HW4

Erik Andersen

2023-11-08

Contents

Setup

```
here::i_am("HW4/HW4.Rmd")
```

```
## here() starts at /Users/johannaallen/Documents/Erik/ECON 587
```

```
# Load packages
pacman::p_load(tidyverse, magrittr, estimatr, fixest, plm, systemfit, tidysynth)
```

```
# Load data
election_df = haven::read_dta(here::here("HW4", "data", "GriffithNoonen2022_Econ587.dta"))
```

Question 1

Note: lm_robust and feols seem to calculate clustered standard errors differently. Feols matches those from the paper, but I've use both based on convenience and when I don't have a standard error to match I defer to lm_robust.

```
# Generate treatment dummy and city/cycle pair for clustering
election_df %<>% mutate(post = if_else(cycle >= 2017, 1, 0),
                        treatment = if_else(city == 'Seattle', 1, 0),
                        city_cycle = as.factor(city):as.factor(cycle),
                        seattle = if_else(city == 'Seattle', 1, 0))

# Run naive regression
election_df %>% lm_robust(candidates_ballot ~ treatment + At_Large*Special,., clusters = city_cycle)
```

a)

```
##                    Estimate Std. Error   t value     Pr(>|t|)   CI Lower
## (Intercept)        3.589078  0.1463080 24.530968 1.197745e-46  3.2991600
## treatment          1.909594  0.5449885  3.503915 6.077719e-03  0.6879128
```

```
## At_Large         -1.413736  0.2442275 -5.788605 1.490323e-06 -1.9096278
## Special           2.310922  0.6487738  3.561985 1.144109e-03  0.9909783
## At_Large:Special -2.349963  0.8527678 -2.755689 1.852349e-02 -4.2243034
##                   CI Upper         DF
## (Intercept)       3.8789950 111.057535
## treatment         3.1312742   9.573626
## At_Large         -0.9178450  34.836368
## Special           3.6308667  32.997352
## At_Large:Special -0.4756222  11.125935
```

```
# Before and after treatment for seattle
(before_after_seattle = election_df |> filter(city == 'Seattle') %>%
  lm_robust(candidates_ballot ~ post + At_Large*Special,., clusters = city_cycle))
```

b)

```
## 1 coefficient  not defined because the design matrix is rank deficient

##                   Estimate Std. Error   t value   Pr(>|t|)  CI Lower  CI Upper
## (Intercept)       5.032967  0.5848685  8.605297 0.07139585 -2.130380 12.196314
## post              3.076923  0.7193253  4.277512 0.13842535 -5.227067 11.380913
## At_Large         -1.494505  0.5541174 -2.697092 0.17503886 -5.566441  2.577430
## Special          -1.538462  0.3047218 -5.048741 0.00144325 -2.257731 -0.819192
## At_Large:Special        NA         NA        NA         NA        NA        NA
##                         DF
## (Intercept)       1.015827
## post              1.042542
## At_Large          1.315985
## Special           7.062124
## At_Large:Special        NA
```

```
# Before and after for non-seattle cities
(before_after_other = election_df |> filter(city != 'Seattle') %>%
  lm_robust(candidates_ballot ~ post + At_Large*Special,., clusters = city_cycle))
```

```
##                    Estimate Std. Error   t value     Pr(>|t|)   CI Lower
## (Intercept)       3.4776955  0.1688514 20.596186 2.878122e-36  3.1423533
## post              0.4148275  0.2448961  1.693892 9.845735e-02 -0.0809163
## At_Large         -1.2231610  0.1989526 -6.148004 7.846422e-07 -1.6288208
## Special           2.3497096  0.6516426  3.605825 1.012284e-03  1.0240282
## At_Large:Special -2.2941949  0.8476360 -2.706580 2.349678e-02 -4.2028308
##                    CI Upper        DF
## (Intercept)       3.8130378 92.231960
## post              0.9105713 38.052344
## At_Large         -0.8175012 31.202301
## Special           3.6753911 33.062712
## At_Large:Special -0.3855589  9.282206
```

```r
# Diff between
summary(before_after_seattle)$coefficients[2,1] - summary(before_after_other)$coefficients[2,1]
```

```
## 1 coefficient  not defined because the design matrix is rank deficient

## [1] 2.662096
```

```r
# Cross sectional estimate before 2017
(cross_before = election_df |> filter(post == 0) %>%
  lm_robust(candidates_ballot ~ seattle + At_Large*Special,., clusters = city_cycle))
```

