

Lab Week 4: Statistical Matching + Fixed Effects

A replication of study analysis in Ahmadia (2015)

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Lab Outline

0. Load in the packages and data
 1. Take a look at focal variables
 2. Checking covariate imbalance (pre-matching).
 3. Conduct a matching analysis (Mahalanobis matching)
 4. Evaluate balance after matching
 5. Estimate regression models for each outcome using the matched sample
 6. Practice fixed effects estimation
-

Applied study & data source

This lab uses open-access replication data from:

Ahmadia, G. N., Glew, L., Provost, M., Gill, D., Hidayat, N. I., Mangubhai, S., Purwanto, P., Fox, H. E. (2015). *Integrating impact evaluation in the design and implementation of monitoring marine protected areas*. Philosophical Transactions of the Royal Society B.

Big idea: MPAs are *not randomly placed*. They may be placed in “better” locations which means that treated and control groups are unlikely to make an *apples-to-apples* comparison. AKA, we are up against the nearly universal causal inference problem with non-experimental data, treatment assignment selection bias.

Ahmadia et al. (2015) uses **statistical matching** to construct a more *apples-to-apples* comparison group. In this lab exercise we will approximately replicate the main matching analysis conducted in this study.

Note

NOTE: When matching, the authors imposed additional restrictions (caliper-style constraints) on some habitat variables. We **do not** fully replicate those constraints here.

Reading reference:

MatchIt Vignette: <https://kosukeimai.github.io/MatchIt/articles/MatchIt.html>

O. Load packages + study data

```
library(tidyverse) # data wrangling + plotting
library(here)      # portable file paths (project-root relative)
library(janitor)   # clean variable names
library(gtsummary) # clean summary tables
library(gt)        # optional: render gtsummary nicely
library(MatchIt)   # matching estimation
library(cobalt)    # balance checks + love plots
library(jtools)    # clean regression output summaries
```

Read in the cleaned survey data

```
data_clean <- read_csv(here("week4", "Ahmadia_2015_DataClean.csv"), show_col_types = FALSE)
```

1. Create variable description table for key variables in the matching analysis

Variable Descriptions (Treatment, Outcomes, Matching Covariates) - Ahmadia (2015)

Label	Description
treated_mpa (Treatment)	Site is inside a Marine Protected Area (1 = inside MPA , 0 = outside MPA).
biomass_fisheries (Outcome)	Biomass of key fisheries families (Serranidae, Lutjanidae, Haemulidae) measured in kg per hectare (kg/ha).
biomass_ecological (Outcome)	Biomass of herbivorous fish families (Acanthuridae, Scaridae, Siganidae) measured in kg per hectare (kg/ha).
dist_deep_water (Covariate)	Covariate: Distance to deep water (50 m depth contour), in meters (m).
ssta_freq (Covariate)	Frequency of sea-surface temperature anomalies (SSTA)
reef_exposure (Covariate)	Reef wave exposure (Exposed, Semi-exposed, Sheltered).
reef_slope (Covariate)	Reef slope (Flat, Slope, Wall)
reef_type (Covariate)	Reef type (Patch, Fringing, Barrier, Atoll).
dist_mangroves (Covariate)	Distance to nearest mangrove habitat, in meters (m).

Variable Descriptions (Treatment, Outcomes, Matching Covariates) - Ahmadia (2015)

Label	Description
dist_fishing_settlement (Covariate)	Distance to nearest fishing settlement, in meters (m).
dist_market (Covariate)	Distance to primary market, in meters (m).
pollution_risk (Covariate)	Watershed pollution risk. (1 = Low; 2 = Medium; 3 = High).
monsoon_direction (Covariate)	Monsoon wind exposure direction. (Northwest (NW), Southeast (SE)).

2. Check imbalance before matching (covariate balance table)

Goal: Compare covariate distributions between **treated_mpa** and control sites *before* matching.

```
data_clean %>%
  select(
    treated_mpa, dist_to_deep_water, ssta_freq, reef_exposure,
    reef_slope, reef_type,
    dist_mangroves, dist_fish_settl, dist_market,
    pollution_risk, monsoon_direction) %>%
  tbl_summary(
    by = treated_mpa,
    statistic = list(
      all_continuous() ~ "{mean} ({sd})",
      all_categorical() ~ "{n} ({p})%"
    )
  ) %>%
  modify_header(label ~ "***Covariate***") %>%
  modify_spanning_header(c("stat_1", "stat_2") ~ "***Group***")
```

