

<sup>1</sup> Supporting Information: The Regional Effects of Marine  
<sup>2</sup> Protected Areas

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<sup>17</sup> **1 Supporting Information (SI)**

<sup>18</sup> **SI Text**

<sup>19</sup> **1.1 Computing environment**

<sup>20</sup> The computing environment needed to reproduce the results presented here is stored in a Docker container  
<sup>21</sup> available hereXX. Interested users can load the container on their system to reproduce the complete analysis  
<sup>22</sup> and manuscript. Analysis were performed in R version 3.6.1 (2019-07-05). Package versions are shown in  
<sup>23</sup> Table.S1.

Table 1: Package versions and sources used in this paper

	package	loadedversion	date	source
assertthat	assertthat	0.2.1	2019-03-21	CRAN (R 3.6.0)
backports	backports	1.1.5	2019-10-02	CRAN (R 3.6.1)
bitops	bitops	1.0-6	2013-08-17	CRAN (R 3.6.0)
bookdown	bookdown	0.13	2019-08-21	CRAN (R 3.6.0)
broom	broom	0.5.2	2019-04-07	CRAN (R 3.6.0)
callr	callr	3.3.2	2019-09-22	CRAN (R 3.6.0)
caret	caret	6.0-84	2019-04-27	CRAN (R 3.6.0)

Table 1: Package versions and sources used in this paper (*continued*)

	package	loadedversion	date	source
cellranger	cellranger	1.1.0	2016-07-27	CRAN (R 3.6.0)
class	class	7.3-15	2019-01-01	CRAN (R 3.6.1)
classInt	classInt	0.4-1	2019-08-06	CRAN (R 3.6.0)
cli	cli	1.1.0	2019-03-19	CRAN (R 3.6.0)
codetools	codetools	0.2-16	2018-12-24	CRAN (R 3.6.1)
colorspace	colorspace	1.4-1	2019-03-18	CRAN (R 3.6.0)
crayon	crayon	1.3.4	2017-09-16	CRAN (R 3.6.0)
curl	curl	0.8.4	2019-08-02	CRAN (R 3.6.0)
curl	curl	4.2	2019-09-24	CRAN (R 3.6.0)
data.table	data.table	1.12.4	2019-10-03	CRAN (R 3.6.1)
DBI	DBI	1.0.0	2018-05-02	CRAN (R 3.6.0)
desc	desc	1.2.0	2018-05-01	CRAN (R 3.6.0)
devtools	devtools	2.2.0	2019-09-07	CRAN (R 3.6.0)
digest	digest	0.6.21	2019-09-20	CRAN (R 3.6.0)
dplyr	dplyr	0.8.3	2019-07-04	CRAN (R 3.6.0)
DT	DT	0.9	2019-09-17	CRAN (R 3.6.1)
e1071	e1071	1.7-2	2019-06-05	CRAN (R 3.6.0)
ellipsis	ellipsis	0.3.0	2019-09-20	CRAN (R 3.6.0)
evaluate	evaluate	0.14	2019-05-28	CRAN (R 3.6.0)
extrafont	extrafont	0.17	2014-12-08	CRAN (R 3.6.0)
extrafontdb	extrafontdb	1.0	2012-06-11	CRAN (R 3.6.0)
forcats	forcats	0.4.0	2019-02-17	CRAN (R 3.6.0)
foreach	foreach	1.4.7	2019-07-27	CRAN (R 3.6.0)
foreign	foreign	0.8-72	2019-08-02	CRAN (R 3.6.0)
fs	fs	1.3.1	2019-05-06	CRAN (R 3.6.0)
gdtools	gdtools	0.2.0	2019-09-03	CRAN (R 3.6.0)
generics	generics	0.0.2	2018-11-29	CRAN (R 3.6.0)
geojson	geojson	0.3.2	2019-01-31	CRAN (R 3.6.0)
geojsonio	geojsonio	0.7.0	2019-04-25	CRAN (R 3.6.0)
geojsonlint	geojsonlint	0.3.0	2019-02-08	CRAN (R 3.6.0)
ggmap	ggmap	3.0.0.901	2019-10-05	Github (dkahle/ggmap@37a8672)
ggplot2	ggplot2	3.2.1	2019-08-10	CRAN (R 3.6.0)
ggsci	ggsci	2.9	2018-05-14	CRAN (R 3.6.0)
ggspatial	ggspatial	1.0.3	2018-12-14	CRAN (R 3.6.0)
glue	glue	1.3.1	2019-03-12	CRAN (R 3.6.0)
gower	gower	0.2.1	2019-05-14	CRAN (R 3.6.0)
gridExtra	gridExtra	2.3	2017-09-09	CRAN (R 3.6.0)
gttable	gttable	0.3.0	2019-03-25	CRAN (R 3.6.0)
haven	haven	2.1.1	2019-07-04	CRAN (R 3.6.0)
here	here	0.1	2017-05-28	CRAN (R 3.6.0)
hms	hms	0.5.1	2019-08-23	CRAN (R 3.6.0)
hrbrthemes	hrbrthemes	0.6.0	2019-01-21	CRAN (R 3.6.0)
htmltools	htmltools	0.4.0	2019-10-04	CRAN (R 3.6.1)
htmlwidgets	htmlwidgets	1.3	2018-09-30	CRAN (R 3.6.0)
httpcode	httpcode	0.2.0	2016-11-14	CRAN (R 3.6.0)
httr	httr	1.4.1	2019-08-05	CRAN (R 3.6.1)

Table 1: Package versions and sources used in this paper (*continued*)

	package	loadedversion	date	source
ipred	ipred	0.9-9	2019-04-28	CRAN (R 3.6.0)
iterators	iterators	1.0.12	2019-07-26	CRAN (R 3.6.0)
jpeg	jpeg	0.1-8	2014-01-23	CRAN (R 3.6.0)
jqr	jqr	1.1.0	2018-10-22	CRAN (R 3.6.0)
jsonlite	jsonlite	1.6	2018-12-07	CRAN (R 3.6.0)
jsonvalidate	jsonvalidate	1.1.0	2019-06-25	CRAN (R 3.6.0)
kernlab	kernlab	0.9-27	2018-08-10	CRAN (R 3.6.0)
KernSmooth	KernSmooth	2.23-15	2015-06-29	CRAN (R 3.6.1)
knitr	knitr	1.25	2019-09-18	CRAN (R 3.6.1)
labeling	labeling	0.3	2014-08-23	CRAN (R 3.6.0)
lattice	lattice	0.20-38	2018-11-04	CRAN (R 3.6.1)
lava	lava	1.6.6	2019-08-01	CRAN (R 3.6.0)
lazyeval	lazyeval	0.2.2	2019-03-15	CRAN (R 3.6.0)
lifecycle	lifecycle	0.1.0	2019-08-01	CRAN (R 3.6.0)
lubridate	lubridate	1.7.4	2018-04-11	CRAN (R 3.6.0)
magrittr	magrittr	1.5	2014-11-22	CRAN (R 3.6.0)
maptools	maptools	0.9-5	2019-02-18	CRAN (R 3.6.0)
MASS	MASS	7.3-51.4	2019-03-31	CRAN (R 3.6.1)
Matrix	Matrix	1.2-17	2019-03-22	CRAN (R 3.6.1)
memoise	memoise	1.1.0	2017-04-21	CRAN (R 3.6.0)
ModelMetrics	ModelMetrics	1.2.2	2018-11-03	CRAN (R 3.6.0)
modelr	modelr	0.1.5	2019-08-08	CRAN (R 3.6.0)
munsell	munsell	0.5.0	2018-06-12	CRAN (R 3.6.0)
nlme	nlme	3.1-141	2019-08-01	CRAN (R 3.6.0)
nnet	nnet	7.3-12	2016-02-02	CRAN (R 3.6.1)
numDeriv	numDeriv	2016.8-1.1	2019-06-06	CRAN (R 3.6.0)
optimx	optimx	2018-7.10	2018-09-30	CRAN (R 3.6.0)
packrat	packrat	0.5.0	2018-11-14	CRAN (R 3.6.0)
patchwork	patchwork	0.0.1	2019-10-03	Github (thomasp85/patchwork@36b4918)
pillar	pillar	1.4.2	2019-06-29	CRAN (R 3.6.0)
pkgbuild	pkgbuild	1.0.5	2019-08-26	CRAN (R 3.6.0)
pkgconfig	pkgconfig	2.0.3	2019-09-22	CRAN (R 3.6.0)
pkgload	pkgload	1.0.2	2018-10-29	CRAN (R 3.6.0)
plyr	plyr	1.8.4	2016-06-08	CRAN (R 3.6.0)
png	png	0.1-7	2013-12-03	CRAN (R 3.6.0)
prettyunits	prettyunits	1.0.2	2015-07-13	CRAN (R 3.6.0)
processx	processx	3.4.1	2019-07-18	CRAN (R 3.6.0)
prodlim	prodlim	2018.04.18	2018-04-18	CRAN (R 3.6.0)
ps	ps	1.3.0	2018-12-21	CRAN (R 3.6.0)
purrr	purrr	0.3.2	2019-03-15	CRAN (R 3.6.0)
R6	R6	2.4.0	2019-02-14	CRAN (R 3.6.0)
Rcpp	Rcpp	1.0.2	2019-07-25	CRAN (R 3.6.0)
readr	readr	1.3.1	2018-12-21	CRAN (R 3.6.0)
readxl	readxl	1.3.1	2019-03-13	CRAN (R 3.6.0)
recipes	recipes	0.1.7	2019-09-15	CRAN (R 3.6.0)
rEDM	rEDM	0.7.4	2019-08-19	Github (ha0ye/rEDM@88554a4)

Table 1: Package versions and sources used in this paper (*continued*)

	package	loadedversion	date	source
remotes	remotes	2.1.0	2019-06-24	CRAN (R 3.6.0)
reshape2	reshape2	1.4.3	2017-12-11	CRAN (R 3.6.0)
rgdal	rgdal	1.4-4	2019-05-29	CRAN (R 3.6.0)
rgeos	rgeos	0.5-1	2019-08-05	CRAN (R 3.6.1)
RgoogleMaps	RgoogleMaps	1.4.4	2019-08-20	CRAN (R 3.6.0)
rjson	rjson	0.2.20	2018-06-08	CRAN (R 3.6.0)
rlang	rlang	0.4.0	2019-06-25	CRAN (R 3.6.0)
rmapshaper	rmapshaper	0.4.1	2018-10-16	CRAN (R 3.6.0)
rmarkdown	rmarkdown	1.16	2019-10-01	CRAN (R 3.6.1)
rpart	rpart	4.1-15	2019-04-12	CRAN (R 3.6.1)
rprojroot	rprojroot	1.3-2	2018-01-03	CRAN (R 3.6.0)
rstudioapi	rstudioapi	0.10	2019-03-19	CRAN (R 3.6.0)
rticles	rticles	0.10	2019-08-21	CRAN (R 3.6.0)
Rttf2pt1	Rttf2pt1	1.3.7	2018-06-29	CRAN (R 3.6.0)
rvest	rvest	0.3.4	2019-05-15	CRAN (R 3.6.0)
scales	scales	1.0.0	2018-08-09	CRAN (R 3.6.0)
sessioninfo	sessioninfo	1.1.1	2018-11-05	CRAN (R 3.6.0)
sf	sf	0.8-0	2019-09-17	CRAN (R 3.6.1)
sp	sp	1.3-1	2018-06-05	CRAN (R 3.6.0)
spasm	spasm	0.1.0.9000	2019-10-09	local
stringi	stringi	1.4.3	2019-03-12	CRAN (R 3.6.0)
stringr	stringr	1.4.0	2019-02-10	CRAN (R 3.6.0)
survival	survival	2.44-1.1	2019-04-01	CRAN (R 3.6.1)
Synth	Synth	1.1-5	2014-01-27	CRAN (R 3.6.0)
systemfonts	systemfonts	0.1.1	2019-07-01	CRAN (R 3.6.0)
testthat	testthat	2.2.1	2019-07-25	CRAN (R 3.6.0)
tibble	tibble	2.1.3	2019-06-06	CRAN (R 3.6.0)
tidyR	tidyR	1.0.0	2019-09-11	CRAN (R 3.6.0)
tidyselect	tidyselect	0.2.5	2018-10-11	CRAN (R 3.6.0)
tidyverse	tidyverse	1.2.1	2017-11-14	CRAN (R 3.6.0)
timeDate	timeDate	3043.102	2018-02-21	CRAN (R 3.6.0)
tinytex	tinytex	0.16	2019-09-17	CRAN (R 3.6.1)
units	units	0.6-4	2019-08-22	CRAN (R 3.6.0)
usethis	usethis	1.5.1	2019-07-04	CRAN (R 3.6.0)
V8	V8	2.3	2019-07-02	CRAN (R 3.6.0)
vctrs	vctrs	0.2.0	2019-07-05	CRAN (R 3.6.0)
viridis	viridis	0.5.1	2018-03-29	CRAN (R 3.6.0)
viridisLite	viridisLite	0.3.0	2018-02-01	CRAN (R 3.6.0)
withr	withr	2.1.2	2018-03-15	CRAN (R 3.6.0)
xfun	xfun	0.10	2019-10-01	CRAN (R 3.6.1)
xml2	xml2	1.2.2	2019-08-09	CRAN (R 3.6.0)
yaml	yaml	2.2.0	2018-07-25	CRAN (R 3.6.0)
zeallot	zeallot	0.1.0	2018-01-28	CRAN (R 3.6.0)

<sup>24</sup> **1.2 Operating Model**

<sup>25</sup> The operating model is a spatial single-species age-structured bio-economic model. The operating model  
<sup>26</sup> itself is organized as an R package, which can be found and installed here. Users can explore the functionality  
<sup>27</sup> of the operating mode through an interactive web application here.

<sup>28</sup> For the population model, numbers  $n$  at time  $t$  for age  $a$  are given by

$$n_{t,a} = \begin{cases} = BH(ssb_{t-1}) & \text{if } a = 1 \\ = n_{t-1,a-1}e^{-(m+qE_{t-1}\times s_{a-1})}, & \text{if } 1 < a < \max(\text{age}) \\ = n_{t-1,a}e^{-(m+qE_{t-1}\times s_a)} + n_{t-1,a-1}e^{-(m+qE_{t-1}\times s_{a-1})}, & \text{if } a = \max(a) \end{cases} \quad (1)$$

<sup>29</sup> where  $BH$  is the Beverton-Holt recruitment function,  $ssb$  is spawning-stock-biomass,  $m$  is natural mortality,  $q$   
<sup>30</sup> is catchability,  $E$  is fishing effort at time  $t$ , and  $s$  is selectivity at age  $a$ .

<sup>31</sup> Selectivity is modeled through a logistic form per

$$s_a = \frac{1}{(1 + e^{-\log(19) \times \frac{l_a - l_{sel}}{\delta_{sel}}})} \quad (2)$$

<sup>32</sup> where  $l_a$  is the mean length at age,  $l_{sel}$  is the length at which on average 50% of individuals are selected  
<sup>33</sup> by the fishery, and  $\delta_{sel}$  are the additional units of length at which on average 95% of fish are selected by the  
<sup>34</sup> fishery.

<sup>35</sup>  $ssb$  is calculated by converting age to mean length, calculating weight at age, maturity at age, and then  
<sup>36</sup> calculating spawning stock biomass as the sum of spawning potential at age in a given time step.

$$l_a = l_\infty \left( 1 - e^{-k(a-a_0)} \right) \quad (3)$$

<sup>37</sup> Weight at age is then given by

$$b_a = w_a \times l_a^{w_b} \quad (4)$$

<sup>38</sup> and maturity  $mat$  is calculated as

$$\frac{1}{(1 + e^{-\log(19) \times \frac{l_a - l_{mat}}{\delta_{mat}}})} \quad (5)$$

<sup>39</sup> where  $l_{mat}$  is the length at which on average 50% of individuals are sexual maturity, and  $\delta_{mat}$  is the units of  
<sup>40</sup> length beyond  $l_{mat}$  at which on average 95% of fish are sexually mature.

<sup>41</sup> Spawning stock biomass at time  $t$  is then calculated as

$$ssb_t = \sum_{a=1}^A w_{a,t} mat_{a,t} n_{a,t} \quad (6)$$

<sup>42</sup> **1.2.1 Recruitment**

<sup>43</sup> Recruitment follows Beverton-Holt dynamics. We do however allow for three variants in the timing of density  
<sup>44</sup> dependence:

- 45      1. Local density dependence: Density dependence occurs independently in each patch, and recruits then  
 46      disperse to nearby patches

$$n_{t,a=1,p} = \left( \frac{0.8 \times r0_p \times h \times ssb_{t-1,p}}{0.2 \times ssb0_p \times (1-h) + (h-0.2) \times ssb_{t-1,p}} \right) \times \mathbf{d}^l \times \epsilon_t \quad (7)$$

47    where  $\mathbf{d}^l$  is the larval movement matrix,  $h$  is Beverton-Holt steepness (constrained between 0.6 and 0.99),  $r0$   
 48    is unfished recruitment, and  $ssb0$  is unfished spawning stock biomass.

- 49      2. Global density dependence: Density dependence is a function of the sum of spawning biomass across all  
 50      patches, and recruits are then distributed according to habitat quality

$$n_{t,a=1,p} = \left( \frac{0.8 \times \sum_{p=1}^P r0_p \times h \times \sum_{p=1}^P ssb_{t-1,p}}{0.2 \times \sum_{p=1}^P ssb0_p \times (1-h) + (h-0.2) \times \sum_{p=1}^P ssb_{t-1,p}} \right) \times hab_p \times \epsilon_t \quad (8)$$

51    where  $hab$  is a vector of habitat quality by patch that sums to 1.

- 52      3. Post-dispersal density dependence: Larvae are distributed throughout the system, and then density  
 53      dependence occurs based on the density of adult biomass at the destination patch.

$$larv_{t,p} = ssb_{t-1} \times \mathbf{d}^l \quad (9)$$

$$n_{t,a=1,p} = \left( \frac{0.8 \times r0_p \times h \times larv_{t,p}}{0.2 \times ssb0_p \times (1-h) + (h-0.2) \times larv_{t,p}} \right) \times \epsilon_t \quad (10)$$

54     $\epsilon$  represents multiplicative recruitment deviates. Deviates are calculated as

$$\epsilon_t = e^{recdev_t}$$

55    ‘ $recdev$ ’ are the log-normal recruitment deviates in time  $t$ .

56    The stochastic component of the deviate is

$$\gamma_t \sim norm(-\sigma_r^2/2, \sigma_r)$$

57    and the final multiplicative recruitment deviate in time  $t$  is then

$$recdev_t = \gamma_t \sqrt{1 - ac_r^2} + recdev_{t-1} ac_r$$

58    where  $ac$  is the autocorrelation of the recruitment function (between 0 and 1).

59    **1.2.2 Dispersal**

60    Dispersal in the model is broken into two components: adult and larval. Both assume a Gaussian dispersal  
 61    kernel of the form

$$m_{s,p_i,p_j} = \frac{1}{\sqrt{2\pi\sigma_{s,p_i}^2}} e^{-\frac{d_{p_i,p_j}^2}{2\sigma_{s,p_i}^2}} \quad (11)$$

62    where  $i$  is the source patch,  $j$  is the destination patch,  $d$  is the distance between patches  $i$  and  $j$  (where  
 63    distance is measured with wrapped edges, such that if there are 50 patches, patch 1 and patch 50 have a  
 64    distance of 1), and  $\sigma_s$  is the movement rate, in units of patches, for life stage  $s$  (adult or larval).

65    We allow the adult dispersal matrix to be affected by adult density dependence. The idea behind this is that  
 66    adult fish will move more as densities increase, and become more sedentary as densities decrease (as habitat  
 67    and food become more available for example). This allows us to simulate a scenario where as MPAs build up  
 68    density they begin to export more adults to the surrounding waters, and if densities are lower in the fished  
 69    areas these fish will actually become more sedentary.

70    Under these conditions, the adult movement rate is a linear function of depletion (measured as  $ssb/ssb_0$ )

$$\sigma_{s=a,p}^* = \max(slope \times d_p + \sigma_{s=a} \times dmod, 0) \quad (12)$$

71    where

$$slope = \sigma_{s=a} - (\sigma_{s=a} \times dmod) \quad (13)$$

72    Under these conditions, when depletion  $d = 1$  (meaning the stock is unfished) the adult movement rate  
 73    equals the max adult movement rate ( $\sigma_{s=a}^* = \sigma_{s=a}$ ). When  $d = 0$   $\sigma_{s=a}^* = \sigma_{s=a} * dmod$ . The greater  $dmod$  is  
 74    then, the more movement rates from a patch decline as density declines.

75    We also allow for a “sprinkler” condition in which MPAs are placed in locations that disperse larvae to a  
 76    much wider area than non-MPA locations. In this world, we simply multiply  $\sigma_{s=l,p}$  by a sprinkler factor (by  
 77    default 4) for any patch  $p$  that would eventually become an MPA (whether or not MPAs are ever introduced).  
 78    In other words, when we compare two scenarios, one with MPA and one without, the “without” scenario still  
 79    has higher larval movement rates in patches that become MPAs in the “with” scenario.

80    **1.2.3 Fleet Dynamics**

81    We allow for three fleet models: constant effort, constant catch, and open-access. Constant effort means  
 82    that total effort across all patches is equal in all time steps (unless MPAs force exit of effort as discussed  
 83    below). Under constant catch, we set a target catch volume (in biomass, summed across all patches). Each  
 84    time step, we calculate the fishing mortality rate that, given the fishable biomass in that time step, would  
 85    produce the target catch. If there is insufficient fishable biomass available to support the target catch, we  
 86    mark the population as crashed and stop the simulation (these crashed simulations are not included in the  
 87    final analysis).

88    Under open-access, fishing effort expands in proportion to a weighted mean of profit-per-unit effort over the  
 89    last  $t$  time steps.

$$profit_t = price \times catch_t - cost \times E_t^2 \quad (14)$$

90    From there, we determine the new effort as

$$E_t = E_{t-1} + \theta \times \sum_{i=t-1-l}^{t-1} w_i \frac{profit_i}{E^i} \quad (15)$$

91 where  $w$  is a weighting function which is just a linear function of time

$$w_i = \frac{i}{\sum_{i=1}^l i} \quad (16)$$

92 and  $l$  is the number of lagged time steps over which to calculate the weighted mean PPUE.

93 The open-access model can enter chaotic dynamics if the model parameters are not properly tuned. To  
94 address this, we first set price at 1, and set a  $\theta$  such that when profits are about as large as they might  
95 conceivably be the fishery doubles in size. We then estimate reference points for the simulated fishery (B<sub>msy</sub>,  
96 F<sub>msy</sub>, MSY), and set a target bionomic equilibrium B/B<sub>msy</sub>. Holding the other parameters constant, we  
97 thing find a cost coefficient that produces the desired bionomic equilibrium.

#### 98 1.2.4 Spatial Fleet Distribution

99 Given a total amount of effort, we then need to distribute that effort in space. In the simplest form, effort is  
100 evenly distributed throughout the available patches.

$$E_{t,p} = E_t \times \frac{open_p}{\sum_{p=1}^P open_p} \quad (17)$$

101 where  $open$  indicates whether patch  $p$  is open to fishing or not.

102 Effort can also be distributed according to spawning stock biomass in fishable patches

$$E_{t,p} = E_t \times \frac{open_{t,p} ssb_{t,p}}{\sum_{p=1}^P open_{t,p} ssb_{t,p}} \quad (18)$$

103 And lastly effort can be distributed according to profit-per-unit-effort

$$E_{t,p} = E_t \times \frac{open_{t,p} ppue_{t,p}}{\sum_{p=1}^P open_{t,p} ppue_{t,p}} \quad (19)$$

104 Under the constant effort or open access scenarios, effort can immediately respond to MPA placement in one  
105 of two ways. Effort can concentrate outside the MPAs (such that the sum of effort before and after MPA  
106 placement stays constant), or effort can leave the MPAs, such that the total effort in the fishery is reduced by  
107 the amount of effort that occurred inside the MPAs immediately before MPA placement. This is intended to  
108 simulate a scenario where fishers that used to use the MPA simply leave the fishery rather than redistribute  
109 outside the MPA, due for example to costs or lack of location specific knowledge to fish outside the MPA.

#### 110 1.2.5 MPA Design

111 MPA design is relatively straightforward. We set a percentage of patches that are to be placed inside no-take  
112 MPAs. MPAs can either be placed continuously (e.g if there are 100 patches and 25% are in MPAs, patches 1  
113 to 25 are in MPAs) or randomly. If the MPAs are placed randomly, we can also set a minimum MPA size.  
114 This controls the patchiness of the MPAs. As the “patchiness” factor approaches zero, the behavior equals  
115 that of random placement. As it approaches 1, the behavior approaches that of continuous placement. In  
116 between, the greater the patchiness, the more clustered together MPAs become.

117 **1.3 Simulations**

118 We use this our operating model to simulate 10,000 different fisheries, where each fishery is a random  
 119 combination of variables, described below

120 Table.S1 - Range of simulated variables

Variable	Distribution
Scientific Name	Drawn from all possible species in <b>FishLife</b> (Thorson et al. (2017))
steepness (h)	$\sim \text{uniform}(0.6, 0.95)$
Adult movement ( $\sigma_{s=a}$ )	$\sim \text{uniform}(0, 0.5 * P)$
Larval movement ( $\sigma_{s=l}$ )	$\sim \text{uniform}(0, 0.5 * P)$
Recruitment variation ( $\sigma_r$ )	$\in \{0, 0.05, .1\}$
Recruitment autocorrelation ( $ac_r$ )	$\in \{0, 0.05, .1\}$
DD adult movement (dmod)	$\in \{0.25, 1\}$
Density-dependence timing	$\in \{\text{local, global, post-dispersal}\}$
% Patches in MPA	$\sim \text{uniform}(0.01, 1)$
Initial fishing relative to natural mortality	$\sim \text{uniform}(0.01, 4)$
Selectivity as a multiple of maturity length	$\sim \text{uniform}(0.1, 1.25)$
Fleet model	$\in \{\text{open-access, constant-effort, constant-catch}\}$
Spatial effort model	$\in \{\text{uniform, biomass, profits}\}$
Years into simulation to start MPA	$\sim \text{round}(\text{uniform}(5, 0.66 * T))$
MPA is sprinkler?	$\in \{\text{TRUE, FALSE}\}$
Randomly place MPA?	$\in \{\text{TRUE, FALSE}\}$
Fleet reaction to MPA	$\in \{\text{concentrate, abandon-ship}\}$
Patchiness	$\sim \text{uniform}(0.01, 0.75)$
MPA habitat factor	$\in \{1, 4\}$

121 One thing to note here is the random sampling of species' scientific names. The effect of MPAs, especially  
 122 over the short term, will clearly be affected by factors such as the growth rate, the mortality rate, and the  
 123 maturity schedule. These life history traits are related through a variety of biological processes, as such  
 124 randomly sampling these parameters can lead to biologically nonsensical "frankenfish". We resolve this by  
 125 using the **FishLife** package (Thorson et al. (2017)) instead. **FishLife** builds off of FishBase, and provides  
 126 estimate of key life history traits taking into account the relationships across these variables. For simulations  
 127 then, we randomly pull a species from **FishLife**, and then pull the available life history information from  
 128 that species for use in the operating model. This allows us to simulate a wide range of life history types in a  
 129 realistic manner.

130 We ran 20,000 simulations from these distributions. Each simulation runs for 50 years in 50 patches (with  
 131 a 25 year unfished burn-in period for conditions in which initial conditions cannot be solved analytically,  
 132 for example when MPAs have better habitat than non-MPAs). For each simulation, we run one scenario  
 133 without MPAs, though taking note of where the MPA would be as needed. For the second scenario, we hold  
 134 everything constant except we now add in the MPAs as dictated by the particular simulation.