c)

```
##                    Estimate Std. Error   t value     Pr(>|t|)   CI Lower
## (Intercept)        3.483982  0.1717835 20.281238 7.342703e-35  3.1425797
## seattle            1.311372  0.3306454  3.966099 3.579362e-03  0.5581377
## At_Large          -1.249706  0.2109556 -5.924024 3.111992e-06 -1.6835384
## Special            2.334200  0.7198830  3.242471 3.263548e-03  0.8538710
## At_Large:Special  -2.453704  0.9915090 -2.474717 3.957582e-02 -4.7562457
##                    CI Upper        DF
## (Intercept)        3.8253838 87.660223
## seattle            2.0646072  8.605266
## At_Large          -0.8158744 25.748241
## Special            3.8145291 25.789416
## At_Large:Special  -0.1511626  7.690471
```

```r
# Cross-Sectional Estimate after 2017
(cross_after = election_df |> filter(post == 1) %>%
  lm_robust(candidates_ballot ~ seattle + At_Large*Special,., clusters = city_cycle))
```

```
##                    Estimate Std. Error   t value     Pr(>|t|)    CI Lower
## (Intercept)        3.888271  0.2287718 16.996285 6.156804e-14   3.4131578
## seattle            4.152392  0.4157658  9.987334 4.508960e-02   0.3551595
## At_Large          -1.182981  0.4156373 -2.846186 2.838772e-02  -2.1928444
## Special            2.397443  1.6596647  1.444535 1.943128e-01  -1.5753525
## At_Large:Special  -2.602733  1.7392122 -1.496501 2.802489e-01 -10.5328616
##                    CI Upper        DF
## (Intercept)        4.3633840 21.478005
## seattle            7.9496236  1.166224
## At_Large          -0.1731178  6.180707
## Special            6.3702393  6.603234
## At_Large:Special   5.3273952  1.886855
```

```r
# Diff between
summary(cross_after)$coefficients[2,1] - summary(cross_before)$coefficients[2,1]
```

```
## [1] 2.841019
```

```r
# Diff-in-Diff
(diff_in_diff = election_df %>% lm_robust(candidates_ballot ~ post*treatment + At_Large*Special,., clus
```

d)

```
##                     Estimate Std. Error   t value     Pr(>|t|)    CI Lower
## (Intercept)        3.4816344  0.1670719 20.839143 5.446786e-37  3.14990526
## post               0.4160744  0.2446621  1.700608 9.717398e-02 -0.07919012
## treatment          1.3031499  0.3317399  3.928227 3.706416e-03  0.54870655
## At_Large          -1.2364427  0.1855647 -6.663136 1.354194e-07 -1.61390204
## Special            2.3455525  0.6512075  3.601851 1.024071e-03  1.02072331
## post:treatment     2.8516842  0.5369667  5.310728 4.185045e-02  0.28116922
## At_Large:Special  -2.4826566  0.8282304 -2.997543 1.198253e-02 -4.30287937
##                     CI Upper        DF
## (Intercept)        3.8133636 93.911451
## post               0.9113388 38.065564
## treatment          2.0575932  8.697657
## At_Large          -0.8589834 33.173207
## Special            3.6703818 33.040951
## post:treatment     5.4221991  1.802658
## At_Large:Special  -0.6624338 11.135367
```

```r
# Coeff of interest is post:treatment
```

```r
# two way fixed effects. We're switching regression functions here because it has prettier output, and
(two_way = election_df %>% feols(candidates_ballot ~ post*treatment | as.factor(city) + as.factor(cycle
```

e)

```
## The variable 'post' has been removed because of collinearity (see $collin.var).

## OLS estimation, Dep. Var.: candidates_ballot
## Observations: 688
## Fixed-effects: as.factor(city): 15,  as.factor(cycle): 10,  At_Large: 2,  Special: 2,  At_Large:Spec
## Standard-errors: Clustered (city_cycle)
##                Estimate   Std. Error    t value   Pr(>|t|)
## treatment      0.242134 1.017151e+05 0.00000238 1.0000e+00
## post:treatment 3.232271 5.569880e-01 5.80312202 3.7753e-08 ***
## ... 1 variable was removed because of collinearity (post)
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 2.32461     Adj. R2: 0.171457
##                 Within R2: 0.016154
```

```r
# Coeff of interest is post:treatment
```

```r
# Test for parallel pre-trends with city fixed effects
election_df |> filter(post == 0 ) |>
  mutate(`cycle*seattle` = cycle*seattle) %>%
  lm_robust(candidates_ballot ~ `cycle*seattle` + At_Large*Special + as.factor(city),., clusters = city_
```