Covariate	Group	
	Control (non-MPA) N = 53 ¹	MPA site N = 108 ¹
dist_to_deep_water	656 (905)	627 (913)

¹ Mean (SD); n (%)

Covariate	Group	
	Control (non-MPA) N = 53 ¹	MPA site N = 108 ¹
ssta_freq	25 (8)	25 (5)
reef_exposure		
Exposed	35 (66%)	92 (85%)
Semi-exposed	18 (34%)	16 (15%)
reef_slope		
Flat	7 (13%)	10 (9.3%)
Slope	45 (85%)	90 (83%)
Wall	1 (1.9%)	8 (7.4%)
reef_type		
Barrier	8 (15%)	10 (9.3%)
Fringing	45 (85%)	93 (86%)
Patch	0 (0%)	5 (4.6%)
dist_mangroves	9,679 (14,229)	4,618 (5,165)
dist_fish_settl	25,646 (28,199)	32,505 (31,537)
dist_market	124,152 (49,763)	139,918 (66,406)
pollution_risk		
High	0 (0%)	1 (0.9%)
Low	33 (62%)	84 (78%)
Medium	20 (38%)	23 (21%)
monsoon_direction		
NW	19 (36%)	62 (57%)
SE	34 (64%)	46 (43%)

¹ Mean (SD); n (%)

✓ Your turn (write answers in the lab)

Q1. Based on the balance table, name two covariates that look most different between MPA and non-MPA sites.

Response: reef exposure (Exposed) and pollution risk (low) look the most different between MPA and non-MPA

Q2. Pick one of those imbalanced covariates and explain why it might confound the estimate of the effect of MPAs on fish biomass.

Response: MPA groups already have some covariates that will make it look as if the MPA has a bigger effect- for exposure, more wave action might deliver more nutrients to primary producers

Matching plan (what are we trying to estimate?)

In `{MatchIt}`, most distance-based matching procedures (like nearest-neighbor matching) target is to estimate:

ATT: Average Treatment effect on the Treated

Why? When using matching methods we typically **keep treated units** and then select control units that most closely match them.

✓ Your turn

Q4. What does **ATT** mean in the context of this MPA evaluation setting?

Response: How much does MPA treatment increase fish biomass compared to similar sites?

3. Mahalanobis Matching

Matching criteria used in Ahmadi (2015)

- `method = "nearest-neighbor"`: Nearest neighbor matching
- `distance = "mahalanobis"`: Mahalanobis distance
- `ratio = 2`: Two controls matched to each treated unit (2:1 ratio; control/treated)
- `replace = TRUE`: Controls can be reused (matched to multiple treated units)

NOTE: This is the *main* matching method implemented in Ahmadi (2015) with the exception of the caliper-style constraints.

```
# 1) Set a seed for reproducible matching
set.seed(2412026)
```

```
# 2) Fit a nearest-neighbor Mahalanobis matching model
match_model <- matchit(
  treated_mpa ~ dist_to_deep_water + ssta_freq + reef_exposure +
```

```

    reef_slope + reef_type + dist_mangroves + dist_fish_settl +
    dist_market + pollution_risk + monsoon_direction,
data = data_clean,
method = "nearest",          # Nearest neighbor matching
distance = "mahalanobis",    # Mahalanobis distance
ratio = 2,                   # 2:1 control/treated ratio)
replace = TRUE )            # With replacement

# Extract matched dataset
matched_data <- match.data(match_model)

# Inspect matching summary
summary(match_model)

```

Call:

```

matchit(formula = treated_mpa ~ dist_to_deep_water + ssta_freq +
  reef_exposure + reef_slope + reef_type + dist_mangroves +
  dist_fish_settl + dist_market + pollution_risk + monsoon_direction,
  data = data_clean, method = "nearest", distance = "mahalanobis",
  replace = TRUE, ratio = 2)

```

Summary of Balance for All Data:

	Means Treated	Means Control	Std. Mean Diff.
dist_to_deep_water	627.0960	655.7936	-0.0314
ssta_freq	25.4444	24.5094	0.1830
reef_exposureExposed	0.8519	0.6604	0.5390
reef_exposureSemi-exposed	0.1481	0.3396	-0.5390
reef_slopeFlat	0.0926	0.1321	-0.1362
reef_slopeSlope	0.8333	0.8491	-0.0422
reef_slopeWall	0.0741	0.0189	0.2108
reef_typeBarrier	0.0926	0.1509	-0.2013
reef_typeFringing	0.8611	0.8491	0.0349
reef_typePatch	0.0463	0.0000	0.2203
dist_mangroves	4618.4108	9679.3287	-0.9799
dist_fish_settl	32505.0449	25646.2642	0.2175
dist_market	139918.0030	124152.3646	0.2374
pollution_riskHigh	0.0093	0.0000	0.0967
pollution_riskLow	0.7778	0.6226	0.3732
pollution_riskMedium	0.2130	0.3774	-0.4016
monsoon_directionNW	0.5741	0.3585	0.4360
monsoon_directionSE	0.4259	0.6415	-0.4360