135 **1.3.0.0.1 Filtering Simulations**

136 After the 20,000 simulations have run, we perform a series of filtering steps to remove runs that either a)  
 137 produced chaotic dynamics during the open-access scenario; b) did not converge to the correct bionomic  
 138 equilibrium in the open-access scenario; or c) crashed the population before the MPAs went into place  
 139 (population falls below 5% of unfished biomass). These filtering steps left us with 9672 viable simulations.

140 **1.3.0.1 Additional Simulation Results**

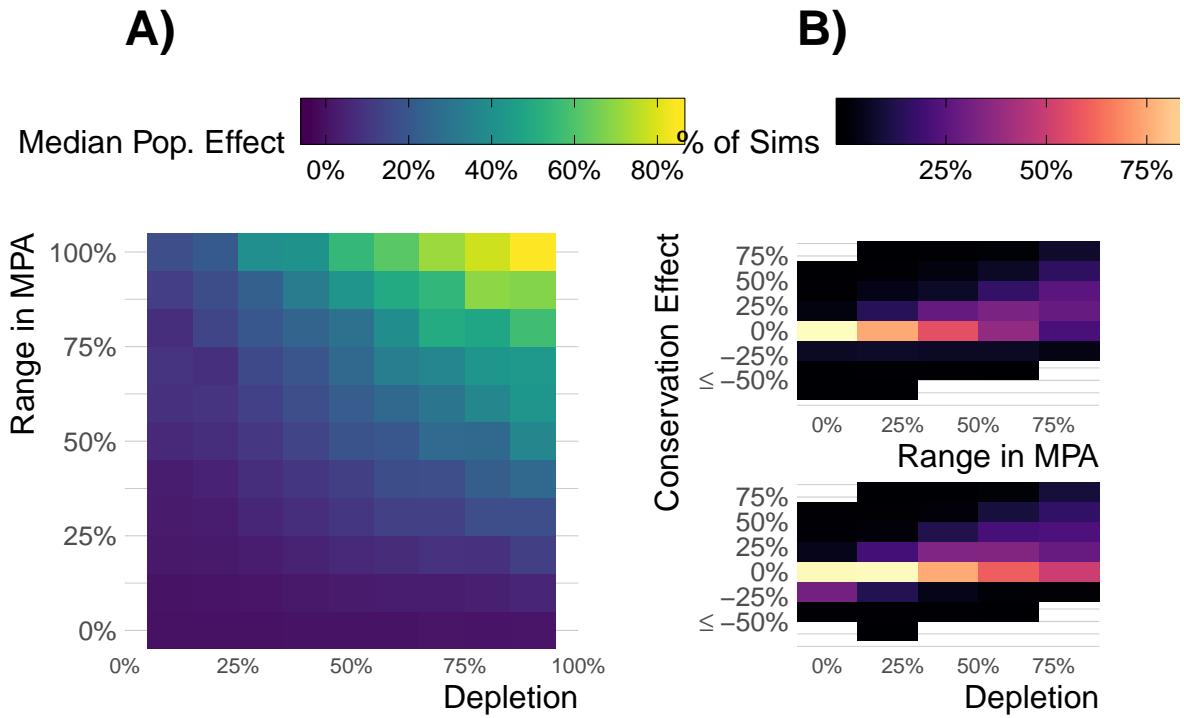


Figure 1: Median (A) and range (B) of equilibrium regional MPA conservation effects (change in total biomass with MPAs relative to without MPAs as a percentage of unfished biomass) across a range of depletion and MPA sizes (and incorporating the full range of scenarios included in our study). ‘Range in MPA’ is the percent of patches covered by an MPA, ‘Depletion’ is the depletion that would have occurred in equilibrium without the MPA

141 Simulation results are presented as percent differences in biomass densities with and without MPAs, in order  
 142 to be comparable to the estimates that the regression model produces. However, this metric presents some  
 143 problems as a measure of how “detectable” an effect size is. As depletion increases, relatively small changes  
 144 in total biomass (relative to the variance in the observation process) can translate into large percent changes  
 145 in biomass. For example, moving from a density of  $.2\text{kg}/\text{m}^2$  to  $.4\text{kg}/\text{m}^2$  translates to a 100% percent increase,  
 146 but only a  $.2\text{kg}/\text{m}^2$  absolute increase, a small value to detect with a real observation program.

147 To illustrate these, we present an alternative to our simulation results in which changes in biomass caused by  
 148 MPAs is scaled by the unfished biomass in the system.

#### 149 1.4 Estimation Model

150 The goal of the estimation model is to estimate the difference in the mean densities of targeted and non-targeted  
 151 species pre-and-post MPA implementation.

##### 152 1.4.1 Data

153 All observation data used in the estimation model were collected by PISCO. PISCO staff also compiled  
 154 allometric information used to convert lengths to expected weights, and hence biomass densities. We do not

155 account for error in this translation step Table.S3 lists the species included in the model. In order to be  
156 included in the estimation model, a species must have been observed at least twice a year every year for at  
157 least 14 years. We also omitted all observations of “young of the year” fish due to inability to identify these  
158 observations to the nearest species level in many cases. We omitted data from 1999 due to changes in the  
159 sampling procedures that occurred after 1999. Per recommendations from PISCO staff we omit observations  
160 from the canopy level of the transects (leaving the middle, bottom, and middle canopy levels).

161 PISCO data report positive observations of fish. In order to use these data in our model we need to add in  
162 zeros for any transect that could have observed a given species of fish but did not. We assume that a fish  
163 could have been observed on a given transect if that species has ever been observed at that site in any time  
164 period in the data (PISCO data are organized by sites, with multiple transect at different locations within the  
165 borders of a site). If a species has never been observed at a site we assume that it does not occur at that site.

166 Interested readers can examine the mean biomass densities of all species in Fig.5-6.

167 We include several additional sources of data in our regression analysis. Temperature readings are included  
168 from the PISCO data for each transect. We also include PISCO data on the estimated surge and visibility.  
169 We augmented these data with information on kelp cover over time from the Santa Barbara Channel Long  
170 Term Ecological Research Network (LTER et al. 2017). We used a k-nearest neighbors algorithm to fill in  
171 missing kelp observations, and matched the interpolated kelp data to the PISCO data at the resolution of  
172 year-month-site (Fig.4).

173 Temperature data were augmented with data from **FishLife** (Thorson et al. 2017) to include the estimated  
174 preferred temperature for a given species, so that we can include deviations from the preferred temperature  
175 envelope as a predictor in the model. This allows different temperatures to have different effects on each  
176 species (and is less computationally intensive than estimating species-temperature slopes) (Fig.2).

177 We also included lagged catch totals in the Santa Barbara region for the commercially harvest species in the  
178 database, in an effort to control for changes in density caused by changes in fishing pressure. Catches were  
179 pulled from the CDFW website (<https://www.wildlife.ca.gov/Fishing/Commercial/Landings>), and extracted  
180 using the **tabulizer** package in R (Leeper 2018) (Fig.3).

Table 3: Species included in estimation model

classcode	Common Name	Scientific Name	Targeted?	Stock Status
pcla	kelp bass	Paralabrax clathratus	TRUE	unknown - increasing CPUE
smys	blue rockfish	Sebastes mystinus	TRUE	Near minimum stock threshold - increasing
ejac	black surfperch	Embiotoca jacksoni	TRUE	unknown
spul	California sheephead	Semicossyphus pulcher	TRUE	Below target levels
rvac	pile perch	Rhacochilus vacca	TRUE	unknown
satr	kelp rockfish	Sebastes atrovirens	TRUE	unknown
elat	striped seaperch	Embiotoca lateralis	TRUE	unknown
saur	brown rockfish	Sebastes auriculatus	TRUE	unknown
cpri	ocean whitefish	Caulolatilus princeps	TRUE	unknown
rtox	rubberlip seaperch	Rhacochilus toxotes	TRUE	unknown
schr	black-and-yellow rockfish	Sebastes chrysomelas	TRUE	unknown
scau	copper rockfish	Sebastes caurinus	TRUE	Signs of overfishing
cpun	blacksmith	Chromis punctipinnis	FALSE	NA
gnig	opaleye	Girella nigricans	FALSE	NA
hrub	garibaldi	Hypsypops rubicundus	FALSE	NA
hsem	rock wrasse	Halichoeres semicinctus	FALSE	NA
ocal	senorita	Oxyjulis californica	FALSE	NA
hros	giant kelpfish	Heterostichus rostratus	FALSE	NA
mcal	halfmoon	Medialuna californiensis	FALSE	NA

Table 3: Species included in estimation model (*continued*)

classcode	Common Name	Scientific Name	Targeted?	Stock Status
opic	painted greenling	Oxylebius pictus	FALSE	NA
bfre	kelp surfperch	Brachyistius frenatus	FALSE	NA
hcar	rainbow seaperch	Hypsurus caryi	FALSE	NA
pfur	white seaperch	Phanerodon furcatus	FALSE	NA

### 181 1.4.2 Model

182 The regression analysis uses a mixed-effects hierarchical model. The raw data are estimated length compositions  
 183 by fish species along a survey transect at a site. Lengths are converted to biomass per allometric relationships  
 184 supplied by PISCO and supplemented by the **FishLife** (Thorson et al. 2017) package in R where needed. We  
 185 performed some minimal data filtering to reduce noise in the data. We only include species that were observed  
 186 at least twice in each year of the dataset (2000-2017) somewhere in the core Channel Islands (Anacapa, Santa  
 187 Cruz, Santa Rosa, San Miguel). While some data are available from 1999, per consultation with PISCO we  
 188 omit those data due to changes in survey protocols. We assign species to targeted and non-targeted groups  
 189 per the PISCO classifications. This filtering process results in 11 non-targeted species and 12 targeted species  
 190 remaining in the analysis.

191 The simplified explanation of the estimation is a hierarchical model in which we first standardize the observed  
 192 biomass densities into an abundance index of each species over time. The abundance indices in each year are  
 193 assumed to be log-normally distributed with means and standard deviations for the targeted and non-targeted  
 194 groups, giving an estimate of the mean densities of targeted and non-targeted species over time. We then  
 195 calculate the difference between mean density of targeted species and the mean density of non-targeted  
 196 species in each year.

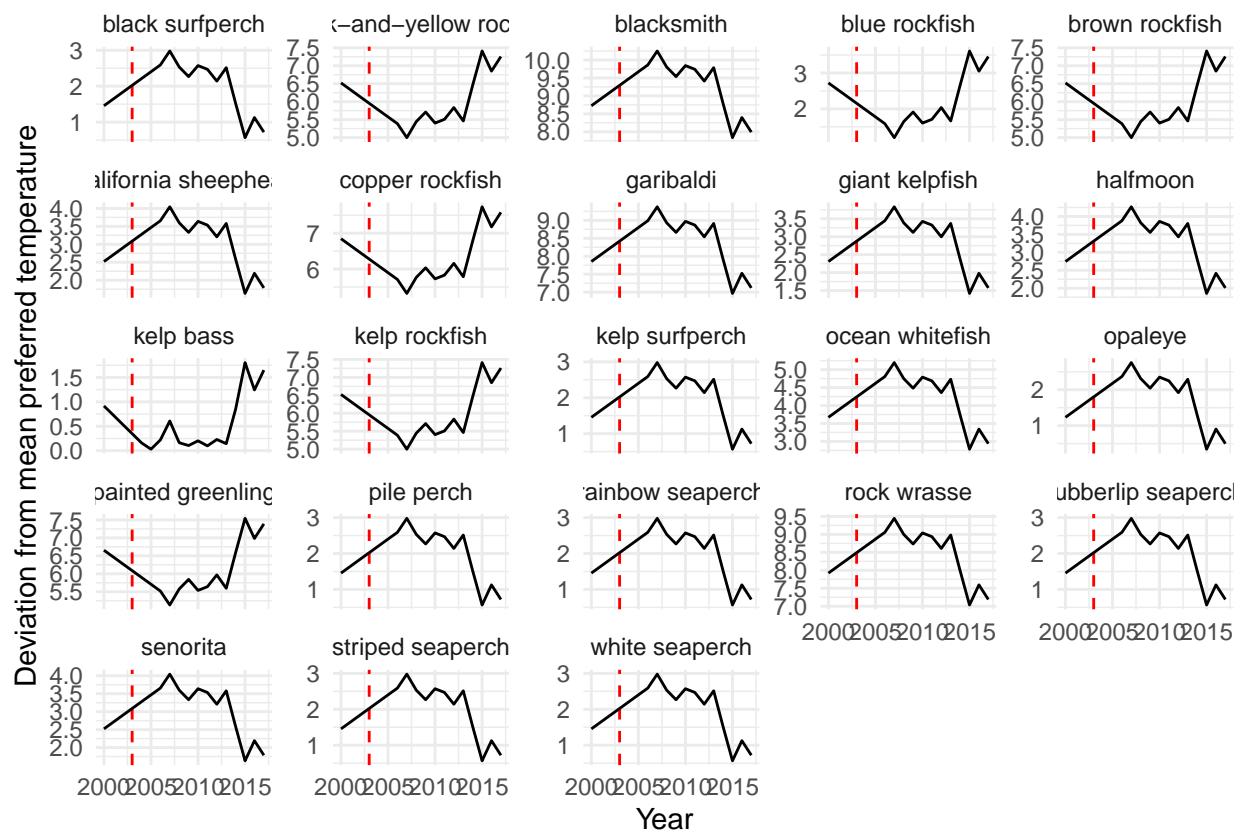


Figure 2: Mean deviations from preferred temperature by species and year

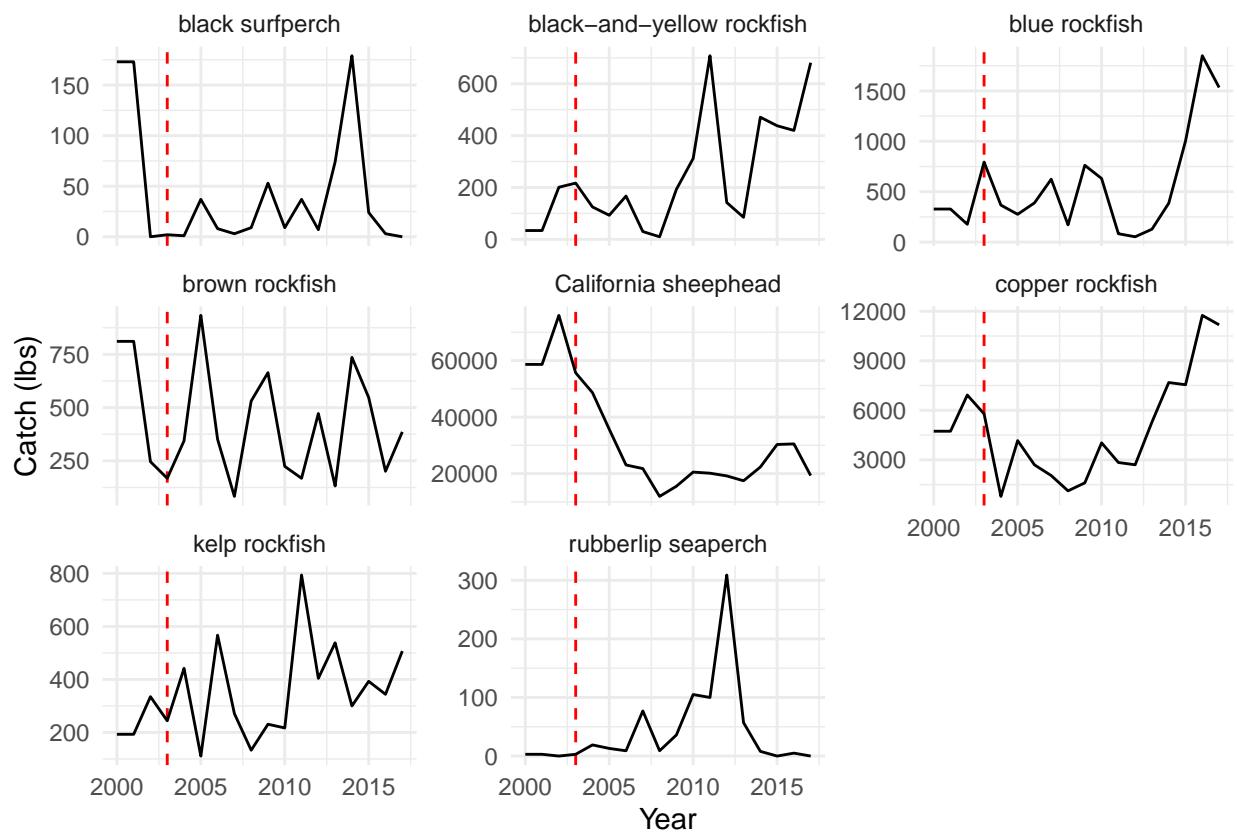


Figure 3: Total CDFW reported commercial catches in the Santa Barbara region

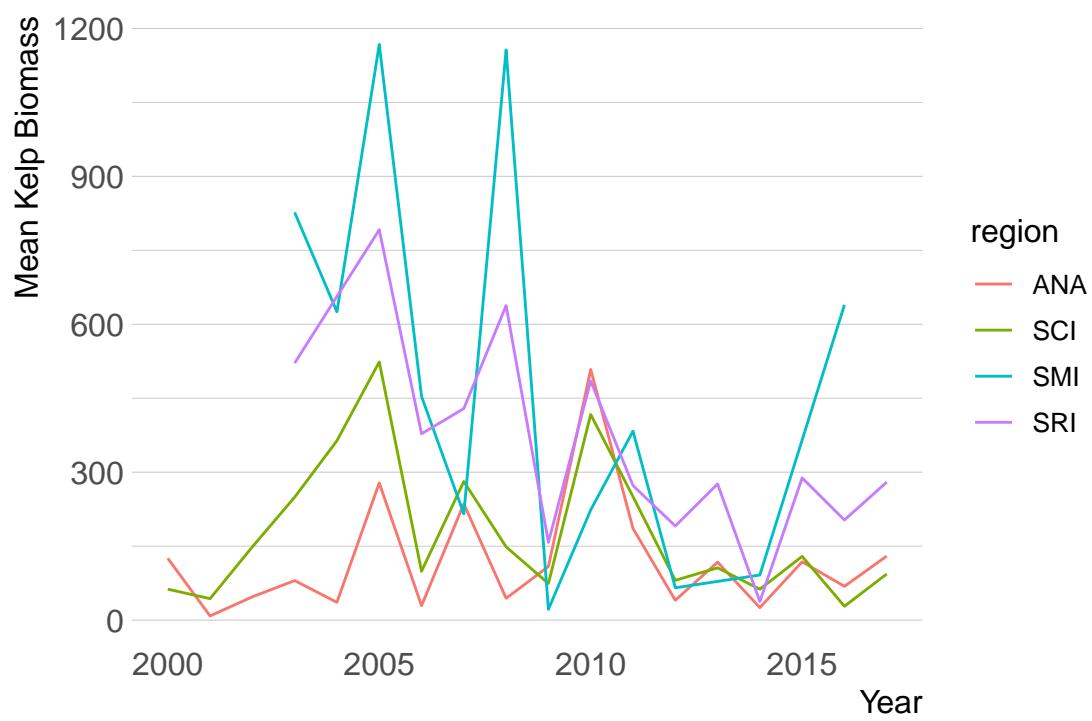


Figure 4: Mean kelp biomass by island over time from SBC LTER

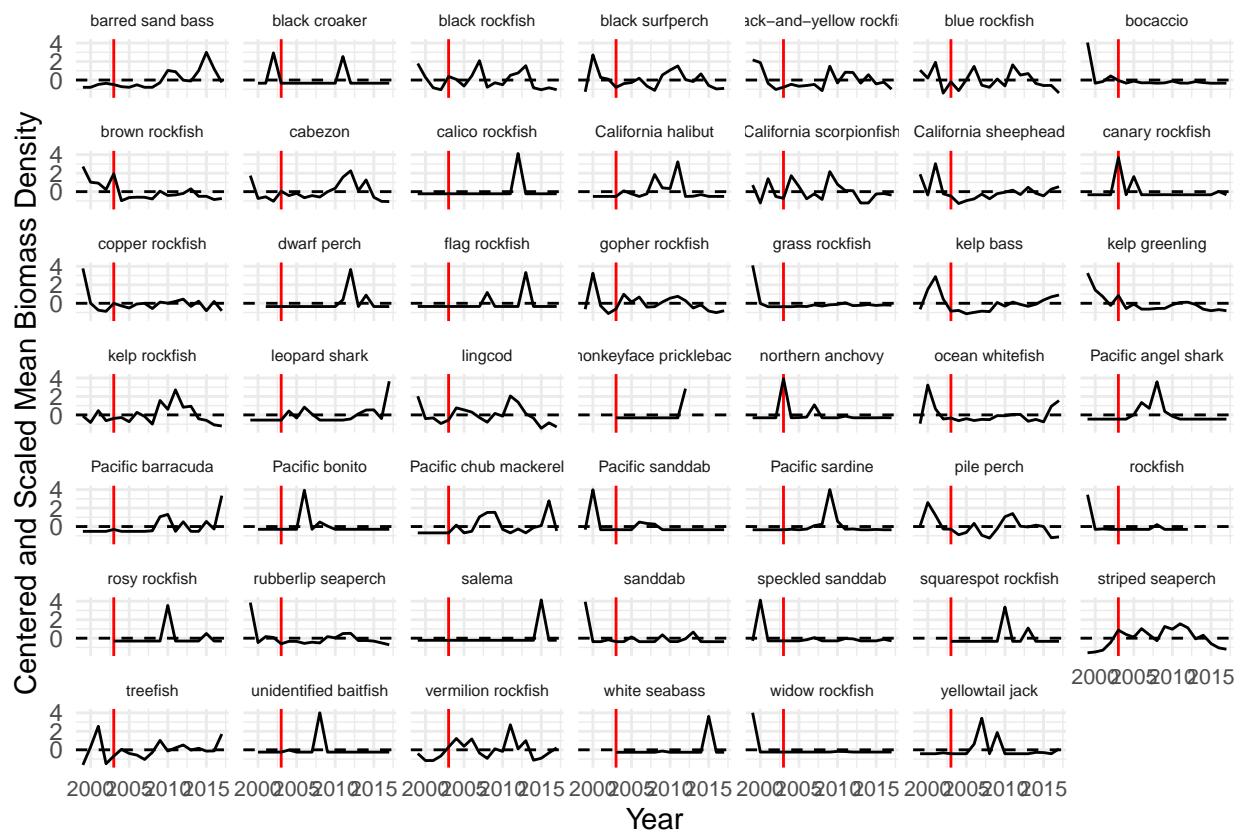


Figure 5: Centered and scaled mean biomass densities of all targeted finfish in analysis before filtering

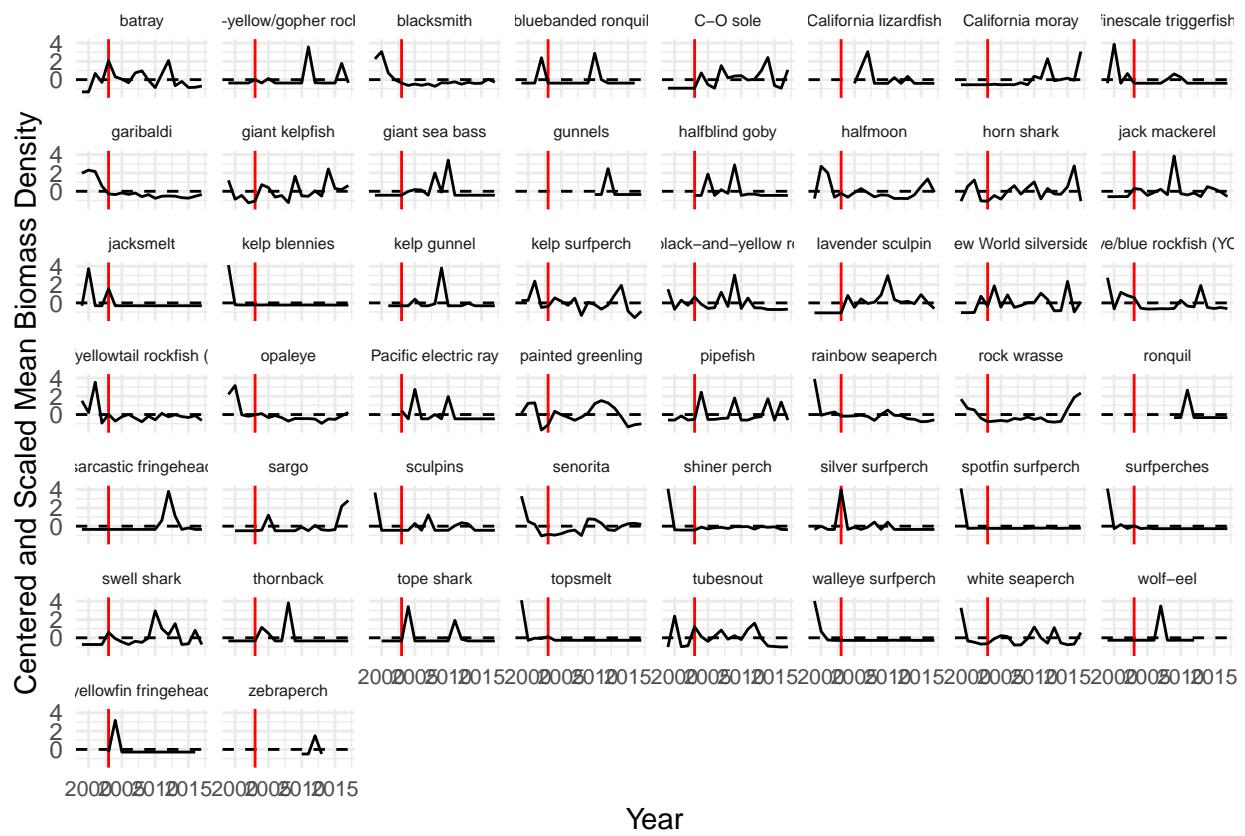


Figure 6: Centered and scaled mean biomass densities of all non-targeted finfish in analysis before filtering

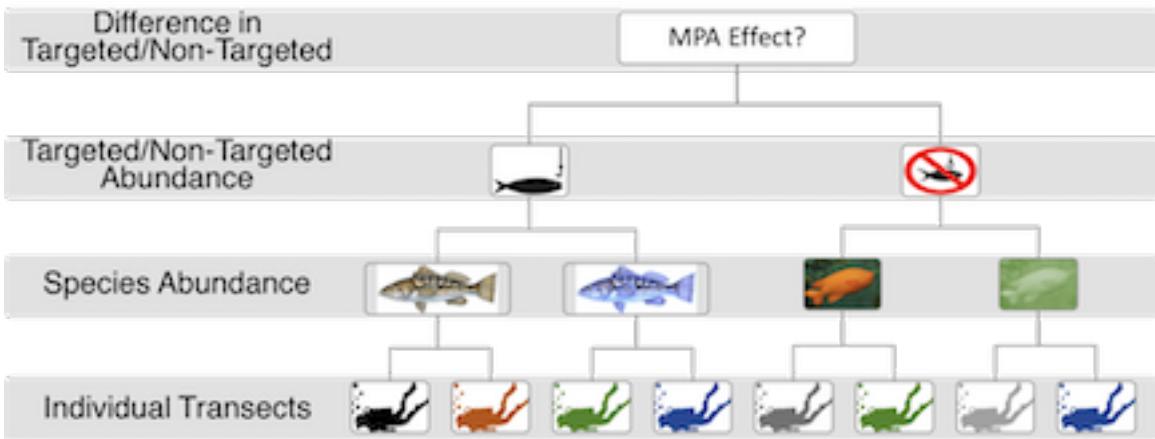


Figure 7: Cartoon illustration of the hierachichal difference-in-difference estimator

197 The first stage of the regression is a log-normal delta model. The model estimates two regressions, the first is  
 198 a binomial generalized linear model (GLM) with a logit link estimating the probability of observing a given  
 199 fish species at a observation  $i$  (transect at time  $t$ ). The probability that a given species was observed  $o$  at a  
 200 given observation is distributed

$$o_{s,i} \sim binomial\left(\frac{1}{1 + e^{-\beta^o X}}\right) \quad (20)$$

201 where  $\beta^o$  are the estimated coefficients for the observation model and  $X$  is a matrix of covariates that include  
 202 random effects for each year in the data (2000 to 2017).

