Displacement of fishing effort by Large Scale Marine Protected Areas*

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Abstract

Large-scale Marine Protected Areas (LSMPAs) have seen a significant increase over the last years. Fishing effort is effectively eliminated within these protected areas upon implementation. The benefits of reducing effort have been largely studied, but little empirical works evaluate what happens to the effort after an MPA is created. The economic and ecological implications of displacing fishing effort are not yet fully understood. We use identification of fishing activity via Automatic Identification Systems (AIS) and causal inference techniques to provide the first analyses of behavioral changes and spatial redistribution of tuna purse seiners due to the implementation of a Large Scale Marine Protected Area in the Pacific Ocean. Our work provides three main findings: 1) aggregate fishing effort remains relatively unaffected; 2) Vessels that fished inside the protected area redistribute to adjacent waters; and 3) We observe a crowding effect for the first years after implementation. Our results not only provide an impact evaluation of the effect of LSMPAs on fishing activity, but provide insights into vessel redistribution dynamics, which may have ecological and economic implications. As countries continue to implement LSMPAs as a way to reach the stated 10% target of ocean protection, managers should consider how fishing effort will change in space and through time to ensure that fishing effort is not just displaced elsewhere, leading to overfishing in adjacent waters. While LSMPAs can provide a wide range of benefits, their implementation must be accompained with traditional fisheries management to maximize their effectiveness.

*Work in progress, do not circulate

1 Introduction

Marine Protected Areas (MPAs) are intended to safeguard parts of the ocean from fishing and other extractive activities. Current international goals aim to protect 10% of the ocean environments by 2020. In an effort to meet this target, the world has seen a rapid increase in MPA coverage (Wood et al., 2008; Sala et al., 2018), largely driven by a small number of Large Scale Marine Protected Areas (LSMPA) Singleton and Roberts (2014); Boonzaier and Pauly (2016); Alger and Dauvergne (2017)). Due to weak property rights, limited habitat transformation, and potentially lower management costs, LSMPAs provide an opportunity to safeguard the oceans Game et al. (2009). Today, a small number of LSMPAs make up at least 80% of the managed areas in the ocean Toonen et al. (2013). LSMPAs may be instrumental in helping us achieve the 10% target by 2020 (McCauley et al., 2016).

Given the relatively recent establishment of most LSMPAs, very little is known about their human dimensions and implication for fisheries (Gray et al., 2017). As with customary MPAs, it is important that we understand the socioeconomic implications of management interventions. One issue of particular importance is that of the displacement or redistribution of fishing effort, which may influence the outcomes of an MPA (Smith and Wilen, 2003). Theoretical models make different assumptions about the way in which fishers will reallocate fishing effort after an area closure. The few empirical works focus on small-scale fisheries and rarely incorporate spatially explicit data. Despite these efforts, marine conservation is yet to identify the response in fishing effort and its management implications.

Recent advances in satellite tracking technologies and near real-time identification of fishing activity provide us with an opportunity to tackle increase governance and answer long-lasting questions. Here, we ask, how do fishers respond to the implementation of LSMPA? After a closure, and if they continue to fish, where do they reallocate fishing effort? We use identification of fishing activity via Automatic Identification Systems (AIS) and causal inference techniques to describe the behavioral changes and spatial redistribution of the industrial tuna purse seine fleet due to the implementation of a Large Scale Marine Protected Areas in the Pacific Ocean.

Our work is novel in the sense that it provides empirical evidence of the effect of Large Scale Marine Protected Areas in fishing behavior and distribution and can help guide future interventions as countries march towards meeting the targeted 10% of ocean protection. Understanding how effort is displaced from LSMPAs might provide insights into how the industrial fleet would react to a high seas closure.

The paper is outlined as follows: Section 2 provides more information on Large Scale Marine Protected Areas and background on empirical studies of effort redistribution. An overview of the Nauru Agreement and associated countries, a description of the fleet that operates in the region, and a brief history of PIPA is also included. Section 3 describes our data and identification strategy. Section 4 presents our results, section 5 provides an extension of our results to other LSMPAs[1] and discusses our results[2].

[1]Not yet. but I think this would be interesting

[2]I might also include a section, after the background, where I explain the different theoretical models of effort redistribution and behavioral responses

2 Background

2.1 Large Scale Marine Protected Areas

The cutoff at which an MPA is considered to be a LSMPA ranges from areas larger than 30,000 km^2 as defined by De Santo (2013) or areas larger than 250,000 km^2, as defined by (Toonen et al., 2013). Figure 1 shows LSMPAs that meet the later, and that are fully no take. LSMPAs are often implemented in the pelagic environment, where the dominant human activity is industrial fishing (Gray et al., 2017; Kroodsma et al., 2018). The early literature on LSMPAs focused on the inherent challenges and difficulties that come with a pelagic environment. Kaplan et al. (2010) claimed that very large MPAs would result in excessive opportunity costs and that these would be difficult to enforce. Game et al. (2009) suggested that most of the challenges could be overcome with the incorporation of technology, in what then became known as Dynamic Ocean Management (Maxwell et al., 2015). The effectiveness and difficulties of implementing LSMPAs are not the focus of this paper [3]. Instead, we focus on the effect and implications of the ones that *have been* implemented.

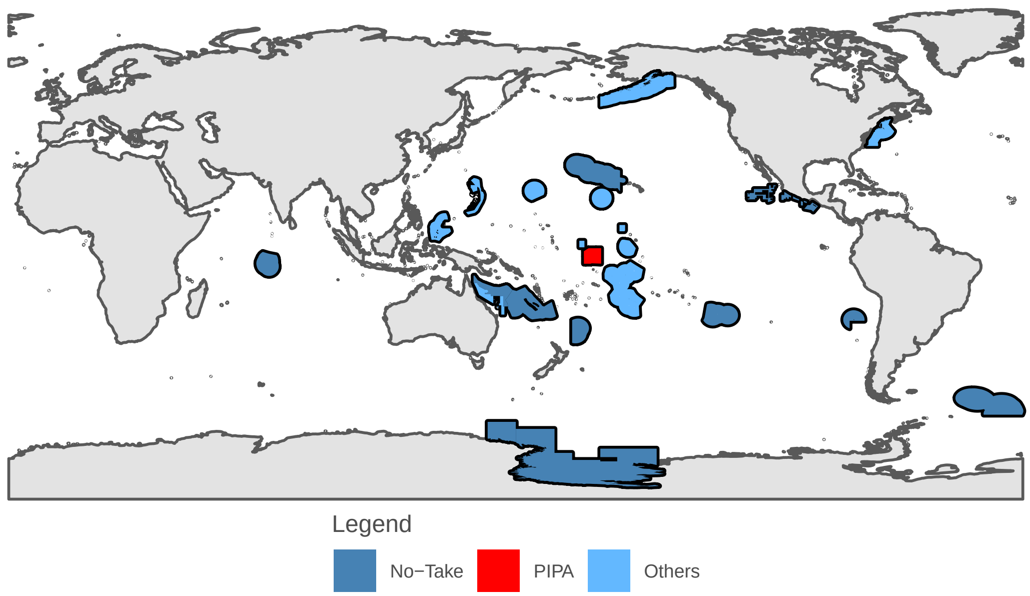

Figure 1: Large Scale Marine Protected Areas. The map shows all areas larger than 250,000 Km^2. Areas in dark blue meet at least one of these conditions: reported no take area is greater than 0, are categorized as IUCN Ia or Ib, their designated english name is 'Protected Area'.

LSMPAs were erroneously assumed to have little social implications due to their remoteness. However, there have been calls to incorporate the human dimensions into LSMPAs management and evaluation (Agardy et al., 2011; Gray et al., 2017). Most research incorporating these dimensions has focused on governance and enforcement of LSMPAs (*i.e.* Alger and Dauvergne (2017); Christie et al. (2017)), but they are yet to be the focus of economic analyses (Gray et al., 2017). Overall, there has been little empirical work regarding LSMPAs. Recent technological advances in vessel-detection

[3] But see Singleton and Roberts (2014), who provide an objective discussion of pros and cons of LSMPAs.

systems allows for the discovery and advancement of many important facets of LSMPAs. For example, (McDermott et al., 2018) show that the anticipation of a LSMPA can lead to preemptive overfishing, which can erode or delay the expected benefits of the intervention. White et al. (2017) combine shark tags and vessel-tracking data to demonstrate that the fairly large Palmyra Atoll National Wildlife Refuge (54,000 Km^2) protects two thirds of the tagged grey reef sharks by effectively excluding fishing effort. More recently, (Bradley et al., 2018) use similar data to highlight cases of potential illegal shark fishing *inside* a 2 million km^2 shark sanctuary. To date, no studies have evaluated the displacement of fishing effort due to LSMPA implementation.

Spatial closures of this magnitude are likely to induce changes in fishers' behavior. Theoretical models of fishing effort redistribution range from the simplistic assumption that effort inside the bounded region disappears, to spatially explicit models that reallocate fishing effort based on habitat characteristics, presence of other vessels, and expected returns (Smith and Wilen, 2003; Hilborn et al., 2006). However, these focus on the long term optimal equilibrium, and redistribution of fishing effort may not always be optimal, especially over the first years (Stevenson et al., 2013).

The empirical research that has been done in customary sized MPAs suggest that resource users may show idiosyncratic responses. For example, Stevenson et al. (2013) show that a network of MPAs displaced fishing effort farther away from ports, resulting in higher *perceived* costs, and increases in catch per unit effort. Cabral et al. (2017) analyse the redistribution of fishing and non-fishing vessels following the implementation of a network of MPAs in California, and find that commercial dive boats follow a fishing-the-line pattern, while some fishing boats follow an ideal free distribution. More recently Elahi et al. (2018) used satellite tracking data to show that a temporal spatial closure caused trawlers to maintain effort but apply it more intensively elsewhere, particularly along the borders and closer to shore. The way in which fishers react to a spatial closure can have major implications in its outcome (Smith and Wilen, 2003; Hilborn et al., 2006) highlighting the need to understand how fishers react to the implementation of LSMPAs, and fishing effort changes and is spatially redistributed. However, all these closures took place within Exclusive Economic Zones, where other regulations exist. This may not always be the case for LSMPAs, where often the entire EEZ is converted into a LSMPA, leaving fishers with the options of moving to the high seas or other countries' EEZs.

2.2 Nauru agreement and the Phoenix Island Protected Area

The Nauru Agreement was established in 1982 by a select group of Pacific island nations to manage their important tuna resources. PNA Members include Federated States of Micronesia, Kiribati, Marshall Islands, Nauru, Palau, Papua New Guinea, Solomon Islands, and Tuvalu. The Nauru Agreement regulated access of foreign vessels (*i.e.* those from non-PNA countries). Holding ~80% of the historical purse seining grounds within their Exclusive Economic Zones, PNA countries gained bargaining power when providing access to foreign fleets (Havice, 2010).

The cooperation that emerged thanks to the PNA allowed for subsequent agreements that strengthened fisheries management, like the Palau Agreement, which limited the number of purse seiners at 205 vessels from 1995-2007[4]. However, the most notable regulation is their approach to manage fishing effort: a Vessel Day Scheme (VDS) implemented in 2007 (Havice, 2013). This effectively modified how fishing effort was managed, from number of vessels under the Palau Agreement to

[4]See Havice (2010) for a detailed description of the Nauru, Palau, and Federal States of Micronesia agreements, their objectives, and outcomes.

fishing hours. The VDS works as follows: Each year, scientific advisers recommend a total number of fishing vessel-days per year. Hours are allocated to each PNA country based on catch history, and they then use or sell fishing rights to other non-PNA countries (Aqorau et al., 2018). While the effectiveness of this scheme has been debated in terms of meeting their fishery management and conservation objectives, the licensing significantly contributes to the economy of these island nations (Havice, 2010).