	Var. Ratio	eCDF Mean	eCDF Max
dist_to_deep_water	1.0168	0.0271	0.0924
ssta_freq	0.4116	0.0749	0.1651
reef_exposureExposed	.	0.1915	0.1915
reef_exposureSemi-exposed	.	0.1915	0.1915
reef_slopeFlat	.	0.0395	0.0395
reef_slopeSlope	.	0.0157	0.0157

reef_slopeWall	.	0.0552	0.0552
reef_typeBarrier	.	0.0584	0.0584
reef_typeFringing	.	0.0121	0.0121
reef_typePatch	.	0.0463	0.0463
dist_mangroves	0.1317	0.0755	0.1707
dist_fish_settl	1.2507	0.0780	0.1988
dist_market	1.7808	0.1061	0.3515
pollution_riskHigh	.	0.0093	0.0093
pollution_riskLow	.	0.1551	0.1551
pollution_riskMedium	.	0.1644	0.1644
monsoon_directionNW	.	0.2156	0.2156
monsoon_directionSE	.	0.2156	0.2156

Summary of Balance for Matched Data:

	Means Treated	Means Control	Std. Mean Diff.
dist_to_deep_water	627.0960	344.4758	0.3097
ssta_freq	25.4444	25.5370	-0.0181
reef_exposureExposed	0.8519	0.8380	0.0391
reef_exposureSemi-exposed	0.1481	0.1620	-0.0391
reef_slopeFlat	0.0926	0.0556	0.1278
reef_slopeSlope	0.8333	0.9120	-0.2112
reef_slopeWall	0.0741	0.0324	0.1591
reef_typeBarrier	0.0926	0.0880	0.0160
reef_typeFringing	0.8611	0.9120	-0.1473
reef_typePatch	0.0463	0.0000	0.2203
dist_mangroves	4618.4108	3903.1137	0.1385
dist_fish_settl	32505.0449	23907.6888	0.2726
dist_market	139918.0030	138886.2537	0.0155
pollution_riskHigh	0.0093	0.0000	0.0967
pollution_riskLow	0.7778	0.7963	-0.0445
pollution_riskMedium	0.2130	0.2037	0.0226
monsoon_directionNW	0.5741	0.5093	0.1311
monsoon_directionSE	0.4259	0.4907	-0.1311
	Var. Ratio	eCDF Mean	eCDF Max Std. Pair Dist.
dist_to_deep_water	3.0661	0.1022	0.2176 0.6162
ssta_freq	1.4678	0.0244	0.0926 0.7032
reef_exposureExposed	.	0.0139	0.0139 0.1434
reef_exposureSemi-exposed	.	0.0139	0.0139 0.1434
reef_slopeFlat	.	0.0370	0.0370 0.1278
reef_slopeSlope	.	0.0787	0.0787 0.2112
reef_slopeWall	.	0.0417	0.0417 0.1591
reef_typeBarrier	.	0.0046	0.0046 0.0160
reef_typeFringing	.	0.0509	0.0509 0.1473
reef_typePatch	.	0.0463	0.0463 0.2203
dist_mangroves	1.6708	0.0714	0.1759 0.7967
dist_fish_settl	1.0892	0.1147	0.3056 0.6229
dist_market	2.0937	0.1334	0.3889 0.5956
pollution_riskHigh	.	0.0093	0.0093 0.0967
pollution_riskLow	.	0.0185	0.0185 0.0445
pollution_riskMedium	.	0.0093	0.0093 0.0226
monsoon_directionNW	.	0.0648	0.0648 0.2247

monsoon_directionSE	.	0.0648	0.0648	0.2247
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Sample Sizes:

	Control	Treated
All	53.	108
Matched (ESS)	17.69	108
Matched	37.	108
Unmatched	16.	0
Discarded	0.	0

✓ Your turn

Q5. Report how many treated units were matched and how many control sites were included in the matched data.

