Supporting Information

Assessing the Population-level Conservation Effects of Marine Protected Areas

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1.1 Computing environment

All code needed to reproduce our main results and manuscript can be found at https://github.com/DanOvando/regional-effects-of-mpas. All analysis were performed in R version 3.6.3 (2020-02-29). Package versions are shown in Table.S1.

Table 1: Package versions and sources used in this paper

	package	loadedversion	date	source
arrayhelpers	arrayhelpers	1.1-0	2020-02-04	CRAN (R 3.6.0)
assertthat	assertthat	0.2.1	2019-03-21	CRAN (R 3.6.0)
backports	backports	1.1.6	2020-04-05	CRAN (R 3.6.2)
base64enc	base64enc	0.1-3	2015-07-28	CRAN (R 3.6.0)
bayesplot	bayesplot	1.7.1	2019-12-01	CRAN (R 3.6.0)

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

	package	loadedversion	date	source
bitops	bitops	1.0-6	2013-08-17	CRAN (R 3.6.0)
bookdown	bookdown	0.18	2020-03-05	CRAN (R 3.6.2)
boot	boot	1.3-24	2019-12-20	CRAN (R 3.6.3)
broom	broom	0.5.6	2020-04-20	CRAN (R 3.6.2)
callr	callr	3.4.3	2020-03-28	CRAN (R 3.6.2)
caret	caret	6.0-86	2020-03-20	CRAN (R 3.6.2)
cellranger	cellranger	1.1.0	2016-07-27	CRAN (R 3.6.0)
class	class	7.3-15	2019-01-01	CRAN (R 3.6.3)
classInt	classInt	0.4-2	2019-10-17	CRAN (R 3.6.0)
cli	cli	2.0.2	2020-02-28	CRAN (R 3.6.0)
coda	coda	0.19-3	2019-07-05	CRAN (R 3.6.0)
codetools	codetools	0.2-16	2018-12-24	CRAN (R 3.6.3)
colorspace	colorspace	1.4-1	2019-03-18	CRAN (R 3.6.0)
colourpicker	colourpicker	1.0	2017-09-27	CRAN (R 3.6.0)
crayon	crayon	1.3.4	2017-09-16	CRAN (R 3.6.0)
crosstalk	crosstalk	1.1.0.1	2020-03-13	CRAN (R 3.6.2)
data.table	data.table	1.12.8	2019-12-09	CRAN (R 3.6.0)
DBI	DBI	1.1.0	2019-12-15	CRAN (R 3.6.0)
dbplyr	dbplyr	1.4.2	2019-06-17	CRAN (R 3.6.0)
desc	desc	1.2.0	2018-05-01	CRAN (R 3.6.0)
devtools	devtools	2.3.0	2020-04-10	CRAN (R 3.6.3)
dials	dials	0.0.4	2019-12-02	CRAN (R 3.6.0)
DiceDesign	DiceDesign	1.8-1	2019-07-31	CRAN (R 3.6.0)
digest	digest	0.6.25	2020-02-23	CRAN (R 3.6.0)
dplyr	dplyr	0.8.5	2020-03-07	CRAN (R 3.6.2)
DT	DT	0.13	2020-03-23	CRAN (R 3.6.2)
dygraphs	dygraphs	1.1.1.6	2018-07-11	CRAN (R 3.6.0)
e1071	e1071	1.7-3	2019-11-26	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)
fansi	fansi	0.4.1	2020-01-08	CRAN (R 3.6.0)
fastmap	fastmap	1.0.1	2019-10-08	CRAN (R 3.6.0)
forcats	forcats	0.5.0	2020-03-01	CRAN (R 3.6.0)
foreach	foreach	1.4.8	2020-02-09	CRAN (R 3.6.0)
fs	fs	1.4.1	2020-04-04	CRAN (R 3.6.2)
gdtools	gdtools	0.2.2	2020-04-03	CRAN (R 3.6.2)
generics	generics	0.0.2	2018-11-29	CRAN (R 3.6.0)
ggmap	ggmap	3.0.0	2019-02-05	CRAN (R 3.6.0)
ggplot2	ggplot2	3.3.0	2020-03-05	CRAN (R 3.6.2)
ggrepel	ggrepel	0.8.2	2020-03-08	CRAN (R 3.6.2)
ggridges	ggridges	0.5.2	2020-01-12	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)
ggtext	ggtext	0.1.0	2020-03-19	Github (wilkelab/ggtext@24e9cd0)

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

	package	loadedversion	date	source
glue	glue	1.4.0	2020-04-03	CRAN (R 3.6.2)
gower	gower	0.2.1	2019-05-14	CRAN (R 3.6.0)
GPfit	GPfit	1.0-8	2019-02-08	CRAN (R 3.6.0)
gridExtra	gridExtra	2.3	2017-09-09	CRAN (R 3.6.0)
gridtext	gridtext	0.1.1	2020-02-24	CRAN (R 3.6.0)
gtable	gtable	0.3.0	2019-03-25	CRAN (R 3.6.0)
gtools	gtools	3.8.2	2020-03-31	CRAN (R 3.6.2)
haven	haven	2.2.0	2019-11-08	CRAN (R 3.6.0)
here	here	0.1	2017-05-28	CRAN (R 3.6.0)
hms	hms	0.5.3	2020-01-08	CRAN (R 3.6.0)
hrbrthemes	hrbrthemes	0.8.0	2020-03-06	CRAN (R 3.6.2)
htmltools	htmltools	0.4.0	2019-10-04	CRAN (R 3.6.0)
htmlwidgets	htmlwidgets	1.5.1	2019-10-08	CRAN (R 3.6.0)
httpuv	httpuv	1.5.2	2019-09-11	CRAN (R 3.6.0)
httr	httr	1.4.1	2019-08-05	CRAN (R 3.6.0)
igraph	igraph	1.2.5	2020-03-19	CRAN (R 3.6.2)
inline	inline	0.3.15	2018-05-18	CRAN (R 3.6.0)
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	0.1-8.1	2019-10-24	CRAN (R 3.6.0)
jsonlite	jsonlite	1.6.1	2020-02-02	CRAN (R 3.6.0)
kernlab	kernlab	0.9-29	2019-11-12	CRAN (R 3.6.0)
KernSmooth	KernSmooth	2.23-16	2019-10-15	CRAN (R 3.6.3)
knitr	knitr	1.28	2020-02-06	CRAN (R 3.6.0)
later	later	1.0.0	2019-10-04	CRAN (R 3.6.0)
lattice	lattice	0.20-38	2018-11-04	CRAN (R 3.6.3)
lava	lava	1.6.7	2020-03-05	CRAN (R 3.6.2)
lhs	lhs	1.0.1	2019-02-03	CRAN (R 3.6.0)
lifecycle	lifecycle	0.2.0	2020-03-06	CRAN (R 3.6.2)
lme4	lme4	1.1-23	2020-04-07	CRAN (R 3.6.2)
loo	loo	2.2.0	2019-12-19	CRAN (R 3.6.0)
lubridate	lubridate	1.7.8	2020-04-06	CRAN (R 3.6.2)
magrittr	magrittr	1.5	2014-11-22	CRAN (R 3.6.0)
markdown	markdown	1.1	2019-08-07	CRAN (R 3.6.0)
MASS	MASS	7.3-51.5	2019-12-20	CRAN (R 3.6.3)
Matrix	Matrix	1.2-18	2019-11-27	CRAN (R 3.6.3)
matrixStats	matrixStats	0.56.0	2020-03-13	CRAN (R 3.6.2)
memoise	memoise	1.1.0	2017-04-21	CRAN (R 3.6.0)
mime	mime	0.9	2020-02-04	CRAN (R 3.6.0)
miniUI	miniUI	0.1.1.1	2018-05-18	CRAN (R 3.6.0)
minqa	minqa	1.2.4	2014-10-09	CRAN (R 3.6.0)
ModelMetrics	ModelMetrics	1.2.2.2	2020-03-17	CRAN (R 3.6.2)
modelr	modelr	0.1.6	2020-02-22	CRAN (R 3.6.0)
munsell	munsell	0.5.0	2018-06-12	CRAN (R 3.6.0)
nlme	nlme	3.1-144	2020-02-06	CRAN (R 3.6.3)
nloptr	nloptr	1.2.2.1	2020-03-11	CRAN (R 3.6.2)

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

	package	loadedversion	date	source
nnet	nnet	7.3-12	2016-02-02	CRAN (R 3.6.3)
numDeriv	numDeriv	2016.8-1.1	2019-06-06	CRAN (R 3.6.0)
optimx	optimx	2020-2.2	2020-02-07	CRAN (R 3.6.0)
parsnip	parsnip	0.0.5	2020-01-07	CRAN (R 3.6.0)
patchwork	patchwork	1.0.0.9000	2020-04-21	Github (thomasp85/patchwork@012fb8b)
pillar	pillar	1.4.3	2019-12-20	CRAN (R 3.6.0)
pkgbuild	pkgbuild	1.0.6	2019-10-09	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)
plotROC	plotROC	2.2.1	2018-06-23	CRAN (R 3.6.0)
plyr	plyr	1.8.6	2020-03-03	CRAN (R 3.6.0)
png	png	0.1-7	2013-12-03	CRAN (R 3.6.0)
prettyunits	prettyunits	1.1.1	2020-01-24	CRAN (R 3.6.2)
pROC	pROC	1.16.2	2020-03-19	CRAN (R 3.6.2)
processx	processx	3.4.2	2020-02-09	CRAN (R 3.6.0)
prodlim	prodlim	2019.11.13	2019-11-17	CRAN (R 3.6.0)
promises	promises	1.1.0	2019-10-04	CRAN (R 3.6.0)
ps	ps	1.3.2	2020-02-13	CRAN (R 3.6.0)
purrr	purrr	0.3.4	2020-04-17	CRAN (R 3.6.3)
R6	R6	2.4.1	2019-11-12	CRAN (R 3.6.0)
Rcpp	Rcpp	1.0.4.8	2020-04-21	Github (RcppCore/Rcpp@4954e56)
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	0.1.10	2020-03-18	CRAN (R 3.6.2)
rEDM	rEDM	1.2.3	2020-03-06	CRAN (R 3.6.2)
remotes	remotes	2.1.1	2020-02-15	CRAN (R 3.6.0)
reprex	reprex	0.3.0	2019-05-16	CRAN (R 3.6.0)
reshape2	reshape2	1.4.4	2020-04-09	CRAN (R 3.6.2)
RgoogleMaps	RgoogleMaps	1.4.5.3	2020-02-12	CRAN (R 3.6.0)
rjson	rjson	0.2.20	2018-06-08	CRAN (R 3.6.0)
rlang	rlang	0.4.5	2020-03-01	CRAN (R 3.6.0)
rmarkdown	rmarkdown	2.1	2020-01-20	CRAN (R 3.6.0)
rpart	rpart	4.1-15	2019-04-12	CRAN (R 3.6.3)
rprojroot	rprojroot	1.3-2	2018-01-03	CRAN (R 3.6.0)
rsconnect	rsconnect	0.8.16	2019-12-13	CRAN (R 3.6.2)
rstan	rstan	2.19.3	2020-02-11	CRAN (R 3.6.0)
rstanarm	rstanarm	2.19.3	2020-02-11	CRAN (R 3.6.2)
rstantools	rstantools	2.0.0	2019-09-15	CRAN (R 3.6.0)
rstudioapi	rstudioapi	0.11	2020-02-07	CRAN (R 3.6.0)
Rttf2pt1	Rttf2pt1	1.3.8	2020-01-10	CRAN (R 3.6.0)
rvest	rvest	0.3.5	2019-11-08	CRAN (R 3.6.0)
scales	scales	1.1.0	2019-11-18	CRAN (R 3.6.0)
sessioninfo	sessioninfo	1.1.1	2018-11-05	CRAN (R 3.6.0)
sf	sf	0.9-1	2020-03-26	Github (r-spatial/sf@69c8d42)
shiny	shiny	1.4.0.2	2020-03-13	CRAN (R 3.6.2)
shinyjs	shinyjs	1.1	2020-01-13	CRAN (R 3.6.0)

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

	package	loadedversion	date	source
shinystan	shinystan	2.5.0	2018-05-01	CRAN (R 3.6.0)
shinythemes	shinythemes	1.1.2	2018-11-06	CRAN (R 3.6.0)
sp	sp	1.4-1	2020-02-28	CRAN (R 3.6.0)
spasm	spasm	1.0.0	2020-04-21	Github (danovando/spasm@bcf6638)
StanHeaders	StanHeaders	2.21.0-1	2020-01-19	CRAN (R 3.6.0)
statmod	statmod	1.4.34	2020-02-17	CRAN (R 3.6.0)
stringi	stringi	1.4.6	2020-02-17	CRAN (R 3.6.2)
stringr	stringr	1.4.0	2019-02-10	CRAN (R 3.6.0)
survival	survival	3.1-8	2019-12-03	CRAN (R 3.6.3)
svUnit	svUnit	1.0.3	2020-04-20	CRAN (R 3.6.2)
Synth	Synth	1.1-5	2014-01-27	CRAN (R 3.6.0)
systemfonts	systemfonts	0.2.0	2020-04-16	CRAN (R 3.6.2)
testthat	testthat	2.3.2	2020-03-02	CRAN (R 3.6.0)
threejs	threejs	0.3.3	2020-01-21	CRAN (R 3.6.2)
tibble	tibble	3.0.1	2020-04-20	CRAN (R 3.6.2)
tidybayes	tidybayes	2.0.3.9000	2020-04-18	Github (mjskay/tidybayes@a830130)
tidyr	tidyr	1.0.2	2020-01-24	CRAN (R 3.6.2)
tidyselect	tidyselect	1.0.0	2020-01-27	CRAN (R 3.6.2)
tidyverse	tidyverse	1.3.0	2019-11-21	CRAN (R 3.6.0)
timeDate	timeDate	3043.102	2018-02-21	CRAN (R 3.6.0)
units	units	0.6-6	2020-03-16	CRAN (R 3.6.3)
usethis	usethis	1.6.0	2020-04-09	CRAN (R 3.6.3)
vctrs	vctrs	0.2.4	2020-03-10	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	2.2.0	2020-04-20	CRAN (R 3.6.2)
workflows	workflows	0.1.1	2020-03-17	CRAN (R 3.6.2)
xfun	xfun	0.13	2020-04-13	CRAN (R 3.6.2)
xml2	xml2	1.3.1	2020-04-09	CRAN (R 3.6.2)
xtable	xtable	1.8-4	2019-04-21	CRAN (R 3.6.0)
xts	xts	0.12-0	2020-01-19	CRAN (R 3.6.0)
yaml	yaml	2.2.1	2020-02-01	CRAN (R 3.6.0)
zoo	zoo	1.8-7	2020-01-10	CRAN (R 3.6.0)

1.2 PISCO Data

All fish data used in the primary difference-in-difference model were collected by PISCO. The dive transect survey methods are described in Caselle et al. (2015), provided below for ease of reference

"Fish assemblages were surveyed annually as part of a long-term monitoring program conducted by the Partnership for Interdisciplinary Studies of Coastal Oceans (PISCO) using standard underwater visual belt survey methods (www.piscoweb.org9). We analyzed data from 47 PISCO sites at the northern Channel Islands that were sampled annually from at least 2003 to 2012. We also excluded 3 sites on Anacapa where a much older MPA had already been established in 1978. MPAs on each island were sampled annually during June-October and we surveyed multiple sites inside and outside of any individual MPA. Details of MPA characteristics such as size and coastline extent are given in Hamilton et al.9. At each site, we conducted 8 to 12 fish transects that measured 30×2×2m at multiple levels in the water column: benthic, midwater, and kelp canopy (when present). Transects are laid out in a stratified random design, with multiple nonpermanent transects located in fixed strata (i.e., outer, middle, and inner edges of the reef). At each level in the water column, one SCUBA diver per transect counted and estimated the sizes of all fish to the nearest centimeter (total length), excluding small cryptic fishes" - Caselle et al. (2015)

We take a number of steps to translate the raw transect data into the total biomass densities used in this study. For the default run, we only include species that were observed at least once for at least 15 of the 18 years of available data. We also exclude "young of the year" observations due the challenges of correctly identifying and measuring these individuals. We omitted data from 1999 due to changes in the sampling procedures that occurred after 1999. Per recommendations from PISCO staff we omit observations from the canopy level of the transects (leaving the middle, bottom, and middle canopy levels).

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

Once zeros have been introduced to the database, we convert positive observations of fish from numbers to biomass. Each observation in the raw database lists the species, the number of individuals seen, and the size of those individuals (either as one value or as a mininum and maximum size for the group seen). PISCO staff compiled allometric information used to convert lengths to expected weights. For each observation then, we convert the observed lengths to weights per these relationships (accounting for variations in length types such as standard vs. total length). When minimum and maximum ranges were reported, we drew a number of samples equal to the number of observed fish in that group from a uniform distribution spanning the minimum and maximum reported size in that group. We assume all length-to-weight conversions are constant and deterministic.

For each species at each transect, we calculate the biomass density of that transect as the sum of the observed biomass divided by the transect area. We then average the biomass densities for each species across all the transects at a given site, and lastly sum these mean species biomass densities to achieve the total mean species biomass at the site level.

We include several additional sources of data in our regression analysis. Temperature readings are included from the PISCO data for each transect. We also include PISCO data on the estimated surge and visibility. We augmented these data with information on kelp cover over time from the Santa Barbara Channel Long Term Ecological Research Network (LTER et al. 2017). We used a k-nearest neighbors algorithm to fill in missing kelp observations, and matched the interpolated kelp data to the PISCO data at the resolution of year-month-site (Fig.2). We include a variable capturing the mean cumulative number of observations across all observers conducting transects, in an effort to control for evoloving observer skill.

We also included lagged catch totals in the Santa Barbara region for the commercially harvest species in the database, in an effort to control for changes in density caused by changes in fishing pressure. Catches were pulled from the CDFW website (https://www.wildlife.ca.gov/Fishing/Commercial/Landings), and extracted using the `tabulizer` package in R (Leeper 2018) (Fig.1).

1.3 Difference-in-Difference Model

The difference-in-difference (DiD) regression amounts to estimating the pre-post MPA difference in the biomass densities of targeted species minus the same difference for non-targeted species in the Channel Islands.