203 The expected density  $d$  of positive observations is modeled per a log-normal distribution

$$\log(d_{s,i}) \sim normal(\beta^d X, \sigma_s) \quad (21)$$

204 where  $\beta^d$  are the estimated coefficients for the expected density model and  $X$  is the same matrix of covariates  
 205 as used in the observation portion of the model and  $\sigma_s$  allows for each species  $s$  to have different standard  
 206 deviations.

207 Our covariate matrix  $X$  contains both fixed and random effects. Fixed effects include the depth level of the  
 208 transect, the sampling site, the month of the observation, the estimated surge at the transect, visibility, the  
 209 depth of the transect, and the experience (and experience squared) of the diver conducting the transect. We  
 210 classify each species into one of two clusters based on the mean longitude the species was encountered at,  
 211 breaking the species into two groups: those primarily found in the western end of the Channel Islands those  
 212 found more in the eastern end. We then estimate random effects for each island for each cluster

$$\beta_{island,cluster} \sim normal(0, \sigma_{cluster}) \quad (22)$$

213 This allows the mean effect of each island to differ for each cluster, e.g. allowing San Miguel, the easternmost  
 214 island, to have a higher mean density for eastern species than for more western species (if the data suggest it).  
 215 The second critical component of the covariate matrix  $X$  are random effects for each year for each species

$$\beta_{year,species} \sim normal(0, \sigma_{species}) \quad (23)$$

216 These  $\beta_{year,species}$  represent our “standardized” estimate of observed abundance of each species in each time  
 217 step, controlling for the included covariates.  
 218 However, we still need to account for changes in the probability of detection over time. For that, we create a  
 219 standard matrix of with rows equal to the number of years and columns corresponding to each of the columns  
 220 in  $X$ , holding everything fixed at mean (or most frequently observed level for factors) levels for all variables  
 221 in  $X$  except for the year and species interaction indices. Calling this standardized matrix  $X^{standard}$ , the  
 222 probability of observing a given species in year  $y$  is then

$$p_{s,y} = \left( \frac{1}{1 + e^{-\beta^o X^{standard}}} \right) \quad (24)$$

223 In the same manner as described by Punt et al. (2000), The standardized index of abundance for species  $s$  in  
 224 year  $y$  then is

$$I_{species,year} = p_{species,year} e^{\beta_{species,year}} \quad (25)$$

225 The next phase of the model requires us to estimate the mean abundance of targeted and non-targeted species  
 226 over time. The concept here is that each  $I_{species,year}$  can be modeled by a regression that contains random  
 227 effects for each year for targeted and non-targeted fishes, the assumption then being that there is a mean  
 228 density for targeted and non-target species, and  $I_{species,year}$  represent deviations from that mean.

$$\log(I_{species,year}) \sim normal(\beta^{effect} X^{effect}, \sigma_I) \quad (26)$$

229  $X^{effect}$  contains both fixed and random effects. The fixed effects include an intercept and the temperature  
 230 deviation for a given species in a year, where temperature deviation is

$$t_{s,y} = (t_s^{pref} - \bar{t}_y)^2 \quad (27)$$

231 where  $t_s^{pref}$  is the preferred temperature for species  $s$  (drawn from FishLife, Thorson et al. (2017)), and  $\bar{t}_y$   
 232 is the mean temperature encountered by that species in year  $y$ . We also include as variables in the model the  
 233 mean kelp cover experienced by a given species in a given year, as well as the total fishery catches reported in  
 234 the previous year for that species in the Santa Barbara region [drawn from the California Department of Fish  
 235 and Wildlife database]. We also include random intercepts for each species in  $X^{effect}$ . The most important  
 236 random effects are year effects for targeted and non-targeted species

$$\beta_{year,targeted} \sim normal(0, \sigma_{targeted}) \quad (28)$$

<sup>237</sup>  $\beta_{year,targeted}$  is the mean log density of targeted species in year  $y$ , controlling for included covariates. Therefore,  
<sup>238</sup> the final step in the model, the divergence in the standardized abundance trends of targeted and non-targeted  
<sup>239</sup> species is

$$divergence_{year} = \beta_{year,targeted=1} - \beta_{year,targeted=0} \quad (29)$$

- <sup>240</sup> The model is fit in TMB to integrate the uncertainty across all levels of the model, with standard errors for  
<sup>241</sup> each coefficient in the model estimated through the Laplace approximation.  
<sup>242</sup> A complete table of estimated coefficients can be seen in Table.S4.

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model

estimate	lower	upper	variable
0.20	0.15	0.25	cumulative_n_obs
0.00	-0.04	0.04	surge
0.09	0.07	0.12	mean_depth
-0.05	-0.08	-0.03	mean_vis
1.47	1.25	1.69	intercept
-0.08	-0.28	0.13	site_side-ANACAPA ADMIRALS-E
-0.04	-0.23	0.15	site_side-ANACAPA ADMIRALS-W
0.10	-0.08	0.27	site_side-ANACAPA BLACK SEA BASS-CEN
0.08	-0.13	0.29	site_side-ANACAPA EAST FISH CAMP-CEN
-0.19	-0.40	0.03	site_side-ANACAPA EAST FISH CAMP-E
-0.34	-0.53	-0.14	site_side-ANACAPA EAST FISH CAMP-W
-0.11	-0.26	0.04	site_side-ANACAPA EAST ISLE-CEN
-0.10	-0.25	0.04	site_side-ANACAPA EAST ISLE-E
-0.33	-0.47	-0.18	site_side-ANACAPA EAST ISLE-W
0.11	-0.05	0.27	site_side-ANACAPA LIGHTHOUSE REEF-CEN
0.05	-0.11	0.20	site_side-ANACAPA LIGHTHOUSE REEF-E
0.05	-0.11	0.21	site_side-ANACAPA LIGHTHOUSE REEF-W
-0.10	-0.25	0.05	site_side-ANACAPA MIDDLE ISLE-CEN
-0.27	-0.43	-0.12	site_side-ANACAPA MIDDLE ISLE-E
0.03	-0.12	0.19	site_side-ANACAPA MIDDLE ISLE-W
0.01	-0.14	0.16	site_side-ANACAPA WEST ISLE-CEN
0.07	-0.08	0.22	site_side-ANACAPA WEST ISLE-E
0.06	-0.09	0.22	site_side-ANACAPA WEST ISLE-W
0.04	-0.11	0.18	site_side-SCI CAVERN POINT-E
0.17	0.03	0.32	site_side-SCI CAVERN POINT-W
0.10	-0.05	0.24	site_side-SCI COCHE POINT-E
0.14	0.00	0.29	site_side-SCI COCHE POINT-W
0.09	-0.06	0.24	site_side-SCI FORNEY-E
0.39	0.24	0.54	site_side-SCI FORNEY-W
0.45	0.30	0.59	site_side-SCI GULL ISLE-E
0.02	-0.13	0.17	site_side-SCI GULL ISLE-W
0.10	-0.05	0.25	site_side-SCI HAZARDS-CEN
-0.23	-0.38	-0.08	site_side-SCI HAZARDS-E
0.04	-0.11	0.19	site_side-SCI HAZARDS-W
0.25	0.08	0.42	site_side-SCI LITTLE SCORPION-E
0.08	-0.08	0.25	site_side-SCI LITTLE SCORPION-W

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.20	0.04	0.35	site_side-SCI_PAINTED_CAVE-CEN
0.30	0.15	0.45	site_side-SCI_PAINTED_CAVE-E
0.14	-0.01	0.30	site_side-SCI_PAINTED_CAVE-W
0.04	-0.10	0.19	site_side-SCI_PELICAN-CEN
0.28	0.13	0.43	site_side-SCI_PELICAN-E
0.46	0.09	0.84	site_side-SCI_PELICAN-FAR_WEST
0.09	-0.06	0.24	site_side-SCI_PELICAN-W
0.06	-0.11	0.24	site_side-SCI_POTATO_PASTURE-E
0.19	0.01	0.37	site_side-SCI_POTATO_PASTURE-W
0.14	-0.03	0.31	site_side-SCI_SAN_PEDRO_POINT-E
0.30	0.14	0.46	site_side-SCI_SAN_PEDRO_POINT-W
0.13	-0.03	0.30	site_side-SCI_SCORPION_ANCHORAGE-CEN
0.31	0.16	0.45	site_side-SCI_SCORPION-E
0.16	0.01	0.31	site_side-SCI_SCORPION-W
0.11	-0.04	0.27	site_side-SCI_VALLEY-CEN
0.03	-0.15	0.21	site_side-SCI_VALLEY-E
-0.09	-0.25	0.07	site_side-SCI_VALLEY-W
0.14	-0.01	0.30	site_side-SCI_YELLOWBANKS-CEN
0.14	-0.16	0.44	site_side-SCI_YELLOWBANKS-E
-0.14	-0.29	0.01	site_side-SCI_YELLOWBANKS-W
0.21	-0.19	0.61	site_side-SMI_BAY_POINT-CEN
-0.41	-0.60	-0.22	site_side-SMI_CROOK_POINT-E
0.06	-0.12	0.25	site_side-SMI_CROOK_POINT-W
-0.15	-0.33	0.04	site_side-SMI_CUYLER-E
-0.11	-0.27	0.05	site_side-SMI_CUYLER-W
0.27	0.11	0.43	site_side-SMI_HARRIS_PT_RESERVE-E
0.04	-0.13	0.22	site_side-SMI_HARRIS_PT_RESERVE-W
0.46	0.29	0.63	site_side-SMI_TYLER_BIGHT-E
0.45	0.28	0.63	site_side-SMI_TYLER_BIGHT-W
0.10	-0.21	0.42	site_side-SRI_BEACON_REEF-E
-0.24	-0.61	0.12	site_side-SRI_BEACON_REEF-W
-0.08	-0.38	0.22	site_side-SRI_BEE_ROCK-E
-0.46	-0.79	-0.12	site_side-SRI_BEE_ROCK-W
-0.42	-0.92	0.08	site_side-SRI_CARRINGTON-CEN
0.29	-0.22	0.80	site_side-SRI_CARRINGTON-E
0.27	-0.12	0.67	site_side-SRI_CARRINGTON-W
0.24	0.07	0.41	site_side-SRI_CHICKASAW-E
0.26	0.08	0.43	site_side-SRI_CHICKASAW-W
-0.10	-0.26	0.06	site_side-SRI_CLUSTER_POINT-N
-0.05	-0.22	0.13	site_side-SRI_CLUSTER_POINT-S
0.10	-0.26	0.47	site_side-SRI_FORD_POINT-CEN
0.02	-0.16	0.20	site_side-SRI_JOHNSONS_LEE_NORTH-E
-0.09	-0.28	0.11	site_side-SRI_JOHNSONS_LEE_NORTH-W
0.21	0.05	0.36	site_side-SRI_JOHNSONS_LEE_SOUTH-E
0.00	-0.16	0.16	site_side-SRI_JOHNSONS_LEE_SOUTH-W

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-0.36	-0.60	-0.12	site_side-SRI_JOLLA_VIEJA-E
-0.28	-0.56	0.00	site_side-SRI_JOLLA_VIEJA-W
0.24	-0.09	0.58	site_side-SRI_MONACOS-E
0.16	-0.17	0.48	site_side-SRI_MONACOS-W
0.06	-0.20	0.33	site_side-SRI_RODES_REF-E
0.21	-0.04	0.45	site_side-SRI_RODES_REF-W
0.09	-0.06	0.24	site_side-SRI_SOUTH_POINT-E
0.19	0.04	0.35	site_side-SRI_SOUTH_POINT-W
0.07	-0.12	0.26	site_side-SRI_TRANCION_CANYON-E
0.14	-0.06	0.33	site_side-SRI_TRANCION_CANYON-W
-0.03	-0.09	0.02	level-CNMD
0.03	-0.01	0.06	level-MID
0.00	-0.05	0.05	factor_month-11
0.14	0.07	0.21	factor_month-12
-0.28	-0.50	-0.07	factor_month-7
-0.02	-0.06	0.02	factor_month-8
-0.02	-0.05	0.01	factor_month-9
-0.05	-0.11	0.01	cumulative_n_obs_2
0.42	0.36	0.48	cumulative_n_obs
-0.04	-0.09	0.00	surge
-0.26	-0.29	-0.23	mean_depth
0.09	0.06	0.11	mean_vis
-0.59	-0.76	-0.42	intercept
-0.38	-0.60	-0.16	site_side-ANACAPA ADMIRALS-E
-0.16	-0.37	0.06	site_side-ANACAPA ADMIRALS-W
-0.39	-0.58	-0.19	site_side-ANACAPA BLACK SEA BASS-CEN
-0.46	-0.70	-0.23	site_side-ANACAPA EAST FISH CAMP-CEN
-0.52	-0.75	-0.28	site_side-ANACAPA EAST FISH CAMP-E
-0.27	-0.49	-0.05	site_side-ANACAPA EAST FISH CAMP-W
0.27	0.10	0.44	site_side-ANACAPA EAST ISLE-CEN
0.34	0.18	0.51	site_side-ANACAPA EAST ISLE-E
-0.05	-0.22	0.12	site_side-ANACAPA EAST ISLE-W
-0.27	-0.45	-0.09	site_side-ANACAPA LIGHTHOUSE REEF-CEN
-0.03	-0.21	0.15	site_side-ANACAPA LIGHTHOUSE REEF-E
-0.21	-0.39	-0.03	site_side-ANACAPA LIGHTHOUSE REEF-W
-0.18	-0.35	-0.01	site_side-ANACAPA MIDDLE ISLE-CEN
-0.48	-0.65	-0.31	site_side-ANACAPA MIDDLE ISLE-E
-0.49	-0.67	-0.32	site_side-ANACAPA MIDDLE ISLE-W
0.07	-0.10	0.24	site_side-ANACAPA WEST ISLE-CEN
-0.06	-0.23	0.11	site_side-ANACAPA WEST ISLE-E
-0.34	-0.51	-0.16	site_side-ANACAPA WEST ISLE-W
0.11	-0.06	0.27	site_side-SCI CAVERN POINT-E
0.12	-0.04	0.29	site_side-SCI CAVERN POINT-W
0.20	0.03	0.36	site_side-SCI COCHE POINT-E
-0.01	-0.17	0.16	site_side-SCI COCHE POINT-W

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-0.50	-0.67	-0.34	site_side-SCI_FORNEY-E
-0.36	-0.52	-0.19	site_side-SCI_FORNEY-W
0.19	0.03	0.35	site_side-SCI_GULL_ISLE-E
-0.08	-0.24	0.09	site_side-SCI_GULL_ISLE-W
0.06	-0.11	0.23	site_side-SCI_HAZARDS-CEN
0.03	-0.14	0.19	site_side-SCI_HAZARDS-E
0.07	-0.10	0.23	site_side-SCI_HAZARDS-W
-0.02	-0.21	0.18	site_side-SCI_LITTLE_SCORPION-E
0.28	0.09	0.47	site_side-SCI_LITTLE_SCORPION-W
0.05	-0.12	0.22	site_side-SCI_PAINTED_CAVE-CEN
0.16	-0.01	0.33	site_side-SCI_PAINTED_CAVE-E
-0.13	-0.30	0.05	site_side-SCI_PAINTED_CAVE-W
0.15	-0.01	0.32	site_side-SCI_PELICAN-CEN
0.17	0.00	0.34	site_side-SCI_PELICAN-E
-0.07	-0.47	0.32	site_side-SCI_PELICAN-FAR_WEST
-0.12	-0.29	0.04	site_side-SCI_PELICAN-W
-0.29	-0.49	-0.09	site_side-SCI_POTATO_PASTURE-E
-0.34	-0.54	-0.15	site_side-SCI_POTATO_PASTURE-W
-0.24	-0.44	-0.05	site_side-SCI_SAN_PEDRO_POINT-E
0.25	0.06	0.43	site_side-SCI_SAN_PEDRO_POINT-W
-0.06	-0.25	0.13	site_side-SCI_SCORPION_ANCHORAGE-CEN
0.05	-0.12	0.21	site_side-SCI_SCORPION-E
-0.16	-0.33	0.00	site_side-SCI_SCORPION-W
-0.21	-0.39	-0.04	site_side-SCI_VALLEY-CEN
-0.95	-1.14	-0.76	site_side-SCI_VALLEY-E
-0.58	-0.76	-0.40	site_side-SCI_VALLEY-W
-0.58	-0.75	-0.41	site_side-SCI_YELLOWBANKS-CEN
-0.65	-0.97	-0.34	site_side-SCI_YELLOWBANKS-E
-0.43	-0.59	-0.26	site_side-SCI_YELLOWBANKS-W
-0.56	-0.97	-0.14	site_side-SMI_BAY_POINT-CEN
-1.52	-1.71	-1.32	site_side-SMI_CROOK_POINT-E
-1.36	-1.55	-1.17	site_side-SMI_CROOK_POINT-W
-1.67	-1.86	-1.48	site_side-SMI_CUYLER-E
-0.97	-1.14	-0.79	site_side-SMI_CUYLER-W
-0.57	-0.75	-0.40	site_side-SMI_HARRIS_PT_RESERVE-E
-1.43	-1.62	-1.25	site_side-SMI_HARRIS_PT_RESERVE-W
-0.68	-0.86	-0.50	site_side-SMI_TYLER_BIGHT-E
-1.00	-1.18	-0.82	site_side-SMI_TYLER_BIGHT-W
-1.58	-1.88	-1.28	site_side-SRI_BEACON_REEF-E
-1.77	-2.12	-1.43	site_side-SRI_BEACON_REEF-W
-1.08	-1.37	-0.80	site_side-SRI_BEE_ROCK-E
-1.16	-1.46	-0.85	site_side-SRI_BEE_ROCK-W
-1.21	-1.67	-0.74	site_side-SRI_CARRINGTON-CEN
-1.29	-1.76	-0.82	site_side-SRI_CARRINGTON-E
-1.26	-1.63	-0.88	site_side-SRI_CARRINGTON-W

