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 a combination of Regression Discontinuity Design and 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. These results are robust to various model specifications and robustness checks. 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 population mobility indicators, along with climate and marine ecosystem quality variables. Based on this database, I conduct various empirical exercises to provide robust causal evidence. I employ regression discontinuity models following the methodology of Calonico et al. (2014), along with Difference-in-Differences models with heterogeneous time effects using the estimators proposed by Callaway and Sant'Anna (2021).

The methods used allow me to obtain robust results regarding the effect of lockdown impositions relative to the start date of these regulations. For the results of both methodologies, 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. 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 describes the data source and the process of constructing the database. Sections 4 and 5 present the main results of the article, distinguishing between authorized and unauthorized fishing, respectively. Sections 6 and 7 show the analysis of heterogeneities and respective robustness tests. 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).

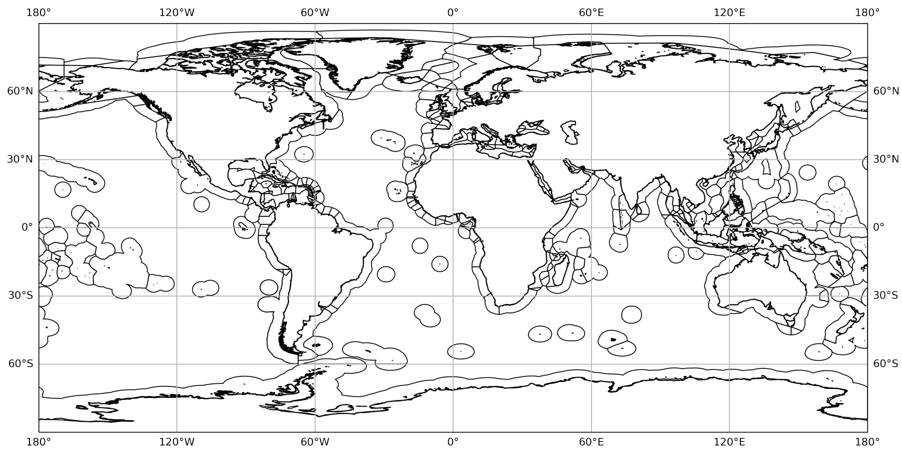


Figure 1: Exclusive Economic Zone Map. Author, using information from Marine Regions Repository.

Legally, EEZs grant full exploitation rights to the country, with coverage extending up to 200 nautical miles from the coast (Englander, 2019). 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 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).

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. In this context, the effects of decreased monitoring and control capacities in the maritime domain due to 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, including monitoring and control, are carried out (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).

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).

[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

3 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,

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

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 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.

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.

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 B1 presents additional descriptive statistics and the data sources for the different variables analyzed in this research.

4 Industrial Fishing Efforts and Strengthening of COVID-19 Related Measures

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:

$$F_{it} = \beta SI_{it} + \gamma X_{it} + \alpha_i + \tau_t + \epsilon_{it} \tag{1}$$

Where F_{it} is the outcome variable, which represents the total number of fishing hours or the number of vessels conducting fishing within an EEZ i or its influence area[5] in week t. SI_{it} 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_i and τ_t are fixed effects for EEZ/country and week, respectively. ϵ_{it} represents the error term with robust standard errors.

The parameter of interest is the coefficient β, which captures the relationship between the continuous change in the stringency index variable and the total fishing efforts. Table

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

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 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.

Causal evidence

The results from equation (1) do not capture an unbiased estimation of the relationship between the strengthening of pandemic-related restrictions and fishing efforts. The main reason is that countries started implementing lockdowns in a heterogeneous manner over time, and equation (1) fails to control for potential unobservable variables that may determine the declaration of lockdowns by a country in a given week compared to other countries. Although the TWFE model offers apparent ease in interpreting its coefficients, it is unclear, given the heterogeneous strengthening of pandemic-related measures, which comparison group the estimation is based on, as there are groups of countries in the sample that never declared a lockdown and groups of countries that, at a certain week, had not yet declared any restrictions, but as the weeks progressed, the probability of them declaring measures increased[6].

For these reasons, in order to attempt to capture a causal effect of this relationship, a Regression Discontinuity estimation is proposed as a first approach.

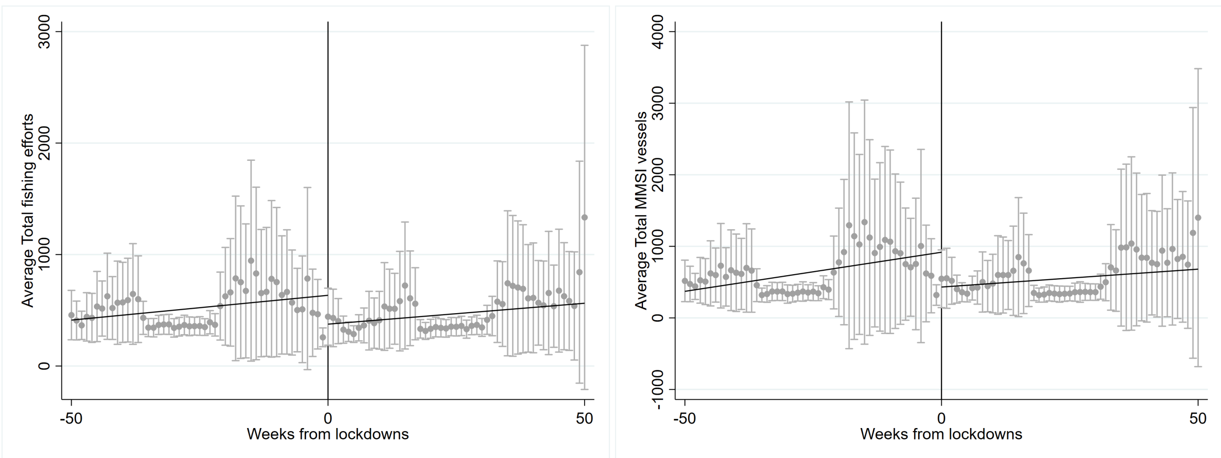
Estimating equations I estimate the following equation:

$$F_{it} = \lambda D_{it} + f(d_{it}) + \delta X_{it} + \sigma_g + \epsilon_{it} \tag{2}$$

[6]For further discussion, see Roth et al. (2023)

Where F_{it} is the same outcome variable as in equation (1). D_{it} is a treatment variable that takes the value of 1 from the day the stringency index becomes positive, indicating the start of lockdowns for each country, and zero if the country has not yet implemented any restrictions. $f(d_{it})$ represents a function of the running variable d_{it}, which represents the weeks relative to the start of lockdown implementation. Similar to equation (1), X_{it} is the vector of observable time-varying covariates, ϵ_{it} represents the estimated standard errors using the nearest neighbor variance estimator. σ_g is a fixed effect for the region. The parameter of interest λ captures the effect of the start of lockdowns on fishing efforts relative to the weeks since the implementation of these COVID-19-related regulations.

Results Figure 2 displays the graphical results of the relationship expressed in equation (2). It can be observed that, on average, fishing efforts and the number of fishing vessels decreased after the implementation of lockdowns, as also observed in the results of equation (1). However, the size of the effect is considerably larger in the estimation of equation (2). Table 4 shows that the reduction in fishing efforts was 198.7 hours per week, with a decrease of approximately 323 fishing vessels within a 29-week estimation window[7] from the date of the lockdown. Figure B5.B displays the distribution before and after the date of the lockdown, indicating that there are no discernible changes in the distribution that could confound the effect found in equation (2). Additionally, Figure B7 presents the results of the assessment of the continuity assumption in the covariates, which indicates that at the cutoff point of the running variable, the only jump found is in the outcome variable and not in the other variables, thus reducing the potential bias in the estimates.



(a) *(b)*

Figure 2: COVID-19 lockdowns and industrial fishing activity. Note: Observations are clustered at 2-week intervals. The observations to the left of the cut-off point are those that have not yet declared a lockdown, while those to the right are those that have declared a lockdown. The bars represent the 95% confidence intervals. Panel (a) shows the average total fishing efforts, and panel (b) shows the average total MMSI vessels.

[7]Optimal bandwidths were estimated using the procedure proposed by Calonico et al. (2014), which is a data-driven selection procedure.

Table 4: RD Model: Stringency change and industrial fishing activity

	Optimal bandwidth		Optimal bandwidth + 10 weeks		Optimal bandwidth + 20 weeks	
	(1)	*(2)*	*(3)*	*(4)*	*(3)*	*(4)*
Panel A. Total Fishing Efforts						
Stringency change	121.2	72.5	-28.39	-80.58	-136.2	-198.7*
	(129.6)	(138.6)	(114.7)	(121.4)	(95.33)	(101.6)
Bandwidth	8.7	9.1	18	19	28	29
Means before lockdown	503.39	503.39	503.39	503.39	503.39	503.39
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,986	93,441	100,986	93,441	100,986	93,441
Panel B. Total MMSI						
Stringency change	182.5	113.6	-26.68	-97.49	-224.8	-323.2*
	(213.6)	(229.8)	(195.0)	(207.5)	(165.2)	(176.4)
Bandwidth	8.5	8.9	18	19	28	29
Means before lockdown	612.7	612.7	612.7	612.7	612.7	612.7
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,986	93,441	100,986	93,441	100,986	93,441

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 RD estimate from Calonico et al. (2014) using the Conventional estimation method. Controls and fixed effects by regions are included. Standard errors in parentheses are based on the nearest neighbor variance estimator. Control variables include temperature, wind speed, and precipitation.

