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Deterring Industrial Vessels from African Coastal Fisheries

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Abstract

Most African coastal nations prohibit industrial vessels from fishing near their shores; these Inshore Exclusion Zones (IEZs) reserve the most productive locations for small-scale, artisanal fishers. However, previous descriptive research suggests that non-compliance by industrial vessels prevents IEZs from benefiting African economies, food security, and fish stocks. Radar data released in 2024 detect industrial vessels without selection, enabling the first causal evaluation of African IEZs. First, regression discontinuity estimates reveal that 6 of 20 African countries successfully deter industrial fishing vessels (Nigeria, Sierra Leone, Liberia, Mauritania, Ghana, and Guinea). Second, bunching estimators obtain counterfactual vessel distributions that are uncontaminated by spillovers outside IEZ boundaries. Third, extensive-margin effects are captured by calibrating a discrete choice vessel location model to the bunching estimates. Back-of-the-envelope bioeconomic calculations indicate that IEZs increase annual artisanal fisher catch by 324 thousand tons—enough to meet key micronutrient requirements for 6.3 million people—without reducing industrial catch.

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Deterring Industrial Vessels from African Coastal Fisheries*

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1 Introduction

Effective management of renewable resources usually requires compliance with the regulations governing resource use. Compliance with these regulations has enabled, for example, the reduction of deforestation in the Brazilian Amazon, the rebuilding of US fish stocks, and the improvement of US water quality (Burgess et al., 2024; Frank & Oremus, 2025; Keiser & Shapiro, 2019). Where undesirable depletion or degradation persists, it is critical to understand the extent to which existing regulations promote intended outcomes.

Small-scale, artisanal fisheries are vital to African countries, employing 9 million Africans and providing at least 20% of key micronutrients to 300 million more (Basurto et al., 2025). To protect these valuable resources, most African coastal nations have established Inshore Exclusion Zones (IEZs) that prohibit industrial vessels from fishing near their shores, thereby reserving the most productive fishing grounds for artisanal fishers. However, non-compliance by industrial vessels could prevent IEZs from benefiting African economies and improving food security (Belhabib et al., 2020; Mullié, 2019; The Economist, 2024). Such concerns exemplify a general skepticism regarding the enforceability of natural resource regulations in African countries (Christensen et al., 2024; Greenstone & Jack, 2015; Ploeg, 2011). We show this pessimism is overstated for the important case of IEZs, demonstrating that effective regulation of coastal fisheries is feasible in Africa.

Previous research on IEZs has not applied causal inference methods and has suffered from incomplete vessel data (Basurto et al., 2024, p. 6). Only in January 2024 was a dataset released that permits observation of all industrial fishing vessels (Paolo et al., 2024). We use these data, which cover the period 2017 to 2021, to perform the first causal evaluation of African IEZs.

Country-level regression discontinuity (RD) designs reveal which countries' IEZs reduce industrial fishing vessel presence and which do not. We demonstrate that fishing opportunities vary smoothly in the distance to countries' coasts and IEZ boundaries. Therefore, discontinuously greater industrial fishing vessel presence just outside a country's IEZ boundary can be attributed to the IEZ. Adjusting for multiple hypothesis testing, we find that 6 out of 20 African countries deter industrial fishing vessels from their IEZs: Nigeria, Sierra Leone, Liberia, Mauritania, Ghana, and Guinea. These six countries principally differ from the others in having stronger fisheries enforcement systems, including more systematic patrols and risk-based inspections.

While the RD analysis identifies where deterrence occurs, it produces upward-biased treatment effect estimates by comparing vessel presence just outside to just inside IEZ boundaries. In the six countries with deterrence effects, the existence of the IEZ increases vessel presence just outside the boundary; some vessels that would have located inside the IEZ locate outside instead. These spillovers mean the vessel presence we observe just outside is greater than the true counterfactual level that would have occurred in the absence of the IEZ, so the RD overestimates the true treatment effect. Such spillover-induced bias is common in RD designs and requires correction (Auerbach et al., 2024; Jardim et al., 2022).

We apply bunching estimators to recover counterfactual vessel density distributions that are free of spillover bias (Kleven & Waseem, 2013). Analogous to a tax notch—which increases total tax liability discontinuously at an income threshold (by raising the average tax rate)—the IEZ boundary creates a discrete increase in expected punishment costs in the six countries with deterrence effects. This induces excess vessel density outside the boundary and a corresponding missing density inside it. By reallocating the excess to the missing region, the estimator reconstructs the smooth distribution that would have prevailed absent the IEZ. We find that, on average across the five (of six) countries with significant bunching effects, industrial fishing vessel presence decreases by 46% inside IEZs.

Our bunching results correspond to intensive-margin effects—the reallocation of vessels from inside IEZs to nearby areas outside IEZs. They assume vessels remain within each country's Exclusive Economic Zone (EEZ), the area extending up to 200 nautical miles from shore where countries have sovereign rights over natural resources. Yet EEZ-level fishing largely determines fish stocks and catches. Estimating this extensive-margin effect is therefore necessary for assessing the economic and ecological impacts of IEZs.

We measure extensive-margin effects by embedding the bunching estimates in a nested logit model of vessel location choice. We estimate the disutility from locating inside an IEZ via indirect inference, selecting the value that matches the bunching-based 46% reduction in vessel density inside IEZs. Among the five countries with deterrence and bunching effects, we find that IEZs reduce EEZ-level industrial fishing vessel presence by between 8% (Nigeria) and 20% (Sierra Leone).

We use these country-level estimates in back-of-the-envelope bioeconomic calculations illustrating the effects of IEZs on fish stocks and artisanal fisher catches. Even under open-access conditions, IEZs can increase stocks and catches. Because artisanal vessels use lower-productivity technologies than industrial vessels, they reach the zero-profit equilibrium at a higher stock level (Gordon, 1954). Across the five countries with deterrence and bunching effects, we calculate that IEZs increase steady-state fish stocks by 2.7 million tons and raise annual artisanal catch by 324 thousand tons. That additional artisanal catch is sufficient to supply essential micronutrient requirements for roughly 6.3 million people. These gains come without reducing industrial catch.

Contributions. While previous descriptive research documents the importance of African artisanal fisheries and the IEZs designed to protect them, our paper is the first to evaluate the causal effects of this widespread regulation (Basurto et al., 2024, 2025; Belhabib et al., 2020). We do so using new satellite-based radar data that observes industrial fishing vessels without selection, unlike research on other regulations whose data comes from vessels choosing to operate transponders (Englander et al., 2025; Fernández-Villaverde et al., 2025). Rather than correcting bias by adding spillover terms to the RD regression as in recent work (Auerbach et al., 2024), we eliminate spillover bias with a bunching estimator that reallocates the excess vessel density. Following indirect inference approaches such as Almagro et al. (2024), we calibrate the inside-IEZ disutility in a structural nested logit model to match our reduced form bunching estimate. By showing that five African countries generate sizable economic, ecological, and nutritional benefits from deterring industrial fishing vessels, we contribute new evidence to the literature on state capacity and the governance of common-pool resources in low- and middle-income settings (Besley & Persson, 2009; Burgess et al., 2012).

Sections 2 and 3 explain our institutional context and data. Sections 4, 5, and 6 detail our empirical strategies—RD, bunching, and discrete choice——and present the corresponding results. Section 7 presents bioeconomic calculations and Section 8 concludes.

2 Institutional Context

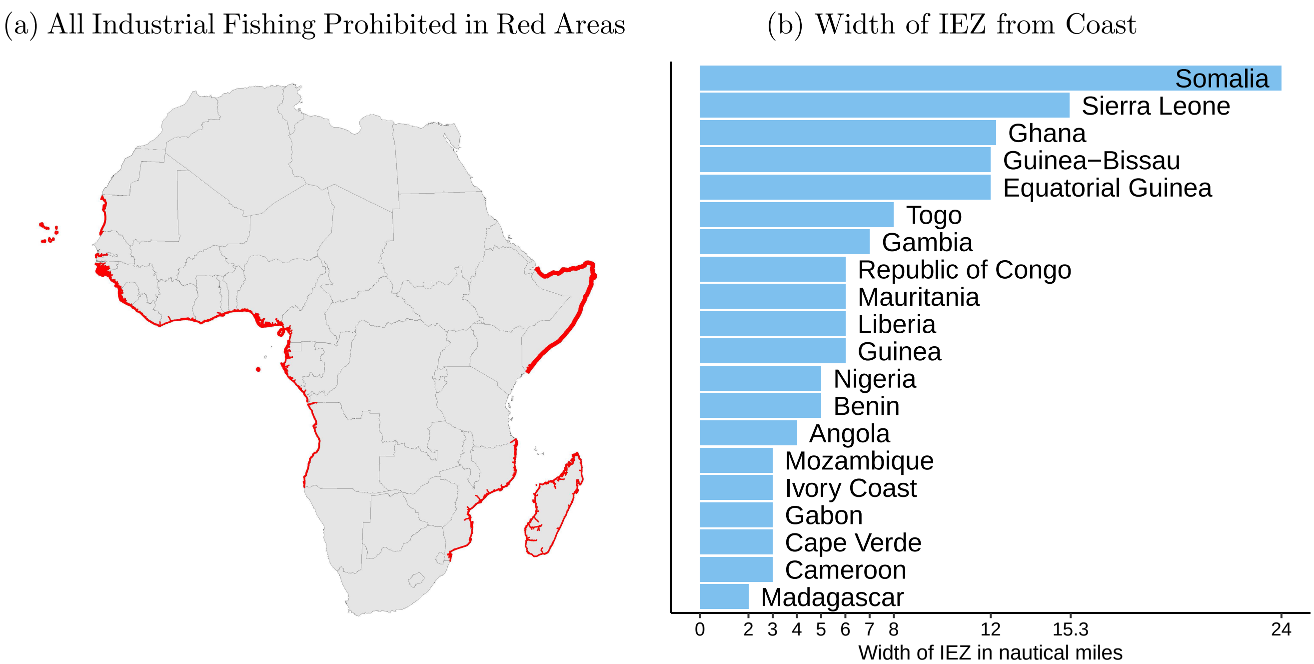
Most African coastal nations have designated IEZs for the exclusive use of small-scale, artisanal fishers (Basurto et al., 2024; Belhabib et al., 2020; FAO, 1991). These IEZs cover an area beginning from each country's coast, and governments prohibit all industrial fishing within their boundaries (Figure 1). Because these nearshore waters are typically the most biologically productive—and the least costly for artisanal fishers to access—IEZs reserve the best fishing grounds for artisanal fishers (Maishal, 2024; Ryan-Keogh et al., 2023).

IEZs are straightforward for governments to enforce. Patrol vessels can visually determine whether an industrial vessel is fishing inside the IEZ and impose penalties—such as confiscation of catch, fines, or imprisonment—on violators (Government of Ghana, 2022; Government of Sierra Leone, 2020; Jueseah et al., 2020; Kargbo et al., 2024; Philippe, 2023; Traore, 2022). In contrast, regulations like total allowable catches or individual vessel quotas (IVQs) require systematic data collection to monitor compliance. IEZs are an example of "regulated open access" (Reimer & Wilen, 2013). They can increase steady-state fish stocks because artisanal vessels use lower-productivity technologies, so the zero-profit equilibrium occurs at a higher stock level than for industrial vessels. Limiting interactions between artisanal and industrial vessels can also enhance safety by reducing collisions and net entanglements (Guilavogui et al., 2004). Although IVQs likely do more to increase fisher profits and fish stocks, IEZs demand less institutional capacity. The feasibility of IEZs, combined with political desire to favor artisanal fishers, helps explain why most African coastal countries have implemented them (Basurto et al., 2024; FAO et al., 2023).

Countries may choose IEZ boundaries to balance the perceived benefits of protecting artisanal fishers against the costs of excluding industrial fishing. Larger IEZs may yield bigger gains to artisanal fishers but also increase the government's enforcement costs and reduce the industrial fishing sector's revenues. Though IEZ boundaries are not chosen randomly, the generally smooth movement of water and fish in the ocean means fishing opportunities may be similar just inside compared to just outside IEZ boundaries, permitting identification of which countries effectively enforce their IEZ and deter industrial fishing vessels (Section 4).

We collected the IEZ boundaries displayed in Figure 1 by comparing those reported in

Figure 1: African Inshore Exclusion Zones (IEZs) in Estimation Sample



Note: 1 nautical mile equals 1.852 kilometers.

Belhabib et al. (2020) to official government documents, other academic articles, and international or non-governmental organization reports. We retained countries in our estimation sample if their IEZ prohibited all industrial fishing. Because our radar data do not distinguish among different fishing methods, we exclude countries like Senegal, where allowed activities vary by fishing method (République du Sénégal, 2015). Appendix A provides details.

Our analyses always aggregate the data to a spatial cross-section because there is little variation in IEZ boundaries over time. Only two countries in our sample changed their IEZ boundaries during our study period of 2017 to 2021. Madagascar's IEZ began in July 2021, so our analyses of that country include only data from July 2021 onward (Carver, 2021). Equatorial Guinea increased its IEZ from 4 to 12 nautical miles (nm) in November 2017, prompting us to treat it as two distinct cross-sections (República de Guinea Ecuatorial, 2017). Our RD analysis therefore uses 21 "country-boundary" spatial cross-sections (compared to 20 unique countries in our estimation sample). All countries except for Ghana and Sierra Leone define their IEZ boundary as a fixed distance from the coast (Appendix A). Figure 1(b) displays the average distances from the coast for Ghana's and Sierra Leone's

IEZ boundaries, as well as Equatorial Guinea's 12 nm boundary.

3 Data

Automatic Identification System (AIS) data revolutionized fisheries research by providing vessel-level fishing data at high spatial and temporal resolution for the globe (Kroodsma et al., 2018). But their key limitation is vessels choose whether to install AIS transponders and when to operate them (Welch et al., 2022). The publication of Paolo et al. (2024) heralds the next era in fisheries research by observing industrial fishing vessels without selection.

Paolo et al. (2024) use Synthetic Aperture Radar (SAR) instruments onboard the Sentinel-1 satellites to detect industrial fishing vessels. SAR instruments actively emit microwaves and measure the energy reflected back from the ocean surface. Vessel hulls scatter these microwaves more than the surrounding ocean surface, allowing observation of vessels regardless of weather conditions, time of day, or whether vessels prefer to remain unseen. SAR observes five times more vessels in African coastal waters than AIS data (Paolo et al., 2024). SAR does not observe artisanal vessels because the detection threshold is about 15 m in hull length—above the size of African artisanal fishing vessels.

Defining industrial fishing vessels. Paolo et al. (2024) overlay SAR and AIS data. SAR vessel detections in the same places and times as AIS data can be categorized into "matched fishing" vessels, "matched non-fishing" vessels, or "matched unknown" because the authors cross-referenced AIS identifiers with vessel registries. The fourth possible category for a SAR vessel detection is "unmatched": these vessels are not broadcasting AIS at the time SAR observes them. Unmatched vessels are the most common type of vessel detected in our study area (Table 1); if we only relied on AIS data, we would not observe these vessels. As an illustrative example, Figure 2(a) displays the four mutually exclusive SAR vessel categories in the waters of Mauritania.

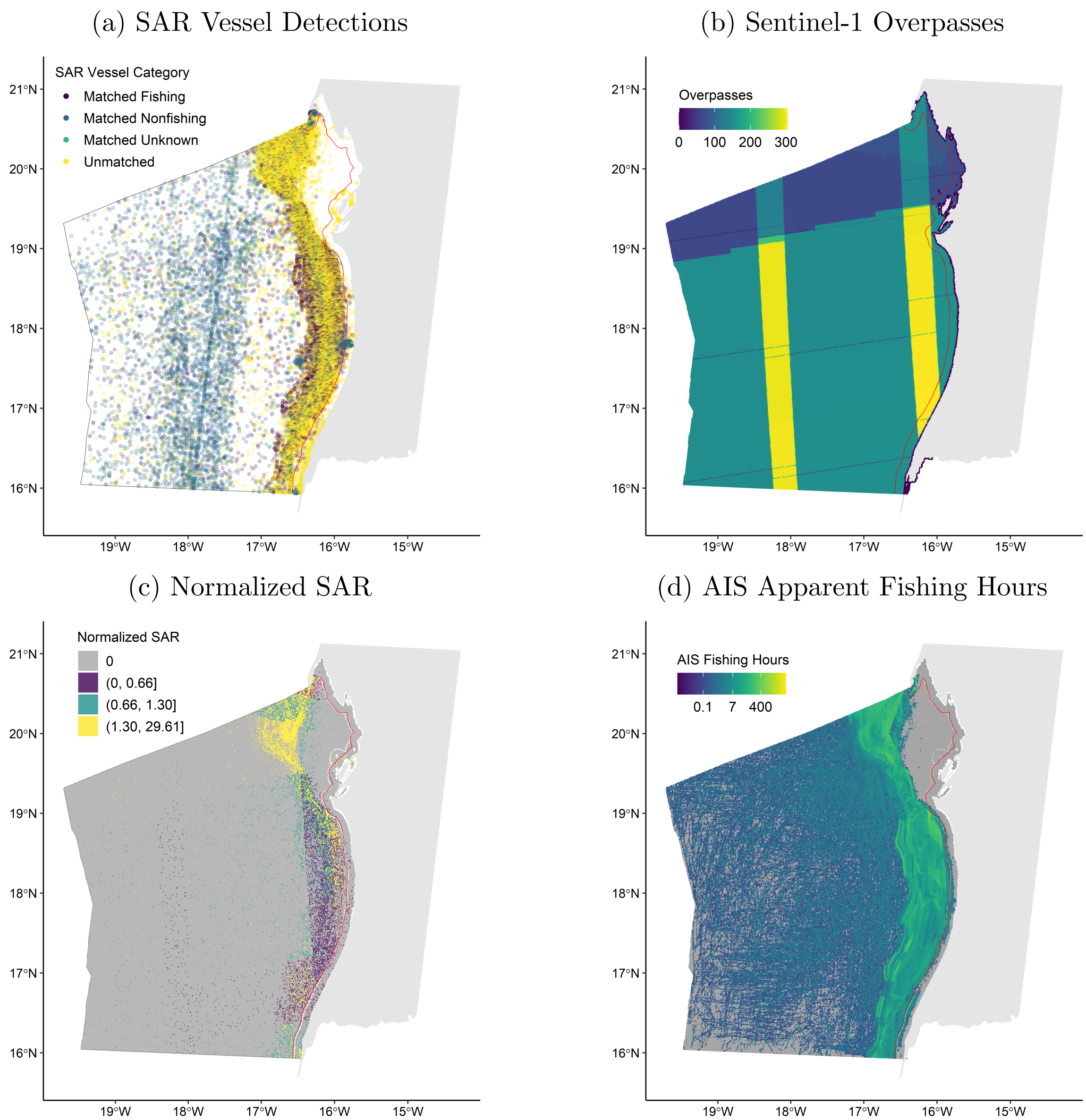
We designate an industrial fishing vessel as any detection classified as matched fishing, matched unknown, or unmatched; matched non-fishing detections serve only in placebo tests. About three-quarters of industrial non-fishing vessels broadcast AIS and are therefore positively identified as matched-non-fishing (Paolo et al., 2024). By excluding only these matched non-fishing vessels, our inclusive rule exploits SAR's principal advantage—the ability to observe all industrial fishing vessels—while confining possible misclassification of non-fishing vessels as fishing vessels to the remaining quarter of non-fishing vessels without AIS. Because the distributions of non-fishing vessels are smooth across IEZ boundaries (Section 4), misclassification is unlikely to bias our RD estimates. In the bunching analysis, the same smoothness means misclassified vessels enter the observed density on each side of the boundary in roughly equal proportion, possibly attenuating the estimates. Finally, because we calibrate the IEZ disutility parameter in the discrete choice model to the bunching estimates, our extensive-margin estimates may be conservative.

Constructing the primary dependent variable. Because the two-satellite Sentinel-1 constellation revisits any given location only every six days—and because near-shore areas are imaged more frequently than offshore ones (Figure 2(b))—we must normalize raw detections by satellite coverage. Specifically, we count the number of Sentinel-1 "overpasses": instances when a Sentinel-1 satellite images a grid cell. If we didn't normalize vessel detections, our analysis would conflate sampling frequency with vessel presence.

