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, and include increases in abundance, biomass, and diversity within the bounded regions. These no-take zones may produce spillover effects, which provide fish for outside areas. However, the economic and ecological implications of displacing fishing effort are not yet fully understood. Novel data products that track fishing effort at the vessel-level allow us to identify changes in fleet- and vessel-level behavior upon the implementation of protected areas, as well as how these redistribute. This papers evaluates the implications of implementing LSMPA, by evaluating changes in fishing hours, showing that vessels in the effected region reduce fishing effort after the implementation of PIPA. Our results are robust to a set of specifications. We also track the relative spatial allocation of fishing events thorugh time, and identify that areas closer to PIPA show an increase in relative fishing hourse due to the displacement of PIPA-fishing vessels. 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.

Introduction

Marine Protected Areas (MPAs) are intended to safeguard parts of the ocean from extractive activities such as fishing. Current international goals aim to "effectively 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, **?**]. A significant part of this rapid increase can be attributed to the designation of a small number of Large Scale Marine Protected Areas [LSMPAs; [Gray et al., 2017]]. These are defined as MPAS with at least 250,000 km^2 in extension [Toonen et al., 2013], and are often implemented in the pelagic environment, where the dominant human activity is industrial fishing [Gray et al., 2017].

Due to weak property rights, limited habitat transformation, and potentially lower management costs, pelagic MPAs provide a great opportunity to safeguard the oceans Game et al. [2009][^d]. A growing body of literature has also shown that closing the high seas to all fishing -effectively, turning them into a LSMPA- could increase fishery yields and profitability of fisheries, without negligible costs to food security [White and Costello, 2014, Sumaila et al., 2015, Sala et al., 2018, Schiller et al., 2018]. However, as with customary MPAs, it is important that we understand the socioeconomic implications of management interventions.

Given the relatively recent establishment of most LSMPAs, very little is known about their human dimensions and implication for fisheries [Gray et al., 2017]. LSMPAs were erroneously assumed to have little social implications due to their remoteness [Agardy et al., 2011, Gray et al., 2017]. However, the anticipation of a LSMPA can lead to preemptive overfishing, which can erode or delay the expected benefits of the intervention [McDermott et al., 2018]. LSMPAs have received great attention in terms of governance and enforcement, but are yet to be the focus of economic analyses [Gray et al., 2017]. For example, McDermott et al. [2018] show that fishing effort within the Phoenix Islands Marine Protected Area (PIPA) is effectively reduced after implementation, and describe changes in fishing behavior pre-implementation. Cabral et al. [2017] analyse the redistribution of fishing and non-fishing vessels following the implementation of MPAs in California, and find that responses are idiosyncratic; commercial dive boats follow a fishing-the-line pattern, while some fishing boats follow an ideal free distribution. The way in which fishers react to a spatial closure can have major implications in its outcome [Hilborn et al., 2006, **?**, **?**]. This highlights the need to understand how fishers react to the implementation of a LSMPA, and fishing effort changes and is spatially redistributed.

The main objective of this paper is to identify how fishers adapt to the implementation of LSMPAs. We combine novel vessel tracking technologies and causal inference techniques to identify behavioral changes of fishing vessels due to the implementation of PIPA. We focus on fishing hours and distance traveled as outcome variables that fishers might adjust following implementation of a LSMPA in an impact-evaluation fashion. Additionally, we evaluate the spatial redistribution of fishing effort that existed within PIPA before its implementation. This work provides novel empirical insights into fisher's responses to the implementation of LSMPAs, and can help guide future interventions.

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[1]. Alongside, we describe the subset of data that we use for these 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.

[1] Global Fishing Watch: globalfishingwatch.org

Data

Automatic Identification Systems are on-board devices intended to provide at-sea safety and prevent ship collisions by broadcasting vessel position, course, and activities to surrounding vessels. These broadcasted messages can be received by satellites and land-based antennas. GFW uses a neural network 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]. Our data contain information for 2012 - 2017. The recent addition of satellites that can receive AIS signals causes an apparent increase in the number of broadcasted AIS messages (*i.e.* points), and therefore number of vessels and fishing hours. The variability in AIS data and ocean conditions require that temporal trends be taken into account. We do that by obtaining 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 data contain over 45 million individual AIS messages (*i.e.* positions) for 371 purse seiners and longliners. A total of 233 vessels have fished within PIPA waters; 217 did so at least once before 2015. However, not all vessels continued to fish elsewhere after PIPA implementation: 34 vessels have no recorded AIS messages after 2015[2], leaving us with 176 vessels that fished inside PIPA before its implementation, and continued to fish elsewhere afterward. New vessels might have also entered the fishery after PIPA closure, and were likely not exposed to the policy intervention in the pre-treatment period. To account for this, we identify a subset of vessels which we track since before the implementation of PIPA, and categorize them as treated or control vessels. Our treatment and control groups are defined as follows.

The treatment group contains all vessels (n = 176) that fished within PIPA at least once before the closure, and that continued to fish elsewhere afterwards. Vessels in the control group meet all three of the following conditions: i) vessels never fished within PIPA waters, ii) vessels belong to other PNA countries, and iii) vessels have fished in surrounding areas (*i.e.* PNA-countries' EEZ) before and after PIPA closure. For each vessel meeting these characteristics, we calculate their total monthly fishing hours. Figure 1 provides a visual representation of the vessel-level fishing events that make up each group through time. Table 1 shows the number of vessels following a BACI design, as well as the fishing hours, before and after PIPA.

[2] The 34 missing vessels might have exited the fishery, been decommissioned or sold (therefore changing their AIS and mmsi), or turned off their AIS transmitters. In either case, we are not able to observe these.