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-0.40	-0.58	-0.21	site_side-SRI_CHICKASAW-E
-0.62	-0.80	-0.43	site_side-SRI_CHICKASAW-W
-0.88	-1.05	-0.70	site_side-SRI_CLUSTER_POINT-N
-1.31	-1.49	-1.12	site_side-SRI_CLUSTER_POINT-S
-0.74	-1.09	-0.39	site_side-SRI_FORD_POINT-CEN
-0.64	-0.83	-0.45	site_side-SRI_JOHNSONS_LEE_NORTH-E
-0.92	-1.11	-0.72	site_side-SRI_JOHNSONS_LEE_NORTH-W
-0.35	-0.51	-0.18	site_side-SRI_JOHNSONS_LEE_SOUTH-E
-0.96	-1.13	-0.79	site_side-SRI_JOHNSONS_LEE_SOUTH-W
-0.82	-1.06	-0.58	site_side-SRI_JOLLA_VIEJA-E
-1.31	-1.57	-1.04	site_side-SRI_JOLLA_VIEJA-W
-1.25	-1.55	-0.95	site_side-SRI_MONACOS-E
-0.76	-1.06	-0.46	site_side-SRI_MONACOS-W
-0.83	-1.09	-0.56	site_side-SRI_RODES_REEF-E
-0.92	-1.17	-0.68	site_side-SRI_RODES_REEF-W
-0.66	-0.83	-0.49	site_side-SRI_SOUTH_POINT-E
-0.58	-0.75	-0.41	site_side-SRI_SOUTH_POINT-W
-0.87	-1.07	-0.68	site_side-SRI_TRANCION_CANYON-E
-0.88	-1.08	-0.69	site_side-SRI_TRANCION_CANYON-W
-1.63	-1.68	-1.57	level-CNMD
-1.46	-1.50	-1.43	level-MID
0.01	-0.04	0.06	factor_month-11
-0.10	-0.17	-0.03	factor_month-12
-0.01	-0.24	0.23	factor_month-7
0.09	0.05	0.13	factor_month-8
0.12	0.09	0.16	factor_month-9
-0.22	-0.27	-0.16	cumulative_n_obs_2
-1.18	-1.71	-0.65	year_classcode-bfre-2000
-0.62	-1.11	-0.12	year_classcode-bfre-2001
-1.48	-1.95	-1.01	year_classcode-bfre-2002
-2.25	-2.56	-1.95	year_classcode-bfre-2003
-1.86	-2.11	-1.62	year_classcode-bfre-2004
-2.03	-2.26	-1.80	year_classcode-bfre-2005
-2.26	-2.51	-2.02	year_classcode-bfre-2006
-1.81	-2.04	-1.58	year_classcode-bfre-2007
-2.53	-2.81	-2.25	year_classcode-bfre-2008
-2.17	-2.39	-1.95	year_classcode-bfre-2009
-2.42	-2.68	-2.17	year_classcode-bfre-2010
-2.18	-2.45	-1.91	year_classcode-bfre-2011
-2.30	-2.56	-2.03	year_classcode-bfre-2012
-2.17	-2.43	-1.92	year_classcode-bfre-2013
-1.87	-2.13	-1.61	year_classcode-bfre-2014
-2.52	-2.81	-2.23	year_classcode-bfre-2015
-2.67	-3.07	-2.26	year_classcode-bfre-2016
-2.39	-2.71	-2.08	year_classcode-bfre-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
1.07	0.48	1.66	year_classcode-cpri-2000
0.67	0.00	1.33	year_classcode-cpri-2001
0.64	-0.02	1.29	year_classcode-cpri-2002
0.60	0.10	1.10	year_classcode-cpri-2003
0.67	0.15	1.19	year_classcode-cpri-2004
0.57	0.14	0.99	year_classcode-cpri-2005
0.59	0.11	1.07	year_classcode-cpri-2006
0.83	0.35	1.32	year_classcode-cpri-2007
0.77	0.30	1.24	year_classcode-cpri-2008
1.06	0.64	1.48	year_classcode-cpri-2009
1.01	0.55	1.48	year_classcode-cpri-2010
1.33	0.80	1.85	year_classcode-cpri-2011
1.48	0.94	2.02	year_classcode-cpri-2012
1.07	0.43	1.72	year_classcode-cpri-2013
1.10	0.53	1.68	year_classcode-cpri-2014
-1.32	-1.73	-0.91	year_classcode-cpri-2015
0.12	-0.20	0.44	year_classcode-cpri-2016
0.46	0.13	0.79	year_classcode-cpri-2017
1.23	0.88	1.58	year_classcode-cpun-2000
1.02	0.68	1.37	year_classcode-cpun-2001
0.39	0.10	0.68	year_classcode-cpun-2002
0.14	-0.10	0.38	year_classcode-cpun-2003
-0.30	-0.54	-0.07	year_classcode-cpun-2004
-0.25	-0.46	-0.04	year_classcode-cpun-2005
-0.41	-0.63	-0.20	year_classcode-cpun-2006
-0.37	-0.58	-0.15	year_classcode-cpun-2007
-0.73	-0.95	-0.52	year_classcode-cpun-2008
0.16	-0.05	0.36	year_classcode-cpun-2009
0.17	-0.05	0.39	year_classcode-cpun-2010
0.35	0.12	0.58	year_classcode-cpun-2011
0.16	-0.07	0.39	year_classcode-cpun-2012
0.13	-0.11	0.36	year_classcode-cpun-2013
-0.24	-0.47	-0.02	year_classcode-cpun-2014
-0.36	-0.57	-0.14	year_classcode-cpun-2015
0.04	-0.17	0.25	year_classcode-cpun-2016
-0.22	-0.44	0.00	year_classcode-cpun-2017
0.66	0.27	1.05	year_classcode-ejac-2000
0.41	0.01	0.81	year_classcode-ejac-2001
0.48	0.13	0.82	year_classcode-ejac-2002
-0.18	-0.45	0.10	year_classcode-ejac-2003
-0.42	-0.68	-0.17	year_classcode-ejac-2004
-0.07	-0.29	0.16	year_classcode-ejac-2005
0.31	0.08	0.54	year_classcode-ejac-2006
-0.09	-0.32	0.13	year_classcode-ejac-2007
-0.90	-1.13	-0.67	year_classcode-ejac-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-0.13	-0.35	0.09	year_classcode-ejac-2009
-0.05	-0.28	0.18	year_classcode-ejac-2010
-0.01	-0.25	0.22	year_classcode-ejac-2011
-0.44	-0.68	-0.20	year_classcode-ejac-2012
-0.28	-0.54	-0.03	year_classcode-ejac-2013
-0.23	-0.48	0.01	year_classcode-ejac-2014
-0.53	-0.79	-0.28	year_classcode-ejac-2015
-0.50	-0.76	-0.24	year_classcode-ejac-2016
-0.84	-1.09	-0.58	year_classcode-ejac-2017
0.11	-0.47	0.68	year_classcode-elat-2000
0.29	-0.27	0.85	year_classcode-elat-2001
0.23	-0.28	0.74	year_classcode-elat-2002
0.28	-0.03	0.59	year_classcode-elat-2003
-0.26	-0.52	0.01	year_classcode-elat-2004
-0.26	-0.48	-0.04	year_classcode-elat-2005
0.27	0.05	0.49	year_classcode-elat-2006
0.12	-0.12	0.37	year_classcode-elat-2007
-0.73	-0.96	-0.49	year_classcode-elat-2008
0.12	-0.09	0.33	year_classcode-elat-2009
0.05	-0.18	0.28	year_classcode-elat-2010
0.02	-0.20	0.25	year_classcode-elat-2011
-0.06	-0.29	0.16	year_classcode-elat-2012
-0.18	-0.46	0.10	year_classcode-elat-2013
-0.20	-0.44	0.03	year_classcode-elat-2014
-0.07	-0.38	0.24	year_classcode-elat-2015
-0.70	-1.04	-0.37	year_classcode-elat-2016
-0.82	-1.18	-0.47	year_classcode-elat-2017
1.46	1.06	1.85	year_classcode-gnig-2000
1.48	1.11	1.86	year_classcode-gnig-2001
1.25	0.92	1.59	year_classcode-gnig-2002
1.33	1.06	1.60	year_classcode-gnig-2003
1.01	0.77	1.25	year_classcode-gnig-2004
1.20	0.98	1.42	year_classcode-gnig-2005
1.22	1.00	1.44	year_classcode-gnig-2006
1.27	1.05	1.49	year_classcode-gnig-2007
1.02	0.80	1.24	year_classcode-gnig-2008
1.32	1.10	1.53	year_classcode-gnig-2009
1.46	1.21	1.70	year_classcode-gnig-2010
1.34	1.10	1.59	year_classcode-gnig-2011
1.46	1.22	1.71	year_classcode-gnig-2012
1.21	0.94	1.48	year_classcode-gnig-2013
1.28	1.04	1.52	year_classcode-gnig-2014
1.11	0.88	1.34	year_classcode-gnig-2015
1.31	1.07	1.55	year_classcode-gnig-2016
1.29	1.06	1.52	year_classcode-gnig-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-0.39	-1.89	1.10	year_classcode-hcar-2000
-1.50	-2.40	-0.61	year_classcode-hcar-2001
-1.99	-2.70	-1.28	year_classcode-hcar-2002
-1.44	-1.93	-0.95	year_classcode-hcar-2003
-1.38	-1.98	-0.78	year_classcode-hcar-2004
-1.47	-1.80	-1.15	year_classcode-hcar-2005
-1.98	-2.31	-1.65	year_classcode-hcar-2006
-1.59	-1.88	-1.29	year_classcode-hcar-2007
-2.68	-2.98	-2.37	year_classcode-hcar-2008
-1.61	-1.92	-1.31	year_classcode-hcar-2009
-1.73	-2.11	-1.36	year_classcode-hcar-2010
-1.56	-2.11	-1.01	year_classcode-hcar-2011
-1.90	-2.34	-1.46	year_classcode-hcar-2012
-2.00	-2.47	-1.53	year_classcode-hcar-2013
-1.87	-2.58	-1.17	year_classcode-hcar-2014
-0.87	-1.79	0.05	year_classcode-hcar-2015
-1.37	-2.23	-0.51	year_classcode-hcar-2016
-1.40	-2.19	-0.62	year_classcode-hcar-2017
-2.80	-3.71	-1.89	year_classcode-hros-2000
-3.55	-4.28	-2.82	year_classcode-hros-2001
-2.91	-3.86	-1.97	year_classcode-hros-2002
-2.59	-3.53	-1.65	year_classcode-hros-2003
-4.13	-4.46	-3.80	year_classcode-hros-2004
-3.71	-4.10	-3.32	year_classcode-hros-2005
-4.09	-4.49	-3.69	year_classcode-hros-2006
-3.89	-4.23	-3.56	year_classcode-hros-2007
-4.28	-4.76	-3.79	year_classcode-hros-2008
-3.66	-3.97	-3.36	year_classcode-hros-2009
-1.29	-2.20	-0.39	year_classcode-hros-2010
-3.54	-4.02	-3.06	year_classcode-hros-2011
-3.59	-3.99	-3.18	year_classcode-hros-2012
-2.25	-3.11	-1.39	year_classcode-hros-2013
-3.54	-4.02	-3.06	year_classcode-hros-2014
-3.31	-3.81	-2.81	year_classcode-hros-2015
-2.57	-3.11	-2.04	year_classcode-hros-2016
-3.94	-4.32	-3.57	year_classcode-hros-2017
1.73	1.38	2.07	year_classcode-hrub-2000
1.78	1.47	2.10	year_classcode-hrub-2001
1.47	1.18	1.77	year_classcode-hrub-2002
1.37	1.10	1.63	year_classcode-hrub-2003
0.89	0.66	1.13	year_classcode-hrub-2004
1.03	0.82	1.25	year_classcode-hrub-2005
0.95	0.73	1.16	year_classcode-hrub-2006
1.10	0.88	1.31	year_classcode-hrub-2007
0.89	0.67	1.10	year_classcode-hrub-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
1.18	0.97	1.39	year_classcode-hrub-2009
1.07	0.83	1.31	year_classcode-hrub-2010
1.00	0.76	1.23	year_classcode-hrub-2011
1.05	0.82	1.29	year_classcode-hrub-2012
1.02	0.78	1.26	year_classcode-hrub-2013
0.34	0.12	0.57	year_classcode-hrub-2014
0.49	0.27	0.71	year_classcode-hrub-2015
0.36	0.14	0.58	year_classcode-hrub-2016
0.70	0.48	0.91	year_classcode-hrub-2017
-0.10	-0.45	0.25	year_classcode-hsem-2000
0.04	-0.34	0.41	year_classcode-hsem-2001
-0.29	-0.68	0.11	year_classcode-hsem-2002
-0.49	-0.90	-0.08	year_classcode-hsem-2003
-0.31	-0.68	0.06	year_classcode-hsem-2004
-1.33	-1.59	-1.07	year_classcode-hsem-2005
-0.85	-1.13	-0.57	year_classcode-hsem-2006
-1.16	-1.39	-0.93	year_classcode-hsem-2007
-1.03	-1.27	-0.80	year_classcode-hsem-2008
-0.56	-0.78	-0.33	year_classcode-hsem-2009
-0.40	-0.68	-0.12	year_classcode-hsem-2010
-0.26	-0.55	0.02	year_classcode-hsem-2011
-0.13	-0.52	0.27	year_classcode-hsem-2012
-0.75	-1.16	-0.34	year_classcode-hsem-2013
-1.88	-2.17	-1.59	year_classcode-hsem-2014
-0.56	-0.77	-0.34	year_classcode-hsem-2015
-0.19	-0.40	0.02	year_classcode-hsem-2016
-0.13	-0.35	0.08	year_classcode-hsem-2017
0.87	0.43	1.32	year_classcode-mcal-2000
0.99	0.58	1.39	year_classcode-mcal-2001
0.27	-0.07	0.62	year_classcode-mcal-2002
0.47	0.18	0.77	year_classcode-mcal-2003
-0.05	-0.32	0.22	year_classcode-mcal-2004
0.12	-0.11	0.34	year_classcode-mcal-2005
-0.15	-0.36	0.06	year_classcode-mcal-2006
0.30	0.07	0.53	year_classcode-mcal-2007
-0.15	-0.39	0.09	year_classcode-mcal-2008
0.43	0.19	0.68	year_classcode-mcal-2009
0.67	0.36	0.98	year_classcode-mcal-2010
0.44	0.11	0.76	year_classcode-mcal-2011
0.71	0.36	1.07	year_classcode-mcal-2012
0.49	0.13	0.84	year_classcode-mcal-2013
0.11	-0.14	0.36	year_classcode-mcal-2014
-0.07	-0.29	0.14	year_classcode-mcal-2015
0.32	0.10	0.54	year_classcode-mcal-2016
0.05	-0.17	0.28	year_classcode-mcal-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.23	-0.13	0.59	year_classcode-ocal-2000
0.16	-0.19	0.51	year_classcode-ocal-2001
-0.36	-0.69	-0.03	year_classcode-ocal-2002
-0.96	-1.20	-0.71	year_classcode-ocal-2003
-0.93	-1.15	-0.70	year_classcode-ocal-2004
-0.81	-1.02	-0.61	year_classcode-ocal-2005
-0.45	-0.66	-0.25	year_classcode-ocal-2006
-0.50	-0.71	-0.30	year_classcode-ocal-2007
-0.94	-1.14	-0.73	year_classcode-ocal-2008
-0.19	-0.38	0.01	year_classcode-ocal-2009
-0.19	-0.40	0.01	year_classcode-ocal-2010
-0.42	-0.64	-0.20	year_classcode-ocal-2011
-0.62	-0.83	-0.40	year_classcode-ocal-2012
-0.46	-0.69	-0.22	year_classcode-ocal-2013
-0.65	-0.87	-0.44	year_classcode-ocal-2014
-0.71	-0.92	-0.50	year_classcode-ocal-2015
-0.63	-0.84	-0.41	year_classcode-ocal-2016
-0.57	-0.79	-0.35	year_classcode-ocal-2017
-1.12	-1.60	-0.64	year_classcode-opic-2000
-1.72	-2.17	-1.28	year_classcode-opic-2001
0.23	-0.84	1.30	year_classcode-opic-2002
-1.93	-2.30	-1.56	year_classcode-opic-2003
-1.68	-1.91	-1.46	year_classcode-opic-2004
-1.91	-2.12	-1.70	year_classcode-opic-2005
-1.70	-1.92	-1.48	year_classcode-opic-2006
-2.09	-2.30	-1.88	year_classcode-opic-2007
-2.19	-2.40	-1.99	year_classcode-opic-2008
-2.07	-2.27	-1.87	year_classcode-opic-2009
-1.94	-2.15	-1.74	year_classcode-opic-2010
-1.84	-2.05	-1.64	year_classcode-opic-2011
-1.80	-2.01	-1.60	year_classcode-opic-2012
-2.06	-2.28	-1.85	year_classcode-opic-2013
-2.35	-2.56	-2.13	year_classcode-opic-2014
-2.49	-2.75	-2.23	year_classcode-opic-2015
-2.52	-2.76	-2.27	year_classcode-opic-2016
-2.39	-2.64	-2.14	year_classcode-opic-2017
1.39	1.07	1.71	year_classcode-pcla-2000
1.45	1.14	1.75	year_classcode-pcla-2001
1.26	0.98	1.53	year_classcode-pcla-2002
0.86	0.61	1.11	year_classcode-pcla-2003
0.56	0.34	0.79	year_classcode-pcla-2004
0.03	-0.17	0.24	year_classcode-pcla-2005
0.26	0.05	0.47	year_classcode-pcla-2006
0.46	0.26	0.67	year_classcode-pcla-2007
0.35	0.14	0.55	year_classcode-pcla-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.98	0.78	1.18	year_classcode-pcla-2009
0.83	0.61	1.06	year_classcode-pcla-2010
1.01	0.79	1.23	year_classcode-pcla-2011
1.02	0.80	1.24	year_classcode-pcla-2012
0.86	0.63	1.08	year_classcode-pcla-2013
0.54	0.33	0.76	year_classcode-pcla-2014
0.49	0.28	0.70	year_classcode-pcla-2015
0.65	0.44	0.86	year_classcode-pcla-2016
0.78	0.58	0.99	year_classcode-pcla-2017
-0.76	-2.00	0.48	year_classcode-pfur-2000
-0.92	-2.05	0.22	year_classcode-pfur-2001
-0.54	-1.89	0.82	year_classcode-pfur-2002
-1.25	-2.15	-0.35	year_classcode-pfur-2003
-1.84	-2.61	-1.06	year_classcode-pfur-2004
-0.67	-1.37	0.03	year_classcode-pfur-2005
-1.00	-1.74	-0.26	year_classcode-pfur-2006
-0.67	-1.74	0.39	year_classcode-pfur-2007
-1.52	-2.54	-0.51	year_classcode-pfur-2008
-1.45	-2.10	-0.79	year_classcode-pfur-2009
-0.92	-1.70	-0.15	year_classcode-pfur-2010
-0.47	-1.42	0.48	year_classcode-pfur-2011
-0.64	-1.79	0.51	year_classcode-pfur-2012
0.37	-1.00	1.75	year_classcode-pfur-2013
-0.75	-1.83	0.33	year_classcode-pfur-2014
0.51	-0.83	1.86	year_classcode-pfur-2015
0.13	-1.13	1.39	year_classcode-pfur-2016
-0.11	-1.36	1.14	year_classcode-pfur-2017
0.95	0.13	1.77	year_classcode-rtox-2000
1.10	0.51	1.69	year_classcode-rtox-2001
0.81	0.34	1.29	year_classcode-rtox-2002
0.79	0.36	1.22	year_classcode-rtox-2003
0.68	0.27	1.08	year_classcode-rtox-2004
0.94	0.61	1.26	year_classcode-rtox-2005
0.87	0.52	1.23	year_classcode-rtox-2006
1.26	0.90	1.62	year_classcode-rtox-2007
1.40	0.96	1.83	year_classcode-rtox-2008
1.31	1.01	1.61	year_classcode-rtox-2009
1.12	0.78	1.47	year_classcode-rtox-2010
0.79	0.48	1.11	year_classcode-rtox-2011
0.93	0.56	1.29	year_classcode-rtox-2012
0.90	0.49	1.31	year_classcode-rtox-2013
1.47	1.01	1.92	year_classcode-rtox-2014
0.51	0.07	0.95	year_classcode-rtox-2015
0.54	0.11	0.98	year_classcode-rtox-2016
-0.18	-0.78	0.41	year_classcode-rtox-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.27	-0.15	0.68	year_classcode-rvac-2000
0.29	-0.11	0.70	year_classcode-rvac-2001
0.05	-0.31	0.41	year_classcode-rvac-2002
-0.27	-0.57	0.02	year_classcode-rvac-2003
-0.39	-0.68	-0.10	year_classcode-rvac-2004
-0.12	-0.36	0.12	year_classcode-rvac-2005
0.28	0.04	0.51	year_classcode-rvac-2006
-0.08	-0.32	0.17	year_classcode-rvac-2007
-0.49	-0.77	-0.22	year_classcode-rvac-2008
-0.20	-0.44	0.04	year_classcode-rvac-2009
-0.13	-0.38	0.11	year_classcode-rvac-2010
0.00	-0.25	0.25	year_classcode-rvac-2011
-0.45	-0.72	-0.18	year_classcode-rvac-2012
0.16	-0.13	0.45	year_classcode-rvac-2013
-0.13	-0.41	0.15	year_classcode-rvac-2014
-0.36	-0.68	-0.05	year_classcode-rvac-2015
-0.14	-0.44	0.17	year_classcode-rvac-2016
-0.67	-1.00	-0.34	year_classcode-rvac-2017
0.78	0.24	1.31	year_classcode-satr-2000
0.87	0.41	1.32	year_classcode-satr-2001
0.69	0.29	1.10	year_classcode-satr-2002
0.35	0.08	0.61	year_classcode-satr-2003
0.02	-0.21	0.26	year_classcode-satr-2004
0.00	-0.21	0.20	year_classcode-satr-2005
0.39	0.18	0.59	year_classcode-satr-2006
0.25	0.04	0.45	year_classcode-satr-2007
-0.10	-0.31	0.10	year_classcode-satr-2008
0.50	0.31	0.69	year_classcode-satr-2009
0.30	0.09	0.51	year_classcode-satr-2010
0.47	0.27	0.67	year_classcode-satr-2011
0.26	0.05	0.47	year_classcode-satr-2012
0.56	0.31	0.80	year_classcode-satr-2013
0.30	0.05	0.54	year_classcode-satr-2014
0.53	0.25	0.80	year_classcode-satr-2015
0.14	-0.13	0.41	year_classcode-satr-2016
-0.20	-0.47	0.07	year_classcode-satr-2017
0.27	-0.74	1.28	year_classcode-saur-2000
-0.05	-0.84	0.75	year_classcode-saur-2001
0.38	-0.61	1.38	year_classcode-saur-2002
-0.14	-0.95	0.68	year_classcode-saur-2003
-0.22	-1.04	0.60	year_classcode-saur-2004
0.06	-0.75	0.86	year_classcode-saur-2005
-0.18	-0.87	0.50	year_classcode-saur-2006
-0.15	-0.78	0.48	year_classcode-saur-2007
-0.27	-0.96	0.43	year_classcode-saur-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.23	-0.43	0.89	year_classcode-saur-2009
0.48	-0.39	1.36	year_classcode-saur-2010
-0.54	-1.18	0.11	year_classcode-saur-2011
-0.48	-1.12	0.16	year_classcode-saur-2012
-0.07	-0.74	0.59	year_classcode-saur-2013
0.07	-0.63	0.77	year_classcode-saur-2014
-0.06	-0.77	0.65	year_classcode-saur-2015
-0.68	-1.51	0.16	year_classcode-saur-2016
-1.62	-2.36	-0.88	year_classcode-saur-2017
0.07	-0.99	1.13	year_classcode-scau-2000
0.39	-0.70	1.48	year_classcode-scau-2001
0.10	-0.87	1.07	year_classcode-scau-2002
-0.56	-1.19	0.06	year_classcode-scau-2003
-0.38	-0.95	0.20	year_classcode-scau-2004
-0.16	-0.71	0.39	year_classcode-scau-2005
-0.08	-0.60	0.44	year_classcode-scau-2006
-0.05	-0.56	0.45	year_classcode-scau-2007
-0.06	-0.59	0.47	year_classcode-scau-2008
0.07	-0.41	0.55	year_classcode-scau-2009
-1.21	-1.66	-0.77	year_classcode-scau-2010
-1.63	-2.03	-1.24	year_classcode-scau-2011
-0.20	-0.67	0.28	year_classcode-scau-2012
-0.99	-1.54	-0.45	year_classcode-scau-2013
-0.47	-1.00	0.06	year_classcode-scau-2014
-0.52	-1.20	0.16	year_classcode-scau-2015
-0.05	-0.60	0.50	year_classcode-scau-2016
-1.11	-1.76	-0.46	year_classcode-scau-2017
0.19	-0.41	0.78	year_classcode-schr-2000
0.22	-0.38	0.82	year_classcode-schr-2001
0.23	-0.34	0.81	year_classcode-schr-2002
0.19	-0.29	0.68	year_classcode-schr-2003
-0.08	-0.44	0.28	year_classcode-schr-2004
-0.03	-0.35	0.30	year_classcode-schr-2005
0.07	-0.27	0.41	year_classcode-schr-2006
-0.12	-0.44	0.20	year_classcode-schr-2007
-0.19	-0.53	0.14	year_classcode-schr-2008
0.01	-0.26	0.27	year_classcode-schr-2009
-0.43	-0.77	-0.08	year_classcode-schr-2010
-0.63	-0.98	-0.27	year_classcode-schr-2011
-0.14	-0.45	0.18	year_classcode-schr-2012
-0.12	-0.48	0.24	year_classcode-schr-2013
-0.01	-0.33	0.30	year_classcode-schr-2014
-0.13	-0.49	0.23	year_classcode-schr-2015
-0.03	-0.39	0.32	year_classcode-schr-2016
-0.51	-0.96	-0.06	year_classcode-schr-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-0.03	-0.42	0.36	year_classcode-smys-2000
0.06	-0.35	0.47	year_classcode-smys-2001
0.10	-0.28	0.49	year_classcode-smys-2002
-0.10	-0.36	0.16	year_classcode-smys-2003
-0.26	-0.53	0.01	year_classcode-smys-2004
0.00	-0.21	0.21	year_classcode-smys-2005
0.32	0.10	0.54	year_classcode-smys-2006
0.39	0.14	0.64	year_classcode-smys-2007
0.19	-0.06	0.44	year_classcode-smys-2008
0.77	0.51	1.04	year_classcode-smys-2009
0.47	0.19	0.76	year_classcode-smys-2010
0.21	-0.01	0.43	year_classcode-smys-2011
0.26	0.01	0.51	year_classcode-smys-2012
0.07	-0.17	0.31	year_classcode-smys-2013
-0.17	-0.38	0.05	year_classcode-smys-2014
-0.24	-0.49	0.00	year_classcode-smys-2015
0.24	-0.04	0.52	year_classcode-smys-2016
-0.45	-0.77	-0.13	year_classcode-smys-2017
1.02	0.61	1.43	year_classcode-spul-2000
1.82	1.46	2.18	year_classcode-spul-2001
1.47	1.11	1.84	year_classcode-spul-2002
1.25	0.97	1.53	year_classcode-spul-2003
0.71	0.44	0.97	year_classcode-spul-2004
0.49	0.27	0.71	year_classcode-spul-2005
0.84	0.62	1.07	year_classcode-spul-2006
1.17	0.94	1.39	year_classcode-spul-2007
0.90	0.67	1.13	year_classcode-spul-2008
0.70	0.49	0.91	year_classcode-spul-2009
0.84	0.61	1.07	year_classcode-spul-2010
1.10	0.87	1.33	year_classcode-spul-2011
1.23	1.00	1.47	year_classcode-spul-2012
1.56	1.31	1.80	year_classcode-spul-2013
1.21	0.96	1.46	year_classcode-spul-2014
0.13	-0.10	0.36	year_classcode-spul-2015
0.39	0.17	0.61	year_classcode-spul-2016
0.78	0.56	1.00	year_classcode-spul-2017
-0.27	-0.70	0.17	year_classcode-bfre-2000
-0.41	-0.82	0.00	year_classcode-bfre-2001
-0.62	-0.99	-0.26	year_classcode-bfre-2002
-0.05	-0.29	0.18	year_classcode-bfre-2003
0.87	0.68	1.07	year_classcode-bfre-2004
0.64	0.48	0.80	year_classcode-bfre-2005
0.21	0.03	0.39	year_classcode-bfre-2006
0.62	0.47	0.78	year_classcode-bfre-2007
-0.51	-0.71	-0.32	year_classcode-bfre-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.76	0.61	0.91	year_classcode-bfre-2009
0.23	0.04	0.42	year_classcode-bfre-2010
-0.23	-0.43	-0.03	year_classcode-bfre-2011
-0.11	-0.30	0.09	year_classcode-bfre-2012
0.76	0.56	0.97	year_classcode-bfre-2013
0.13	-0.07	0.32	year_classcode-bfre-2014
-0.41	-0.63	-0.20	year_classcode-bfre-2015
-1.32	-1.60	-1.04	year_classcode-bfre-2016
-0.58	-0.81	-0.35	year_classcode-bfre-2017
-1.00	-1.56	-0.44	year_classcode-cpri-2000
-1.41	-1.99	-0.83	year_classcode-cpri-2001
-1.77	-2.33	-1.22	year_classcode-cpri-2002
-1.72	-2.12	-1.31	year_classcode-cpri-2003
-2.16	-2.57	-1.74	year_classcode-cpri-2004
-2.00	-2.32	-1.67	year_classcode-cpri-2005
-2.16	-2.53	-1.80	year_classcode-cpri-2006
-2.33	-2.70	-1.96	year_classcode-cpri-2007
-2.28	-2.64	-1.91	year_classcode-cpri-2008
-2.06	-2.38	-1.74	year_classcode-cpri-2009
-2.05	-2.42	-1.69	year_classcode-cpri-2010
-2.45	-2.86	-2.04	year_classcode-cpri-2011
-2.52	-2.94	-2.10	year_classcode-cpri-2012
-2.63	-3.14	-2.12	year_classcode-cpri-2013
-2.61	-3.06	-2.16	year_classcode-cpri-2014
-1.60	-1.90	-1.29	year_classcode-cpri-2015
-0.89	-1.14	-0.64	year_classcode-cpri-2016
-0.93	-1.19	-0.68	year_classcode-cpri-2017
2.14	1.70	2.58	year_classcode-cpun-2000
1.51	1.15	1.88	year_classcode-cpun-2001
1.70	1.41	1.99	year_classcode-cpun-2002
1.55	1.35	1.75	year_classcode-cpun-2003
1.07	0.89	1.26	year_classcode-cpun-2004
1.09	0.95	1.24	year_classcode-cpun-2005
1.21	1.06	1.36	year_classcode-cpun-2006
0.89	0.74	1.03	year_classcode-cpun-2007
0.79	0.64	0.94	year_classcode-cpun-2008
1.44	1.30	1.58	year_classcode-cpun-2009
1.35	1.19	1.52	year_classcode-cpun-2010
0.87	0.70	1.04	year_classcode-cpun-2011
0.77	0.60	0.94	year_classcode-cpun-2012
1.11	0.93	1.29	year_classcode-cpun-2013
1.07	0.90	1.25	year_classcode-cpun-2014
1.73	1.56	1.91	year_classcode-cpun-2015
2.26	2.08	2.44	year_classcode-cpun-2016
1.82	1.65	2.00	year_classcode-cpun-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.83	0.43	1.22	year_classcode-ejac-2000
0.36	-0.01	0.72	year_classcode-ejac-2001
0.50	0.20	0.79	year_classcode-ejac-2002
0.70	0.49	0.91	year_classcode-ejac-2003
0.80	0.62	0.99	year_classcode-ejac-2004
0.78	0.62	0.93	year_classcode-ejac-2005
0.69	0.53	0.85	year_classcode-ejac-2006
0.47	0.31	0.62	year_classcode-ejac-2007
0.68	0.53	0.83	year_classcode-ejac-2008
0.79	0.64	0.93	year_classcode-ejac-2009
0.96	0.79	1.13	year_classcode-ejac-2010
0.75	0.58	0.93	year_classcode-ejac-2011
0.65	0.48	0.82	year_classcode-ejac-2012
0.63	0.44	0.82	year_classcode-ejac-2013
0.63	0.45	0.81	year_classcode-ejac-2014
0.36	0.18	0.55	year_classcode-ejac-2015
0.34	0.16	0.52	year_classcode-ejac-2016
0.69	0.51	0.87	year_classcode-ejac-2017
-0.18	-0.70	0.33	year_classcode-elat-2000
-0.23	-0.72	0.26	year_classcode-elat-2001
-0.30	-0.75	0.15	year_classcode-elat-2002
-0.11	-0.41	0.18	year_classcode-elat-2003
0.16	-0.10	0.43	year_classcode-elat-2004
0.22	-0.01	0.45	year_classcode-elat-2005
0.24	0.00	0.47	year_classcode-elat-2006
-0.49	-0.73	-0.24	year_classcode-elat-2007
-0.09	-0.32	0.14	year_classcode-elat-2008
0.24	0.02	0.47	year_classcode-elat-2009
0.46	0.21	0.70	year_classcode-elat-2010
0.48	0.24	0.73	year_classcode-elat-2011
0.47	0.23	0.71	year_classcode-elat-2012
-0.02	-0.29	0.24	year_classcode-elat-2013
0.47	0.22	0.72	year_classcode-elat-2014
-0.40	-0.69	-0.11	year_classcode-elat-2015
-0.57	-0.85	-0.28	year_classcode-elat-2016
-0.37	-0.66	-0.08	year_classcode-elat-2017
0.11	-0.18	0.39	year_classcode-gnig-2000
0.08	-0.19	0.35	year_classcode-gnig-2001
-0.05	-0.30	0.20	year_classcode-gnig-2002
-0.04	-0.24	0.17	year_classcode-gnig-2003
0.27	0.07	0.46	year_classcode-gnig-2004
0.12	-0.04	0.27	year_classcode-gnig-2005
0.22	0.06	0.38	year_classcode-gnig-2006
0.06	-0.09	0.22	year_classcode-gnig-2007
-0.04	-0.20	0.11	year_classcode-gnig-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.10	-0.05	0.26	year_classcode-gnig-2009
-0.12	-0.30	0.06	year_classcode-gnig-2010
-0.19	-0.38	-0.01	year_classcode-gnig-2011
-0.22	-0.40	-0.03	year_classcode-gnig-2012
-0.44	-0.66	-0.22	year_classcode-gnig-2013
-0.15	-0.34	0.03	year_classcode-gnig-2014
0.08	-0.09	0.26	year_classcode-gnig-2015
-0.06	-0.24	0.12	year_classcode-gnig-2016
0.10	-0.08	0.27	year_classcode-gnig-2017
-2.28	-3.76	-0.79	year_classcode-hcar-2000
-0.92	-1.75	-0.10	year_classcode-hcar-2001
-0.70	-1.34	-0.06	year_classcode-hcar-2002
-1.24	-1.67	-0.82	year_classcode-hcar-2003
-2.11	-2.60	-1.63	year_classcode-hcar-2004
-1.08	-1.37	-0.79	year_classcode-hcar-2005
-0.94	-1.23	-0.65	year_classcode-hcar-2006
-0.79	-1.06	-0.52	year_classcode-hcar-2007
-0.86	-1.13	-0.58	year_classcode-hcar-2008
-1.03	-1.31	-0.75	year_classcode-hcar-2009
-1.17	-1.50	-0.84	year_classcode-hcar-2010
-2.20	-2.64	-1.76	year_classcode-hcar-2011
-1.66	-2.03	-1.29	year_classcode-hcar-2012
-1.41	-1.80	-1.02	year_classcode-hcar-2013
-2.47	-2.99	-1.94	year_classcode-hcar-2014
-2.95	-3.66	-2.24	year_classcode-hcar-2015
-2.85	-3.47	-2.24	year_classcode-hcar-2016
-2.41	-3.01	-1.81	year_classcode-hcar-2017
-1.65	-2.36	-0.94	year_classcode-hros-2000
-1.13	-1.67	-0.59	year_classcode-hros-2001
-2.30	-3.00	-1.60	year_classcode-hros-2002
-2.97	-3.64	-2.30	year_classcode-hros-2003
-0.21	-0.44	0.02	year_classcode-hros-2004
-1.31	-1.56	-1.05	year_classcode-hros-2005
-1.27	-1.53	-1.01	year_classcode-hros-2006
-0.91	-1.13	-0.70	year_classcode-hros-2007
-1.89	-2.20	-1.59	year_classcode-hros-2008
-0.68	-0.87	-0.48	year_classcode-hros-2009
-3.58	-4.27	-2.89	year_classcode-hros-2010
-1.77	-2.08	-1.45	year_classcode-hros-2011
-1.30	-1.57	-1.03	year_classcode-hros-2012
-3.07	-3.71	-2.44	year_classcode-hros-2013
-1.74	-2.07	-1.42	year_classcode-hros-2014
-1.86	-2.20	-1.52	year_classcode-hros-2015
-2.06	-2.44	-1.69	year_classcode-hros-2016
-0.92	-1.17	-0.66	year_classcode-hros-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.23	-0.09	0.56	year_classcode-hrub-2000
0.31	0.00	0.62	year_classcode-hrub-2001
0.15	-0.11	0.42	year_classcode-hrub-2002
-0.16	-0.39	0.06	year_classcode-hrub-2003
0.09	-0.11	0.29	year_classcode-hrub-2004
0.08	-0.08	0.25	year_classcode-hrub-2005
0.18	0.01	0.35	year_classcode-hrub-2006
0.05	-0.12	0.21	year_classcode-hrub-2007
0.07	-0.09	0.23	year_classcode-hrub-2008
-0.02	-0.18	0.14	year_classcode-hrub-2009
-0.37	-0.56	-0.17	year_classcode-hrub-2010
-0.20	-0.39	-0.01	year_classcode-hrub-2011
-0.27	-0.46	-0.08	year_classcode-hrub-2012
-0.10	-0.30	0.09	year_classcode-hrub-2013
-0.06	-0.24	0.13	year_classcode-hrub-2014
0.04	-0.13	0.22	year_classcode-hrub-2015
0.31	0.13	0.50	year_classcode-hrub-2016
0.42	0.24	0.60	year_classcode-hrub-2017
0.31	-0.11	0.72	year_classcode-hsem-2000
-0.20	-0.61	0.21	year_classcode-hsem-2001
-0.80	-1.19	-0.40	year_classcode-hsem-2002
-1.52	-1.90	-1.14	year_classcode-hsem-2003
-1.58	-1.92	-1.24	year_classcode-hsem-2004
-0.82	-1.04	-0.59	year_classcode-hsem-2005
-1.03	-1.28	-0.78	year_classcode-hsem-2006
-0.10	-0.28	0.09	year_classcode-hsem-2007
-0.32	-0.52	-0.13	year_classcode-hsem-2008
-0.29	-0.48	-0.11	year_classcode-hsem-2009
-1.03	-1.29	-0.78	year_classcode-hsem-2010
-1.13	-1.39	-0.88	year_classcode-hsem-2011
-2.10	-2.46	-1.74	year_classcode-hsem-2012
-1.83	-2.19	-1.46	year_classcode-hsem-2013
-0.95	-1.20	-0.70	year_classcode-hsem-2014
0.54	0.36	0.73	year_classcode-hsem-2015
0.75	0.56	0.93	year_classcode-hsem-2016
0.80	0.62	0.98	year_classcode-hsem-2017
-0.45	-0.92	0.02	year_classcode-mcal-2000
-0.37	-0.80	0.05	year_classcode-mcal-2001
-0.53	-0.89	-0.17	year_classcode-mcal-2002
-0.74	-1.03	-0.46	year_classcode-mcal-2003
-0.82	-1.08	-0.57	year_classcode-mcal-2004
-0.40	-0.59	-0.21	year_classcode-mcal-2005
0.11	-0.06	0.28	year_classcode-mcal-2006
-0.54	-0.73	-0.35	year_classcode-mcal-2007
-0.86	-1.07	-0.65	year_classcode-mcal-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-0.96	-1.17	-0.75	year_classcode-mcal-2009
-1.42	-1.70	-1.14	year_classcode-mcal-2010
-1.69	-1.99	-1.39	year_classcode-mcal-2011
-1.89	-2.21	-1.57	year_classcode-mcal-2012
-1.70	-2.04	-1.37	year_classcode-mcal-2013
-0.76	-0.99	-0.54	year_classcode-mcal-2014
0.24	0.06	0.43	year_classcode-mcal-2015
0.24	0.06	0.43	year_classcode-mcal-2016
-0.05	-0.25	0.15	year_classcode-mcal-2017
1.02	0.63	1.42	year_classcode-ocal-2000
0.82	0.47	1.18	year_classcode-ocal-2001
0.61	0.31	0.90	year_classcode-ocal-2002
1.27	1.07	1.47	year_classcode-ocal-2003
1.54	1.36	1.73	year_classcode-ocal-2004
1.69	1.54	1.83	year_classcode-ocal-2005
1.57	1.42	1.72	year_classcode-ocal-2006
1.61	1.47	1.75	year_classcode-ocal-2007
1.67	1.53	1.81	year_classcode-ocal-2008
2.25	2.10	2.39	year_classcode-ocal-2009
1.81	1.64	1.97	year_classcode-ocal-2010
1.10	0.93	1.27	year_classcode-ocal-2011
1.21	1.04	1.38	year_classcode-ocal-2012
0.83	0.64	1.01	year_classcode-ocal-2013
1.44	1.26	1.61	year_classcode-ocal-2014
1.86	1.68	2.04	year_classcode-ocal-2015
1.48	1.31	1.65	year_classcode-ocal-2016
1.35	1.18	1.53	year_classcode-ocal-2017
-0.51	-0.99	-0.04	year_classcode-opic-2000
-0.44	-0.87	-0.02	year_classcode-opic-2001
-2.51	-3.29	-1.73	year_classcode-opic-2002
-1.15	-1.47	-0.83	year_classcode-opic-2003
0.49	0.30	0.68	year_classcode-opic-2004
0.50	0.35	0.66	year_classcode-opic-2005
0.02	-0.16	0.19	year_classcode-opic-2006
0.17	0.01	0.33	year_classcode-opic-2007
0.54	0.39	0.70	year_classcode-opic-2008
0.64	0.50	0.79	year_classcode-opic-2009
1.07	0.91	1.24	year_classcode-opic-2010
1.04	0.87	1.22	year_classcode-opic-2011
1.12	0.95	1.28	year_classcode-opic-2012
0.74	0.55	0.93	year_classcode-opic-2013
0.39	0.21	0.58	year_classcode-opic-2014
-0.70	-0.93	-0.48	year_classcode-opic-2015
-0.25	-0.45	-0.04	year_classcode-opic-2016
-0.39	-0.60	-0.17	year_classcode-opic-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
1.99	1.57	2.41	year_classcode-pcla-2000
1.86	1.49	2.23	year_classcode-pcla-2001
1.55	1.27	1.83	year_classcode-pcla-2002
0.97	0.76	1.18	year_classcode-pcla-2003
1.21	1.02	1.41	year_classcode-pcla-2004
1.03	0.88	1.18	year_classcode-pcla-2005
1.26	1.10	1.41	year_classcode-pcla-2006
1.05	0.90	1.19	year_classcode-pcla-2007
1.16	1.01	1.31	year_classcode-pcla-2008
1.34	1.19	1.48	year_classcode-pcla-2009
0.93	0.76	1.11	year_classcode-pcla-2010
0.95	0.77	1.13	year_classcode-pcla-2011
0.94	0.77	1.12	year_classcode-pcla-2012
0.90	0.71	1.08	year_classcode-pcla-2013
1.15	0.98	1.33	year_classcode-pcla-2014
1.58	1.40	1.75	year_classcode-pcla-2015
1.59	1.42	1.77	year_classcode-pcla-2016
2.06	1.88	2.24	year_classcode-pcla-2017
-2.86	-4.04	-1.68	year_classcode-pfur-2000
-2.72	-3.75	-1.69	year_classcode-pfur-2001
-3.77	-5.05	-2.48	year_classcode-pfur-2002
-3.01	-3.72	-2.30	year_classcode-pfur-2003
-2.63	-3.14	-2.12	year_classcode-pfur-2004
-2.99	-3.52	-2.47	year_classcode-pfur-2005
-2.98	-3.52	-2.44	year_classcode-pfur-2006
-3.98	-4.78	-3.18	year_classcode-pfur-2007
-3.64	-4.33	-2.95	year_classcode-pfur-2008
-2.64	-3.07	-2.21	year_classcode-pfur-2009
-3.06	-3.64	-2.48	year_classcode-pfur-2010
-3.90	-4.69	-3.11	year_classcode-pfur-2011
-4.19	-5.10	-3.27	year_classcode-pfur-2012
-5.09	-6.51	-3.67	year_classcode-pfur-2013
-4.08	-4.96	-3.20	year_classcode-pfur-2014
-5.23	-6.60	-3.87	year_classcode-pfur-2015
-4.70	-5.86	-3.53	year_classcode-pfur-2016
-4.48	-5.59	-3.38	year_classcode-pfur-2017
-1.76	-2.48	-1.05	year_classcode-rtox-2000
-1.28	-1.83	-0.73	year_classcode-rtox-2001
-1.07	-1.51	-0.64	year_classcode-rtox-2002
-1.57	-1.94	-1.19	year_classcode-rtox-2003
-1.71	-2.05	-1.36	year_classcode-rtox-2004
-1.53	-1.79	-1.26	year_classcode-rtox-2005
-1.66	-1.95	-1.37	year_classcode-rtox-2006
-1.92	-2.22	-1.62	year_classcode-rtox-2007
-2.39	-2.75	-2.03	year_classcode-rtox-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-1.37	-1.60	-1.13	year_classcode-rtox-2009
-1.49	-1.77	-1.20	year_classcode-rtox-2010
-1.25	-1.50	-0.99	year_classcode-rtox-2011
-1.73	-2.03	-1.42	year_classcode-rtox-2012
-1.75	-2.09	-1.41	year_classcode-rtox-2013
-2.28	-2.66	-1.90	year_classcode-rtox-2014
-2.18	-2.55	-1.82	year_classcode-rtox-2015
-2.08	-2.44	-1.71	year_classcode-rtox-2016
-2.58	-3.02	-2.13	year_classcode-rtox-2017
-0.14	-0.52	0.25	year_classcode-rvac-2000
-0.23	-0.59	0.14	year_classcode-rvac-2001
-0.15	-0.46	0.16	year_classcode-rvac-2002
0.09	-0.13	0.32	year_classcode-rvac-2003
-0.13	-0.34	0.08	year_classcode-rvac-2004
0.03	-0.13	0.20	year_classcode-rvac-2005
0.06	-0.11	0.23	year_classcode-rvac-2006
-0.20	-0.37	-0.04	year_classcode-rvac-2007
-0.41	-0.58	-0.23	year_classcode-rvac-2008
-0.08	-0.24	0.08	year_classcode-rvac-2009
0.23	0.05	0.41	year_classcode-rvac-2010
0.03	-0.15	0.21	year_classcode-rvac-2011
-0.02	-0.21	0.16	year_classcode-rvac-2012
-0.51	-0.74	-0.29	year_classcode-rvac-2013
-0.41	-0.62	-0.21	year_classcode-rvac-2014
-0.73	-0.96	-0.51	year_classcode-rvac-2015
-0.77	-1.00	-0.53	year_classcode-rvac-2016
-0.53	-0.75	-0.31	year_classcode-rvac-2017
0.87	0.33	1.42	year_classcode-satr-2000
1.19	0.73	1.66	year_classcode-satr-2001
0.96	0.56	1.36	year_classcode-satr-2002
0.73	0.45	1.01	year_classcode-satr-2003
0.77	0.50	1.03	year_classcode-satr-2004
0.53	0.30	0.75	year_classcode-satr-2005
0.76	0.53	0.99	year_classcode-satr-2006
0.38	0.15	0.60	year_classcode-satr-2007
0.34	0.12	0.57	year_classcode-satr-2008
0.88	0.66	1.10	year_classcode-satr-2009
1.11	0.87	1.35	year_classcode-satr-2010
1.35	1.11	1.59	year_classcode-satr-2011
0.83	0.59	1.07	year_classcode-satr-2012
0.65	0.39	0.90	year_classcode-satr-2013
0.40	0.14	0.66	year_classcode-satr-2014
0.26	-0.02	0.53	year_classcode-satr-2015
0.02	-0.25	0.29	year_classcode-satr-2016
0.33	0.06	0.61	year_classcode-satr-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-3.52	-4.77	-2.27	year_classcode-saur-2000
-2.64	-3.56	-1.72	year_classcode-saur-2001
-3.88	-5.05	-2.71	year_classcode-saur-2002
-3.46	-4.30	-2.63	year_classcode-saur-2003
-3.69	-4.50	-2.88	year_classcode-saur-2004
-3.88	-4.70	-3.06	year_classcode-saur-2005
-3.20	-3.85	-2.55	year_classcode-saur-2006
-3.09	-3.69	-2.49	year_classcode-saur-2007
-3.42	-4.09	-2.75	year_classcode-saur-2008
-3.35	-3.99	-2.72	year_classcode-saur-2009
-4.12	-5.02	-3.23	year_classcode-saur-2010
-2.98	-3.53	-2.43	year_classcode-saur-2011
-3.00	-3.56	-2.44	year_classcode-saur-2012
-3.04	-3.71	-2.38	year_classcode-saur-2013
-3.52	-4.21	-2.83	year_classcode-saur-2014
-3.63	-4.35	-2.91	year_classcode-saur-2015
-3.47	-4.18	-2.76	year_classcode-saur-2016
-2.60	-3.11	-2.08	year_classcode-saur-2017
-1.69	-2.82	-0.55	year_classcode-scau-2000
-2.12	-3.30	-0.95	year_classcode-scau-2001
-1.90	-2.86	-0.94	year_classcode-scau-2002
-1.44	-1.89	-0.99	year_classcode-scau-2003
-1.65	-2.07	-1.23	year_classcode-scau-2004
-2.12	-2.51	-1.73	year_classcode-scau-2005
-1.79	-2.16	-1.43	year_classcode-scau-2006
-1.92	-2.28	-1.57	year_classcode-scau-2007
-2.06	-2.44	-1.69	year_classcode-scau-2008
-1.82	-2.16	-1.48	year_classcode-scau-2009
-0.94	-1.25	-0.63	year_classcode-scau-2010
-0.53	-0.82	-0.25	year_classcode-scau-2011
-1.37	-1.72	-1.03	year_classcode-scau-2012
-1.32	-1.69	-0.95	year_classcode-scau-2013
-1.43	-1.81	-1.06	year_classcode-scau-2014
-2.03	-2.52	-1.53	year_classcode-scau-2015
-1.66	-2.07	-1.26	year_classcode-scau-2016
-1.56	-2.01	-1.12	year_classcode-scau-2017
-1.72	-2.70	-0.74	year_classcode-schr-2000
-1.80	-2.74	-0.86	year_classcode-schr-2001
-1.80	-2.64	-0.95	year_classcode-schr-2002
-2.23	-2.83	-1.62	year_classcode-schr-2003
-1.62	-2.03	-1.21	year_classcode-schr-2004
-1.87	-2.22	-1.51	year_classcode-schr-2005
-1.92	-2.29	-1.54	year_classcode-schr-2006
-1.73	-2.07	-1.39	year_classcode-schr-2007
-1.85	-2.21	-1.50	year_classcode-schr-2008