Therefore, for each 0.01° grid cell we (i) sum industrial fishing vessel detections over time—2017 to 2021 for 18 countries, July 2021 through December 2021 for Madagascar, and two separate cross-sections for Equatorial Guinea (Section 2)—and (ii) sum the number of Sentinel-1 overpasses over the same periods. The primary dependent variable in our analysis is the number of industrial fishing vessels detected per 100 overpasses, i.e. 100 times the ratio of these two sums (Figure 2(c)). This dependent variable excludes cells with zero overpasses because in these cases we do not know whether the absence of industrial fishing vessel detections in these cells represent true zeros. 98.7% of cells with zero overpasses occur in the EEZs of Cape Verde, Madagascar, Angola, or Somalia. We also exclude cells from our analysis that intersect an IEZ boundary. Finally, we exclude cells within 1 kilometer (km) of shore because Paolo et al. (2024) do not classify objects in these cells.

AIS apparent fishing hours. SAR data are more comprehensive in that they contain more vessels, but AIS data are richer in the following sense. AIS data contain an apparent fishing hours variable, which Kroodsma et al. (2018) predict from vessel movement and characteristics, whereas SAR data contain only the presence of industrial fishing vessels.

Figure 2: Sentinel-1 SAR and AIS Data in Mauritanian Waters, 2017-2021



Notes: Spatial cross-section (a) points and (b) to (d) 0.01° grid cell data inside Mauritania's Exclusive Economic Zone between 2017 and 2021. (c) Normalized SAR is the number of industrial fishing vessels detected per 100 Sentinel-1 overpasses. In all subfigures, the IEZ boundary is the red line and Mauritania's coast is the light-grey polygon.

Table 1: Sentinel-1 SAR and AIS Summary Statistics

	N (1)	% Obs > 0 (2)	Min (3)	Median (4)	Mean (5)	Max (6)
A. Sentinel-1 SAR						
Overpasses	4,983,107	79.0%	0.25	148.0	165.2	1,186.0
Matched Fishing	4,983,107	0.7%	1	1	1.3	71
Matched Nonfishing	4,983,107	1.8%	1	1	2.3	191
Matched Unknown	4,983,107	0.3%	1	1	1.3	46
Unmatched	4,983,107	2.2%	1	1	1.6	119
Normalized SAR	3,904,864	3.2%	0.056	0.662	0.785	54.248
B. AIS						
Fishing Hours	4,895,943	23.3%	0.002	0.5	4.7	14,514

Notes: This table summarizes the data used in the regression discontinuity analysis, where each observation is a 0.01° grid cell within one of 21 country-boundary cross-sections. Column 1 is the number of observations (N) and Column 2 reports the share of observations with positive values. Columns 3 to 6 give the minimum, median, mean, and maximum conditional on positive values. Normalized SAR is the number of industrial fishing vessels detected per 100 Sentinel-1 overpasses; cells with zero overpasses are excluded. The Fishing Hours row (AIS apparent fishing hours) applies the same spatial exclusions as Normalized SAR, so its N is slightly smaller than rows summarizing raw overpasses and vessel detections.

Additionally, AIS data contain more information on the characteristics of vessels, such as the type of fishing method they practice and the country they are registered in, whereas SAR data contain only an estimate of the length of each vessel. We therefore sum AIS apparent fishing hours between 2017 and 2021 into the same 0.01° grid cell cross-sections as the SAR data, dropping any cell that lies within 1 km of shore or intersects an IEZ boundary (Global Fishing Watch, 2024, 2025). We rely on SAR data for our primary outcome variable because of the importance of observing vessels without selection. But comparing results in SAR data to results using AIS data can help compensate for the two limitations of the SAR data.

Variables for placebo tests. We assess the validity of our RD design by testing for discontinuities in non-fishing vessel presence, oceanic depth, sea surface temperature, and chlorophyll (NASA, 2014, 2019; NOAA, 2022). For consistency with the SAR data we aggregate these variables into the same 0.01° grid cell cross-sections, removing cells within 1 km of shore, intersecting an IEZ boundary, or with zero non-missing observations. Non-fishing vessel presence is the number of matched non-fishing vessels per 100 Sentinel-1 overpasses.

4 Regression Discontinuity Design and Results

This section identifies which countries deter industrial fishing vessels from their IEZ. Then it explores what distinguishes these countries.

4.1 Empirical Strategy

Identification relies on the standard RD assumption that, aside from the discrete policy change at the IEZ boundary, the conditional expectation of the potential outcomes varies smoothly in distance to the coast. Then, a discontinuous increase in industrial fishing vessel presence just outside a country's IEZ boundary can be attributed to the IEZ.

We implement the same RD design for five outcomes. The primary outcome is industrial fishing vessel presence. Four placebo outcomes—non-fishing vessel presence, oceanic depth, sea surface temperature, and chlorophyll—assess the validity of our identification assumption by testing whether fishing opportunities and other determinants of industrial fishing vessel presence vary smoothly with distance to the coast.

We use one-sided z-statistics to test whether industrial fishing vessel presence is discontinuously higher just outside a country's IEZ.[1] Discontinuously lower vessel presence just outside an IEZ would more likely reflect random variation than deterrence, because vessel presence inside an area is unlikely to increase due to a permanent and longstanding fishing restriction like IEZs—unlike variable restrictions that might temporarily signal higher fishing productivity within their boundaries (Englander, 2023). For consistency, we also use one-sided z-statistics to assess placebo variables. First, we test whether non-fishing vessel presence increases just outside IEZs, as this could reveal underlying discontinuities affecting vessel presence generally. Second, we examine if oceanic depth increases just outside IEZ boundaries, as discontinuously greater depth could change the abundance and composition of catchable fish. Oceanic depth is also unlikely to decrease moving away from shore and thus outward from an IEZ. Lastly, we estimate whether sea surface temperature decreases and chlorophyll increases just outside IEZ boundaries. Both patterns could indicate upwelling—when cold, nutrient-rich water rises to the surface, enhancing fishing productivity.

[1] The rdrobust package computes z-statistics rather than t-statistics (Calonico et al., 2023).

To control the family-wise false-discovery rate we apply the Benjamini–Hochberg procedure separately to the 21 primary tests and the 84 placebo tests (Benjamini & Hochberg, 1995). We report Benjamini-Hochberg adjusted p-values, known as q-values, and consider a result statistically significant if its q-value is less than 0.05.

Let y_i denote any of the five outcomes for $0.01°$ grid cell i. We estimate

$$y_i = \alpha + \beta_1 \mathbb{1}\{i \notin IEZ\} + \beta_2 Distance_i + \beta_3 Distance_i \times \mathbb{1}\{i \notin IEZ\} + \epsilon_i, \tag{1}$$

where $\mathbb{1}\{i \notin IEZ\}$ equals 1 for cells outside the IEZ and $Distance_i$ is the distance in km from the cell centroid to the coast (or to the IEZ boundary for Ghana and Sierra Leone). The coefficient β_1 measures the discontinuity.

We estimate Equation 1 separately for each of the 21 country-boundary spatial cross-sections, employing the default options of the rdrobust package to limit researcher degrees of freedom. These default options include mean-squared-error (MSE) optimal bandwidth selection, a common bandwidth on both sides of the boundary, local-linear specification for the running variable, a triangular kernel, and heteroskedasticity-robust nearest-neighbor standard errors (Calonico et al., 2023). Regression tables present the conventional (non-bias-corrected) point estimate with its heteroskedasticity-robust standard error, the q-value for the one-sided test, the MSE-optimal bandwidth, and the number of observations that fall within that bandwidth.

We complement the tables with rdrobust's rdplot command. Each figure shows binned sample means (points) alongside local-linear fits through the non-binned raw data (lines). To match the difference in intercepts on either side of the boundary with the point estimate, we set three non-default options—the optimal bandwidth from the corresponding regression, triangular kernel, and local-linear specification. We use default options in all other instances, including calculating the number of bins and the bin endpoints with the mimicking variance evenly-spaced method using spacings estimators to aid visual inference (Calonico et al., 2015; Korting et al., 2023).

Of the 84 placebo tests, only one rejects the null hypothesis: non-fishing vessel presence at the Republic of the Congo IEZ boundary (Table B1 and Figure B1). All six countries that deter industrial fishing vessels pass every placebo test, supporting the identification assumption for these countries (Figures B2 to B7). Pooling data across country-boundaries likewise yields no significant discontinuities in any of the four placebo outcomes (Table B2 and Figure B8).

4.2 Results

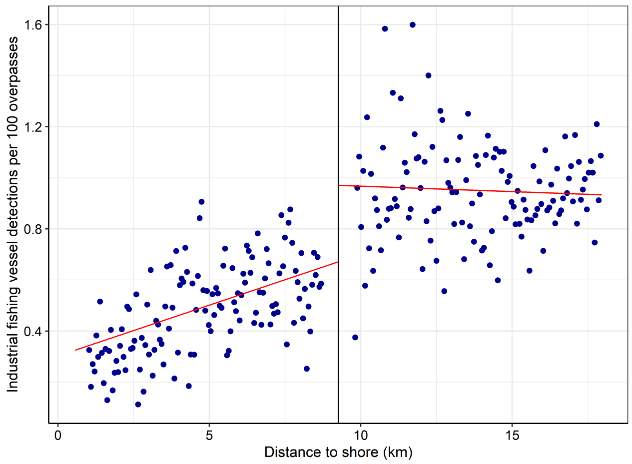
Industrial fishing vessel presence is significantly higher just outside the IEZ boundaries of six countries: Nigeria, Sierra Leone, Liberia, Mauritania, Ghana, and Guinea (Figure 3). Outside these six countries, industrial fishing vessel presence is not higher just outside the boundary, indicating that these countries do not deter industrial fishing vessels from their IEZs (Table 2). Comparing the level of industrial fishing vessel presence just outside with the level just inside shows that presence falls by 31% (Nigeria) to 63% (Liberia) at the six countries' IEZ boundaries.

Applying the same RD design to AIS apparent fishing hours—and controlling that separate family of 21 tests with its own Benjamini-Hochberg adjustment—demonstrates the value of SAR data for evaluating IEZs (Table B3). The AIS regressions still identify deterrence in five of the six SAR countries (Nigeria, Sierra Leone, Liberia, Mauritania, and Ghana), but Guinea now falls below the statistical significance threshold, while five new countries—Cameroon, the Republic of the Congo, Equatorial Guinea (12 nm boundary), Gabon, and Madagascar—appear to deter industrial fishing. AIS therefore suggests deterrence in ten cases rather than six, and the implied percentage decreases are larger: at Sierra Leone's boundary, for example, AIS apparent fishing hours fall by 88 percent compared with a 56 percent decline in SAR industrial fishing vessel presence (Figure B9). Because vessels can decide whether to carry an AIS transponder and when to switch it on, AIS overstates both the prevalence and the strength of deterrence; the SAR data, which observe vessels without selection, provide the more credible measure.

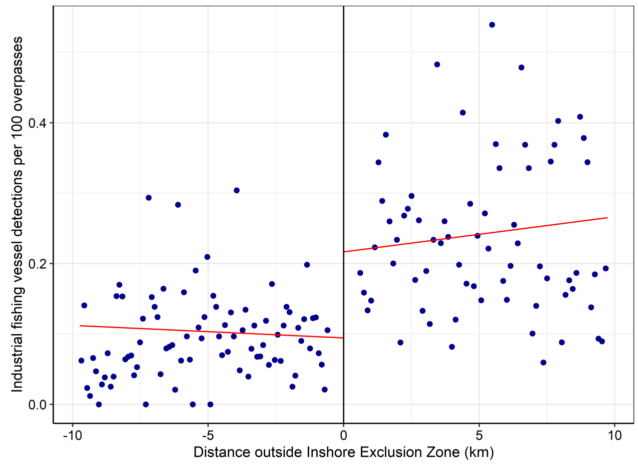
Pooling data across all 21 country-boundaries illustrates an average deterrence effect: industrial fishing vessel presence is 28% lower just inside IEZ boundaries compared to just outside (Figure B10a). The corresponding pooled AIS estimate is a much larger 67% decrease in apparent fishing hours at IEZ boundaries (Figure B10b).

Figure 3: Discontinuities in Industrial Fishing Vessel Presence at IEZ Boundaries

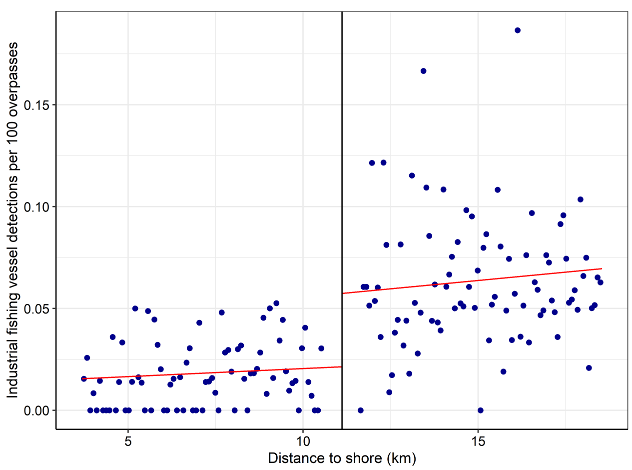
(a) Nigeria



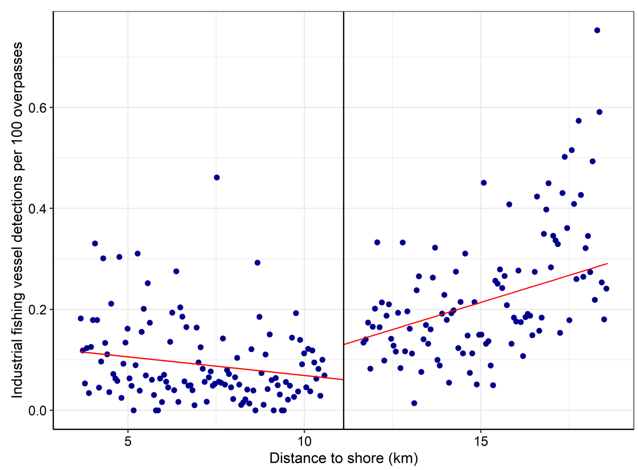
(b) Sierra Leone



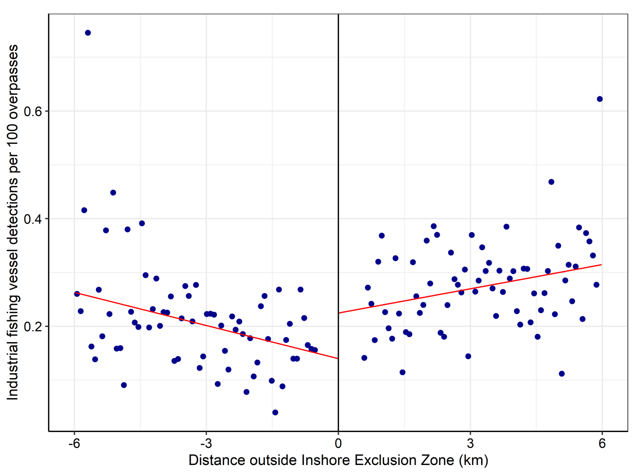
(c) Liberia



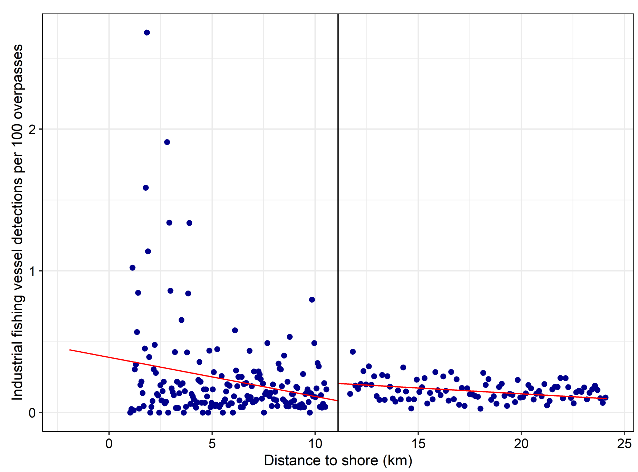
(d) Mauritania



(e) Ghana



(f) Guinea



Note: Subfigures reproduce the regressions corresponding to the first six rows of Table 2.

Table 2: Estimated Discontinuities in Industrial Fishing Vessel Presence at IEZ Boundaries

Country-Boundary (1)	Coefficient (2)	Std. Error (3)	q-value (4)	Bandwidth (5)	N (6)
Nigeria	0.299	(0.049)	0.0000	8.693	10,307
Sierra Leone	0.122	(0.030)	0.0002	9.736	5,306
Liberia	0.036	(0.010)	0.0018	7.426	6,219
Mauritania	0.070	(0.021)	0.0028	7.477	8,113
Ghana	0.085	(0.029)	0.0055	5.984	4,936
Guinea	0.122	(0.041)	0.0055	13.034	6,782
Madagascar	0.006	(0.003)	0.0566	5.342	30,950
Cape Verde	0.016	(0.013)	0.2876	12.307	9,938
Republic of Congo	0.073	(0.074)	0.3772	13.305	2,862
Eq. Guinea - 12 nm	0.003	(0.004)	0.4946	5.540	5,405
Cameroon	0.160	(0.317)	0.5853	1.859	815
Mozambique	0.003	(0.008)	0.6473	6.226	24,500
Gambia	0.012	(0.144)	0.7553	8.463	1,044
Ivory Coast	-0.015	(0.049)	0.9260	8.357	4,918
Guinea-Bissau	-0.007	(0.012)	1.0000	6.370	3,436
Gabon	-0.027	(0.037)	1.0000	10.815	9,367
Angola	-0.020	(0.020)	1.0000	9.339	19,146
Eq. Guinea - 4 nm	-0.016	(0.007)	1.0000	8.446	6,332
Somalia	-0.005	(0.002)	1.0000	5.041	22,005
Togo	-0.211	(0.055)	1.0000	19.017	1,304
Benin	-0.385	(0.077)	1.0000	11.681	1,850

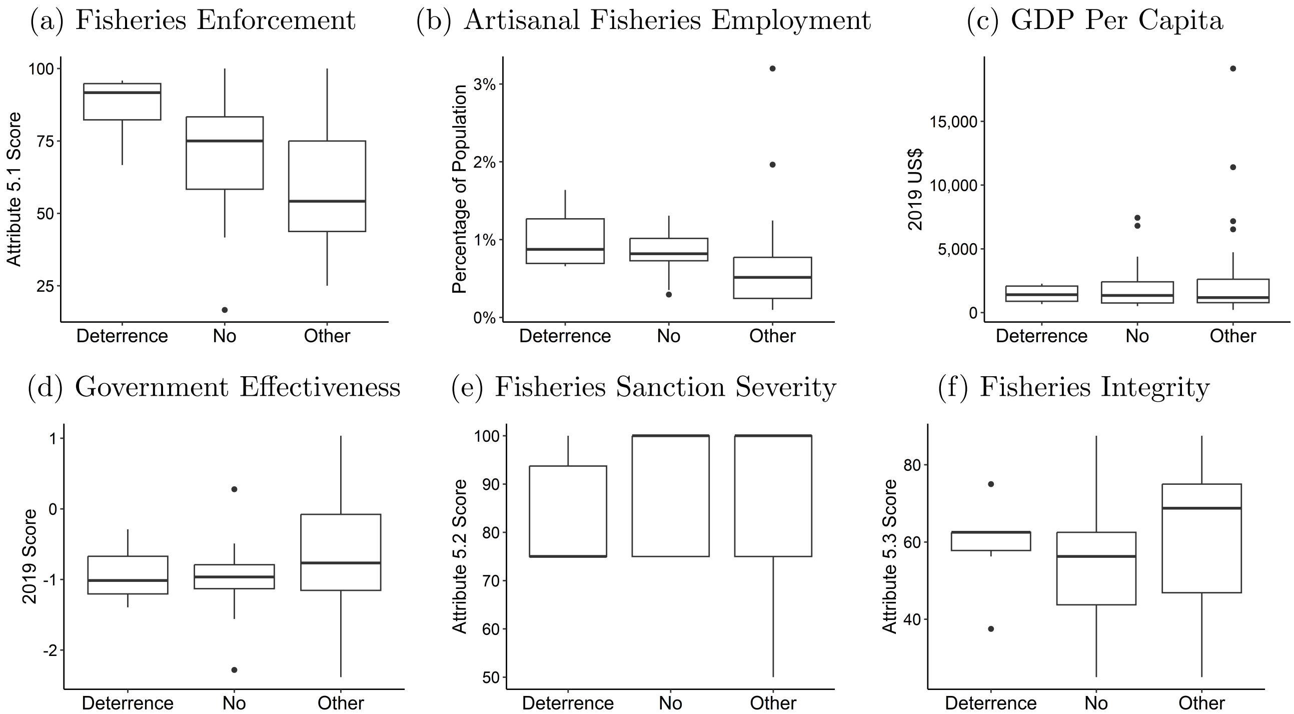
Notes: Each row presents a separate regression result, with Column 1 indicating the data used. Columns 2 to 6 report the point estimate, standard error, q-value, optimal bandwidth in km, and number of observations within that bandwidth.