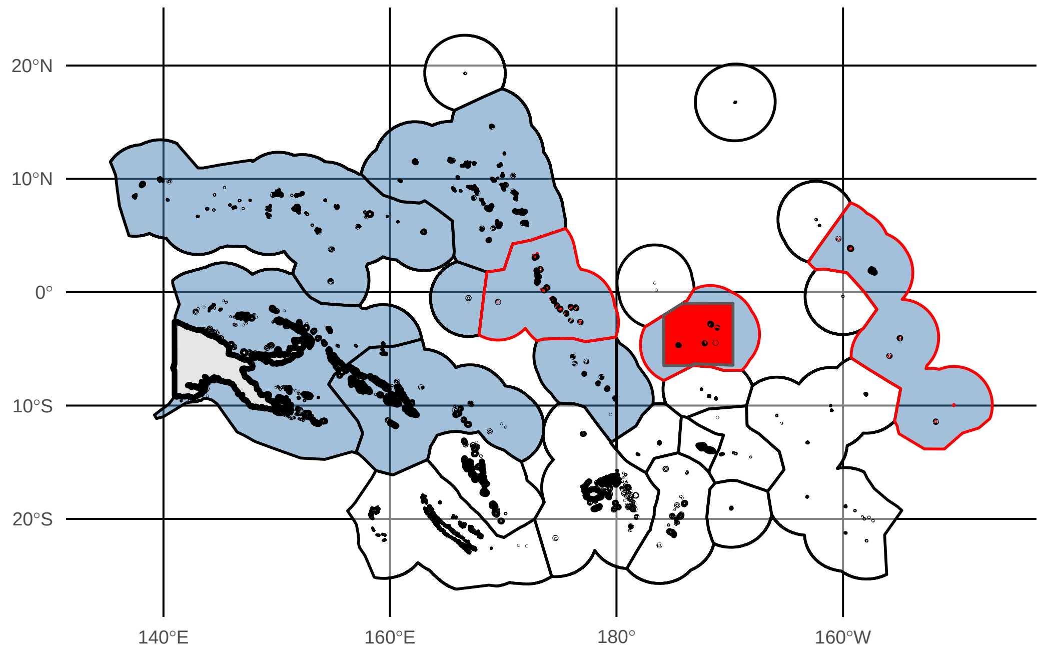

Figure 2: Map of the Exclusive Economic Zones (EEZs) of the region of interest. Countries that belong to the PNA are shown in blue, while empty polygons indicates all others. A red line indicates the Kiribati EEZ, and a solid red polygon delineates PIPA.

The main tuna species caught in the region are skipjack (*Katsuwonus pelamis*), yellowfin (*Thunnus albacares*), albacore (*Thunnus alalunga*) and bigeye (*Thunnus obesus*). From these, the first two are amongst the top-10 species represented in global fisheries production statistics, with 2016 catches increasing relative to the 2005-2014 average (FAO, 2018). This region of the Pacific has historically accounted for a large portion of tuna catches (Aqorau and Bergin, 1997). Today, the PNA controls close to 50% of the global skipjack tuna production (PNA, 2018). A large portion of these catches derive from purse seine vessels licensed under the VDS. Fishing vessels from Australia, New Zealand, China, France, Korea, Japan, the Philippines, Taiwan, and the United States participate in the purse-seining VDS.

One of the most notable and recent management interventions in the region is the implementation of the Phoenix Island Protected Area (PIPA) by the government of Kiribati. PIPA was first declared in 2006, and established in 2008 with only 4% of it was declared as no-take. In January 1$^{\text{st}}$, 2015, the no-take area within PIPA was expanded to a total area of 397,447 km^2, roughly 1.5 times the size of Ecuador. Figure 4 shows a map of the PNA countries and the Phoenix Island Protected Area.

The closure of such a large area in one of the most important fishing regions in the world provides a great opportunity to evaluate the behavioral responses and redistribution of fishing effort by vessels that used to fish there. PIPA has been the focus of previous research, showing that fishing effort is effectively reduced after implementation (McCauley et al., 2016; McDermott et al., 2018). To this, we pose two questions: How do individual vessels respond to the sudden exclusion of such a big area? And where did all the vessels go? In the next sections we describe the data and methods used to answer this questions.

3 Methods

This section is divided into two main parts. First, we provide a general description of AIS data and the process of identification of vessel-level fishing events done by Global Fishing Watch[5]. Alongside, we describe the subset of data used on our analyses. When relevant, we also point out possible shortcomings in the data, or factors that must be considered in the later analyses. We then move on to explain our empirical strategy for the identification of the behavioral changes and redistribution of fishing effort.

3.1 Data

Automatic Identification Systems (AIS) are on-board devices that provide at-sea safety and prevent ship collisions by broadcasting vessel position, course, and activity to surrounding vessels. These broadcasted messages can be received by satellites and land-based antennas. GFW uses convolutional neural networks to infer vessel characteristics and whether each broadcasted position represents a fishing event, thus allowing us to estimate near real-time fishing events globally since 2012 (Kroodsma et al., 2018).

The amount of data gathered is dependent on the number of antennas and satellites that can pick up the signals. In June 1st 2014 satellite count increased from 3 to 6, and then to 10 in January 1st 2016. This causes an increase in the number of *received* AIS messages (*i.e.* points), and therefore an apparent increase in the number of vessels and fishing hours. However, the addition of satellites "affects" all vessels in the same way. The variability in AIS data and ocean conditions require that temporal trends be taken into account. We do that by including specific controls in our identification strategy and using a subset of data that meet a BACI design -which gives us the full tracks for vessels affected and unaffected by the implementation of PIPA.

Our analysis focuses on purse seine vessels, the most important fishery for PNA countries[6]. We identify a total of 103 purse seiners that fished in PNA waters at least once before 2015[7]. These vessels represent over 26 million individual observations for the 2012 - 2017 period. We identify 65 vessels that have fished inside PIPA at least once since 2012. From these, 62 did so before the announcement (*i.e.* 09/01/2014 *sensu* (McDermott et al., 2018)) but are only able to track 61 for the complete period of study before and after its implementation[8]. On the other hand, 38 vessels never fished inside PIPA but we only have data for 26 vessels before and after.

[5] Global Fishing Watch: globalfishingwatch.org

[6] We perform some of the same analyses for longliners and include them in the Appendix

[7] New vessels that entered the fishery after 2015 were not exposed to the policy intervention in the pre-treatment period and are therefore excluded from our analyses.

[8] 1 vessel never fished again after August 18, 2013.

Therefore, our treatment group contains all purse seiners (n = 61) that fished within PIPA at least once before the announcement, and that continued to fish elsewhere after the January 2015 implementation. Vessels in the control group meet the following two conditions: i) vessels never fished within PIPA waters, and ii) vessels have fished in surrounding areas (*i.e.* PNA-countries' EEZ) before and after PIPA closure (n = 26).

We include three additional definitions of control groups as a robustness check: one with only vessels that belong to PNA countries (n = 7), and one that excludes Chinese vessels (n = 21). Our third control is made up of Japanese purse seiners that fish in the Pacific but that never fished inside PIPA (n = 27)[9]. Our definition of treatment and control groups leaves us with 61 and 21 treated and control vessels, which have just over 22 million observations where about 22% are identified as fishing events.

For each vessel we calculate total daily fishing hours and obtain panel data with 37,800 observations. Table 1 shows the number of vessels following a BACI design, as well as the fishing hours, before and after PIPA. Fig. 4 shows that mean fishing hours for purse seiners have an abrupt increase, just before January 1st, 2015. This trend is observed for both treated and control groups. Across all measures, the treatment and control vessels follow similar patterns, confirming our claim that the control group provides a plausible counterfactual. Figure S1 provides a visual representation of the vessel-level fishing events that make up each group through time. We use this data to answer our key questions: How do the 61 purse seiners modify their behavior as compared to the different control groups, and where do they go after the spatial closure? The following section describes our empirical identification strategies.

Table 1: Number of fishing vessels and mean daily fishing hours by group before and after PIPA implementation.

Group	n	Before	After	Change (A / B)
Control	26	11.74	20.13	1.72
Treatment	61	10.67	18.36	1.72

[9] Using Taiwanese vessels was the original idea, but there are only 4 vessels with pre-2015 data. I need to further identify proper Taiwanese vessels, as I am currently using the entire Pacific ocean

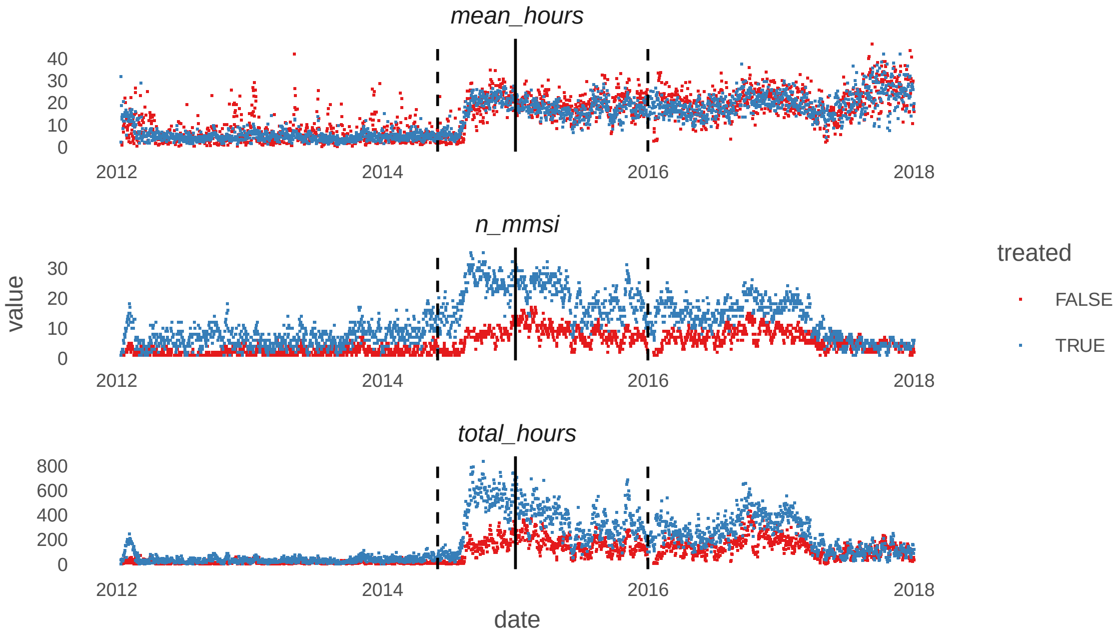

Figure 3: Fishing hours and number of vessels by month for all vessels. Vertical dashed lines indicates dates when satellites were added, solid line indicates PIPA closurePIPA closure.

3.2 Analyses

The first analysis focuses on identifying the response of fishing vessels to PIPA closure. A spatial closure might cause fishers to modify their behavior as they adapt to a new state of the world. Some may have to travel further distances to find new fishing grounds, which would lead them to fish harder to compensate for the associated extra fuel costs. If fishers had developed experience for fishing in particular sites, being excluded might impose a learning cost on them, as they identify new fishing grounds. This would result in increased search times. However, if the area of influence of a vessel is significantly larger than that of the spatial closure, they might already know other places and times where to fish. Our variables of interests intend to capture these possible reactions.