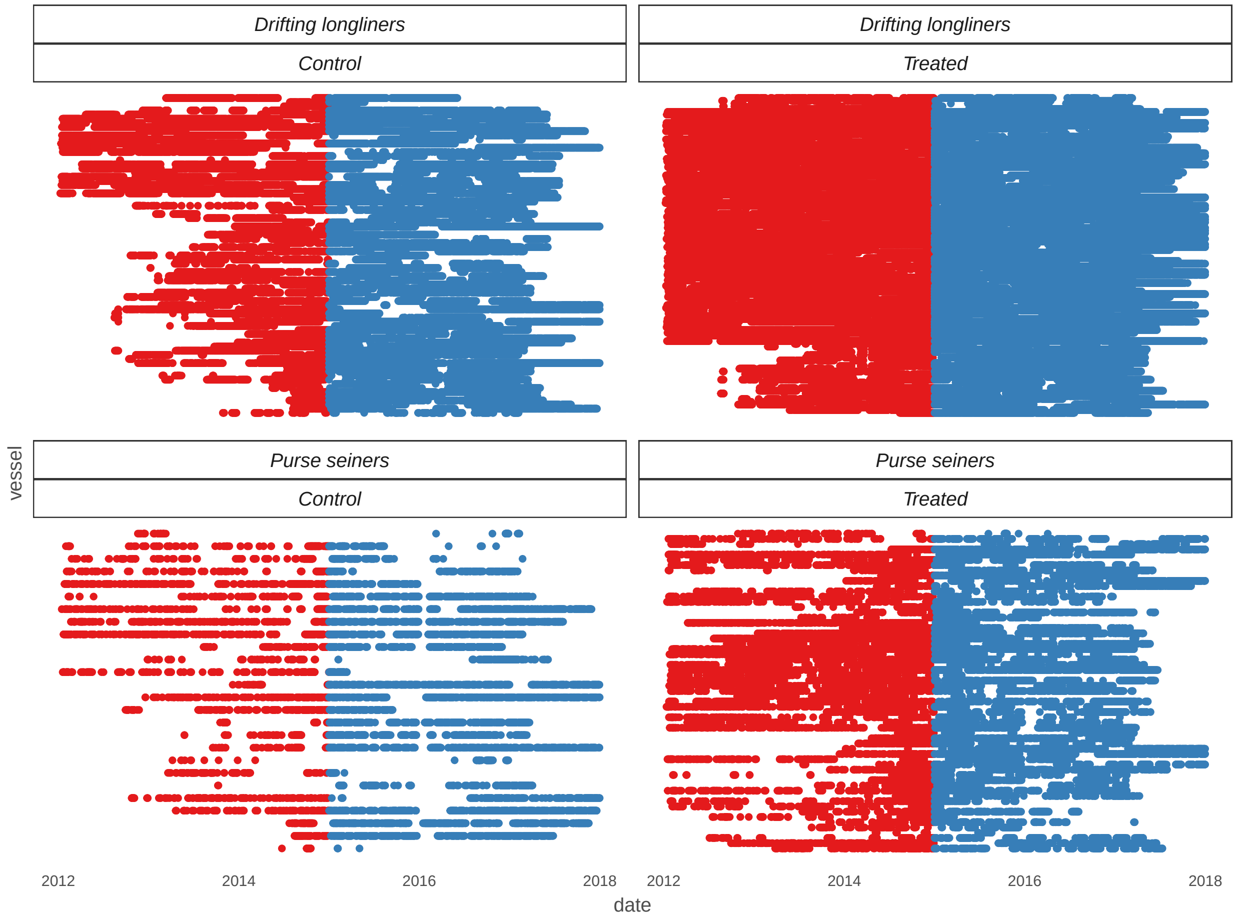


Figure 1: Stream of fishing events by vessels through time. Each line represents a vessel, with dots indicating months with fishing activity and colors indicating the pre and post periods.

Table 1: Number of fishing vessels and fishing hours by gear and treatment group before and after PIPA.

Gear	Treatment	n	Before	After	Change (A / B)
drifting_longlines	FALSE	77	39.03181	37.79044	0.9681958
drifting_longlines	TRUE	115	41.62659	40.43857	0.9714600
purse_seines	FALSE	26	11.73804	20.13247	1.7151474
purse_seines	TRUE	61	10.66939	18.36289	1.7210820

Analysis

The first analysis focuses on identifying the response of fishing vessels to PIPA closure. Our variables of interests are fishing effort, indicated by total fishing hours per month, and distance traveled (Km) on every fishing trip. We compare fishing hours[3] before and after the implementation of PIPA using a Difference-in-Differences approach, where we track the variable of interest for vessels that used to fish inside PIPA and vessels that never fished inside PIPA, before and after PIPA implementation. Our specification is the following:

$$y_{i,t} = \alpha + \beta_1 Post_t + \beta_2 Treat_i + \beta_3 Post_t \times Treat_i + \mu_1 Y_t + \mu_2 Y_t^2 + \phi_t + \gamma_i + \epsilon_{i,t}$$

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, μ_1 and μ_2 are coefficients for a second order polynomial for years (Y_t), while ϕ_t and γ_i represent month-, and flag-level dummies that account for seasonality or country-level management interventions[4].

Our second part of the analyses focuses on the redistribution of fishing effort. In other words, identifying where do vessels that used to fish inside PIPA go after its establishment. We calculate the monthly relative distribution of fishing hours by all treated vessels across all fished EEZs and the high seas. These trends are shown in Figure 3, and the relative temporal change is presented in Table **??**. EEZs that had sporadic fishing events were pooled into a group of "others", leaving us with a total of n = 23 and n = 0[5] spatially defined regions (*i.e.* EEZs, High Seas, "other EEZs", and PIPA) for purse seiners and longliners, respectively.

To evaluate this change in effort allocation, we regress our variable of interest (*i.e.*fishing hours) on the interaction between a dummy variable indicating the policy intervention and a dummy variable for countries. This gives us the by-country change in proportional allocation of fishing effort:

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

Our variable of interest, $y_{i,t}$ represents the proportion of fishing hours that country i receives at time t. *Post* also represents a policy dummy that takes the value of 0 for all dates before implementation of PIPA, and 1 otherwise. *Country* is a dummy variable for countries,

[3] And soon, distance

[4] An earlier specification included years as a dummy variable. Such results are included in the appendix, but are similar to the ones found under current specification.

[5] This number is likely to change upon finalizing the spatial analysis of longliners, which is currently running.

interpreted as individual EEZs, the high seas, and a group of "other EEZs". Our parameter of interest is $\beta_{3,i}$, which captures the country-level change in proportional fishing effort.

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 [?]. Raw data and code used in this work are available on github.

Results

Our data suggest that purse seiners and longliners have different responses to the implementation of a Large-Scale Marine Protected Areas. Fig. 2 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. The pattern closely corresponds with the increase in total hours, but the total number of vessels doesn't entirely follow this pattern. The increase in fishing hours might be caused by the increased number of satellites[6]. Longliners, however, show no apparent trend with a clear seasonality [Ortuño-Crespo et al., 2018]. The number of mmsi codes also increases slightly through time, but becomes stable after 2015. For both gears and across all measures, the treatment and control vessels follow similar patterns, confirming our claim that the control group provides a plausible counterfactual.

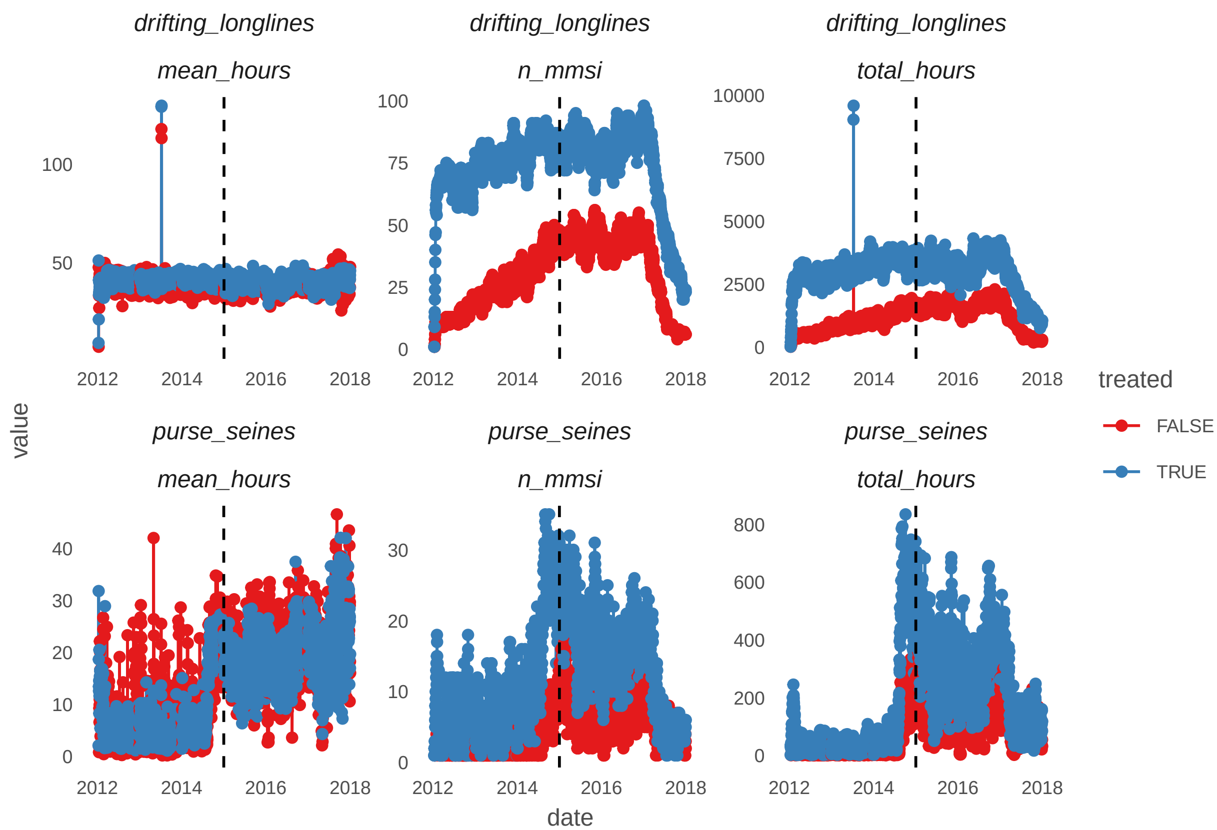


Figure 2: Fishing hours and number of vessels by month for all vessels. Vertical dashed line indicates PIPA closure.