4.3 What Distinguishes the Six "Deterrence" Countries?

Figure 4 contrasts the 6 countries that deter industrial fishing vessel presence from their IEZ ("Deterrence") with the 14 other countries in our estimation sample ("No") and the remaining Sub-Saharan African countries ("Other"). The boxplots explore what might explain deterrence heterogeneity across countries, rather than formally testing mechanisms.

Figure 4(a) displays the "Compliance Monitoring and Surveillance" score (Attribute 5.1) from the Minderoo Foundation (2021) survey of country fisheries experts. The index measures the overall strength of a country's enforcement regime—for example, how systematic patrols are and whether inspections target the vessels most likely to violate fisheries regu-

Figure 4: Deterrence Countries Enforce More



Notes: "Deterrence" countries are Nigeria, Sierra Leone, Liberia, Mauritania, Ghana, and Guinea. The 14 other countries in our estimation sample comprise the "No" category. "Other" contains all remaining Sub-Saharan African countries with non-missing data for each variable. In subfigures (a), (e) and (f) the "Other" group consists of the coastal countries Comoros, Democratic Republic of the Congo, Djibouti, Eritrea, Kenya, Namibia, São Tomé and Príncipe, Senegal, Seychelles, South Africa and Tanzania; subfigures (b), (c) and (d) additionally include land-locked countries whenever their data are available.

lations.[2] Deterrence countries score roughly one inter-quartile range above non-deterrence ("No") countries and well above the other group; their median is 92 versus 75 and 54.

The figure's other potential explanatory variables exhibit much less separation. First, a larger percentage of the population working as artisanal fishers could give governments stronger incentives to deter industrial fishing. But using the most recent estimates available (Virdin et al., 2023; World Bank, 2024a), in 2016 the median was 0.87% in deterrence countries and 0.82% in non-deterrence countries (Figure 4(b)). Higher income or stronger

[2]The index value is the unweighted average of six questions, each scored between 0 and 100: (5.1.1) Plan of action to prevent, deter and eliminate illegal, unreported and unregulated fishing; (5.1.2) Targeted port inspections; (5.1.3) Targeted at-sea inspections; (5.1.4) Inspecting agency (dedicated fisheries officers versus other officials); (5.1.5) Randomized inspections; and (5.1.6) Risk-based inspection prioritization (Minderoo Foundation, 2021). Minderoo data collected between August 2019 and May 2020.

general governance could likewise enable deterrence, yet both GDP per capita and the World Governance Indicator "Government Effectiveness" show similar distributions across the three sets of countries in Figures 4(c)-(d) (World Bank, 2024b, 2025).

Figures 4(e)-(f) return to the Minderoo fisheries governance indices. Deterrence countries do not set more severe *de jure* penalties for fisheries violations (Attribute 5.2), nor are they markedly more free from corruption in enforcing fisheries regulations (Attribute 5.3). Consistent with the economics of crime literature, the probability of punishment—best proxied by the Compliance Monitoring and Surveillance score in Figure 4(a)—appears more important for deterrence than the penalty severity of Figure 4(e) (Chalfin & McCrary, 2017).

These comparisons are descriptive and non-exhaustive, yet they offer a plausible explanation for the RD results: the countries with deterrence effects are those with the most vigorous fisheries enforcement regimes (i.e., highest Compliance Monitoring and Surveillance scores).

5 Bunching Estimator and Results

The RD definition of deterrence is a discontinuous increase in industrial fishing vessel presence just outside the IEZ boundary. Because this excess density is induced by the policy itself, vessel presence just outside the boundary exceeds the counterfactual level that would have occurred in the absence of the IEZ. The RD estimates, which compare vessel presence just inside to just outside, therefore overstate the effect of IEZs.

To avoid spatial spillover bias and estimate an effect across the entire IEZ—not just at the boundary—we adapt the bunching estimator developed for tax notch settings (Kleven & Waseem, 2013). When a notch raises the average tax rate, some taxpayers shift reported income below the threshold, creating excess density ("bunching") below the notch and missing density above it. An IEZ boundary creates an analogous discontinuity in expected punishment costs. This causes some vessels to relocate from inside to outside the IEZ, generating excess density outside and missing density inside. Just as income would follow a smooth distribution absent the tax notch, industrial fishing vessel presence would display a natural shape absent IEZs, falling smoothly as distance to shore increases (Extended Data Fig. 10b of Paolo et al., 2024). In both contexts agents manipulate their location with respect to a threshold, and the bunching estimator recovers the counterfactual density by reallocating the excess mass to the missing region. While bunching estimators are standard in public economics, this is the first application in a natural resources setting.

The estimator rests on three main assumptions. Monotonicity allows the IEZ to displace vessels from inside to outside but not in the opposite direction. An intensive-margin assumption fixes industrial fishing vessel presence inside each country's EEZ; we estimate extensive-margin effects in Section 6.[3] Finally, absent the policy, vessel presence varies smoothly with distance from the coast near the boundary.

Let z^* denote the notch and z_l and z_u the lower and upper boundaries of the manipulation zone. Tax applications typically pick z_l by visual inspection and expand z_u until the excess mass between z^* and z_l equals the missing mass between z^* and z_u (Kleven, 2016). We invert this procedure. Because all locations inside an IEZ are "taxed" and Paolo et al. (2024) do not classify objects within 1 km of the coast, we fix $z_u = 1$ km and search seaward for $z_l > z^*$.[4] Starting from $z_l = z^* + 0.1$ km, we increase z_l in 0.1 km increments until

$$B(z_l) = M(z_l) \tag{2}$$

where $B(z_l)$ is the excess industrial fishing vessel presence (observed minus counterfactual) in $(z^*, z_l]$, and $M(z_l)$ is the corresponding missing mass (counterfactual minus observed vessel presence) inside the IEZ.

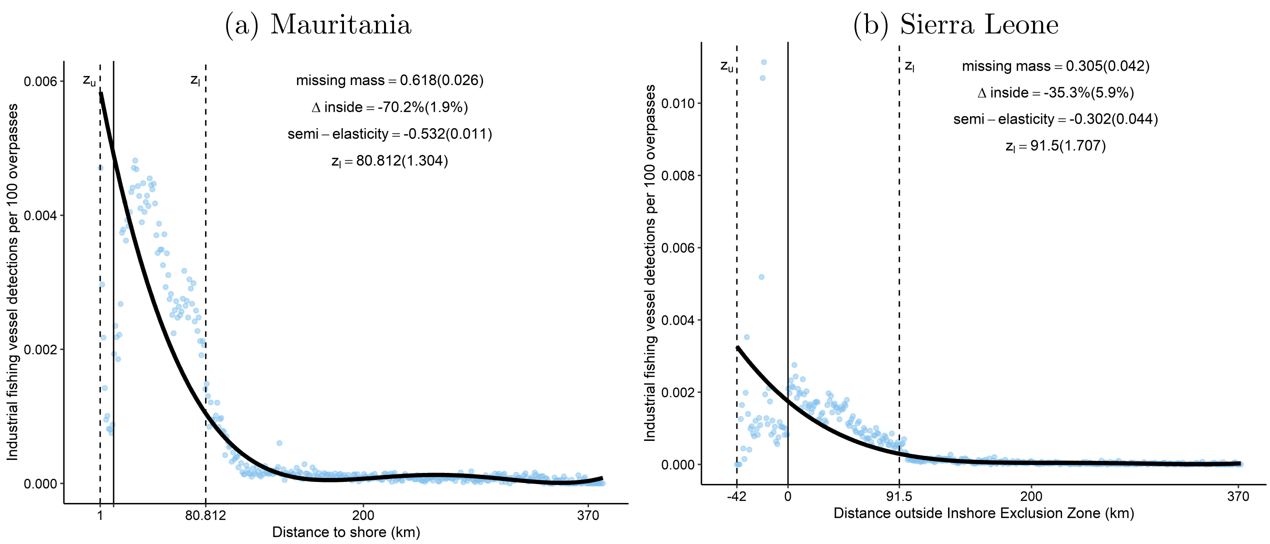
Before searching for a country's z_l we aggregate its 0.01° cross-section into distance-to-shore bins of width h, where h equals the country-specific RD-optimal bin width. The dependent variable is the sum of industrial fishing vessel detections divided by 100 times the sum of Sentinel-1 overpasses. We approximate each country's counterfactual distribution by fitting a fourth-order polynomial to all bins in the country's EEZ whose midpoint distance exceeds z_l—that is, the portion lying seaward of the manipulation zone—and interpolating the fit over the full support.[5] Estimating the polynomial on the seaward side alone imposes a

[3] Alternative bunching estimators that accommodate extensive-margin responses require additional assumptions, such as specifying both boundaries of the manipulation zone (Pollinger, 2024).

[4] For Sierra Leone and Ghana, z_u equals the negative of the maximum inland extent of the IEZ boundary plus 1 km.

[5] We re-fit the polynomial at each trial value of z_l; the search stops at the first z_l for which $B(z_l) = M(z_l)$.

Figure 5: Bunching Countries with Highest and Lowest Percent Reductions Inside IEZs



Notes: 1 km wide binned data (blue dots) displayed for easier visualization of polynomial fit (black curve) outside the manipulation zone. The two dashed vertical lines mark the manipulation zone boundaries and the solid vertical line indicates the IEZ boundary. Numeric estimates (top, center-right) correspond to the specification with RD-optimal bin widths.

stronger identifying restriction than the conventional two-sided fit, but the fixed 1 km coastward boundary z_u eliminates ad-hoc visual choice and, as Kleven (2016) notes, one-sided estimation can result in more robust estimates when extensive-margin responses are strong (p. 451-452). The resulting counterfactual embeds vessels' equilibrium interactions; congestion and other strategic behavior are already present in the observed densities on which the polynomial is fitted.

We calculate bootstrapped standard errors because the Sentinel-1 satellites do not observe all locations simultaneously. The residual bootstrap common in the tax literature treats the population as fully observed and therefore understates uncertainty here (Chetty et al., 2011; Kleven, 2016). Instead, we draw 0.01° grid cells with replacement, recompute the RD-optimal bin width, repeat the bunching estimator, and save the estimated bunching and missing masses. We repeat this procedure 1,000 times for each country.

We estimate the bunching model separately for each of the six deterrence countries.

Hence the final z_l need not be known ex ante.

Table 3: Bunching-Estimated Reductions in Industrial Fishing Vessel Presence Inside IEZs

Country (1)	Missing Mass (2)	Percent Change (3)	Semi-Elasticity (4)	Outer Width (km) (5)
Mauritania	0.618	-70.2%	-0.532	69.7
	(0.026)	(1.9%)	(0.011)	(1.30)
Ghana	0.254	-42.3%	-0.353	45.0
	(0.021)	(3.2%)	(0.023)	(4.44)
Nigeria	0.440	-41.0%	-0.344	9.5
	(0.017)	(1.4%)	(0.010)	(0.25)
Liberia	0.020	-40.1%	-0.337	7.6
	(0.003)	(5.9%)	(0.041)	(0.71)
Sierra Leone	0.305	-35.3%	-0.302	91.5
	(0.042)	(5.9%)	(0.044)	(1.71)

Notes: Bunching estimates for each country use a fourth-order global polynomial and RD-optimal bin widths. Semi-elasticities in Column 4 equal –log(1 − Percent Change). Column 5 is the estimated width of the zone of manipulation outside the IEZ ($z_l - z^*$). Standard errors (bootstrapped for Columns 2, 3, and 5; delta method for Column 4) appear in parentheses.

For Guinea the algorithm halts at the first iteration because the implied missing mass is negative, so no bunching is detected; the discussion below therefore refers to the remaining five countries.

Figure 5 plots the fitted counterfactual for the two extremes of the distribution of effects—Mauritania (largest percentage reduction) and Sierra Leone (smallest). The dots show 1 km-wide binned data for ease of inspection; panels for Ghana, Nigeria, and Liberia appear in Figure B11, and Figure B12 reproduces all five panels with RD-optimal bin widths.

Table 3 reports the numerical estimates. Column 3 shows that the policy reduces industrial fishing vessel presence inside the IEZ by 35 to 42 percent in four of the five countries, with Mauritania an outlier at 70 percent. Averaging across the five yields a 45.8 percent reduction, the moment to which we calibrate the nested logit model in Section 6. The Column 5 estimated outer width of the manipulation zone—z_l minus z^*—demonstrates variation across countries in the spatial extent over which bunching occurs. We obtain similar results using a third-order polynomial (Table B4).

6 Vessel Location Choice Model and Results

The bunching analysis demonstrates that five IEZs reduce industrial fishing vessel presence inside their boundaries. This reduction likely occurs because vessels perceive an expected punishment cost from illegally fishing inside these IEZs. However, our bunching estimator assumes these displaced vessels relocate to other areas within the same country's EEZ—an intensive-margin effect. Because IEZs typically encompass the most biologically productive waters, increasing the expected cost of fishing there may reduce a country's overall attractiveness to industrial fishing vessels. Rather than locating in less productive offshore areas, some vessels may exit the country's EEZ entirely—an extensive-margin response (Barrett, 2024). We use a nested logit model of vessel location choice to estimate the extensive-margin effect of each of the five countries' IEZs.

6.1 Model Setup

Since SAR data do not contain vessel identities, we treat each SAR industrial fishing vessel detection as an independent decision maker. As in the RD and bunching, we analyze vessel location decisions as a spatial cross-section.

We define the market as a one country buffer around the five countries, allowing vessels to locate within the EEZ of any of the five countries or any bordering EEZ (Figure B13). There is no outside option. Instead, the bordering EEZs serve as relocation options outside the five focal EEZs.

In the upper nest, vessel i chooses among K countries' EEZs. In the lower nest, the vessel selects an interior spatial alternative j within the chosen EEZ k. For the five countries with bunching effects, we divide the EEZ into three alternatives: (1) the IEZ area itself, (2) the manipulation zone outside the IEZ identified in Section 5, and (3) the remainder of the EEZ. This disaggregation will allow us to match the key model parameter to our bunching estimate. For the bordering countries, we model their entire EEZs as single undivided alternatives.

6.2 Utility Specification

The indirect utility that vessel i derives from locating in alternative j within EEZ k is

$$
\begin{aligned}
U_{ijk} &= V_{ijk} + \varepsilon_{ijk} \qquad (3) \\
V_{ijk} &= \beta_1 \cdot \mathrm{IEZ}_{jk} + \beta_2 \cdot \log(\mathrm{Area}_{jk}) + \\
&\quad \beta_3 \cdot \log(\mathrm{Distance}_{jk}) + \beta_4 \cdot (\mathrm{Length}_i \times \log(\mathrm{Distance}_{jk})) + \\
&\quad \theta \cdot \mathbf{Env}_{jk} + \gamma \cdot \mathbf{EEZChar}_k \qquad (4)
\end{aligned}
$$

where V_{ijk} is the observable component of utility and ε_{ijk} is the random component. IEZ_{jk} is an indicator for whether alternative j in EEZ k is an IEZ. Area_{jk} denotes the area in square kilometers of alternative j. $\mathrm{Distance}_{jk}$ measures the distance in km from the centroid of alternative j to the main port in country k, defined as the port with the most anchorage points (Global Fishing Watch, 2023). We include an interaction term between vessel length in meters, Length_i, and distance to port to capture potential heterogeneity in travel costs by vessel size.

The vector $\mathbf{Env}_{jk}$ captures alternative-specific attributes that affect fish catches. These are the means and standard deviations of chlorophyll, sea surface temperature, and ocean depth, measured between 2017 and 2021.[6] $\mathbf{EEZChar}_k$ includes three predetermined variables at the EEZ level, all measured in 2012 from Costello et al. (2016). These are the log of total biomass in tons (summed across all fish stocks), which captures resource abundance; the log of catch-weighted average fish price, which affects revenue; and the fraction of catch from pelagic species, which proxies for the mobility of fish stocks.[7]

6.3 Estimation Procedure and Calibration

We use weighted exogenous sampling maximum likelihood to account for the non-uniform overpass frequency of the Sentinel-1 satellites. We introduce alternative-specific weights $\tilde{w}_j$ and estimate the following weighted log-likelihood:

[6] For chlorophyll and sea surface temperature, we calculate standard deviations across all pixel-year observations within each alternative. Ocean depth is time-invariant.

[7] For Western Sahara, which had missing values for these variables, we imputed biomass with the ratio of total biomass to EEZ area across all other countries in the market, and we set price and pelagic fraction equal to those of Mauritania, its only neighbor in the market.

$$\log L = \sum_i \sum_j \tilde{w}_j \alpha_{ij} \log P_{ij}, \tag{5}$$

where $\alpha_{ij} = 1$ if vessel i chooses alternative j and $\alpha_{ij} = 0$ otherwise, P_{ij} is the predicted probability that vessel i chooses alternative j, and $\tilde{w}_j$ is the normalized inverse probability of alternative j being imaged by Sentinel-1.[8]

Our key parameter of interest in Equation 4 is β_1, which captures the average disutility of locating inside an IEZ relative to any non-IEZ alternative in the choice set. Rather than estimating this parameter freely, we calibrate it to match the empirical moment from our bunching analysis: IEZs reduce industrial fishing vessel presence by an average of 45.8% across the five countries. Free estimation would risk omitted variable bias—while we control for the primary determinants of vessel location choice, data do not exist for some important IEZ-specific characteristics. For example, IEZs likely contain higher biomass than offshore alternatives, which would make $\hat{\beta}_1$ less negative than the true disutility.

We simulate counterfactual scenarios where each country's IEZ is dissolved individually. In each counterfactual, we set the IEZ indicator to zero for that country's IEZ (retaining the IEZ as an alternative in the choice set), allowing vessels to reoptimize their location choices without the disutility associated with that country's IEZ. We calculate the predicted increase in vessel location shares within the dissolved IEZ area. Specifically, for each of the five countries, we compute the percentage change in vessel shares: $\frac{\text{SQ share} - \text{CF share}}{\text{CF share}}$, where SQ denotes the status quo (with all IEZs in place) and CF denotes the counterfactual (with the country's IEZ dissolved). We then choose β_1 to minimize the squared difference between the average predicted reduction across all five countries and our bunching estimate:

$$\hat{\beta}_1 = \arg\min_{\beta_1} \left(\overline{\Delta^{\text{sim}}}(\beta_1) - \Delta^{\text{bunching}} \right)^2 \tag{6}$$

where $\overline{\Delta^{\text{sim}}}(\beta_1) = \frac{1}{5}\sum_{k=1}^{5} \Delta_k^{\text{sim}}(\beta_1)$ is the average model-predicted reduction across the five countries given β_1 and $\Delta^{\text{bunching}} = 0.458$ is the average reduction from our bunching analysis.