We use daily fishing hours, daily proportion of fishing vs. non-fishing hours, and daily distance traveled (km). We compare our variable of interest before and after the implementation of PIPA using a Difference-in-Differences approach, where we track the variable of interest for vessels described in the previous section. Our specification is the following:

$$y_{i,t} = \alpha + \beta_1 Post_t + \beta_2 Treat_i + \beta_3 Post_t \times Treat_i + \phi_t + \gamma_i + \theta_t + \epsilon_{i,t}$$

Where $y_{i,t}$ is the variable of interest for vessel i in time period t. A dummy variable $Post_t$ takes the value of 0 for all dates prior to PIPA implementation and a value of 1 for all dates including and following PIPA implementation. $Treat_i$ is a dummy variable indicating whether a vessel belongs to the control ($Treat_i = 0$) or treatment ($Treat_i = 1$) group. α is the standard intercept, β_1 captures the temporal trend change, β_2 captures the difference between treated and control groups, and β_3 is our parameter of interest: de DiD estimate capturing the treatment effect. Finally, ϕ_t and γ_i

represent month- and flag-level dummies that account for seasonality or country-level management interventions. θ_t are dummies to account for the addition of more satellites. [10].

Our second part of the analyses focuses on the redistribution of fishing effort. The role of institutions may play an important role. As stated before, LSMPAs often span the entirety of an EEZ. In the case of purse seining in the PNA, vessels purchase access to the fishery at the beginning of the season. If a vessel decides to fish within the PNA, they've already made the decision to pay for access, expecting higher returns from fishing there than in the High Seas. In the particular case of PIPA, one would expect that a vessel holding a permit to fish in I-Kiribati waters would then move to other fishing grounds within Kiribati after the closure. Alternatively, if a vessel fishes illegally in I-Kiribati waters before the implementation, one would expect them to reallocate to other regions with equal or less enforcement. In this case, they might then choose to move to other I-Kiribati waters, waters of countries that have similar enforcement levels, or the High Seas.

We discretize spatial units by using a polygon for PIPA[11] and distinct spatial units for each EEZ of each country. Some vessels might shift from EEZs into the high seas, but we are interested in knowing *where* in the high seas, so we incorporate additional regions by using a 1 degree buffer of the high seas around each of the EEZ regions. The rest of the high seas are merged into a single spatial unit. For example, if we were to do this only for Kiribati, we would have 8 spatial units: PIPA, three EEZs, three 1-degree buffers of high seas around each EEZs, and the rest of the high seas. Whenever the buffers overlapped between themselves, we randomly clipped one on to the other.

We then take this spatial polygons and rasterize them to a 1-degree grid (See Figure S10), which we then use to rasterize points of fishing activity. For each cell, we calculate the total monthly fishing hours by treated and control vessels (See Figure 6). Since we are interested in the redistribution of fishing effort, we use this gridded data to calculate the proportion of fishing hours that each region receives each month relative to the total fishing hours observed across all regions and all cells in that month.

We use this measure to evaluate the change in effort allocation by regressing it on the interaction between a year dummy and a dummy for regions:

$$y_{i,t} = \alpha + \beta_1 Year_t + \beta_{2,i} Region_i + \beta_{3,i} Year_t \times Region_i + \epsilon_{i,t}$$

Our variable of interest, $y_{i,t}$ represents the proportion of fishing hours that region i receives at time t. Years are modelled as factors ($Year_t$), using 2012 as the reference level. *Region* is a dummy variable for regions defined above. Our parameter of interest is $\beta_{3,i}$, which captures the yearly by-country change in proportional allocation of fishing effort relative to 2012.

All regression coefficients were estimated via ordinary least squares, and heteroskedastic-robust standard errors were calculated. All analyses were performed in R version 3.5.1 (R Core Team, 2018). Raw data and code used in this work are available on github.

[10] We test for other more complex specifications that interact a quarterly dummy or year-month dummies with the treatment group and find qualitatively the same results.

[11] we would expect to see a decrease here

4 Results

Regressions coefficients for our DiD analysis are shown in Table 2. Columns 1 -3 use all data for controls. Columns 4 - 6 use only PNA vessels as controls, and columns 7 - 9 exclude Chinese vessels. Columns 10 and 11 use Japanese vessels in the Pacific as controls, and hence don't include flag fixed-effects to avoid perfect colinearity between Japanese flag and control[12]. Our DiD analysis shows an overall increase in purse seine fishing hours, even after accounting for the introduction of new satellites (Table 2). This coefficient estimate is consistent for different model specifications and across groups of treatment and controls, and effectively represents the patterns observed in Figure 4.

The β_3 coefficient indicating our treatment effect suggests that, relative to the control, treated vessels fish less, in the order of 0.5 hours per day. Another way to interpret this is that the increase in fishing effort by treated vessels has occurred at a lower rate than control vessels. The effect varying between $\beta_3 = -0.515$ and $\beta_3 = -0.934$. These values are equivalent to a 15 - 28 reduction in fishing hours per month. However, this result is only robust and significant ($p < 0.01$) in the simplest specification of the Diff-in-Diff. When reducing the linear structure of the $Pre \times Post$ design and instead interacting the treatment dummy with quarterly or year-month combinations we are not able to reject the null hypotheses of no change, suggesting that the total fishing hours remains similar for the displaced vessels (Figs. S2-S9). Since vessels don't seem to be fishing less (or at least not much less), an obvious question arises: where are they fishing now?

Figure 6 provides a spatial representation of these changes. Note that 2013 effort distribution is roughly similar across vessels. Then in 2014 there is a sharp increase in fishing hours by treated vessels inside PIPA (blue paradox). In 2015 treated vessels then allocate more effort to the easternmost Kiribati EEZ (see Figure) and the high seas. In 2016 spatial distribution of fishing effort is again similar across groups. It is evident that the increase in relative fishing effort is greater for for regions closer to PIPA.

Along a similar line, Figure 7 shows a detailed temporal evolution of the relative allocation of fishing effort[13]. It shows shows the change in fishing effort inside PIPA, including the preemptive fishing and immediate reduction previously reported (McDermott et al., 2018). I-Kiribati waters in KIR 1 and KIR 2 show an increase in fishing effort for 2015; the same pattern is observed for their respective High Seas buffers, and the general High Seas. Other regions farther away from PIPA don't show a clear pattern under visual inspection.

We then move on to our regression results, presented as a figure showing the year-region interaction coefficient estimates for each region as a stream of changes through time (Fig. 8 and Table 3). As noted before, the marginal change in the relative allocation of fishing effort relative to 2012 increases in 2014 for PIPA. Most coefficients are not statistically significant, but follow the same trends previously discussed, with a tendency for regions closer to PIPA to show an increase in the relative allocation of fishing effort in the post-implementation period. The largest increase is observed for the I-Kiribati EEZ 2, where the redistribution of treated vessels caused a 15% increase in the *relative* allocation of fishing effort within I-Kiribati waters. This displacement is likely causing a crowding effect after PIPA-fishing vessels redistribute to other areas.

We use the rasterized effort to evaluate if the PIPA closure increased crowdness otuside the LSMPA. We count the number of raster cells that had both treated and control vessels each year (Fig. 9A).

[12]Results of the same analysis is shown for longliners in S1

[13]Recall that to evaluate the redistribution of fishing effort we only track fishing vessels that belong to the treated group.

The pattern observed here could just be an artifact of satellite detections increasing though time. Thereforem we also calculate a spatial correlation of presence/absence and observe similar patterns (Fig. 9B). While this are at the year level and cannot assure that vessels were in effect at the same time in the same vessel, it provides an accurate depiction of what we would expect to find if our claims of displacement are true. Spatial overlap increases in 2015 as vessels from PIPA are excluded, and that measure slowly returns to its previous state.

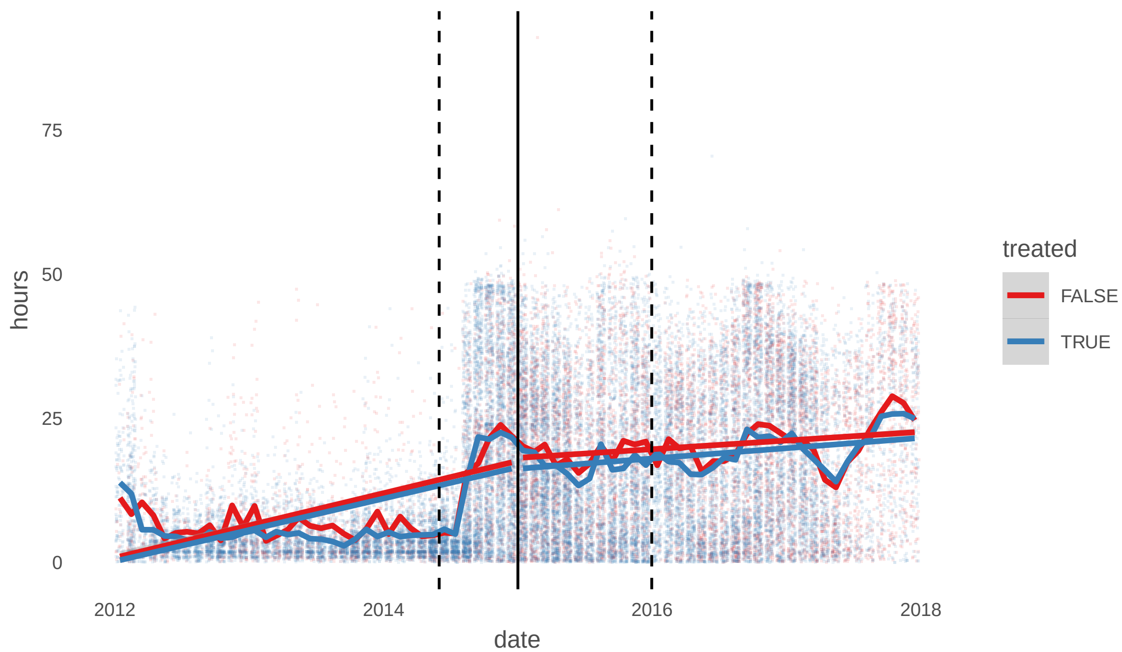

Figure 4: Daily fishing hours for all vessels in our main treatment-control groups. Solid straight lines show a linear trend by period (pre-psot) and treatment. The other red and blue lines show monthly avarages. Vertical dashed lines indicates dates when satellites were added, solid line indicates PIPA closurePIPA closure.

Table 2: Difference-in-differences estimates for 3 different controls and 3 different specifications. The first three columns use all data for controls. Columns 4 - 6 use only PNA vessels as controls, and columns 7 - 9 exclude Chinese vessels. Columns 10 and 11 use Japanese vessels in the Pacific as controls, and hence don't include flag FEs. Numbers in parentheses are heteroskedastic-robust standard errors.