5 Lockdown Measures Effects on Unauthorized Industrial Fishing

The previous section presented the changes in total industrial fishing activity, both authorized and unauthorized. In this section, I present the results of the causal estimations of the lockdown on unauthorized fishing, which are the main findings of this article. To capture causal effects, two methodological approaches are proposed: i) regression discontinuity design and ii) differences in differences. These proposed methodologies aim to address the issues associated with the estimation in the TWFE model of Equation (1).

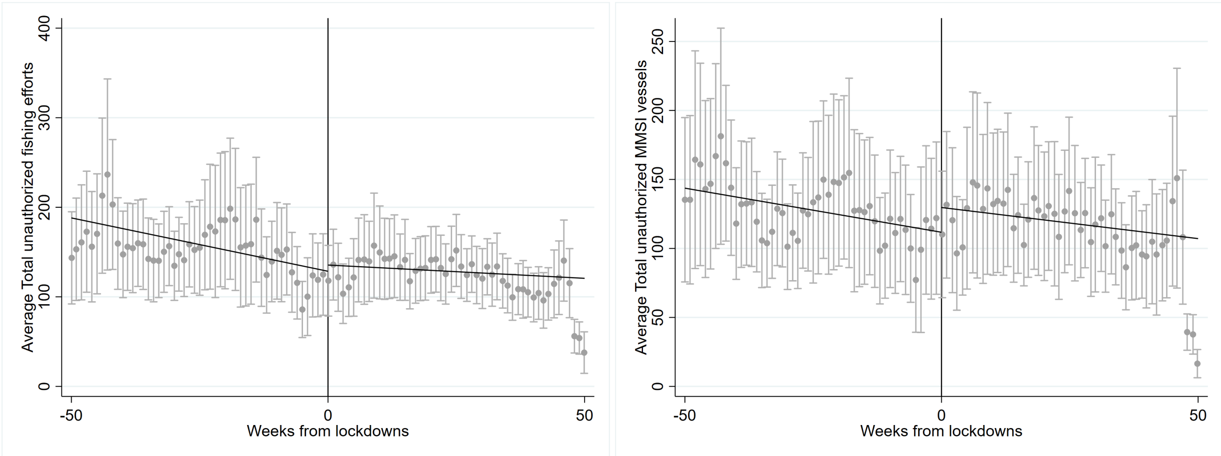
Unauthorized Industrial fishing with Regression Discontinuity Desing

Estimating equation The regression to be estimated is similar to Equation (2), with a modification in the outcome variable as follows:

$$UF_{it} = \eta D_{it} + f(d_{it}) + \gamma X_{it} + \sigma_g + \epsilon_{it} \tag{3}$$

Here, UF_{it} represents the total hours of unauthorized fishing or the number of fishing vessels engaging in unauthorized fishing in EEZ i in week t. The parameter of interest, η, captures the effect of the start of lockdowns on unauthorized industrial fishing activity relative to the date of the lockdown.

Results Figure 3 presents the results of Equation (3). It can be observed that, on average, unauthorized fishing activity increased in terms of both hours and the number of vessels. However, Table 5 indicates that this effect is not statistically significant under the different specifications proposed, except for the effect on the number of hours of unauthorized fishing within a 36-week estimation window. When controls are included, an increase of 35.18 hours per week is observed.



(a) *(b)*

Figure 3: Covid-19 lockdowns and unauthorized industrial fishing activity. Note: Observations are clustered in 2-week intervals. The observations to the left of the cut-off point represent periods before the declaration of lockdowns, while those to the right represent periods after the declaration of lockdowns. The bars represent the 95% confidence intervals. Panel (a) shows the average total fishing efforts, and panel (b) shows the average total MMSI vessels.

Table 5: *RD Model: Stringency change and unauthorized industrial fishing activity*

	Optimal bandwidth		**Optimal bandwidth + 10 weeks**		**Optimal bandwidth + 20 weeks**	
	(1)	*(2)*	*(3)*	*(4)*	*(3)*	*(4)*
Panel A. Total Fishing Efforts						
Stringency change	7.33	11.36	9.92	16.55	22.85	35.18*
	(19.52)	(21.83)	(19.25)	(21.38)	(16.43)	(18.25)
Bandwidth	16.9	15.6	27	26	37	36
Means before lockdown	155.8	155.8	155.8	155.8	155.8	155.8
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,562	24,066	27,562	24,066	27,562	24,066
Panel B. Total MMSI						
Stringency change	10.32	28.84	9.83	24.5	17.41	25.48
	(21.34)	(22.32)	(21.42)	(22.84)	(18.55)	(20.02)
Bandwidth	21.02	23.3	31	33	41	43
Means before lockdown	127.01	127.01	127.01	127.01	127.01	127.01
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,562	24,066	27,562	24,066	27,562	24,066

Note: * p<.10, * p<.05, ** p<.01. The dependent variable is unauthorized fishing activity in Panel A, and the total number of unauthorized MMSI vessels in Panel B. Each column presents the results of an RD estimate based on Calonico et al. (2014) with robust estimation method. Control variables and fixed effects by regions are included. Standard errors are shown in parentheses, calculated using the nearest neighbor variance estimator. Control variables include temperature, wind speed, and precipitation.

The lack of significance in the presented results can be explained by the fact that the positive change in the stringency index variable does not imply a complete development of the restrictions. Instead, it signifies only the beginning of such restrictions. As observed in Figure B4, it is not until week 10, on average, that countries considerably strengthened their pandemic-related restrictions, even though the onset of these restrictions occurred from week 4. Additionally, Figure B6.A shows that the days relative to the positive change in the stringency index do not indicate a sudden shift in the probability of implementing measures such as stay-at-home requirements, suggesting the need for an estimation strategy that takes this into account.

Estimating equation To account for the fact that the change in the stringency index does not fully capture the probability of treatment, I propose estimating a Fuzzy Regression Discontinuity (FRD) model, which estimates equation (2) in two stages using the stay-at-home requirement as an instrumental variable. This allows me to utilize the exogenous variation generated by the change in the stringency index on the stay-at-home requirement as an explanatory variable in the relationship with unauthorized fishing activity. The equations to be estimated are as follows:

Stage 1: Treatment Assignment Equation

$$T = \lambda D_{it} + f(d_{it}) + \delta X_{it} + \sigma_g + \epsilon_{it} \tag{4}$$

Stage 2: Outcome Equation

$$UF_{it} = \lambda D_{it} + f(d_{it}) + \beta \hat{T} + \delta X_{it} + \sigma_g + \varepsilon_{it} \tag{5}$$

Where T is the treatment variable, representing the stay-at-home requirement, and $\hat{T}$ is the exogenous change in T due to the positive change in the stringency index. The parameter of interest is β, which captures the effect of this relationship.

Results Table 6 presents the results of the second stage of the FRD, i.e., the results of equation (5). It can be observed that there is a positive and significant effect of strengthening pandemic-related restrictions on the number of hours of unauthorized fishing activity and the number of vessels, increasing by 137.7 hours and 96.4 vessels per week, respectively. These results hold robustly when using other treatment variables associated with lockdowns such as internal movement restrictions and workplace closing, as shown in Table B3 and Table B4. The largest effect is observed when using workplace closing as the treatment, where an increase of 158.5 hours in unauthorized activity and approximately 109 vessels is obtained. Figure B8 and Figure B9 present the graphical results of the relationship in equation (5) for the total hours of unauthorized fishing activity and the number of vessels by regions, respectively. Table B5 shows the results using different measures of stringency response. The increase in unauthorized fishing activity remains consistent across different specifications, with significance found only when using the economics support index variable.

Table 6: *Fuzzy RD Model: Stringency change and unauthorized industrial fishing activity with stay-at-home mandate treatment*

	Optimal bandwidth		**Optimal bandwidth + 10 weeks**		**Optimal bandwidth + 20 weeks**	
	(1)	*(2)*	*(3)*	*(4)*	*(3)*	*(4)*
Panel A. Total Fishing Efforts						
Stringency change (2nd stage)	-1,504.4	51.89	184.5*	318.4***	90.51*	137.7***
	(2,326)	(499.5)	(101.4)	(118.3)	(47.96)	(52.15)
Bandwidth	16.9	15.6	27	26	37	36
Means before lockdown	155.8	155.8	155.8	155.8	155.8	155.8
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,562	24,066	27,562	24,066	27,562	24,066
Panel B. Total MMSI						
Stringency change (2nd stage)	-51,344	994.9	122	163.8**	79.26	96.37**
	(36,168)	(1,504)	(81.94)	(73.95)	(48.4)	(47.61)
Bandwidth	21.02	23.3	31	33	41	43
Means before lockdown	127.01	127.01	127.01	127.01	127.01	127.01
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,562	24,066	27,562	24,066	27,562	24,066

Note: * p<.10, * p<.05, ** p<.01. The dependent variable in Panel A is unauthorized fishing activity, and in Panel B it is total mmsi unauthorized vessels. Each column represents the results of a robust RD estimate from Calonico et al. (2014). The model includes controls and fixed effects by regions. Standard errors in parentheses are based on the nearest neighbor variance estimator. Control variables include temperature, wind speed, and precipitation.