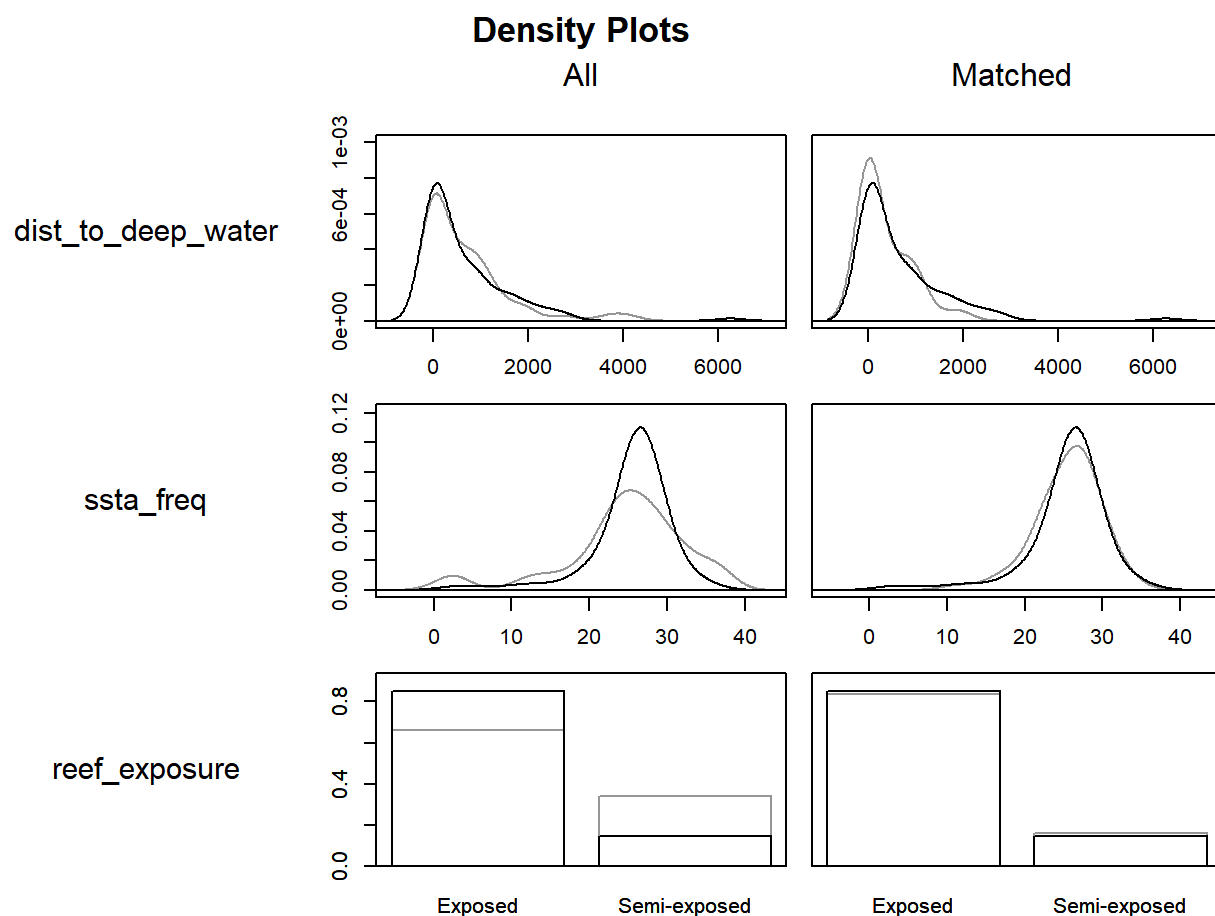
Response: treated units was 108, control was 37

Q6. Find the covariate with the largest standardized mean difference (SMD) *after matching*. Which covariate is it?

Response: After matching the standard mean difference of distance to deep water got larger.