Our DiD analysis shows that treated purse seiners reduce their fishing effort after PIPA

[6]Need to check this. Not sure any satellites were incorporated during 2014. It is also possible that PNA countries started enforcing the requirement of having an AIS unit. On either case, both treatment and control groups seem to be affected equally.

implementation in the order of 16 hours per month. This result is robust and significant ($p < 0.05$) for all model specifications, with the effect varying between $\beta_3 = -16.457$ and $\beta_3 = -18.709$. Model specifications that include the year polynomial show lower values for the β_1 coefficient associated to the $Post_t$ policy dummy, and show positive and negative values for μ_1 and μ_2, the linear and quadratic terms for Y_t, respectively. These effectively represent the patterns observed in Figure 2.

Longliners show a similar pattern of effort reduction. However, the magnitude of the β_3 coefficient is smaller (ranging from $\beta_3 = -9.851$ to $\beta_3 = -14.850$) and not significant across all model specifications. This, along with higher standard error values suggest that longliners have a smaller and more variable response to the implementation of LSMPAs.

Regressions coefficients for each gear type are shown in Tables **??** and 4. Column (1) presents the DiD regression with no fixed effects, column (2) includes month fixed effects, column (3) includes month and the second degree polynomial for years, and column (4) includes all of the above and country-level fixed effects.

Recall that to evaluate the redistribution of fishing effort we only track fishing vessels that belong to the treated group. In this case, we calculate the proportion of fishing effort allocated every month to each spatially explicit region outlined by EEZs and the high seas. For purse seiners, these represent 9 main EEZs, PIPA, the high seas, and a group of other EEZs. Figure 3 shows the monthly relative fishing hours that each region received by all 176 treated vessels. The top-left panel shows the change in fishing effort inside PIPA, including the preemptive fishing and immediate reduction previously reported [McDermott et al., 2018].

The change in the relative allocation of fishing effort by purse seiners increases in eight of the 12 regions after PIPA implementation (Table 2). The largest increase is observed for the I-Kiribati EEZ, with an average increase of 0.11 ($p < 0.001$). In other words, the redistribution of treated vessels caused a 10% increase in the *relative* allocation of fishing effort within I-Kiribati waters. The only decrease is observed for Papua New Guinea, but the coefficient is not significant. Figure 4 provides a spatial representation of these changes. It is evident that the increase in relative fishing effort is greater for for regions closer to PIPA.

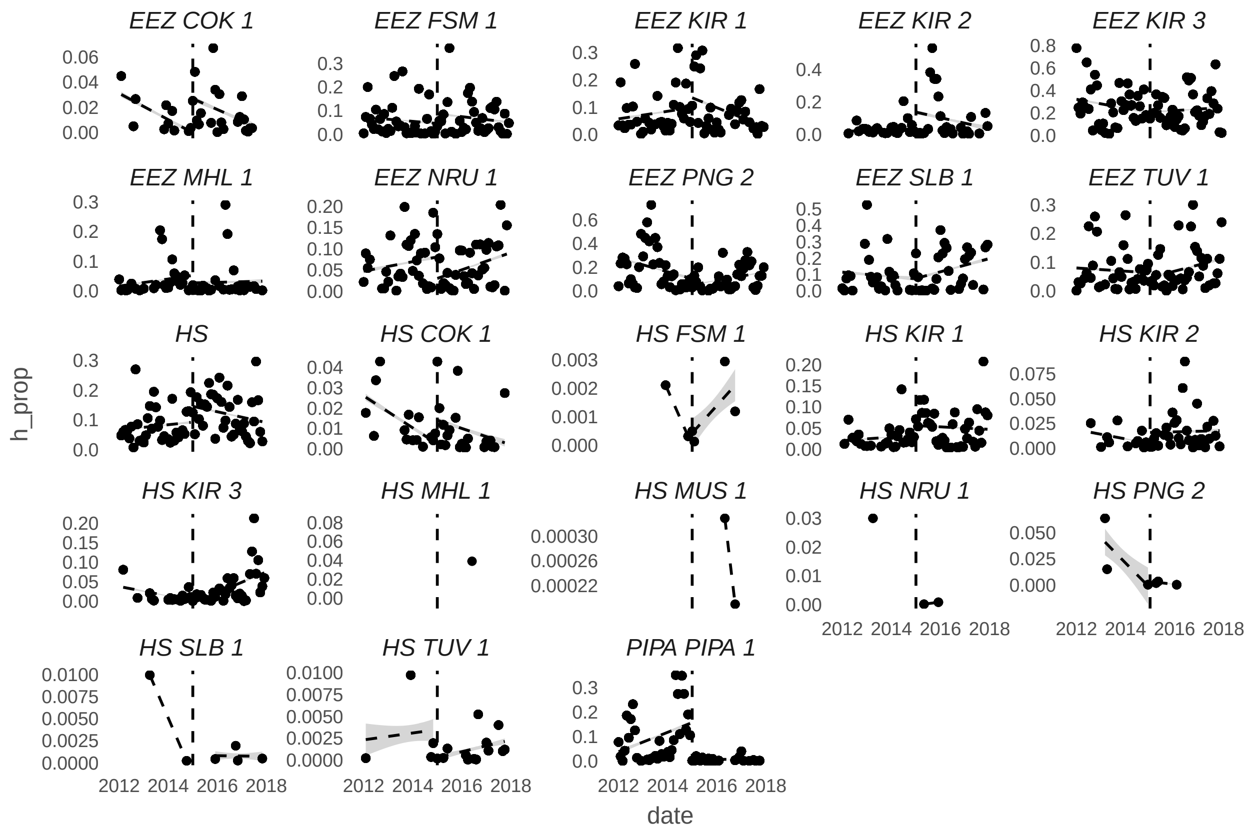


Figure 3: Monthly relative allocation of fishing effort by PIPA-fishing vessels before and after PIPA for 9 EEZs, PIPA, the high seas and ‘other EEZs’.

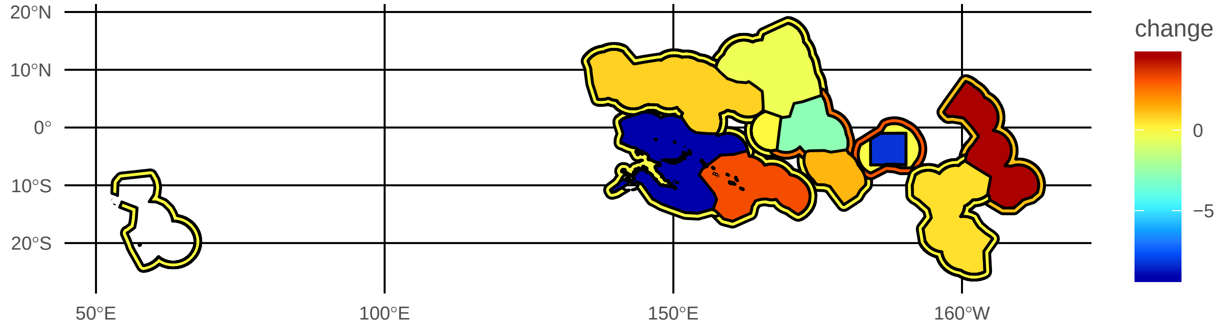


Figure 4: Spatial representation of the mean change in the monthly allocation of fishing effort for purse seiners.