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
-1.23	-1.53	-0.94	year_classcode-schr-2009
-1.34	-1.69	-1.00	year_classcode-schr-2010
-1.20	-1.53	-0.87	year_classcode-schr-2011
-1.40	-1.74	-1.06	year_classcode-schr-2012
-1.61	-2.01	-1.21	year_classcode-schr-2013
-1.24	-1.60	-0.89	year_classcode-schr-2014
-1.43	-1.83	-1.02	year_classcode-schr-2015
-1.72	-2.13	-1.32	year_classcode-schr-2016
-1.53	-1.96	-1.09	year_classcode-schr-2017
1.19	0.69	1.70	year_classcode-smys-2000
0.68	0.21	1.16	year_classcode-smys-2001
0.47	0.05	0.89	year_classcode-smys-2002
0.45	0.16	0.74	year_classcode-smys-2003
-0.20	-0.49	0.08	year_classcode-smys-2004
0.27	0.04	0.50	year_classcode-smys-2005
0.29	0.05	0.52	year_classcode-smys-2006
-0.51	-0.76	-0.26	year_classcode-smys-2007
-0.56	-0.81	-0.30	year_classcode-smys-2008
-0.68	-0.93	-0.42	year_classcode-smys-2009
-0.55	-0.83	-0.27	year_classcode-smys-2010
0.49	0.24	0.74	year_classcode-smys-2011
-0.14	-0.40	0.11	year_classcode-smys-2012
0.22	-0.04	0.48	year_classcode-smys-2013
0.81	0.56	1.06	year_classcode-smys-2014
0.32	0.05	0.58	year_classcode-smys-2015
-0.33	-0.61	-0.05	year_classcode-smys-2016
-0.51	-0.83	-0.20	year_classcode-smys-2017
0.66	0.27	1.05	year_classcode-spul-2000
0.93	0.57	1.28	year_classcode-spul-2001
0.22	-0.09	0.53	year_classcode-spul-2002
0.39	0.17	0.61	year_classcode-spul-2003
0.15	-0.05	0.35	year_classcode-spul-2004
0.61	0.46	0.77	year_classcode-spul-2005
0.57	0.41	0.73	year_classcode-spul-2006
0.47	0.32	0.62	year_classcode-spul-2007
0.29	0.13	0.44	year_classcode-spul-2008
0.96	0.82	1.11	year_classcode-spul-2009
0.71	0.53	0.88	year_classcode-spul-2010
0.69	0.52	0.87	year_classcode-spul-2011
0.39	0.21	0.56	year_classcode-spul-2012
0.57	0.38	0.76	year_classcode-spul-2013
0.19	0.00	0.37	year_classcode-spul-2014
0.71	0.53	0.89	year_classcode-spul-2015
1.41	1.24	1.58	year_classcode-spul-2016
1.37	1.20	1.55	year_classcode-spul-2017

Table 4: Complete table of estimated coefficients from hierarchical difference-in-difference model (*continued*)

estimate	lower	upper	variable
0.00	0.00	0.00	region_cluster-1-ANA
0.00	0.00	0.00	region_cluster-1-SCI
0.00	0.00	0.00	region_cluster-1-SMI
0.00	0.00	0.00	region_cluster-1-SRI
-0.79	-1.04	-0.54	region_cluster-3-ANA
-0.46	-0.67	-0.24	region_cluster-3-SCI
0.16	-0.06	0.38	region_cluster-3-SMI
0.04	-0.18	0.26	region_cluster-3-SRI
0.00	0.00	0.00	region_cluster-1-ANA
0.00	0.00	0.00	region_cluster-1-SCI
0.00	0.00	0.00	region_cluster-1-SMI
0.00	0.00	0.00	region_cluster-1-SRI
-2.36	-2.57	-2.15	region_cluster-3-ANA
-1.03	-1.22	-0.84	region_cluster-3-SCI
1.63	1.43	1.83	region_cluster-3-SMI
0.93	0.74	1.13	region_cluster-3-SRI
-0.19	-0.68	0.31	mpa_effect
-0.08	-0.55	0.40	mpa_effect
0.17	-0.29	0.63	mpa_effect
0.18	-0.25	0.61	mpa_effect
-0.15	-0.57	0.27	mpa_effect
-0.18	-0.59	0.23	mpa_effect
0.11	-0.30	0.53	mpa_effect
-0.13	-0.54	0.29	mpa_effect
0.10	-0.32	0.53	mpa_effect
-0.04	-0.45	0.37	mpa_effect
0.00	-0.42	0.42	mpa_effect
0.29	-0.13	0.71	mpa_effect
0.25	-0.16	0.67	mpa_effect
0.24	-0.19	0.66	mpa_effect
0.38	-0.05	0.81	mpa_effect
-0.19	-0.63	0.24	mpa_effect
-0.15	-0.57	0.28	mpa_effect
-0.39	-0.82	0.05	mpa_effect

<sup>243</sup> Figures S8:S10 present estimated effects for covariates included in the model, along with the raw estimated  
<sup>244</sup> mean trends of the targeted and non-targeted species (while the difference between these trends is presented  
<sup>245</sup> in our main results).

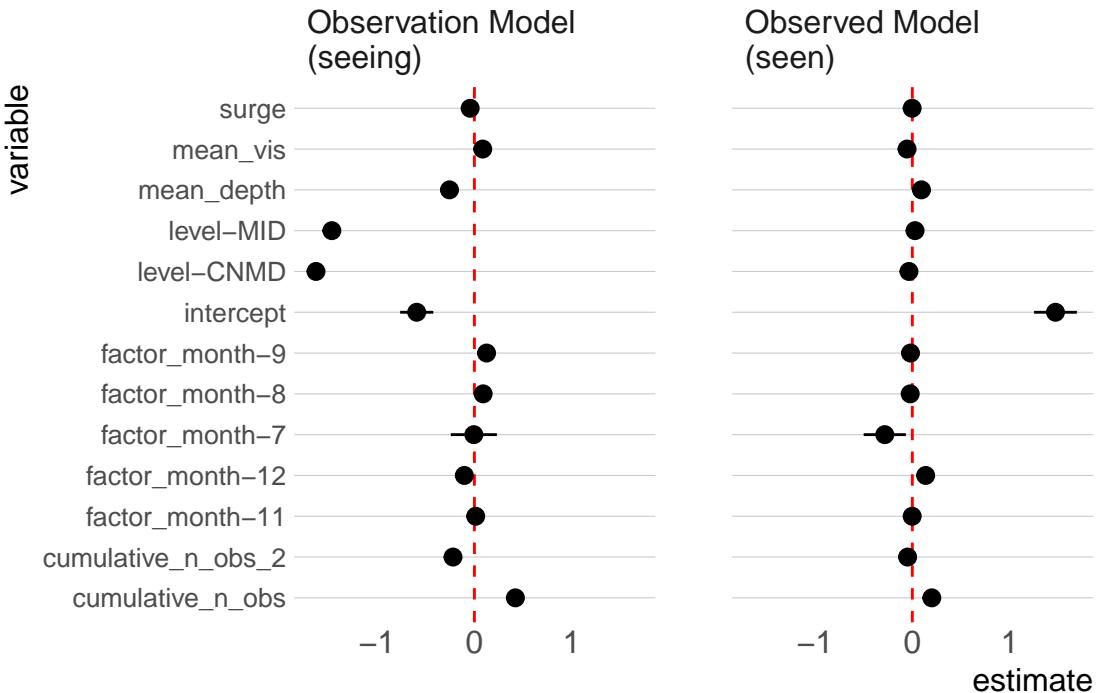


Figure 8: Estimated coefficients for non-spatial fixed effects in observation model (seeing) and observed model (seen)

#### 246 1.4.3 Regression Diagnostics

- 247 We include visual diagnostics of our estimation model. All coefficients passed convergence criteria for TMB.
- 248 Looking first at the predictions of the model for the positive observations in the data (i.e. using the full  
249 model to predict biomass densities, and then comparing those predictions to cases where some positive  
250 biomass densities were observed), the model diagnostics show no clear problems. The  $R^2$  of the model is  
251 0.43. Residuals do not exhibit trends, though some grouping the residuals is evident. The quantile-quantile  
252 plot suggest that on the assumption of log-normal errors on the observed densities is reasonable, though the  
253 model appears to have some slight problems estimating the highest observed densities (Fig.S11).
- 254 In order to evaluate the ability of the model to estimate positive observations, we can compare the binned  
255 predicted probability of a positive observation to the proportion of observations in that bin that recorded  
256 positive observations. If our model is working well, we would expect a group of fisheries that our model  
257 estimates on average should have a 50% probability of a positive observation, then we should expect about  
258 50% of those observations to have positive observations. This is indeed what we see from the model (Fig.S12).
- 259 We can also examine the receiver-operator-curve (ROC) to assess the performance of the observation  
260 component of the model. The area under the curve (AUC) value for the model is 0.84 (on a scale of 0.5 to 1),  
261 indicating the model is an overall good predictor of whether or not a given observation of biomass densities  
262 will be positive or not.

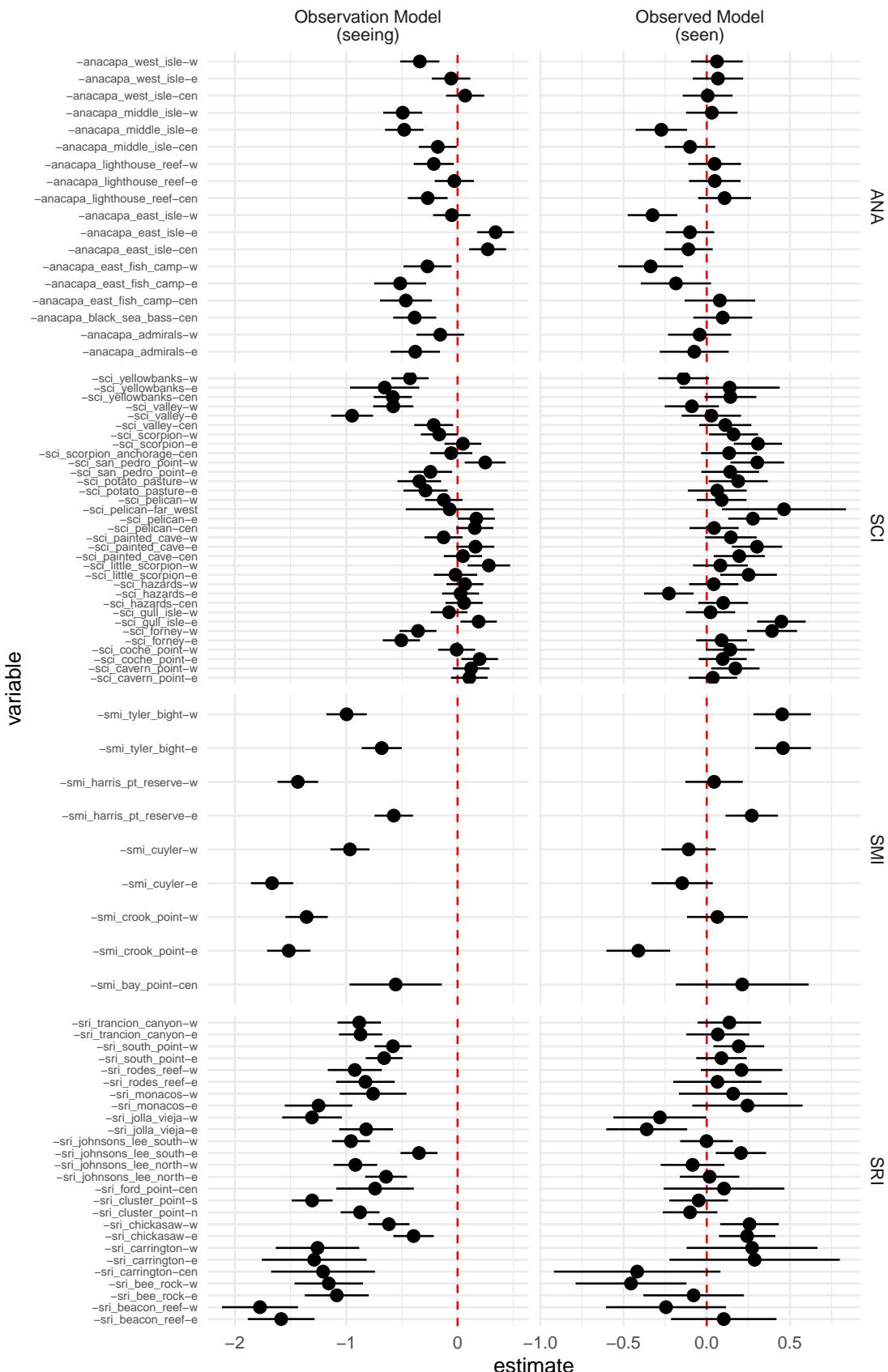


Figure 9: Estimated coefficients for spatial random effects in observation model (seeing) and observed model (seen)