[8] Let O_j denote the total number of satellite overpasses summed across all grid cells within alternative j. The non-normalized weight is $w_j = \frac{\sum_{j=1}^{J} O_j}{O_j}$. This gives higher weight to less sampled alternatives. We then normalize these weights to have mean one: $\tilde{w}_j = \frac{w_j}{\bar{w}}$, where $\bar{w} = \frac{1}{J}\sum_{j=1}^{J} w_j$.

Table 4: EEZ-Level Industrial Fishing Vessel Location Shares: Effect of Each Country's IEZ

	Observed (1)	Status Quo (2)	Counterfactual (3)	Percent Difference (4)
Mauritania	0.1329	0.1321	0.1585	-16.6212%
		(0.00129)	(0.00163)	(0.12220%)
Ghana	0.1286	0.1130	0.1342	-15.8407%
		(0.00109)	(0.00129)	(0.05007%)
Nigeria	0.4379	0.4391	0.4780	-8.1431%
		(0.00235)	(0.00240)	(0.08464%)
Liberia	0.0256	0.0397	0.0474	-16.1965%
		(0.00095)	(0.00109)	(0.19923%)
Sierra Leone	0.0702	0.0648	0.0812	-20.1425%
		(0.00077)	(0.00098)	(0.13375%)

Notes: Standard errors (in parentheses) are heteroskedasticity-robust and calculated using a parametric bootstrap, where we draw 1,000 times from the estimated distribution of model parameters and recalculate predicted shares.

Our calibration approach is in the spirit of indirect inference methods like those of Almagro et al. (2024), where a structural parameter is chosen to match a reduced form estimate. Figure B14 illustrates our calibration: at $\beta_1 = -0.46$, the model predicts an average reduction in vessel shares of 0.457, closely matching our target of a 0.458 reduction.

Table 4 reports industrial fishing vessel location shares by country for the observed data, model-predicted status quo, and counterfactuals in which each country's IEZ is dissolved. Across all five countries, IEZs reduce the predicted share of industrial fishing vessels at the EEZ level by 8% (Nigeria) to 20% (Sierra Leone), as vessels relocate to other countries' EEZs. Model-predicted status quo shares correspond well to observed data, both at the EEZ level (Table 4) and when aggregated by alternative type across countries (Table B5).

Table B6 displays our coefficient estimates. When we estimate β_1 freely (Column 1), we obtain a coefficient of about -0.4, compared to our calibrated value of -0.46 (Column 2). This difference is consistent with our expectation that omitted IEZ-specific characteristics could bias the freely estimated coefficient toward zero.

7 Bioeconomic Impacts

What do reductions in EEZ-level industrial fishing vessel presence mean for fish stocks and artisanal fisher catches? Here we present a back-of-the-envelope calculation that translates our Table 4 estimates into these outcomes. We parameterize a bioeconomic model using data on artisanal and industrial fishing, fish growth rates, and biomass estimates. With this model, we compare steady-state equilibria with and without IEZs. Our approach aggregates each country's fish stocks to a single stock. We take vessel presence as our measure of fishing effort (intensity of fishing activity) for the industrial sector, and model industrial catch as linear in vessel presence. Appendix C provides details.

Table 5 displays our numeric estimates of how IEZs affect fish biomass and catches; Figure C1 illustrates these results. IEZs increase steady-state fish biomass in all five countries, with percentage increases ranging from 3.6% in Nigeria to 52.8% in Liberia. These differences reflect variation in the reductions in industrial fishing vessel presence and the biological characteristics of each country's fish stocks. In three of five countries, industrial catches slightly increase despite reduced vessel presence; when stocks are depleted, reducing fishing can increase catch.

Summing over countries, IEZs increase fish biomass by approximately 2.7 million tons and annual artisanal fisher catch by 324 thousand tons. Using Basurto et al. (2025)'s estimates of the nutritional content of artisanal fisher catches, this additional catch provides sufficient calcium, iron, selenium, zinc, vitamin A, and omega-3 to meet the complete requirements of approximately 6.3 million people.

The small standard errors reported in Table 5 account only for uncertainty in the estimated changes in industrial fishing vessel presence, not uncertainty in biological parameters, most of which lack associated uncertainty metrics. As such, these standard errors understate the total uncertainty in our estimates.

7.1 Robustness Checks

Our baseline calculations hold artisanal fishing effort fixed at observed levels in the counterfactual scenario. This assumption is necessary because comprehensive artisanal fishing data

Table 5: Observed Levels and Estimated Changes in Biomass and Fish Catch from IEZs

	Biomass		Artisanal Catch		Industrial Catch	
	Observed (1)	Difference (2)	Observed (3)	Difference (4)	Observed (5)	Difference (6)
Mauritania	8,457.7	1,388.1	934.7	153.4	1,092.0	-2.7
		(11.37)		(1.26)		(0.16)
Ghana	1,601.2	460.8	245.4	70.6	199.9	30.7
		(1.50)		(0.23)		(0.12)
Nigeria	3,377.6	116.5	484.1	16.7	88.9	-4.5
		(1.30)		(0.19)		(0.05)
Liberia	1,071.2	370.1	25.9	8.9	126.6	27.7
		(4.54)		(0.11)		(0.41)
Sierra Leone	1,590.9	399.4	296.4	74.4	127.9	7.9
		(2.94)		(0.55)		(0.10)
Total	16,098.6	2,734.9	1,986.4	324.1	1,635.3	59.1
		(12.74)		(1.41)		(0.46)

Notes: All values are in thousands of tons. "Observed" columns represent the status quo with the country's IEZ, and "Difference" columns show status quo minus counterfactual (no-IEZ) values. The "Total" row is the sum of values from the five individual country rows. Delta method standard errors (parentheses) account only for uncertainty in estimated changes in industrial fishing vessel presence.

do not exist at the spatial resolution required to estimate how IEZs affect artisanal effort. However, in reality, the reduction in industrial competition from IEZs may induce higher artisanal fishing effort, suggesting that artisanal effort could be lower in the absence of a country's IEZ. We therefore calculate how much artisanal effort would need to decrease in the counterfactual to fully offset the biomass gains from each country's IEZ. Since we estimate industrial effort increases in the counterfactual (due to the absence of the IEZ), artisanal effort must decrease sufficiently to keep total fishing effort—and thus biomass levels—identical across scenarios. We calculate that artisanal effort would need to decrease by 23.3% in Mauritania, 15.3% in Ghana, 1.6% in Nigeria, 94.6% in Liberia, and 10.9% in Sierra Leone to eliminate the biomass gain from each country's IEZ. Even in this scenario where biomass gains are eliminated, there would still be distributional changes in catch allocation across sectors. The share of total catch going to artisanal fishers would be higher in the status quo than in these counterfactual scenarios by 10.7 percentage points (pp) in Mauritania, 8.5 pp in Ghana, 1.4 pp in Nigeria, 16.0 pp in Liberia, and 7.6 pp in Sierra Leone.

Our baseline model also assumes fish stocks are confined within each country's EEZ, ignoring potential cross-country biological spillovers. This assumption could overstate the gains from each country's IEZ because when a country's fish stock decreases (as in its no-IEZ counterfactual), it may be partially replenished through immigration from neighboring areas. To test the sensitivity of our results to this assumption, we incorporate cross-country biological spillovers using two different sets of parameter values (Appendix C.1 and Table C1). First, we calibrate spillover parameters based on larval exchange estimates from Ramesh et al. (2019), representing modest spillovers. Second, we employ parameters calibrated from Lynham and Villaseñor-Derbez (2024)'s findings on highly migratory tuna near marine protected areas, providing an upper bound for adult fish spillovers. As shown in Table C2, accounting for biological spillovers reduces our estimates, but the effects remain large. Summing biomass gains over the five countries, we find a 19.3% gain in the first parameterization and a 14.3% gain in the second, compared to a 20.5% increase in our baseline model without spillovers. Similarly, artisanal fisher catch increases by 18.3% and 13.4% in the two spillover scenarios, versus 19.5% in the baseline. The relative stability of these results highlights an advantage of analyzing policies at the large spatial scale of an EEZ: potential biological spillovers are less acute.

8 Conclusion

This paper evaluates the extent to which protective regulations in African coastal fisheries achieve deterrence and deliver benefits. Using radar data that can detect all industrial fishing vessels, we provide the first causal estimates of the effects of African Inshore Exclusion Zones. Our regression discontinuity analysis reveals that 6 of 20 countries successfully deter industrial fishing vessels from their IEZs. Bunching estimates show that 5 of these countries reduce industrial fishing vessel presence inside IEZs by an average of 46%. Embedding these estimates in a discrete choice model, we find that IEZs reduce country-level industrial fishing vessel presence by 8% to 20%. Across the five countries with deterrence and bunching effects, back-of-the-envelope calculations indicate that IEZs increase steady-state fish stocks by 2.7

million tons and raise annual artisanal catch by 324 thousand tons—sufficient to meet the micronutrient requirements of 6.3 million people.

We calculate that the additional artisanal catch generated by IEZs in 2019—the midpoint of our study period—was worth approximately \$227 million across the five countries (Appendix C.2). To gauge whether those gains plausibly outweigh the public resources needed to enforce IEZs, we compare them with fisheries ministry budgets. For Mauritania, Ghana, Liberia, and Sierra Leone—which account for \$201 million of the additional artisanal catch revenue—we were able to find 2019 budgets, which sum to roughly \$25 million. The additional artisanal revenue exceeds these entire ministry budgets by an order of magnitude, despite IEZ enforcement representing just one component of ministries' activities. Moreover, the industrial sector appears to bear minimal costs: despite limited access to productive nearshore waters, industrial catches remain stable or even increase due to larger fish stocks. This simple comparison suggests that in countries successfully enforcing IEZs, the policy would likely pass a benefit-cost test.

One could critique IEZs as preventing structural transformation—why preserve labor-intensive artisanal fishing when a handful of technologically advanced industrial vessels could harvest fish at lower cost? This perspective should be weighed against three considerations. First, the 9 million Africans employed in artisanal fishing face limited alternatives (Basurto et al., 2025). In economies with scarce formal employment, the realistic outside options are often subsistence agriculture or dangerous irregular migration (Hu & Libois, 2023). Second, artisanal and industrial fisheries serve different markets: artisanal catches primarily feed local populations while industrial vessels are more likely to export their catch, making artisanal fisheries more valuable for meeting domestic nutritional needs (Basurto et al., 2025; Gephart et al., 2024). Third, African countries' attempts to develop domestic industrial fishing sectors have tended to yield disappointing results (Standing, 2017). In this context, IEZs represent a feasible policy that—when enforced—benefits fish populations, supports employment, and provides essential micronutrients to millions of people.

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Supplemental Appendix

Deterring Industrial Vessels from African Coastal Fisheries

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Appendix A explains how we construct our IEZ boundaries. Appendix B presents results and robustness checks for our regression discontinuity, bunching, and discrete choice analyses. Appendix C details our back-of-the-envelope calculations of how a country's IEZ affects fish stocks and catches.

A IEZ Boundaries

Our IEZ boundaries data begin from Table 1 of Belhabib et al. (2020). We retain boundaries corresponding to complete prohibitions on all industrial fishing, dropping partial prohibitions on certain kinds of industrial fishing because our radar data do not distinguish among vessels' fishing methods. We validated each country's IEZ boundary against official government documents, other academic articles, and international or non-governmental organization reports, resulting in the following differences in our data compared to Belhabib et al. (2020):

- Equatorial Guinea expanded its IEZ from 4 to 12 nautical miles in November 2017 (República de Guinea Ecuatorial, 2017). We treat Equatorial Guinea as two distinct units in our analysis: one for before November 2017 with an IEZ boundary of 4 nautical miles, and another for after November 2017 with an IEZ boundary of 12 nautical miles.
- Ghana's IEZ boundary is the maximum of: (1) the 30 meter isobath (the line connecting points where the ocean depth is 30 meters) and (2) 6 nautical miles from shore

(Republic of Ghana, 2002). In Figure 1(b) we display the boundary's average distance to shore. We calculate this average distance as 12.2 nautical miles, compared to the 12 nautical miles reported in Belhabib et al. (2020).

- Guinea's Inshore Exclusion Zone is 6 nautical miles (Beye Traore, 2021).
- We exclude from our analysis Mauritius, a small island far east of mainland Africa, and Mayotte, a non-sovereign French overseas department.
- Madagascar's 2 nautical mile IEZ began in July 2021 (Carver, 2021). Though the legislation only specifically prohibits industrial shrimp trawling, "due to the characteristics of traditional fishing and the geography of the country, the 2 nm-trawling ban serves de facto as a small-scale fishing zone" (Philippe, 2023).
- We exclude Senegal from our analysis because its IEZ depends on vessels' fishing methods and other characteristics (République du Sénégal, 2015).
- Sierra Leone's IEZ boundary is defined by 7 pairs of longitude-latitude coordinates (Baio et al., 2017). In Figure 1(b) we display the boundary's average distance to shore. We calculate this average distance as 15.2 nautical miles, compared to the 6 nautical miles reported in Belhabib et al. (2020).

We use Exclusive Economic Zone boundaries data from Flanders Marine Institute (2023).

B Empirical Appendix Figures and Tables

Table B1: Placebo Test Results for Discontinuities at IEZ Boundaries

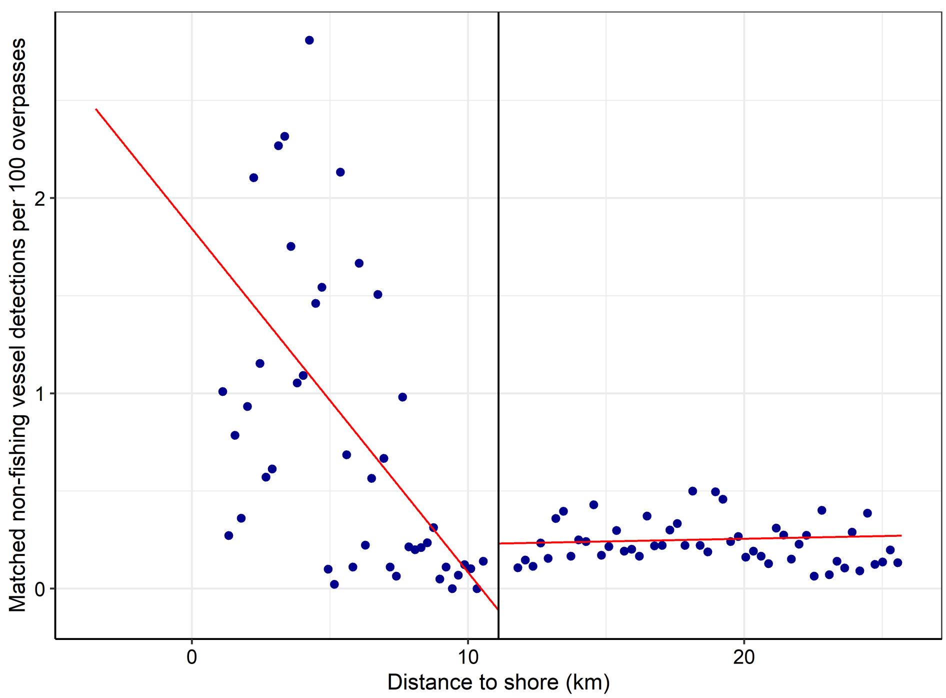
Country-Boundary (1)	Outcome (2)	Coefficient (3)	SE (4)	q-value (5)	Bandwidth (6)	N (7)
Republic of Congo	Nonfishing	0.342	0.105	0.0444	14.59	3,018
Madagascar	Chlorophyll	0.146	0.051	0.0946	5.25	43,283
Angola	SST	-0.226	0.091	0.1801	4.73	10,992
Madagascar	Nonfishing	0.005	0.002	0.2079	5.07	29,820
Benin	Chlorophyll	0.194	0.088	0.2079	7.28	1,332
Eq. Guinea - 4 nm	Depth	-77.105	36.276	0.2079	6.40	5,299
Eq. Guinea - 4 nm	Nonfishing	0.011	0.005	0.2079	9.13	6,685
Gambia	Depth	-1.369	0.665	0.2079	6.80	817
Liberia	Chlorophyll	0.148	0.077	0.2548	5.91	4,845
Guinea-Bissau	Nonfishing	0.003	0.002	0.2877	14.96	9,438
Sierra Leone	Nonfishing	0.040	0.026	0.4692	11.21	6,107
Cape Verde	Depth	-58.928	39.330	0.4692	4.42	7,887
Mauritania	Depth	-1.286	1.022	0.6524	5.71	6,028
Cameroon	Depth	-9.237	7.710	0.6524	1.17	384
Gambia	Nonfishing	0.035	0.029	0.6524	12.33	1,552
Togo	Chlorophyll	0.046	0.040	0.6767	9.79	761
Eq. Guinea - 12 nm	Chlorophyll	0.097	0.088	0.6767	4.67	4,453
Gambia	SST	-0.065	0.068	0.7930	7.29	885
Guinea	Chlorophyll	0.058	0.064	0.8010	8.55	4,920
Angola	Depth	-9.631	11.164	0.8155	5.18	12,185
Mauritania	Nonfishing	0.021	0.027	0.8166	9.99	11,209
Guinea-Bissau	Chlorophyll	0.072	0.098	0.8166	7.25	3,948
Sierra Leone	Depth	-1.529	2.096	0.8166	5.11	2,650
Mozambique	Depth	-4.560	6.430	0.8166	3.63	16,732
Eq. Guinea - 12 nm	Nonfishing	0.006	0.009	0.8166	6.32	6,275
Mauritania	SST	-0.035	0.058	0.8739	5.95	6,312
Cameroon	SST	-0.093	0.221	0.9112	0.95	249
Nigeria	Chlorophyll	0.069	0.163	0.9112	5.00	5,687
Mozambique	SST	-0.022	0.054	0.9112	3.38	15,327
Republic of Congo	Chlorophyll	0.047	0.134	0.9112	9.74	2,388
Guinea	SST	-0.012	0.035	0.9112	5.76	3,167
Liberia	Nonfishing	0.002	0.007	0.9112	10.76	8,975
Guinea	Depth	-0.222	0.721	0.9112	5.93	3,263
Mozambique	Nonfishing	0.006	0.019	0.9112	4.50	20,400
Republic of Congo	Depth	-0.328	1.158	0.9112	7.15	1,715
Ghana	Chlorophyll	0.013	0.048	0.9112	7.33	6,152

Guinea-Bissau	SST	-0.007	0.047	0.9806	6.46	3,477
Eq. Guinea - 12 nm	SST	-0.008	0.053	0.9806	7.66	7,713
Somalia	Chlorophyll	0.000	0.007	1.0000	5.90	26,224
Somalia	Depth	-0.524	14.743	1.0000	8.84	40,666
Eq. Guinea - 4 nm	Chlorophyll	-0.007	0.126	1.0000	9.67	7,608
Mauritania	Chlorophyll	-0.009	0.159	1.0000	6.71	7,208
Sierra Leone	Chlorophyll	-0.012	0.086	1.0000	7.78	4,212
Liberia	Depth	0.246	1.139	1.0000	8.09	6,836
Eq. Guinea - 12 nm	Depth	24.178	94.967	1.0000	5.09	4,912
Cape Verde	Chlorophyll	-0.003	0.008	1.0000	7.71	13,258
Somalia	SST	0.005	0.014	1.0000	9.99	46,320
Nigeria	SST	0.005	0.016	1.0000	3.80	4,143
Eq. Guinea - 4 nm	SST	0.018	0.051	1.0000	9.17	7,545
Benin	SST	0.012	0.029	1.0000	6.62	1,200
Madagascar	SST	0.026	0.052	1.0000	2.96	24,009
Sierra Leone	SST	0.007	0.014	1.0000	8.87	4,853
Liberia	SST	0.005	0.009	1.0000	5.44	4,419
Cameroon	Chlorophyll	-1.225	2.113	1.0000	1.43	555
Guinea	Nonfishing	-0.145	0.248	1.0000	9.90	5,856
Guinea-Bissau	Depth	0.251	0.429	1.0000	7.94	4,363
Nigeria	Nonfishing	-0.140	0.179	1.0000	9.77	10,973
Ghana	Nonfishing	-0.089	0.109	1.0000	9.77	8,337
Angola	Chlorophyll	-0.123	0.139	1.0000	7.17	19,312
Ghana	Depth	2.416	2.485	1.0000	6.81	5,682
Madagascar	Depth	3.746	3.669	1.0000	2.57	20,019
Republic of Congo	SST	0.021	0.020	1.0000	11.12	2,916
Cameroon	Nonfishing	-1.225	1.112	1.0000	2.37	1,154
Somalia	Nonfishing	-0.001	0.001	1.0000	6.18	27,649
Cape Verde	Nonfishing	-0.015	0.013	1.0000	8.80	7,564
Mozambique	Chlorophyll	-0.072	0.063	1.0000	3.74	17,434
Gabon	Nonfishing	-0.087	0.069	1.0000	10.79	9,355
Ghana	SST	0.022	0.016	1.0000	7.23	6,066
Ivory Coast	Chlorophyll	-0.193	0.135	1.0000	4.55	3,351
Togo	SST	0.009	0.007	1.0000	10.50	822
Gabon	SST	0.090	0.061	1.0000	5.15	9,150
Nigeria	Depth	0.915	0.577	1.0000	5.31	6,089
Gambia	Chlorophyll	-0.156	0.083	1.0000	6.08	723
Ivory Coast	Nonfishing	-0.474	0.227	1.0000	9.77	5,495
Gabon	Depth	4.665	2.220	1.0000	5.17	10,582
Angola	Nonfishing	-0.108	0.051	1.0000	10.61	20,726
Cape Verde	SST	0.042	0.019	1.0000	6.34	11,664
Gabon	Chlorophyll	-0.370	0.148	1.0000	7.04	8,920
Togo	Depth	7.453	2.876	1.0000	5.13	377
Togo	Nonfishing	-3.350	1.232	1.0000	13.56	1,077
Benin	Nonfishing	-0.637	0.211	1.0000	15.04	2,179

Benin	Depth	5.663	1.777	1.0000	7.51	1,374
Ivory Coast	SST	0.112	0.023	1.0000	5.37	4,943
Ivory Coast	Depth	12.771	1.435	1.0000	6.74	6,510

Notes: Each row presents a separate regression result. Column 1 indicates the data used and Column 2 specifies the placebo outcome variable. SST is Sea Surface Temperature and Nonfishing is non-fishing vessel presence. Columns 3 to 5 report the point estimate, standard error (SE), and q-value for the IEZ boundary discontinuity indicator. Some q-values are identical across different regressions due to the Benjamini-Hochberg procedure's monotonicity constraint. Column 6 is the optimal bandwidth in km and Column 7 is the number of observations that fall within that bandwidth.