Table 2: Change in the relative allocation of fishing hours by purse seiners for each region. Asterisks indicate significance levels. Numbers in parenthesis represent heteroskedastic-robust standard errors.

	Dependent variable:
	h_prop
post	0.005^{***} (0.001)
countryEEZ FSM 1	0.052^{***} (0.001)
countryEEZ KIR 1	0.067^{***} (0.002)
countryEEZ KIR 2	0.020^{***} (0.001)
countryEEZ KIR 3	0.250^{***} (0.003)
countryEEZ MHL 1	0.022^{***} (0.001)
countryEEZ NRU 1	0.049^{***} (0.001)
countryEEZ PNG 2	0.184^{***} (0.004)
countryEEZ SLB 1	0.062^{***} (0.002)
countryEEZ TUV 1	0.059^{***} (0.001)
countryHS	0.073^{***} (0.001)
countryHS COK 1	0.001^{***} (0.0004)
countryHS FSM 1	-0.004^{***} (0.0003)
countryHS KIR 1	0.015^{***} (0.001)
countryHS KIR 2	-0.001^{*} (0.0003)
countryHS KIR 3	0.002^{***} (0.0004)
countryHS MHL 1	-0.004^{***} (0.0003)
countryHS MUS 1	-0.004^{***} (0.0003)
countryHS NRU 1	-0.003^{***} (0.001)
countryHS PNG 2	-0.001^{*} (0.001)
countryHS SLB 1	-0.003^{***} (0.0003)
countryHS TUV 1	-0.003^{***} (0.0003)
countryPIPA PIPA 1	0.083^{***} (0.002)
post:countryEEZ FSM 1	0.003 (0.002)
post:countryEEZ KIR 1	-0.007^{***} (0.002)
post:countryEEZ KIR 2	0.040^{***} (0.003)
post:countryEEZ KIR 3	-0.033^{***} (0.005)
post:countryEEZ MHL 1	-0.010^{***} (0.002)
post:countryEEZ NRU 1	-0.005^{***} (0.002)
post:countryEEZ PNG 2	-0.096^{***} (0.004)
post:countryEEZ SLB 1	0.026^{***} (0.004)
post:countryEEZ TUV 1	0.007^{***} (0.002)
post:countryHS	0.034^{***} (0.002)
post:countryHS COK 1	-0.005^{***} (0.001)
post:countryHS FSM 1	-0.005^{***} (0.001)
post:countryHS KIR 1	0.024^{***} (0.001)
post:countryHS KIR 2	0.005^{***} (0.001)
post:countryHS KIR 3	0.020^{***} (0.001)
post:countryHS MHL 1	-0.004^{***} (0.001)
post:countryHS MUS 1	-0.005^{***} (0.001)
post:countryHS NRU 1	-0.006^{***} (0.001)
post:countryHS PNG 2	-0.007^{***} (0.001)
post:countryHS SLB 1	-0.006^{***} (0.001)

Discusion

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 shows that the implementation of PIPA caused treated vessels to reduce their fishing hours, and that this effect is greater for purse seiners than longliners. Even though treated vessels fish less, their relative allocation of fishing hours increased for all other fishing grounds. 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. 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.

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 the reduction in fishing effort represents a positive or negative impact. A decrease in fishing effort is associated to an increase in catches (and therefore greater CPUE) only when the entire fleet does it, and if previous levels of effort were greater than F_{MEY} (*i.e.* the effort that would yield the maximum economic yield). Therefore, it is plausible that the reduction of fishing hours is not done by choice, but rather results from fishers having 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.

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 is assembled in a similar way, with fishing positions before and after the implementation of PIPA and vessels grouped into treated and control groups. Our BACI design, along with our difference-in-differences analysis allows us to make causal inferences about the effect that large scale marine protected areas have on fishing effort.

The different responses observed between purse seiners and longliners might have two possible explanations. It is likely that PIPA did not contain habitat that longliners would consider optimal. Therefore, the sporadic fishing events that occurred there are of little importance to the fleet, and it is unlikely that the implementation of PIPA has an effect on them.

Alternatively, the differences may be due to the nature of each fishing gear. Purse seiners are often constrained by seafloor and termocline depth, and have a smaller spatial footprint [Kroodsma et al., 2018]. Tuna purse seiners are known to have greater proportion of null sets (*i.e.* where purse seines effectively cast their nets, but no catch is obtained) during El Niño years, where the termocline deepens in the Eastern Pacific [Dreyfus-Leon, 2015]. On the other hand, longliners may be more flexible as to where they can deploy their longlines. Ortuño-Crespo et al. [2018] evaluated the ecological niche of the pelagic longline fleet, and suggest that the fleet may be under-utilizing the ocean, meaning that they can easily redistribute elsewhere.

Our work suggests that the implementation of LSMPAs can have important implications for purse seiners, and less so for longliners. We also show that fishing effort is redistributed to areas close by. Future management interventions that aim to close large portion of the oceans 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.

Appendix

Other model specifications

Year as dummy variables

Table 3: Fishing hours from GFW for purse seiners (n = 106; 38 control, 68 treatment). Asterisks indicate significance levels. Numbers in parenthesis represent heteroskedastic-robuste 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			

```
## [[1]]
##
## Call:
## lm(formula = hours ~ post * treated, data = data)
##
## Coefficients:
##  (Intercept)          post       treated  post:treated
##      11.7380        8.3944       -1.0687       -0.7009
##
##
```

Table 4: Fishing hours from GFW for longliners (n = 203; 88 control, 115 treatment).. Asterisks indicate significance levels. Numbers in parenthesis represent heteroskedastic-robuste standard errors.

	Dependent variable:			
	hours			
	(1)	(2)	(3)	(4)
post	-1.241^{***}	-1.026^{***}	-0.944^{***}	13.292^{***}
	(0.116)	(0.116)	(0.157)	(0.330)
treated	2.595^{***}	2.708^{***}	2.639^{***}	1.493^{***}
	(0.101)	(0.101)	(0.102)	(0.116)
post:treated	0.053	-0.069	-0.029	-0.060
	(0.133)	(0.133)	(0.134)	(0.135)
Constant	39.032^{***}	38.105^{***}	38.388^{***}	36.993^{***}
	(0.089)	(0.131)	(0.150)	(0.178)
Month FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Flag FE	No	No	No	Yes
Observations	227,873	227,873	227,873	227,873
R^2	0.010	0.015	0.016	0.030
Note:				*p<0.1; **p<0.05; ***p<0.01