f)

```
##                                Estimate  Std. Error     t value    Pr(>|t|)
## (Intercept)                  2.61737498   0.6806467  3.84542368 0.001919360
## `cycle*seattle`              0.02270571   0.1054667  0.21528802 0.839067652
## At_Large                    -0.58221412   0.6531859 -0.89134518 0.397820022
## Special                      2.09787700   0.7094717  2.95695649 0.006562754
## as.factor(city)Everett       0.09229728   0.2540772  0.36326465 0.721950716
## as.factor(city)Fresno        0.44821546   0.7859007  0.57032070 0.575168600
## as.factor(city)Kent         -0.51730178   0.7314056 -0.70727072 0.488036352
## as.factor(city)Long Beach    0.58296929   0.7551091  0.77203321 0.450032048
## as.factor(city)Los Angeles   0.87710483   0.8223267  1.06661357 0.301657175
## as.factor(city)Oakland       0.84713582   0.6959637  1.21721273 0.243515366
## as.factor(city)Sacramento   -0.10868224   0.7831453 -0.13877660 0.891141168
## as.factor(city)San Diego     1.61794347   0.8343269  1.93922012 0.068313138
## as.factor(city)San Francisco 3.10363527   1.0643772  2.91591679 0.009509639
## as.factor(city)San Jose      1.05015478   0.7657501  1.37140657 0.187677658
## as.factor(city)Seattle     -43.98711312 211.5877470 -0.20789064 0.844508853
## as.factor(city)Spokane       1.00151275   0.6198537  1.61572452 0.128156710
## as.factor(city)Tacoma        0.22637502   0.7372229  0.30706455 0.762201459
## as.factor(city)Vancouver     0.01870994   0.7106490  0.02632796 0.979264248
## At_Large:Special            -2.11754216   0.9889547 -2.14119226 0.065691290
##                                CI Lower    CI Upper        DF
## (Intercept)                   1.1514895   4.0832605 13.410494
## `cycle*seattle`              -0.2589267   0.3043381  4.444237
## At_Large                     -2.0787689   0.9143407  8.308997
## Special                       0.6389979   3.5567561 25.804075
## as.factor(city)Everett       -0.4537625   0.6383571 13.700873
## as.factor(city)Fresno        -1.1971190   2.0935500 18.927705
## as.factor(city)Kent          -2.0487985   1.0141949 18.882110
## as.factor(city)Long Beach    -1.0025283   2.1684669 18.148142
## as.factor(city)Los Angeles   -0.8632433   2.6174530 16.335654
## as.factor(city)Oakland       -0.6446456   2.3389172 14.091844
## as.factor(city)Sacramento    -1.7519792   1.5346147 18.315657
## as.factor(city)San Diego     -0.1349110   3.3707979 18.000187
## as.factor(city)San Francisco  0.8608137   5.3464568 17.285079
## as.factor(city)San Jose      -0.5626224   2.6629320 17.398520
## as.factor(city)Seattle     -609.2121979 521.2379716  4.439416
## as.factor(city)Spokane       -0.3262404   2.3292659 14.193774
## as.factor(city)Tacoma        -1.3187694   1.7715194 18.622601
## as.factor(city)Vancouver     -1.4664569   1.5038768 19.432707
## At_Large:Special             -4.4102515   0.1751672  7.763005
```

```r
# Without city fixed effects
election_df |> filter(post == 0 ) |>
  mutate(`cycle*seattle` = cycle*seattle) %>%
  lm_robust(candidates_ballot ~ `cycle*seattle` + At_Large*Special,., clusters = city_cycle)
```

```
##                       Estimate   Std. Error   t value     Pr(>|t|)
## (Intercept)       3.4839204269 0.1717858601 20.280601 7.356064e-35
## `cycle*seattle`   0.0006526184 0.0001645432  3.966243 3.622109e-03
## At_Large         -1.2492194845 0.2108990280 -5.923306 3.119727e-06
## Special           2.3342613913 0.7198837316  3.242553 3.262880e-03
## At_Large:Special -2.4537123028 0.9913706812 -2.475070 3.955425e-02
##                       CI Lower     CI Upper        DF
## (Intercept)       3.1425137385  3.825327115 87.661216
## `cycle*seattle`   0.0002774112  0.001027826  8.553285
## At_Large         -1.6829384936 -0.815500475 25.744068
## Special           0.8539309881  3.814591794 25.789449
## At_Large:Special -4.7559305212 -0.151494084  7.690509
```

```r
# Estimate non-parallel trends test
election_df |> mutate(`seattle*cycle` = seattle*cycle, `seattle*post` = seattle*post) %>%
  feols(candidates_ballot ~ cycle +  `seattle*cycle` + `seattle*post` + At_Large*Special + as.factor(ci
```

g)

```
## OLS estimation, Dep. Var.: candidates_ballot
## Observations: 688
## Standard-errors: Clustered (city_cycle)
##                          Estimate Std. Error   t value   Pr(>|t|)
## (Intercept)            -20.656995  36.952526 -0.559014 0.57699111
## cycle                    0.011666   0.018385  0.634537 0.52670327
## `seattle*cycle`          0.009090   0.077642  0.117076 0.90695722
## `seattle*post`           3.449166   0.942599  3.659207 0.00035048 ***
## At_Large                -0.607777   0.381554 -1.592898 0.11330234
## Special                  2.079146   0.640201  3.247646 0.00143779 **
## as.factor(city)Everett  -0.039343   0.243753 -0.161406 0.87199235
## as.factor(city)Fresno    0.228285   0.535630  0.426198 0.67057845
## ... 13 coefficients remaining (display them with summary() or use argument n)
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 2.33584   Adj. R2: 0.173464
```

```r
# Coef of interest is seattle*post
```

```r
# Run part g again but only with cities in washington
election_df |> filter(state == 'Wash') |>
  mutate(`seattle*cycle` = seattle*cycle, `seattle*post` = seattle*post) %>%
  feols(candidates_ballot ~ cycle +  `seattle*cycle` + `seattle*post` + At_Large*Special + as.factor(ci
```