The simplified form of this model is

$$d_i \sim Gamma(e^{\beta_0+\beta_1 T_i+\beta_2 MPA_i+\beta_3 T_i MPA_i+\mathbf{B^c X_i}+\mathbf{B^s S_i}}, shape, scale) \tag{1}$$

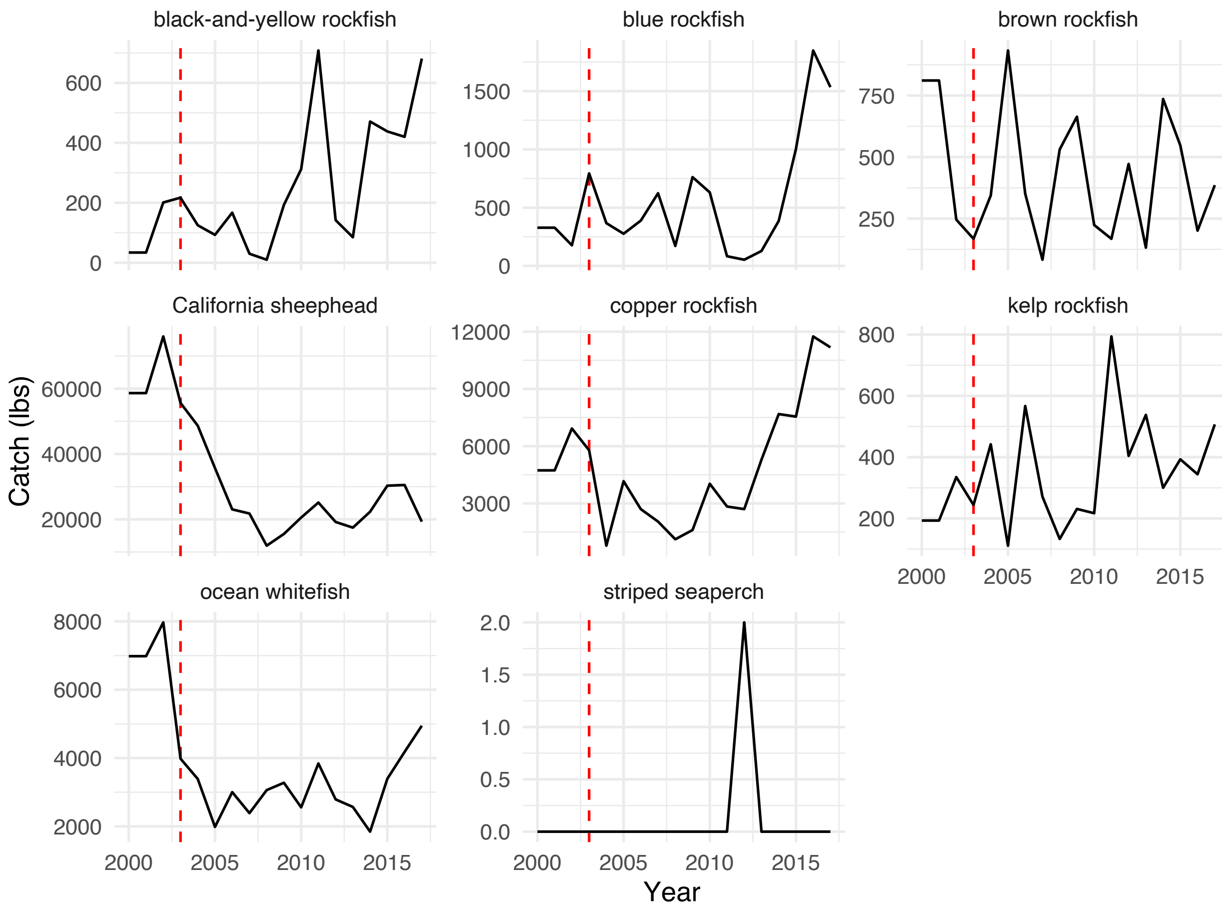

Figure 1: Total CDFW reported commercial catches in the Santa Barbara region

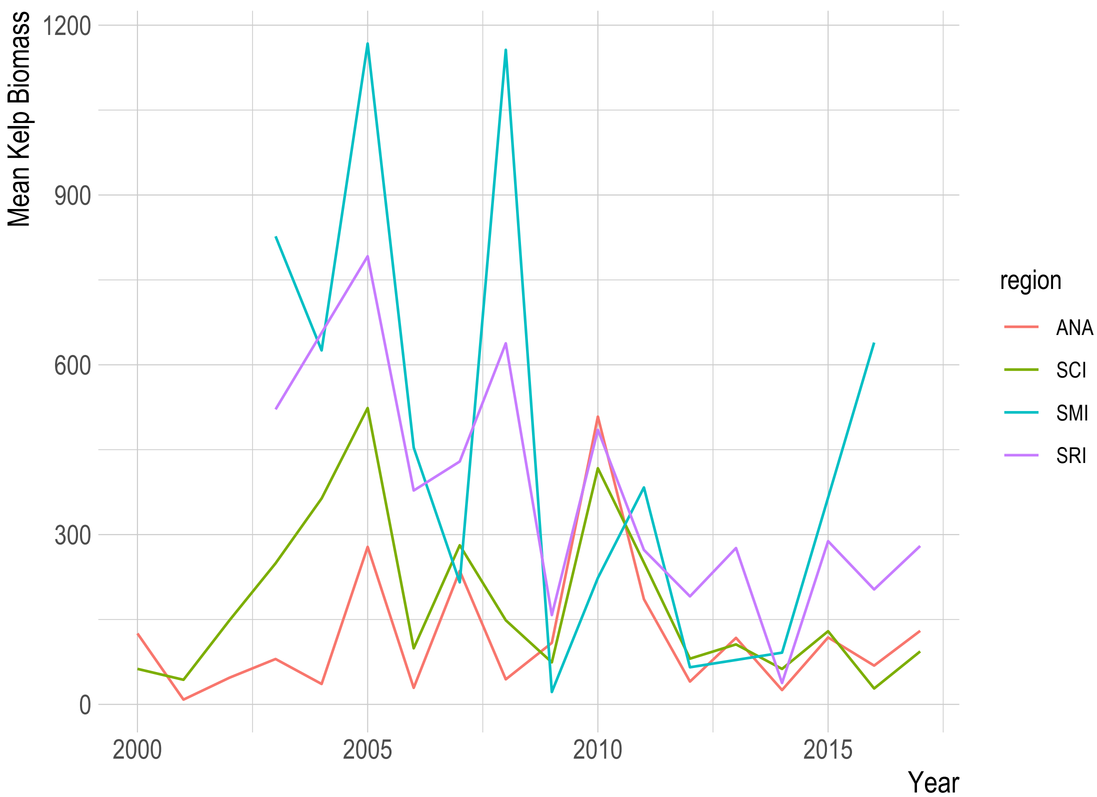

Figure 2: Mean kelp biomass by island over time from SBC LTER

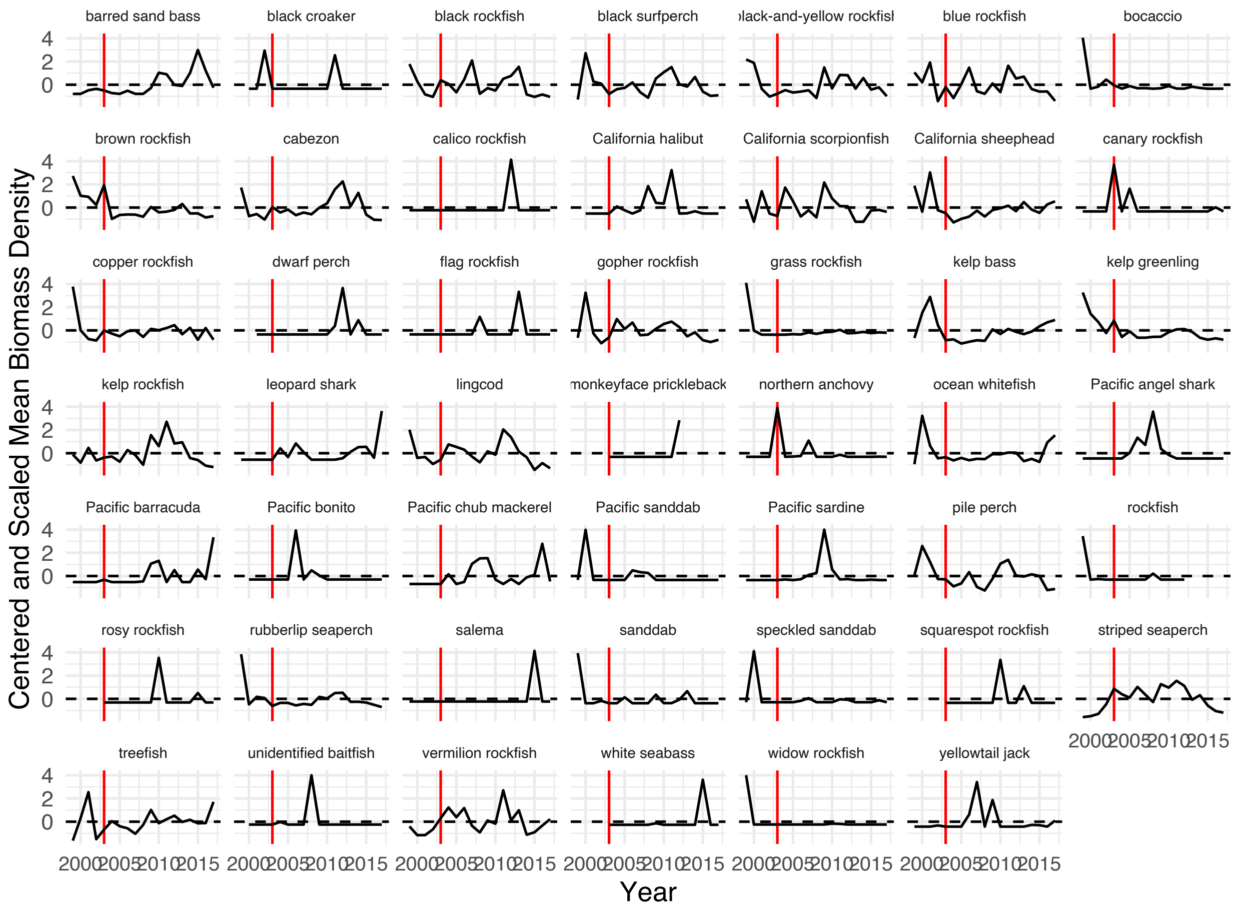

Figure 3: Centered and scaled mean biomass densities of all targeted finfish in analysis before filtering

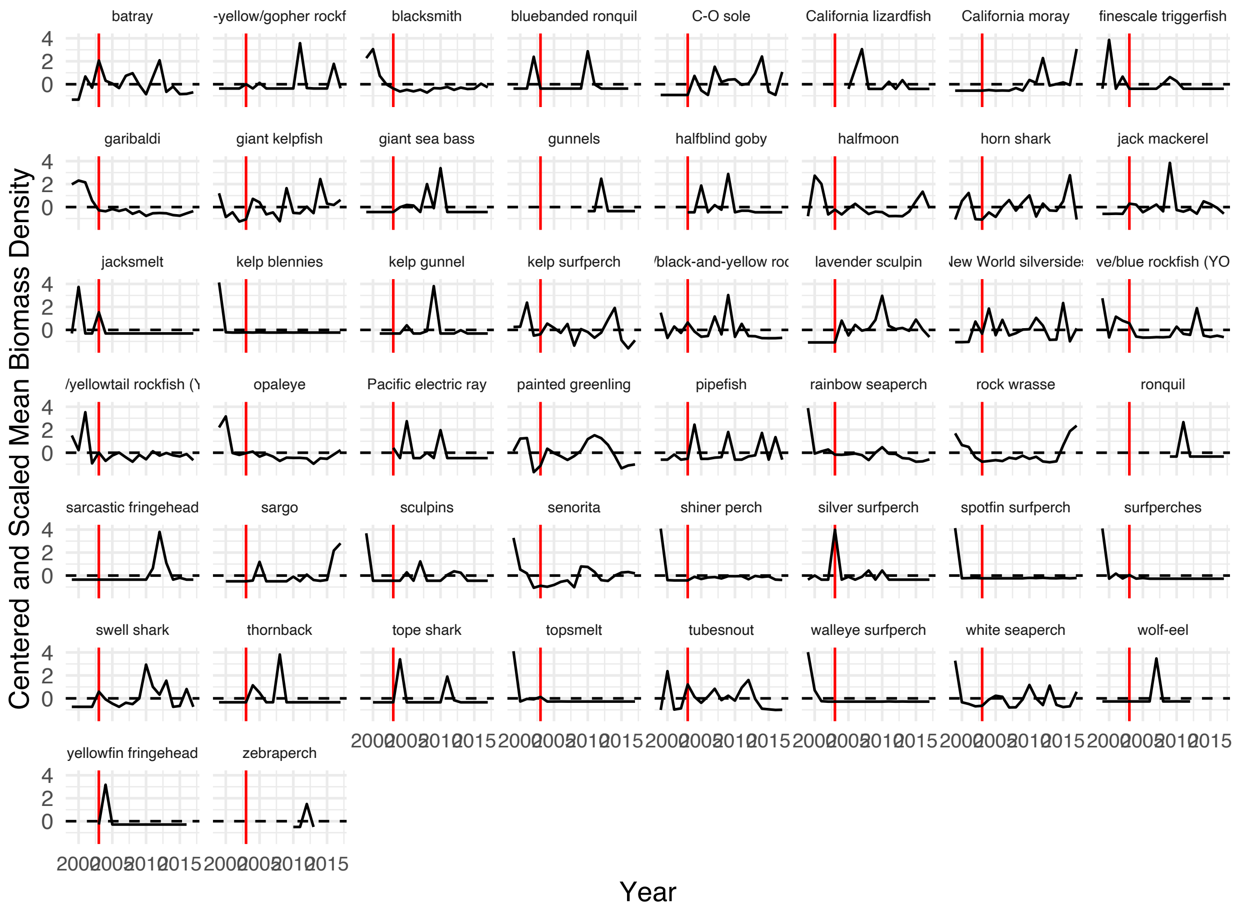

Figure 4: Centered and scaled mean biomass densities of all non-targeted finfish in analysis before filtering

The full list of included coefficients and their estimated values can be seen in Table.2.

To provide greater detail on this process, we first conduct the data pre-processing described earlier. From there, we aggregated data to the level of total mean biomass density of targeted and non-targeted species at each site each year. As such, our base model estiamtes the effect of the MPAs on total mean biomass density of targeted species, though we also explore the effect on alternative specifications such as mean biomass of targeted species. the model was then fit using the `rstanarm` package in R (5000 iterations, 2500 warmup, 4 chains, adapt_delta = 0.85).

The intercept prior was was determined using the `rstanarm` `autoscale` function. For the non-intercept terms, we manually set a normal(0,2) prior. This implies that coefficeints such as the MPA effect have a prior that provides support for an effect size centered on zero with a range of roughly -4 to 4. Since the covariates are centered and scaled, and the dependent variable is on the log-scale, this is an extremely diffuse prior (e.g. a one standard deviation change in an independent variable changes the dependent variable by 4 on the log scale).

The full table of covariates and their posterior means and 89% credible interval can be found in Table.S2. "var" refers to variable, `"_2"` indicates a squared term. tex is the mean cumulative number of observations of the observers collecting the raw data, surge is the mean reported surge across transects, kelp is the mean kelp coverage at the site, temp is the water temperature, regional_temp_dev is the water temperature at a given site scaled by the mean water temperature at that site. Targeted is a boolean marker indicating whether the given observation is for targeted or non-targeted species.

Table 2: Posterior means and credible interval for key model coefficients

term	mean	lower_89th_ci	upper_89th_ci
(Intercept)	-2.81	-3.08	-2.55
targeted	0.05	-0.13	0.24
year_bins(2003,2006]	-0.82	-1.06	-0.56
year_bins(2006,2009]	-0.86	-1.18	-0.53
year_bins(2009,2012]	-0.84	-1.18	-0.50
year_bins(2012,2015]	-0.96	-1.29	-0.63
year_bins(2015,2018]	-0.57	-0.92	-0.23
var_tex	0.20	0.05	0.35
var_tex_2	-0.07	-0.18	0.03
var_surge	0.09	0.00	0.17
var_kelp	-0.06	-0.10	-0.01
var_lag_catch	0.06	-0.04	0.18
var_temp	0.26	0.07	0.45
regional_temp_dev	-0.22	-0.38	-0.04
regional_temp_dev_2	0.01	-0.02	0.04
targeted:year_bins(2003,2006]	0.28	0.04	0.52
targeted:year_bins(2006,2009]	0.51	0.26	0.75
targeted:year_bins(2009,2012]	0.59	0.35	0.84
targeted:year_bins(2012,2015]	0.30	0.04	0.56
targeted:year_bins(2015,2018]	-0.07	-0.34	0.20

We include a series of standard visual diagnostic plot for Bayesian models below, with brief descriptions of the key outcome of the diagnostic included in the figure captions. The model had 0 divergences or max tree depth saturations.

`##`

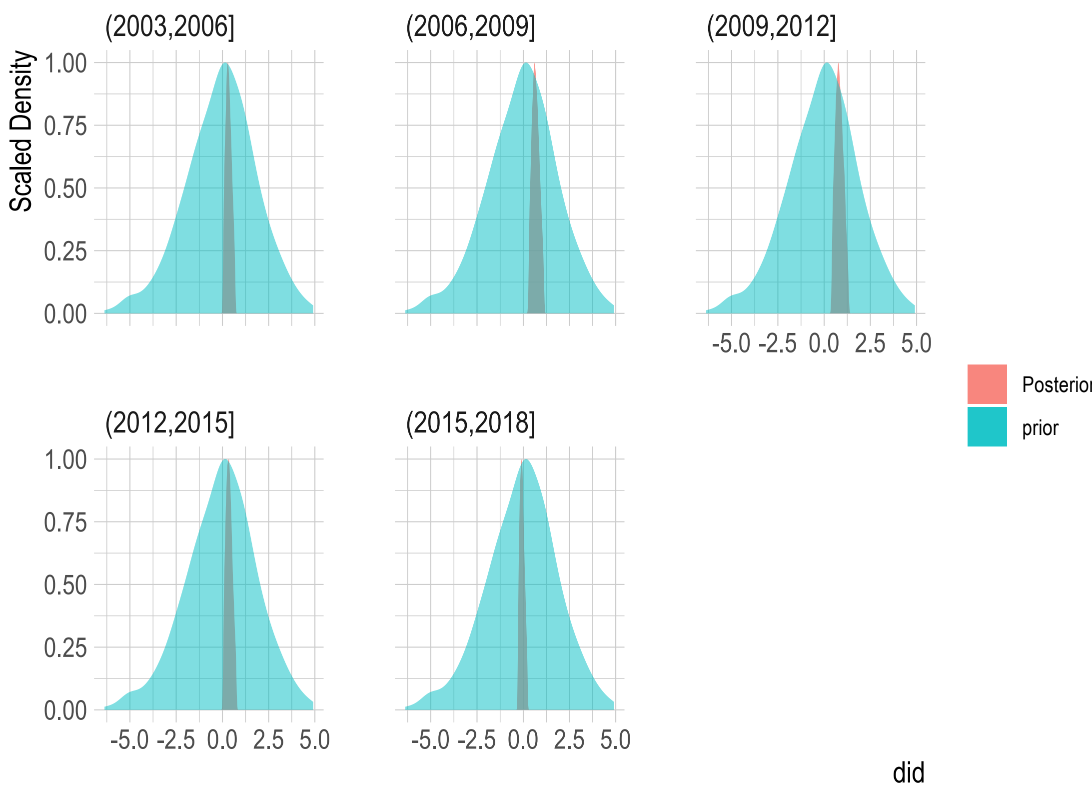

Figure 5: Prior and posterior distributions of the estimated MPA effect over time

```
## Divergences:
##
## Tree depth:
##
## Energy:
```

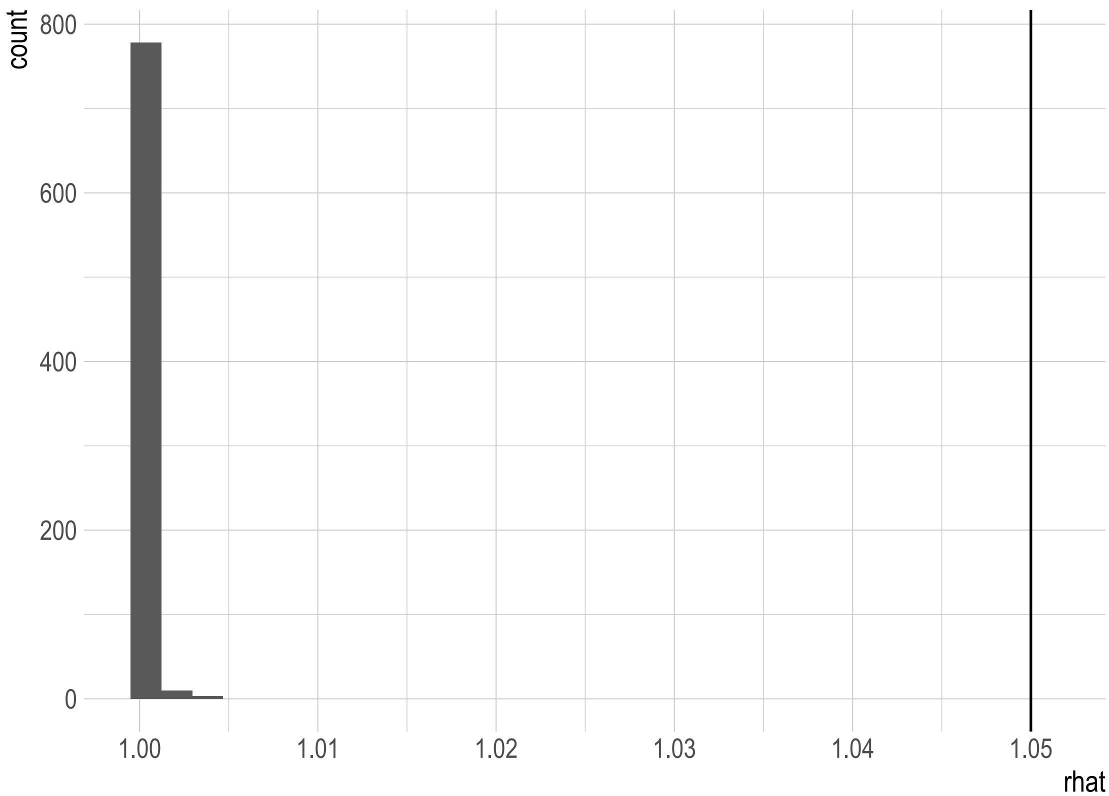

Figure 6: Histogram of potential scale reduction statistic Rhat. All values are below 1.05, indicating there is not evidence of chain convergence failure

1.3.1 Additional Difference-in-difference Runs

We include a variety of additional model runs designed to explore the sensitivity of our key results to various assumptions and data processing steps included in our base results. Description and key message are provided inside figure captions.