Visualize balance on the covariates using `plot()` with `type = "density"`

```
plot(match_model, type = "density", interactive = FALSE,
      which.xs = ~dist_to_deep_water + ssta_freq + reef_exposure)
```



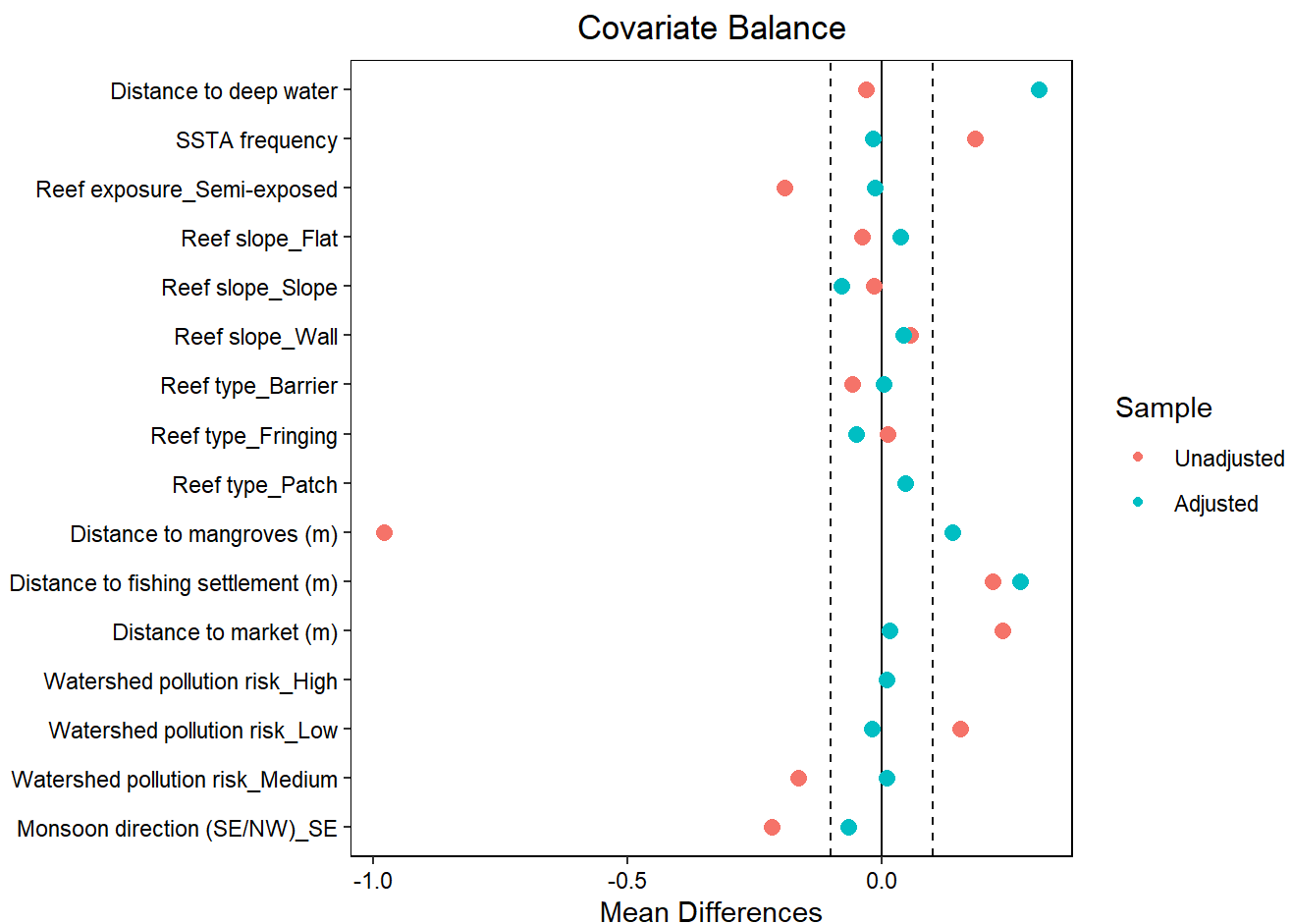
4. Evaluate balance after matching (love plot + balance table)

Create nicer variable labels for plots/tables

```
nice_names <- data.frame(
  old = c(
    "dist_to_deep_water", "ssta_freq", "reef_exposure", "reef_slope",
    "reef_type", "dist_mangroves", "dist_fish_settl", "dist_market",
    "pollution_risk", "monsoon_direction"),
  new = c(
    "Distance to deep water", "SSTA frequency", "Reef exposure", "Reef slope",
    "Reef type", "Distance to mangroves (m)", "Distance to fishing settlement (m)",
    "Distance to market (m)", "Watershed pollution risk", "Monsoon direction (SE/NW)"))
```

Create a **Love plot** to visualize standardized mean differences (before & after matching)

```
love.plot(
  match_model,
  stats = "mean.diffs",
  thresholds = c(m = 0.1),
  var.names = nice_names)
```



5. Estimate differences in outcomes using the matched sample

- When matching *with replacement*, some control sites were matched multiple times and receive larger weights.
- So we estimate outcome differences using the `weights` provided by `match.data()`.