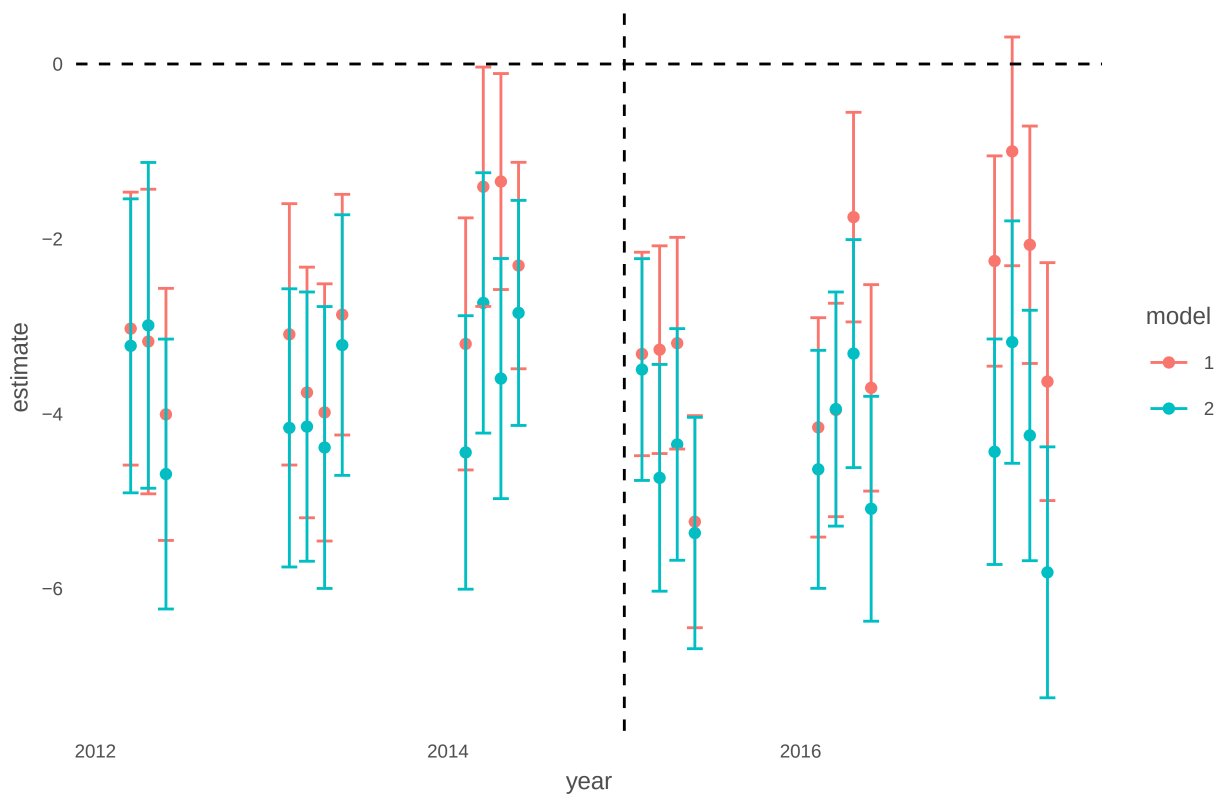
```
## [[2]]
##
## Call:
## lm(formula = hours ~ post * treated + month_c, data = data)
##
## Coefficients:
##  (Intercept)         post      treated    month_c10    month_c11
##      11.2808       9.3338      -0.7699       2.8855       3.6875
##    month_c12     month_c2     month_c3     month_c4     month_c5
##       3.0010      -0.9889      -2.2384      -3.6433      -4.5904
##     month_c6     month_c7     month_c8     month_c9  post:treated
##      -4.4198      -3.5805       0.3173       2.8648      -0.8990
##
##
## [[3]]
##
## Call:
## lm(formula = hours ~ post * treated + month_c + flag, data = flag_data)
##
## Coefficients:
##  (Intercept)         post      treated    month_c10    month_c11
##     13.94161      9.13865      0.04064      2.63902      3.55558
##    month_c12     month_c2     month_c3     month_c4     month_c5
##      2.59370     -1.06244     -2.41158     -4.00798     -4.91378
##     month_c6     month_c7     month_c8     month_c9      flagECU
##     -4.97737     -3.35106      0.20410      2.30467     -6.18817
##      flagESP      flagFSM      flagKOR      flagMHL      flagOTH
##     -2.94857     -4.72899     -3.70832     -1.87867     -2.24359
##      flagTWN  post:treated
##     -2.49301     -0.90817
## [[1]]
##
## Call:
## lm(formula = hours ~ post * treated, data = data)
##
## Coefficients:
##  (Intercept)         post      treated  post:treated
##     11.41504      8.22194     -0.01516      -2.01435
##
##
## [[2]]
##
## Call:
## lm(formula = hours ~ post * treated + month_c, data = data)
```

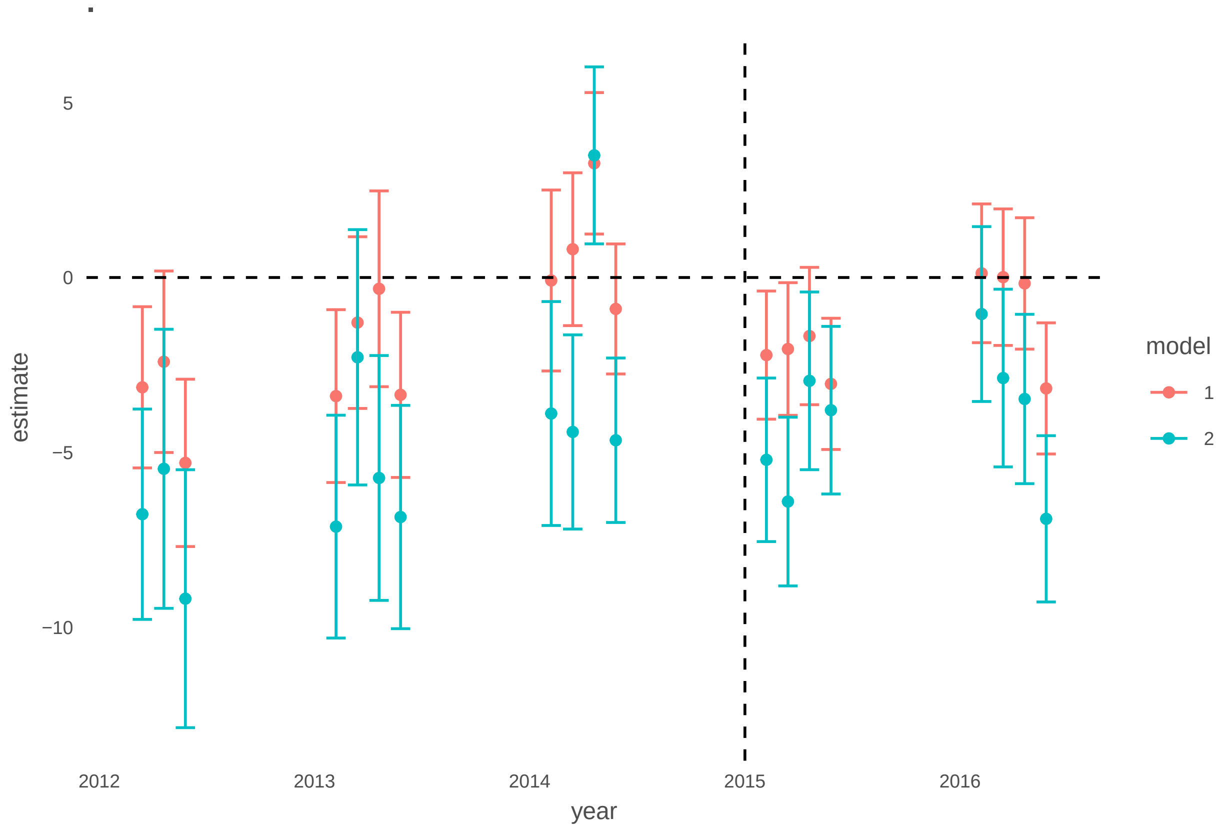
```
##
## Coefficients:
##  (Intercept)          post       treated     month_c10     month_c11
##      10.9718        8.6646        0.0589        3.1399        4.2030
##    month_c12      month_c2      month_c3      month_c4      month_c5
##       2.8778       -0.8801       -2.1805       -4.0561       -4.0234
##     month_c6      month_c7      month_c8      month_c9  post:treated
##      -4.7427       -4.4566        0.9716        4.9466       -2.0474
##
##
## [[3]]
##
## Call:
## lm(formula = hours ~ post * treated + month_c + flag, data = flag_data)
##
## Coefficients:
##  (Intercept)          post       treated     month_c10     month_c11
##        8.160         8.923         2.910         3.489         4.775
##    month_c12      month_c2      month_c3      month_c4      month_c5
##        3.087        -1.082        -1.776        -4.186        -4.108
##     month_c6      month_c7      month_c8      month_c9       flagMHL
##       -5.336        -4.115         1.249         4.322         2.969
## post:treated
##       -2.984
```