Our base run uses data collected by PISCO. As a robustness check to our main results, we repeated our analysis utilizing data provided by the Kelp Forest Monitoring Program (KFM) conducted in the Channel Islands.

We include one run using only variables availale in both datasets, to explore sensitivity of our results to selected covariates (Fig.16).

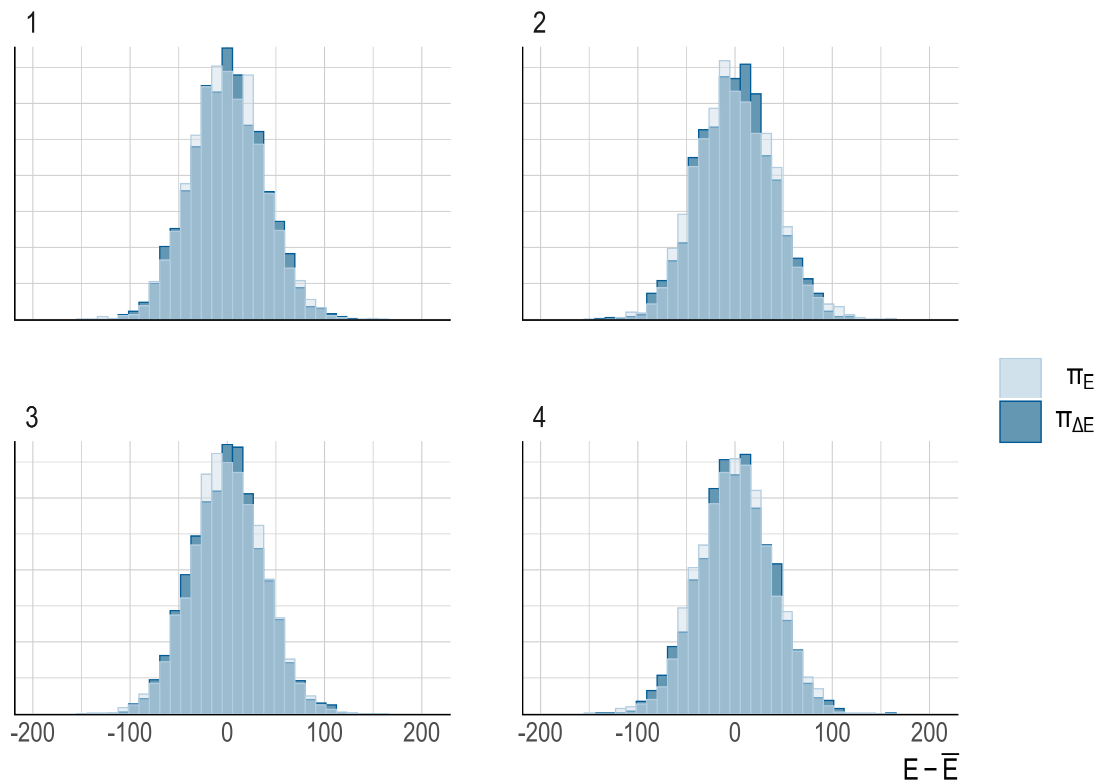

Figure 7: HMC energy diagnostic plots. Closely matching histograms shows there is no evidence of excessively fat tails

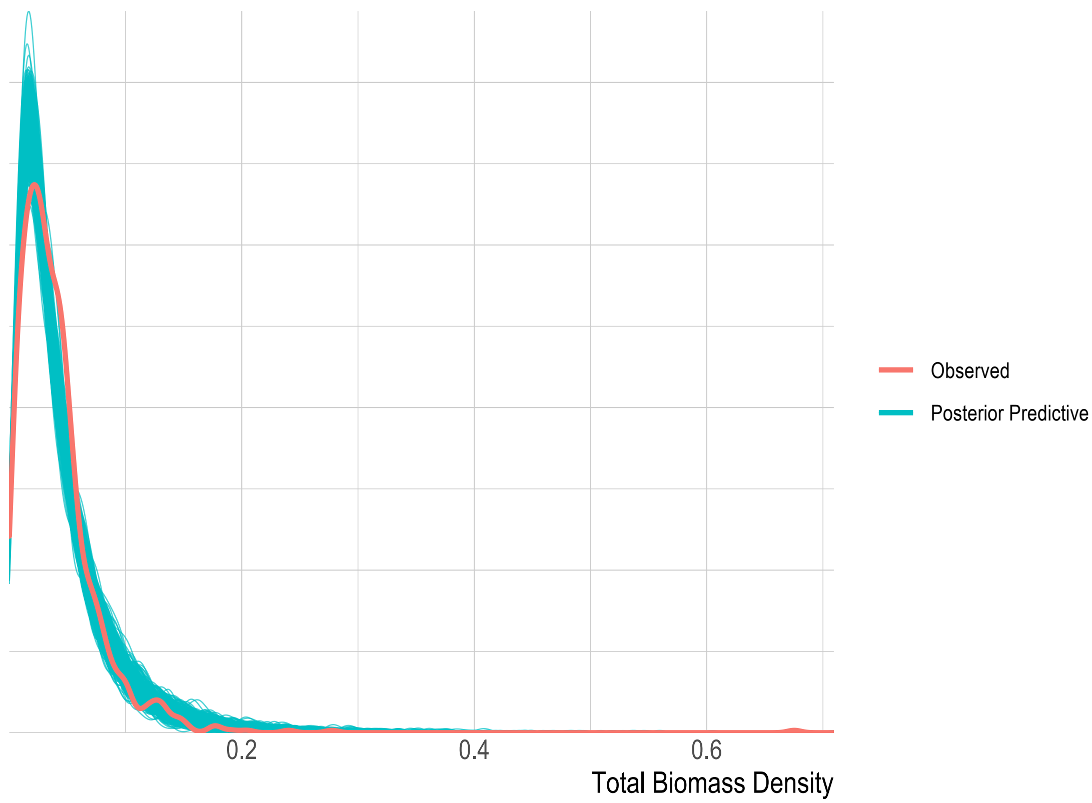

Figure 8: Posterior Predictive distribution of total biomass density (blue lines) and observed distribution of total biomass density (red line)

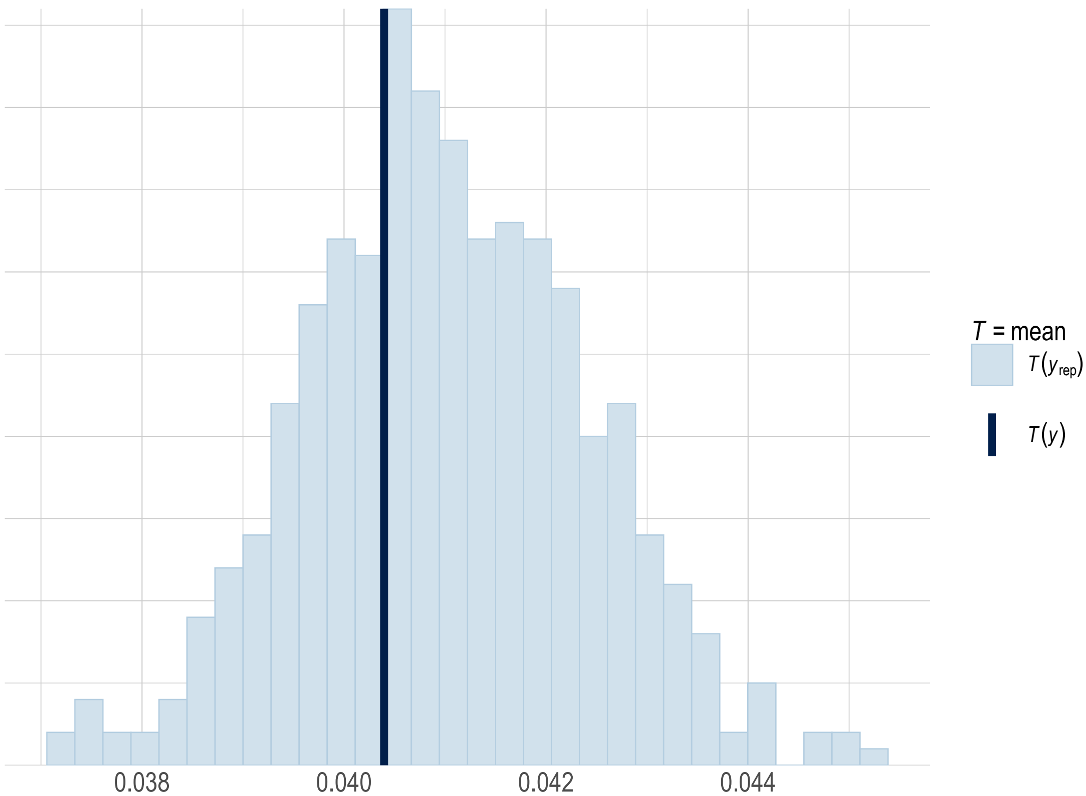

Figure 9: (#fig:mean_test_plot)Posterior predictive mean (distribution) and empirical mean of total biomass density. Posterior predictive mean adequately covers empirical mean.

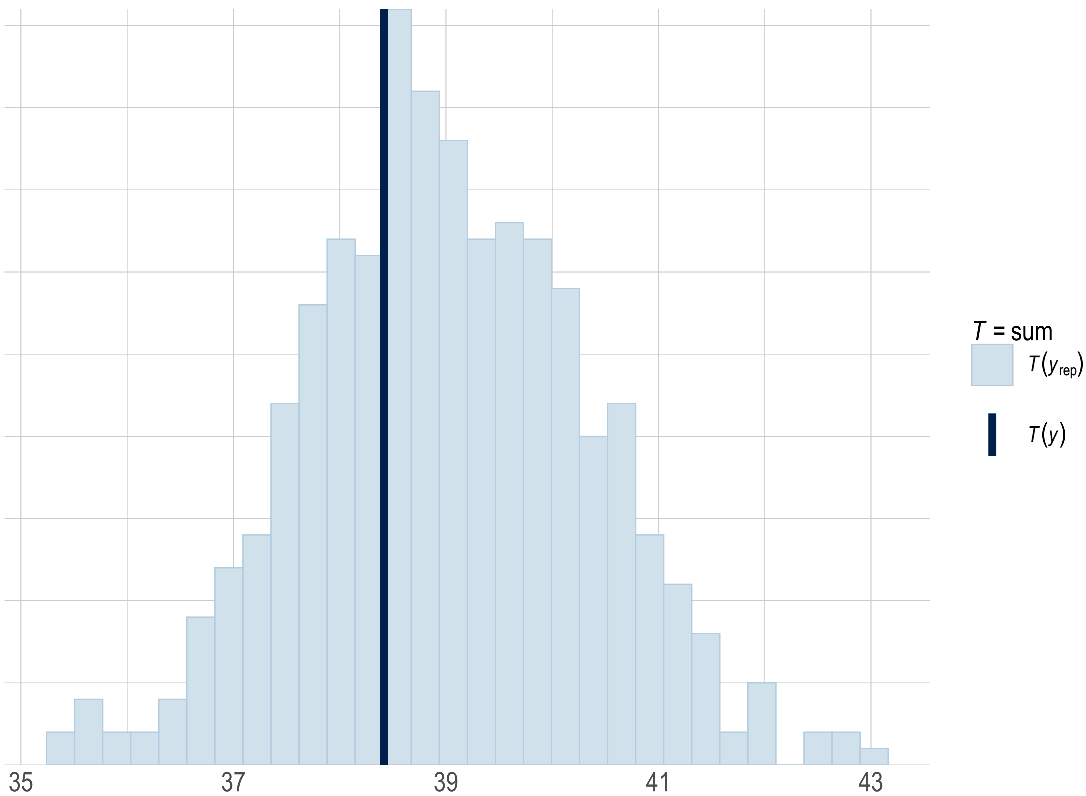

Figure 10: (#fig:sum_test_plot)Posterior predictive sum (distribution) and empirical sum of total biomass density. Posterior predictive sum adequately covers empirical sum.

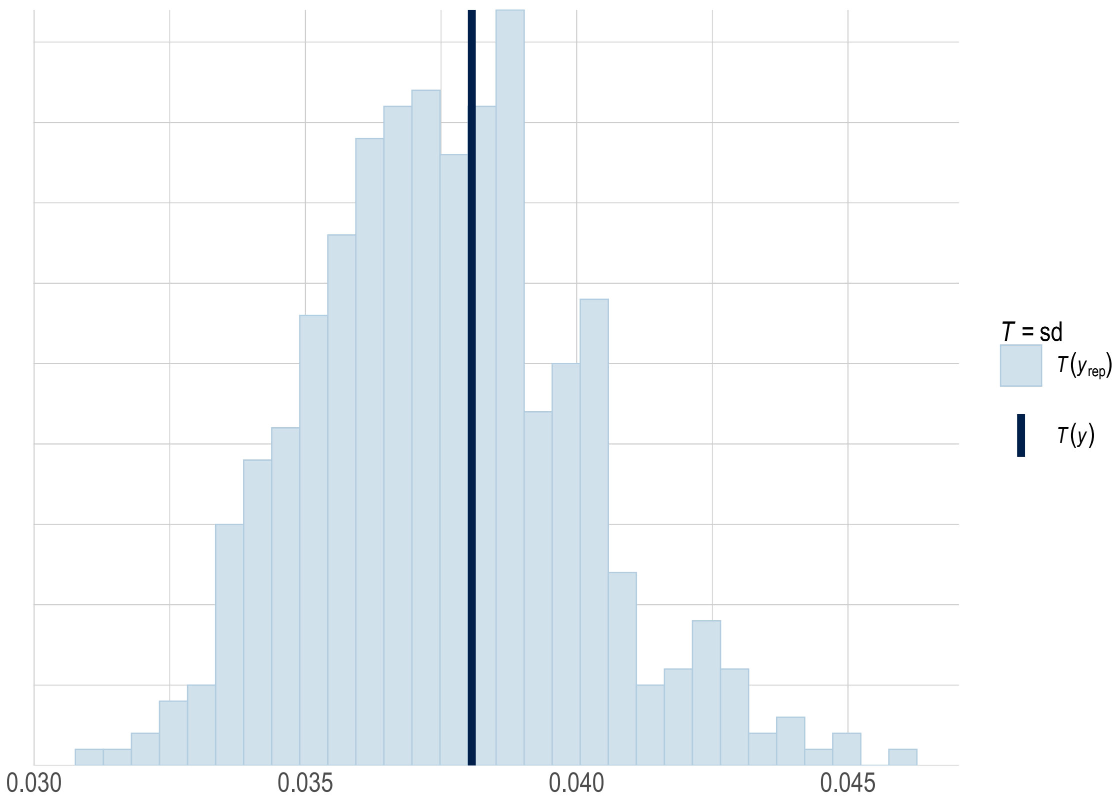

Figure 11: (#fig:sd_test_plot)Posterior predictive standard deviation (distribution) and empirical standard deviation of total biomass density. Posterior predictive standard deviation adequately covers empirical standard deviation

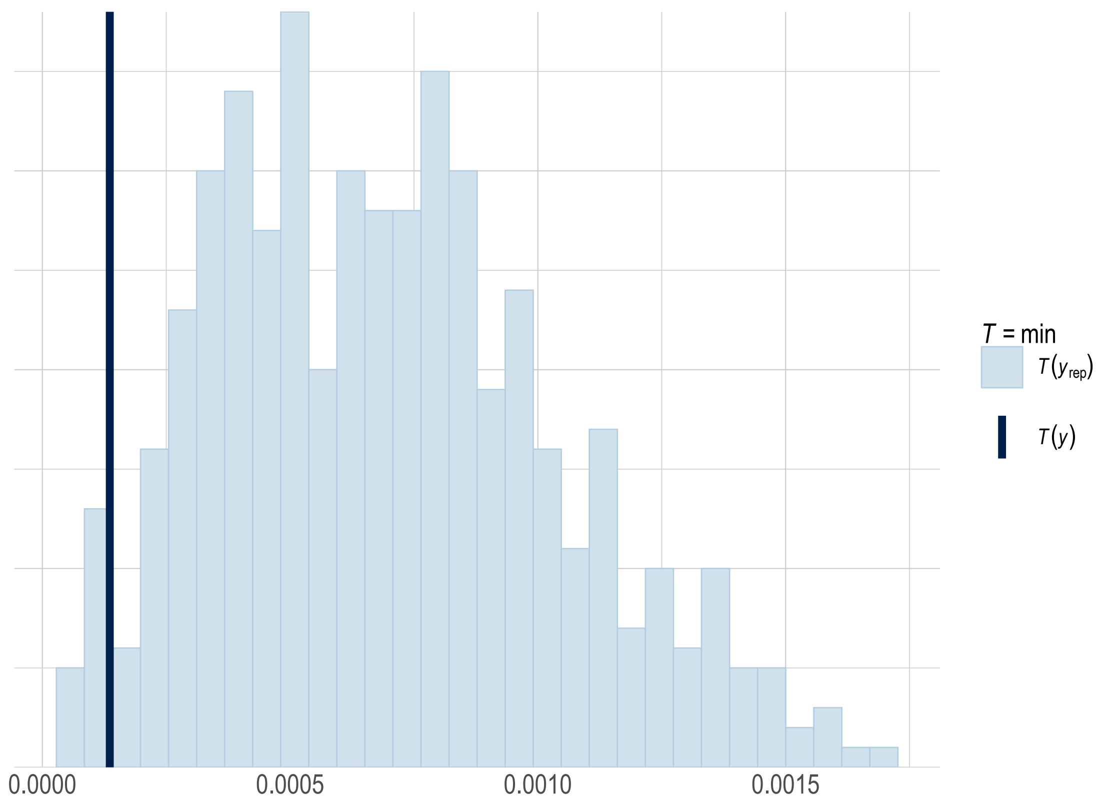

Figure 12: (#fig:min_test_plot)Posterior predictive minimum (distribution) and empirical minimum of log total biomass density. Model slightly overpredicts minimum value in the data

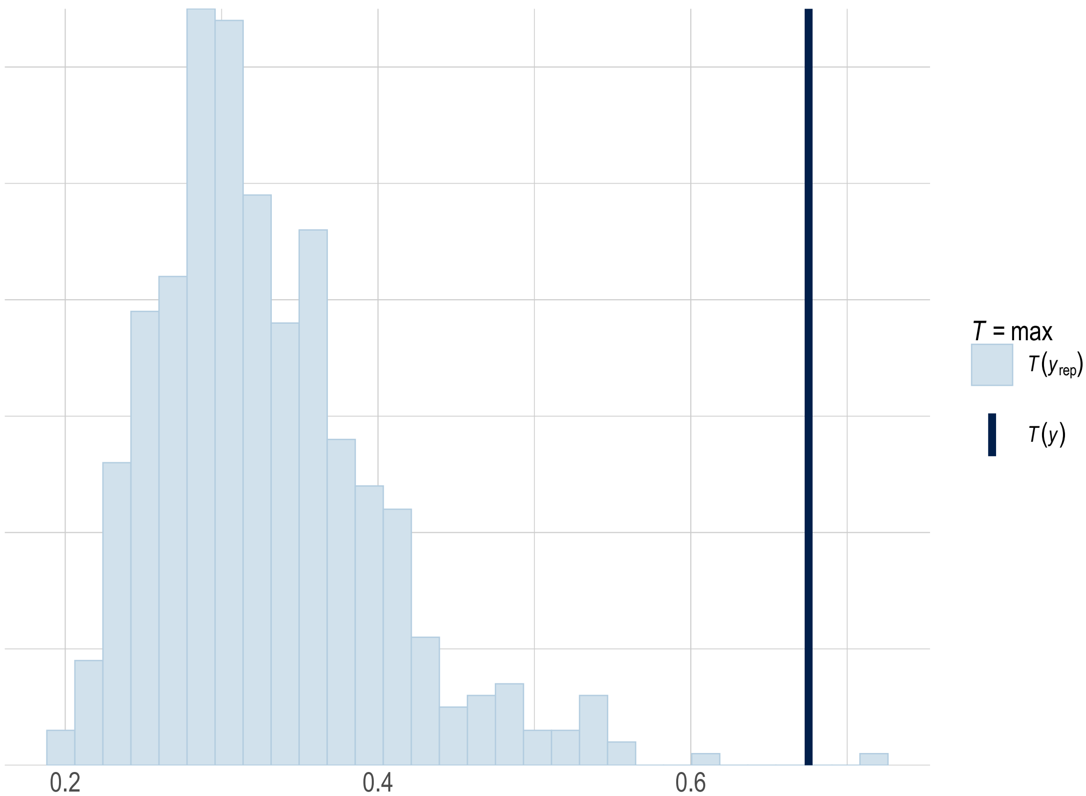

Figure 13: (#fig:max_test_plot)Posterior predictive maximum (distribution) and empirical maximum of total biomass density. Model underestimates true maximum of the data.