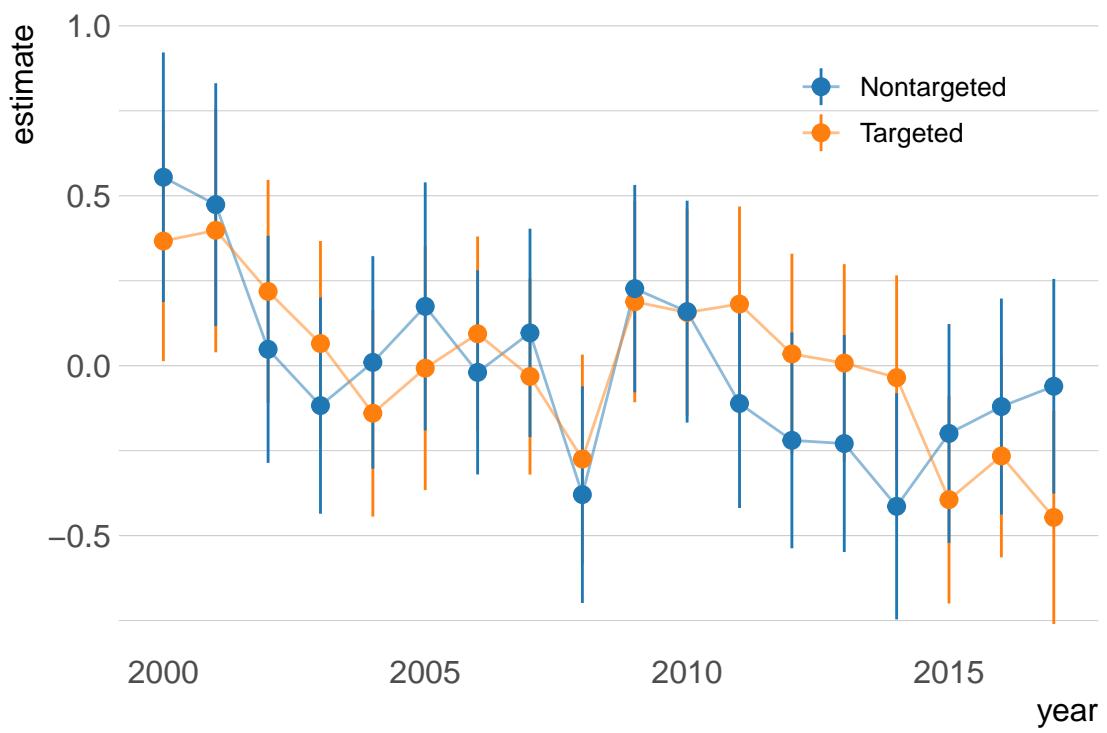


Figure 10: Trends in standardized mean abundance of targeted and non-targeted species

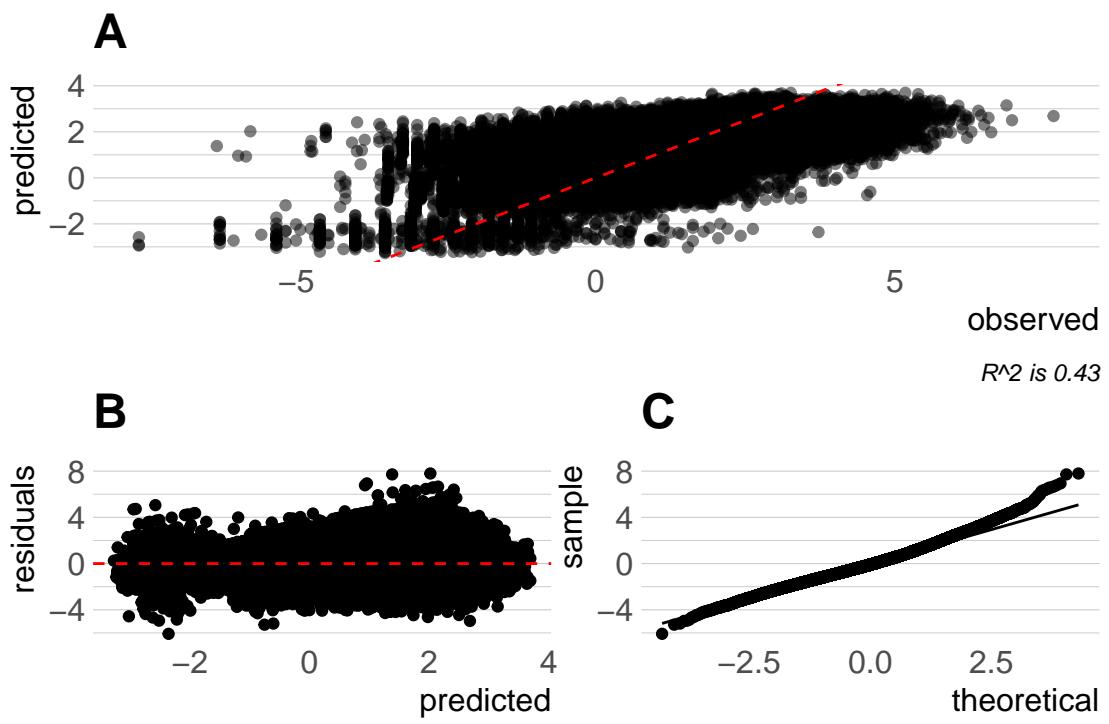


Figure 11: High level diagnostics for observed component of Delta-GLM: Observed vs predicted log densities (A), predicted log density vs residuals (B), and a normal qq-plot of the residuals (C)

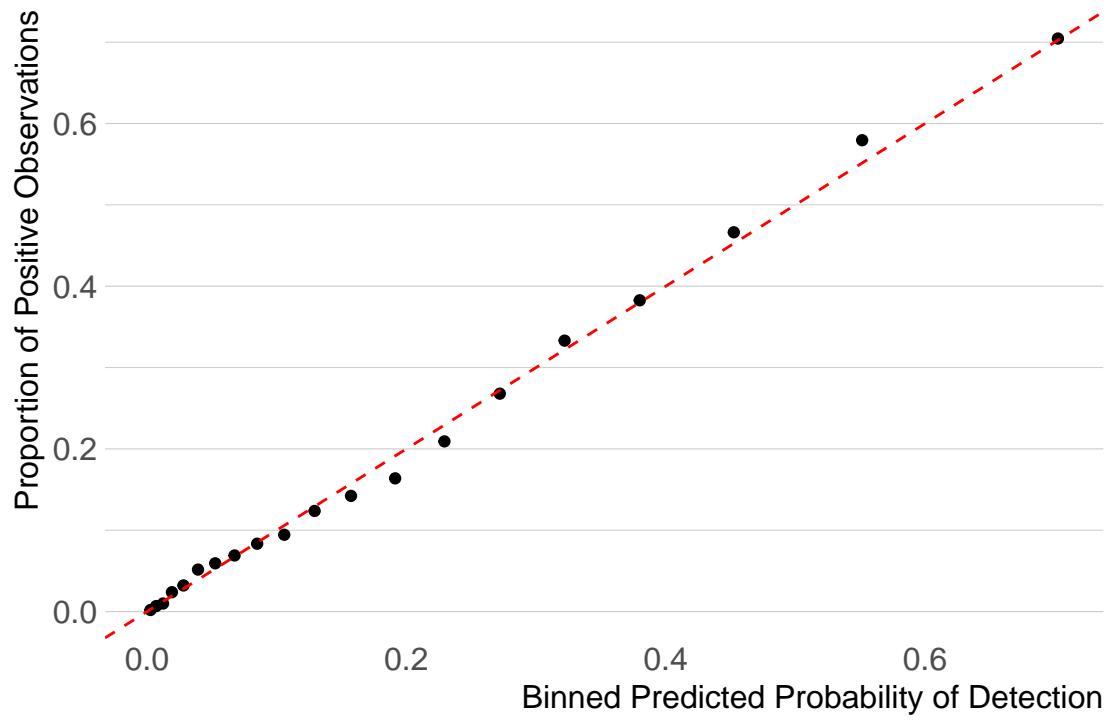


Figure 12: Binned mean predicted probability of detection provided by the first stage of the hurdle model vs observed proportion of positive detections

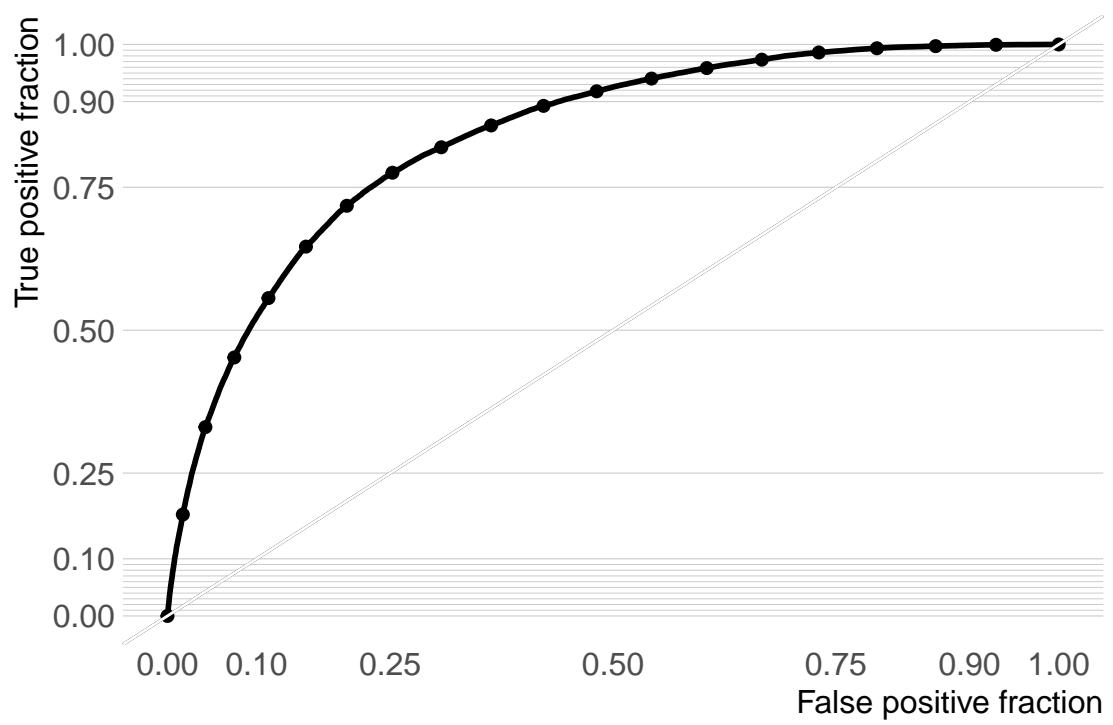


Figure 13: Receiver operating characteristic curve of predictions of positive biomass densities

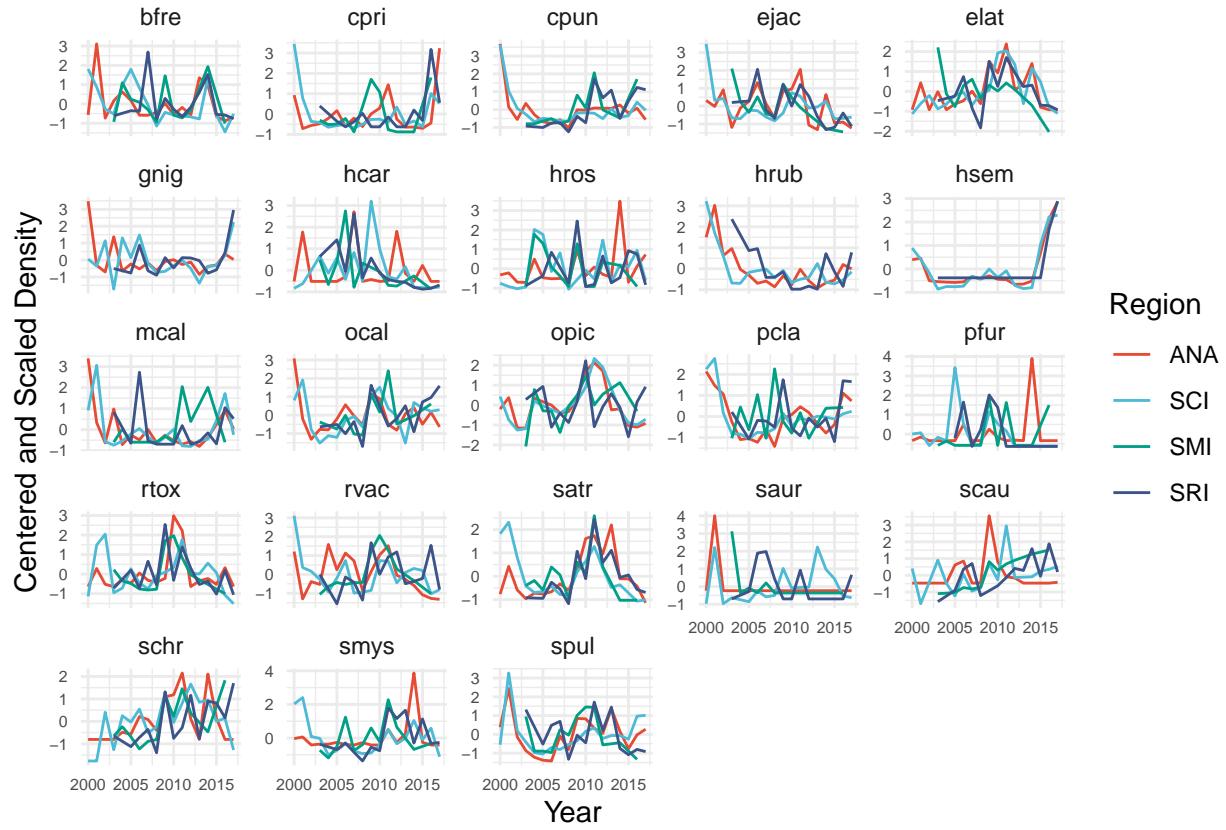


Figure 14: Mean density by island by year for each fish species included in the analysis

#### 263 1.4.4 Standardized Abundance Indices

264 Overall most species showed consistent trends in biomass densities across the different islands at which they  
265 have been observed (Fig.S14).

266 The standardized indices of abundance generally did not very substantially from the raw mean densities  
267 by species over time. However, for some species, such as blue rockfish, the standardized abundance index  
268 suggests much higher biomass densities in the pre-MPA period than those reported in the raw data. We  
269 suspect this is largely a function of changes in sampling sites over time, that the standardization is better  
270 able to account for (Fig.S15).

271 We include a variety of environmental, observation, and temporal indicators in our model. Inclusion of highly  
272 co-linear variables in a model can inflate standard errors and obscure “true” effects. To account for this we  
273 calculated the Pearson’s correlation coefficients for all of the continuous data included in our model to ensure  
274 that none of the included variables had correlation coefficients greater than 0.7, a general rule of thumb  
275 for co-inclusion of variables. We did not find problematic levels of correlation among any of our included  
276 continuous variables.

#### 277 1.5 Alternative estimation models

278 Our proposed identification strategy attempts to control for non-MPA (and not directly modeled) related  
279 changes in abundances through the trend in the non-targeted species. However, a simpler alternative would be  
280 to simply compare densities before-and-after MPA implementation, while explicitly controlling for non-MPA

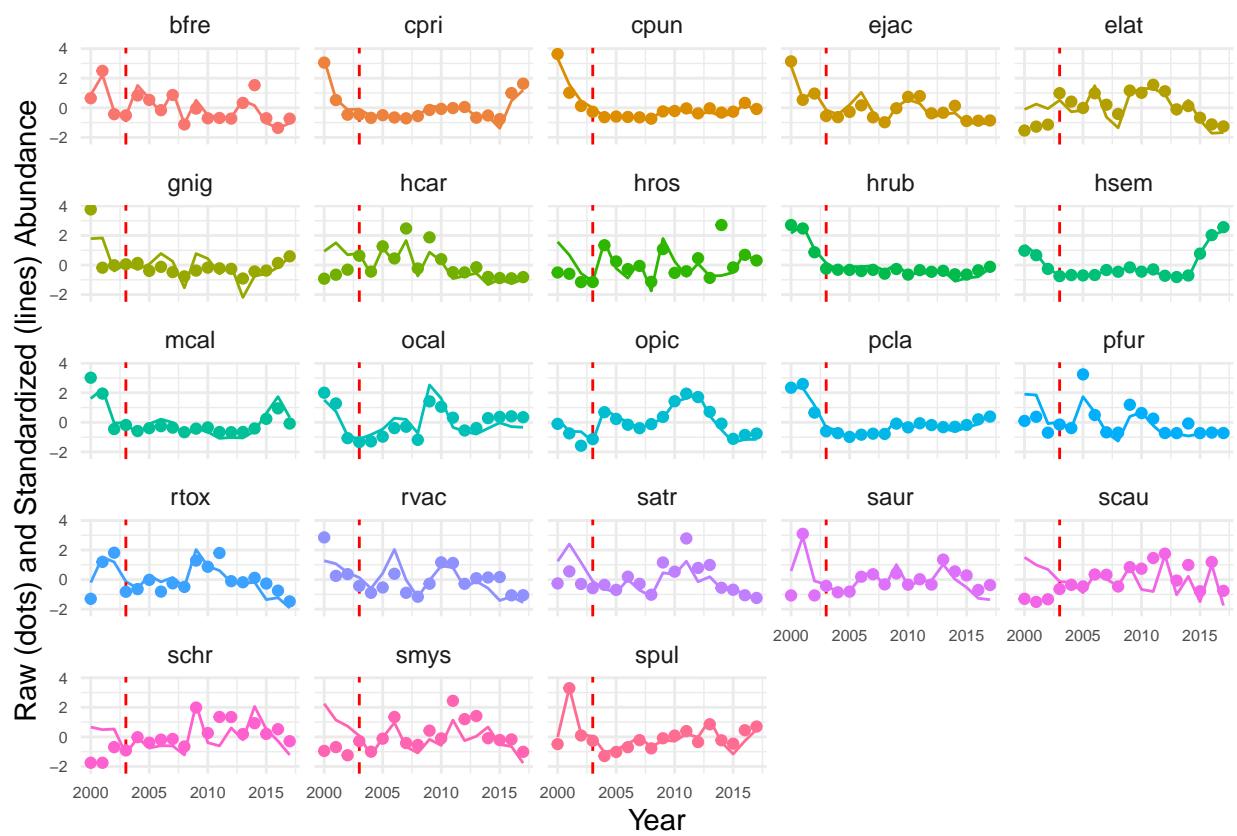


Figure 15: Raw (points) and standardized (lines) indices of abundance for each of the fishes included in the analysis

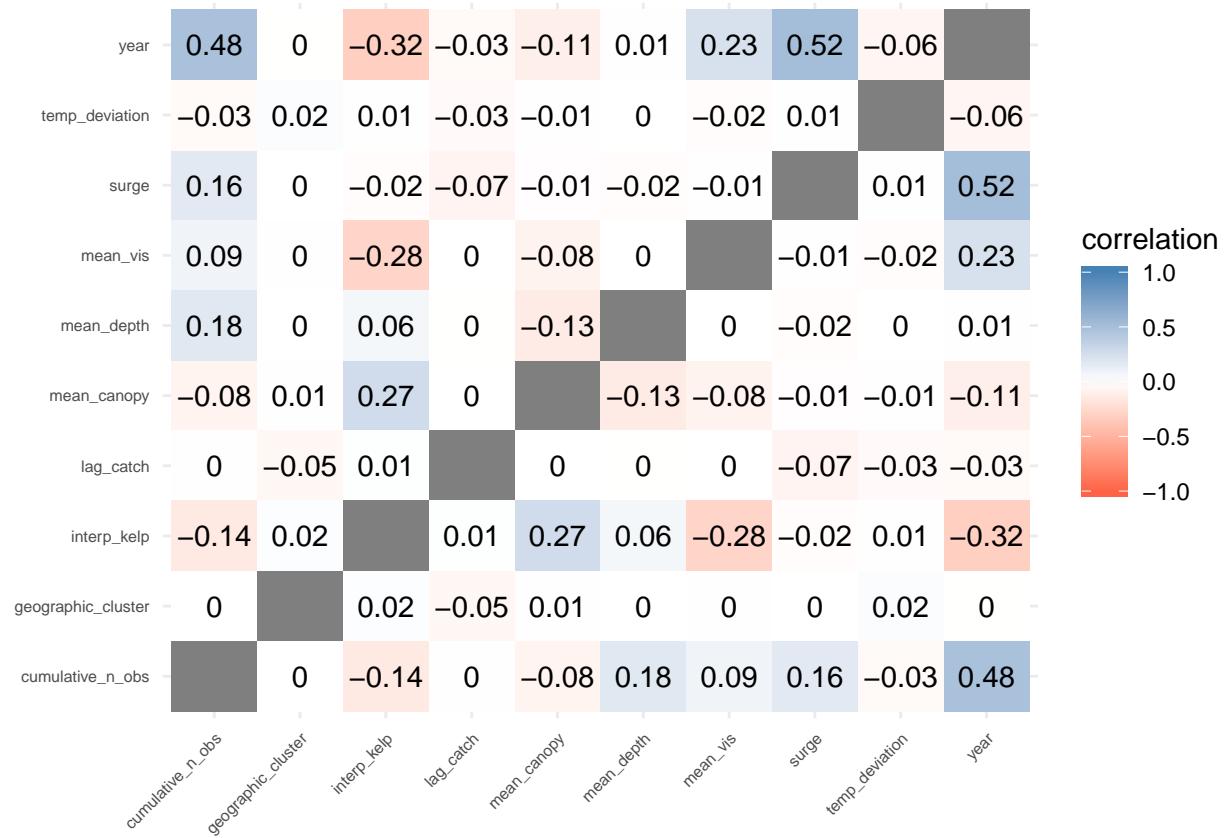


Figure 16: Pearson correlation coefficients of continuos data included in the regression model

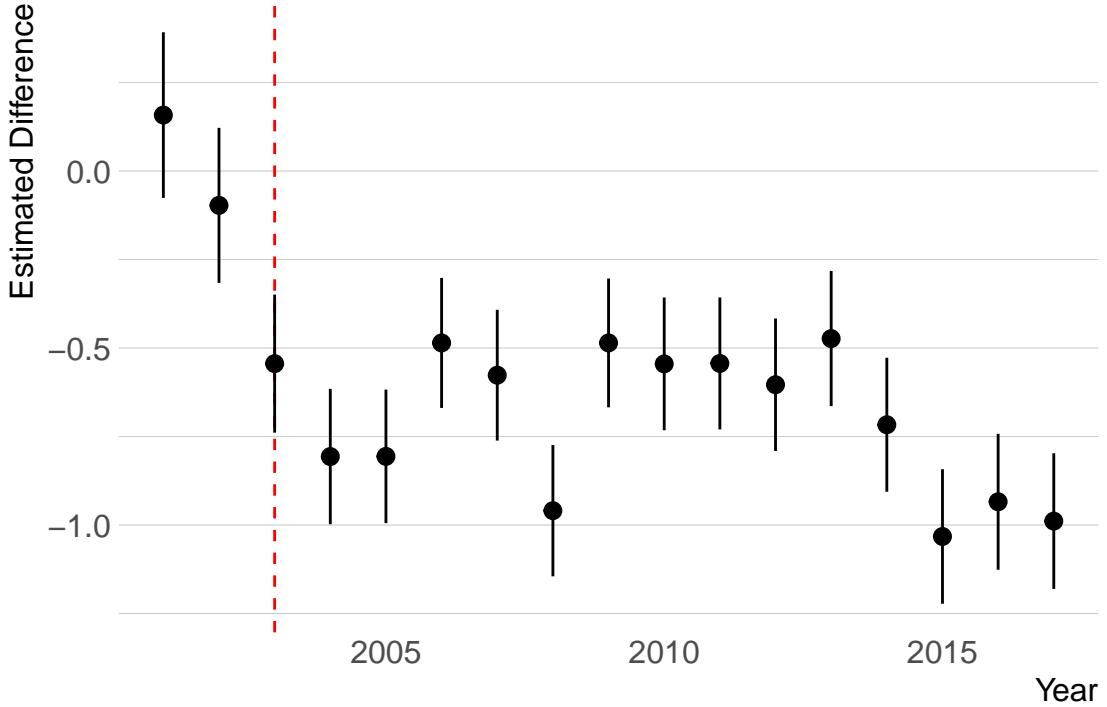


Figure 17: Selection on observables identification strategy. Plotted estimates are fixed effects of year on log-density (relative to the year 2000), controlling for observer experience, temperature deviations, and kelp cover, with random effects for species and region

related factors that we believe may have some effect on densities (a “selection on observables” strategy). To that end, we fit a mixed-effects regression that models log densities of targeted species only (positive observations only, for the sake of simplicity) as a function of temperature deviations, kelp cover, observer experience, random effects for species and region, and fixed effects for each year in the data (omitting the year 2000). The hypothesis here is that any non-MPA related factors that affect densities are accounted for in the observed variables included in the model.

Using this model, densities of targeted species appear to have been declining steadily since 2000, and appear to have plateaued off since the implementation of MPAs in 2003. Without an identification strategy such as the one employed in this study then, all we could conclude is that densities appear to be lower post-MPA, and have not increased substantially over time (Fig.S17).

The estimation model used for our main results is complicated. We feel this complexity is justified in order to best capture the uncertainty inherent in the challenging task of conducting underwater visual surveys, as well as the spatio-temporal nature of the underlying data. However, we also ran several simpler models in order to examine the sensitivity of our results to the model structure selected here.

Much of the complexity of our model comes from the integration of a standardized abundance index for each of the species, which are then compiled into a standardized index of abundance index for targeted species as a whole.

In one simpler approach, we aggregated the PISCO data into mean biomass densities by species and year across all the Channel Islands. Since all included species have at least some positive observations in each year,

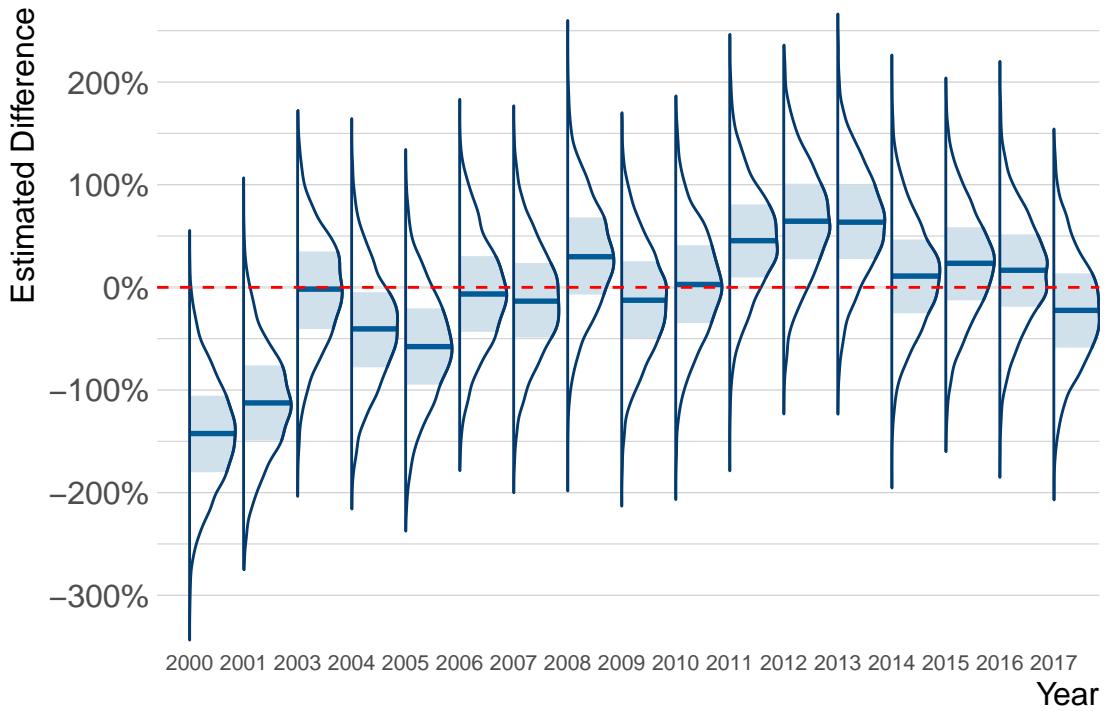
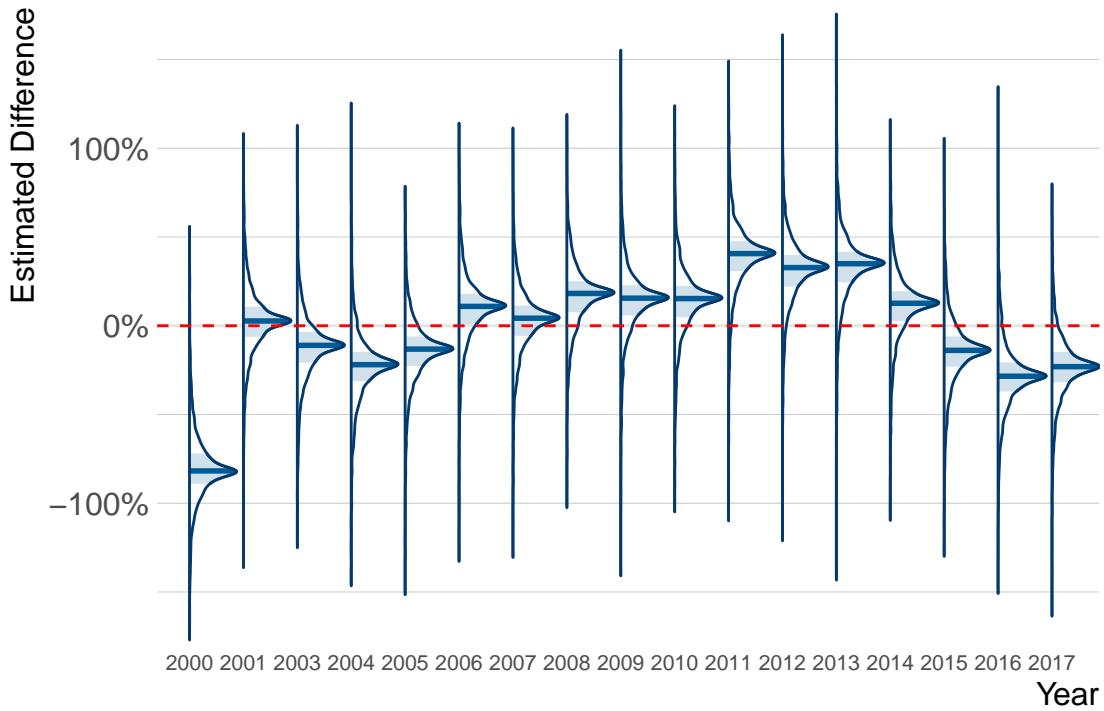


Figure 18: Results of simplified difference-in-difference regression. The model estimates the difference in the mean trend of densities of targeted and non-targeted species over time, controlling for the mean densities of each individual species group. Data are initially aggregated to the level of species-by-year.