h)

```
## OLS estimation, Dep. Var.: candidates_ballot
## Observations: 271
```

```
## Standard-errors: Clustered (city_cycle)
##                           Estimate Std. Error   t value   Pr(>|t|)
## (Intercept)             -38.240157  32.816162 -1.165284 0.24791658
## cycle                     0.020719   0.016317  1.269808 0.20841874
## `seattle*cycle`          -0.030685   0.070213 -0.437022 0.66346011
## `seattle*post`            3.377484   0.803842  4.201678 0.00007792 ***
## At_Large                 -1.224017   0.336493 -3.637574 0.00052659 ***
## Special                   0.421414   0.472777  0.891358 0.37583467
## as.factor(city)Everett   -0.037126   0.244028 -0.152136 0.87952347
## as.factor(city)Kent      -1.089632   0.434107 -2.510054 0.01442061 *
## as.factor(city)Seattle   63.028414 140.921960  0.447258 0.65608998
## as.factor(city)Spokane    0.452110   0.402590  1.123002 0.26532891
## as.factor(city)Tacoma    -0.530504   0.458624 -1.156731 0.25137154
## as.factor(city)Vancouver -0.544142   0.414108 -1.314009 0.19319503
## At_Large:Special         -0.392882   0.673163 -0.583636 0.56136840
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 1.30606   Adj. R2: 0.39376
```

```
# Now just with california cities
election_df |> filter(state == "Calif" | city == 'Seattle') |>
  mutate(`seattle*cycle` = seattle*cycle, `seattle*post` = seattle*post) %>%
  feols(candidates_ballot ~ cycle +  `seattle*cycle` + `seattle*post` + At_Large*Special + as.factor(ci
```

```
## OLS estimation, Dep. Var.: candidates_ballot
## Observations: 467
## Standard-errors: Clustered (city_cycle)
##                               Estimate Std. Error   t value   Pr(>|t|)
## (Intercept)                 -16.696634  54.165717 -0.308251 7.5861e-01
## cycle                         0.009805   0.026949  0.363813 7.1686e-01
## `seattle*cycle`               0.003645   0.079923  0.045607 9.6373e-01
## `seattle*post`                3.471152   0.942289  3.683745 3.9410e-04 ***
## At_Large                     -0.622814   0.532903 -1.168718 2.4564e-01
## Special                       2.263234   0.705515  3.207917 1.8588e-03 **
## as.factor(city)Long Beach     0.399402   0.453965  0.879808 3.8133e-01
## as.factor(city)Los Angeles    0.725977   0.510028  1.423405 1.5811e-01
## as.factor(city)Oakland        0.649710   0.482584  1.346316 1.8162e-01
## as.factor(city)Sacramento    -0.371266   0.459199 -0.808509 4.2095e-01
## as.factor(city)San Diego      1.430143   0.523890  2.729852 7.6370e-03 **
## as.factor(city)San Francisco  2.321297   0.748241  3.102337 2.5728e-03 **
## as.factor(city)San Jose       0.586129   0.429198  1.365639 1.7549e-01
## as.factor(city)Seattle       -6.007003 160.509657 -0.037425 9.7023e-01
## At_Large:Special             -3.903134   0.766237 -5.093899 1.9486e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 2.72111   Adj. R2: 0.118186
```

Question 2

```
# First we have to refine the models as the appropriate type of object because r is kinda stupid
diff_in_diff_plm = election_df %>% plm(candidates_ballot ~ post*treatment + At_Large*Special,.)
```

Part b)

```
## Warning in pdata.frame(data, index): duplicate couples (id-time) in resulting pdata.frame
##  to find out which, use, e.g., table(index(your_pdataframe), useNA = "ifany")
```

```
two_way_plm = election_df %>% feols(candidates_ballot ~ post*treatment + as.factor(city) + as.factor(cy
```

```
## The variables 'as.factor(city)Seattle' and 'as.factor(cycle)2019' have been removed because of colli
```

```
# Test with phtest from plm
plm::phtest(diff_in_diff_plm, two_way_plm)
```

```
##
##  Hausman Test
##
## data:  candidates_ballot ~ post * treatment + At_Large * Special
## chisq = 5.5693, df = 5, p-value = 0.3504
## alternative hypothesis: one model is inconsistent
```

Part c)

Question 3

```
# Collapse by city_cycle
balanced_df = election_df |>
  mutate(cycle = factor(election_df$cycle, labels = 1:10), # Renumber cycles 1 through 10
         city_cycle = as.factor(city):as.factor(cycle)) |> # Remake this variable using new numbering
  group_by(city_cycle) |>
  summarise(candidates_ballot = mean(candidates_ballot, na.rm = T),
            post = mean(post, na.rm = T),
            treatment = mean(treatment, na.rm = T),
            At_Large = mean(At_Large, na.rm = T),
            Special = mean(Special, na.rm = T),
            seattle = mean(seattle, na.rm = T),
            Pct_general = mean(Pct_general, na.rm = T),
            inc_run = mean(inc_run, na.rm = T),
            inc_win = mean(inc_win, na.rm = T),
            inc_pct_general = mean(inc_pct_general, na.rm = T),
            Votes_total_general = mean(Votes_total_general, na.rm = T),
            donors = mean(donors, na.rm = T),
            total_Less200 = mean(total_Less200, na.rm = T),
            donors_Less200  = mean(donors_Less200, na.rm = T),
            pop = mean(pop, na.rm = T),
            pop100k = mean(pop100k, na.rm = T),
            state = unique(state)) |>
  mutate(city = stringr::word(city_cycle, sep = ":"),
         cycle = as.numeric(stringr::word(city_cycle, start = -1, sep = ":")))
```

```r
(balanced_dd = balanced_df %>% lm_robust(candidates_ballot ~ post*treatment + At_Large*Special,., clust
```