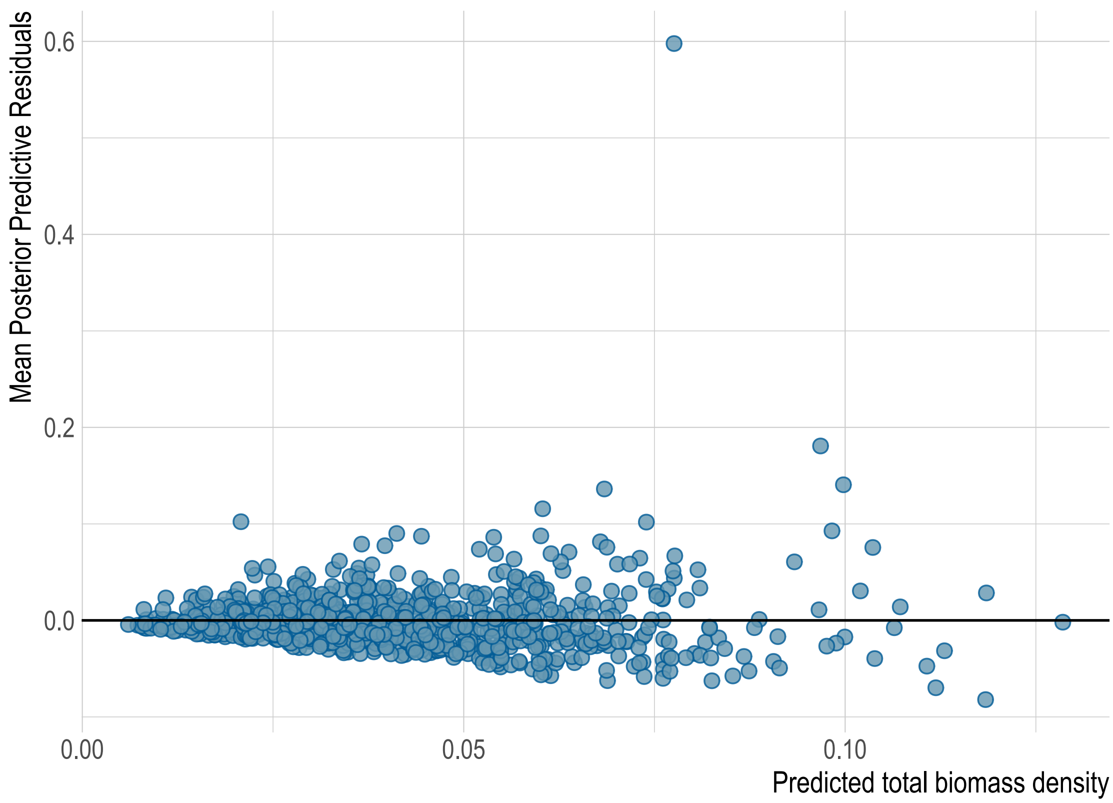

Figure 14: Posterior predictive total biomass densities plotted against mean posterior predictive residuals

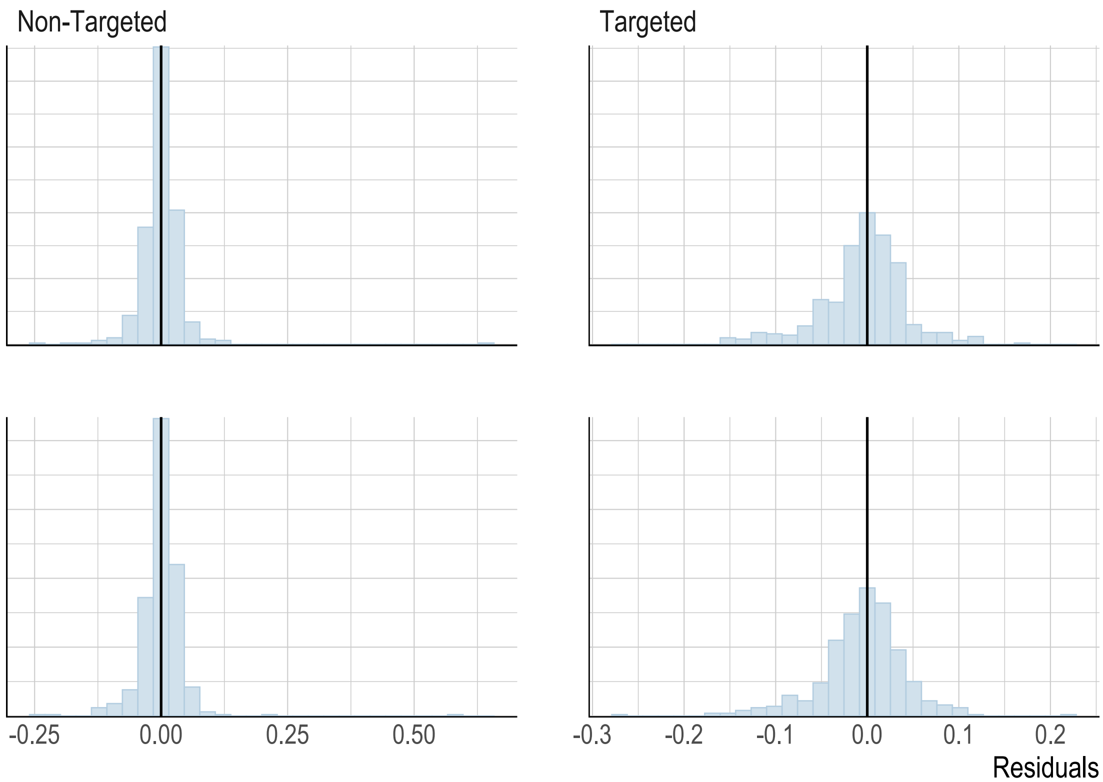

Figure 15: Histograms of residuals for targeted and non-targeted obesrvations.

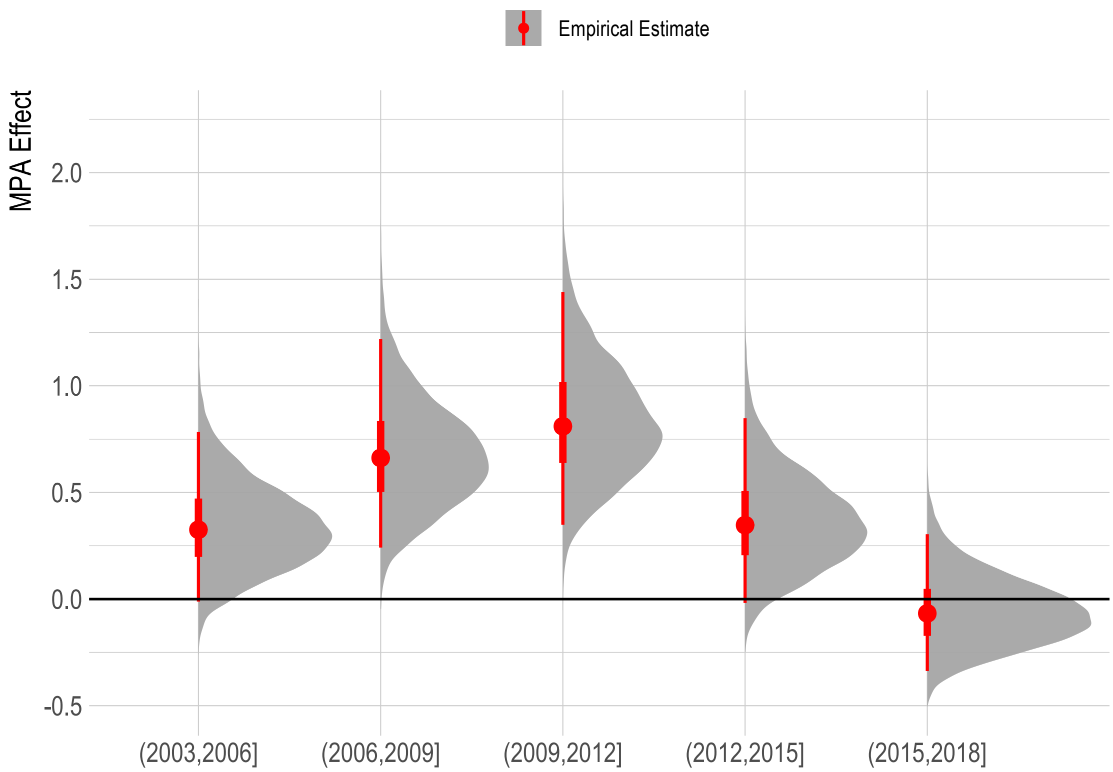

Figure 16: Model fit to PISCO data but only using variables also available for KFM data

We fit an alternative model using data from the KFM program to test whether a different dataset from the same region provides different results. KFM based results are qualitatively similer to those from PISCO data (Fig.17)

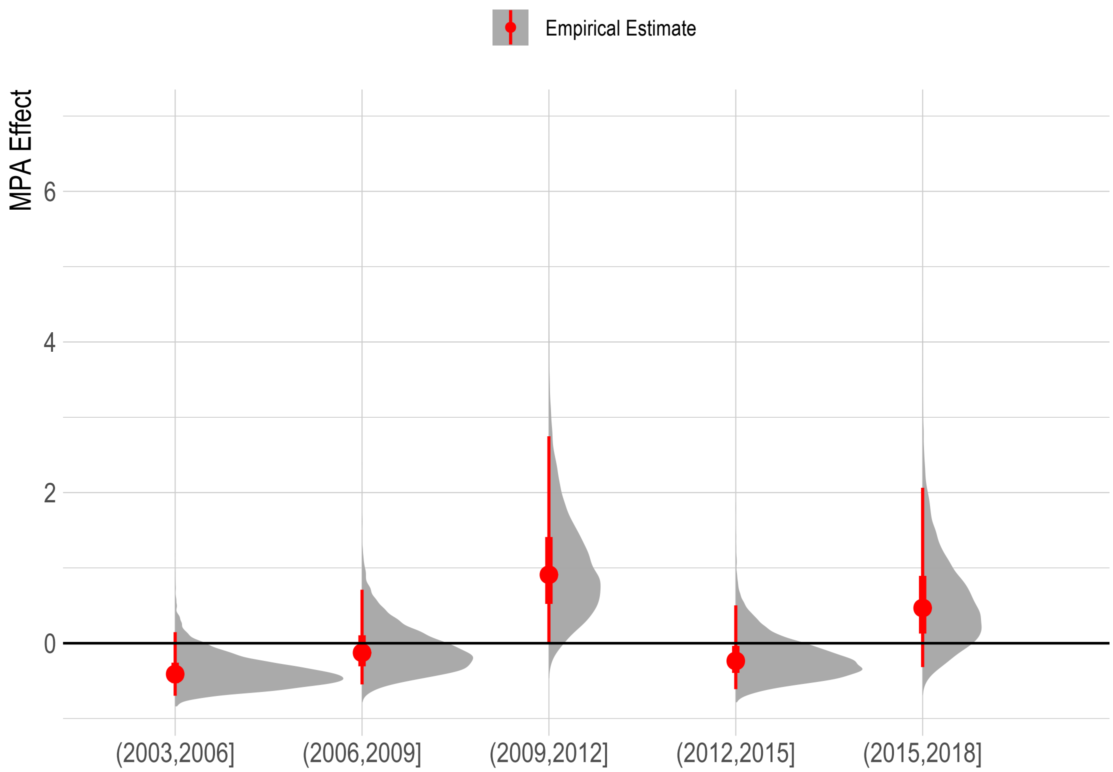

Figure 17: Model fit to KFM data. Results are more uncertain than using PISCO data, but follow the same trend estimated from the PISCO data.

We ran a version of the model using data from only inside MPAs. This serves as a test of whether our results are being entirely driven by the outside-MPA data, and allows us to compare results from inside MPAs to those outside (Fig.18).

We ran a version of the model using data from only outside MPAs. This serves as a test of whether our results are being entirely driven by the inside-MPA data, and allows us to compare results from inside MPAs to those outside (Fig.19).

We include a model run using nearly all observed species, to test whether our results are being influenced by omissino of rarely observed species (Fig.20).

For ease of interpretation and model convergence, our default model estimates MPA effects in three-year bins. For this run we estimate the effect annually, relative to the year 2000. Results show the same overall trend and magnitude reported in our base model (Fig.21).

Our base run estimates the effect of MPAs on total biomass densities of targeted finfish. For this run, we instead estimate the effect on mean biomass densities of targeted species. Results show the same pattern as our base run (Fig.22).

Figure 18: Estimated MPA effects using PISCO data from inside MPAs only. The base model uses data from both inside and outside MPAs. These results show that the same general trend holds when only using data from inside the MPAs, though the model estimates greater probability of higher positive effects with only MPA data, compared to the model fit using all the data.

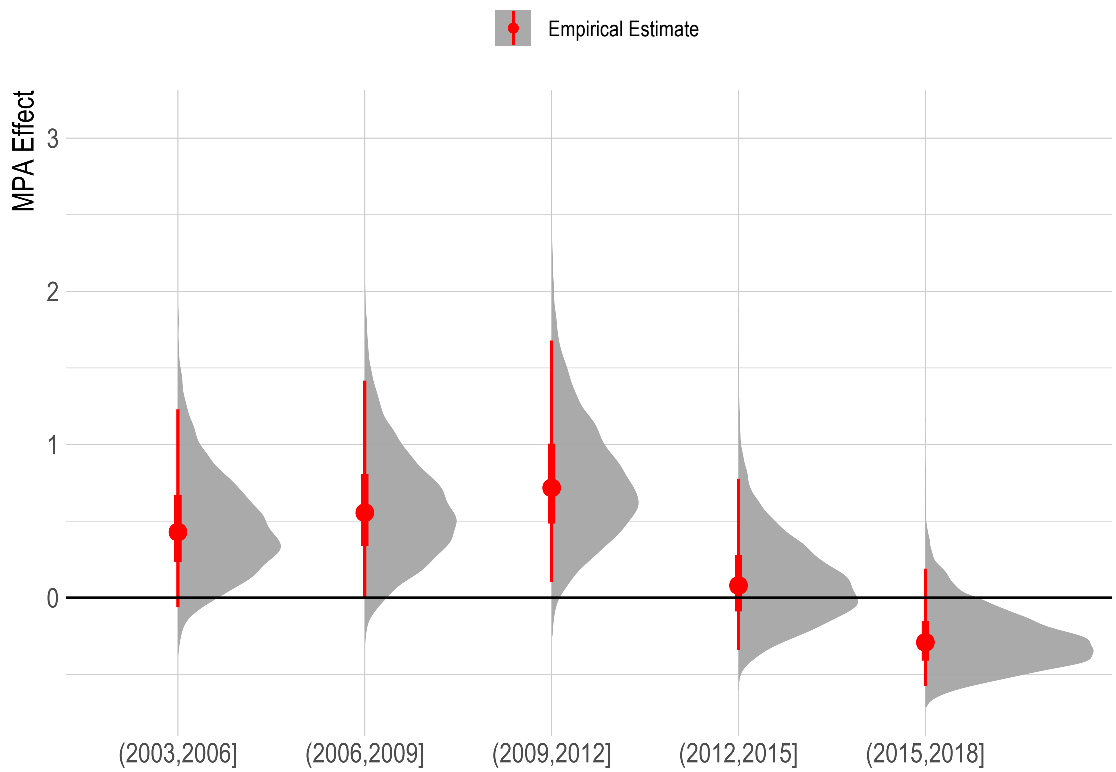

Figure 19: Estimated MPA effects using PISCO data from outside MPAs only. The base model uses data from both inside and outside MPAs. These results show that the same general trend holds when only using data from outside the MPAs, though the model estimates less probability of high positive effects witout MPA data, compared to the model fit using all the data.

Figure 20: The base model only includes consistently observed species of finfish. For this run, we include species that have been seen in at least two years (down from fifteen). The results remain essentially unchanged.

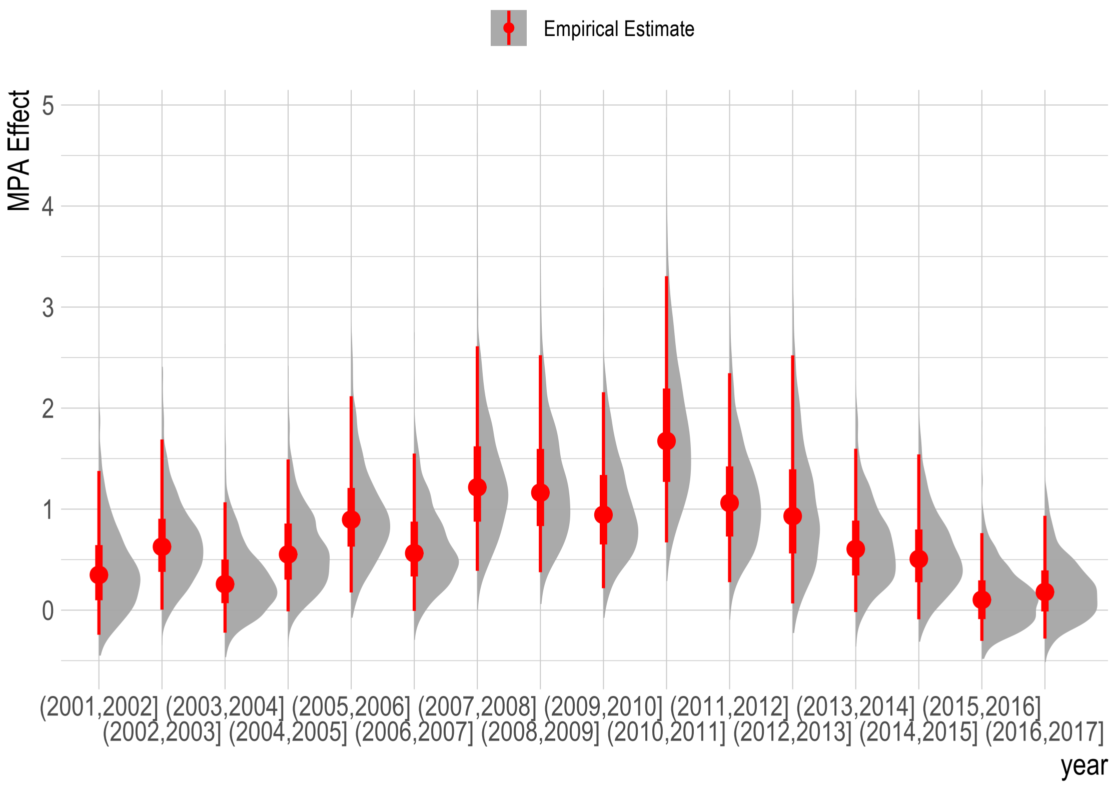

Figure 21: For ease of interpretation and model convergence, our default model estimates MPA effects in three-year bins. For this run we estimate the effect annually, relative to the year 2000. Results show the same overall trend and magnitude reported in our base model.

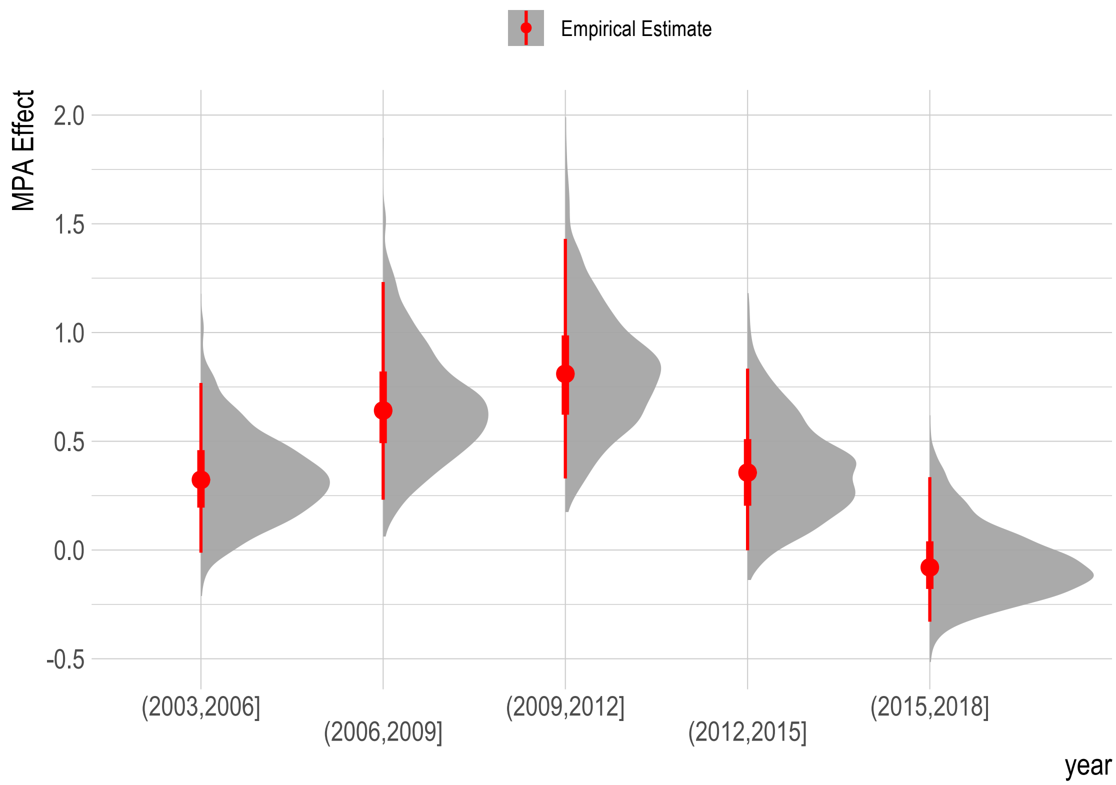

Figure 22: Our base run estimates the effect of MPAs on total biomass densities of targeted finfish. For this run, we instead estimate the effect on mean biomass densities of targeted species. Results show the same pattern as our base run.