Regression (Outcome 1): Herbivorous fisheries families biomass

```
reg_ecological <- lm(biomass_ecological~treated_mpa, data = matched_data,
                    weights = weights)
```

```
summ(reg_ecological, model.fit = FALSE)
```

Observations	145			
Dependent variable	biomass_ecological			
Type	OLS linear regression			
	Est.	S.E.	t val.	p
(Intercept)	290.77	106.02	2.74	0.01
treated_mpa/MPA site	79.50	122.84	0.65	0.52
Standard errors: OLS				

Regression (Outcome 2): Key fisheries families biomass

```
reg_fisheries <- lm(biomass_fisheries~treated_mpa, data = matched_data,
                    weights = weights)
```

```
summ(reg_fisheries, model.fit = FALSE)
```

Observations	145			
Dependent variable	biomass_fisheries			
Type	OLS linear regression			
	Est.	S.E.	t val.	p
(Intercept)	64.23	52.47	1.22	0.22
treated_mpa/MPA site	107.78	60.79	1.77	0.08
Standard errors: OLS				

View biomass differences by treatment group as simple weighted mean comparisons:

```
matched_data %>%
  group_by(treated_mpa) %>%
```

```

summarize(
  n_obs = n(),
  avg_biomass_ecological = weighted.mean(biomass_ecological, w = weights),
  avg_biomass_fisheries = weighted.mean(biomass_fisheries, w = weights),
  .groups = "drop") %>%
gt() %>%
tab_header(title = "Weighted mean outcomes in matched sample")

```

Weighted mean outcomes in matched sample			
treated_mpa	n_obs	avg_biomass_ecological	avg_biomass_fisheries
Control (non-MPA)	37	290.7664	64.2348
MPA site	108	370.2682	172.0131

✓ Your turn

Q7. Interpret one coefficient from the regressions above (choose ecological or fisheries). Write the interpretation of coefficient in plain language.

Response: Looking at the fisheries regression, there is an increase in average biomass in MPA treatment sites compared to non-MPA treatment of 107 kg/ha.

Q8. What is the biggest remaining threat to causal interpretation of regression coefficients after matching?

Response: There may still be unobserved covariates not included in the model. These matching experiments do not account for unobserved selection bias.

6. Fixed Effects Estimation - An Applied Example

Replication of fixed effects estimator from applied study:

Dudney, J., Willing, C. E., Das, A. J., Latimer, A. M., Nesmith, J. C., & Battles, J. J. (2021). *Nonlinear shifts in infectious rust disease due to climate change*. *Nature communications*, 12(1), 5102.

In this section we will look at a simple fixed effects (FE) example using panel-style data, where the same units (plots) are observed over multiple years (1995, 2016).

The key issue: observations from the same plot are likely to share stable characteristics (soil type, microclimate, slope, management history) that we don't measure well—and those unobserved factors can bias a naïve regression.

Read in the data & change fixed effect to factor variables

By Coding `plot` and `year` as factors lets us include them as indicator (dummy) variables in an FE regression.

```
data_fe <- read_csv(here("week4", "Dudney2021_study_data.csv"), show_col_types = FALSE) %>%
  mutate(year = factor(year), plot = factor(plot))
```

Estimate a “no fixed effects” baseline model

```
mod1_nofe <- lm(perinc ~ vpd + I(vpd^2) + dbh + density,
  data = data_fe)
```

```
summ(mod1_nofe, model.fit = FALSE, digits = 3)
```

Observations	294			
Dependent variable	perinc			
Type	OLS linear regression			
	Est.	S.E.	t val.	p
(Intercept)	-0.615	0.122	-5.027	0.000
vpd	0.126	0.022	5.712	0.000
I(vpd^2)	-0.005	0.001	-5.119	0.000
dbh	-0.001	0.001	-2.499	0.013
density	-0.000	0.000	-3.287	0.001
Standard errors: OLS				

Estimate the fixed effects model: Add in the fixed effects for `plot` & `year`

- `plot` fixed effects absorb all time-invariant differences across plots (e.g., baseline soil quality)
- `year` fixed effects absorb common shocks shared by all plots in a given year (e.g., a region-wide drought year)

```
fe_lm <- lm(perinc ~ vpd + I(vpd^2) + dbh + density + plot + year,
  data = data_fe)
```

```
summ(fe_lm, model.fit = FALSE, digits = 3)
```