Unauthorized Industrial fishing with Staggered DiD model

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 regression discontinuity model, the 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 as in the case of the RD 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?

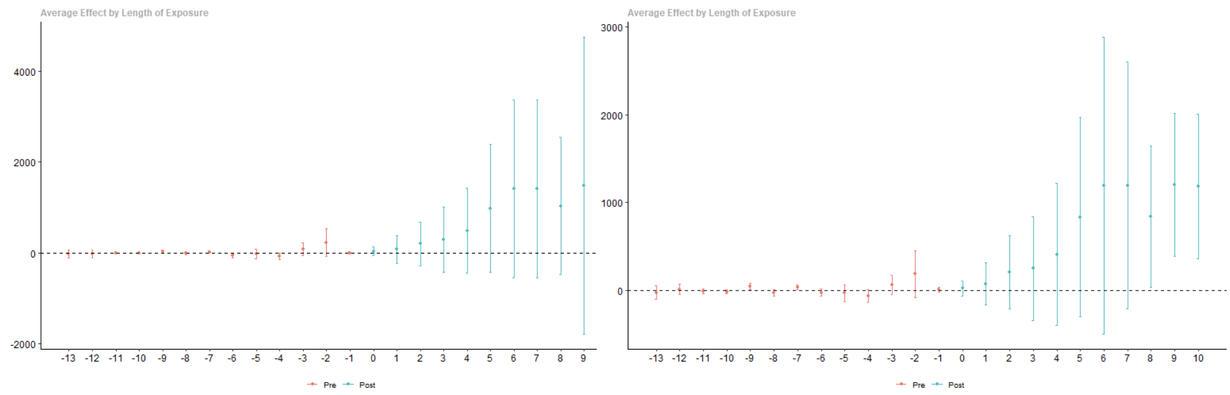
Estimating equation To address the question of this section, I employ the DiD estimator proposed by Callaway and Sant'Anna (2021), which follows the following specification of the dynamic Two-Way Fixed Effects (TWFE) model:

$$UF_{it} = \sum_{\varphi=-S}^{T_{-1}} \gamma_j D_{i,\varphi} + \sum_{\varphi=T_{+1}}^{M} \delta_\varphi D_{i,\varphi} + \lambda_i + \lambda_t + \epsilon_{it} \tag{6}$$

Where UF_{it} 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 posttreatment 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 4 displays the estimation results for each week relative to the start date of the lockdowns. There is no significant evidence of an increase in the number of hours of unauthorized fishing activity. However, it is found that the number of industrial fishing vessels engaging in unauthorized activity in the EEZs of other countries significantly increases from week 8 onward since the start of the lockdowns. Table 7 presents the results depicted in Figure 4. It can be observed that the effect on the number of vessels is approximately 1,072 vessels per week globally.



(a) *(b)*

Figure 4: 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 B10 and Figure B11 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 B7 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 B6 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.

Table 7: *DiD model: Covid-19 lockdowns and unauthorized industrial fishing activity*

Event time	Total Fishing		Total mmsi	
	Estimate	Std. Error	Estimate	Std. Error
-13	-24.91	41.97	-29.27	32.99
-12	-22.24	37.85	9.25	27.66
-11	2.42	10.20	-14.63	12.82
-10	-7.89	10.68	-19.62	10.68
-9	32.85*	15.19	43.74*	16.05
-8	-11.51	13.34	-31.44	15.78
-7	20.67	13.89	32.25*	12.51
-6	-63.46*	22.26	-29.64	17.40
-5	-29.63	49.30	-35.78	40.26
-4	-77.52*	34.62	-68.05	31.98
-3	78.47	62.49	58.33	47.9
-2	225.97	142.96	183.55	117.30
-1	3.13	13.75	5.26	12.93
0	37.06	45.87	22.03	37.39
1	75.11	139.44	72.42	103.9
2	199.88	221.99	205.41	181.9
3	289.89	329.13	247.74	259.72
4	490.62	432.40	406.10	354.37
5	982.33	651.92	832.27	496.09
6	1410.29	904.38	1188.47	741.20
7	1410.81	909.82	1193.49	615.18
8	1035.37	701.21	839.18*	351.73
9	1478.60	1515.30	1198.21*	356.34
10	1470.16	1507.98	1179.5*	360.38

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

6 Heterogeneity Analysis

In this section, I conducted an analysis of potential heterogeneities associated with unauthorized fishing activity. I evaluated the results obtained from the FRD and DiD methodologies based on the distributions of overall fishing activity, the stringency index, changes in mobility indicators during the pandemic at workplaces and residences, and the distribution of the Ocean Health Index.

Table 8 presents the estimation results. There is no evidence of heterogeneity according to the analyzed variables. For those significant estimates, the coefficients maintain the signs of the effects throughout the distributions. When disaggregating the components of the Ocean Health Index, based on the estimates obtained from the DiD model (Table B8), it can be observed that a better indicator in the components leads to decreases in unauthorized fishing activity compared to the results obtained for countries with indicators below the median.

Table 8: Heterogeneity analysis

	DiD Model		FRD Model	
	Total Fishing	Total mmsi	Total Fishing	Total mmsi
Panel A. Fishing quintile				
1st quintile	17.35*	8.89	75.38*	24.57
	(4.20)	(9.42)	(18.99)	(34.02)
Obs	3,203	3,203	7,404	7,404
2nd quintile	556.2*	513.3*	670.4*	715.1*
	(131.1)	(71.14)	(232.2)	(260.8)
Obs	2,980	2,980	4,739	4,739
3rd quintile	-78.36*	-57.7*	231.4	228.9
	(14.62)	(11.11)	(146.0)	(194.8)
Obs	2,673	2,673	6,980	6,980
4th quintile	56.3	97.59	-12.63	57.62
	(149.6)	(106.2)	(121.0)	(124.5)
Obs	1,604	1,604	4,943	4,943
Panel B. Stringency index				
1st quintile	896.4*	737.6*	706.5*	415.8*
	(113.2)	(96.77)	(148.4)	(115.5)
Obs	2,116	2,116	3,483	3,483
2nd quintile	0.13	-31.3	-3.12	-149.9
	(16.15)	(17.48)	(55.01)	(103.5)
Obs	2,923	2,923	7,515	7,515
3rd quintile	-82.62*	-35.58*	618.1*	1,148*
	(21.22)	(14.65)	(208.3)	(236.0)
Obs	3,689	3,689	8,493	8,493
4th quintile	4.20*	28.65	33.91	113***
	(20.32)	(26.13)	(30.22)	(27.99)
Obs	1,732	1,732	4,575	4,575
Panel C. Google mobility report: Residential				
1st quintile	284.0*	241.3*	85.67	72.81
	(15.73)	(18.72)	(187.0)	(165.1)
Obs	2,249	2,249	4,040	4,040
2nd quintile	21.09	4.56	1.61	-172.9
	(17.57)	(14.13)	(77.28)	(179.2)
Obs	1,830	1,830	3,481	3,481
3rd quintile	-12.37	-18.25	-414.5*	-284.2*
	(27.29)	(19.21)	(133.5)	(94.71)
Obs	1,335	1,335	3,400	3,400
4th quintile	58.78	49.64*	594.4	1,265
	(30.91)	(19.34)	(686.7)	(788.2)
Obs	1,610	1,610	2,663	2,663
Panel D. Google mobility report: Worplaces				
1st quintile	46.97	55.92	73.62	38.29
	(28.45)	(48.33)	(105.6)	(90.31)
Obs	2,090	2,090	4,683	4,683
2nd quintile	-36.26	-7.94	98.87	395.8
	(22.41)	(65.47)	(427.2)	(486.9)
Obs	1,987	1,987	3,456	3,456
3rd quintile	16.38	15.73	-324.8	-397.5
	(28.93)	(54.38)	(168.7)	(346.3)
Obs	1,807	1,807	3,127	3,127
4th quintile	238.2	195.6	7.54	-82.84
	(407.3)	(137.2)	(187.7)	(189.4)
Obs	1,140	1,140	2,318	2,318
Panel E. Ocean Health Index				
Above median	-14.98	-3.20	299.6*	496.8*
	(22.80)	(24.66)	(110.1)	(128.9)
Obs	5,399	5,399	13,189	13,189
Below median	476.5*	398.7*	67.06	-21.4
	(226.0)	(166.2)	(55.66)	(67.55)
Obs	5,081	5,081	10,877	10,877

Note: Signif. codes: '*' confidence band does not cover 0. Control Group: Not Yet Treated, Anticipation Periods: 0 Estimation Method: Doubly Robust. All estimations were performed using the estimator proposed by Callaway and Sant'Anna (2021) and Fuzzy RD with the estimator proposed by Calonico et al. (2014), using internal mobility restrictions as the treatment. For the DiD model, standard errors are clustered by region, and for the Fuzzy RD model, they are estimated based on the nearest neighbor variance estimator and are presented in parentheses. The median of the Ocean Health Index is 69.33.