Appropriately addressing the problem of "missing" observations is a critical challenge in any field observation study. If no observations of a given fish species were recorded on a given transect, should the density of that species on that transect be marked as zero, and influence the estimate of the overall mean density accordingly? The obvious answer seems to be yes, but what if that species simply does not live in the environment covered by a particular transect, or was not present during the particular time of the diver's observation? For our base runs, we assign a value of zero density on a given transect for any fish species that has been observed at least once at a given site at any time in our data but was not observed on that particular transect. If that species was never observed at that site, we do not include a zero for that species. Our rationale for this is that given the shifting nature of the sampled sites, and the intensity of sampling at those sites, we do not want to skew density trends by changes in the amount of suitable habitat for a given species sampled. However, this is clearly a strong assumption. For example, perhaps the decreasing trend in mean densities from 2000 to 2004 is due to increased number of sites (and therefore zeros) included in the data. To assess the potential importance of this choice, we can compare the mean densities of targeted and non-targeted species over time with the added zeros to the mean densities using only positive observations (i.e. not including any zeros in the data, (Fig.S23). The trends in the raw densities, and most importantly the mean trends of targeted and non-targeted fishes, are nearly identical whether or not zeros are added, providing strong evidence that our choice of how to incorporate missing observations into the data are not strongly influencing our overall results.

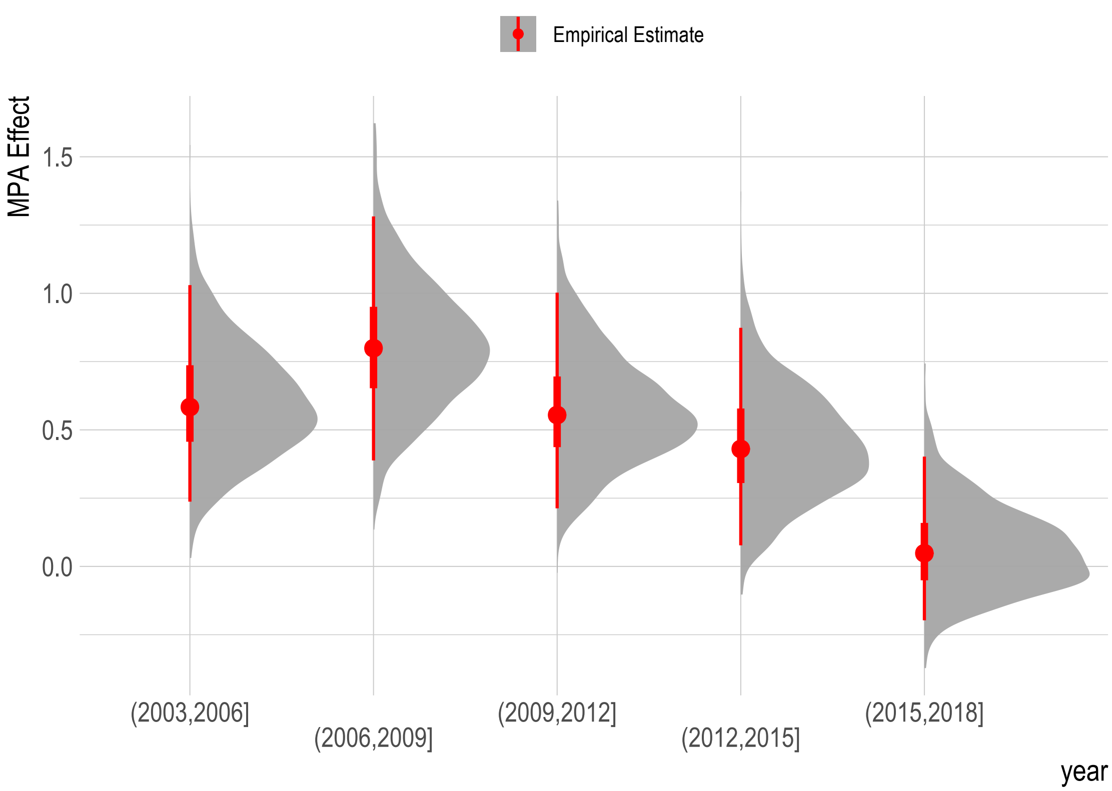

Figure 23: Our base run estimates the effect of MPAs on total biomass densities of targeted finfish. For this run, we instead estimate the effect on mean biomass densities of targeted species. Results show the same pattern as our base run.

1.3.2 Transect Level Difference-in-difference Model

Our base model aggregated the data to the level of total biomass densities of targeted and non-targeted species. This serves to average out some of the sampling noise from the indivudla transect level, and we would argue is the appropriate level of estimation for many key policy questions. However, this approach does oversimplify the data collection process, treating the total biomass densities at the year/site level as estimated without error.

As an added robustness test, we include version of the model in which we operate at the level of individual transect observations. The raw data are estimated length compositions by fish species along a survey transect at a site. Lengths are converted to biomass per allometric relationships supplied by PISCO and supplemented by the `FishLife` (Thorson et al. 2017) package in R where needed. We performed some minimal data filtering to reduce noise in the data. We only include species that were observed at least twice in each year of the dataset (2000-2017) somewhere in the core Channel Islands (Anacapa, Santa Cruz, Santa Rosa, San Miguel). While some data are available from 1999, per consultation with PISCO we omit those data due to changes in survey protocols. We assign species to targeted and non-targeted groups per the PISCO classifications. This filtering process results in 11 non-targeted species and 12 targeted species remaining in the analysis.

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

It is important to note that this model asks a slightly different question than our base model. The base model estimates the effect on total mean biomass of targeted finfish at the site level. This model estimates the effect on the mean biomass density of targeted finfish across all sites.

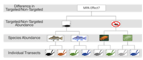

Figure 24: Cartoon illustration of the hierarchichal difference-in-difference estimator

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

$$o_{s,i} \sim binomial(\frac{1}{1+e^{-\beta^o X}}) \tag{2}$$

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

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

$$log(d_{s,i}) \sim normal(\beta^d X, \sigma_s) \tag{3}$$

where β^d are the estimated coefficients for the expected density model and X is the same matrix of covariates as used in the observation portion of the model and σ_s allows for each species s to have different standard deviations.

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

$$\beta_{island,cluster} \sim normal(0, \sigma_{cluster}) \tag{4}$$

This allows the mean effect of each island to differ for each cluster, e.g. allowing San Miguel, the easternmost island, to have a higher mean density for eastern species than for more western species (if the data suggest it).

The second critical component of the covariate matrix X are random effects for each year for each species

$$\beta_{year,species} \sim normal(0, \sigma_{species}) \tag{5}$$

These $\beta_{year,species}$ represent our "standardized" estimate of observed abundance of each species in each time step, controlling for the included covariates.

However, we still need to account for changes in the probability of detection over time. For that, we create a standard matrix of with rows equal to the number of years and columns corresponding to each of the columns in X, holding everything fixed at mean (or most frequently observed level for factors) levels for all variables in X except for the year and species interaction indices. Calling this standardized matrix $X^{standard}$, the probability of observing a given species in year y is then

$$p_{s,y} = (\frac{1}{1+e^{-\beta^o X^{standard}}}) \tag{6}$$

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

$$I_{species,year} = p_{species,year} e^{\beta_{species,year}} \tag{7}$$

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

$$log(I_{species,year}) \sim normal(\beta^{effect} X^{effect}, \sigma_I) \tag{8}$$

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

$$t_{s,y} = (t_s^{pref} - \bar{t_y})^2 \tag{9}$$

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

$$\beta_{year,targeted} \sim normal(0, \sigma_{targeted}) \tag{10}$$

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

$$divergence_{year} = \beta_{year,targeted=1} - \beta_{year,targeted=0} \tag{11}$$

The model is fit in TMB to integrate the uncertainty across all levels of the model, with standard errors for each coefficient in the model estimated through the Laplace approximation.

A complete table of estimated coefficients can be seen in Table.S3.

Table 3: 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
1.19	0.88	1.49	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	-0.48	-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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
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
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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
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
-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_REEF-E
0.21	-0.04	0.45	site_side-SRI_RODES_REEF-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
0.26	0.05	0.48	factor_month-8
0.26	0.05	0.48	factor_month-9
0.28	0.07	0.50	factor_month-10
0.28	0.06	0.50	factor_month-11
0.42	0.20	0.64	factor_month-12
-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
-0.60	-0.89	-0.31	intercept
-0.38	-0.60	-0.16	site_side-ANACAPA_ADMIRALS-E
-0.16	-0.37	0.06	site_side-ANACAPA_ADMIRALS-W

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
-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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
-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
0.10	-0.14	0.33	factor_month-8
0.13	-0.11	0.37	factor_month-9
0.01	-0.23	0.24	factor_month-10
0.02	-0.22	0.26	factor_month-11

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-0.10	-0.34	0.14	factor_month-12
-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	-2.10	-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
-2.29	-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
1.07	0.48	1.66	year_classcode-cpri-2000
0.67	0.00	1.33	year_classcode-cpri-2001
0.63	-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	0.12	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	0.45	year_classcode-cpri-2016
0.46	0.13	0.79	year_classcode-cpri-2017
1.23	0.88	1.58	year_classcode-cpun-2000
1.03	0.68	1.37	year_classcode-cpun-2001
0.39	0.11	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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
-0.35	-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	0.14	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	0.14	year__classcode-ejac-2007
-0.90	-1.13	-0.67	year__classcode-ejac-2008
-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	-0.27	year__classcode-ejac-2015
-0.50	-0.76	-0.24	year__classcode-ejac-2016
-0.84	-1.09	-0.58	year__classcode-ejac-2017
0.10	-0.47	0.68	year__classcode-elat-2000
0.29	-0.27	0.85	year__classcode-elat-2001
0.23	-0.29	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
-0.72	-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	0.04	year__classcode-elat-2014
-0.07	-0.38	0.24	year__classcode-elat-2015

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-0.70	-1.04	-0.37	year_classcode-elat-2016
-0.82	-1.18	-0.46	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	1.25	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
-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
-1.58	-1.88	-1.29	year_classcode-hcar-2007
-2.67	-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	-2.46	-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	-1.88	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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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	-3.56	year__classcode-hros-2017
1.73	1.38	2.07	year__classcode-hrub-2000
1.78	1.47	2.10	year__classcode-hrub-2001
1.48	1.18	1.77	year__classcode-hrub-2002
1.37	1.11	1.63	year__classcode-hrub-2003
0.90	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	0.68	1.10	year__classcode-hrub-2008
1.18	0.97	1.39	year__classcode-hrub-2009
1.07	0.83	1.31	year__classcode-hrub-2010
1.00	0.77	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	0.15	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	-1.06	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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-0.19	-0.40	0.02	year_classcode-hsem-2016
-0.13	-0.35	0.08	year_classcode-hsem-2017
0.88	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	0.12	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
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	-0.70	-0.30	year_classcode-ocal-2007
-0.94	-1.14	-0.73	year_classcode-ocal-2008
-0.18	-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	-1.90	-1.46	year_classcode-opic-2004
-1.91	-2.11	-1.70	year_classcode-opic-2005
-1.70	-1.92	-1.48	year_classcode-opic-2006

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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	0.99	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	0.06	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
0.98	0.78	1.18	year_classcode-pcla-2009
0.84	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
-0.91	-2.04	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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
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	0.28	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	0.97	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	0.50	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
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
-0.13	-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	1.09	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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
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	-0.62	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
-0.26	-0.96	0.43	year__classcode-saur-2008
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	-0.73	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	1.47	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	0.40	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	-0.44	year__classcode-scau-2013
-0.47	-1.00	0.06	year__classcode-scau-2014
-0.52	-1.20	0.16	year__classcode-scau-2015

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-0.05	-0.60	0.50	year_classcode-scau-2016
-1.11	-1.76	-0.46	year_classcode-scau-2017
0.18	-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	-0.95	-0.06	year_classcode-schr-2017
-0.03	-0.42	0.36	year_classcode-smys-2000
0.06	-0.35	0.47	year_classcode-smys-2001
0.10	-0.29	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
-0.16	-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
1.03	0.61	1.44	year_classcode-spul-2000
1.82	1.47	2.18	year_classcode-spul-2001
1.48	1.11	1.84	year_classcode-spul-2002
1.25	0.98	1.53	year_classcode-spul-2003
0.71	0.44	0.97	year_classcode-spul-2004
0.49	0.28	0.71	year_classcode-spul-2005
0.84	0.62	1.07	year_classcode-spul-2006

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
1.17	0.95	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
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
-1.78	-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	-2.33	-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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
-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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
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
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	-2.29	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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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	-3.28	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	-1.84	-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
-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	-0.50	year_classcode-rvac-2015

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
-3.53	-4.78	-2.28	year_classcode-saur-2000
-2.64	-3.57	-1.72	year_classcode-saur-2001
-3.88	-5.06	-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	-2.74	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	-4.19	-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
-2.13	-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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-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
-0.54	-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
-2.02	-2.52	-1.53	year_classcode-scau-2015
-1.66	-2.07	-1.26	year_classcode-scau-2016
-1.56	-2.00	-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	-2.65	-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
-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	-1.05	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
-0.55	-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

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-0.33	-0.61	-0.05	year_classcode-smys-2016
-0.51	-0.83	-0.20	year_classcode-smys-2017
0.66	0.27	1.06	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
0.28	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
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	-0.69	0.30	mpa_effect
-0.08	-0.56	0.40	mpa_effect.1
0.17	-0.29	0.62	mpa_effect.2
0.18	-0.25	0.61	mpa_effect.3
-0.15	-0.57	0.27	mpa_effect.4
-0.18	-0.59	0.23	mpa_effect.5
0.11	-0.30	0.53	mpa_effect.6
-0.13	-0.54	0.29	mpa_effect.7
0.11	-0.32	0.54	mpa_effect.8

Table 3: Complete table of estimated coefficients from hierarchical difference-in-difference model *(continued)*

estimate	lower	upper	variable
-0.04	-0.45	0.37	mpa_effect.9
0.00	-0.42	0.42	mpa_effect.10
0.29	-0.12	0.71	mpa_effect.11
0.26	-0.16	0.67	mpa_effect.12
0.24	-0.19	0.67	mpa_effect.13
0.38	-0.05	0.81	mpa_effect.14
-0.19	-0.63	0.24	mpa_effect.15
-0.14	-0.57	0.28	mpa_effect.16
-0.38	-0.82	0.05	mpa_effect.17

Figures S25:S27 present estimated effects for covariates included in the model, along with the raw estimated mean trends of the targeted and non-targeted species (while the difference between these trends is presented in our main results).

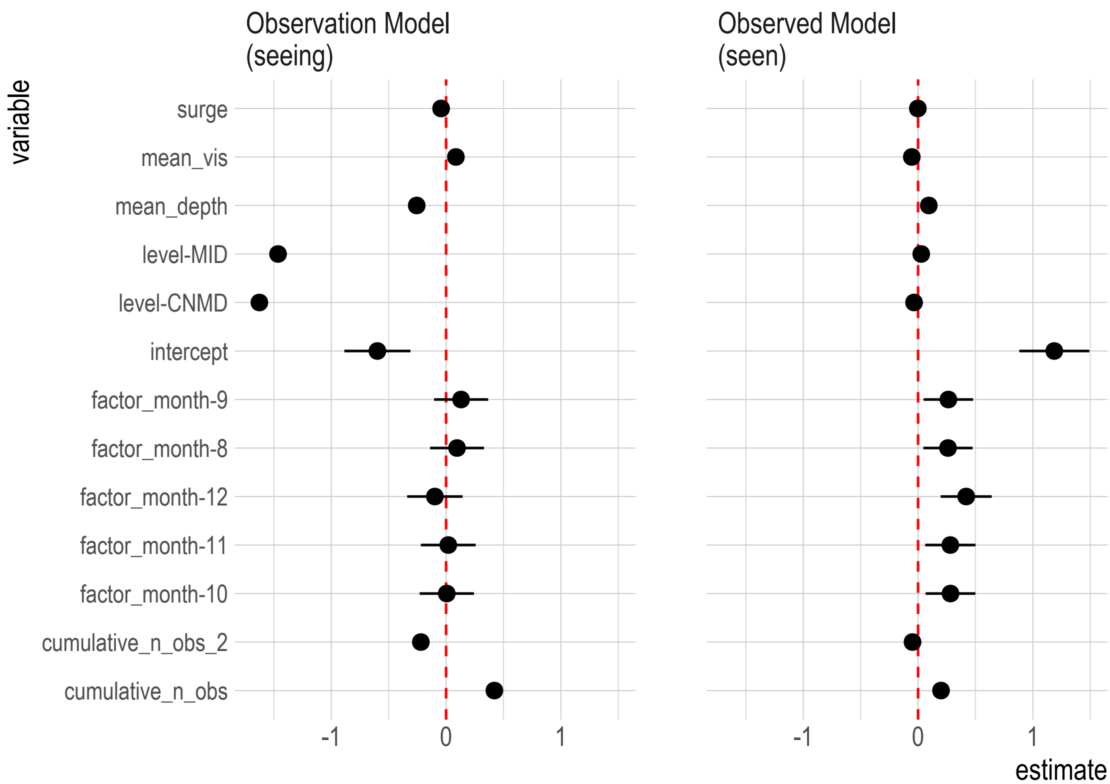

Figure 25: Estimated coefficients for non-spatial fixed effects in observation model (seeing) and observed model (seen)

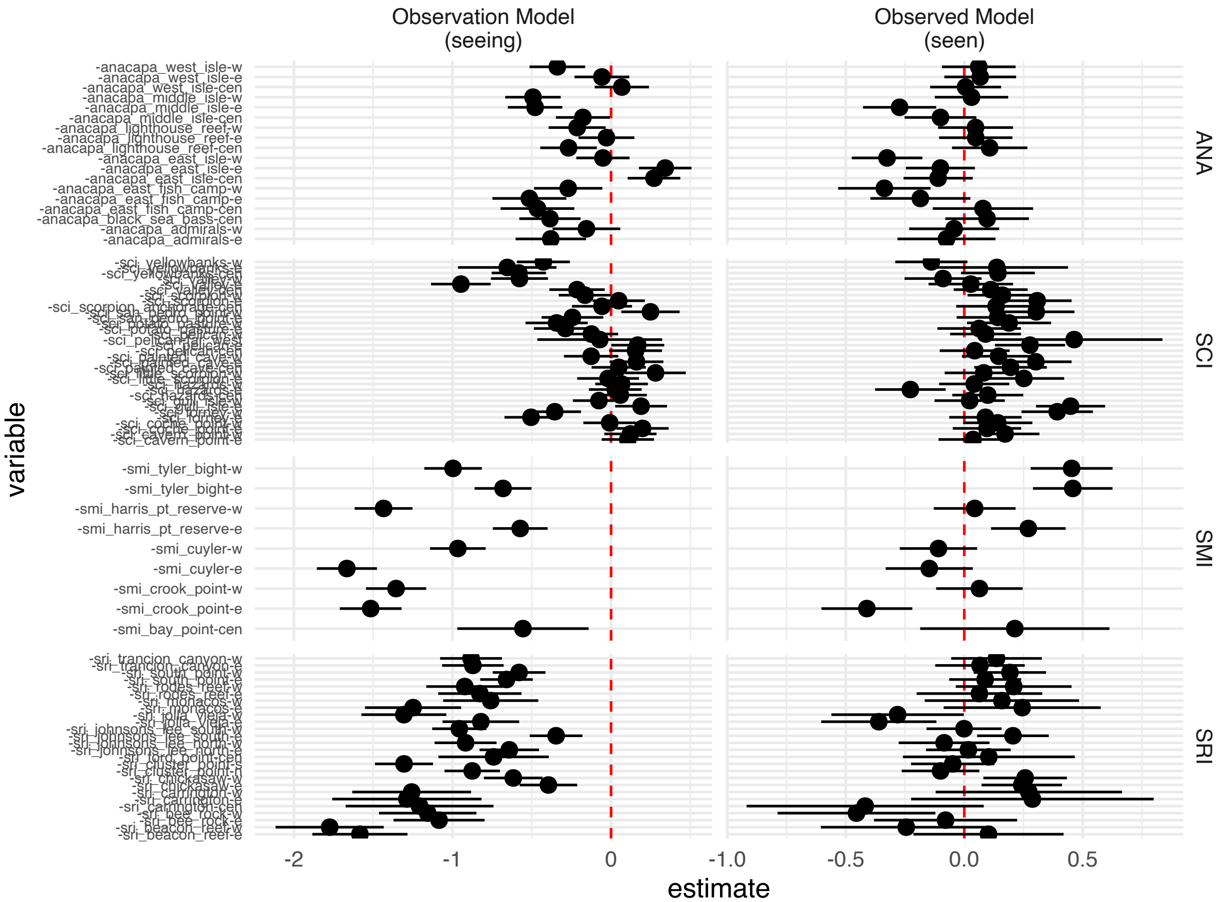

Figure 26: Estimated coefficients for spatial random effects in observation model (seeing) and observed model (seen)