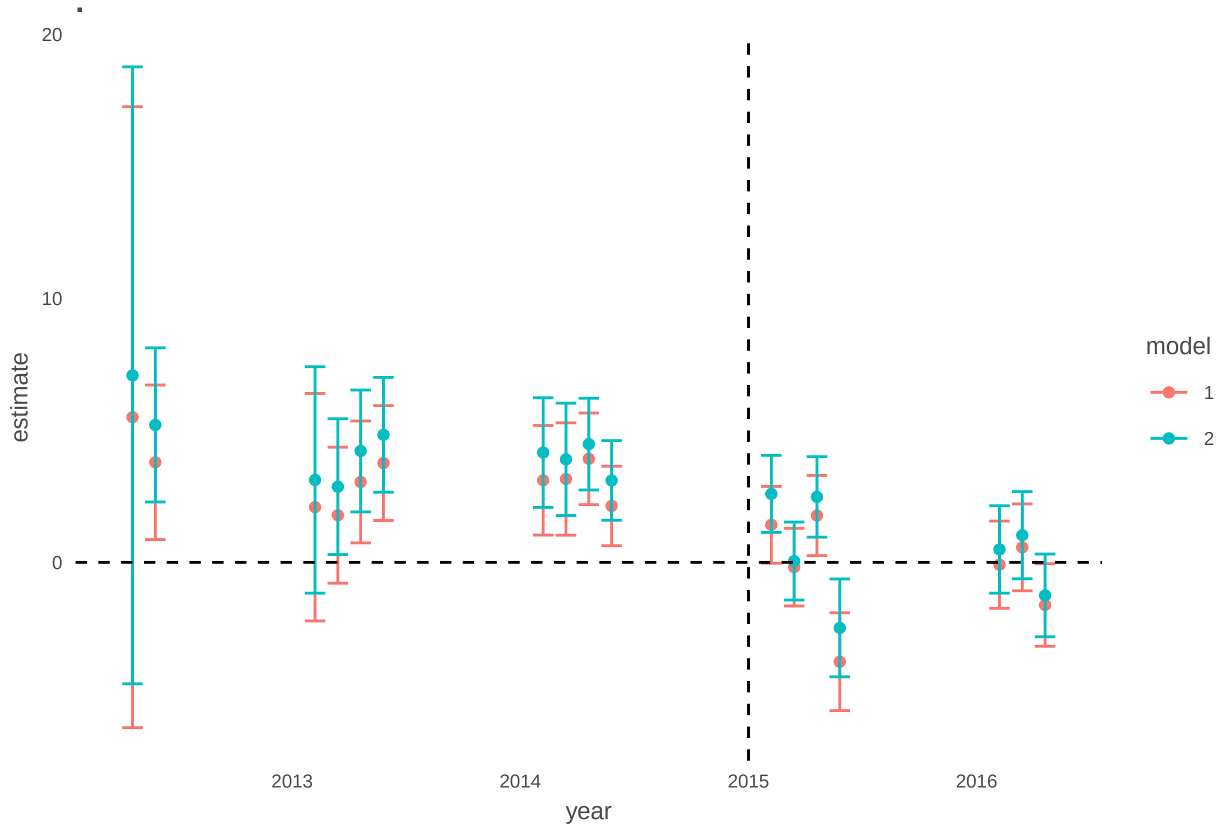
```
## [[1]]
##
## Call:
## lm(formula = hours ~ post * treated, data = data)
##
## Coefficients:
##  (Intercept)          post       treated  post:treated
##      11.1998        9.0182       -0.5304       -1.3247
##
##
## [[2]]
##
## Call:
## lm(formula = hours ~ post * treated + month_c, data = data)
##
## Coefficients:
##  (Intercept)          post       treated     month_c10     month_c11
##     10.74814      10.57403      -0.03924       2.43719       3.37646
##    month_c12      month_c2      month_c3      month_c4      month_c5
##      2.62526      -1.19664      -2.77934      -3.76747      -4.65285
```

```
##     month_c6      month_c7      month_c8      month_c9  post:treated
##     -4.79738      -3.64640       0.15290       3.15125      -2.13569
##
##
## [[3]]
##
## Call:
## lm(formula = hours ~ post * treated + month_c + flag, data = flag_data)
##
## Coefficients:
##  (Intercept)          post       treated     month_c10     month_c11
##      14.3391       10.4923        0.4295        2.2241        3.1505
##    month_c12      month_c2      month_c3      month_c4      month_c5
##       2.0719       -1.2564       -2.8501       -4.0129       -5.0320
##     month_c6      month_c7      month_c8      month_c9       flagECU
##      -5.3231       -3.4871       -0.2020        2.2869       -5.4622
##      flagESP       flagFSM       flagKOR       flagMHL       flagOTH
##      -3.3566       -1.4486       -4.2977       -2.3611       -3.3106
##      flagTWN  post:treated
##      -3.2657       -2.2534
## [[1]]
##
## Call:
## lm(formula = hours ~ post * treated, data = data)
##
## Coefficients:
##  (Intercept)          post       treated  post:treated
##      11.4202        7.8750       -0.7508       -0.1815
##
##
## [[2]]
##
## Call:
## lm(formula = hours ~ post * treated + month_c, data = data)
##
## Coefficients:
##  (Intercept)          post       treated     month_c10     month_c11
##      10.9725        8.7780       -0.4452        2.8476        3.6473
##    month_c12      month_c2      month_c3      month_c4      month_c5
##       3.0113       -1.1434       -2.4295       -3.5424       -4.4423
##     month_c6      month_c7      month_c8      month_c9  post:treated
##      -4.5243       -3.6704        0.2277        3.0019       -0.3310
##
##
```