7 Robustness Checks

A set of robustness analyses was conducted to assess the robustness of the results. For the FRD model, the results remain robust across different polynomial degrees (Table 10) and different bandwidths around the start date of the lockdowns (Figure B12). When excluding observations from countries closest to the start date of the lockdown, the significances and sign directions remain robust (Table 9). Table 11 presents the results of the placebo test, where the effect is calculated by simulating a different start date for the lockdowns. As expected, no significant effects are found in the estimates, suggesting that the effect identified in equation (5) is specifically attributed to the start of the restrictions and not due to alternative reasons.

Table 9: *Covid-19 lockdowns and unauthorized industrial fishing activity - "Donut" FRD with stay-at-home requirement treatment*

	Total Fishing Efforts			**Total MMSI**		
	Optimal bandwidth	**Optimal bandwidth + 10 weeks**	**Optimal bandwidth + 20 weeks**	**Optimal bandwidth**	**Optimal bandwidth + 10 weeks**	**Optimal bandwidth + 20 weeks**
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Panel A. Excluding observations 2 weeks near the lockdown date						
Stringency change (2nd stage)	3,037**	267.5***	120.6**	315.5*	142.5**	81.85*
	(1,271)	(100.6)	(46.65)	(187.2)	(65.44)	(43.69)
Obs	23,389	23,389	23,389	23,390	23,391	23,392
Panel B. Excluding observations 5 weeks near the lockdown date						
Stringency change (2nd stage)	37,384***	348.9***	169.9***	576.5***	243.7***	127.6***
	(3,690)	(99.81)	(51.24)	(164.8)	(66.86)	(45.63)
Obs	22,185	22,185	22,185	22,185	22,185	22,185
Bandwidth	16	26	36	23.3	33	43
Means before lockdown	155.8	155.8	155.8	127.01	127.01	127.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: * p<.10, * p<.05, ** p<.01. Panel A displays the effects of the Fuzzy RD model, excluding observations within 2 weeks of the lockdown date, while Panel B excludes observations within 5 weeks of the lockdown date. Each column presents the results of an RD estimate following the methodology proposed by Calonico et al. (2014) with robust estimation method. The analysis includes control variables for temperature, wind speed, and precipitation, as well as fixed effects by regions. Standard errors are shown in parentheses and are based on the nearest neighbor variance estimator.

Table 10: *Covid-19 lockdowns and unauthorized industrial fishing activity - Analysis by polynomials*

	Total Fishing Efforts			**Total MMSI**		
	Optimal bandwidth	**Optimal bandwidth + 10 weeks**	**Optimal bandwidth + 20 weeks**	**Optimal bandwidth**	**Optimal bandwidth + 10 weeks**	**Optimal bandwidth + 20 weeks**
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*-6*
Panel A. p = 1						
Stringency change (2nd stage)	1,168	318.4***	137.7***	376.0*	163.8**	96.37**
	(1,682)	(118.3)	(52.15)	(220.7)	(73.95)	(47.61)
Panel B. p = 2						
Stringency change (2nd stage)	-192.0	-0.067	99,018***	85.62	2,513**	729.7***
	(799.7)	(312.3)	(8,530)	(382.9)	(978.8)	(258.2)
Panel B. p = 3						
Stringency change (2nd stage)	-519.9	-44.29	56.31	163.8	176.9	152.6
	(1,427)	(564.3)	(228.1)	(1,088)	(304.5)	(264.1)
Bandwidth	15.6	26	36	23.3	33	43
Means before lockdown	155.8	155.8	155.8	127.01	127.01	127.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,066	24,066	24,066	24,066	24,066	24,066

Note: * p<.10, * p<.05, ** p<.01. Panel A displays the effects of the Fuzzy RD model with a polynomial grade of 1, Panel B with a polynomial grade of 2, and Panel C with a polynomial grade of 3. Each column presents the results of an RD estimate following the methodology proposed by Calonico et al. (2014) with robust estimation method. The analysis includes control variables for temperature, wind speed, and precipitation, as well as fixed effects by regions. Standard errors are shown in parentheses and are based on the nearest neighbor variance estimator.

Table 11: *Placebo test*

	Total Fishing Efforts	Total MMSI
	(1)	*(2)*
Panel A. 10 weeks before lockdown date		
Stringency change (2nd stage)	9,271	6,988
	(28,647)	(25,710)
Obs	11,398	11,398
Panel B. 5 weeks before lockdown date		
Stringency change (2nd stage)	-2.2e+5	-92,490
Obs	(1.6e+5)	(82,656)
	11,398	11,398
Panel C. 5 weeks after lockdown date		
Stringency change (2nd stage)	68.48	122.4
	(125.1)	(149.9)
Obs	12,421	12,421
Panel D. 10 weeks after lockdown date		
Stringency change (2nd stage)	275	221.2
	(584.7)	(645.5)
Obs	12,421	12,421
Bandwidth	36	43
Means before lockdown	155.8	127.01
Controls	Yes	Yes
EEZ and week FE	Yes	Yes

Note: * p<.10, * p<.05, ** p<.01. Each column indicates the results of a Fuzzy RD model using stay-at-home requirements as the treatment, estimated with the method proposed by Calonico et al. (2014) with robust estimation. Controls and fixed effects by regions are included. Standard errors in parentheses based on the nearest neighbor variance estimator. Control variables are temperature, wind speed, and precipitation.

8 Conclusions

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 results show that the imposition of restrictions contributed to a decrease in total fishing efforts. However, contrary to the overall fishing dynamics, unauthorized fishing activity increased. This could be associated with the hypothesis that the reduction in maritime monitoring and control capacities in certain regions led to the exploitation of this situation. The economic shock generated by the pandemic may have resulted in the elimination or disruption of monitoring and control-related jobs, or the personnel involved in these activities may have been reassigned to other pandemic-related tasks, leading to a reduced capacity to control unauthorized fishing. Similarly, 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). Further research is needed to test the hypotheses regarding the different mechanisms that explain the findings observed in this study.

These results have two 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.

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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.

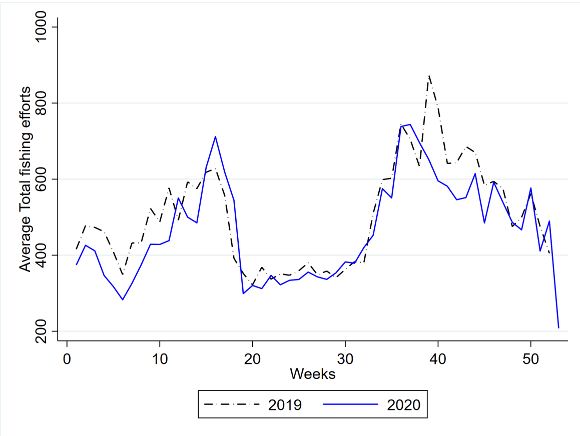
For the categorization of fishing authorization type for each recorded fishing data in the database, as explained in the main document, it was necessary to consolidate a database of fishing access agreements by countries compiled by Sea Around Us (SAU) following FAO guidelines. SAU collects information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



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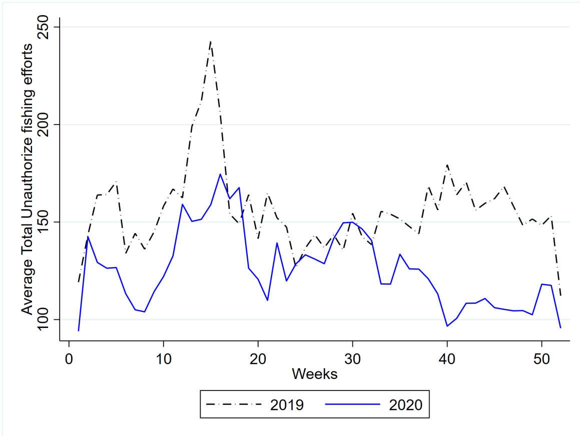
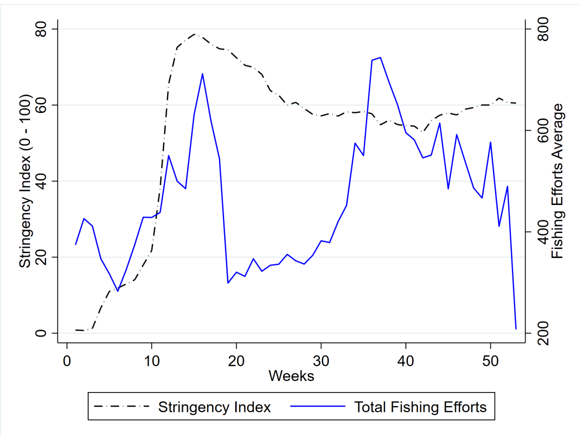


(b)

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.