a)

```
##                    Estimate Std. Error   t value     Pr(>|t|)     CI Lower
## (Intercept)       3.3401293  0.1480135 22.566386 2.056905e-37  3.045788596
## post              0.4599459  0.2317381  1.984766 5.384058e-02 -0.007956569
## treatment         1.3007818  0.3151338  4.127713 1.558274e-03  0.610131373
## At_Large         -1.1388473  0.2237478 -5.089871 4.992818e-05 -1.604442178
## Special           2.7139952  1.2718688  2.133864 4.412227e-02  0.077957966
## post:treatment    3.1471380  0.5398269  5.829902 3.463689e-02  0.598376846
## At_Large:Special -3.8642866  1.6287793 -2.372505 2.829334e-02 -7.271621670
##                    CI Upper        DF
## (Intercept)       3.6344700 84.006723
## post              0.9278485 41.296486
## treatment         1.9914322 11.399532
## At_Large         -0.6732524 20.790281
## Special           5.3500325 22.241167
## post:treatment    5.6958992  1.825647
## At_Large:Special -0.4569515 19.144368
```

```r
(balanced_two = balanced_df %>% feols(candidates_ballot ~ post*treatment | as.factor(city) + as.factor(
```

b)

```
## The variable 'post' has been removed because of collinearity (see $collin.var).

## OLS estimation, Dep. Var.: candidates_ballot
## Observations: 150
## Fixed-effects: as.factor(city): 15,  as.factor(cycle): 10,  At_Large: 5,  Special: 11,  At_Large:Spe
## Standard-errors: Clustered (city_cycle)
##                 Estimate   Std. Error   t value   Pr(>|t|)
## treatment      -1.61004 14096.048234 -0.000114 9.9991e-01
## post:treatment  3.58461     0.390617  9.176783 3.4324e-16 ***
## ... 1 variable was removed because of collinearity (post)
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 0.857167     Adj. R2: 0.503075
##                  Within R2: 0.085821
```

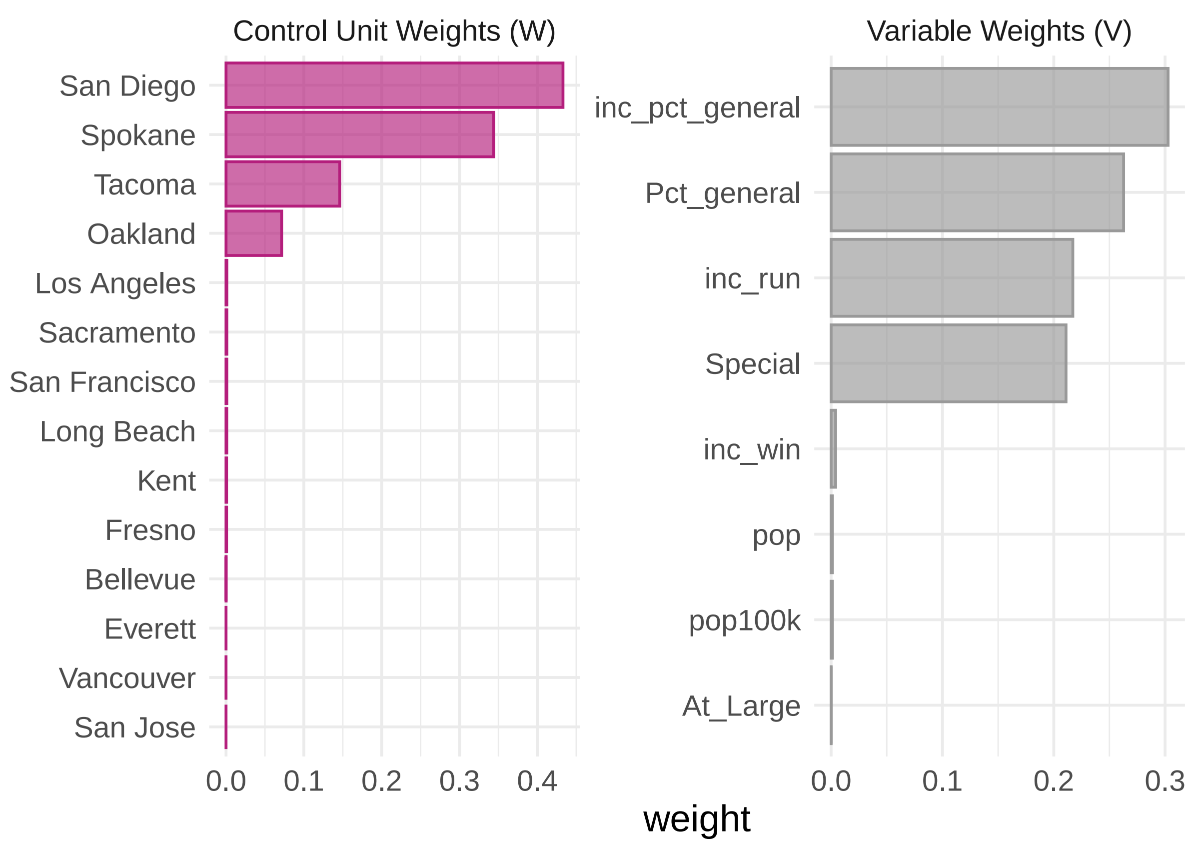
```r
# Generate synthetic object
all_synth = balanced_df |>
  synthetic_control(outcome = candidates_ballot,
                    unit = city,
                    time = cycle,
```

```
                   i_unit = 'Seattle',
                   i_time = 8) |>
  # I can only use these predictors because for pretty much all other values there are some city/cycles

  generate_predictor(At_Large = At_Large,
                    Special = Special,
                    Pct_general = Pct_general,
                    inc_run = inc_run,
                    inc_win = inc_win,
                    inc_pct_general = inc_pct_general,
                    pop = pop,
                    pop100k = pop100k) |>

  generate_weights() |>
  generate_control()
```

```
plot_weights(all_synth)
```