- 300 this removes the complication of dealing with the probability of detection problem in the raw data, while of  
 301 course assuming that the net effects of all of the other factors included in our main model are on average  
 302 zero (e.g. observer skill, visibility, etc.). A difference-in-difference model fit to these simplified data show  
 303 qualitatively similar (though much more uncertain) results to our full model. In particular, the model shows  
 304 the same gradual increase in targeted densities relative to non-targeted until 2013, followed by an attenuation  
 305 of this trend. Importantly, though, this simplified model fails to correct for some pre-MPA differences in the  
 306 two groups, leading to negative “effects” of the MPAs being estimated before the MPAs themselves went in  
 307 place. While these sort of anticipatory effects are certainly possible (McDermott et al. 2019), in this case we  
 308 would suggest the likelier explanation—given that these anticipatory effects disappear in the full model—is  
 309 that our full model provides important controls for pre-MPA characteristics (Fig.S18)
- 310 As an even simpler approach, we aggregated the data to the level of targeted and non-targeted species, and  
 311 estimated the divergence in their trends over time.



312

313 We can also explore the effects of our species filtering by running a simplified regression but now including all  
314 the species in the database, no matter of how infrequently they are observed.

### 315 1.5.1 Synthetic controls

316 Synthetic controls are an alternative method for attempting to estimate the causal effect of a policy intervention  
317 (Abadie, Diamond, and Hainmueller 2010). A difference-in-difference approach assumes that some observable  
318 group serves as an adequate control for the state of the treated group in an untreated world. In our default  
319 case, we assume that the mean standardized index of non-targeted species are our control for the targeted  
320 species. Alternatively, synthetic controls use timeseries of treated and non-treated groups before and after  
321 treatment to construct a new “control” group built by weighting the pre-treatment timeseries of un-treated  
322 observations (together with covariates) such that the synthetic control group matches the trends in the  
323 treated group pre-treatment.

324 We chose to present difference-in-difference as our main result since it better allows us to capture the  
325 uncertainty in the data generating process through our hierarchical model. However, we felt that it was worth  
326 exploring whether synthetic controls provided substantially different results than our default model.

327 For the first synthetic control, we pulled our standardized mean index of abundance for targeted species  
328 as a whole from our difference-in-difference model as our treated group. We then pull the standardized  
329 indices of abundance for each of the non-targeted groups from the difference-in-difference to use as the  
330 candidate untreated components for the synthetic controls. A complete synthetic control analysis would  
331 require more extensive validation of the methods, but we use this approach simply to explore whether we  
332 observe substantially divergent results in the synthetic control versus the difference-in-difference model.

333 We centered and scaled the candidate abundance indices to facilitate model convergence given the very  
334 few number of pre-treatment years available. The results of a synthetic control model are presented as the

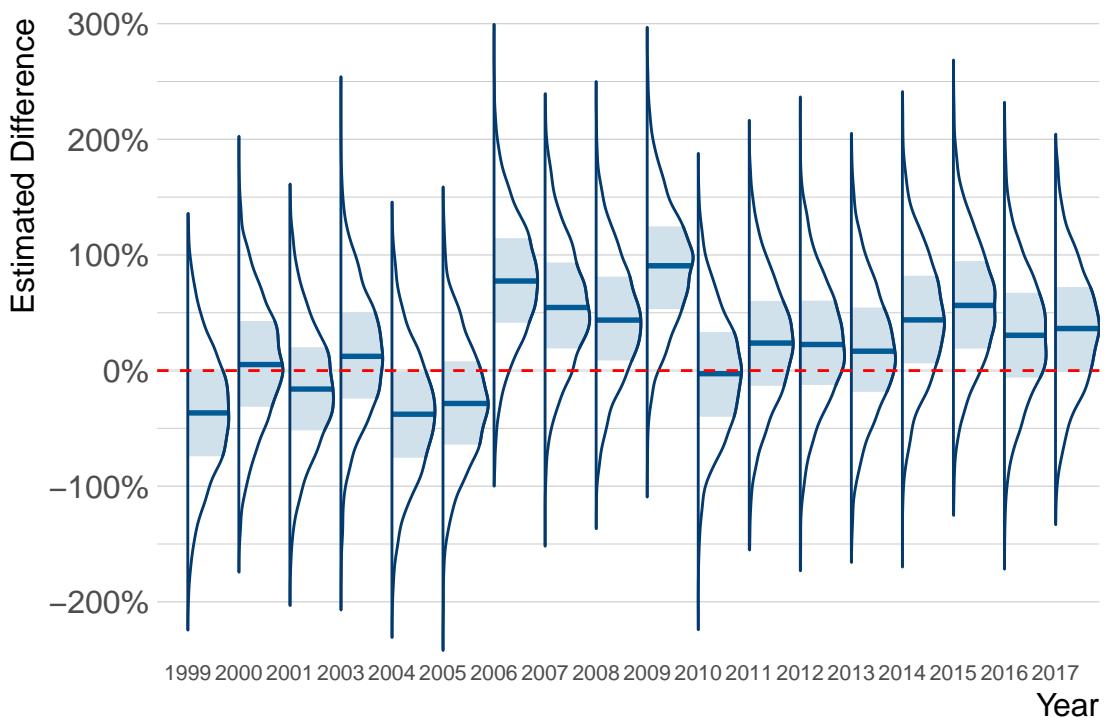


Figure 19: Results of simplified difference-in-difference regression including all observed finfish. The model estimates the difference in the mean trend of densities of targeted and non-targeted species over time, controlling for the mean densities of each individual species group. Data are initially aggregated to the level of species-by-year.



Figure 20: Difference in centered and scaled standardized targeted abundance and synthetic standardized targeted abundance

335 difference between the observed treatment outcome and the synthetic control (the difference in this case  
 336 being in units of standard deviations). The model was not able to construct an adequate synthetic control at  
 337 this level, as shown by the differences between the treated group and the synthetic control pre-treatment.  
 338 However, we would note that the post-treatment results do show similarities with our main results, namely a  
 339 lack of a clear divergence between the treatment and the control, and an upwards trend up through the early  
 340 2010s followed by a decline (Fig.S20).

341 As an extension, we repeated this process, but now treating each targeted species individually as the treated  
 342 group, and the non-targeted species as the non-targeted. This is intended to explore whether we see clearer  
 343 signals for individual species than we do for the targeted class as a whole.

344 Overall we see similarly unclear results as the aggregate targeted synthetic control (and our main results).  
 345 The synthetic control was better constructed for some individual species, but not clearly for any one, and most  
 346 species showed some evidence of the upward-then-downward trend seen throughout our results (Fig.S21).

## 347 1.6 Testing Model Assumptions

### 348 1.6.1 Simulation testing

349 We state that a difference-in-difference model using targeted and non-targeted species is capable (conditional  
 350 on assumptions) of estimating the causal effect of MPAs. We simulated MPA outcomes to test this claim.

351 We first test our estimation strategy under idealized circumstances, where recruitment is deterministic and



Figure 21: Synthetic control gaps for each targeted species

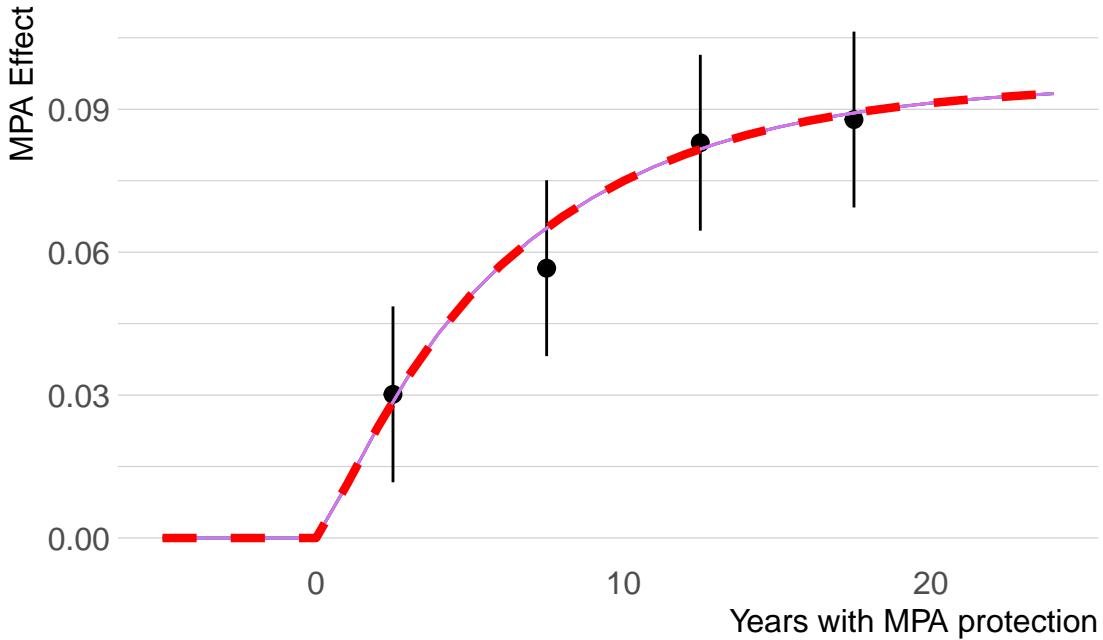


Figure 22: Simulated mean (red dashed line) and individual species (solid lines) MPA effects over time, along with difference-in-difference estimated MPA effects (mean with 95% confidence intervals)

352 PISCO divers all have constant and perfect observer skills. We simulate five species that vary only in their  
 353 maximum size and length at maturity. For each of these species, we set one version that is targeted by fishing  
 354 and one that is not. We set a constant fishing mortality rate for each simulated targeted species, and then  
 355 ran two matched simulations, one with MPAs and one without. We then have our simulated divers sample  
 356 data from each of these scenarios, and then pass the sampled biomass densities to a simplified version of  
 357 our difference-in-difference model (omitting the probability of detection step). We can then compare the  
 358 difference-in-difference estimates of the MPA effect to the true simulated effect. The difference in difference  
 359 model is able to capture the simulated MPA effect under these circumstances (Fig.S22)

360 We then simulated a more complex example. We use the actual targeted and non-targeted species from  
 361 our model. We assign species predominately seen in the western Channel Islands as “cold water” and those  
 362 in the eastern Channel Islands as “warm water”. We allow for stochasticity in recruitment. We use El  
 363 Niño data as a simulated environmental recruitment driver, where we assume that El Niño events produce  
 364 negative recruitment shocks for cold water species and *vice versa* for warm water species. We simulate three  
 365 different divers each with different base skill levels, visual selectivities, and an evolving skill rate (such that  
 366 observers get better over time). We hold fishing mortality rates constant for each species, although that  
 367 fishing mortality affects each species differently because of intrinsic biological differences in maturity-at-age  
 368 and steepness. We then test the ability of the difference-in-difference model to isolate the mean MPA effect  
 369 across all of these targeted species, which our results show it is capable of doing (Fig.S23).

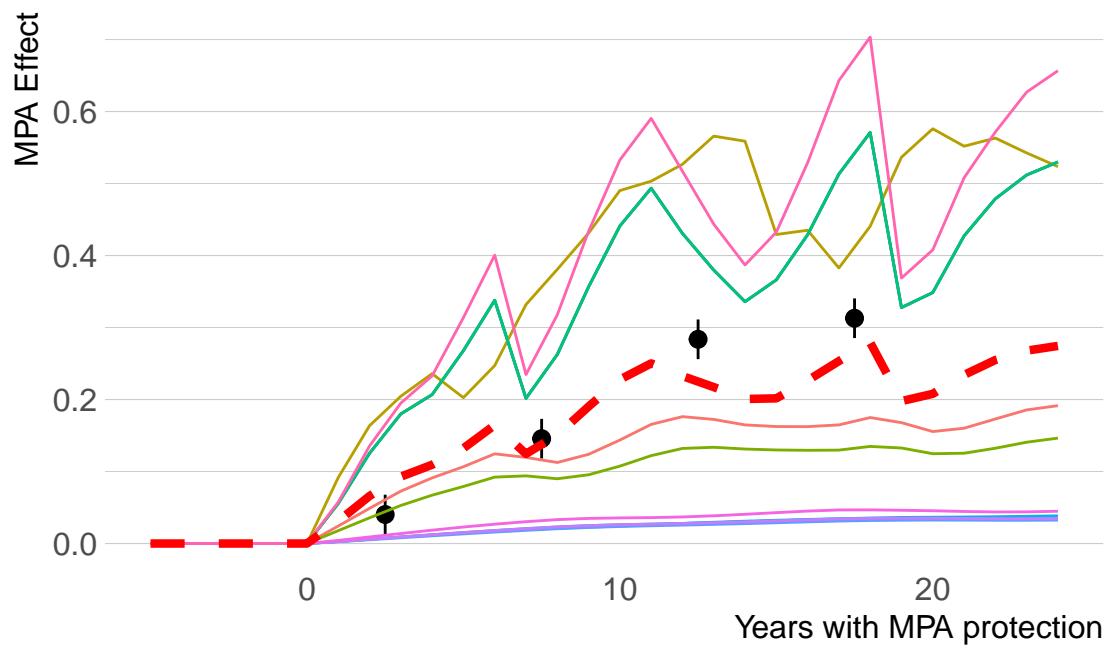


Figure 23: Simulated mean (red dashed line) and individual species (solid lines) MPA effects over time, along with difference-in-difference estimated MPA effects (mean with 95% confidence intervals)

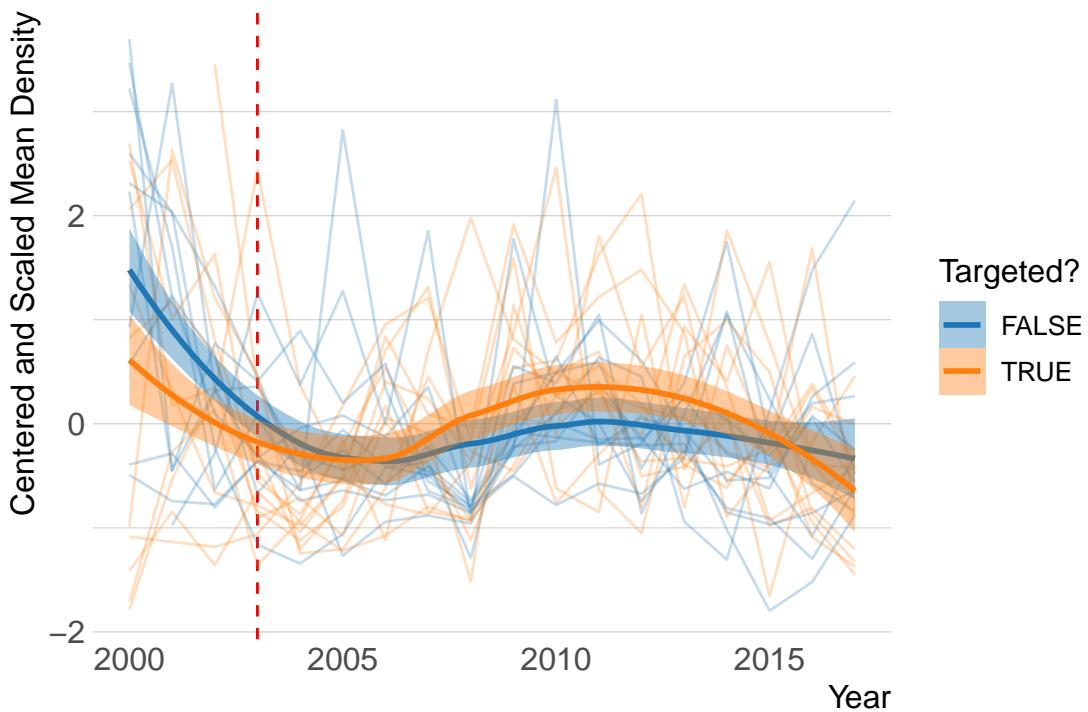


Figure 24: Centered and scaled mean annual density, excluding zeros, of included fishes (points) and smoothed means of targeted and non-targeted groups (line) over time

### 370 1.6.2 Sensitivity to “missing” observations

371 Appropriately addressing the problem of “missing” observations is a critical challenge in any field observation  
 372 study. If no observations of a given fish species were recorded on a given transect, should the density of that  
 373 species on that transect be marked as zero, and influence the estimate of the overall mean density accordingly?  
 374 The obvious answer seems to be yes, but what if that species simply does not live in the environment covered  
 375 by a particular transect, or was not present during the particular time of the diver’s observation? For our  
 376 base runs, we assign a value of zero density on a given transect for any fish species that has been observed  
 377 at least once at a given site at any time in our data but was not observed on that particular transect. If  
 378 that species was never observed at that site, we do not include a zero for that species. Our rationale for this  
 379 is that given the shifting nature of the sampled sites, and the intensity of sampling at those sites, we do  
 380 not want to skew density trends by changes in the amount of suitable habitat for a given species sampled.  
 381 However, this is clearly a strong assumption. For example, perhaps the decreasing trend in mean densities  
 382 from 2000 to 2004 is due to increased number of sites (and therefore zeros) included in the data. To assess the  
 383 potential importance of this choice, we can compare the mean densities of targeted and non-targeted species  
 384 over time with the added zeros to the mean densities using only positive observations (i.e. not including  
 385 any zeros in the data, (Fig.S24). The trends in the raw densities, and most importantly the mean trends  
 386 of targeted and non-targeted fishes, are nearly identical whether or not zeros are added, providing strong  
 387 evidence that our choice of how to incorporate missing observations into the data are not strongly influencing  
 388 our overall results.

389 **1.6.3 Testing SUTVA with Convergent Cross Mapping**

390 The difference-in-difference model also assumes that the targeted and non-targeted fishes do not directly or  
391 indirectly affect each other. This assumption is clearly violated on some level: all the fishes in this analysis are  
392 part of the same ecosystem and therefore interact to some degree. For example, if the protection of targeted  
393 predatory fishes results in increased mortality of non-targeted fishes, the model would attribute that as an  
394 increased regional effect (greater divergence between the abundance of targeted and non-targeted species).  
395 Given the time scale of analysis (15 years of protection), we do not feel that massive trophic cascades are  
396 likely to have developed yet, given both the pace and complexity of trophic cascade development (Babcock  
397 et al. 2010; Pershing et al. 2015). A complete assessment of evidence for trophic cascades in the Channel  
398 Islands is beyond the scope of this study, but to address this question somewhat we utilized convergent cross  
399 mapping *sensu* Sugihara et al. (2012) to test for a significant causal signal between different broad trophic  
400 groups in the data, implemented in the rEDM package in R.

401 Convergent cross mapping is a nonlinear forecasting method that uses observed time series data to test for  
402 significant causal links between variables. Following methods laid out in Clark et al. (2015) and Sugihara  
403 et al. (2012), we pool the abundance of each broad trophic group by region (Fig.S25. This uses the data  
404 from the islands as “replicates”, requiring the assumption that the islands are all part of the same dynamic  
405 system, but allowing us to take advantage of the extra information provided by each island to further resolve  
406 the reconstructed manifolds. Using these aggregations, we then test whether the variables can be properly  
407 embedded, i.e., if they have predictable manifold dynamics. We do this through a simplex forecasting test,  
408 using an individual timeseries’ own lags to build a manifold. For each timeseries, the “best embedding  
409 dimension” is an approximation of the dimensionality of the dynamic system, in other words, the number of  
410 dimensions that define and predict the evolving states of the timeseries. This analysis shows that only the  
411 carnivore, piscivore, and planktivores groups show evidence of significant predictability (that is, that past  
412 dynamics of these species groups can predict future dynamics, Fig.S26).

413 Focusing on just these three groups then (removing herbivores), we can test for causal relationships between  
414 groups using convergent cross mapping and the logic of Takens’ theorem of dynamic systems. Generalizations  
415 of Takens’ theorem indicate that if two variables (in our case, species or physical variables) are part of the  
416 same dynamic system, their individual dynamics should reflect their relative causal influence (Sugihara et al.  
417 2012). In other words, if one variable is causally forced by another, that forcing should leave a signature on  
418 the first time series. Convergent cross mapping (CCM) tests for causation by using the attractor/manifold  
419 built from the time series of one variable to predict another (hence the “cross-mapping”). In simple terms,  
420 the *causal effect of A on B is determined by how well B cross-maps A*.

421 There are two criteria for CCM to establish causality: First, and most obviously, predictive cross-map skill  
422 using all available data should be significantly greater than zero. Second, that predictability should be  
423 convergent. Convergence means that cross-mapped estimates improve with library length (the number of  
424 state-space vectors used to build the attractor), because the attractor is more fully resolved and therefore  
425 estimation error should decline. Convergence is key to distinguishing causation from simple or spurious  
426 correlation. If two variables are spuriously correlated and not causally linked, CCM should fail to satisfy this  
427 second criterion. Based on these criteria, there is little evidence of significant dynamic interactions between  
428 trophic groups (Fig.S27-29). Cross-mapping produced positive predictive skill, but was non-convergent for all  
429 cross-mappings with the exception of carnivores cross-mapping planktivores (providing some evidence that  
430 planktivore dynamics may be a driver of carnivore dynamics). This analysis provides evidence that trophic  
431 cascades are unlikely to be a significant driver of our results. It is important to note though that this analysis  
432 does not mean that trophic cascades could not emerge in this system, rather that we do not detect them  
433 with these data at this time.

434 **1.7 Repeat Analysis with Kelp Forest Monitoring Data**

435 As a robustness check to our main results, we repeated our analysis utilizing data provided by the Kelp  
436 Forest Monitoring Program (KFM) conducted in the Channel Islands. Despite having similar but different

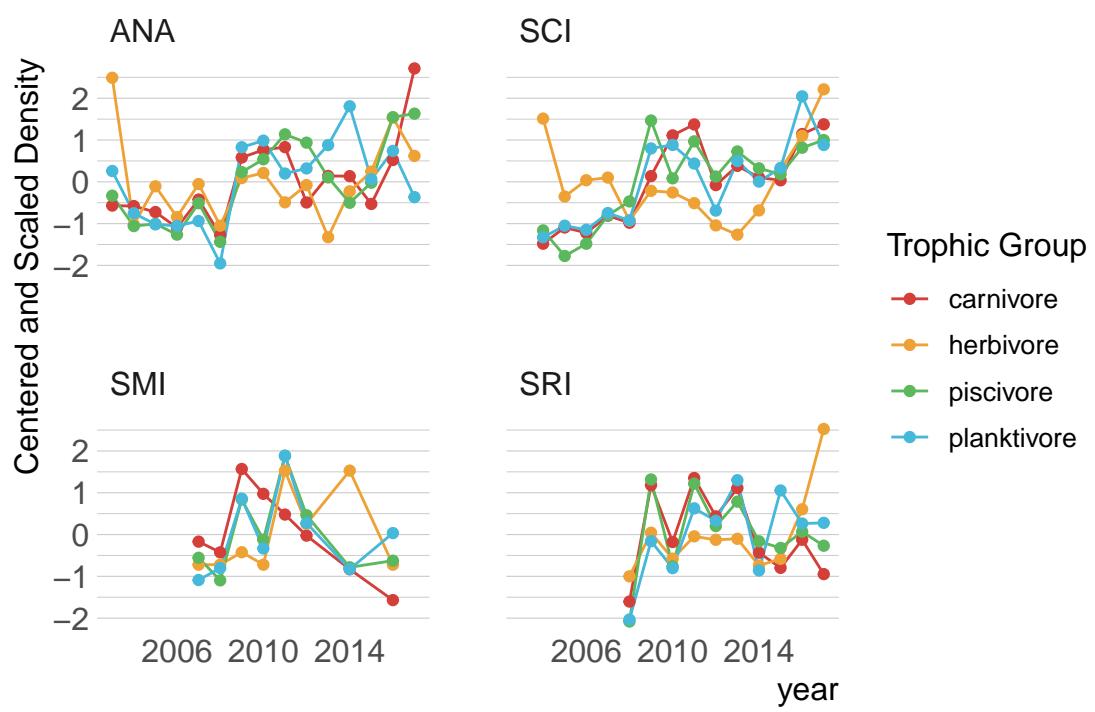


Figure 25: Centered and scaled densities by broad trophic group and island over time