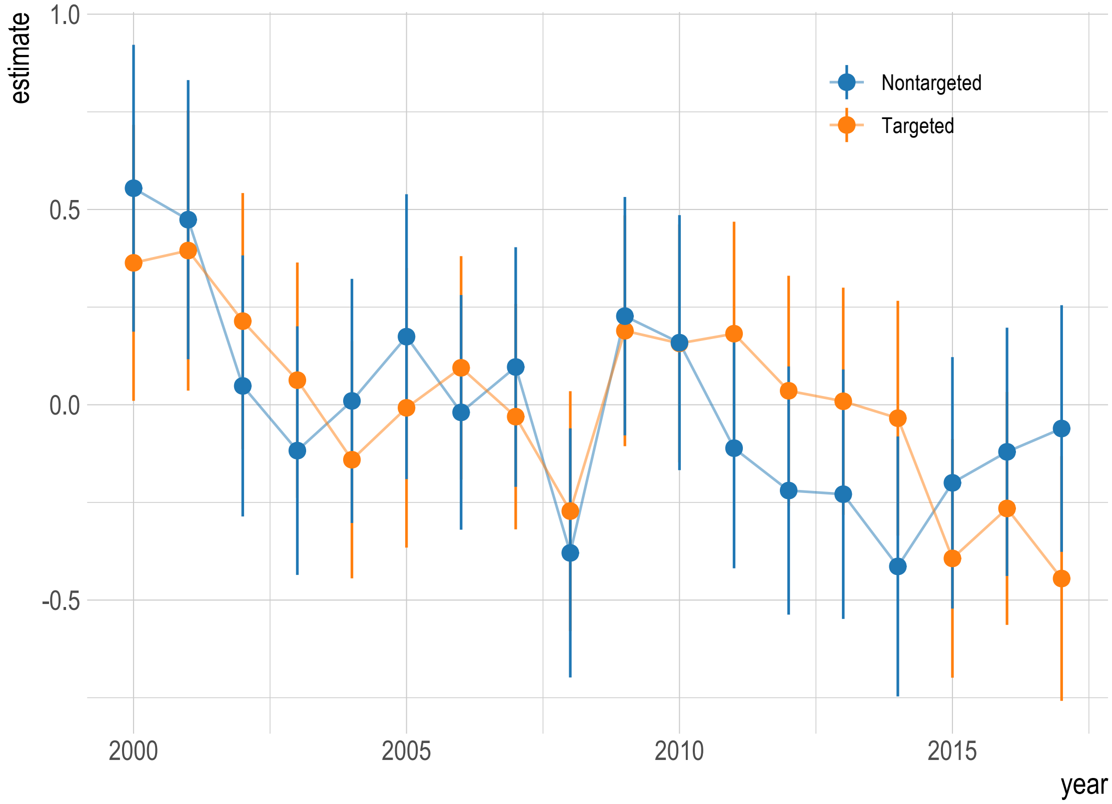

Figure 27: Trends in standardized mean abundance of targeted and non-targeted species

1.3.2.1 Transect Level Regression Diagnostics We include visual diagnostics of our estimation model. All coefficients passed convergence criteria for TMB.

Looking first at the predictions of the model for the positive observations in the data (i.e. using the full model to predict biomass densities, and then comparing those predictions to cases where some positive biomass densities were observed), the model diagnostics show no clear problems. The R^2 of the model is 0.43. Residuals do not exhibit trends, though some grouping the residuals is evident. The quantile-quantile plot suggest that on the assumption of log-normal errors on the observed densities is reasonable, though the model appears to have some slight problems estimating the highest observed densities (Fig.S28).

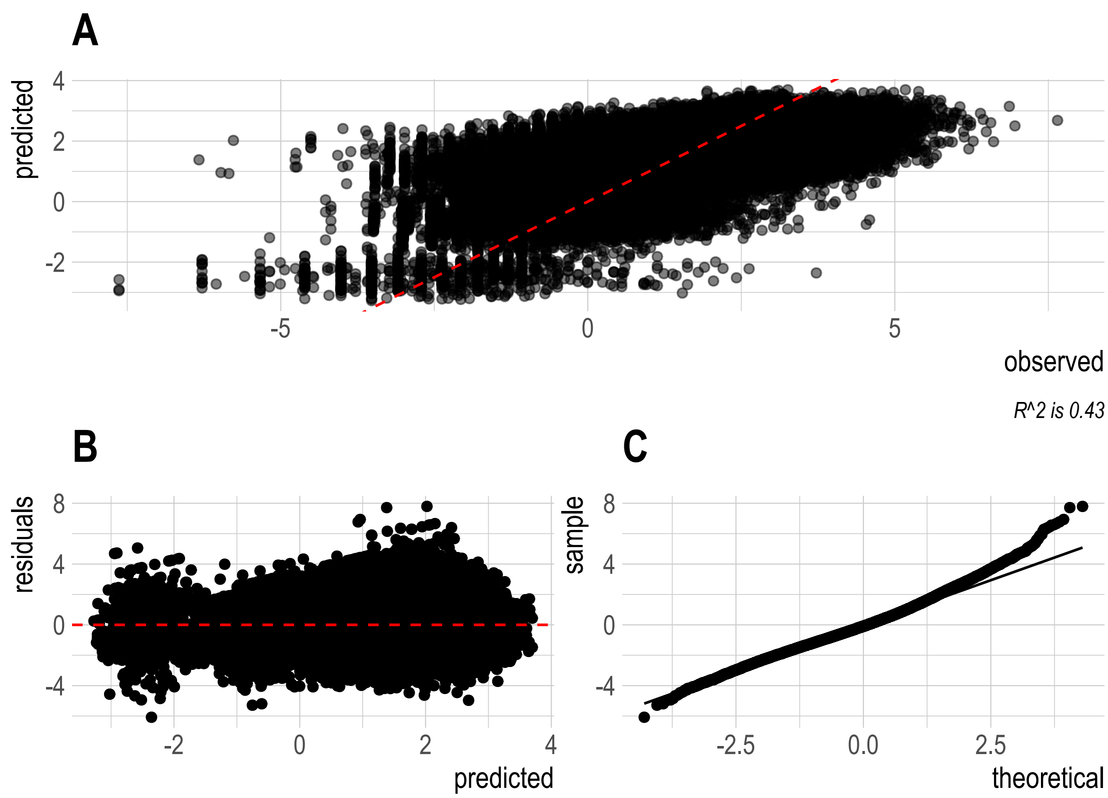

Figure 28: High level diagnostics for observed compontent of Delta-GLM: Observed vs predicted log densities (A), predicted log density vs residuals (B), and a normal qq-plot of the residuals (C)

In order to evaluate the ability of the model to estimate positive observations, we can compare the the binned predicted probability of a positive observation to the proportion of observations in that bin that recorded positive observations. If our model is working well, we would expect a group of fisheries that our model estimates on average should have a 50% probability of a positive observation, then we should expect about 50% of those observations to have positive observations. This is indeed what we see from the model (Fig.S29).

We can also examine the receiver-operator-curve (ROC) to assess the performance of the observation 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), indicating the model is an overall good predictor of whether or not a given observation of biomass densities will be positive or not.

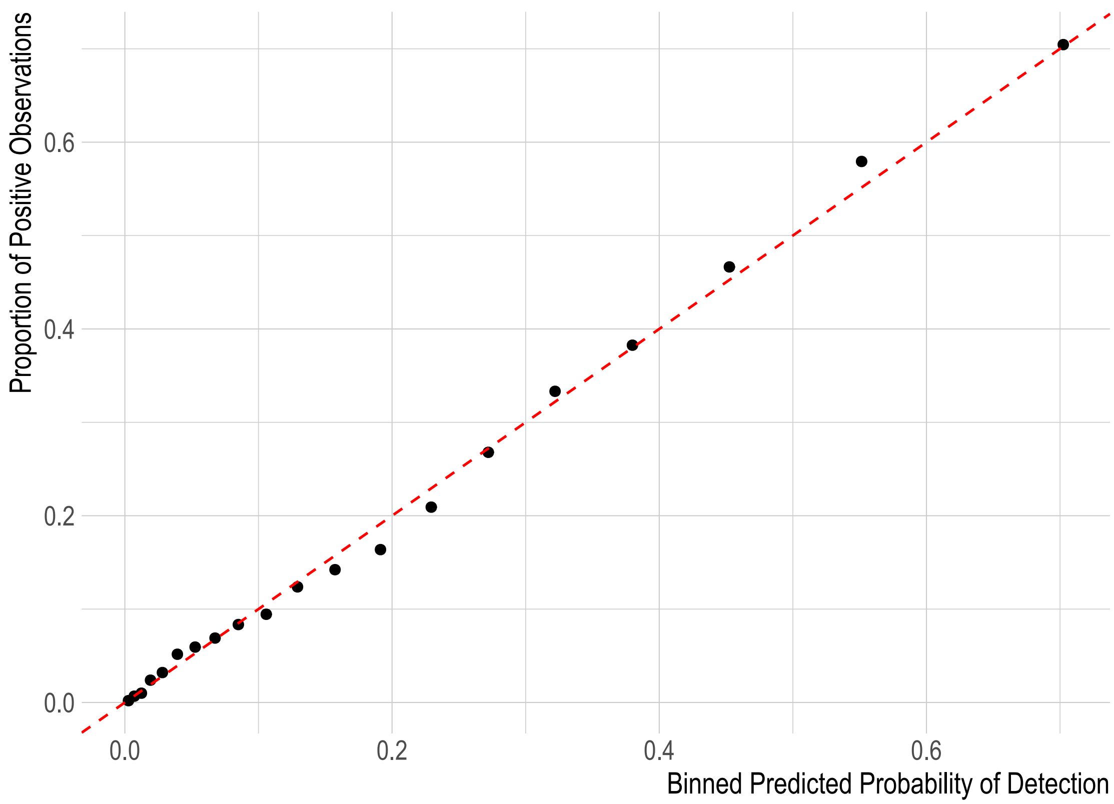

Figure 29: Binned mean predicted probability of detection provided by the first stage of the hurdle model vs observed proportion of positive detections

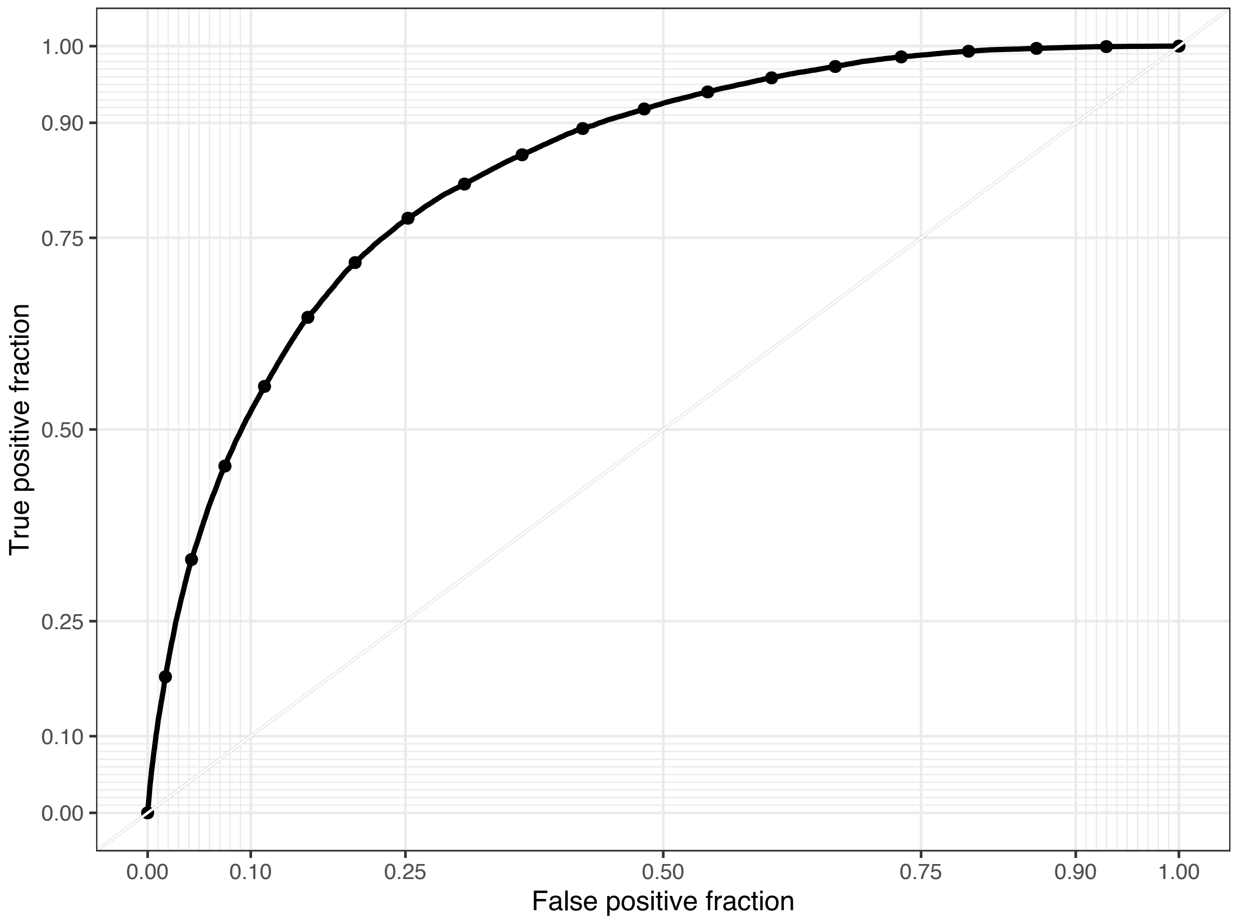

Figure 30: Receiver operating characteristic curve of predictions of positive biomass densities

1.3.2.2 Standardized Abundance Indices Overall most species showed consistent trends in biomass densities across the different islands at which they have been observed (Fig.S31).

Figure 31: Mean density by island by year for each fish species included in the analysis

The standardized indices of abundance generally did not very substantially from the raw mean densities by species over time. However, for some species, such as blue rockfish, the standardized abundance index suggests much higher biomass densities in the pre-MPA period than those reported in the raw data. We suspect this is largely a function of changes in sampling sites over time, that the standardization is better able to account for (Fig.S32).

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

1.3.3 Synthetic controls

Synthetic controls are an alternative method for attempting to estimate the causal effect of a policy intervention (Abadie, Diamond, and Hainmueller 2010). A difference-in-difference approach assumes that some observable group serves as an adequate control for the state of the treated group in an untreated world. In our default

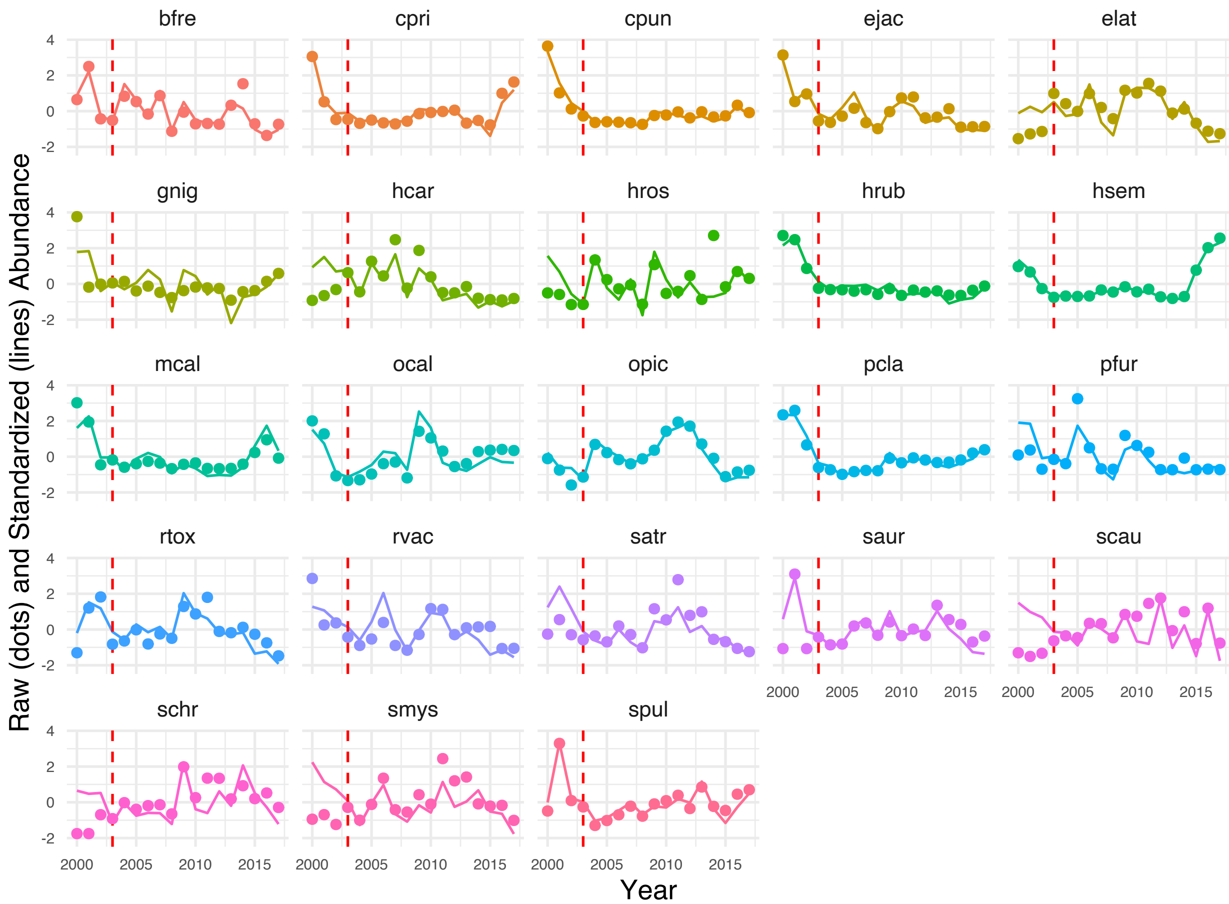

Figure 32: Raw (points) and standardized (lines) indices of abundance for each of the fishes included in the analysis

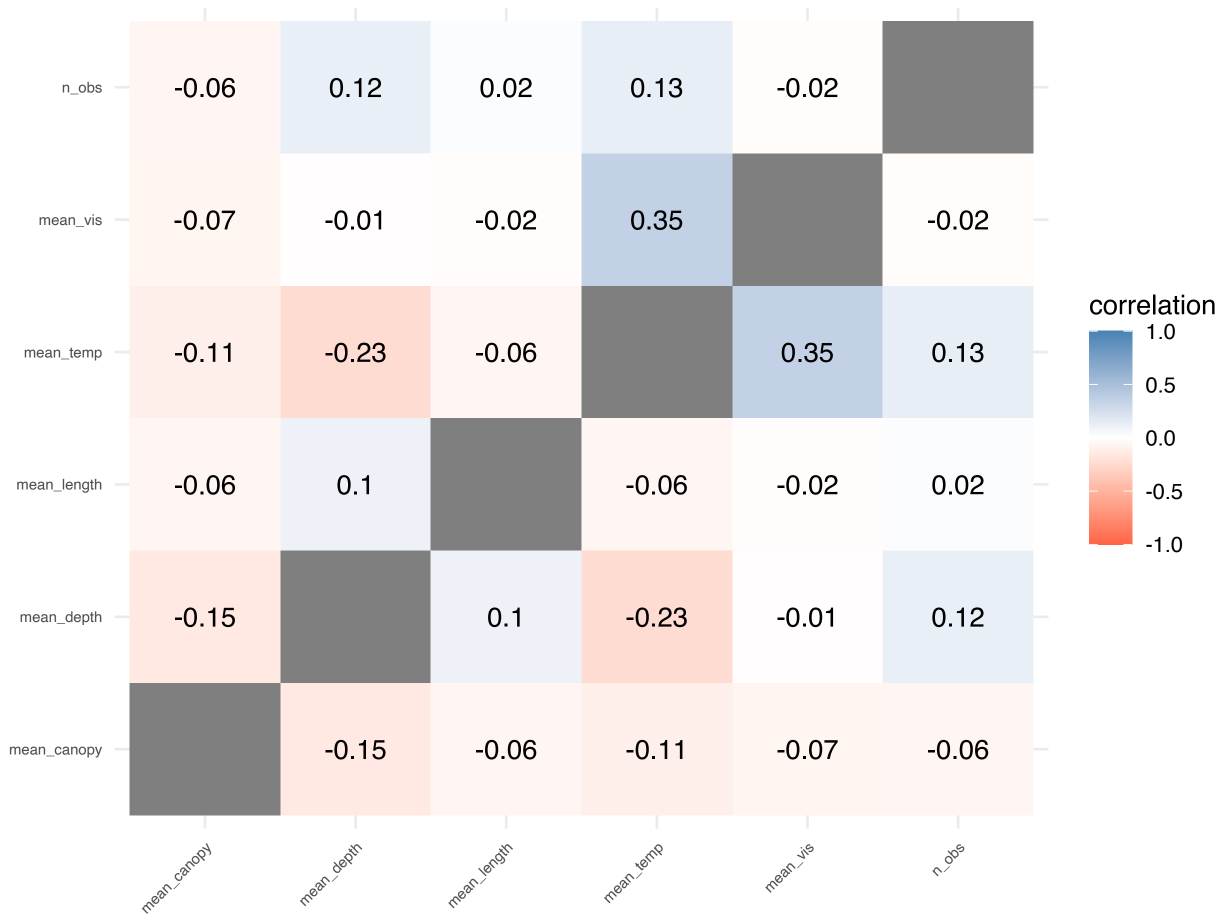

Figure 33: Pearson correlation coefficients of continuos data included in the regression model

case, we assume that the mean standardized index of non-targeted species are our control for the targeted species. Alternatively, synthetic controls use timeseries of treated and non-treated groups before and after treatment to construct a new "control" group built by weighting the pre-treatment timeseries of un-treated observations (together with covariates) such that the synthetic control group matches the trends in the treated group pre-treatment.