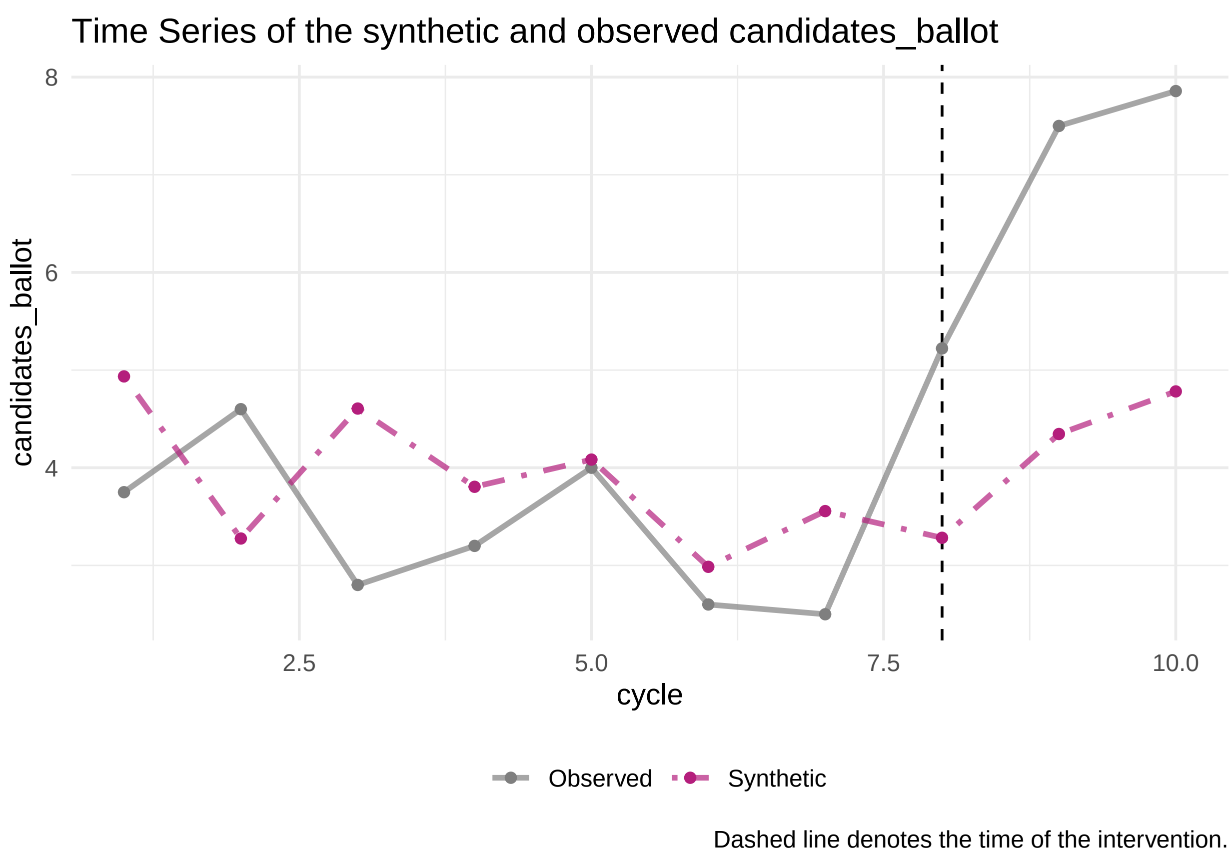
c)

```
grab_unit_weights(all_synth) |> arrange(desc(weight))
```

```
## # A tibble: 14 x 2
##    unit                weight
##    <chr>                <dbl>
```

```
##   1 San Diego     0.433
##   2 Spokane       0.344
##   3 Tacoma        0.146
##   4 Oakland       0.0715
##   5 Los Angeles   0.00103
##   6 Sacramento    0.00102
##   7 San Francisco 0.00101
##   8 Long Beach    0.000939
##   9 Kent          0.000676
##  10 Fresno        0.000675
##  11 Bellevue      0.000157
##  12 Everett       0.00000312
##  13 Vancouver     0.00000145
##  14 San Jose      0.0000000318
```

```
plot_trends(all_synth)
```