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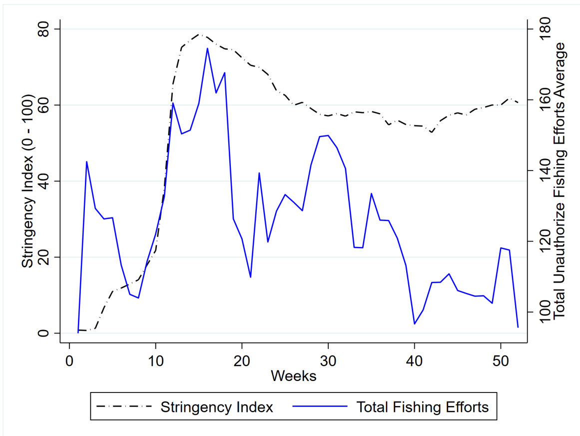


(b)

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.

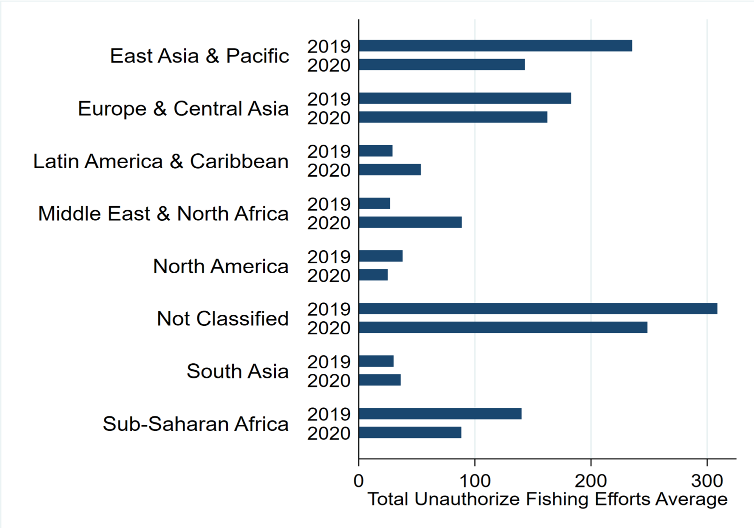


Figure B3: Total unauthorized fishing efforts by year and regions. Author, using information from GFW and Sea Around Us. Note: The figure displays the cumulative number of countries that introduced lockdowns as a black dashed line and the average stringency index for 2020 as a blue solid line.

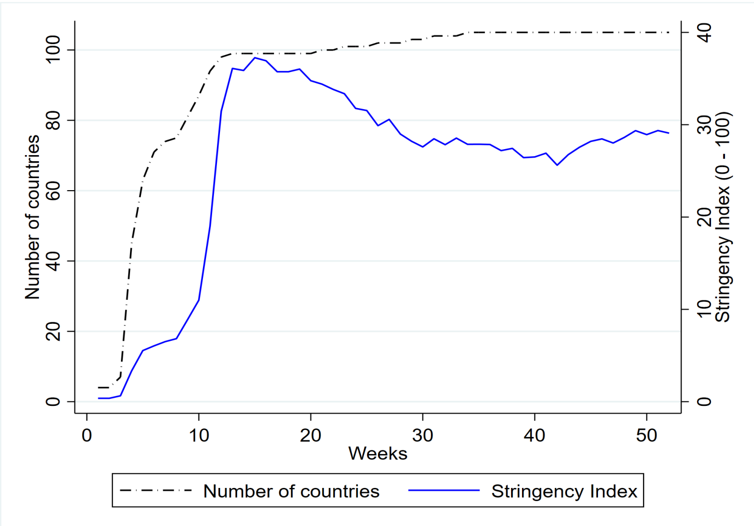


Figure B4: Cumulative number of countries that introduced lockdowns and average stringency index. Author, using information from OxCGRT. Note: The figure displays the cumulative number of countries that introduced lockdowns as a black dashed line and the average stringency index for 2020 as a blue solid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

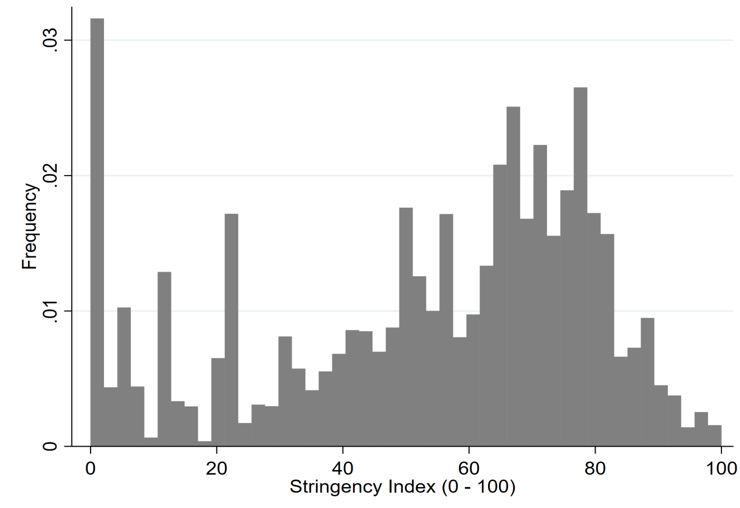
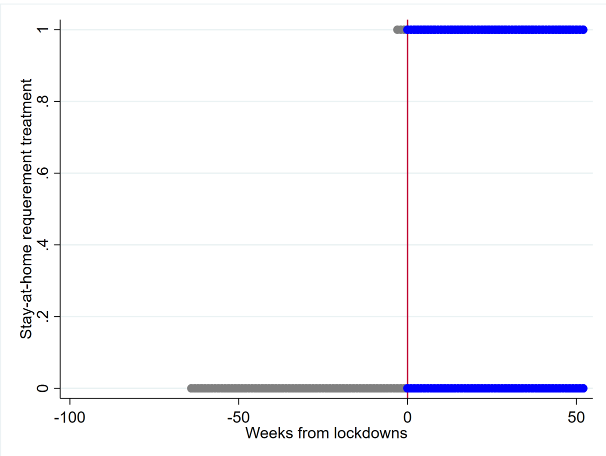


Figure B5: Stringency index distribution, 2020. Note: The figure shows a histogram with bin=47, start=0, width=2.1276596



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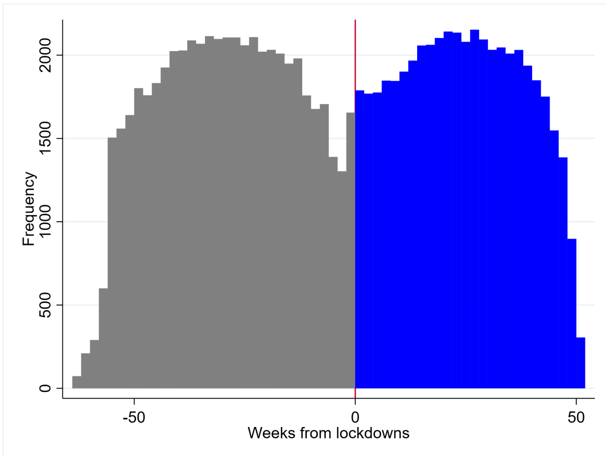
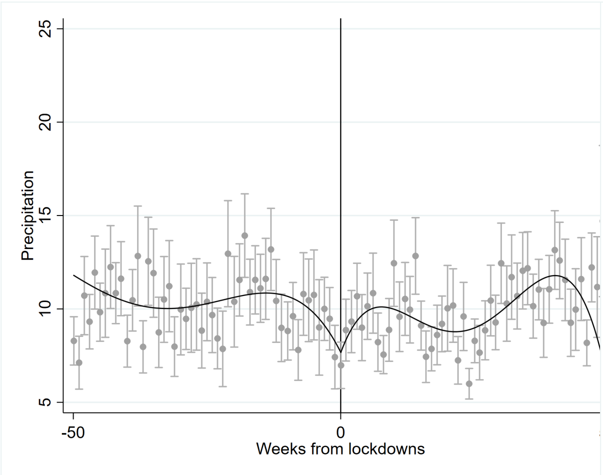


(b)

Figure B6: Validations. Note: Panel (A) Probability of stay-at-home requirement treatment, and Panel (B) Distribution of the database relative to the days from the lockdown dates.