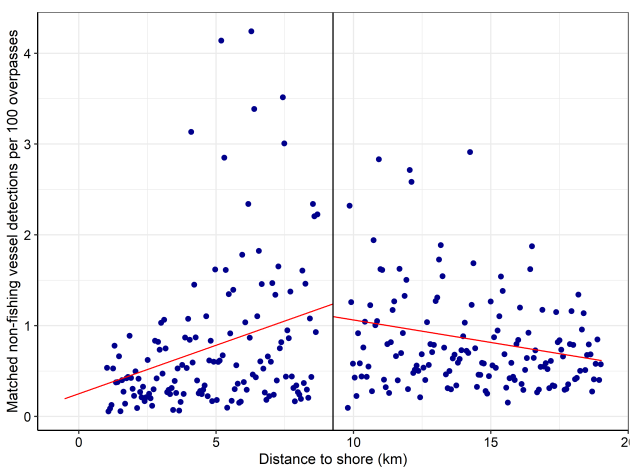
Figure B1: Non-Fishing Vessel Presence Near the Republic of the Congo's IEZ Boundary



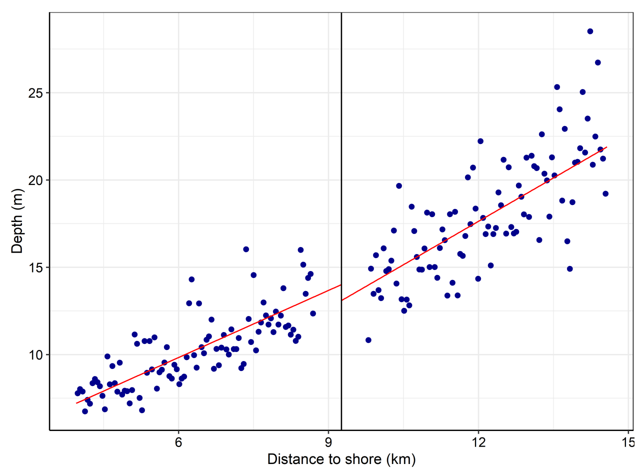
Notes: The dependent variable is non-fishing vessel presence: the number of matched non-fishing vessels detected per 100 Sentinel-1 overpasses. The q-value is 0.044.

Figure B2: Nigeria Placebo Tests

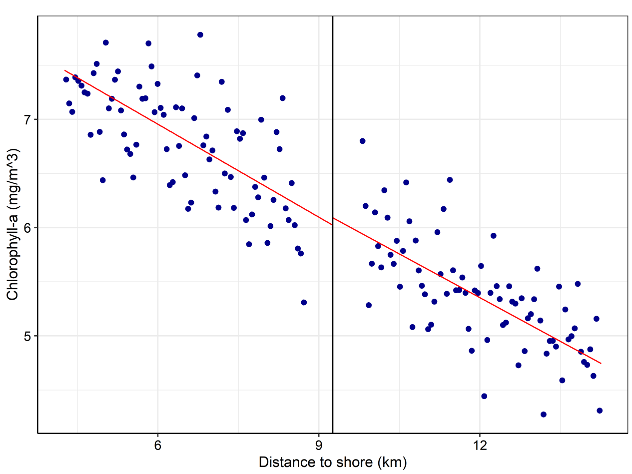
(a) Non-Fishing Vessel Presence



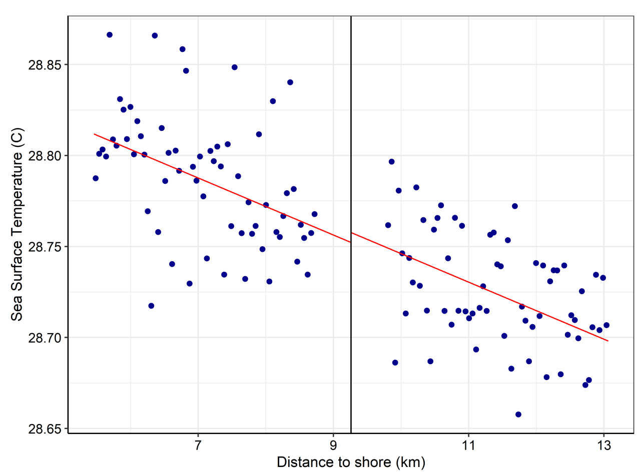
(b) Oceanic Depth



(c) Chlorophyll



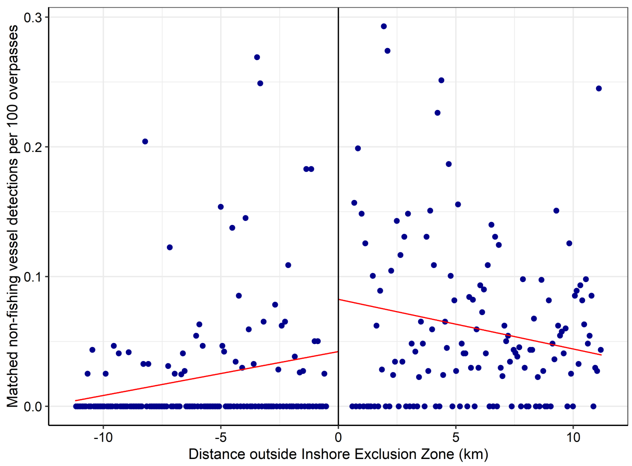
(d) Sea Surface Temperature



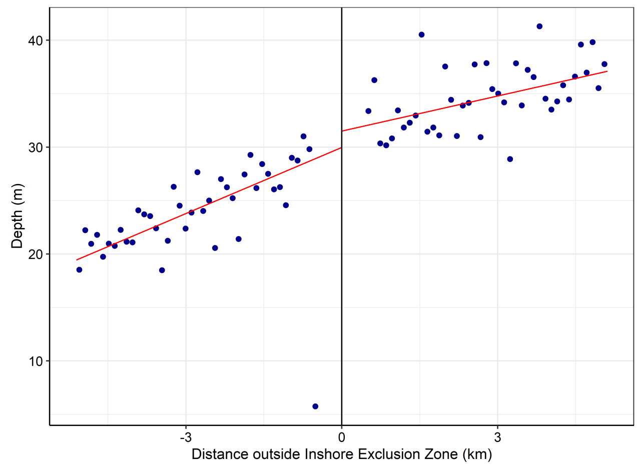
Notes: Each subfigure illustrates the estimated discontinuity at Nigeria's IEZ boundary using a different placebo outcome. Table B1 reports the corresponding coefficients, standard errors, q-values, optimal bandwidths, and number of observations within those optimal bandwidths.

Figure B3: Sierra Leone Placebo Tests

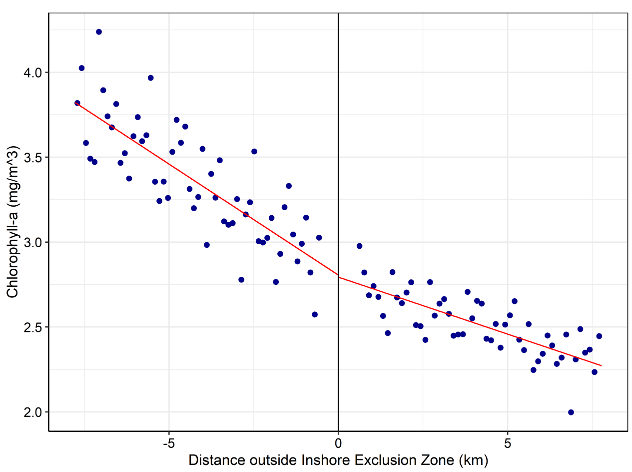
(a) Non-Fishing Vessel Presence



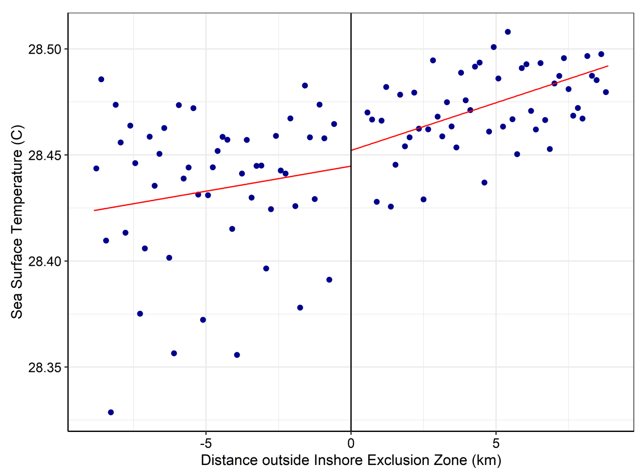
(b) Oceanic Depth



(c) Chlorophyll



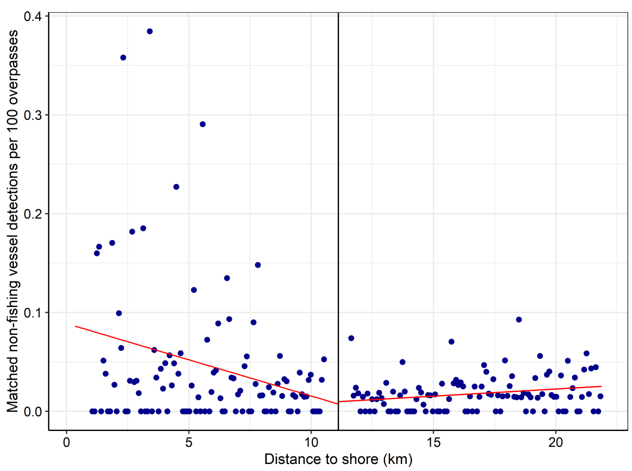
(d) Sea Surface Temperature



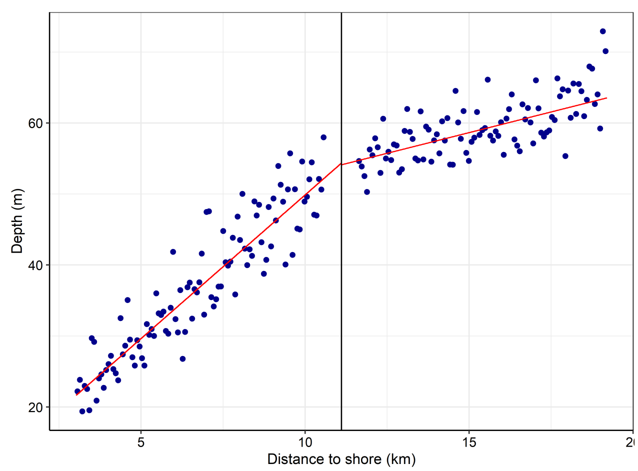
Notes: Each subfigure illustrates the estimated discontinuity at Sierra Leone's IEZ boundary using a different placebo outcome. Table B1 reports the corresponding coefficients, standard errors, q-values, optimal bandwidths, and number of observations within those optimal bandwidths.

Figure B4: Liberia Placebo Tests

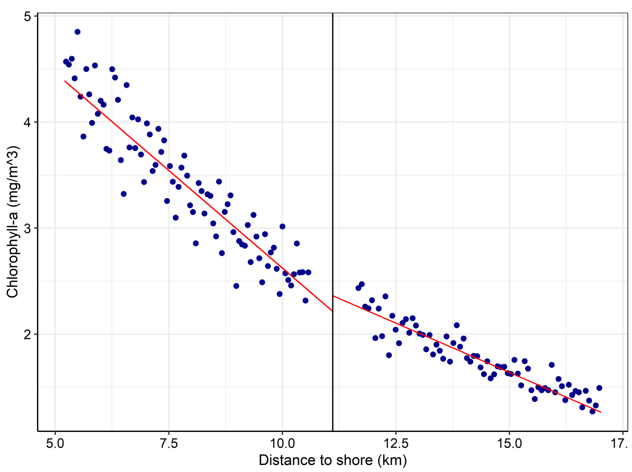
(a) Non-Fishing Vessel Presence



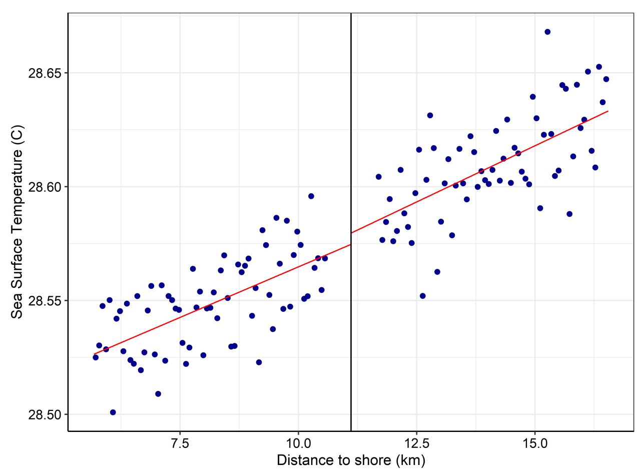
(b) Oceanic Depth



(c) Chlorophyll



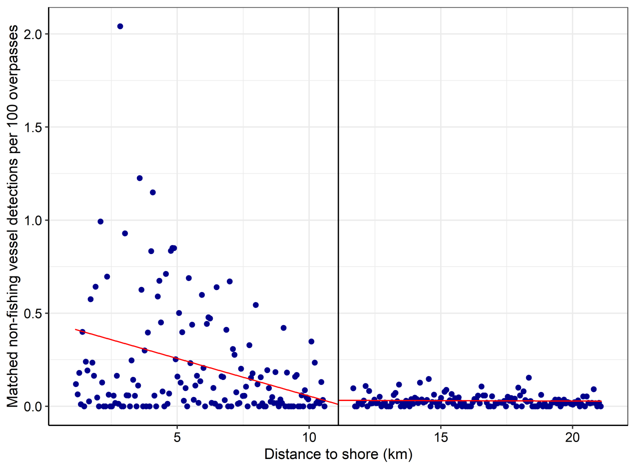
(d) Sea Surface Temperature



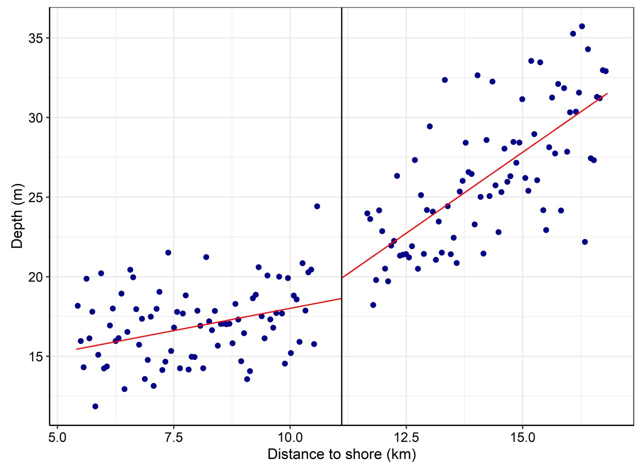
Notes: Each subfigure illustrates the estimated discontinuity at Liberia's IEZ boundary using a different placebo outcome. Table B1 reports the corresponding coefficients, standard errors, q-values, optimal bandwidths, and number of observations within those optimal bandwidths.

Figure B5: Mauritania Placebo Tests

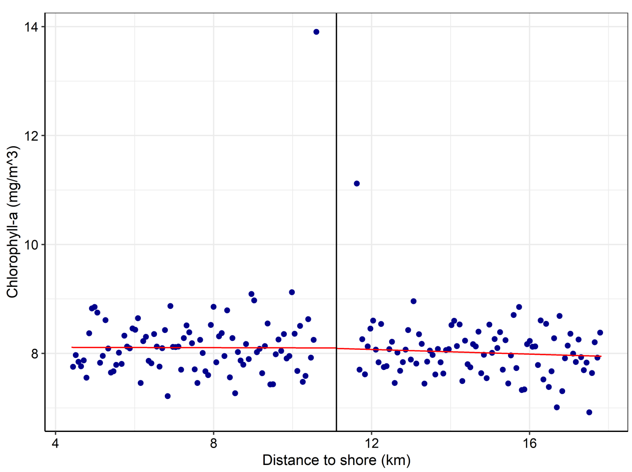
(a) Non-Fishing Vessel Presence



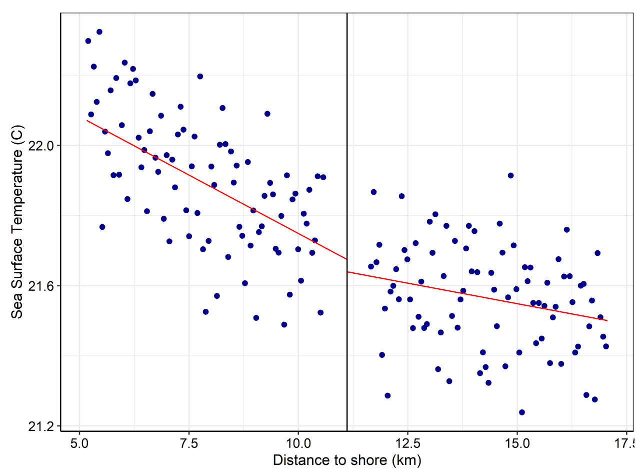
(b) Oceanic Depth



(c) Chlorophyll



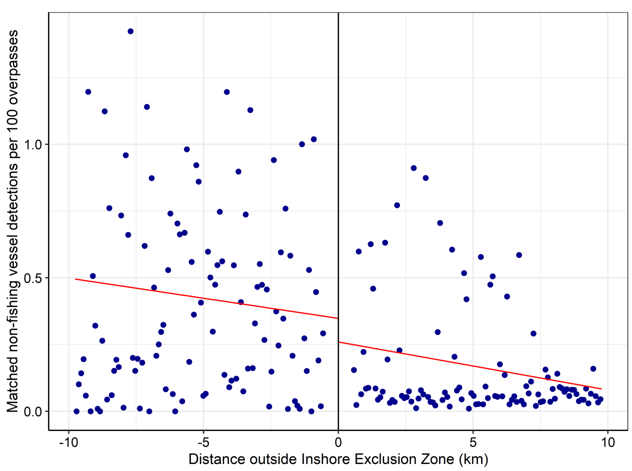
(d) Sea Surface Temperature



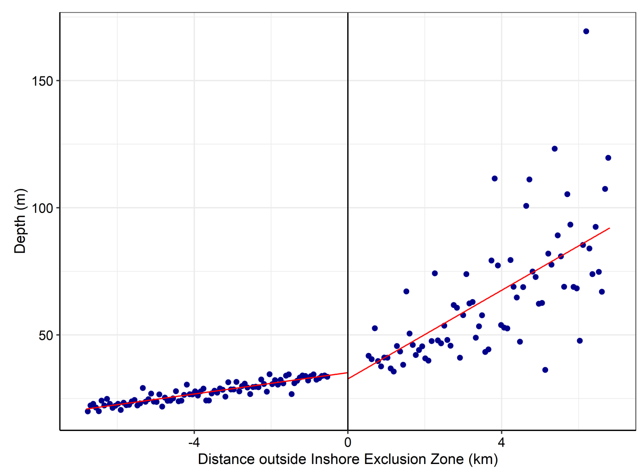
Notes: Each subfigure illustrates the estimated discontinuity at Mauritania's IEZ boundary using a different placebo outcome. Table B1 reports the corresponding coefficients, standard errors, q-values, optimal bandwidths, and number of observations within those optimal bandwidths.