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

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

We centered and scaled the candidate abundance indices to facilitate model convergence given the very few number of pre-treatment years available. The results of a synthetic control model are presented as the difference between the observed treatment outcome and the synthetic control (the difference in this case being in units of standard deviations). The model was not able to construct an adequate synthetic control at this level, as shown by the differences between the treated group and the synthetic control pre-treatment. However, we would note that the post-treatment results do show similarities with our main results, namely a lack of a clear divergence between the treatment and the control, and an upwards trend up through the earl 2010s followed by a decline (Fig.S34).

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

Overall we see similarly unclear results as the aggregate targeted synthetic control (and our main results). The synthetic control was better constructed for some individual species, but not clearly for any one, and most species showed some evidence of the upward-then-downward trend seen throughout our results (Fig.S35).

1.4 Testing Model Assumptions

1.4.1 Simulation testing

We state that a difference-in-difference model using targeted and non-targeted species is capable (conditional on assumptions) of estimating the causal effect of MPAs. We simulated MPA outcomes to test this claim. We first test our estimation strategy under idealized circumstances, where recruitment is deterministic and PISCO divers all have constant and perfect observer skills. We simulate five species that vary only in their maximum size and length at maturity. For each of these species, we set one version that is targeted by fishing and one that is not. We set a constant fishing mortality rate for each simulated targeted species, and then ran two matched simulations, one with MPAs and one without. We then have our simulated divers sample data from each of these scenarios, and then pass the sampled biomass densities to a simplified version of our difference-in-difference model (omitting the probability of detection step). We can then compare the difference-in-difference estimates of the MPA effect to the true simulated effect. The difference in difference model is able to capture the simulated MPA effect under these circumstances (Fig.S36)

We then simulated a more complex example. We use the actual targeted and non-targeted species from our model. We assign species predominately seen in the western Channel Islands as "cold water" and those in the eastern Channel Islands as "warm water". We allow for stochasticity in recruitment. We use El Niño data as a simulated environmental recruitment driver, where we assume that El Niño events produce negative recruitment shocks for cold water species and *vice versa* for warm water species. We simulate three different divers each with different base skill levels, visual selectivities, and an evolving skill rate (such that

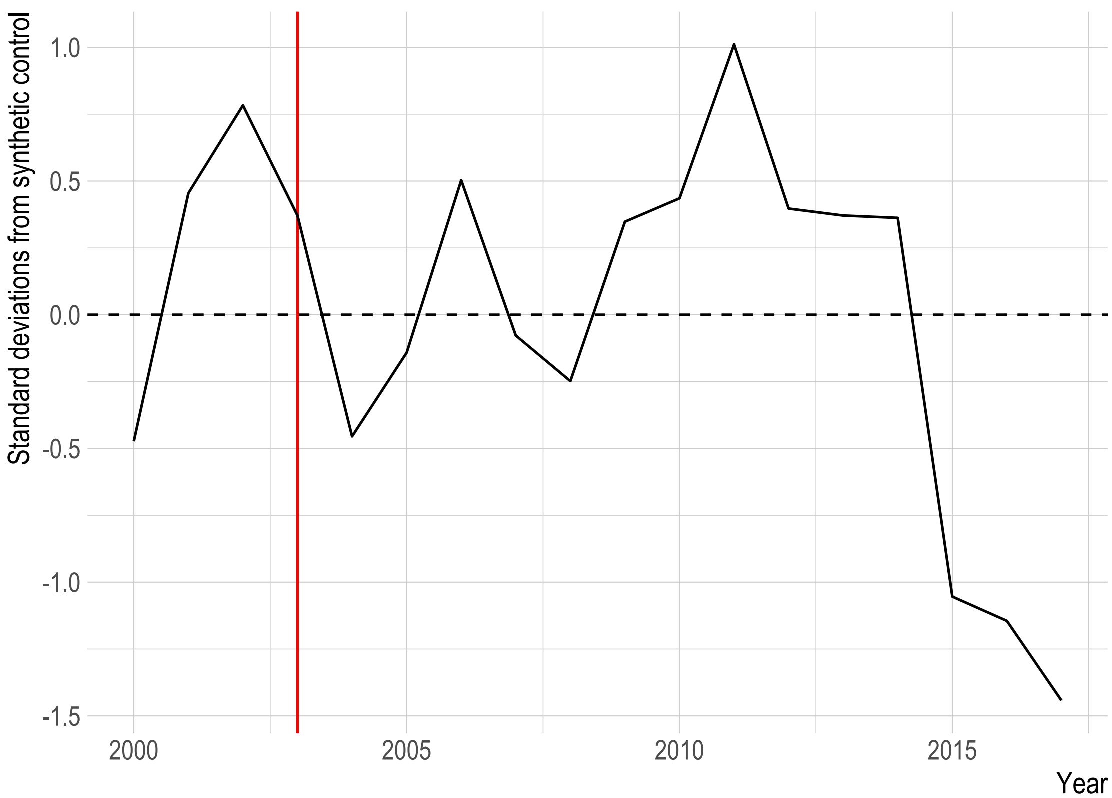

Figure 34: Difference in centered and scaled standardized targeted abundance and synthetic standardized targeted abundance

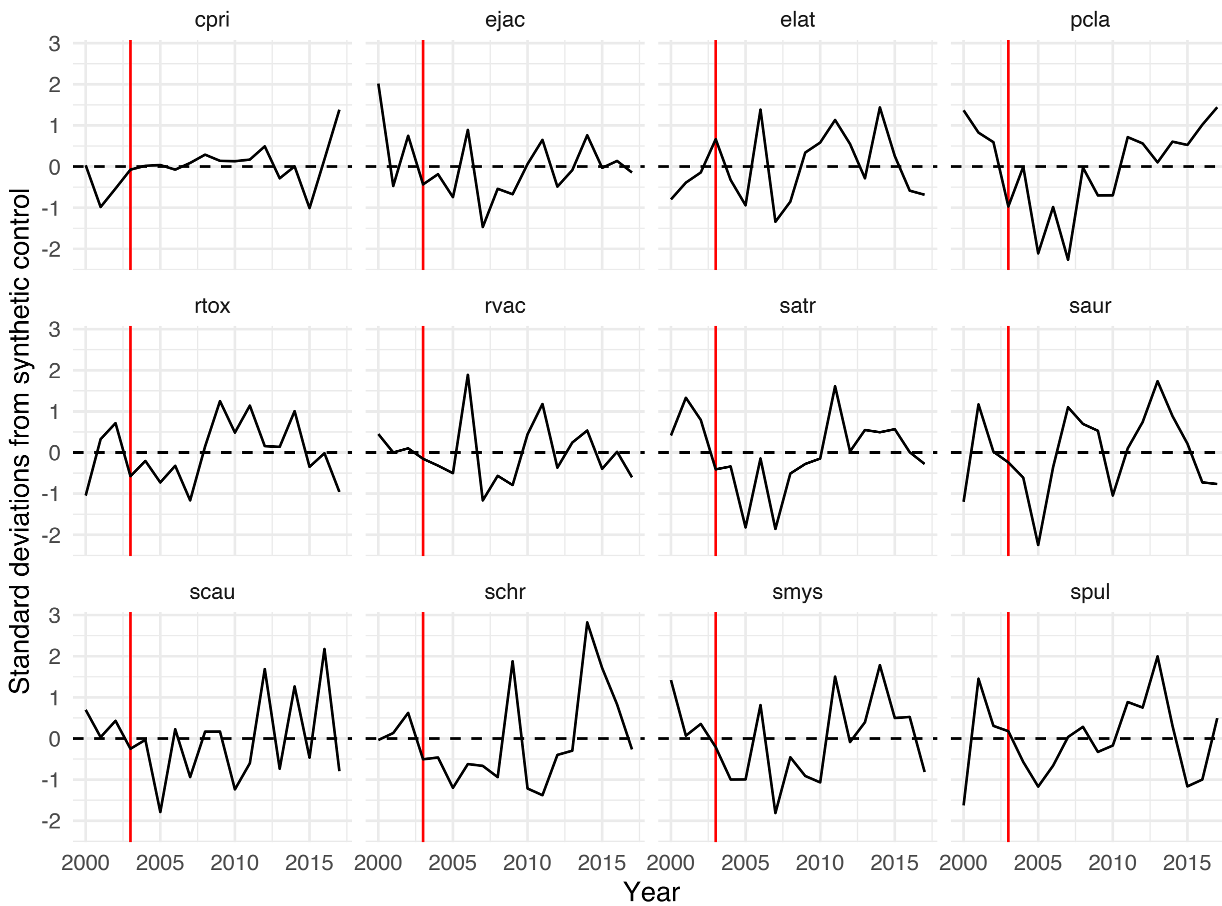

Figure 35: Synthetic control gaps for each targeted species

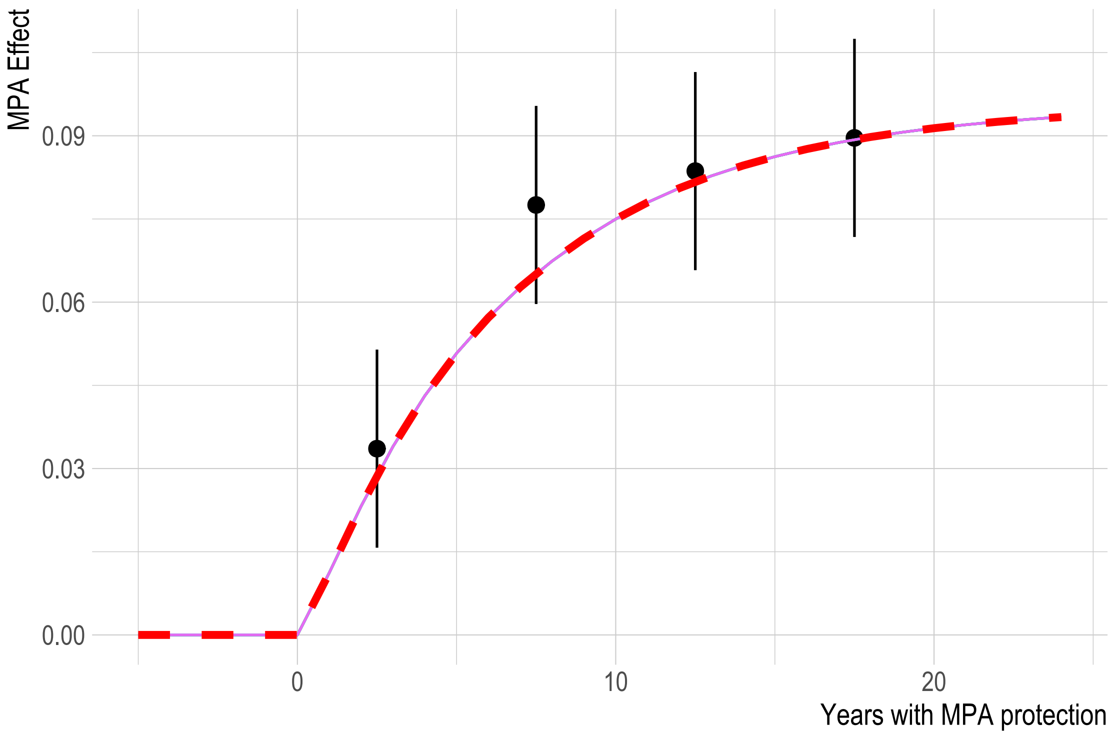

Figure 36: Simulated mean (red dashed line) and individual species (solid lines) MPA effects over time, along with difference-in-difference estimated MPA effects (mean with 95% confidence intervals)

observers get better over time). We hold fishing mortality rates constant for each species, although that fishing mortality affects each species differently because of intrinsic biological differences in maturity-at-age and steepness. We then test the ability of the difference-in-difference model to isolate the mean MPA effect across all of these targeted species, which our results show it is capable of doing (Fig.S37).

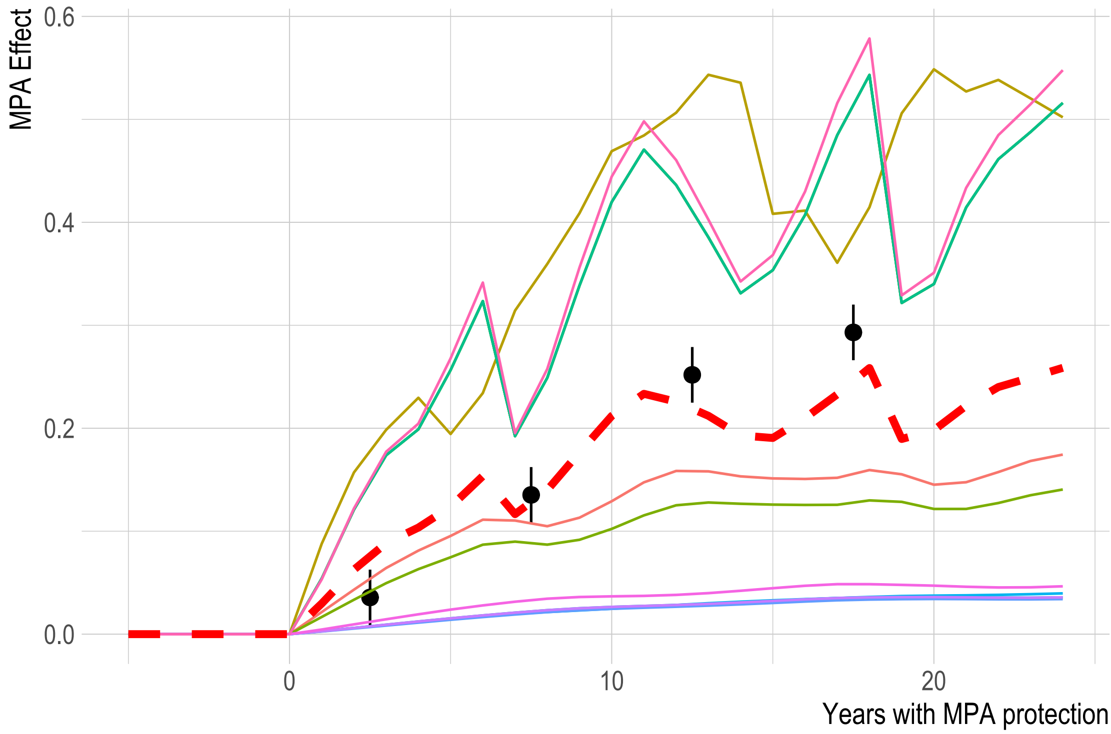

Figure 37: Simulated mean (red dashed line) and individual species (solid lines) MPA effects over time, along with difference-in-difference estimated MPA effects (mean with 95% confidence intervals)

1.4.2 Testing SUTVA with Convergent Cross Mapping

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

Convergent cross mapping is a nonlinear forecasting method that uses observed time series data to test for significant causal links between variables. Following methods laid out in Clark et al. (2015) and Sugihara et al. (2012), we pool the abundance of each broad trophic group by region (Fig.S38. This uses the data from the islands as "replicates", requiring the assumption that the islands are all part of the same dynamic system, but allowing us to take advantage of the extra information provided by each island to further resolve the reconstructed manifolds. Using these aggregations, we then test whether the variables can be properly embedded, i.e., if they have predictable manifold dynamics. We do this through a simplex forecasting test, using an individual timeseries' own lags to build a manifold. For each timeseries, the "best embedding dimension" is an approximation of the dimensionality of the dynamic system, in other words, the number of dimensions that define and predict the evolving states of the timeseries. This analysis shows that only the carnivore, piscivore, and planktivores groups show evidence of significant predictability (that is, that past dynamics of these species groups can predict future dynamics, Fig.S39).

Figure 38: Centered and scaled densities by broad trophic group and island over time

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

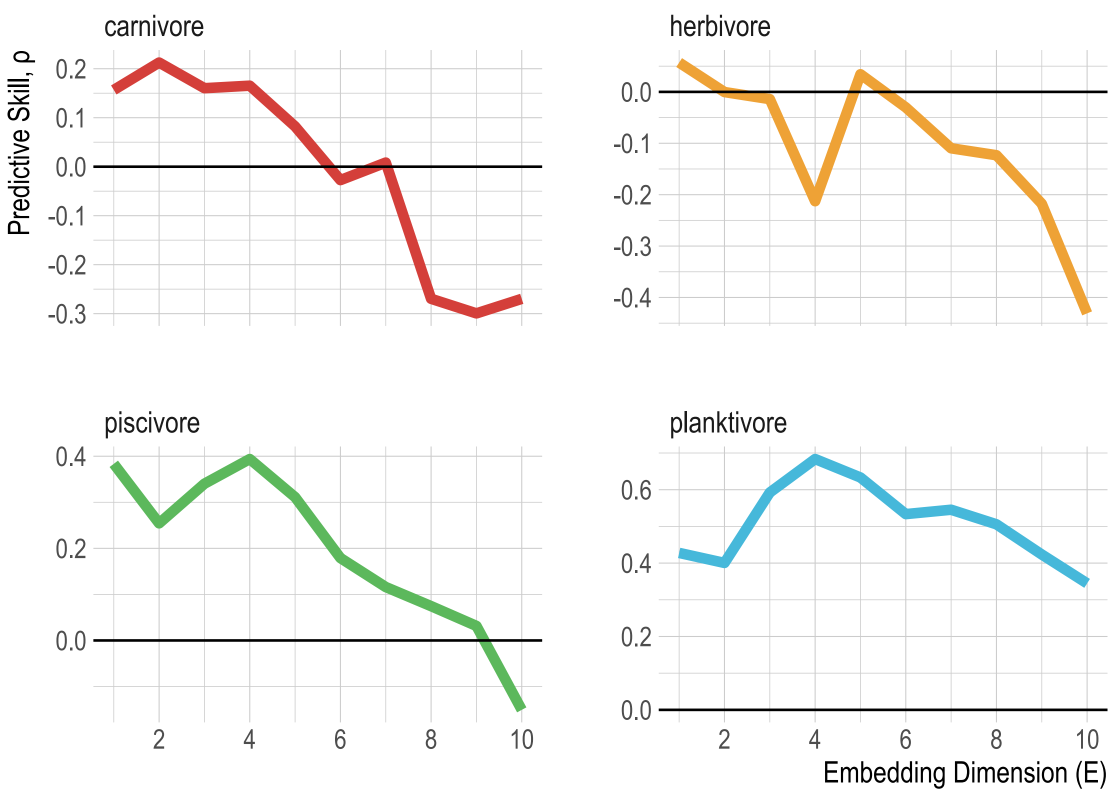

Figure 39: Predictive skill as a function of embedding dimensions

There are two criteria for CCM to establish causality: First, and most obviously, predictive cross-map skill using all available data should be significantly greater than zero. Second, that predictability should be convergent. Convergence means that cross-mapped estimates improve with library length (the number of state-space vectors used to build the attractor), because the attractor is more fully resolved and therefore estimation error should decline. Convergence is key to distinguishing causation from simple or spurious correlation. If two variables are spuriously correlated and not causally linked, CCM should fail to satisfy this second criterion. Based on these criteria, there is little evidence of significant dynamic interactions between trophic groups (Fig.S40-42). Cross-mapping produced positive predictive skill, but was non-convergent for all cross-mappings with the exception of carnivores cross-mapping planktivores (providing some evidence that planktivore dynamics may be a driver of carnivore dynamics). This analysis provides evidence that trophic cascades are unlikely to be a significant driver of our results. It is important to note though that this analysis does not mean that trophic cascades could not emerge in this system, rather that we do not detect them with these data at this time.