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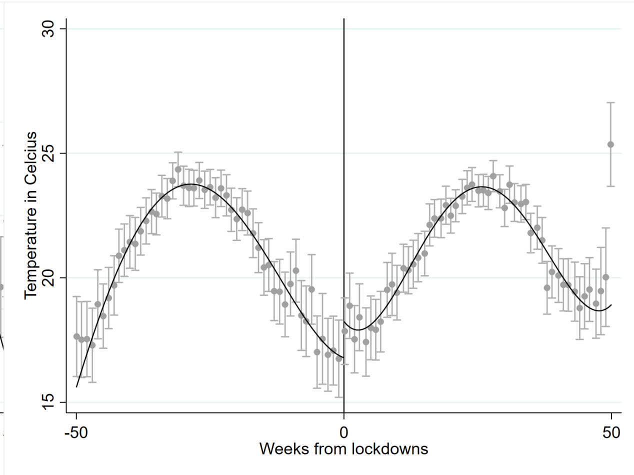

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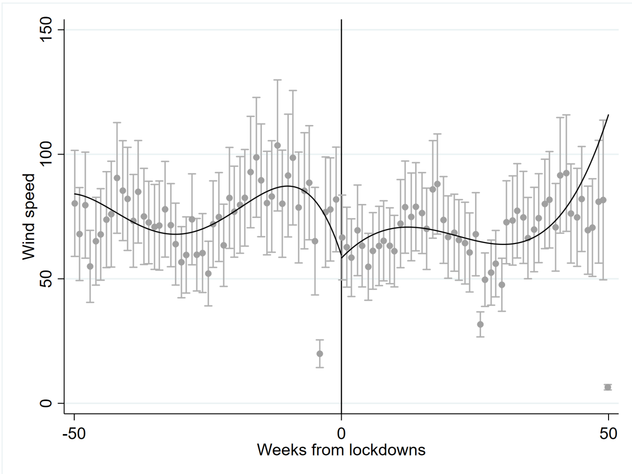


(c)

Figure B7: Covid-19 lockdowns and covariates. Note: Observations are clustered at 2-week intervals. The observations to the left of the cutoff point are those that have not yet declared a lockdown, while those to the right are those that have declared a lockdown. The bars represent the 95% confidence intervals. Panel (a) shows precipitation, panel (b) shows temperature, and panel (c) shows wind speed.

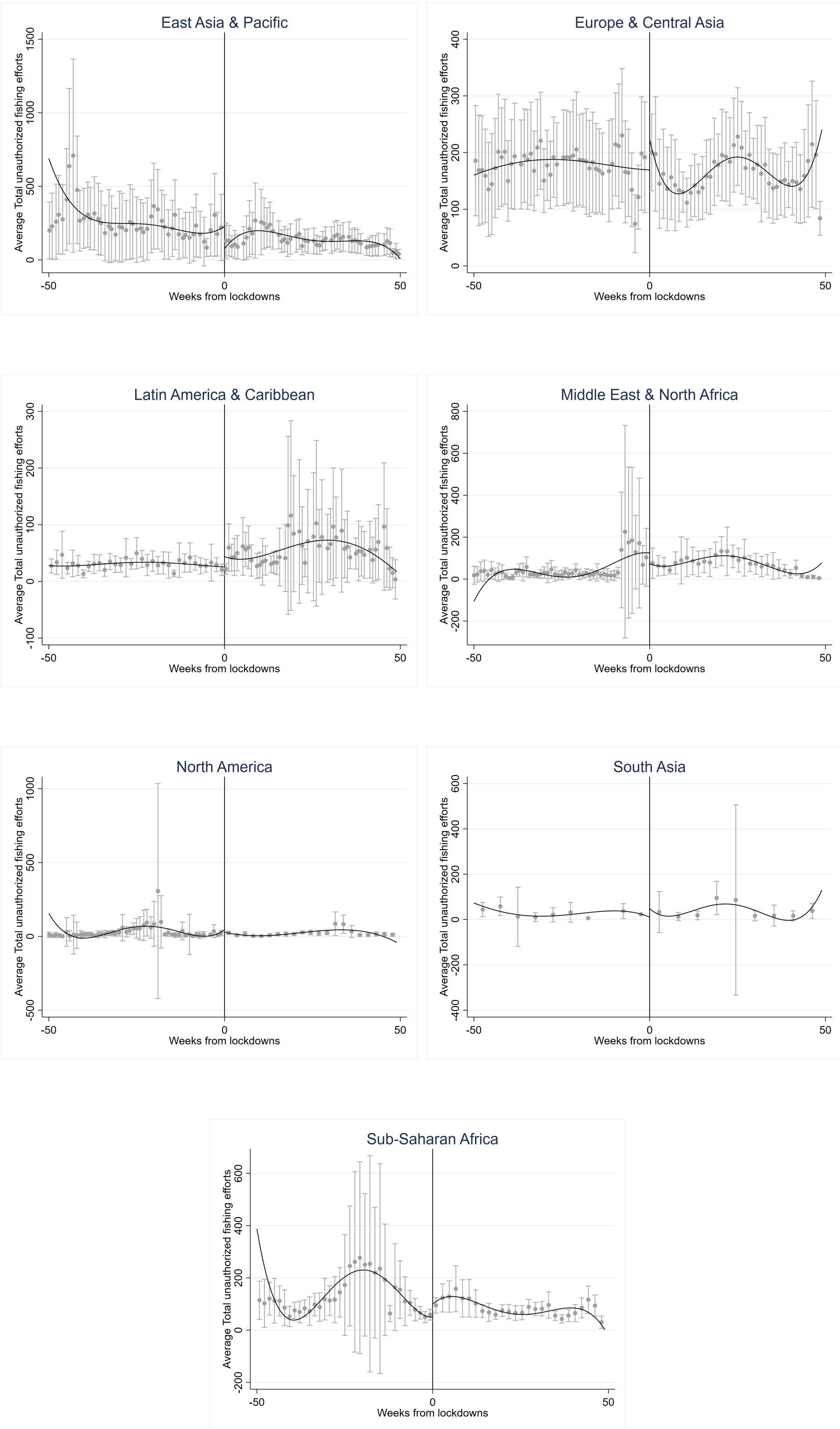


Figure B8: Covid-19 lockdowns and unauthorized industrial fishing efforts by region. Note: Observations are clustered at 2-week intervals. The observations to the left of the cutoff point are those that have not yet declared a lockdown, while those to the right are those that have declared a lockdown. The bars represent the 95% confidence intervals.

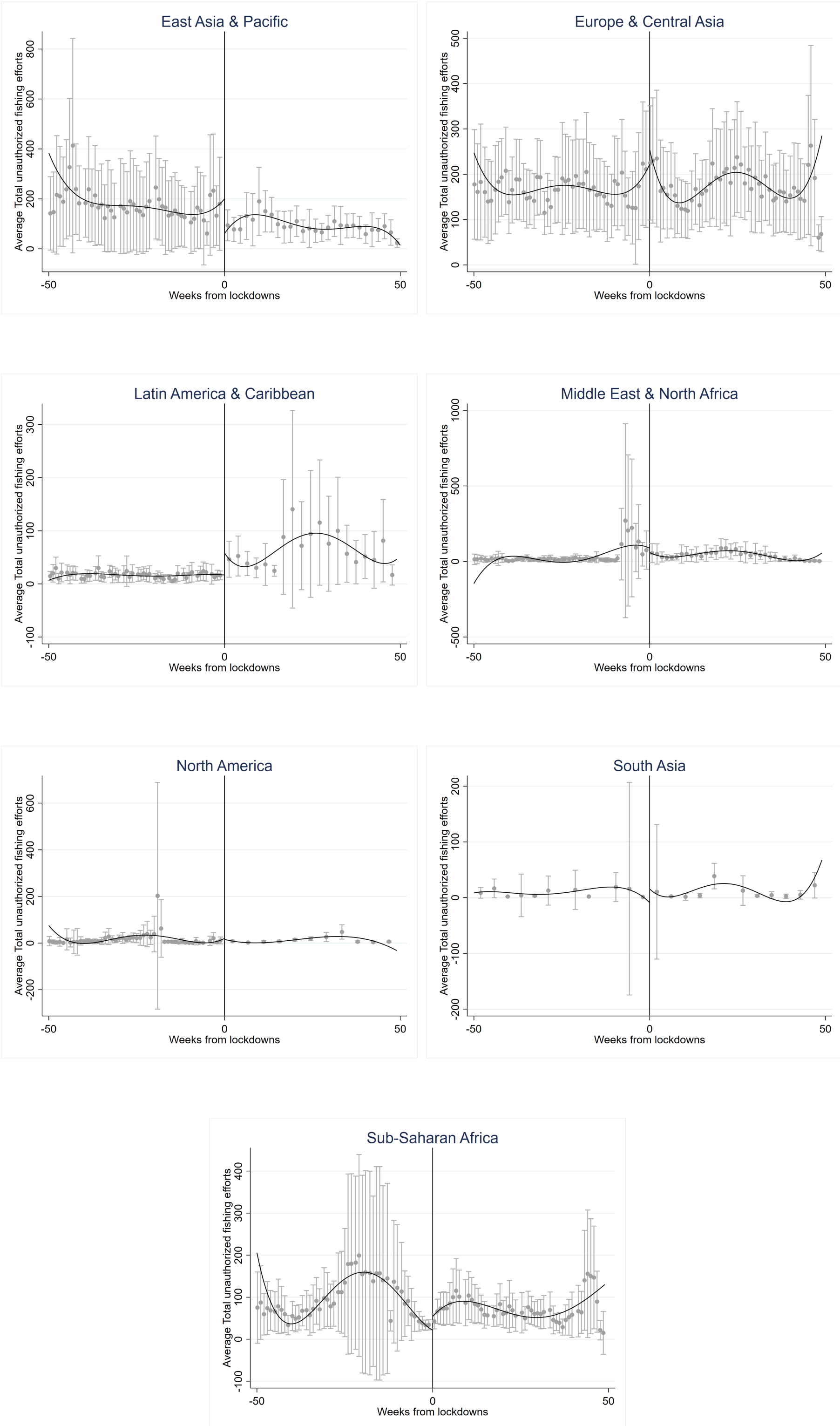
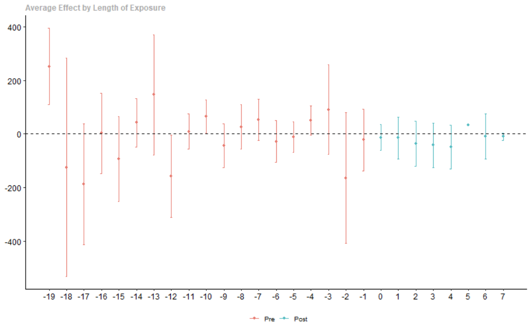
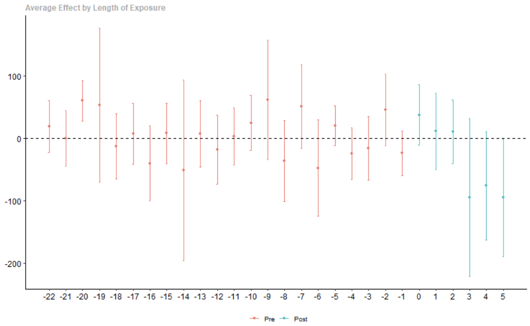