Figure B6: Ghana Placebo Tests

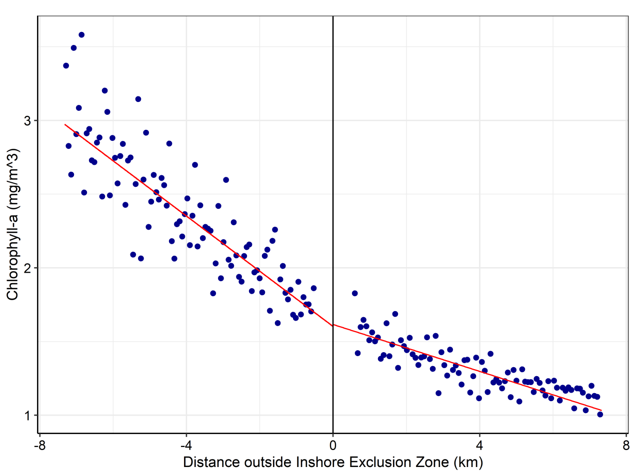
(a) Non-Fishing Vessel Presence



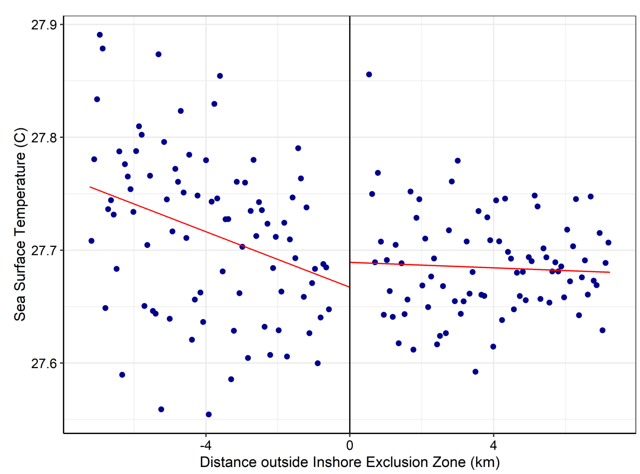
(b) Oceanic Depth



(c) Chlorophyll



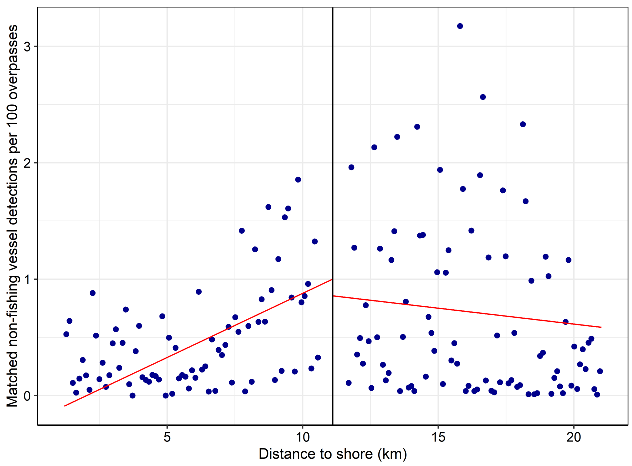
(d) Sea Surface Temperature



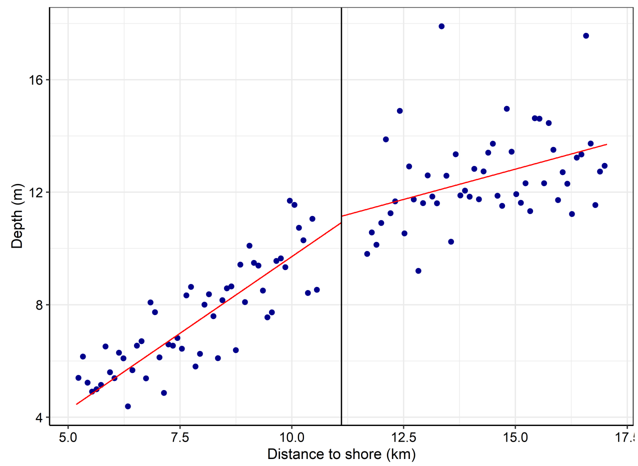
Notes: Each subfigure illustrates the estimated discontinuity at Ghana's IEZ boundary using a different placebo outcome. Table B1 reports the corresponding coefficients, standard errors, q-values, optimal bandwidths, and number of observations within those optimal bandwidths.

Figure B7: Guinea Placebo Tests

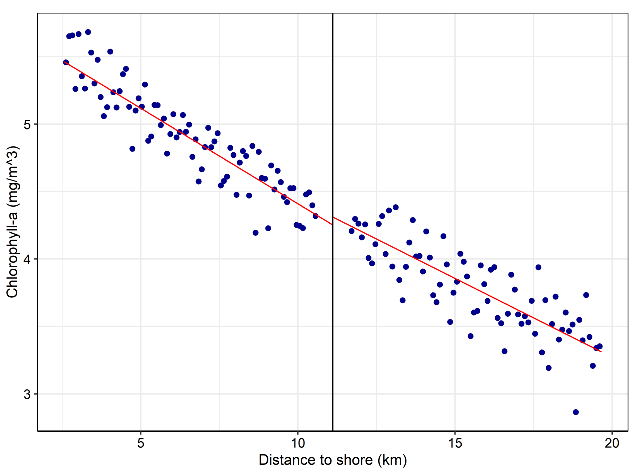
(a) Non-Fishing Vessel Presence



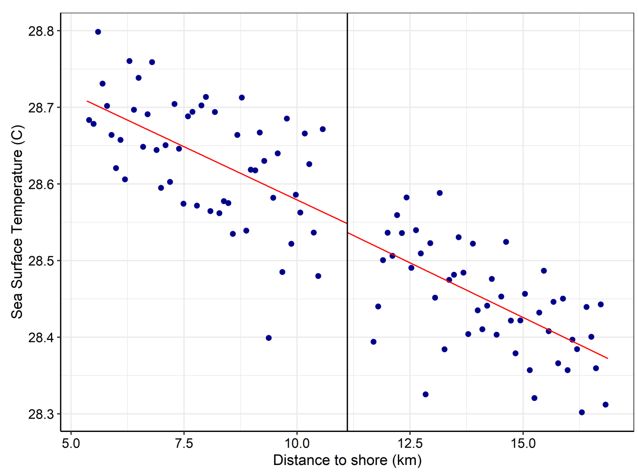
(b) Oceanic Depth



(c) Chlorophyll



(d) Sea Surface Temperature



Notes: Each subfigure illustrates the estimated discontinuity at Guinea's IEZ boundary using a different placebo outcome. Table B1 reports the corresponding coefficients, standard errors, q-values, optimal bandwidths, and number of observations within those optimal bandwidths.

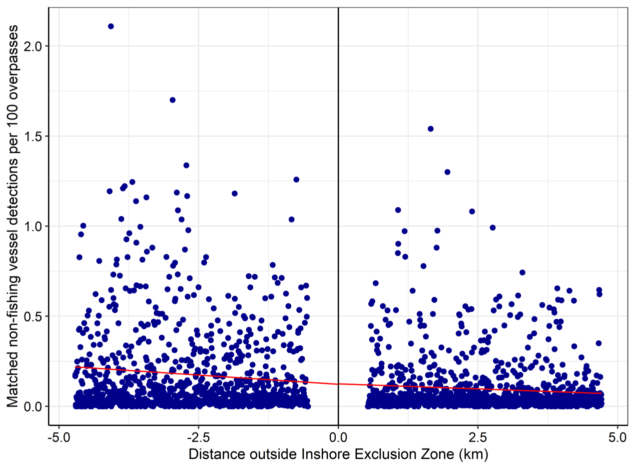
Table B2: RD Estimates Pooled Across All Country–IEZ Boundaries

Outcome Variable (1)	Coefficient (2)	Std. Error (3)	p-value (4)	Bandwidth (5)	N (6)
A. Placebo Outcomes					
Nonfishing	0.0023	(0.0225)	0.4595	4.7133	133,494
Depth	0.7446	(17.5041)	0.5170	2.2466	61,671
Chlorophyll	-0.1514	(0.0961)	0.9424	1.9639	51,311
Sea Surface Temperature	-0.0350	(0.0606)	0.2822	2.0053	52,824
B. Fishing Outcomes					
Normalized SAR	0.0323	(0.0065)	0.0000	4.2234	119,804
AIS Fishing Hours	3.4513	(0.2622)	0.0000	9.5510	255,939

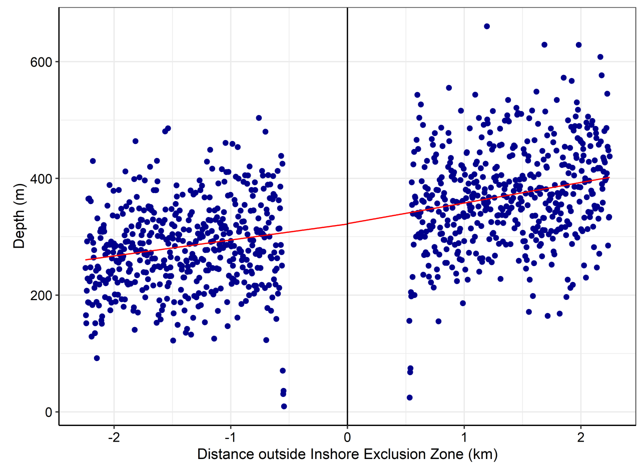
Notes: Each row reports a separate RD estimate obtained by pooling every 0.01° grid cell from the 21 country–boundary cross-sections and estimating Equation 1 with the outcome shown in Column 1. The running variable is the distance in km from the cell centroid to the IEZ boundary. "Nonfishing", "Normalized SAR", and "AIS Fishing Hours" indicate non-fishing vessel presence, industrial fishing vessel presence, and AIS apparent fishing hours, respectively. Columns 2 and 3 report the point estimate and standard error. Figure B8 visualizes the Panel A regressions and Figure B10 visualizes the Panel B regressions. Because this pooled exercise is illustrative rather than a formal hypothesis test, we report unadjusted p-values in Column 4. These one-sided p-values use the same directional hypotheses as the non-pooled regressions. Columns 5 and 6 display the optimal bandwidth in km and the number of observations within that bandwidth.

Figure B8: Pooled Placebo Tests

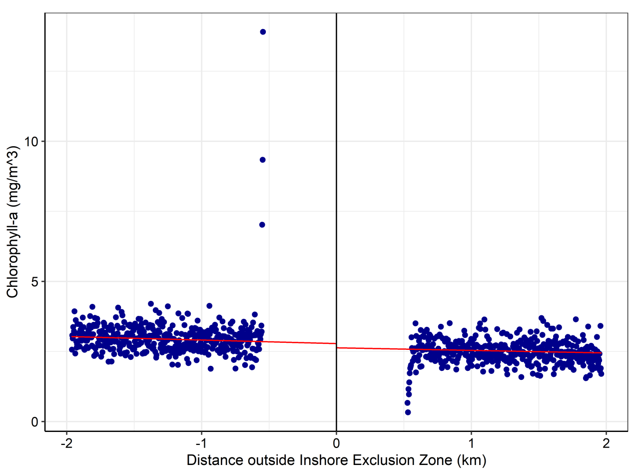
(a) Non-Fishing Vessel Presence



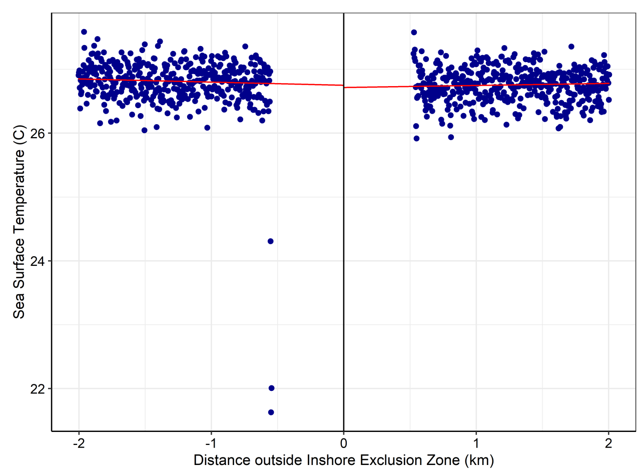
(b) Oceanic Depth



(c) Chlorophyll



(d) Sea Surface Temperature



Notes: Each subfigure illustrates the estimated discontinuity at IEZ boundaries, pooling every 0.01° grid cell across the 21 country–boundary cross-sections. The corresponding coefficients, standard errors, p-values, and number of observations are reported in Panel A of Table B2.

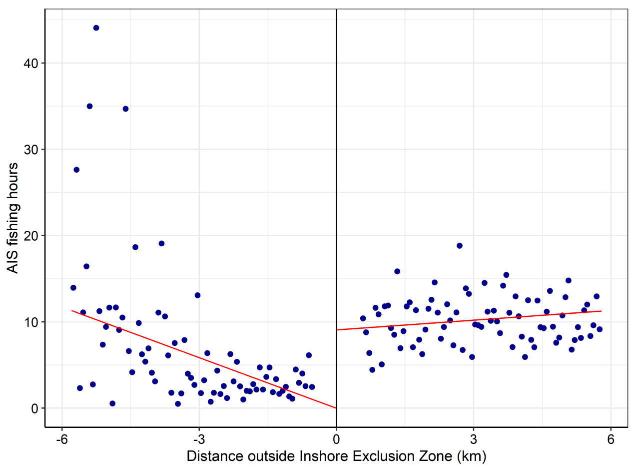
Table B3: Estimated Discontinuities in AIS Apparent Fishing Hours at IEZ Boundaries

Country-Boundary (1)	Coefficient (2)	Std. Error (3)	q-value (4)	Bandwidth (5)	N (6)
Ghana	9.079	(0.881)	0.0000	5.795	4,765
Liberia	6.428	(0.630)	0.0000	5.378	4,365
Nigeria	31.425	(3.362)	0.0000	7.458	8,913
Republic of Congo	1.761	(0.345)	0.0000	6.751	1,604
Sierra Leone	1.184	(0.264)	0.0000	6.901	3,701
Eq. Guinea - 12 nm	0.189	(0.073)	0.0170	5.112	4,939
Mauritania	4.476	(1.859)	0.0241	8.838	9,754
Gabon	1.992	(0.931)	0.0378	6.613	6,831
Madagascar	0.210	(0.098)	0.0378	4.487	29,374
Cameroon	291.809	(146.746)	0.0491	1.196	408
Guinea	2.465	(1.434)	0.0817	12.643	6,688
Ivory Coast	0.738	(0.541)	0.1512	9.505	5,403
Cape Verde	0.015	(0.018)	0.3296	6.705	10,547
Benin	0.021	(0.036)	0.4155	15.266	2,208
Angola	-0.580	(0.497)	1.0000	5.130	12,044
Somalia	-0.014	(0.010)	1.0000	9.116	41,988
Mozambique	-0.623	(0.369)	1.0000	5.548	24,339
Togo	-11.722	(6.394)	1.0000	10.389	813
Gambia	-4.928	(1.625)	1.0000	8.360	1,031
Eq. Guinea - 4 nm	-0.807	(0.220)	1.0000	8.961	6,595
Guinea-Bissau	-2.468	(0.393)	1.0000	7.106	3,872

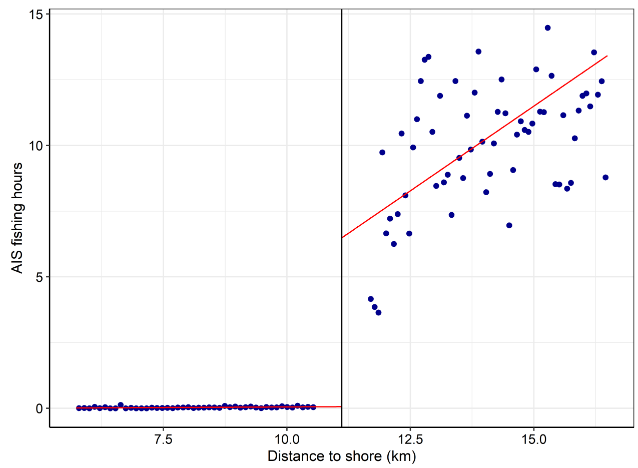
Notes: Each row presents a separate regression result, with Column 1 indicating the data used. Columns 2 to 6 report the point estimate, standard error, q-value, optimal bandwidth in km, and number of observations within that bandwidth.