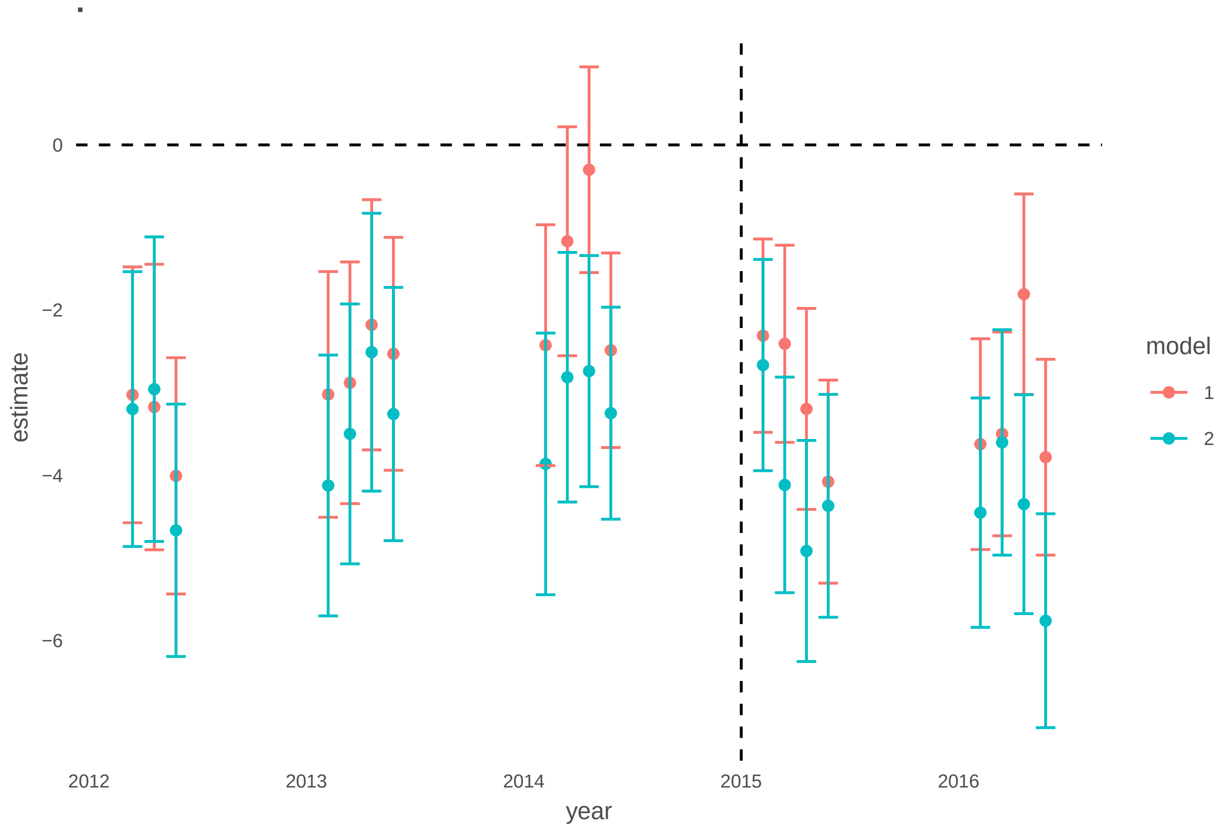
```
## [[3]]
##
## Call:
## lm(formula = hours ~ post * treated + month_c + flag, data = flag_data)
##
## Coefficients:
##  (Intercept)          post       treated     month_c10     month_c11
##    14.036151      8.770151      0.557241      2.444760      3.320156
##    month_c12      month_c2      month_c3      month_c4      month_c5
##     2.456643     -1.307835     -2.707138     -4.024565     -4.841901
##     month_c6      month_c7      month_c8      month_c9       flagECU
##    -5.275270     -3.545459      0.001697      2.319940     -6.396277
##      flagESP       flagFSM       flagKOR       flagMHL       flagOTH
##    -3.432356     -4.833825     -4.212230     -1.836510     -3.284000
##      flagTWN  post:treated
##    -2.637666     -0.454598
```