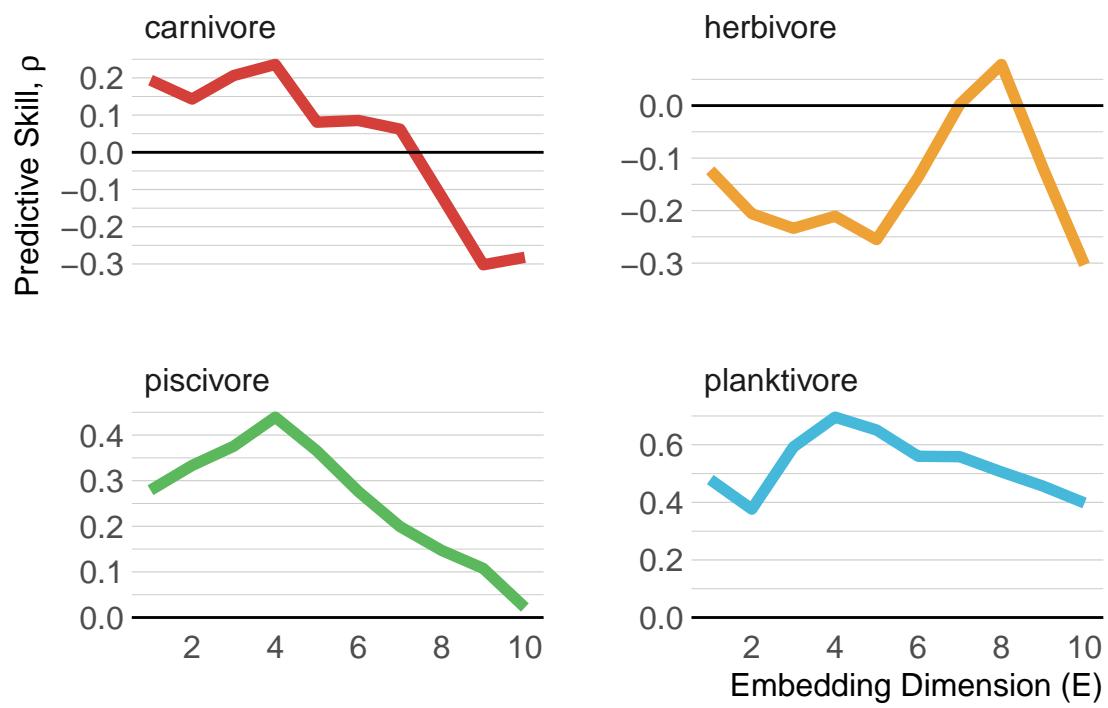


Figure 26: Predictive skill as a function of embedding dimensions

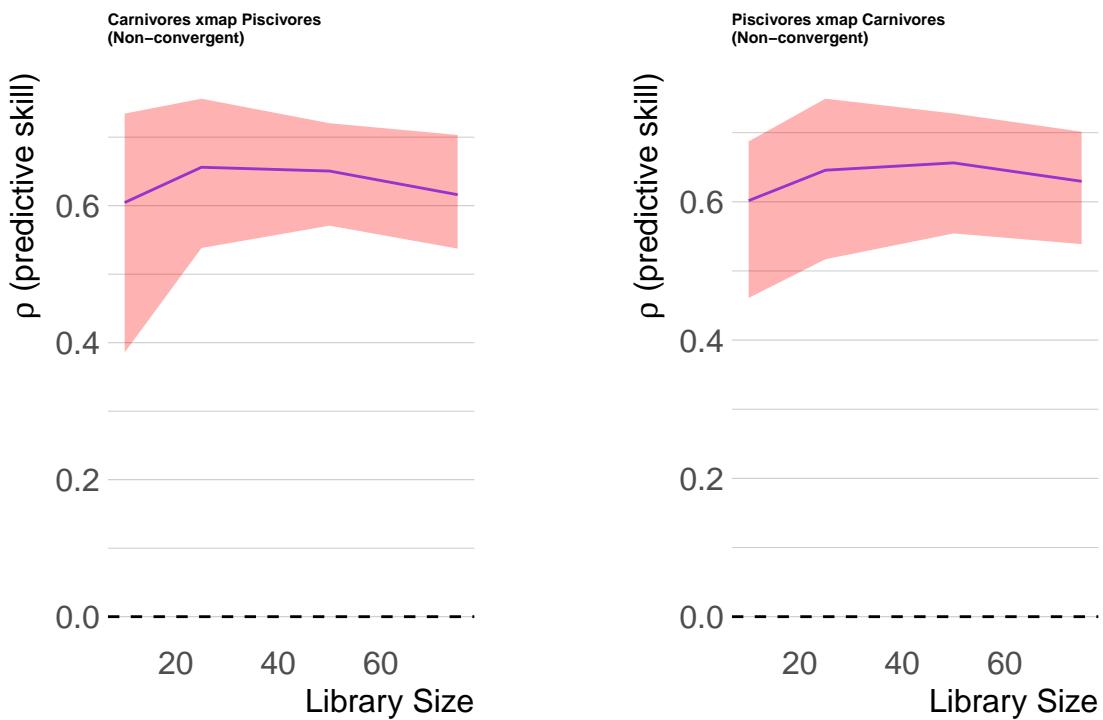


Figure 27: Cross mapping of effect of piscivores on carnivores (A) and carnivores on piscivores (B) in the PISCO data from 2000 to 2017. Shaded region show 95% confidence interval

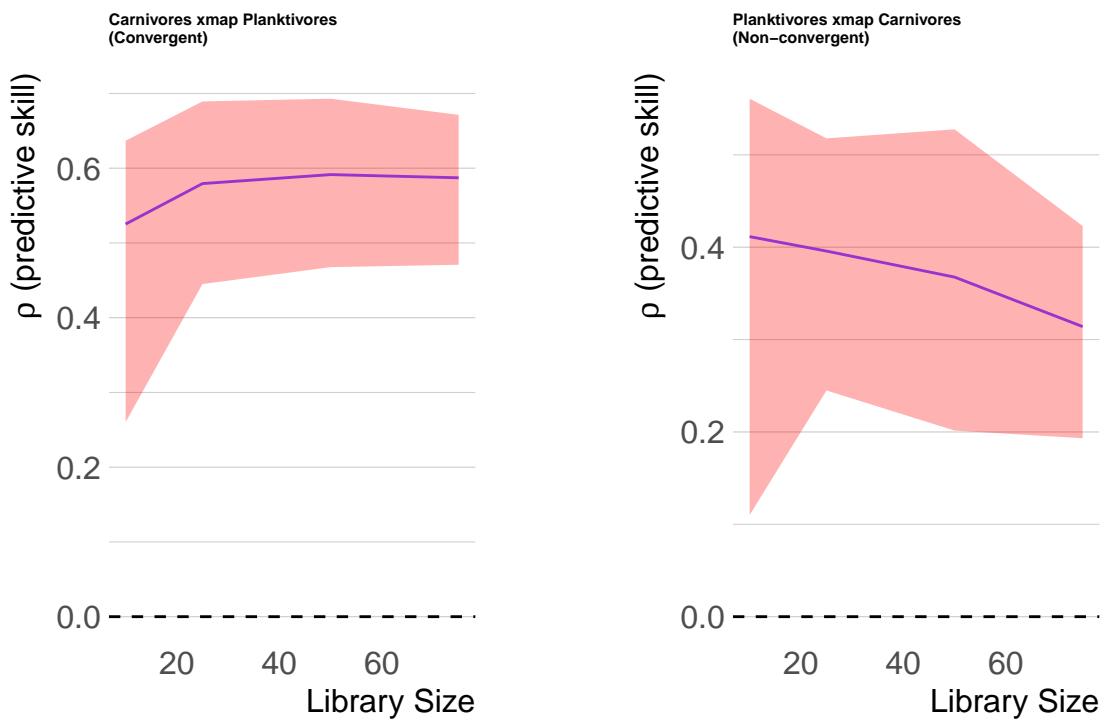


Figure 28: Cross mapping of effect of planktivores on carnivores (A) and carnivores on planktivores (B) in the PISCO data from 2000 to 2017. Shaded region show 95% confidence interval

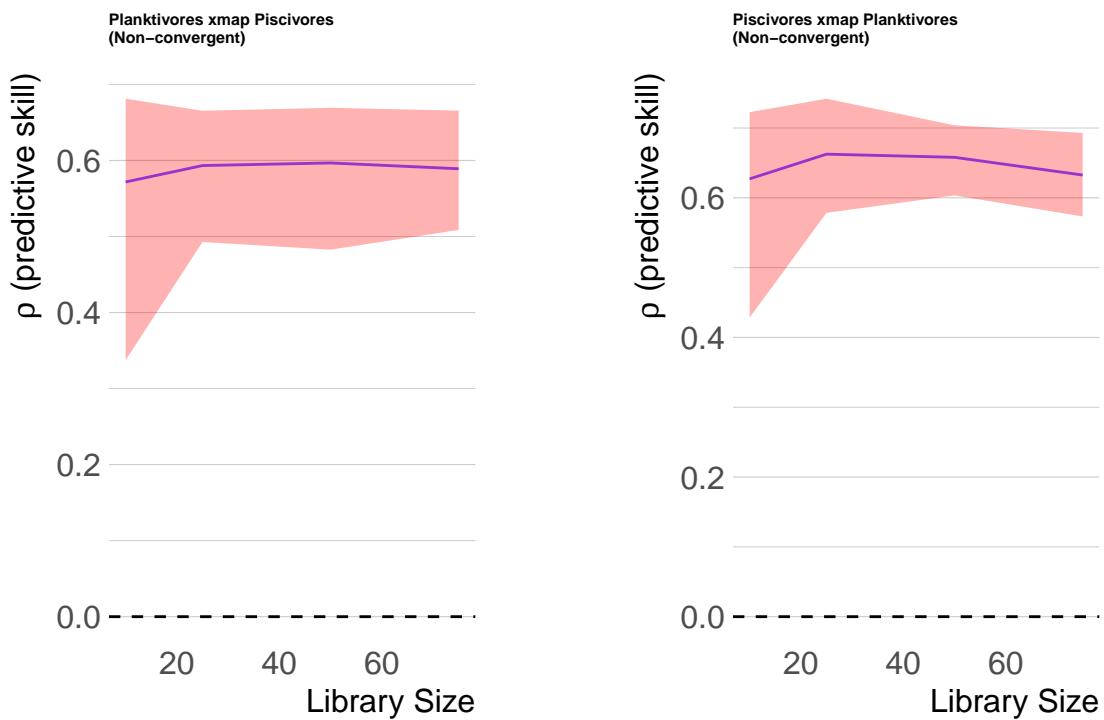


Figure 29: Cross mapping of effect of piscivores on carnivores (A) and carnivores on planktivores (B) in the PISCO data from 2000 to 2017. Shaded region show 95% confidence interval

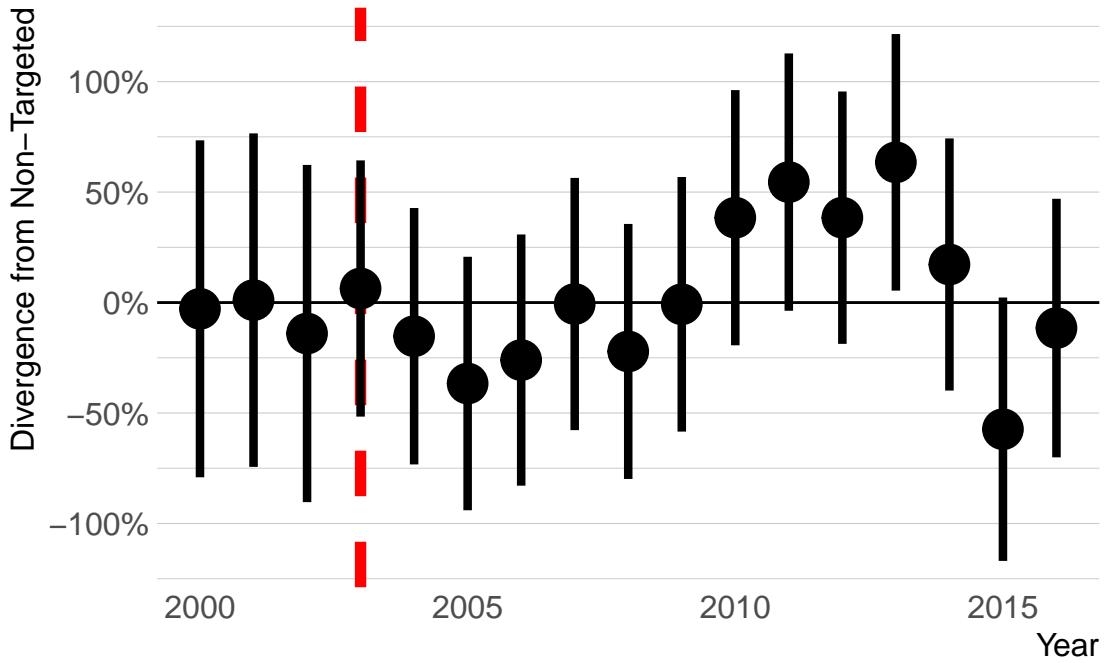


Figure 30: Estimated divergence in biomass densities of targeted and non-targeted fishes in the Channel Islands (i.e. integrated across inside and outside of MPAs) using the KFM data . MPAs are implemented in 2003 (red dashed line). Estimates are from a regression on  $\log(\text{abundance index})$ , and so estimated effects roughly correspond to percentage changes

<sup>437</sup> methods and survey locations, we find almost identical estimated trends in divergences between targeted and  
<sup>438</sup> non-targeted species using the KFM data (Fig.S30).

## <sup>439</sup> 1.8 MPA Only Analysis

<sup>440</sup> Given trends in mean densities observed in the raw data, the “regional conservation effect” estimated by  
<sup>441</sup> our model—defined as the divergence in trends between the targeted and non-targeted species across the  
<sup>442</sup> Channel Islands region—is not surprising. By jumping through countless statistical hoops we reach a similar  
<sup>443</sup> conclusion that we would just by looking at the divergences in the mean trends. The integration of data from  
<sup>444</sup> inside and outside of MPAs is a possible explanation for this lack of a clear regional effect. If spillover is  
<sup>445</sup> limited or has simply not developed yet, especially relative to the effect of fishing outside of MPAs, then it is  
<sup>446</sup> possible that there is a clear positive effect inside the MPAs, a clear negative effect outside, and when we  
<sup>447</sup> look across both types of sites we get an unclear average of the two.

<sup>448</sup> To address this, we can first repeat some exploratory data analysis of trends in densities inside and outside  
<sup>449</sup> the MPAs for targeted and non-targeted species. Caselle et al. (2015) provides a thorough look at this  
<sup>450</sup> question of differences inside and outside of MPAs. We update that analysis here to account for our specific  
<sup>451</sup> questions of trend divergence, potential differences in filtering methods, to include data up through 2017,  
<sup>452</sup> and to utilize our estimation method on just the inside-MPA data. For all exploratory analyses, we consider  
<sup>453</sup> the same top 23 consistently observed species. Looking first at simple trends in total mean biomass density

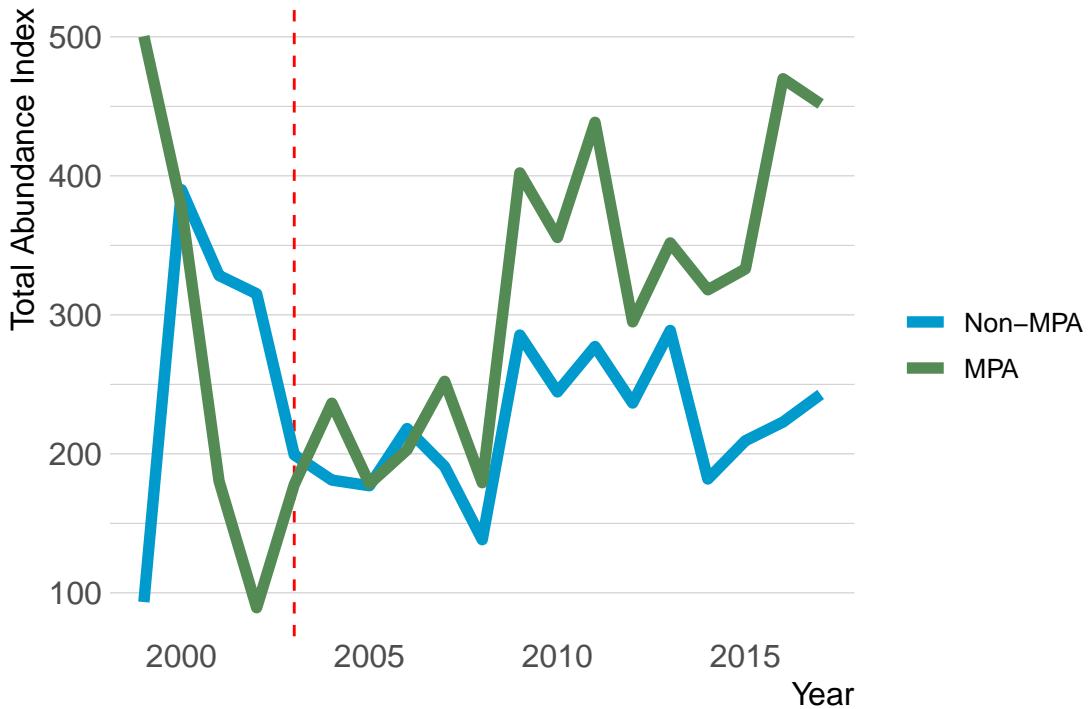


Figure 31: Annual mean aggregate biomass density (summed across all fishes) inside and outside of eventual MPA locations over time. Red dashed line indicates MPA implementation year

454 across these species inside and outside of MPAs, we find evidence that biomass densities inside the MPAs is  
 455 increasing faster (and is higher inside) than outside (Fig.S31).

456 Our proposed identification strategy here though is not that total biomass density should be different inside  
 457 and outside, but that the non-targeted species should serve as the control to the targeted. If we believe that  
 458 the MPA effects are greater inside the MPA, then we would expect to see stronger divergences in biomass  
 459 densities between these two targeted and non-targeted fishes inside the MPAs than outside

460 Here we see a different picture. While there is some visual evidence that the targeted species were diverging  
 461 from the non-targeted faster inside the MPAs than outside, both inside and outside we see that the trend  
 462 in total biomass density of targeted species is trending downward, relative to the trend in the non-targeted  
 463 species in recent years. This analysis is of total biomass density. However, our model estimates the mean  
 464 difference in targeted and non-targeted species. Both have their advantages, but we chose the mean to reflect  
 465 a hypothesis that the MPAs would provide positive benefits across all targeted species. The total biomass  
 466 density could be strongly affected by a sharp increase or decrease in one or two species, even if the mean  
 467 trend is different. Examining the mean trends though, we see the same results (Fig.S33).

468 Lastly, we can examine both the mean and individual trend to check clear species-by-species outliers in the  
 469 overall biomass density trends. This analysis shows noise, but overall the targeted and non-targeted species  
 470 seem to be following similar trends within their respective groups

471 These visual assessments suggest that similar to our results looking both inside and outside of MPAs, we  
 472 would expect that our estimation model fitted only on data from inside eventual MPAs would reach similar  
 473 conclusions as our results fitted to data from both inside and outside MPAs. To test this, we re-ran our

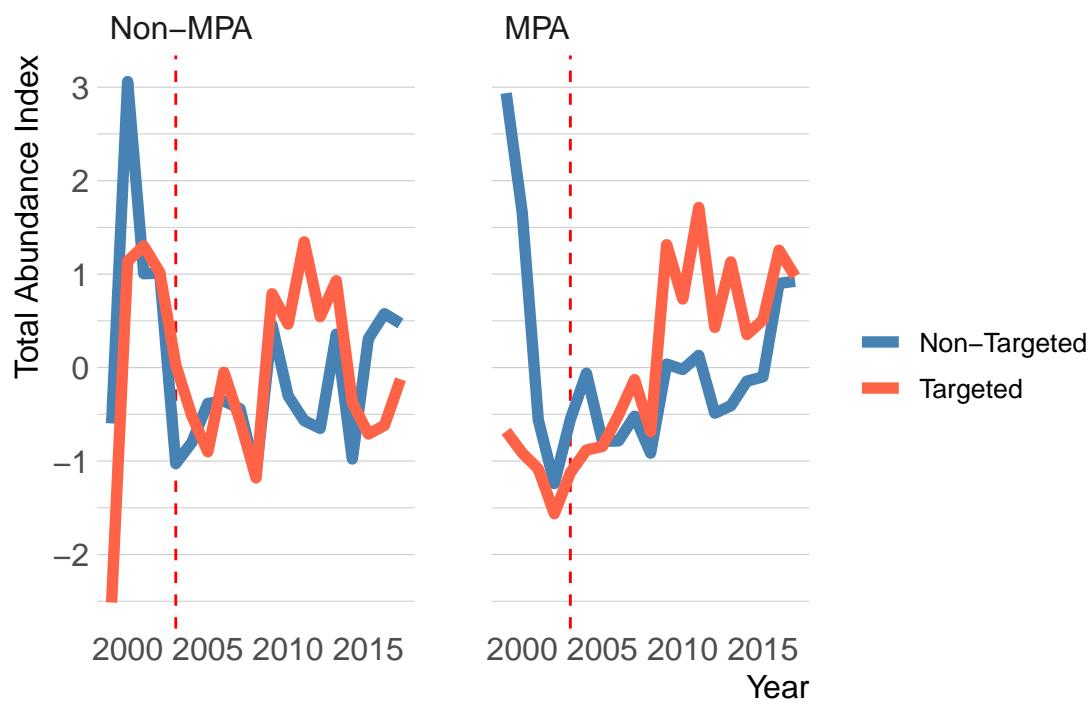


Figure 32: Trends in total biomass density inside and outside of eventual MPAs for targeted and non-targeted fishes. Red dashed line indicates MPA implementation year

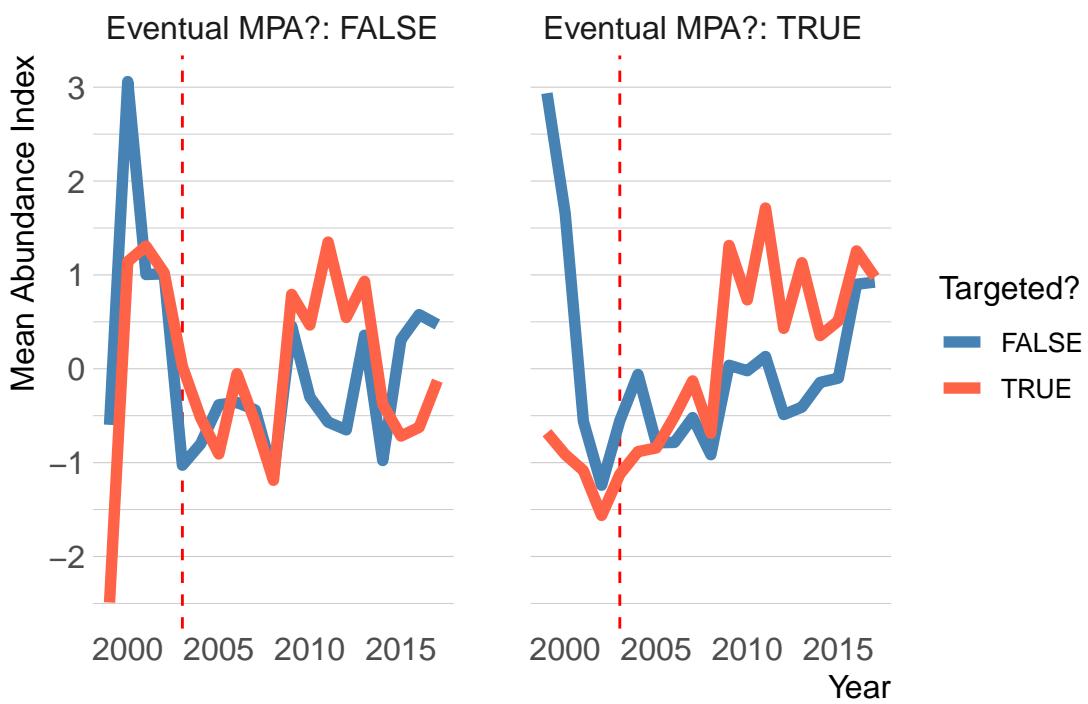


Figure 33: Trends in mean total biomass density inside and outside of eventual MPAs for targeted and non-targeted fishes. Red dashed line indicates MPA implementation year

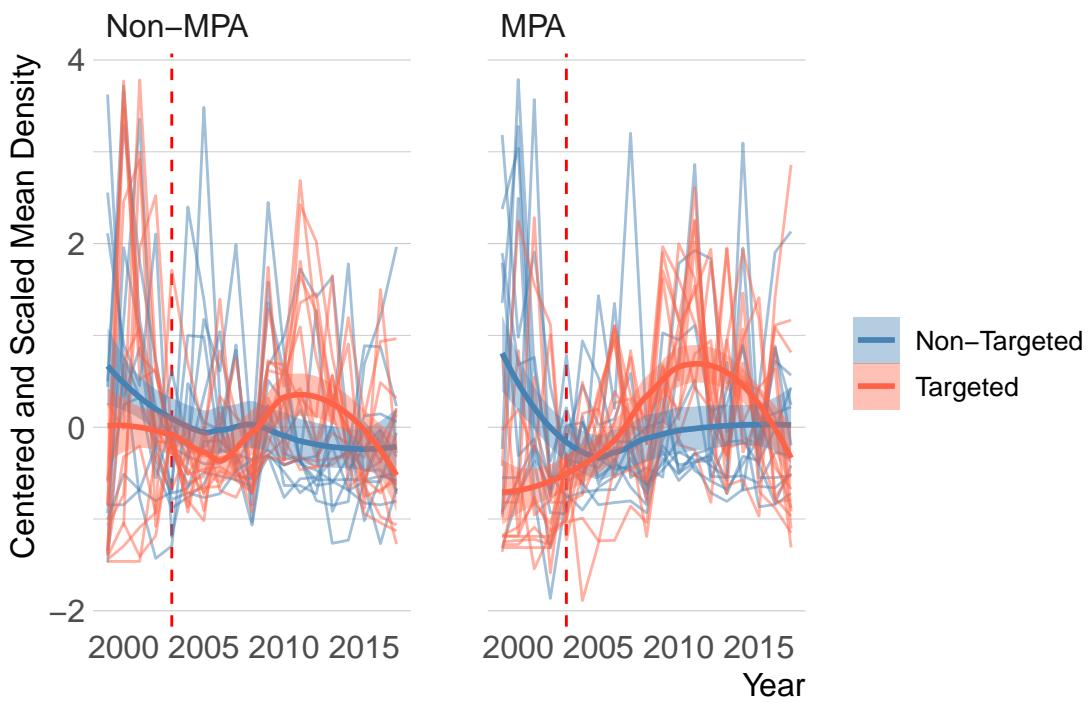


Figure 34: Centered and scaled biomass density trends for each fish grouped by targeted and non targeted (pale lines) and fitted LOESS smoother (with 95% confidence intervals around mean) and mean by targeted and non-targeted groups, inside and outside od MPAs. Red dashed line indicates MPA implementation year

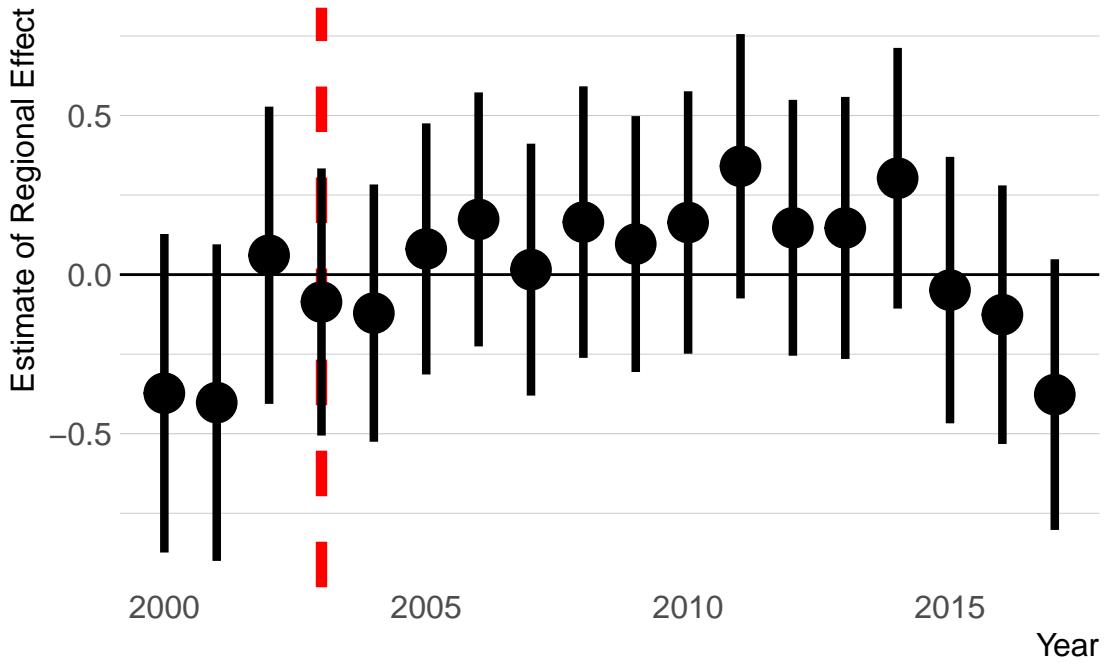


Figure 35: Estimated divergence in biomass densities of targeted and non-targeted fishes inside eventual Channel Islands MPAs. MPAs are implemented in 2003 (red dashed line). Estimates are from a regression on  $\log(\text{abundance index})$ , and so estimated effects roughly correspond to percentage changes

474 analysis, but only using data from sites that are eventually placed inside MPAs. Our results reflect the  
 475 same trends as displayed in the raw data and the statistical region-wide analysis, providing robust statistical  
 476 support to the conclusions we would reach from visually examining the raw data (Fig.S 35).

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