Figure B9: Covid-19 lockdowns and unauthorized industrial MMSI vessels by region. Note: Observations are clustered at 2-week intervals. The observations to the left of the cutoff point are those that have not yet declared a lockdown, while those to the right are those that have declared a lockdown. The bars represent the 95% confidence intervals.



(a)



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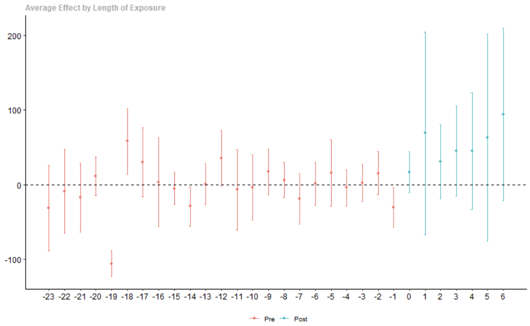

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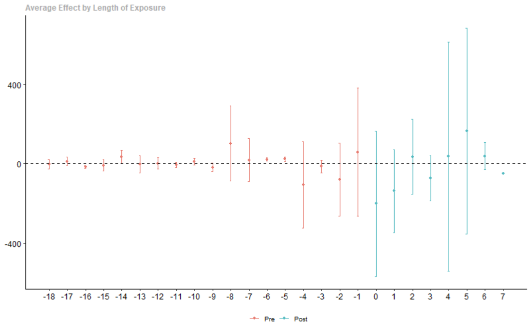

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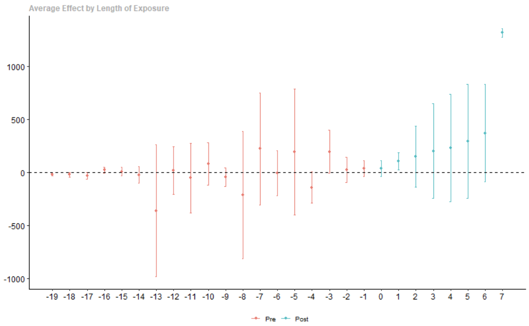
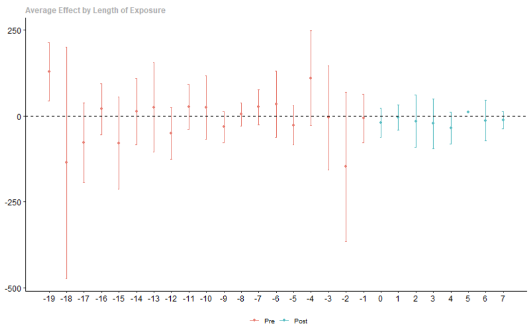
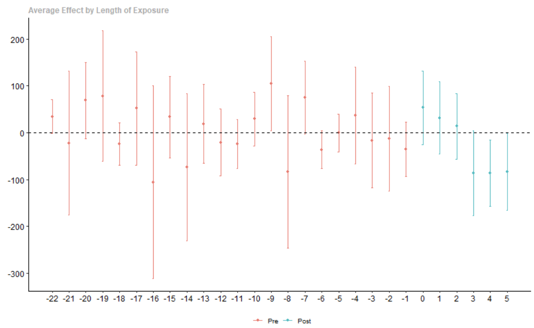


(e)

Figure B10: 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)



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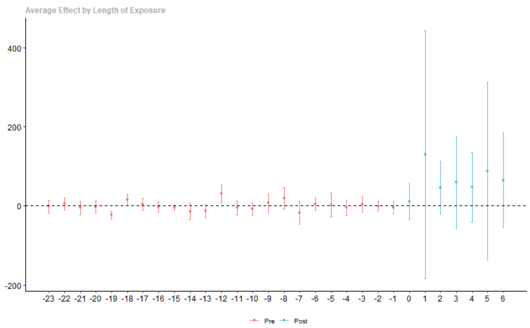

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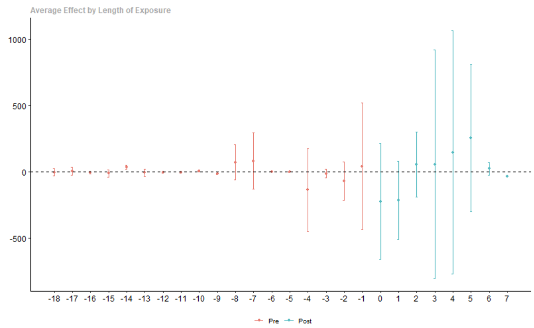

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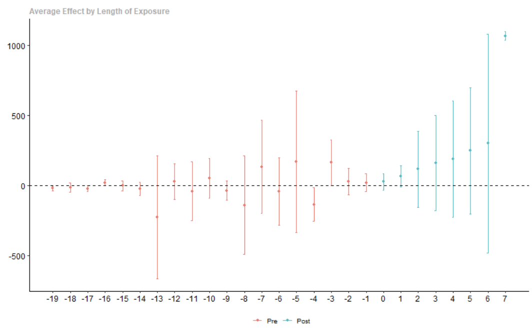
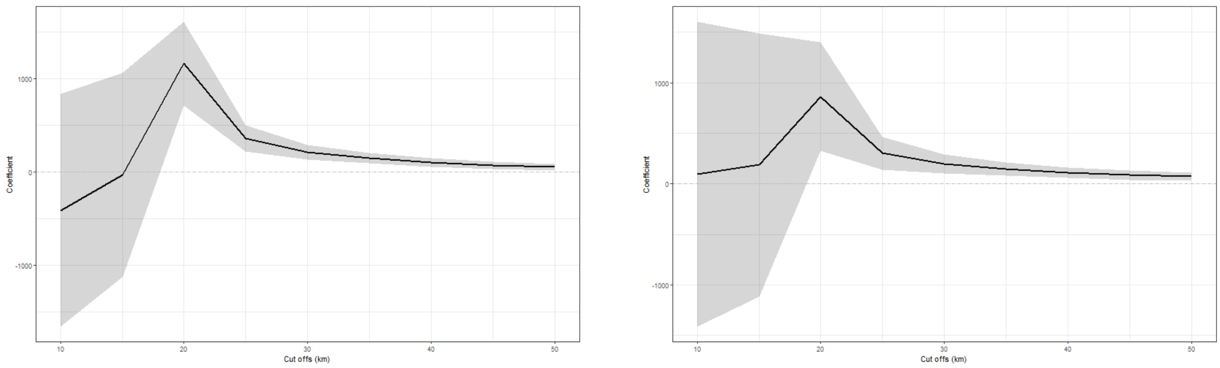


(e)

Figure B11: 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)*

Figure B12: Bandwidth sensitivity test. Note: The graph presents the estimate of the treatment effect for different bandwidths at 5-week intervals up to 50 weeks. The shaded area represents the 95% confidence intervals. The regressions are performed with nearest neighbor corrected standard errors. Panel (a) shows the total unauthorized industrial fishing, and Panel (b) shows the total unauthorized MMSI vessels.

