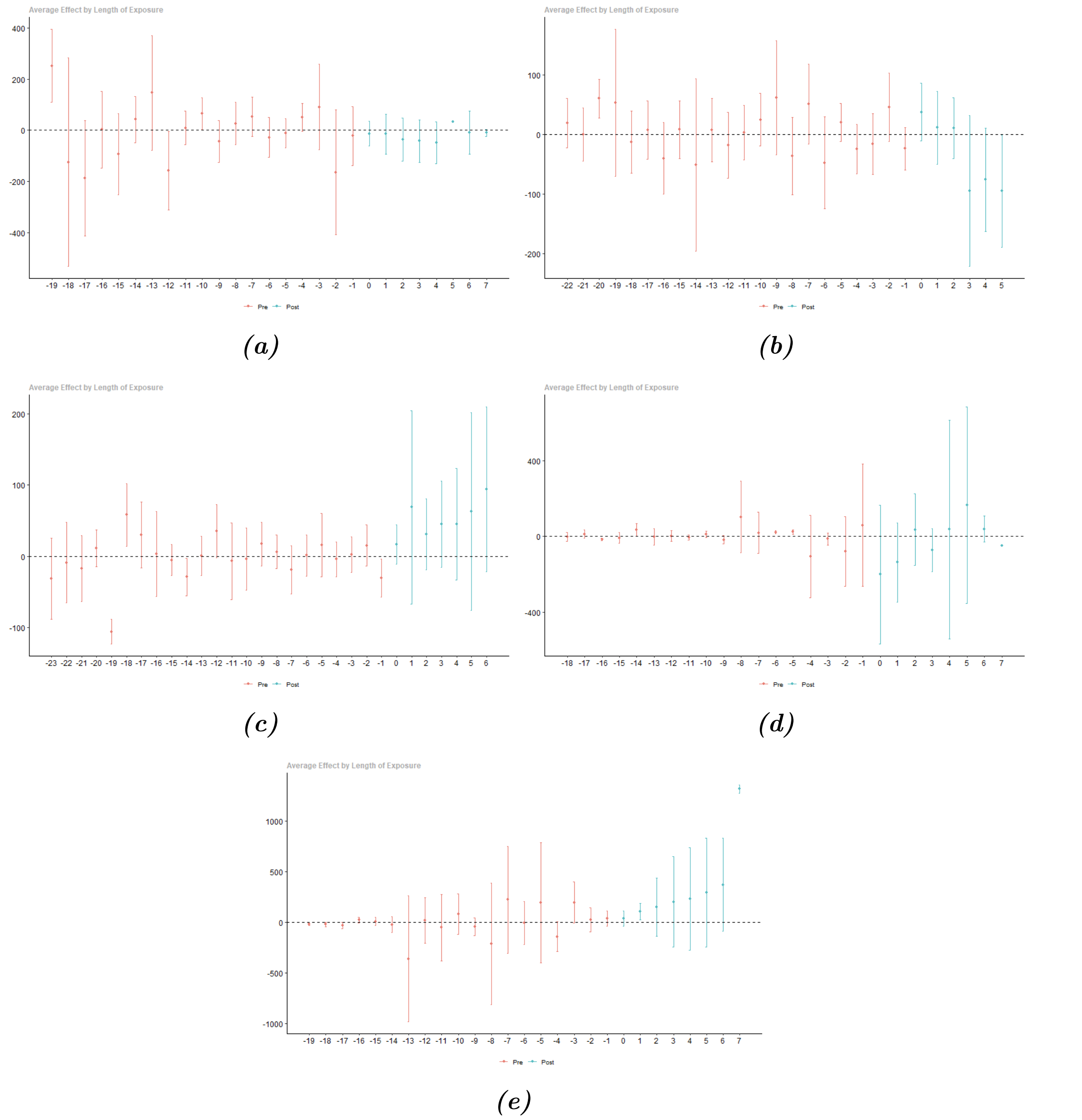
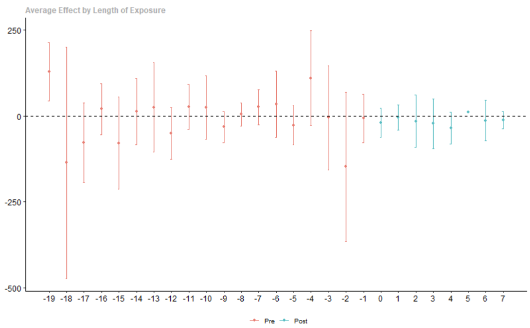
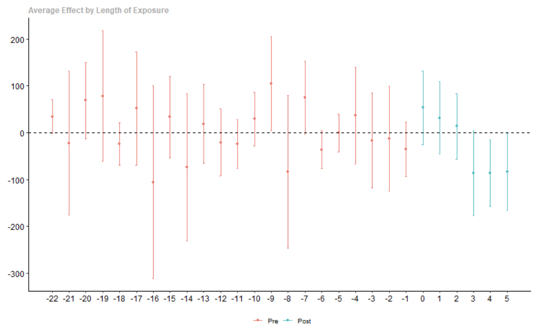