Observations	294
--------------	-----

Dependent variable	perinc			
Type	OLS linear regression			
	Est.	S.E.	t val.	p
(Intercept)	-1.199	0.770	-1.556	0.122
vpd	0.227	0.093	2.449	0.016
I(vpd^2)	-0.010	0.002	-4.209	0.000
dbh	-0.001	0.001	-0.973	0.332
density	-0.001	0.000	-2.275	0.024
plot2	0.092	0.177	0.516	0.606
plot3	0.140	0.180	0.778	0.438
plot4	0.118	0.186	0.634	0.527
plot5	0.181	0.185	0.978	0.330
plot6	0.136	0.126	1.079	0.283
plot7	0.007	0.101	0.066	0.948
plot8	0.198	0.262	0.757	0.450
plot9	0.070	0.149	0.472	0.638
plot10	0.156	0.117	1.336	0.184
plot11	0.147	0.169	0.871	0.385
plot13	0.160	0.167	0.957	0.340
plot14	0.344	0.122	2.816	0.006
plot15	0.107	0.198	0.542	0.589
plot16	0.207	0.222	0.933	0.352
plot17	0.161	0.121	1.329	0.186
plot18	0.125	0.187	0.668	0.505
plot19	0.107	0.194	0.554	0.580
plot20	0.138	0.204	0.677	0.500
plot21	0.144	0.179	0.805	0.422
plot22	0.197	0.158	1.249	0.214
plot23	0.090	0.141	0.638	0.525
plot24	0.112	0.158	0.704	0.483
plot25	0.142	0.230	0.618	0.537
plot26	0.186	0.223	0.831	0.408
plot28	0.170	0.190	0.894	0.373
Standard errors: OLS				

	Est.	S.E.	t val.	p
plot29	0.078	0.155	0.504	0.615
plot30	0.266	0.230	1.157	0.249
plot31	0.131	0.160	0.815	0.416
plot32	0.103	0.157	0.656	0.513
plot34	0.118	0.194	0.610	0.543
plot35	0.265	0.261	1.017	0.311
plot36	0.025	0.121	0.207	0.836
plot37	0.131	0.165	0.799	0.426
plot38	0.747	0.088	8.439	0.000
plot39	-0.012	0.091	-0.134	0.894
plot40	0.082	0.090	0.915	0.362
plot41	0.231	0.121	1.907	0.059
plot42	0.423	0.263	1.607	0.110
plot43	0.366	0.142	2.584	0.011
plot44	0.296	0.202	1.462	0.146
plot45	0.038	0.116	0.333	0.740
plot46	0.248	0.143	1.733	0.085
plot47	0.543	0.143	3.795	0.000
plot48	0.107	0.133	0.801	0.425
plot49	0.059	0.092	0.643	0.521
plot51	0.577	0.114	5.039	0.000
plot52	0.178	0.256	0.695	0.488
plot53	0.152	0.252	0.604	0.547
plot54	0.323	0.113	2.857	0.005
plot55	0.204	0.192	1.060	0.291
plot56	0.203	0.267	0.761	0.448
plot57	0.172	0.180	0.957	0.340
plot58	0.020	0.114	0.179	0.858
plot59	0.221	0.219	1.010	0.314
plot60	0.105	0.214	0.489	0.625
plot61	0.136	0.119	1.135	0.258
plot62	0.141	0.224	0.629	0.531

Standard errors: OLS

	Est.	S.E.	t val.	p
plot63	0.234	0.188	1.242	0.216
plot64	0.201	0.299	0.674	0.502
plot65	0.083	0.186	0.449	0.654
plot66	0.120	0.130	0.924	0.357
plot67	0.084	0.124	0.683	0.496
plot68	0.074	0.090	0.822	0.412
plot69	0.201	0.161	1.248	0.214
plot70	0.276	0.113	2.449	0.016
plot71	0.126	0.201	0.630	0.530
plot72	0.221	0.174	1.266	0.208
plot73	0.044	0.123	0.356	0.722
plot74	0.069	0.130	0.529	0.598
plot75	0.043	0.123	0.347	0.729
plot76	0.155	0.252	0.618	0.538
plot77	0.207	0.228	0.905	0.367
plot78	0.295	0.205	1.439	0.152
plot79	0.145	0.234	0.619	0.537
plot80	0.266	0.252	1.057	0.292
plot82	0.239	0.273	0.876	0.383
plot83	0.237	0.261	0.908	0.365
plot84	0.260	0.270	0.965	0.336
plot85	0.298	0.297	1.001	0.319
plot86	0.120	0.209	0.576	0.565
plot87	0.088	0.124	0.710	0.479
plot88	0.296	0.093	3.199	0.002
plot89	0.175	0.125	1.400	0.164
plot90	0.018	0.101	0.175	0.861
plot91	0.017	0.102	0.166	0.868
plot92	0.078	0.150	0.522	0.602
plot93	0.170	0.154	1.100	0.273
plot94	-0.001	0.095	-0.012	0.990
plot95	0.234	0.141	1.666	0.098