	Dependent variable:										
	hours										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constant	6.345^{***}	7.863^{***}	10.322^{***}	7.124^{***}	9.007^{***}	9.933^{***}	6.057^{***}	7.584^{***}	10.194^{***}	22.625^{***}	24.731^{***}
	(0.186)	(0.274)	(0.404)	(0.265)	(0.341)	(0.620)	(0.193)	(0.279)	(0.538)	(0.629)	(0.683)
post	-0.052	1.134^{***}	1.115^{***}	-1.199^{***}	-0.279	0.124	-0.284	1.013^{***}	1.166^{***}	2.330^{***}	3.991^{***}
	(0.303)	(0.304)	(0.339)	(0.435)	(0.429)	(0.436)	(0.318)	(0.318)	(0.357)	(0.890)	(0.877)
treated	-1.142^{***}	-0.839^{***}	0.010	-1.977^{***}	-1.675^{***}	0.626	-0.877^{***}	-0.536^{**}	0.150	-18.190^{***}	-18.257^{***}
	(0.214)	(0.209)	(0.281)	(0.284)	(0.274)	(0.416)	(0.221)	(0.215)	(0.297)	(0.673)	(0.661)
sate2	12.579^{***}	11.589^{***}	11.340^{***}	12.709^{***}	11.850^{***}	11.749^{***}	12.631^{***}	11.599^{***}	11.349^{***}	14.346^{***}	12.967^{***}
	(0.197)	(0.199)	(0.232)	(0.212)	(0.213)	(0.246)	(0.199)	(0.201)	(0.235)	(0.303)	(0.309)
sate3	14.675^{***}	13.587^{***}	13.328^{***}	14.799^{***}	13.894^{***}	13.795^{***}	14.958^{***}	13.804^{***}	13.566^{***}	15.187^{***}	13.719^{***}
	(0.260)	(0.262)	(0.307)	(0.286)	(0.287)	(0.329)	(0.264)	(0.266)	(0.315)	(0.402)	(0.410)
post:treated	-0.515^{*}	-0.833^{***}	-0.934^{***}	0.562	0.373	-0.176	-0.439	-0.814^{***}	-1.084^{***}	-3.209^{***}	-3.715^{***}
	(0.281)	(0.276)	(0.310)	(0.413)	(0.402)	(0.407)	(0.293)	(0.287)	(0.326)	(0.811)	(0.799)
Control	All	All	All	PNA	PNA	PNA	-CHN	-CHN	-CHN	JPN	JPN
Month FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Flag FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No
Observations	37,840	37,840	30,359	30,583	30,583	25,034	36,415	36,415	28,934	34,047	34,047
R^2	0.171	0.200	0.208	0.178	0.208	0.215	0.173	0.203	0.211	0.260	0.280

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

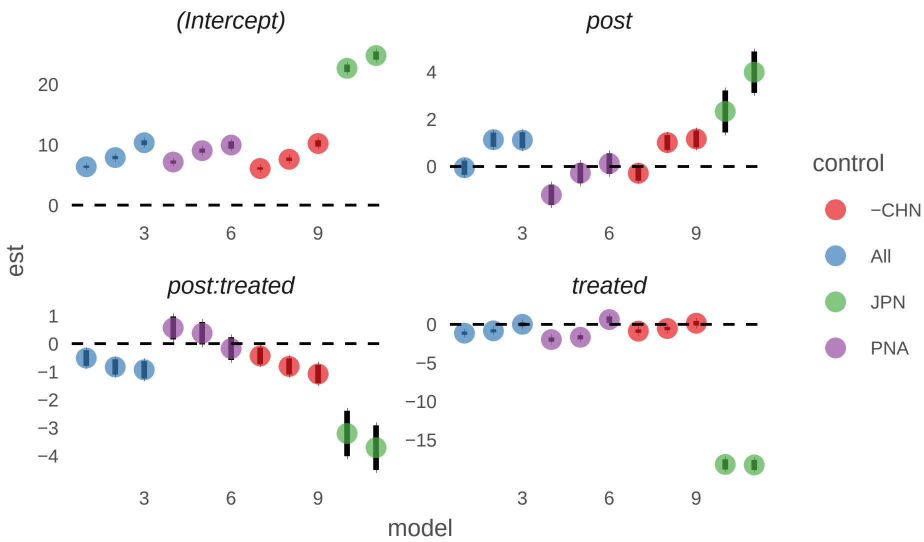

Figure 5: Coefficient estimates for each model. Top pannel indicates variable, x-axis represents model specification, and y-axis coefficient estimate.

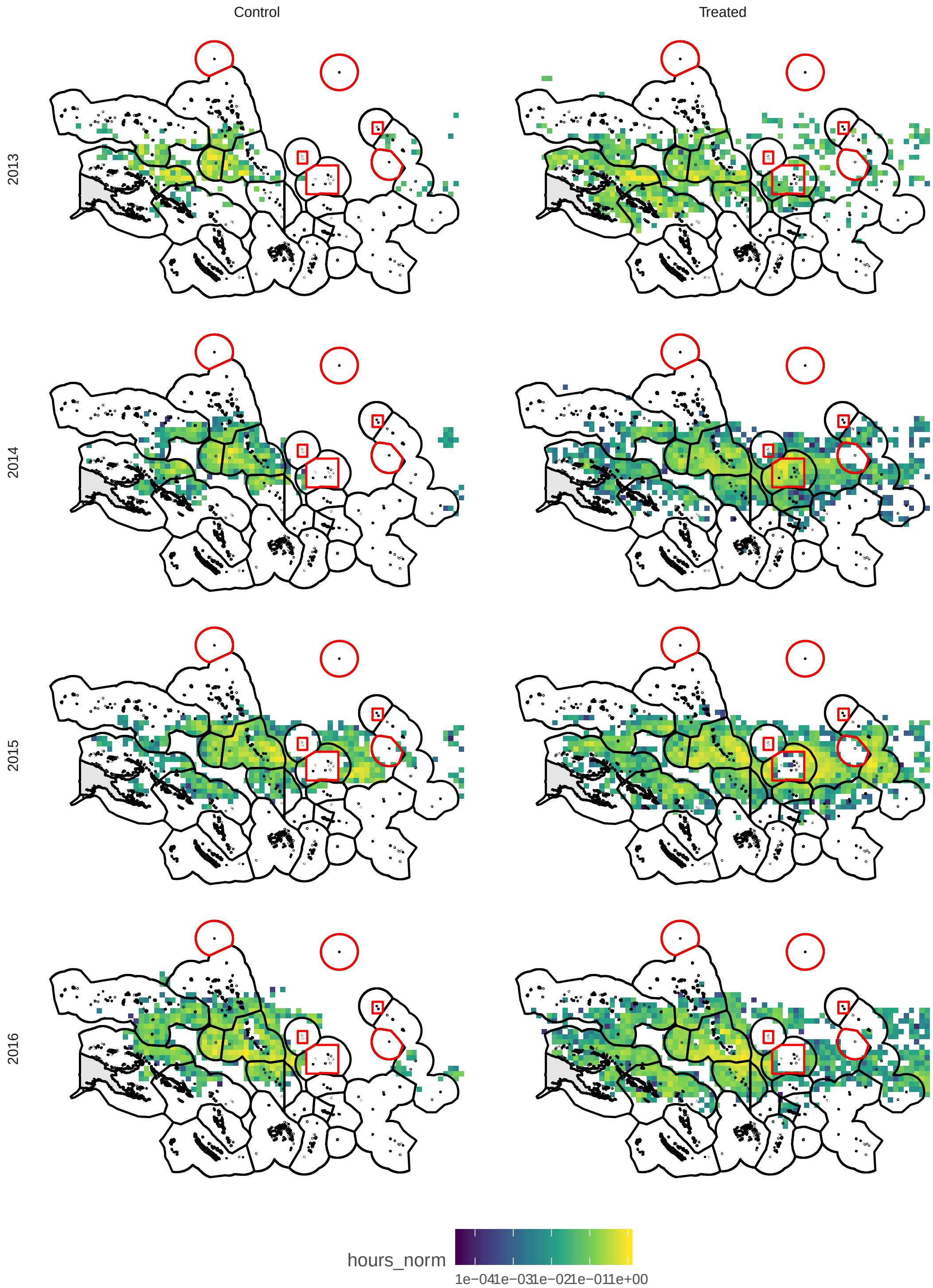

Figure 6: Yearly spatial distribution of fishing effort by treated and control vessels. Colors have been adjusted relative to the maximum observed by group and year. Red polygons show LGMPAs in the region. For visualization purpose sonly some years are presented, the full 2012 - 2017 period is shown in Figure S11.

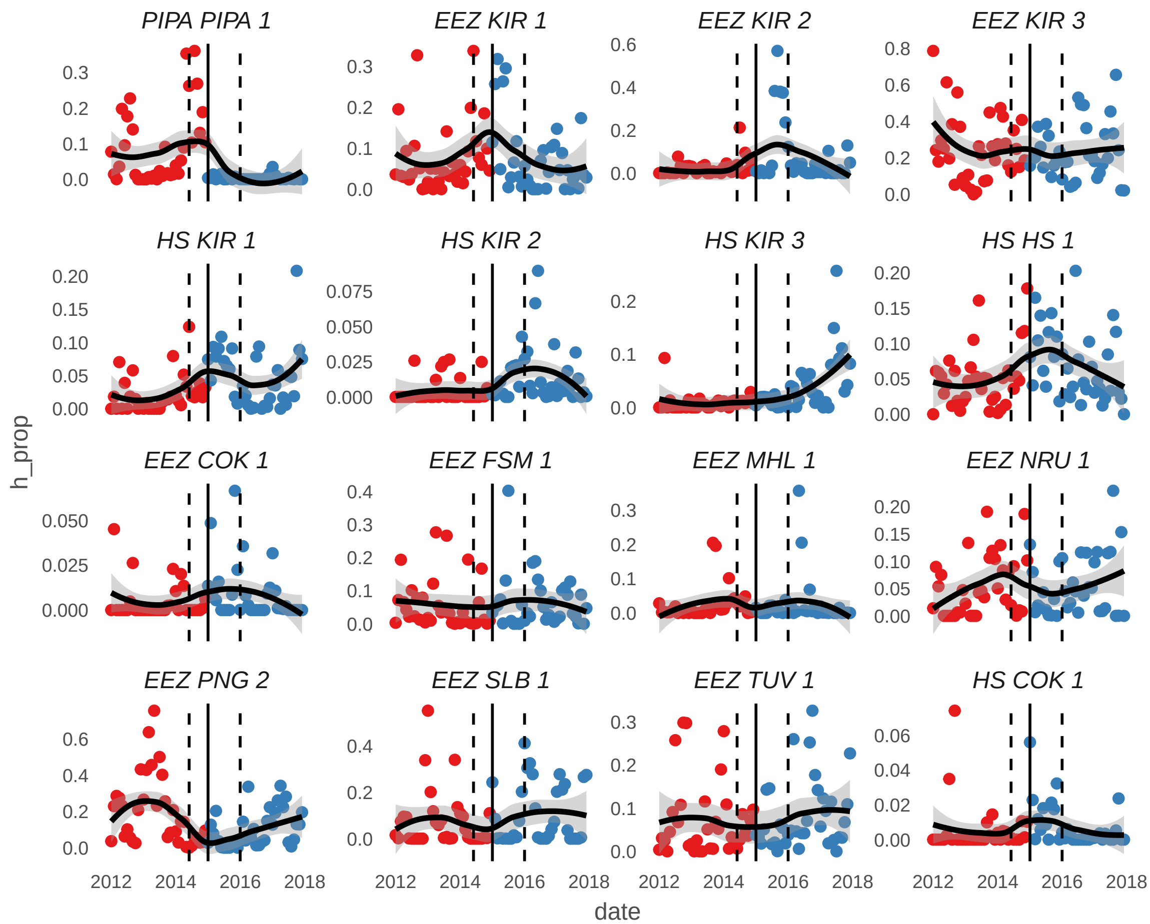

Figure 7: Monthly relative allocation of fishing effort by PIPA-fishing vessels before and after PIPA by region. Colors indicate the pre-post period. Solid line across points shows local mean with a region-specific loess smoother. Vertical dashed lines indicates dates when satellites were added, solid line indicates PIPA closurePIPA closure. Note that inflection points of the loess smoother are not affected by the addition of satellites.