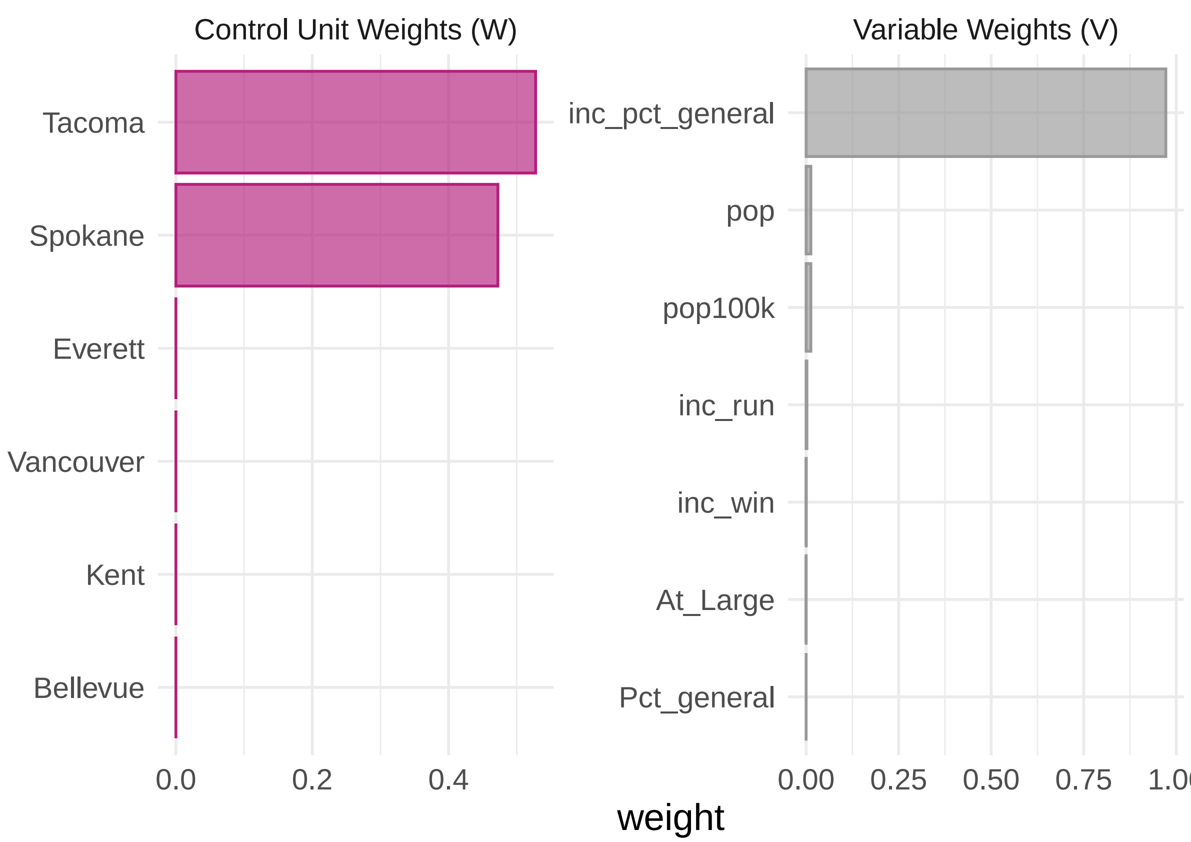

```
# Generate synthetic control for only cities in washington
washington_synth = balanced_df |> filter(state == 'Wash') |>
  synthetic_control(outcome = candidates_ballot,
                    unit = city,
                    time = cycle,
```

```r
                    i_unit = 'Seattle',
                    i_time = 8) |>

  generate_predictor(At_Large = At_Large, # I had to remove special because there's no variation in it
                     Pct_general = Pct_general,
                     inc_run = inc_run,
                     inc_win = inc_win,
                     inc_pct_general = inc_pct_general,
                     pop = pop,
                     pop100k = pop100k) |>

  generate_weights() |>
  generate_control()
```

```r
plot_weights(washington_synth)
```



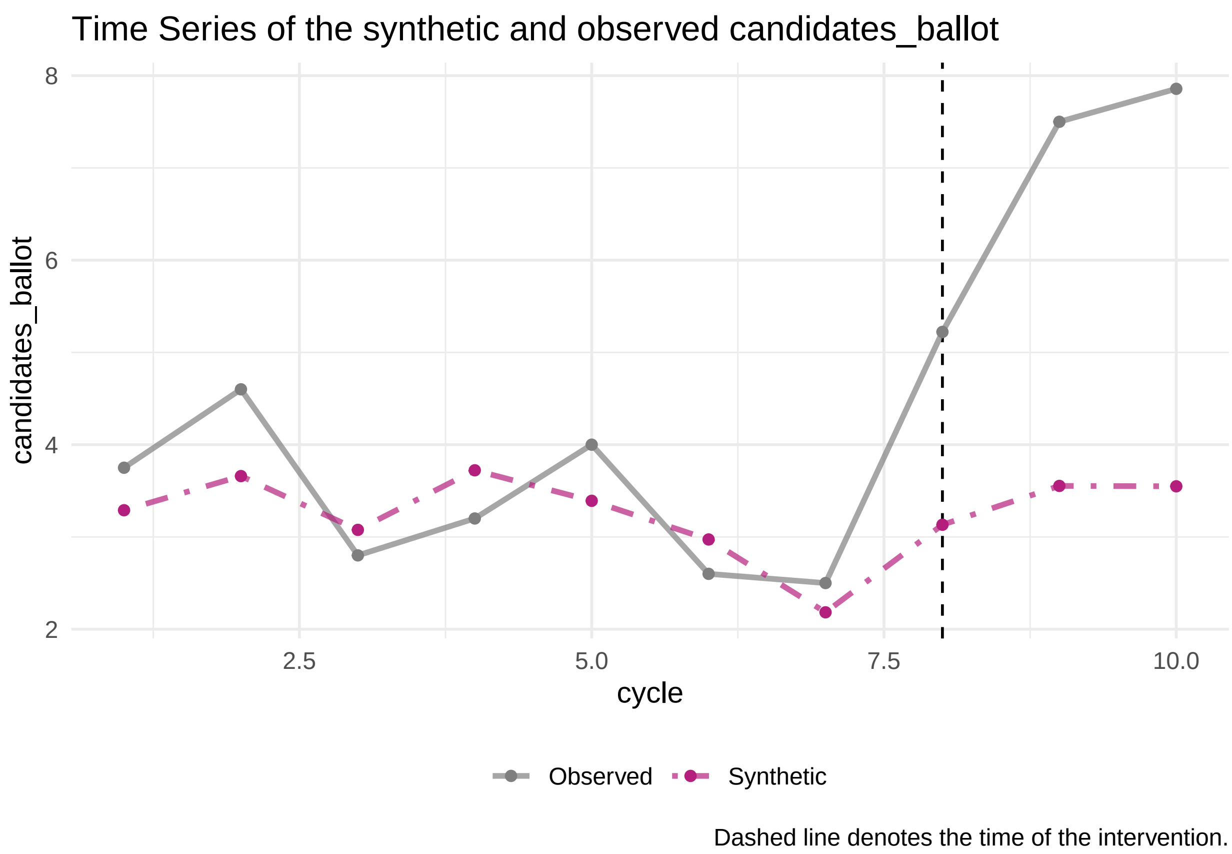
d)

```r
grab_unit_weights(washington_synth) |> arrange(desc(weight))
```

```
## # A tibble: 6 x 2
##   unit          weight
##   <chr>          <dbl>
## 1 Tacoma     0.528
## 2 Spokane    0.472
```

```
## 3 Everett   0.00000800
## 4 Vancouver 0.00000600
## 5 Kent      0.00000440
## 6 Bellevue  0.000000326
```

```
plot_trends(washington_synth)
```