Figure B9: Discontinuities in AIS Apparent Fishing Hours

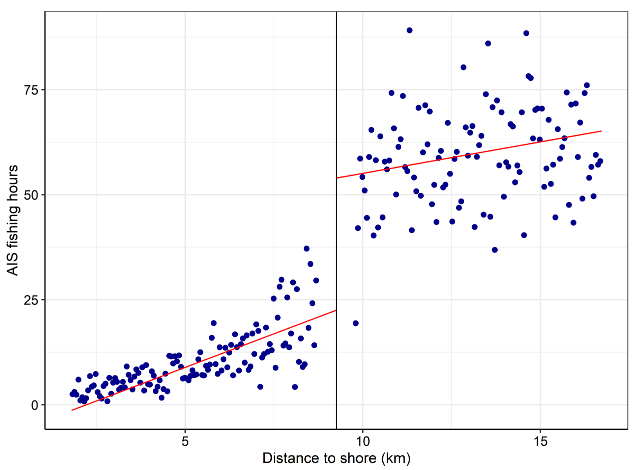
(a) Ghana



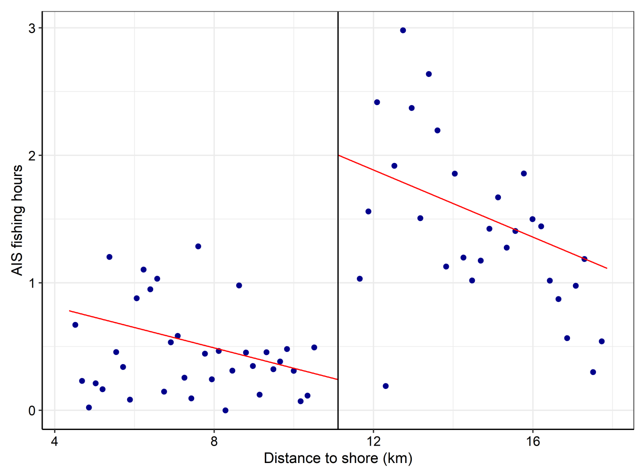
(b) Liberia



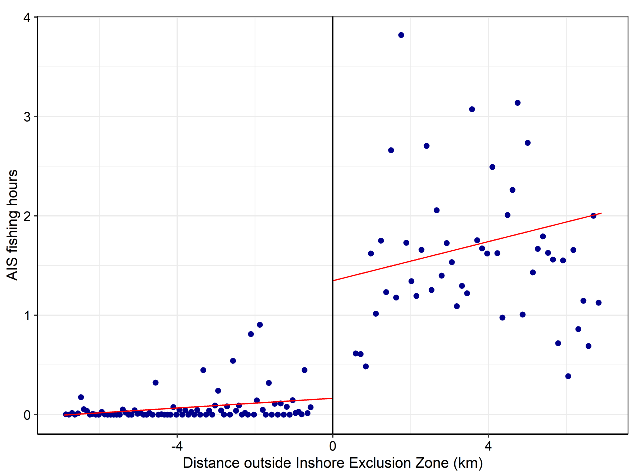
(c) Nigeria



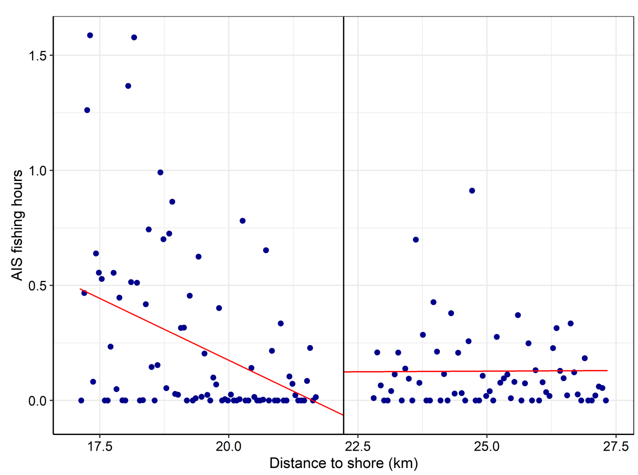
(d) Republic of Congo



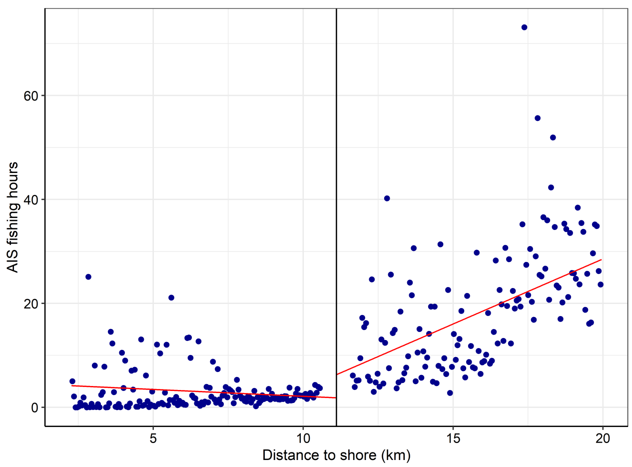
(e) Sierra Leone



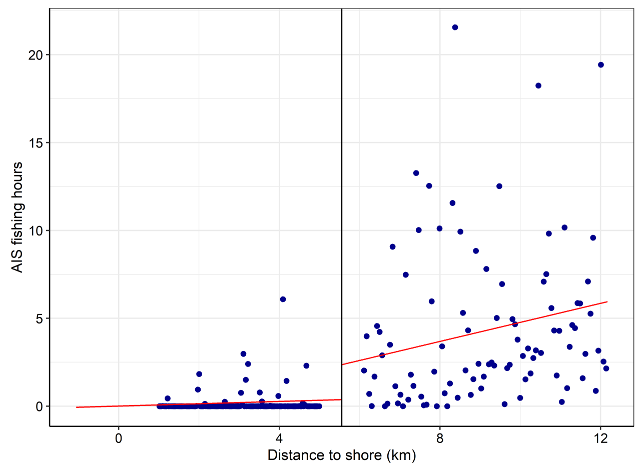
(f) Equatorial Guinea - 12 nm



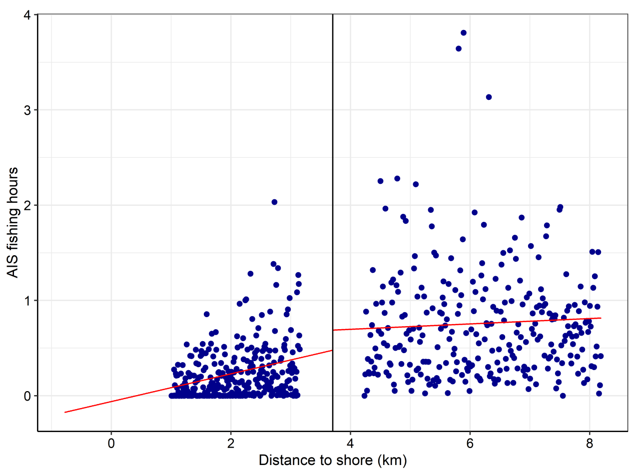
(g) Mauritania



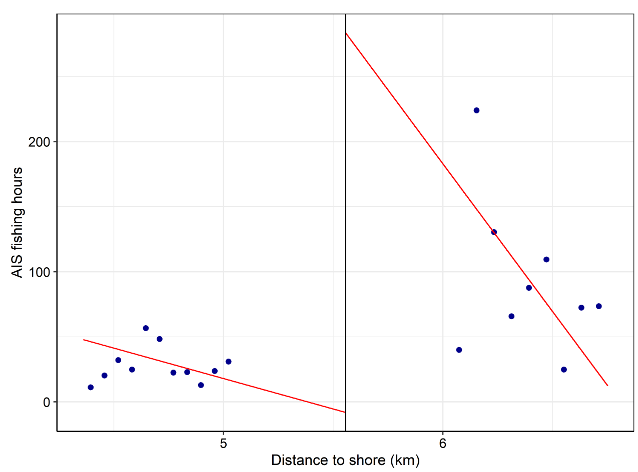
(h) Gabon



(i) Madagascar



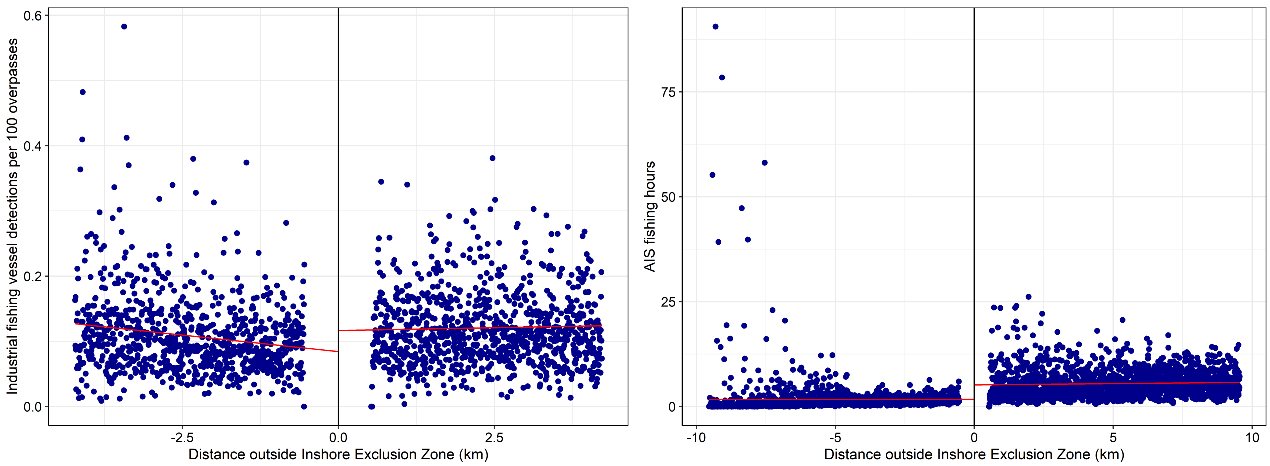
(j) Cameroon



Note: Subfigures reproduce the regressions corresponding to the first 10 rows of Table B3.

Figure B10: Pooled Fishing RD Estimates

(a) Normalized SAR (b) AIS Apparent Fishing Hours



Notes: Each subfigure illustrates the estimated discontinuity at IEZ boundaries, pooling every 0.01° grid cell across the 21 country–boundary cross-sections. The corresponding coefficients, standard errors, p-values, and number of observations are reported in Panel B of Table B2.

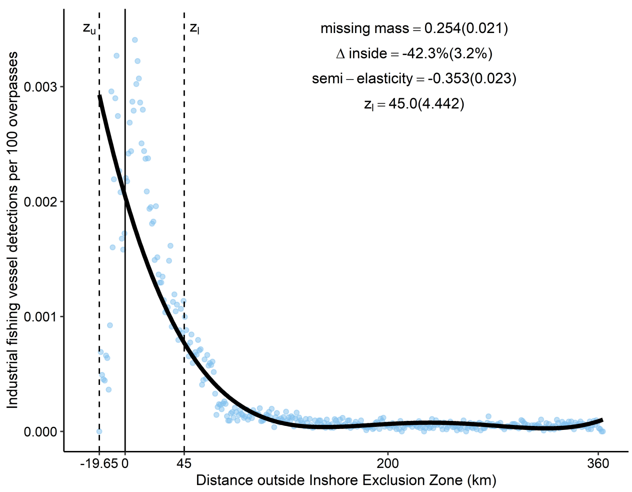
Table B4: Bunching Results with Third-Order Polynomial

Country (1)	Missing Mass (2)	Percent Change (3)	Semi-Elasticity (4)	Outer Width (km) (5)
Mauritania	0.489	-65.1%	-0.501	59.3
	(0.026)	(1.9%)	(0.011)	(1.30)
Ghana	0.190	-35.4%	-0.303	17.4
	(0.021)	(3.2%)	(0.023)	(4.44)
Liberia	0.013	-30.1%	-0.263	4.5
	(0.003)	(5.9%)	(0.041)	(0.71)
Sierra Leone	0.211	-27.4%	-0.242	74.1
	(0.042)	(5.9%)	(0.044)	(1.71)
Nigeria	0.231	-26.8%	-0.237	4.4
	(0.017)	(1.4%)	(0.010)	(0.25)

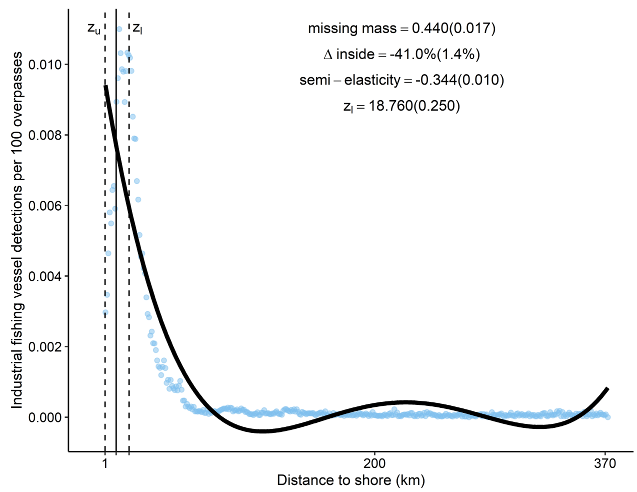
Notes: Bunching estimates for each country using a third-order global polynomial and RD-optimal bin widths. Semi-elasticities in Column 4 equal $-\log(1 - \text{Percent Change})$. Column 5 is the estimated width of the zone of manipulation outside the IEZ ($z_l - z^*$). Standard errors (bootstrapped for Columns 2, 3, and 5; delta method for Column 4) appear in parentheses.

Figure B11: Bunching Countries with Intermediate Percent Reductions Inside IEZs

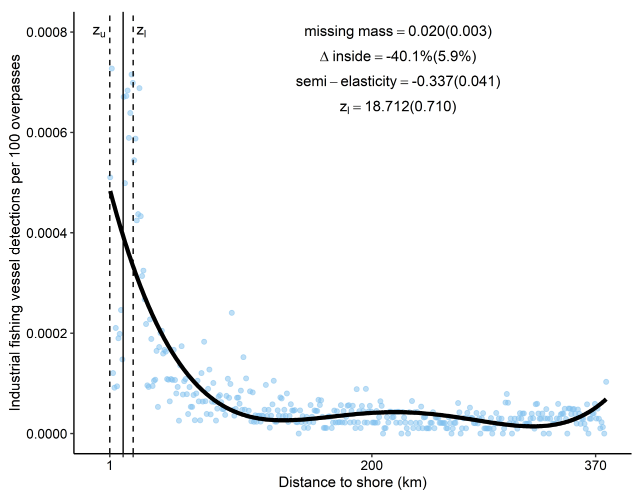
(a) Ghana



(b) Nigeria

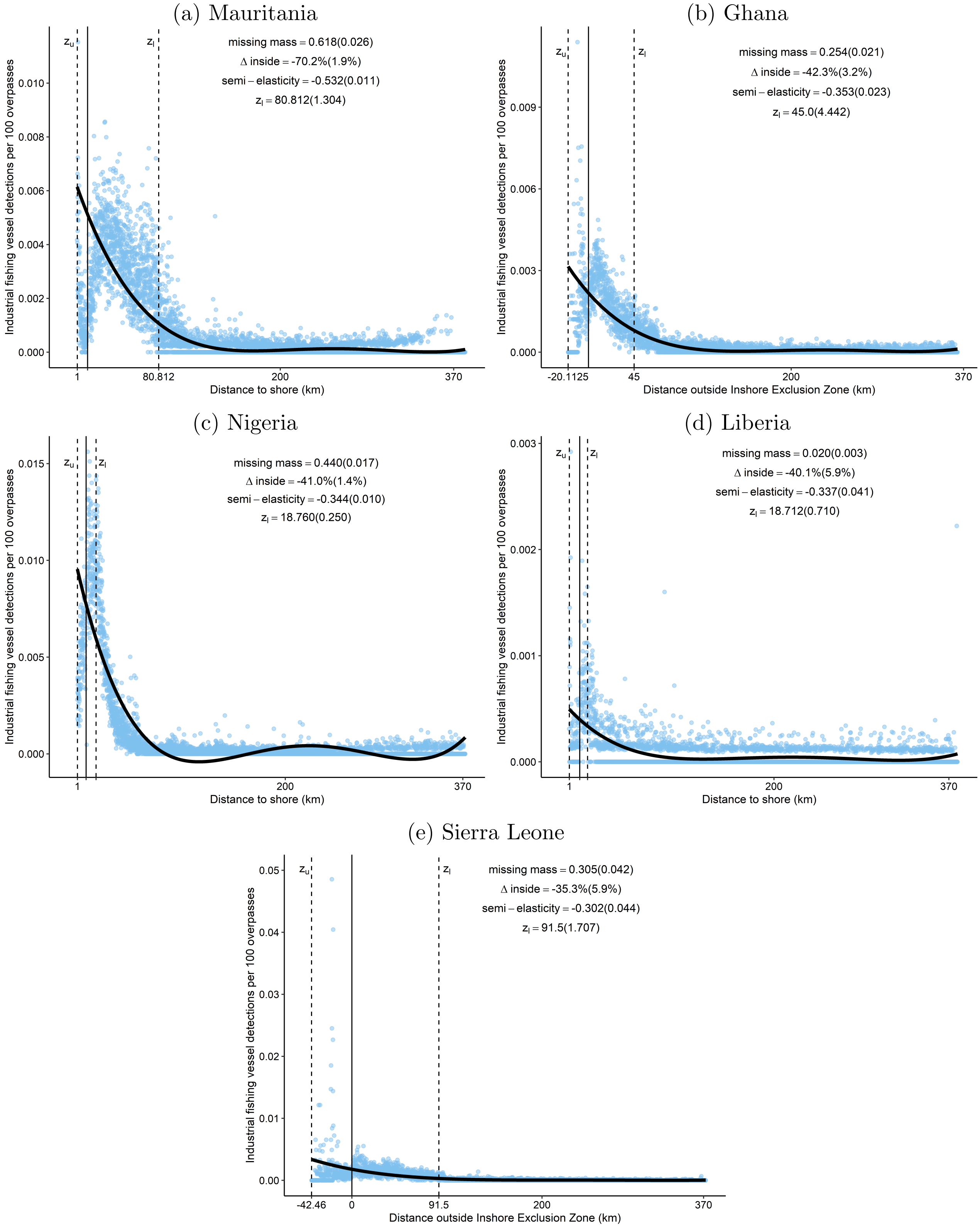


(c) Liberia



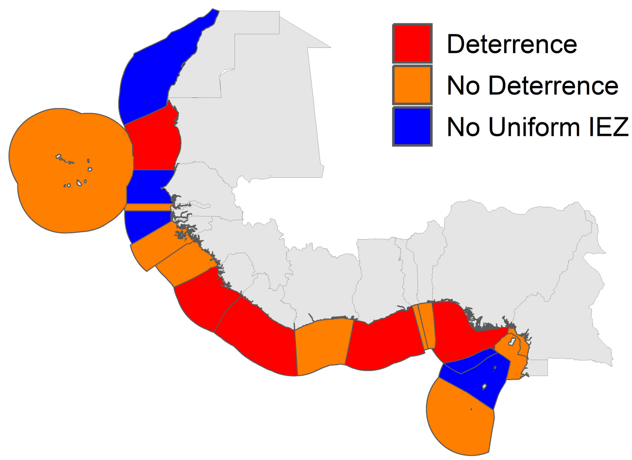
Notes: 1 km wide binned data (blue dots) displayed for easier visualization of fourth-order polynomial fit (black curve) outside the manipulation zone. The two dashed vertical lines mark the manipulation zone boundaries and the solid vertical line indicates the IEZ boundary. Numeric estimates (top, center-right) correspond to the specification with RD-optimal bin widths.

Figure B12: Bunching Results with RD-Optimal Bin Widths



Notes: These figures correspond to the numeric estimates displayed in Table 3. They use a fourth-order global polynomial and RD-optimal bin widths.

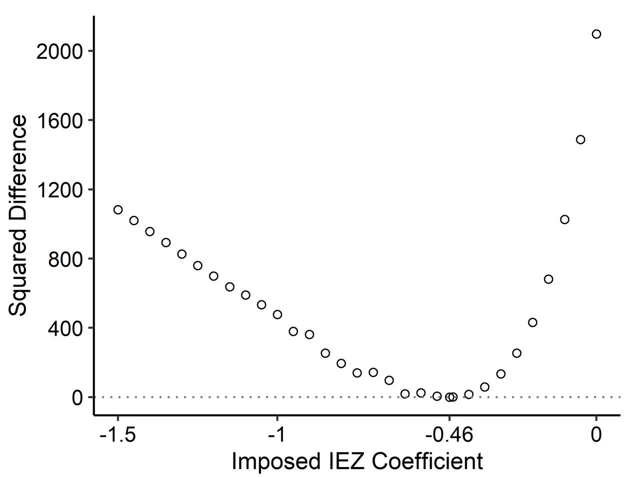
Figure B13: Upper Nest EEZs in the Choice Model



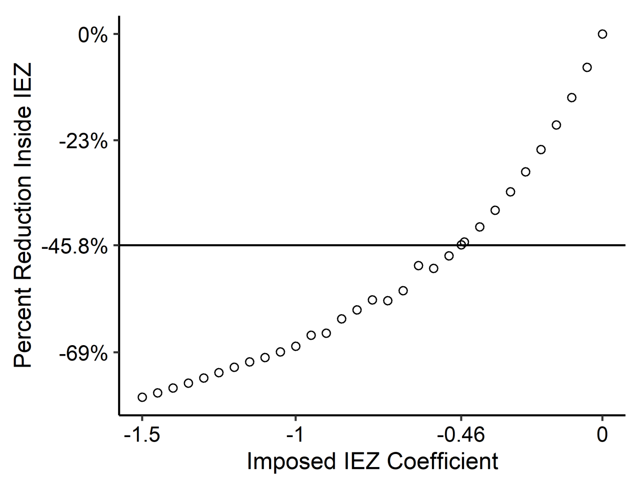
Notes: This figure depicts the EEZs available in the choice set, defined as a one country buffer around the countries with deterrence and bunching effects (red). Orange EEZs belong to countries in our estimation sample that lack deterrence or bunching effects (Cape Verde, Guinea, Gambia, Guinea-Bissau, Ivory Coast, Togo, Benin, Equatorial Guinea, and Cameroon). The southernmost polygon is part of the EEZ of Equatorial Guinea. Blue EEZs belong to Western Sahara, Senegal, and São Tomé and Príncipe, who do not have uniform IEZs (those that prohibit all industrial fishing).