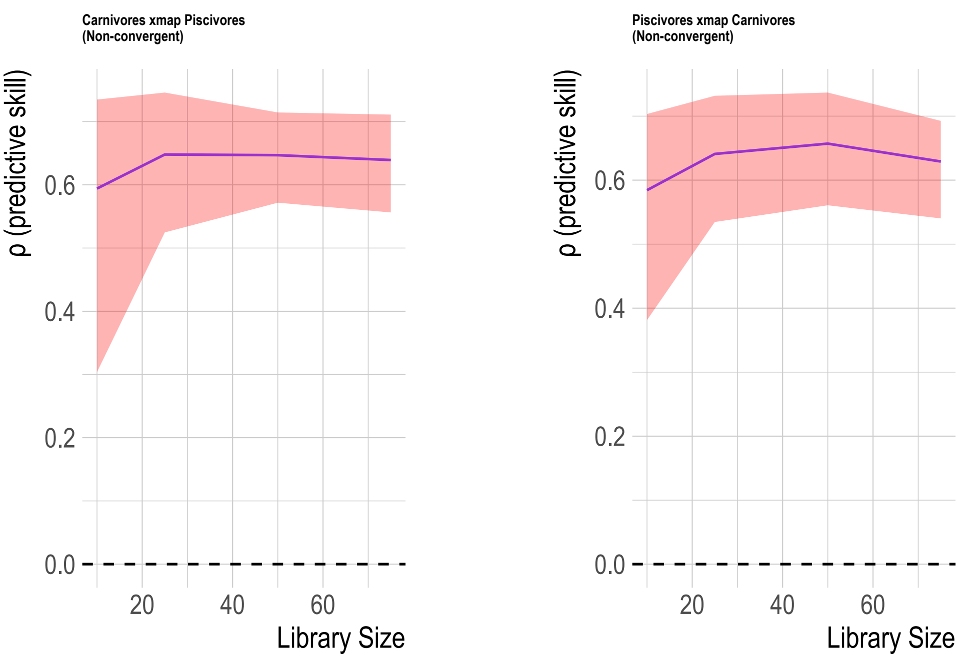

Figure 40: Cross mapping of effect of piscivores on carnivores (A) and carnivores on piscivores (B) in the PISCO data from 2000 to 2017. Shaded region show 95% confidence interval

1.5 Operating Model

The model consists of 50 patches with wrapped edges (picture the waters around a circular island). For any one simulation we randomly pull a species and its associated life history from the `FishLife` (Thorson

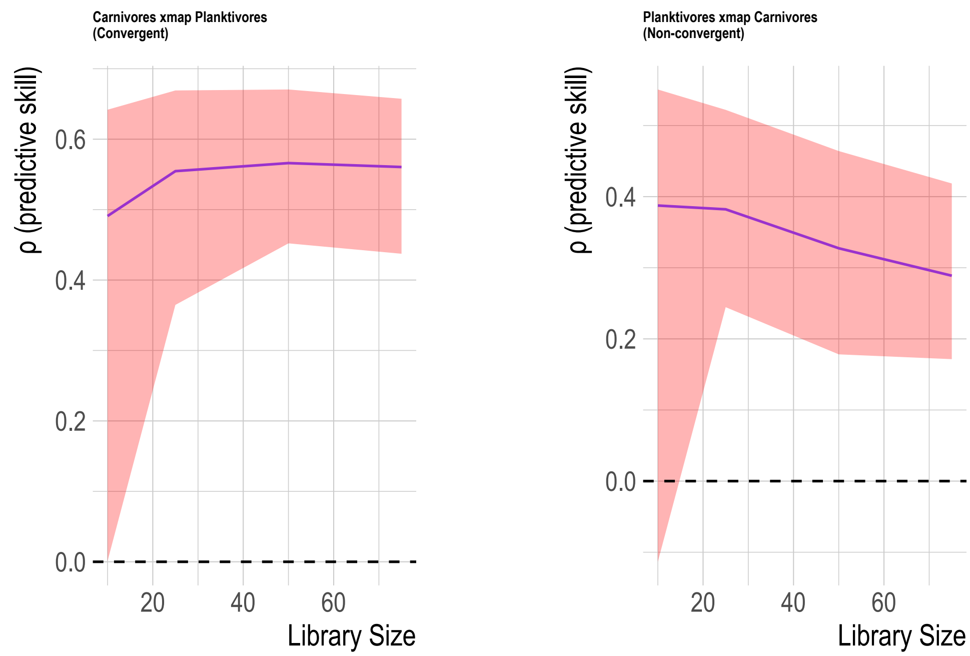

Figure 41: Cross mapping of effect of planktivores on carnivores (A) and carnivores on planktivores (B) in the PISCO data from 2000 to 2017. Shaded region show 95% confidence interval

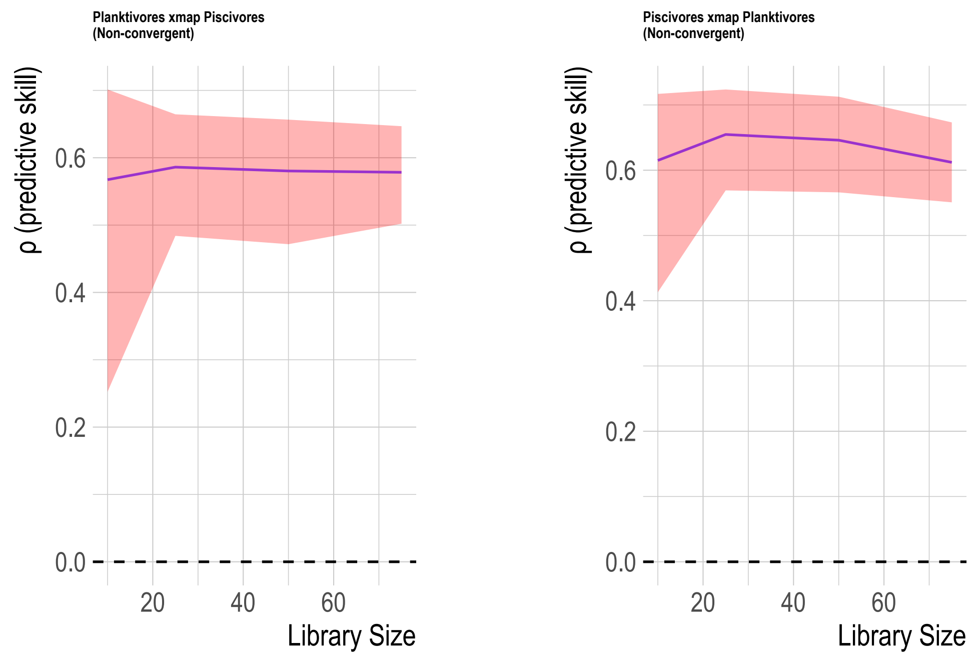

Figure 42: Cross mapping of effect of piscivores on carnivores (A) and carnivores on planktivores (B) in the PISCO data from 2000 to 2017. Shaded region show 95% confidence interval

et al. 2017) package in R. We pair these data with randomly selected values between 0.6 and 0.95 for Beverton-Holt steepness (as parameterized in Mace 1994), as well as larval and adult dispersal rates. We randomly assign whether adult fish preferentially move towards patches with lower relative densities, as well as one of three potential types of recruitment density dependence (building off of Babcock and MacCall 2011). Simulations are also assigned random fleet dynamics (open access ,constant effort, constant catch), responses to MPA (leave the fishery or concentrate outside MPAs), a fleet dispersal model (uniform in response to catch-per-unit-effort, in response to profit-per-unit-effort)

Each simulation is assigned an MPA scenario, defined by the number and size of MPAs, the placement of those MPAs, and the year that the MPAs are put in place. The population begins at unfished equilibrium and then fishing effort is applied in accordance to the fleet model. The MPAs are then placed during the randomly selected start year, allowing some runs to explore how the early dynamics of the MPA play out when the fishery and population they are placed on is not already at equilibrium. Each simulation is run to equilibrium with and without the selected MPA strategy (holding all else constant). We then measure the difference in biomass densities each time step in the scenario with and without the MPAs to calculate the population effect of the MPAs over time.

The operating model is a spatial single-species age-structured bio-economic model. The operating model itself is organized as an R package, which can be found and installed at https://github.com/DanOvando/spasm. Users can explore the functionality of the operating mode through an interactive web application at https://danovando.shinyapps.io/simmpa/.

For the population model, numbers n at time t for age a are given by

$$n_{t,a} = \begin{cases} = BH(ssb_{t-1}) & \text{if } a = 1 \\ = n_{t-1,a-1}e^{-(m+qE_{t-1}\times s_{a-1})}, & \text{if } 1 < a < max(age) \\ = n_{t-1,a}e^{-(m+qE_{t-1}\times s_{a})} + n_{t-1,a-1}e^{-(m+qE_{t-1}\times s_{a-1})}, & \text{if } a = max(a) \end{cases} \tag{12}$$

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

Selectivity is modeled through a logistic form per

$$s_a = \frac{1}{(1 + e^{-log(19)\times\frac{l_a - l_{sel}}{\delta_{sel}}})} \tag{13}$$

where l_a is the mean length at at age, l_sel is the length at which on average 50% of individuals are selected by the fishery, and δ_{sel} are the additional units of length at which on average 95% of fish are selected by the fishery.

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

$$l_a = l_\infty\left(1 - e^{-k(a-a_0)}\right) \tag{14}$$

Weight at age is then given by

$$b_a = w_a \times l_a^{w_b} \tag{15}$$

and maturity mat is calculated as

$$\frac{1}{(1 + e^{-log(19)\times\frac{l_a - l_{mat}}{\delta_{mat}}})} \tag{16}$$

where l_{mat} is the length at which on average 50% of individuals are sexual maturity, and δ_{mat} is the units of length beyond l_{mat} at which on average 95% of fish are sexually mature.

Spawning stock biomass at time t is then calculated as

$$ssb_t = \sum_{a=1}^{A} w_{a,t} mat_{a,t} n_{a,t} \tag{17}$$

1.5.1 Recruitment

Recruitment follows Beverton-Holt dynamics. We do however allow for three variants in the timing of density dependence:

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

$$n_{t,a=1,p} = \left(\frac{0.8 \times r0_p \times h \times ssb_{t-1,p}}{0.2 \times ssb0_p \times (1-h) + (h-0.2) \times ssb_{t-1,p}}\right) \times \boldsymbol{d^l} \times \epsilon_t \tag{18}$$

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

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

$$n_{t,a=1,p} = \left(\frac{0.8 \times \sum_{p=1}^{P} r0_p \times h \times \sum_{p=1}^{P} ssb_{t-1,p}}{0.2 \times \sum_{p=1}^{P} ssb0_p \times (1-h) + (h-0.2) \times \sum_{p=1}^{P} ssb_{t-1,p}}\right) \times hab_p \times \epsilon_t \tag{19}$$

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

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

$$larv_{t,p} = ssb_{t-1} \times \boldsymbol{d^l} \tag{20}$$

$$n_{t,a=1,p} = \left(\frac{0.8 \times r0_p \times h \times larv_{t,p}}{0.2 \times ssb0_p \times (1-h) + (h-0.2) \times larv_{t,p}}\right) \times \epsilon_t \tag{21}$$

ϵ represents multiplicative recruitment deviates. Deviates are calculated as

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

'*recdev* are the log-normal recruitment deviates in time t.

The stochastic component of the deviate is

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

and the final multiplicative recruitment deviate in time t is then

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

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

1.5.2 Dispersal

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

$$m_{s,p_i,p_j} = \frac{1}{\sqrt{2\pi\sigma_{s,p_i}^2}} e^{-\frac{d_{p_i,p_j}^2}{2\sigma_{s,p_i}^2}} \tag{22}$$

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

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

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

$$\sigma_{s=a,p}^* = max(slope \times d_p + \sigma_{s=a} \times dmod, 0) \tag{23}$$

where

$$slope = \sigma_{s=a} - (\sigma_{s=a} \times dmod) \tag{24}$$

Under these conditions, when depletion $d = 1$ (meaning the stock is unfished) the adult movement rate 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 then, the more movement rates from a patch decline as density declines.

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

1.5.3 Fleet Dynamics

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

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

$$profit_t = price \times catch_t - cost \times {E_t}^2 \tag{25}$$

From there, we determine the new effort as

$$E_t = E_{t-1} + \theta \times \sum_{i=t-1-l}^{t-1} w_i \frac{profit_i}{E^i} \tag{26}$$

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

$$w_i = \frac{i}{\sum_{i=1}^{l} i} \tag{27}$$

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

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

1.5.4 Spatial Fleet Distribution

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

$$E_{t,p} = E_t \times \frac{open_p}{\sum_{p=1}^{P} open_p} \tag{28}$$

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

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

$$E_{t,p} = E_t \times \frac{open_{t,p} ssb_{t,p}}{\sum_{p=1}^{P} open_{t,p} ssb_{t,p}} \tag{29}$$

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

$$E_{t,p} = E_t \times \frac{open_{t,p} ppue_{t,p}}{\sum_{p=1}^{P} open_{t,p} ppue_{t,p}} \tag{30}$$

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

1.5.5 MPA Design

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

1.6 Simulations

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

Table.S1 - Range of simulated variables

Variable	Distribution
Scientific Name	Drawn from all possible species in `FishLife` (Thorson et al. (2017))
steepness (h)	~uniform(0.6,0.95)
Adult movement ($\sigma_{s=a}$)	~uniform(0,0.25 * P)
Larval movement ($\sigma_{s=l}$)	~uniform(0,0.25 * P)
Recruitment variation (σ_r)	$\in \{0, 0.05, .1, .2\}$
Recruitment autocorrelation (ac_r)	$\in \{0, 0.05, .1, .2\}$
DD adult movement (dmod)	$\in \{0.25, 1\}$
Density-dependence timing	$\in \{local, global, post-dispersal\}$
% Patches in MPA	~uniform(0.01,1)
Initial fishing relative to natural mortality	~uniform(0.01,4)
Selectivity as a multiple of maturity length	~uniform(0.1,1.25)
Fleet model	$\in \{open-access, constant-effort, constant-catch\}$
Spatial effort model	$\in \{uniform, biomass, profits\}$
Years into simulation to start MPA	~round(uniform(5,0.66 * T))
MPA is sprinkler?	$\in \{TRUE, FALSE\}$
Randomly place MPA?	$\in \{TRUE, FALSE\}$
Fleet reaction to MPA	$\in \{concentrate, abandon-ship\}$
Patchiness	~uniform(0.01,0.75)
MPA habitat factor	$\in \{1, 4\}$

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

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

1.6.0.0.1 Filtering Simulations After the 20,000 simulations have run, we perform a series of filtering steps to remove runs that either a) produced chaotic dynamics during the open-access scenario; b) did not converge to the correct bionomic equilibrium in the open-access scenario; or c) crashed the population before the MPAs went into place (population falls below 5% of unfished biomass). These filtering steps left us with 9252 viable simulations.

1.6.0.1 Additional Simulation Results Simulation results are presented as percent differences in biomass densities with and without MPAs, in order to be comparable to the estimates that the regression model produces. However, this metric presents some problems as a measure of how "detectable" an effect size is. As depletion increases, relatively small changes in total biomass (relative to the variance in the observation process) can translate into large percent changes in biomass. For example, moving from a density of 0.02kg/m^2 to 0.04kg/m^2 translates to a 100% percent increase, but only a $.02\text{kg/m}^2$ absolute increase, a small value to detect with a real observation program.

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

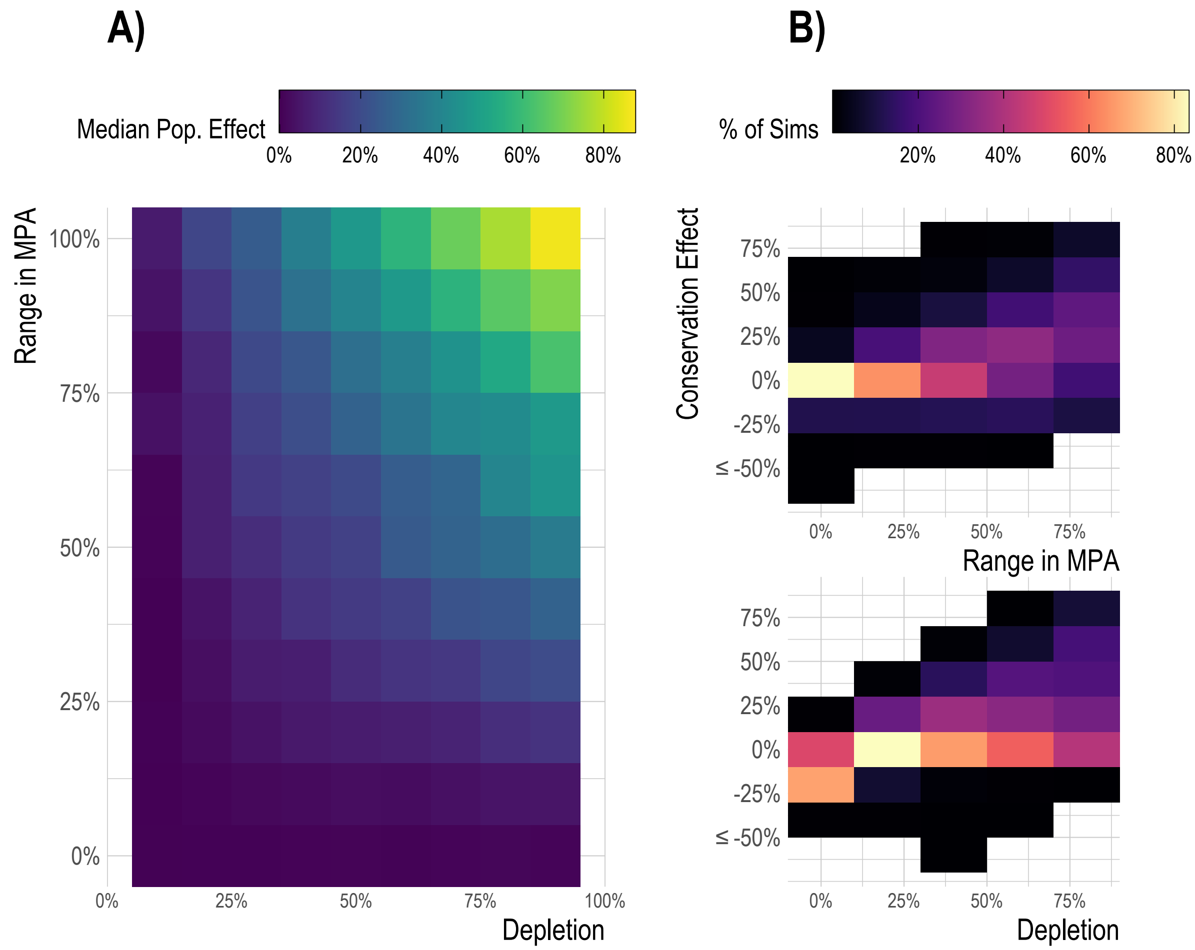

Figure 43: Median (A) and range (B) of equilibrium population-level MPA conservation effects (change in total biomass with MPAs relative to without MPAs as a percentage of unfished biomass) across a range of depletion and MPA sizes (and incorporating the full range of scenarios included in our study). '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

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