Table 3: Coefficient estimates for the interaction of year and region. Each row represents a region, each color a year. Numbers in parentheses are heteroskedatic-robust standard errors. R2 = 0.47 (F(95, 1056) = 9.99; p < 0.001). * < 0.1; ** p < 0.05; ***p < 0.01.

term	2013	2014	2015	2016	2017
PIPA PIPA 1	-0.062 (0.026)**	0.085 (0.043)**	-0.086 (0.026)***	-0.079 (0.025)***	-0.074 (0.025)***
EEZ KIR 1	-0.034 (0.030)	0.035 (0.038)	0.042 (0.045)	-0.035 (0.031)	-0.023 (0.032)
EEZ KIR 2	0.001 (0.009)	0.032 (0.019)*	0.142 (0.061)**	0.014 (0.013)	0.014 (0.015)
EEZ KIR 3	-0.188 (0.075)**	-0.061 (0.072)	-0.118 (0.069)*	-0.093 (0.083)	-0.098 (0.083)
HS KIR 1	-0.003 (0.011)	0.016 (0.012)	0.038 (0.013)***	0.004 (0.013)	0.037 (0.018)**
HS KIR 2	0.009 (0.006)	0.004 (0.006)	-0.000 (0.009)	0.022 (0.010)**	0.008 (0.006)
HS KIR 3	-0.002 (0.009)	0.003 (0.009)	-0.008 (0.011)	0.022 (0.011)*	0.064 (0.024)***
HS HS 1	0.021 (0.015)	0.027 (0.017)	0.045 (0.017)***	0.030 (0.017)*	0.014 (0.015)
EEZ FSM 1	0.018 (0.033)	-0.015 (0.025)	0.000 (0.037)	0.012 (0.025)	-0.001 (0.021)
EEZ MHL 1	0.037 (0.022)	0.025 (0.010)**	-0.006 (0.009)	0.052 (0.032)	-0.000 (0.006)
EEZ NRU 1	0.046 (0.021)**	0.044 (0.020)**	0.003 (0.017)	0.033 (0.015)**	0.050 (0.025)**
EEZ PNG 2	0.196 (0.072)***	-0.106 (0.041)***	-0.132 (0.043)***	-0.064 (0.048)	0.001 (0.049)
EEZ SLB 1	0.083 (0.056)	-0.019 (0.032)	-0.009 (0.038)	0.081 (0.053)	0.076 (0.046)*
EEZ TUV 1	-0.055 (0.037)	-0.033 (0.040)	-0.063 (0.037)*	0.018 (0.046)	-0.026 (0.038)
HS COK 1	-0.003 (0.008)	-0.004 (0.008)	-0.003 (0.011)	-0.007 (0.008)	-0.003 (0.008)

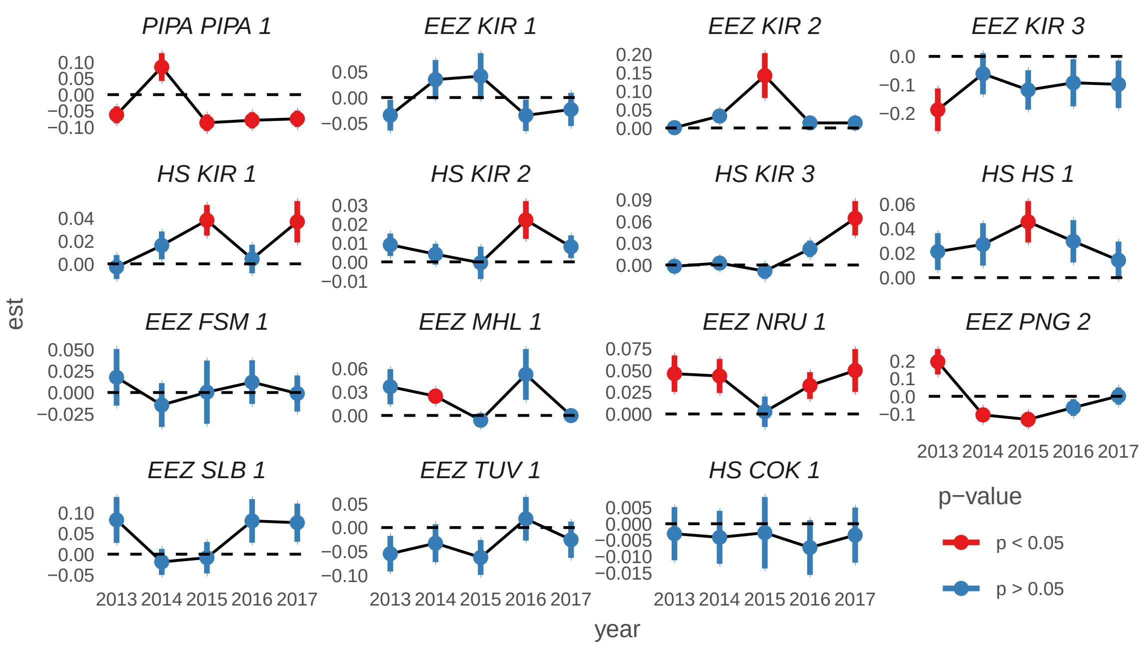

Figure 8: Coefficient estimates for the redistribution regression. Each pannel shows the region-specific coefficients, with heteroskedastick-robust standard errors as error bars. The horizontal dashed line represents 0 chenge relative to the 2012 region-specific levels.

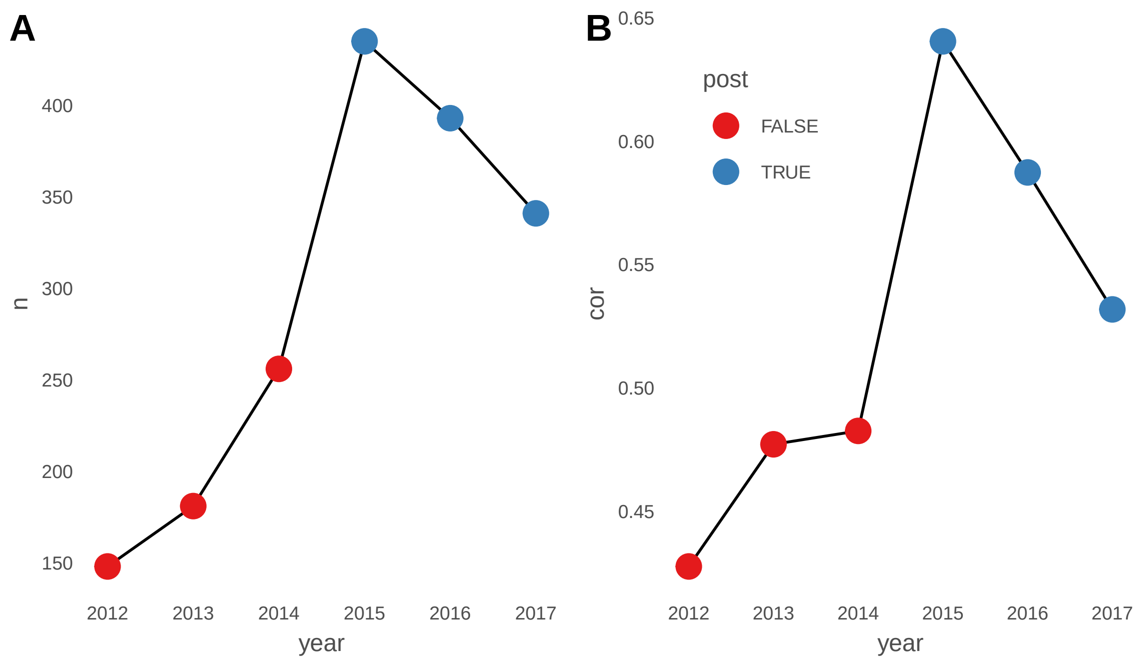

Figure 9: Number of cells that had treated and control vessels (A) and spatial correlation in the presence-absence of treated and control vessels per cell (B).

5 Discussion

Our findings provide interesting insights into the effect that LSMPAs can have on vessel behavior and the redistribution of fishing effort. These collection of results show that the implementation of PIPA had little effect on the effort exerted by purse seiners. However, regions adjacent to PIPA show an increase in the relative amount of fishing effort, suggesting that effort is simply redisplaced to closeby areas. This does not imply that there is more fishing effort exerted by treated vessels, but rather that each region receives a greater portion of the post-PIPA fishing effort of these same vessels, which is lower than pre-PIPA levels. Additionally, we show that post-PIPA there is a concentration of effort leading to crowding. In this section we discuss the implications of vessel-level reductions in fishing effort and the increase in relative allocation of the remaining effort through space. We also provide plausible explanations as to why purse seiners seem to be more reactive to the spatial closure.

Previous studies on insular environments suggest that vessels move to distant places, which might be translated as increased costs (Stevenson et al., 2013). Nevertheless, they do not use counterfactuals that could help account for system- or fleet-level changes that occur through time. Others have used similar satellite-tracking systems to show that fishing effort accumulates near the edges of spatial closures, yielding greater catches (Murawski et al., 2005). Yet, these vessel tracks do not cover the pre-reserve period, making it difficult identify the contribution of spatial closures to the observed spatial distribution of fishing vessels. Recent work by Elahi et al. (2018) identified that total fishing effort in a focal region where a short-term MPA was implemented showed little change, likely indicating that fishers redistributed fishing effort to compensate for the reduction in available space. Our data, which is assembled in a similar way, allows us to make similar inferences about the unobserved change in aggregate fishing effort and its spatial redistribution.

The role of the institutions at play is evident. Vessels that fished inside PIPA before the implementation were, ultimately, fishing in I-Kiribati waters likely under a VDS license. Uppon the implementation, some of these redistribute to other areas of the I-Kiribat EEZ and the high seas for the year immediately after the closure. As stated before, it is reasonable for a vessel holding a license to fish in I-Kiribati waters to simply reallocate their effor to other parts of that EEZ. However, the shift to the high seas may not follow the same logic. Instead, it is possible that vessels that redistribute to the high seas were opperating in I-Kiribati illegally, and decide to reallocate in the high seas to continue fishing without a license. These patterns provide us with interesting insight sinto fishing behavior, which may become useful in tackling Illegal, Unreported and Unregulted (IUU) fisheries.

A major shortcoming of our analyses is that we do not observe catches or revenues, which ultimately are the factors that guide the decision making process of profit-maximizing agents. Therefore, it is difficult to know whether lack of change in fishing hours represents a positive or negative impact. An additional thing that we are yet to test is the changes in non-fishing hours sepnt at sea. It is plausible that fishing hours remain constant, but vessels have to increase search time. Upon being relocated, fishers may not identify the best fishing grounds as easily as before, and therefore invest a greater proportion of their time searching for their catch. Further analysis of temporal trends in non-fishing hours, as well as distance traveled should provide us with insights as to why fishers reduced fishing hours. However, the widespread footprint of the treated fleet may suggest that they are well aqquainted with the region (See Fig. 6), and its unlikely that they would need to learn or identify new fishing grounds.