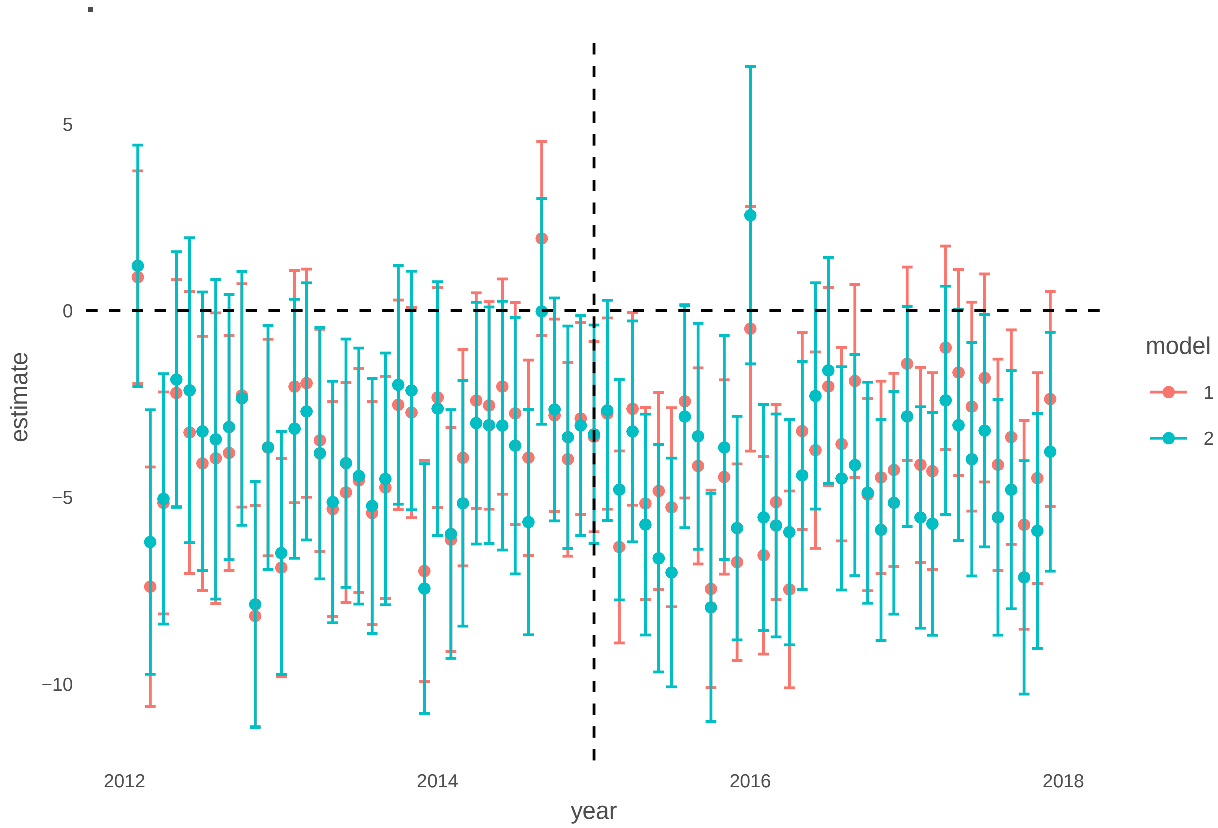

5
0
−5
−10
estimate
2012
2013
2014
2015
2016
year
model
1
2



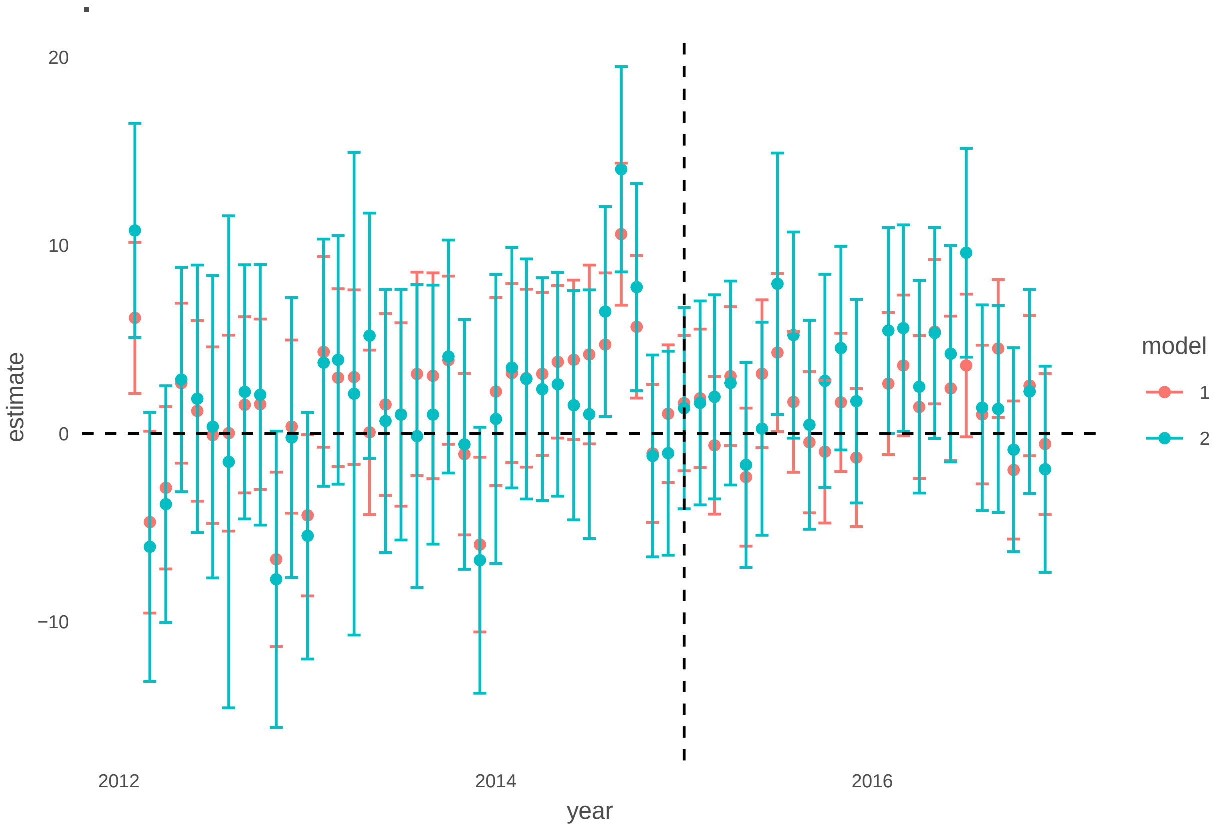
400



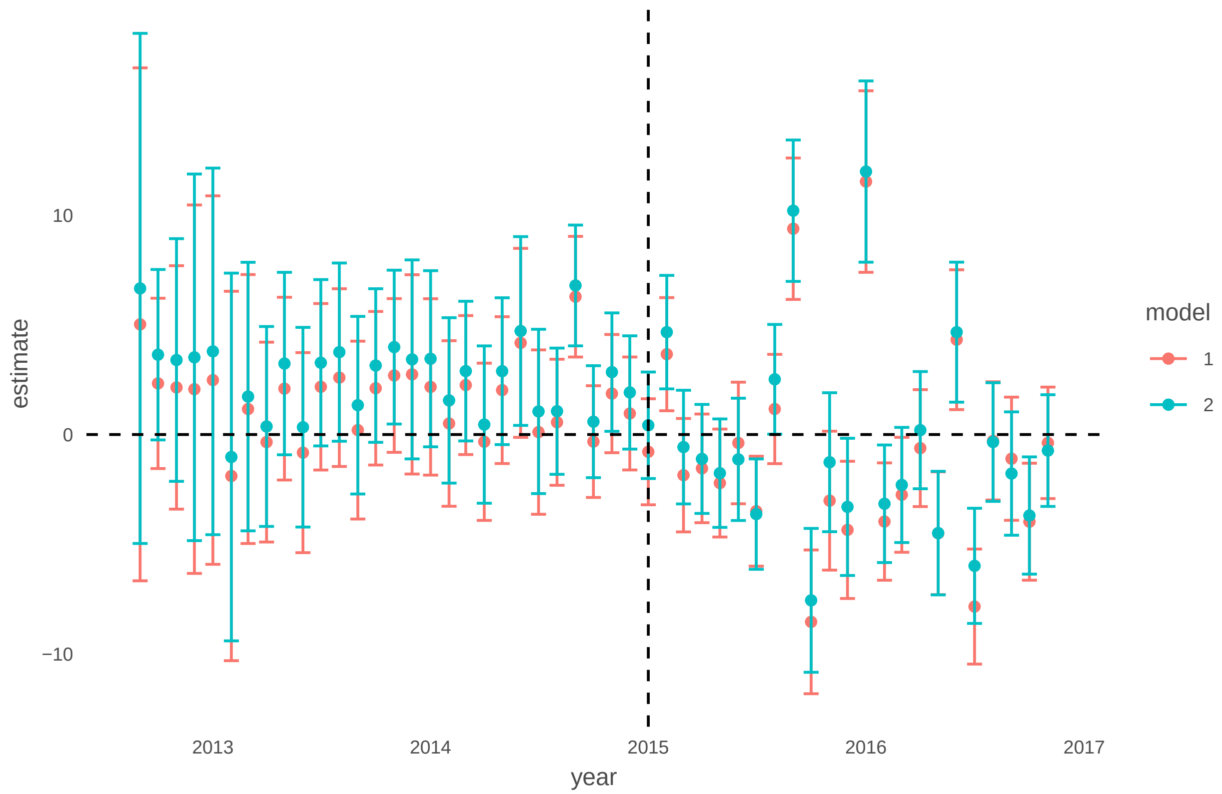
401



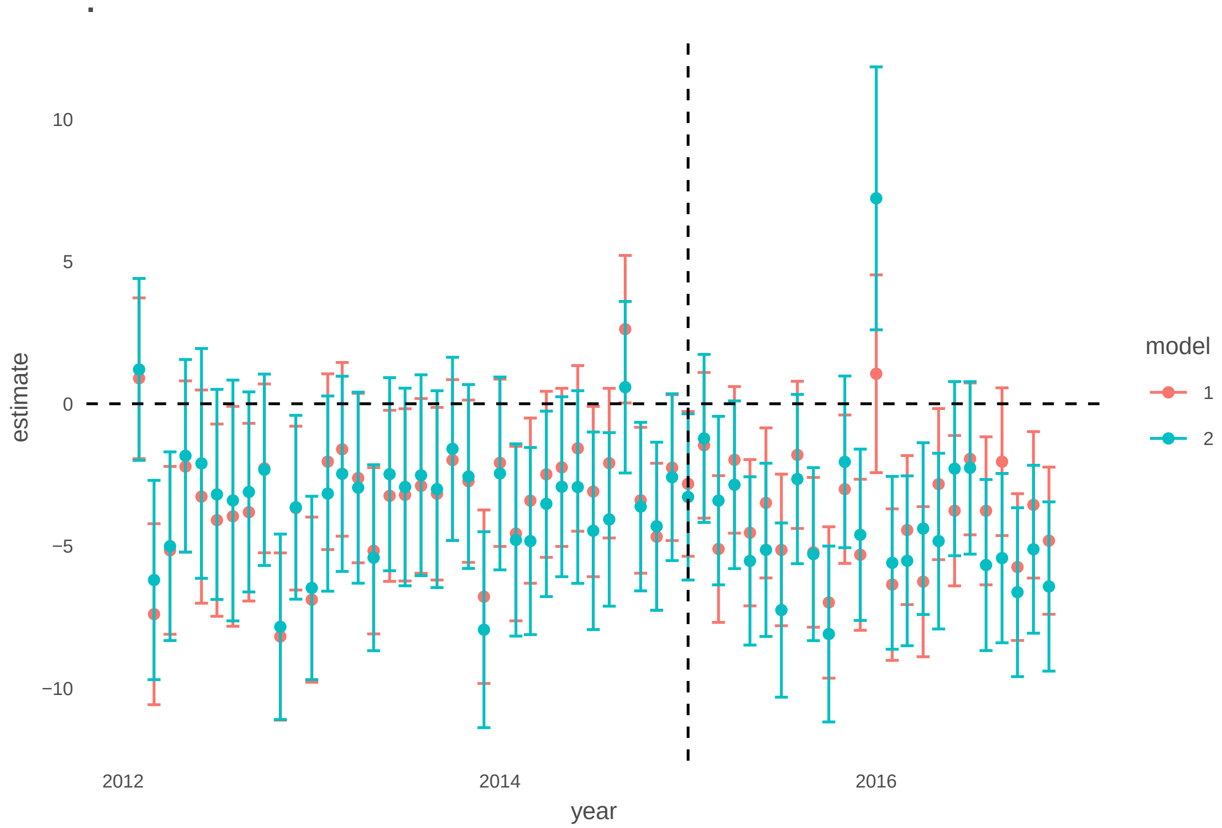
402



403



404



405

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