Figure B14: Calibration of the IEZ Disutility Parameter β_1

(a) Minimization of Equation 6



(b) Average Reduction in Vessel Shares



Notes: The (a) squared difference minimized in Equation 6 and (b) model-predicted average reduction in vessel shares inside IEZs. The solid horizontal line in (b) indicates the bunching moment.

Table B5: Observed and Model-Predicted Vessel Location Shares

	Observed (1)	Status Quo (2)
Inside IEZ	0.2496	0.2383
		(0.00166)
Zone of Manipulation	0.5082	0.5084
		(0.00204)
Rest of EEZ	0.0376	0.0419
		(0.00030)
Total EEZ	0.7953	0.7887
		(0.00127)
Rest of Market	0.2047	0.2113
		(0.00127)
N	249,244	249,244
Pseudo R^2	0.2230	

Notes: Row values represent the sum of shares across alternatives as follows: Inside IEZ (five IEZ alternatives), Zone of Manipulation (five outside IEZ manipulation zone alternatives), Rest of EEZ (five remainder of EEZ alternatives), Total EEZ (all alternatives within the five countries' EEZs), and Rest of Market (all other countries' EEZs in the choice set). Standard errors (in parentheses) are heteroskedasticity-robust and calculated using a parametric bootstrap, where we draw 1,000 times from the estimated distribution of model parameters and recalculate predicted shares.

Table B6: Nested Logit Coefficients

	(1)	(2)
1{IEZ}	-0.39856	-0.46
	(0.01179)	
log(biomass)	0.48191	0.46655
	(0.00880)	(0.00680)
log(price)	0.53647	0.42964
	(0.04144)	(0.03080)
log(area)	-0.14905	-0.14831
	(0.00632)	(0.00653)
Fraction pelagic	-1.27296	-1.28564
	(0.05770)	(0.05849)
log(km to port)	0.65413	0.64700
	(0.02321)	(0.02335)
Vessel length $\times$ log(km to port)	0.00066	0.00063
	(0.00023)	(0.00023)
Sea surface temperature, average	-0.23956	-0.23059
	(0.00320)	(0.00281)
Sea surface temperature, sd	-1.05077	-1.03090
	(0.02948)	(0.02982)
Chlorophyll, average	-0.16027	-0.15645
	(0.00807)	(0.00820)
Chlorophyll, sd	0.35697	0.37060
	(0.01338)	(0.01265)
Depth, average	0.00053	0.00053
	(1e-05)	(0.00001)
Depth, sd	3e-05	0.00000
	(2e-05)	(0.00002)
Nest parameters		
Mauritania	0.37700	0.38395
	(0.07650)	(0.07588)
Ghana	1	1
Nigeria	0.55517	0.58828
	(0.10371)	(0.08629)
Liberia	0.52363	0.52242
	(0.10085)	(0.09992)
Sierra Leone	0.70152	0.71153
	(0.10922)	(0.10995)
N	249,244	249,244
Pseudo R^2	0.22303	0.22297

Notes: Column 1 shows freely estimated parameters; Column 2 shows parameters with β_1 calibrated to match our bunching moment. Ghana's nest parameter is fixed to 1 to avoid a singular covariance matrix, while all other nest parameters are freely estimated. Standard errors (in parentheses) are heteroskedasticity-robust.

C Biological Calculations Appendix

Let $E_{i,n}$ denote observed industrial fishing effort, which we measure as industrial fishing vessel presence inside the EEZ of country n. Let $E_{a,n}$ denote observed artisanal fishing effort, which we take from Rousseau et al. (2024) as kilowatts of engine power multiplied by days at sea, summed over artisanal vessels to the EEZ level. Fish biomass inside the EEZ is X_n (tons of fish summed over species). This approach treats each country's fish stocks as a single aggregated stock.

The change in biomass over time equals the Pella-Tomlinson growth function minus industrial catch minus artisanal catch:

$$\frac{dX_n}{dt} = \frac{\phi + 1}{\phi} g_n X_n \left[1 - \left(\frac{X_n}{\kappa_n} \right)^{\phi} \right] - \lambda_{i,n} E_{i,n} X_n - \lambda_{a,n} E_{a,n} X_n,$$

where g_n is the intrinsic growth rate, κ_n is the carrying capacity, $\phi = 0.188$ is the shape parameter (Thorson et al., 2012), and $\lambda_{i,n}, \lambda_{a,n}$ are sector-specific catchability coefficients. Setting $\frac{dX_n}{dt} = 0$ gives the status quo equilibrium:

$$0 = \frac{\phi + 1}{\phi} g_n X_n \left[1 - \left(\frac{X_n}{\kappa_n} \right)^{\phi} \right] - \lambda_{i,n} E_{i,n} X_n - \lambda_{a,n} E_{a,n} X_n. \tag{7}$$

Biomass estimates are not available for every fish stock. To scale up biomass estimates to include all of a country's fish stocks, we calculate a normalized ratio (X/X_{MSY}) that can be applied to unassessed species. We use stock assessments from our sample period of 2017 to 2021 to calculate status quo biomass levels. For Ghana and Mauritania, we compute averages over the 2017 and 2019 Nansen surveys (EAF-Nansen Programme, 2019; Ministry of Fisheries and Aquaculture Development, 2022). These research vessel surveys are conducted by Norway's Institute of Marine Research in collaboration with African scientists. Sierra Leone's data come from the 2019 Nansen survey (Ministry of Fisheries and Marine Resources, 2020), while Liberia's data are from the 2017 survey (Jueseah, 2021). We could not obtain stock assessments for Nigeria, so we assign Nigeria the κ-weighted mean X/X_{MSY} ratio of the four assessed countries. This value is 0.313, indicating fish stocks that are depleted below the levels that would occur from fishing at maximum sustainable yield (X_{MSY}).

Under Pella-Tomlinson growth, $X_{\mathrm{MSY}} = 0.4\,\kappa_n$, so we convert each survey biomass to $X/X_{\mathrm{MSY}} = X_n/(0.4\,\kappa_n)$ using species- and country-level g and κ values from Costello et al. (2016). Country-level biomass-to-carrying-capacity ratios are calculated as κ-weighted averages across assessed species within each country. For countries with multiple species or multiple years of data, we weight by carrying capacity when aggregating to obtain a single X/X_{MSY} ratio per country.

Using the X/X_{MSY} ratios derived from stock assessments, we determine the total carrying capacity κ_n for each country by rearranging the equilibrium condition in Equation (7). With this comprehensive carrying capacity estimate that accounts for all stocks, we then solve for the equilibrium biomass X_n numerically using the bisection method on the interval 0–$0.4\kappa_n$. This interval assumes each country's aggregated fish stock is at or below maximum sustainable yield levels (X_{MSY}), consistent with FAO data indicating that 85% of West African fish stocks are overfished or fully exploited (Box 28 of FAO (2024)). We use data on industrial and artisanal catch inside each country's EEZ in 2017 from Sea Around Us (Belhabib, Baio, et al., 2020; Kane et al., 2020; Polido et al., 2020). Sea Around Us catch data contain more stocks than Costello et al. (2016), so using it gives a more comprehensive estimate of each country's total carrying capacity. For species present in Sea Around Us but absent from Costello et al. (2016), we assign the κ-weighted average intrinsic growth rate from the available species within each country.

We calculate sector-specific catchability coefficients:

$$\lambda_{a,n} = \frac{C_{a,n}}{E_{a,n}X_n} \qquad \text{and} \qquad \lambda_{i,n} = \frac{C_{i,n}}{E_{i,n}X_n},$$

where $C_{a,n}$ (artisanal) and $C_{i,n}$ (industrial) are total catches in tons. Allowing separate λ values for the two fleets accommodates differences in production technology and differences in the measurement scales of the fishing effort proxies. This functional form assumes that catch is linear in industrial fishing vessel presence.

Tildes indicate the no-IEZ counterfactual values. Holding the parameters $(g_n, \kappa_n, \phi, \lambda_{a,n}, \lambda_{i,n})$ fixed leaves three unknowns in the counterfactual equilibrium: $\tilde{X}_n$, $\tilde{E}_{i,n}$, and $\tilde{E}_{a,n}$. Using Column 4 of Table 4, we calculate $\tilde{E}_{i,n} = E_{i,n}/(1+\text{percent difference})$. This leaves two unknowns but only one equation. To solve for $\tilde{X}_n$, we assume artisanal effort is unchanged: $\tilde{E}_{a,n} = E_{a,n}$. This assumption is necessitated by the absence of comprehensive artisanal fishing data at sufficiently high spatial resolution for estimating effects of IEZs on artisanal vessels. We solve the equilibrium condition for $\tilde{X}_n$ algebraically:

$$0 = \frac{\phi + 1}{\phi} g_n \tilde{X}_n \left[1 - \left(\frac{\tilde{X}_n}{\kappa_n} \right)^{\phi} \right] - \lambda_{i,n} \tilde{E}_{i,n} \tilde{X}_n - \lambda_{a,n} E_{a,n} \tilde{X}_n. \tag{8}$$

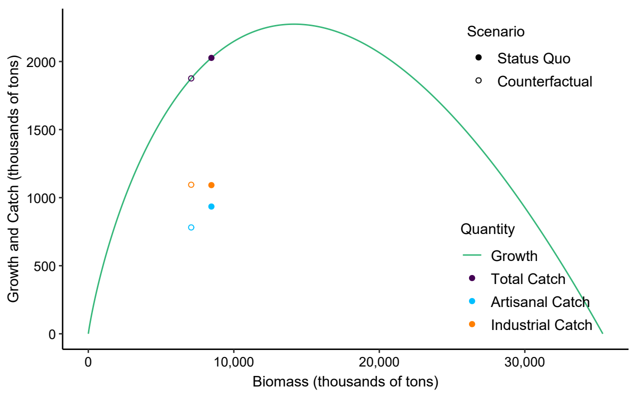
Counterfactual sectoral catches are then:

$$\tilde{C}_{i,n} = \lambda_{i,n} \tilde{E}_{i,n} \tilde{X}_n \qquad \text{and} \qquad \tilde{C}_{a,n} = \lambda_{a,n} E_{a,n} \tilde{X}_n.$$

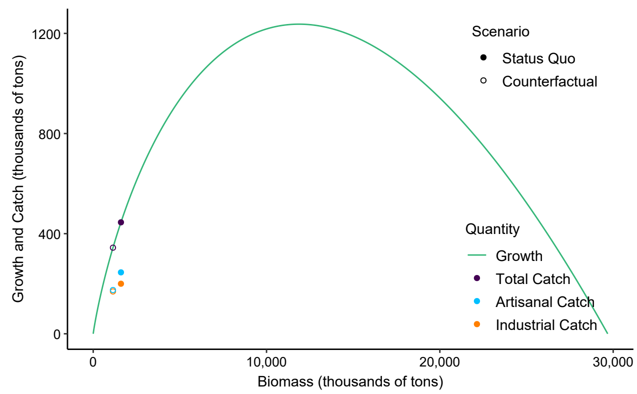
To calculate nutritional benefits from IEZs, we use data from Basurto et al. (2025) on the percentage of six key micronutrients (calcium, iron, selenium, zinc, vitamin A, and omega-3) supplied by artisanal fisher catch from each country's EEZ. We determine what fraction of micronutrients is due to the existence of each country's IEZ by dividing the IEZ-induced gain in artisanal catch by the country's total micronutrient supply from all sources. Finally, we multiply this micronutrient fraction by each country's population to estimate the number of people whose micronutrient needs are fully met because of the existence of IEZs.

Figure C1: Status Quo and Counterfactual Biomasses and Fish Catches for the Five Countries with Deterrence and Bunching Effects

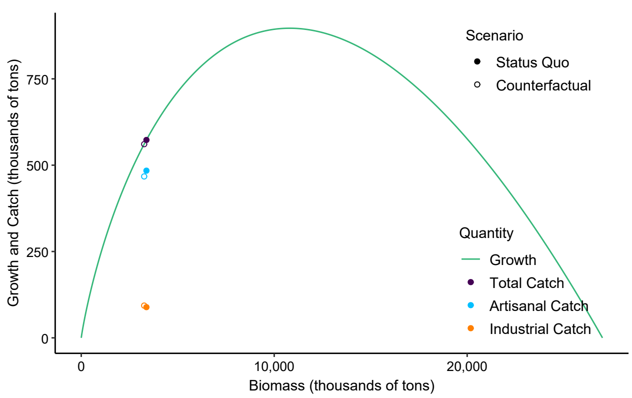
(a) Mauritania



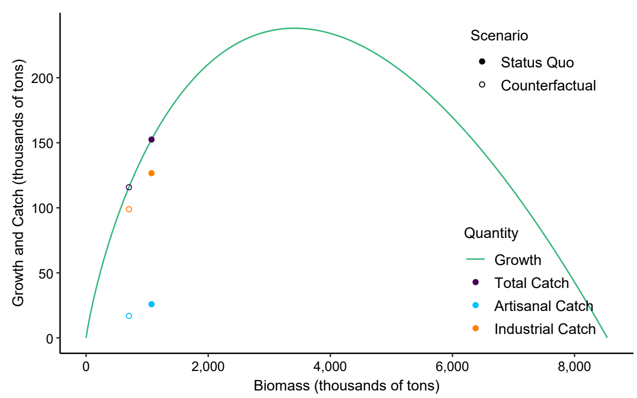
(b) Ghana



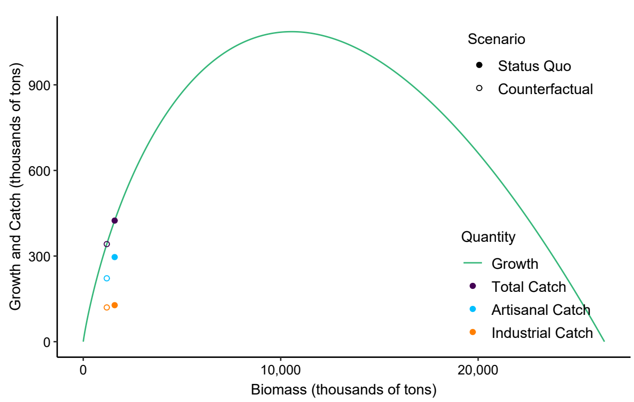
(c) Nigeria



(d) Liberia



(e) Sierra Leone



Notes: These figures illustrate the numeric estimates displayed in Table 5. The x-axis is biomass and the y-axis is catch or growth of the stock at that level of biomass. Points indicate equilibria in the status quo (solid) and no-IEZ counterfactual (hollow) scenarios.

C.1 Biological Spillovers Robustness Check

To bring potential fish spillovers into the calculation we add one extra term to the steady-state condition for each country n:

$$\frac{\phi+1}{\phi} g_n X_n \cdot (1-(\frac{X_n}{\kappa_n})^{\phi}) + m_n \cdot (X_{SQ,n} - X_n) = \lambda_{i,n} E_{i,n} X_n - \lambda_{a,n} E_{a,n} X_n. \tag{9}$$

The new parameter m_n is the slope of net biological inflow when the domestic stock deviates from its status quo level $X_{SQ,n}$. When $X_n < X_{SQ,n}$ and $m_n > 0$, immigration raises the country's net biomass growth and the steady-state stock. Our baseline calculations implicitly set $m_n = 0$. We do not re-calculate the status quo values because those values are already calibrated from data that include whatever cross-boundary flows occur in practice.

Ramesh et al. (2019) provides the only recent country-level estimates of biological spillover, but their analysis is restricted to larval exchange and therefore excludes the movement of juveniles and adults. We take their measure r_n—the share of each country's catch that began life in another EEZ—and convert it into a spillover slope by multiplying by the exploitation rate $u_n = \frac{C_n^{tot}}{X_{SQ,n}}$ (fraction of biomass caught each year). The product $m_n^R = r_n u_n$ tells us how many tons of extra inflow arrive for every ton by which the stock falls below its status quo level.

Because Ramesh et al. (2019) focuses on larvae, we also consider a second, extreme value corresponding to highly mobile adults. Lynham and Villaseñor-Derbez (2024) find that tuna catch per unit effort is 12%-18% higher within 100 nautical miles outside nine large marine protected areas. Tuna are among the most migratory fished species, so the midpoint of their estimate, 15 percent, is a reasonable upper bound on adult spillover. Again scaling by the exploitation rate gives $m_n^L = 0.15u_n$. Table C1 displays the spillover parameter values for each country. Table C2 displays the results from accounting for these biological spillovers alongside our baseline results.

Table C1: Parameters for Biological Spillovers Robustness Checks

	u_n	r_n	m_n^R	m_n^L
Mauritania	0.240	0.02356	0.006	0.036
Ghana	0.278	0.03155	0.009	0.042
Nigeria	0.170	0.00432	0.001	0.025
Liberia	0.142	0.01515	0.002	0.021
Sierra Leone	0.267	0.00743	0.002	0.040

Table C2: Percent Changes in Biomass and Fish Catch from IEZs: Comparing Models With and Without Biological Spillovers

	Biomass (%Δ)			Artisanal Catch (%Δ)			Industrial Catch (%Δ)		
	None	Ramesh	Lynham	None	Ramesh	Lynham	None	Ramesh	Lynham
Mauritania	19.6	18.7	15.1	19.6	18.7	15.1	-0.2	-1.0	-4.0
Ghana	40.4	34.3	22.4	40.4	34.3	22.4	18.2	13.0	3.0
Nigeria	3.6	3.5	2.6	3.6	3.5	2.6	-4.9	-4.9	-5.8
Liberia	52.8	49.7	33.4	52.8	49.7	33.4	28.0	25.4	11.8
Sierra Leone	33.5	32.3	19.3	33.5	32.3	19.3	6.6	5.6	-4.7
Total	20.5	19.3	14.3	19.5	18.3	13.4	3.8	2.5	-2.3

Notes: "None" reports percent changes from the primary specification without cross-country biological spillovers. "Ramesh" incorporates spillovers calibrated from Ramesh et al. (2019) and "Lynham" incorporates spillovers calibrated from Lynham and Villaseñor-Derbez (2024).

C.2 Artisanal Fisher Revenue and Ministerial Budgets

Using Sea Around Us catch data, which includes landed value (tons caught times price per ton) at the level of country-sector-taxon, we computed tons-weighted average prices for the artisanal sector in each country for 2019 (Belhabib, Baio, et al., 2020; Kane et al., 2020; Polido et al., 2020). We then multiplied these prices by the additional artisanal catch that is due to each country's IEZ. Across all five countries, this additional artisanal catch was worth $226,655,100 in 2019.

We were able to obtain 2019 budget data for fisheries ministries in four of the five countries. Mauritania's Ministère des Pêches et de l'Économie Maritime had a total budget of 389,455,382 ouguiyas in 2019 (Chez Vlane, 2018). Ghana's Ministry of Fisheries and Aquaculture Development received a total budget of 59,592,448 Ghanaian cedis in 2019 (Ministry of Fisheries and Aquaculture Development, 2020). Liberia's National Fisheries and Aquaculture Authority budgets in Fiscal Years 2018/19 and 2019/20 were approximately 5.2 million Liberian dollars and 4.7 million Liberian dollars (Liberia National Fisheries and Aquaculture Authority, 2024). These fiscal years extended from July 1 to June 30, so we use the average of the two in order to estimate a budget of 4,950,000 Liberian dollars for calendar year 2019. Sierra Leone's Ministry of Fisheries and Marine Resources received a total budget allocation of Le34.98 billion for the 2019 fiscal year (Keili, 2018). Converting these budgets to 2019 USD using historical exchange rates from July 2019, the combined ministerial budgets totaled $25,486,590.

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