Our work suggests that the implementation of LSMPAs has little impact on purse seiners fishng effort. We also show that fishing effort is redistributed to areas close by, and that this leads to a potentially negative crowding effect. A growing body of literature suggests that closing the high seas to all fishing could increase fishery yields and profitability of fisheries, with negligible costs to food security (White and Costello, 2014; Sumaila et al., 2015; Sala et al., 2018; Schiller et al., 2018). Such management interventions should consider how fishing effort will change in space and through time, and the ecological implications of this redistribution to ensure that fishing effort is not just displaced elsewhere, leading to overfishing in adjacent waters. While LSMPAs can provide a wide range of benefits, their implementation must be accompained with traditional fisheries management to maximize effectiveness.

6 Further work

- Distance traveled
- Non-fishing hours at sea
- Monthly crowdnes??
- Repeat raster exercise for Revillagigedo and other recently implemented LSMPAs. It would be great to have a pannel figure of 3 or 4 other LSMPAs that show wher effort was and where it went to generalize our results.
- John talked about this being relevant to Palau (their upcoming LSMPA). We might want to talk about where the vessels that are there would go.

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7 Appendix

7.1 Stream of data by vessel, group, and period

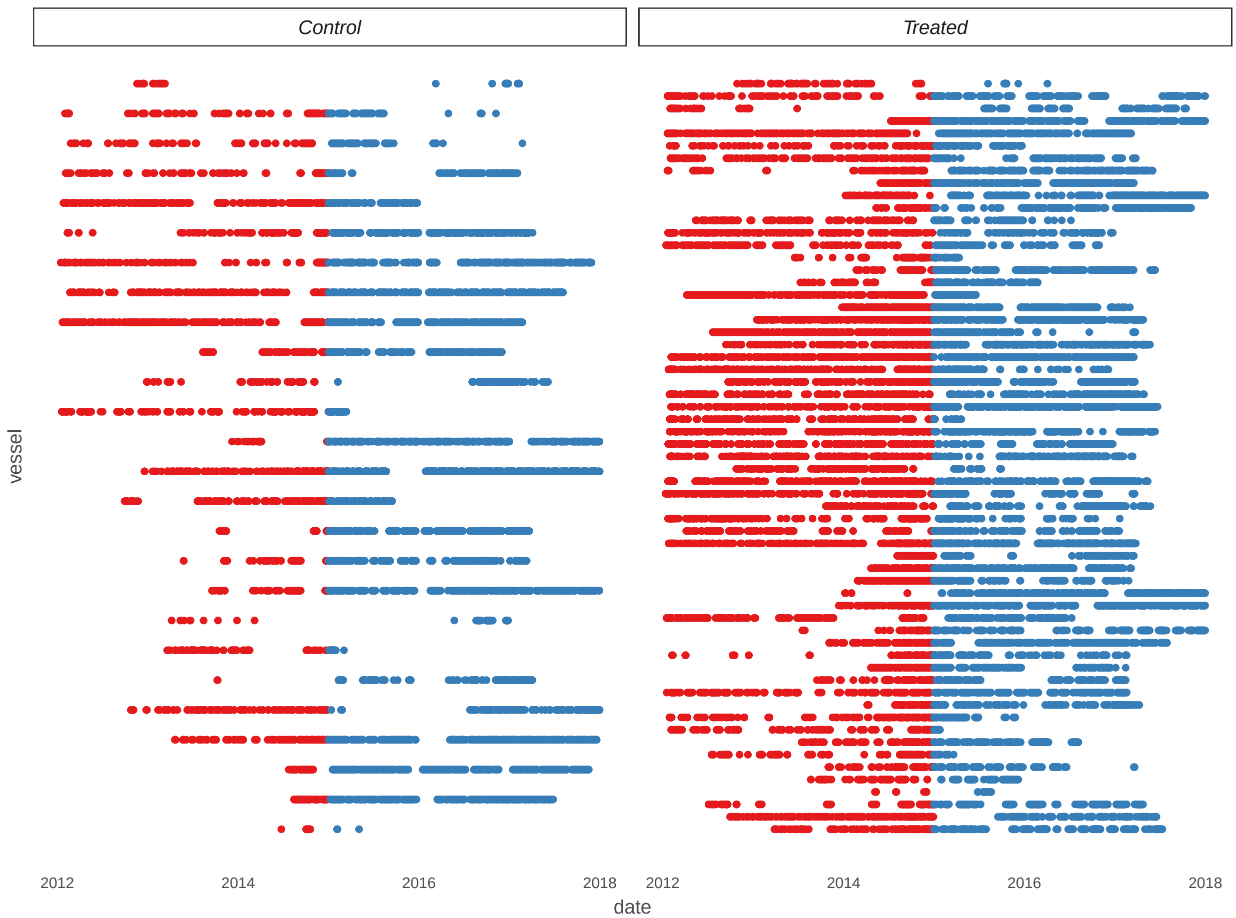

Figure S1: Stream of fishing events by vessels through time. Each line represents a vessel, with dots indicating months with fishing activity and colors indicating the pre and post periods.

7.2 Longliners

Longliners show a similar pattern of effort reduction. However, the magnitude of the β_3 coefficient is smaller (ranging from $\beta_3 = -0.98$ to $\beta_3 = -1.125$) and not significant unless including month and flag FEs for the general treatment-control groups, or when excluding Chinese vessels. This, along with higher standard error values suggest that longliners have a smaller and more variable response to the implementation of LSMPAs.

Table S1: Difference-in-differences estimates for 2 different controls and 3 different specifications. The first three columns use all data for controls. Columns 4 - 6 exclude Chinese vessels. Numbers in parentheses are heteroskedastic-robust standard errors.

	Dependent variable:					
	hours					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	39.192***	38.411***	36.520***	39.402***	38.636***	34.402***
	(0.095)	(0.132)	(0.169)	(0.102)	(0.140)	(0.236)
post	−1.014***	−0.189	0.710***	−1.400***	−0.574***	0.896***
	(0.143)	(0.145)	(0.158)	(0.163)	(0.165)	(0.186)
treated	2.544***	2.570***	2.724***	2.349***	2.391***	3.299***
	(0.101)	(0.101)	(0.121)	(0.110)	(0.110)	(0.135)
sate2	−0.495***	−1.488***	−0.898***	−0.561***	−1.497***	−1.015***
	(0.099)	(0.105)	(0.110)	(0.104)	(0.110)	(0.114)
sate3	−0.313**	−1.150***	0.050	−0.375***	−1.129***	0.001
	(0.129)	(0.132)	(0.143)	(0.134)	(0.138)	(0.149)
post:treated	0.098	0.056	−1.125***	0.532***	0.427***	−1.280***
	(0.134)	(0.134)	(0.148)	(0.149)	(0.149)	(0.171)
Control	All	All	All	-CHN	-CHN	-CHN
Month FE	No	Yes	Yes	No	Yes	Yes
Flag FE	No	No	Yes	No	No	Yes
Observations	227,873	227,873	217,467	209,135	209,135	198,729
R^2	0.010	0.016	0.022	0.010	0.016	0.023
Note:						*p<0.1; **p<0.05; ***p<0.01

7.3 Other model specifications for purse seiners

We include a second degree polynomial for years as:

$$y_{i,t} = \alpha + \beta_1 Post_t + \beta_2 Treat_i + \beta_3 Post_t \times Treat_i + \phi_t + \gamma_i + \omega Y_t + \Omega Y_t^2 + \epsilon_{i,t}$$

\begin{table}[!htbp] \caption{Fishing hours from GFW for purse_seiners. Asterisks indicate significance levels. Numbers in parentheses represent heteroskedastic-robust standard errors.}

	Dependent variable:			
	hours			
	(1)	(2)	(3)	(4)
post	8.394***	9.334***	14.934***	17.284***
	(0.267)	(0.254)	(0.312)	(0.403)
treated	−1.069***	−0.770***	−0.993***	0.259
	(0.249)	(0.234)	(0.219)	(0.269)
post:treated	−0.701**	−0.899***	−0.530*	−0.580**
	(0.308)	(0.295)	(0.283)	(0.292)
Constant	11.738***	11.281***	7.574***	10.077***
	(0.220)	(0.292)	(0.318)	(0.422)
Month FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Flag FE	No	No	No	Yes
Observations	37,840	37,840	37,840	37,840
R^2	0.087	0.136	0.179	0.192
Note:				*p<0.1; **p<0.05; ***p<0.01

\end{table}

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7.3.1 Quarterly DID interactions

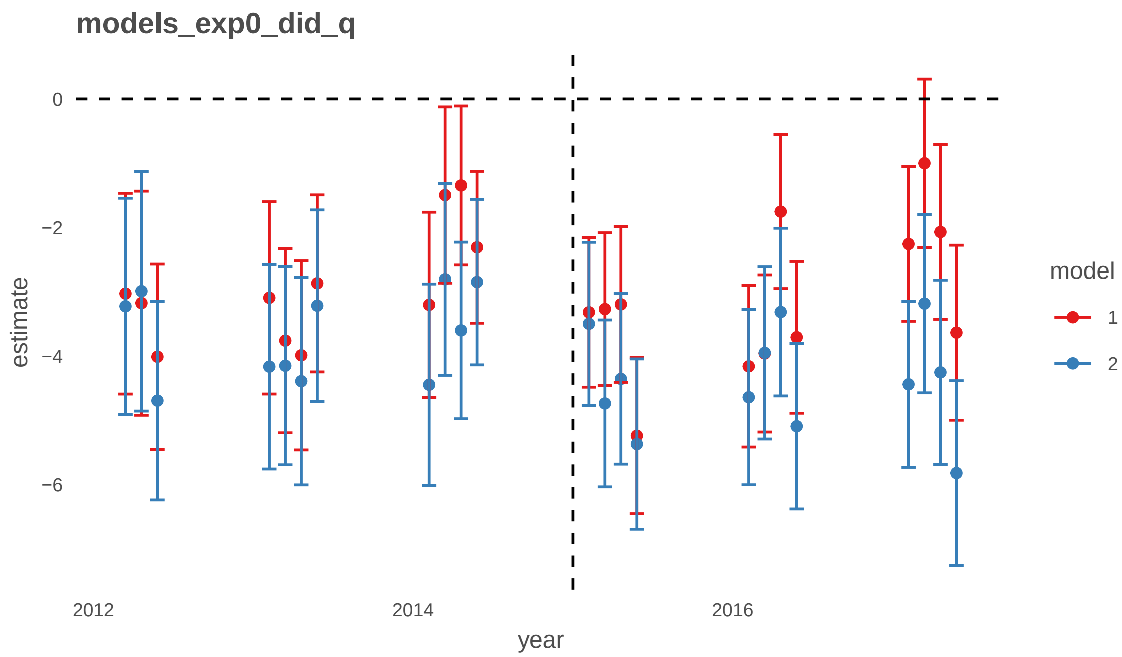

Figure S2: Interaction of quarters and treatment. Control group is all vessels.