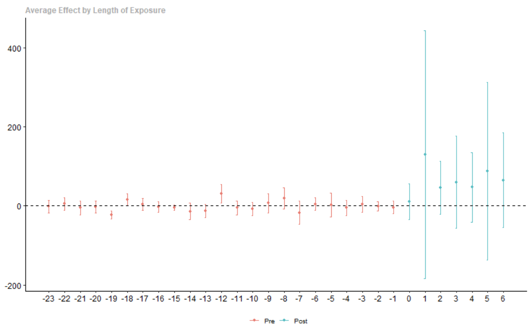
Figure B6: Covid-19 lockdowns and unauthorized industrial fishing efforts by region. Note: Panel A shows the results for East Asia & Pacific, Panel B for Europe & Central Asia, Panel C for Latin America & Caribbean, Panel D for Middle East & North Africa, and Panel E for South Asia.



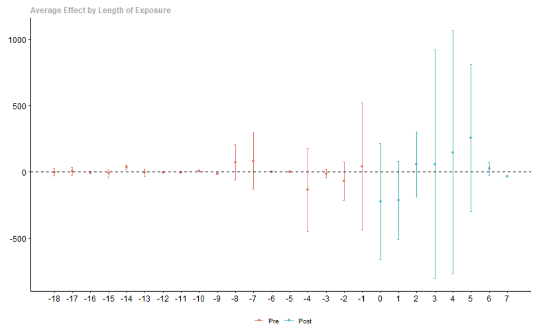
(a)



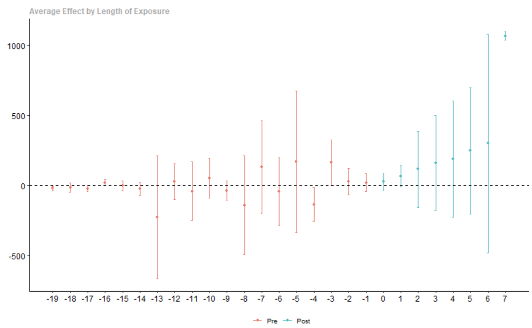
(b)



(c)



(d)



(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: Total MMSI				
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
Total MMSI	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
Mobility Rates									
Retail & recreation	Changes in people's mobility (percent) in retail and recreation	31.36	65.66	-84	545	-	-	-	-
Grocery & pharmacy	Changes in people's mobility (percent) in grocery and pharmacy	46.53	60.86	-58	615	-	-	-	-
Parks	Changes in people's mobility (percent) in parks	163.7	195.9	-69	1206	-	-	-	-
Transit stations	Changes in people's mobility (percent) in transit stations	49.19	80.85	-75	524	-	-	-	-
Workplaces	Changes in people's mobility (percent) in workplaces	12.64	29.51	-74	260	-	-	-	-
Residential	Changes in people's mobility (percent) in residential	19.66	11.69	-4	63	-	-	-	-
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		**Total mmsi**	
	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		**Total mmsi**	
	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.