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: *Fuzzy RD Model: Stringency change and unauthorized industrial fishing activity with internal movement restriction treatment*

	Optimal bandwidth		**Optimal bandwidth + 10 weeks**		**Optimal bandwidth + 20 weeks**	
	(1)	*(2)*	*(3)*	*(4)*	*(3)*	*(4)*
Panel A. Total Fishing Efforts						
Stringency change (2nd stage)	10,294***	1,041	199.3**	332.1***	93.89**	140.5***
	(2,361)	(726.9)	(105.5)	(120.3)	(49.53)	(53.15)
Bandwidth	16.9	15.6	27	26	37	36
Means before lockdown	155.8	155.8	155.8	155.8	155.8	155.8
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,562	24,066	27,562	24,066	27,562	24,066
Panel B. Total MMSI						
Stringency change (2nd stage)	574.4*	490.7***	129.1	167.4**	82.24*	98.24**
	(337.9)	(187.1)	(84.80)	(75.21)	(49.75)	(48.06)
Bandwidth	21.02	23.3	31	33	41	43
Means before lockdown	127.01	127.01	127.01	127.01	127.01	127.01
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,562	24,066	27,562	24,066	27,562	24,066

Note: * p<.10, * p<.05, ** p<.01. The dependent variable in Panel A is unauthorized fishing activity, and in Panel B is the total number of unauthorized vessels (mmsi). Each column represents the results of an RD estimate using the robust estimation method proposed by Calonico et al. (2014). The model includes controls and fixed effects by regions. Standard errors in parentheses are based on the nearest neighbor variance estimator. Control variables include temperature, wind speed, and precipitation.

Table B4: *Fuzzy RD Model: Stringency change and unauthorized industrial fishing activity with workplace closing treatment*

	Optimal bandwidth		**Optimal bandwidth + 10 weeks**		**Optimal bandwidth + 20 weeks**	
	(1)	*(2)*	*(3)*	*(4)*	*(3)*	*(4)*
Panel A. Total Fishing Efforts						
Stringency change (2nd stage)	-760.7	61.48	232.6*	380.8***	105.8*	158.5***
	(1,511)	(491.5)	(121.3)	(136.7)	(55.26)	(59.65)
Bandwidth	16.9	15.6	27	26	37	36
Means before lockdown	155.8	155.8	155.8	155.8	155.8	155.8
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,562	24,066	27,562	24,066	27,562	24,066
Panel B. Total MMSI						
Stringency change (2nd stage)	-20,506	711.6	149.2	190.7**	92.41*	109.6**
	(13,834)	(1,203)	(97.02)	(85.38)	(54.61)	(52.54)
Bandwidth	21.02	23.3	31	33	41	43
Means before lockdown	127.01	127.01	127.01	127.01	127.01	127.01
Controls	No	Yes	No	Yes	No	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,562	24,066	27,562	24,066	27,562	24,066

Note: * p<.10, * p<.05, ** p<.01. In Panel A, the dependent variable is unauthorized fishing activity, while in Panel B it is the total number of unauthorized vessels (mmsi). Each column presents the results of an RD estimation using the robust estimation method proposed by Calonico et al. (2014). The model includes controls and fixed effects by regions. Standard errors in parentheses are calculated based on the nearest neighbor variance estimator. The control variables consist of temperature, wind speed, and precipitation.

Table B5: *Fuzzy RD Model: Stringency change and unauthorized industrial fishing activity with stay-at-home requirement treatment - Alternative stringency indexes*

	Total Fishing Efforts			**Total MMSI**		
	Optimal bandwidth	**Optimal bandwidth + 10 weeks**	**Optimal bandwidth + 20 weeks**	**Optimal bandwidth**	**Optimal bandwidth + 10 weeks**	**Optimal bandwidth + 20 weeks**
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Panel A. Goverment response index						
Stringency change (2nd stage)	91.51	299.6*	74.91	519.6	125.6	63.18
	(431.5)	(163.6)	(60.65)	(361.8)	(87.32)	(52.94)
Obs	24,066	24,066	24,066	24,066	24,066	24,066
Panel B. Containment and health index						
Stringency change (2nd stage)	50.29	46.80	35.1	-12.08	-13.0	-4.78
	(64.1)	(38.42)	(30.65)	(55.82)	(41.53)	(35.73)
Obs	23,575	23,575	23,575	23,575	23,575	23,575
Panel C. Economic suport index						
Stringency change (2nd stage)	90.86	367.6**	123.8**	576.6*	163.6*	90.91*
	(474.9)	(154.5)	(59.08)	(332.4)	(85.24)	(52.17)
Obs	24,066	24,066	24,066	24,066	24,066	24,066
Bandwidth	15.6	26	36	23.3	33	43
Means before lockdown	155.8	155.8	155.8	127.01	127.01	127.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EEZ and week FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: * p<.10, * p<.05, ** p<.01. In Panel A, the estimation effect is based on the government response index, in Panel B it is based on the containment and health index, and in Panel C it is based on the economic support index. Each column presents the results of an RD estimation using the robust estimation method proposed by Calonico et al. (2014). The model includes controls and fixed effects by regions. Standard errors in parentheses are calculated based on the nearest neighbor variance estimator. The control variables consist of temperature, wind speed, and precipitation.

Table B6: *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.

Table B7: *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 B8: *Heterogeneity Analisis by Ocean Health Index Components*

	DiD Model		FRD Model	
	Total Fishing	**Total mmsi**	**Total Fishing**	**Total mmsi**
Panel A. Above median				
Ocean Health Index related to biodiversity	502.1*	411.9	311.9*	220.8*
	(228.5)	(269.7)	(69.35)	(50.66)
Obs	5,129	5,129	12,013	12,013
Ocean Health Index related to economies	2.68	11.54	-56.31	-155.6
	(11.12)	(22.33)	(70.17)	(94.54)
Obs	4,515	4,515	11,898	11,898
Ocean Health Index related to fisheries	8.25	-0.94	-59.82	-80.47
	(17.78)	(22.78)	(73.98)	(74.84)
Obs	4,531	4,531	11,629	11,629
Ocean Health Index related to food provision	-43.16	-27.97	70.6	61.12
	(35.13)	(48.25)	(73.73)	(78.19)
Obs	4,307	4,307	9,886	9,886
Ocean Health Index related to iconic species	-19.11	-17.30	64.98*	69.27*
	(17.49)	(15.06)	(27.79)	(33.68)
Obs	5,187	5,187	12,975	12,975
Ocean Health Index related to livelihoods	-31.87	-9.52	342.2*	386.4*
	(28.50)	(35.86)	(94.92)	(102.5)
Obs	6,241	6,241	13,105	13,105
Ocean Health Index related to livelihoods and economies	-28.17	-6.59	300.6*	335.4*
	(26.70)	(29.82)	(89.44)	(96.38)
Obs	6,322	6,322	13,412	13,412
Ocean Health Index related to mariculture	-39.1*	-23.65	35.33	80.63
	(18.80)	(30.61)	(87.42)	(117.2)
Obs	6,356	6,356	13,785	13,785
Ocean Health Index related to natural products	-27.97	-3.66	264.8*	350.8*
	(39.97)	(20.77)	(109.2)	(126.1)
Obs	5,656	5,656	11,713	11,713
Panel B. Below median				
Ocean Health Index related to biodiversity	15.43	18.25	104.7	124.6
	(64.98)	(122.0)	(77.73)	(106.0)
Obs	5,351	5,351	12,053	12,053
Ocean Health Index related to economies	737.9*	620.3*	352.8*	430.9*
	(104.1)	(206.5)	(79.51)	(87.52)
Obs	5,965	5,965	12,168	12,168
Ocean Health Index related to fisheries	466.0*	400.5	268.3*	272.0*
	(203.3)	(216.7)	(75.84)	(96.45)
Obs	5,949	5,949	12,437	12,437
Ocean Health Index related to food provision	366.1	322.1*	270.5*	260.4*
	(175.0)	(143.0)	(72.26)	(92.29)
Obs	6,173	6,173	14,180	14,180
Ocean Health Index related to iconic species	268.4	245.6*	247.9	248.3
	(146.3)	(115.3)	(143.4)	(170.6)
Obs	5,293	5,293	11,091	11,091
Ocean Health Index related to livelihoods	540.4*	447.4*	67.1	30.73
	(146.7)	(106.1)	(52.05)	(79.47)
Obs	4,239	4,239	10,961	10,961
Ocean Health Index related to livelihoods and economies	533.9*	442.8*	68.59	33.27
	(55.90)	(38.79)	(54.26)	(83.07)
Obs	4,158	4,158	10,654	10,654
Ocean Health Index related to mariculture	538.7*	450.2*	258.1*	165.8*
	(37.40)	(28.19)	(60.48)	(47.53)
Obs	4,124	4,124	10,281	10,281
Ocean Health Index related to natural products	467.1*	391.2*	138.0*	95.57
	(212.4)	(171.5)	(56.93)	(70.98)
Obs	4,806	4,806	12,353	12,353

Note: Signif. codes: '*' confidence band does not cover 0. Control Group: Not Yet Treated, Anticipation Periods: 0. Estimation Method: Doubly Robust. All DiD estimates were calculated using the estimator proposed by Callaway and Sant'Anna (2021), and Fuzzy RD estimates were obtained using the estimator by Calonico et al. (2014) with internal movement restrictions as the treatment. For the DiD model, standard errors are clustered by region, while for the Fuzzy RD model, they are estimated based on the nearest neighbor variance estimator and shown in parentheses. The medians for each component are as follows: biodiversity (71.16), economies (99.91), fisheries (49.31), food provision (54.07), iconic species (62.02), livelihoods (78.31), livelihoods and economies (84.6), mariculture (7.92), and natural products (84.43).