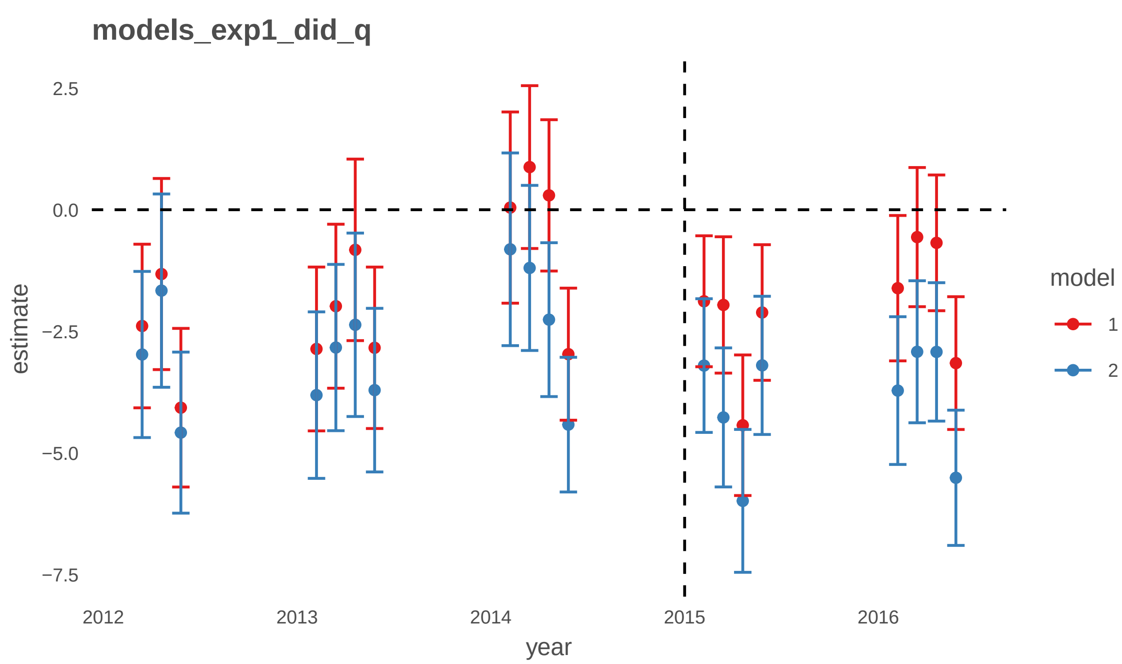

Figure S3: Interaction of quarters and treatment. Control group is vessels from PNA.

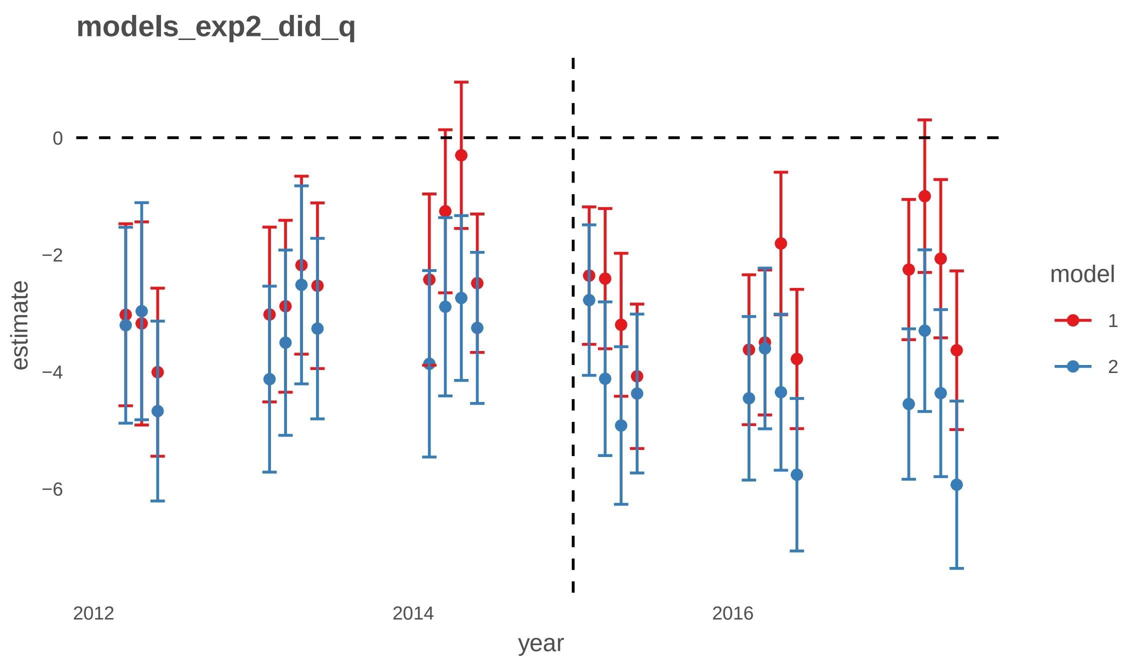

Figure S4: Interaction of quarters and treatment. Control group excludes Chinese vessels.

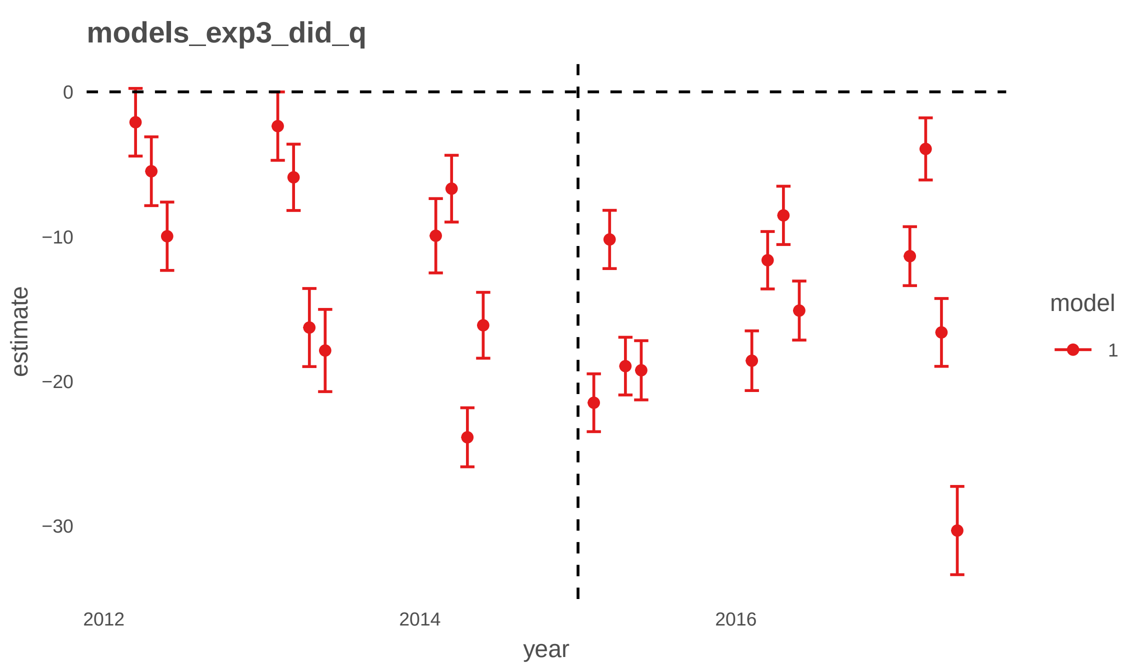

Figure S5: Interaction of quarters and treatment. Control group is japanese vessels.

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7.3.2 Year-month DID interactions

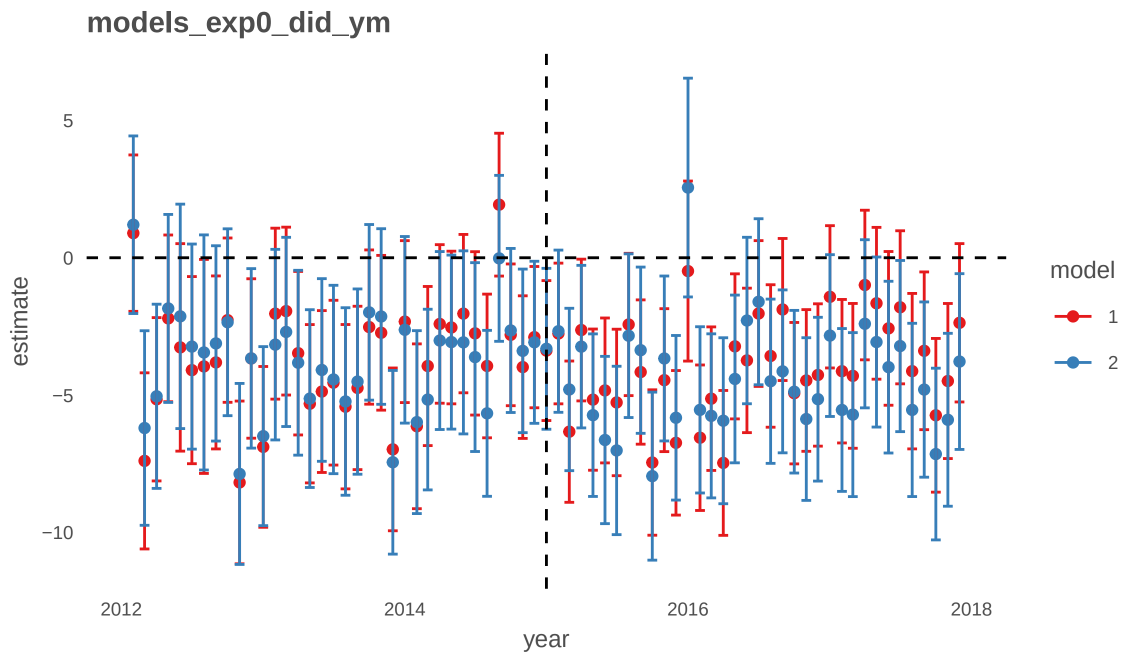

Figure S6: Interaction of year-month and treatment. Control group is all vessels.

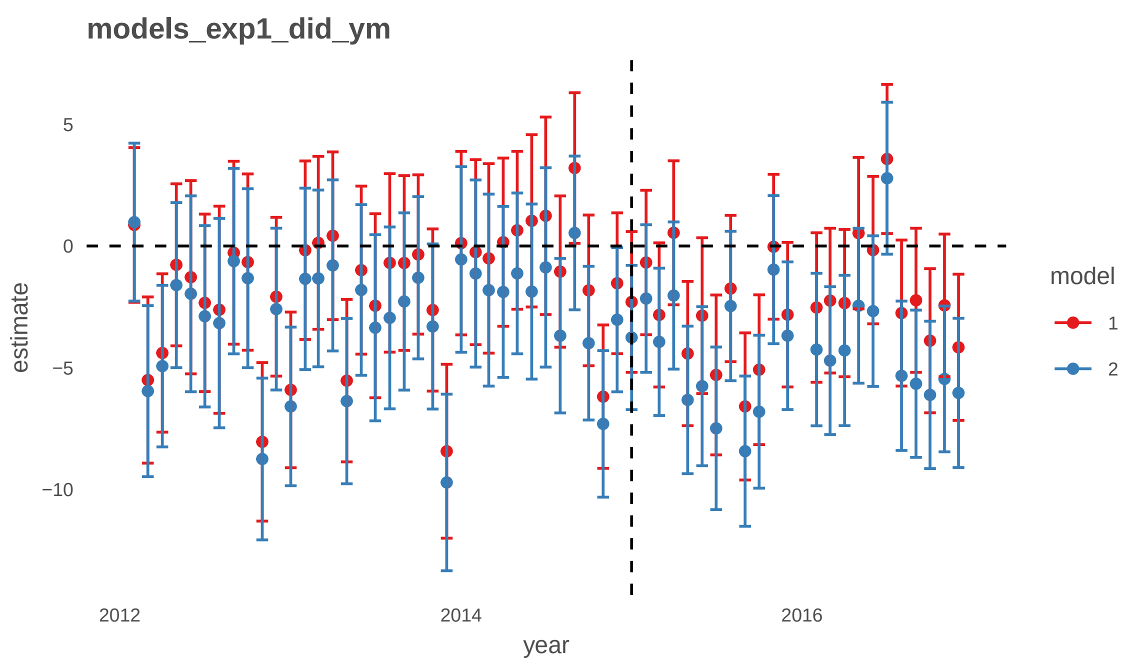

Figure S7: Interaction of year-month and treatment. Control group is vessels from PNA.