Standard errors: OLS

	Est.	S.E.	t val.	p
plot96	0.083	0.096	0.858	0.392
plot97	0.216	0.150	1.440	0.152
plot98	0.180	0.162	1.108	0.270
plot99	0.125	0.159	0.785	0.434
plot100	0.019	0.117	0.165	0.869
plot101	0.088	0.119	0.745	0.457
plot102	0.010	0.114	0.084	0.933
plot103	0.171	0.174	0.980	0.329
plot104	0.157	0.173	0.909	0.365
plot105	0.117	0.171	0.687	0.493
plot106	0.102	0.090	1.140	0.256
plot107	0.038	0.112	0.334	0.739
plot108	0.086	0.120	0.716	0.475
plot110	0.092	0.153	0.601	0.549
plot111	0.074	0.096	0.767	0.444
plot112	0.201	0.105	1.912	0.058
plot113	0.090	0.128	0.704	0.482
plot114	0.270	0.089	3.038	0.003
plot115	0.008	0.109	0.075	0.941
plot116	0.111	0.121	0.918	0.360
plot117	0.057	0.108	0.530	0.597
plot118	0.169	0.167	1.014	0.312
plot119	0.074	0.167	0.444	0.658
plot120	0.139	0.182	0.767	0.444
plot121	0.191	0.092	2.073	0.040
plot122	0.033	0.132	0.252	0.802
plot123	0.072	0.113	0.634	0.527
plot124	0.080	0.142	0.565	0.573
plot125	0.381	0.224	1.695	0.092
plot126	0.106	0.126	0.845	0.400
plot127	0.172	0.138	1.245	0.215
plot128	0.505	0.104	4.851	0.000

Standard errors: OLS

	Est.	S.E.	t val.	p
plot129	0.104	0.171	0.607	0.545
plot130	0.292	0.196	1.490	0.138
plot131	0.195	0.175	1.118	0.266
plot132	0.254	0.094	2.705	0.008
plot133	0.258	0.145	1.783	0.077
plot134	0.386	0.269	1.434	0.154
plot135	0.103	0.132	0.777	0.438
plot136	0.053	0.095	0.553	0.581
plot137	0.136	0.221	0.615	0.539
plot138	0.244	0.198	1.232	0.220
plot139	0.095	0.154	0.616	0.539
plot140	0.295	0.094	3.143	0.002
plot141	0.158	0.150	1.058	0.292
plot142	0.139	0.184	0.756	0.451
plot143	0.105	0.117	0.896	0.372
plot145	-0.020	0.090	-0.218	0.828
plot146	0.342	0.268	1.276	0.204
plot147	0.367	0.275	1.335	0.184
plot148	0.214	0.129	1.664	0.098
plot149	0.231	0.131	1.757	0.081
plot150	0.245	0.199	1.233	0.220
plot151	0.119	0.196	0.607	0.545
plot152	0.340	0.099	3.426	0.001
plot153	0.186	0.128	1.448	0.150
plot154	0.065	0.103	0.636	0.526
year2016	-0.050	0.072	-0.693	0.490

Standard errors: OLS

✓ Your turn

Q9. Compare the coefficient on **vpd** in the **no-FE model** vs the **FE model**. Did the estimate get larger, smaller, or change sign? What does that suggest about confounding from unobserved plot differences?

Response: vpd increases on fixed effect model, this means that plot and year were confounding the weight of vapor pressure deficit in the first model without fixed effects.

Q10. Why include **year** fixed effects? Give one concrete example of a “year shock” that could bias estimates if not controlled (choose a different example than provided above).

Response: Year helps include factors such as drought, rain events, etc., so including it will help reduce the weight in treatment that should really be attributed to outside effects.

Q11. Why include **plot** fixed effects? Give one concrete example of a “time-invariant plot difference” that could bias estimates if not controlled (choose a different example than provided above).

Response: Conditions will vary depending on plot so the effect of treatment will not necessarily be the same across plots- this might depend on geographic factors.