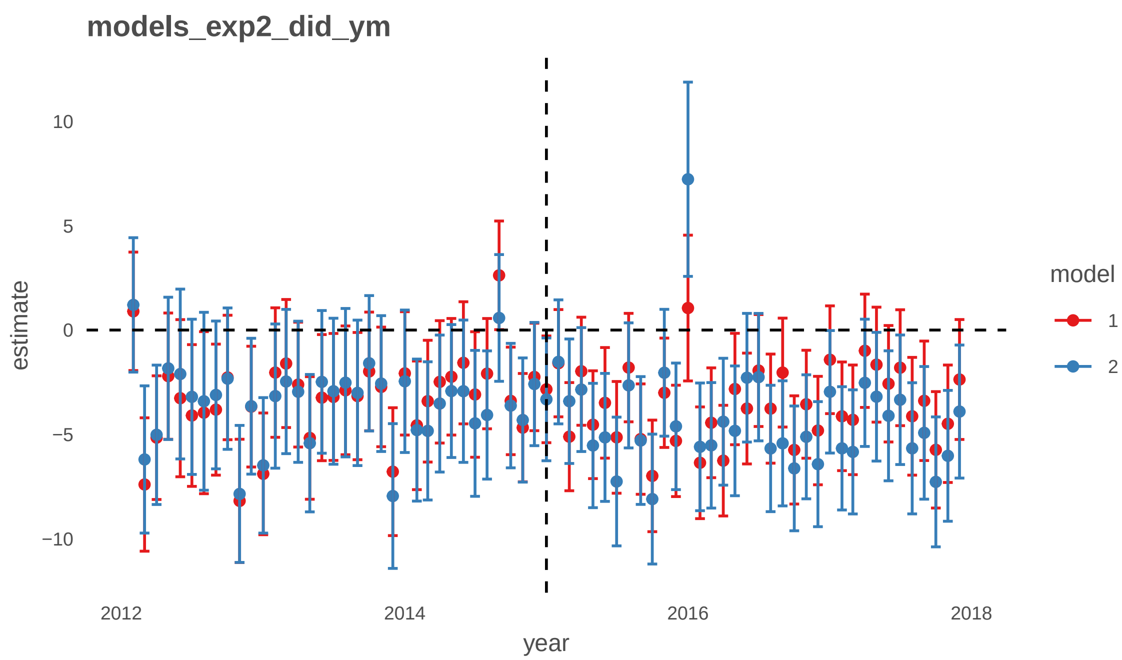

Figure S8: Interaction of year-month and treatment. Control group excludes Chinese vessels.

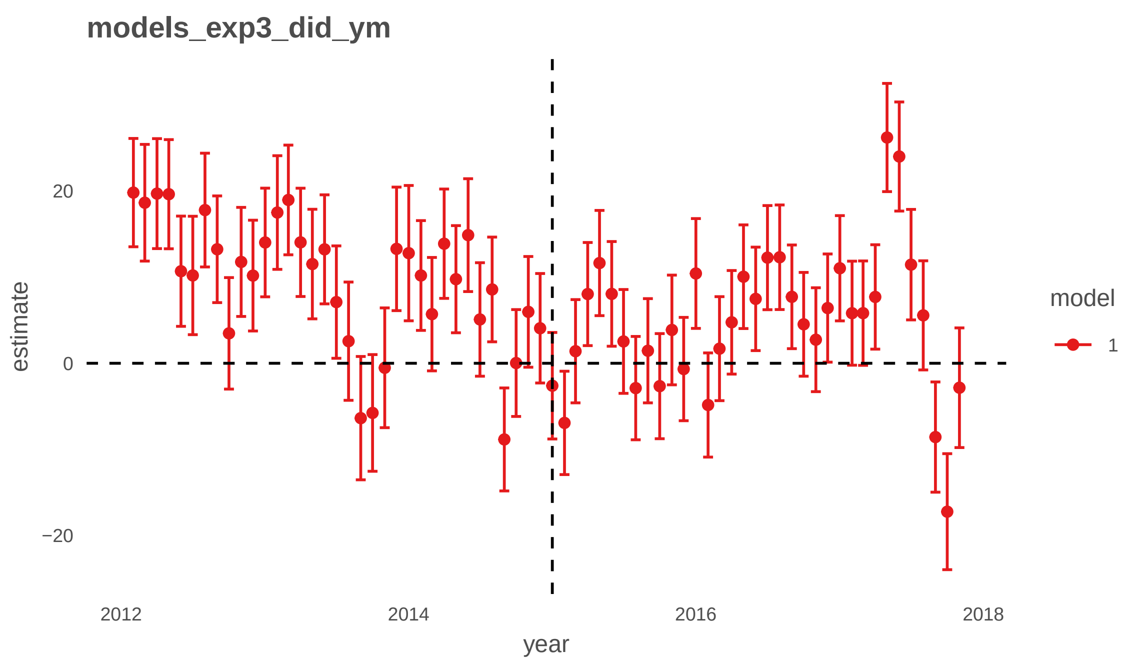

Figure S9: Interaction of year-month and treatment. Control group is japanese vessels.

7.4 Effort redistribution

7.5 Rasterized regions

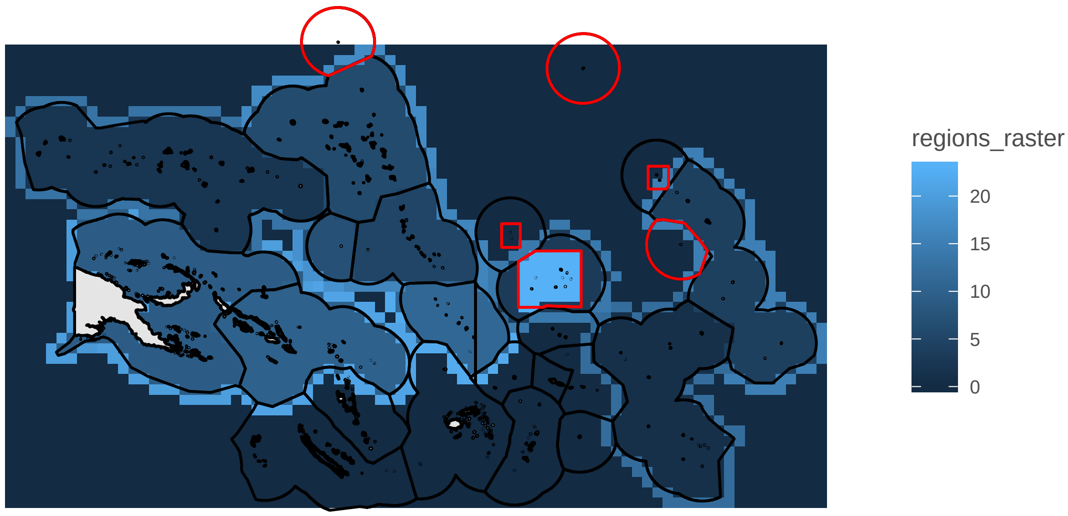

Figure S10: Rasterized regions. Each color (number) indicates a distinct region.

7.5.1 Fishing raster

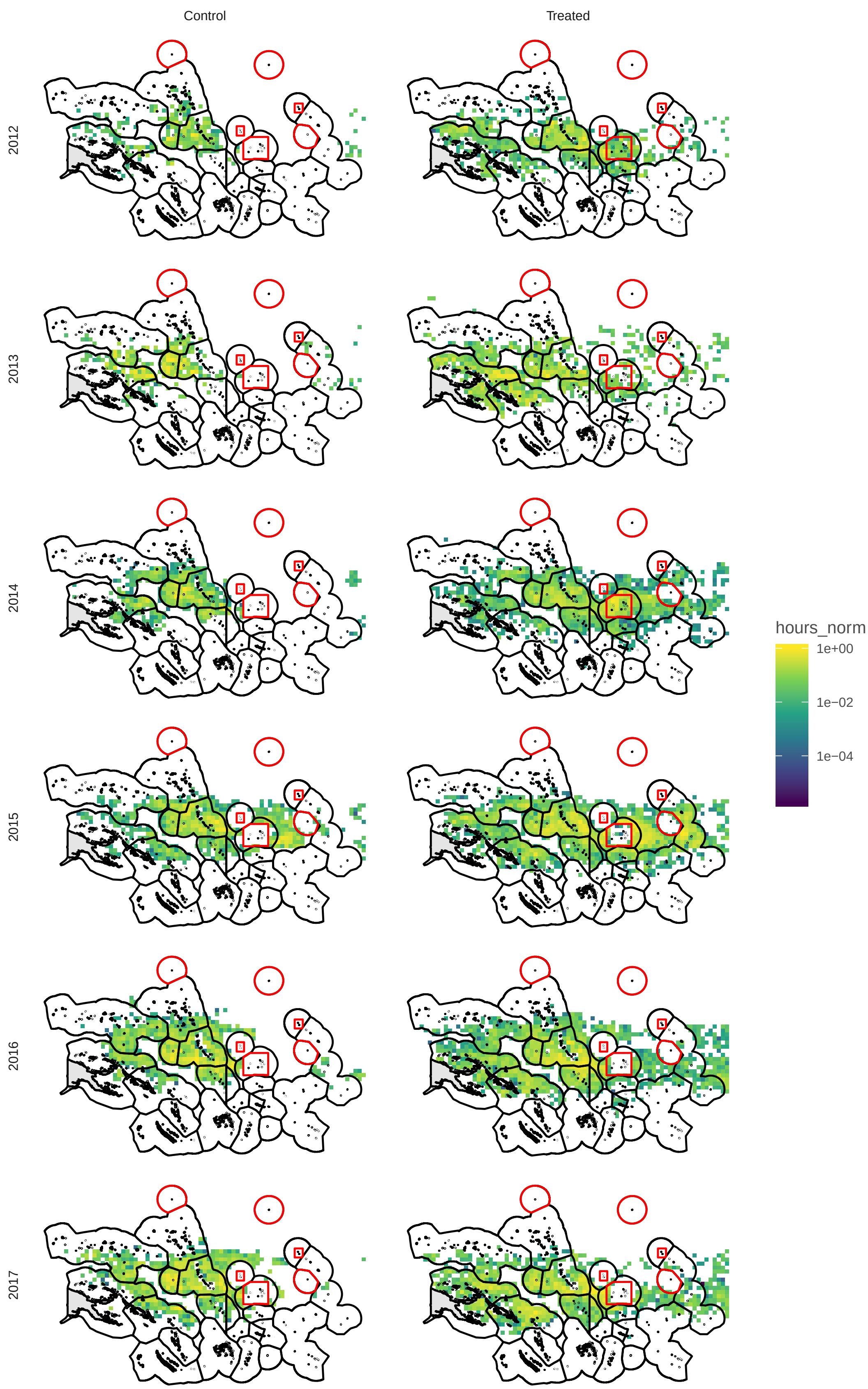

Figure S11: Yearly rasters of fishing hours for each group.