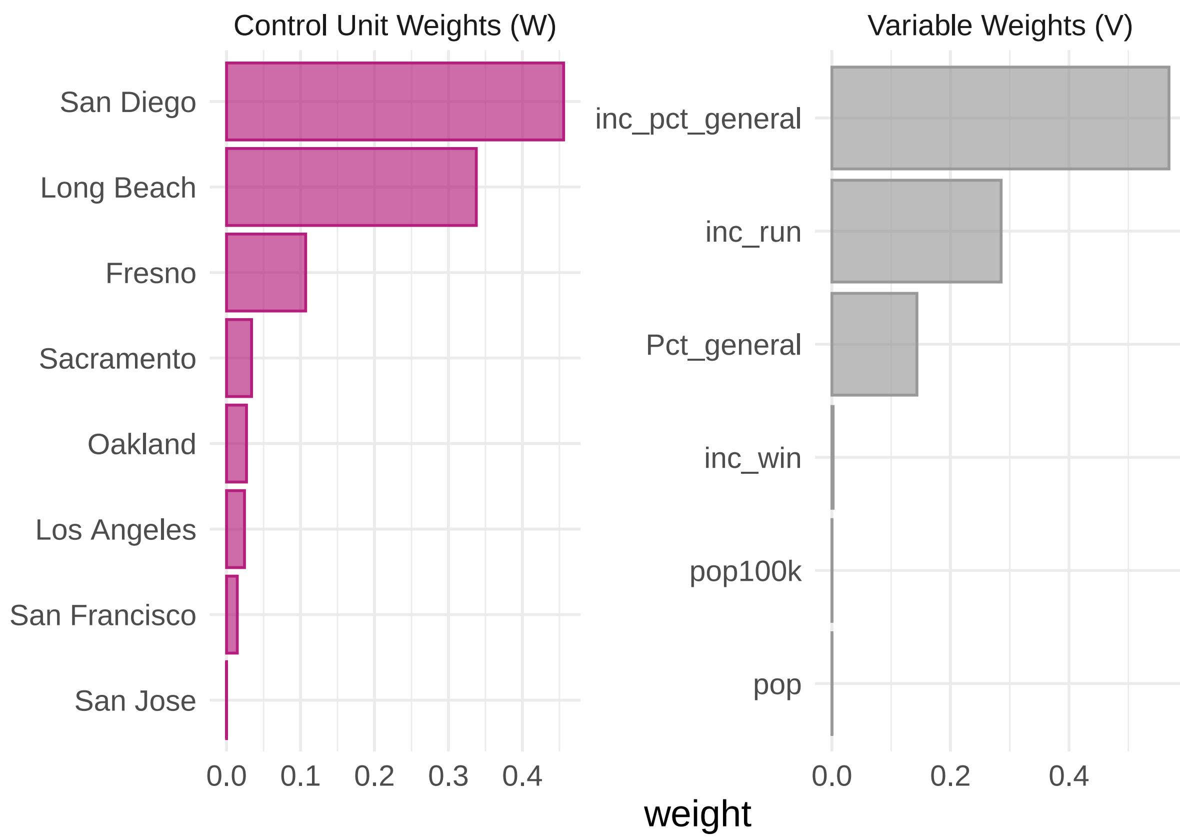



```
# Generate synthetic control for only cities in washington
california_synth = balanced_df |> filter(state == 'Calif' | city == 'Seattle') |>
  synthetic_control(outcome = candidates_ballot,
                    unit = city,
                    time = cycle,
                    i_unit = 'Seattle',
                    i_time = 8) |>

  generate_predictor(Pct_general = Pct_general,
                     inc_run = inc_run,
                     inc_win = inc_win,
                     inc_pct_general = inc_pct_general,
                     pop = pop,
                     pop100k = pop100k) |>
```

```
  generate_weights() |>
  generate_control()
```

```
plot_weights(california_synth)
```

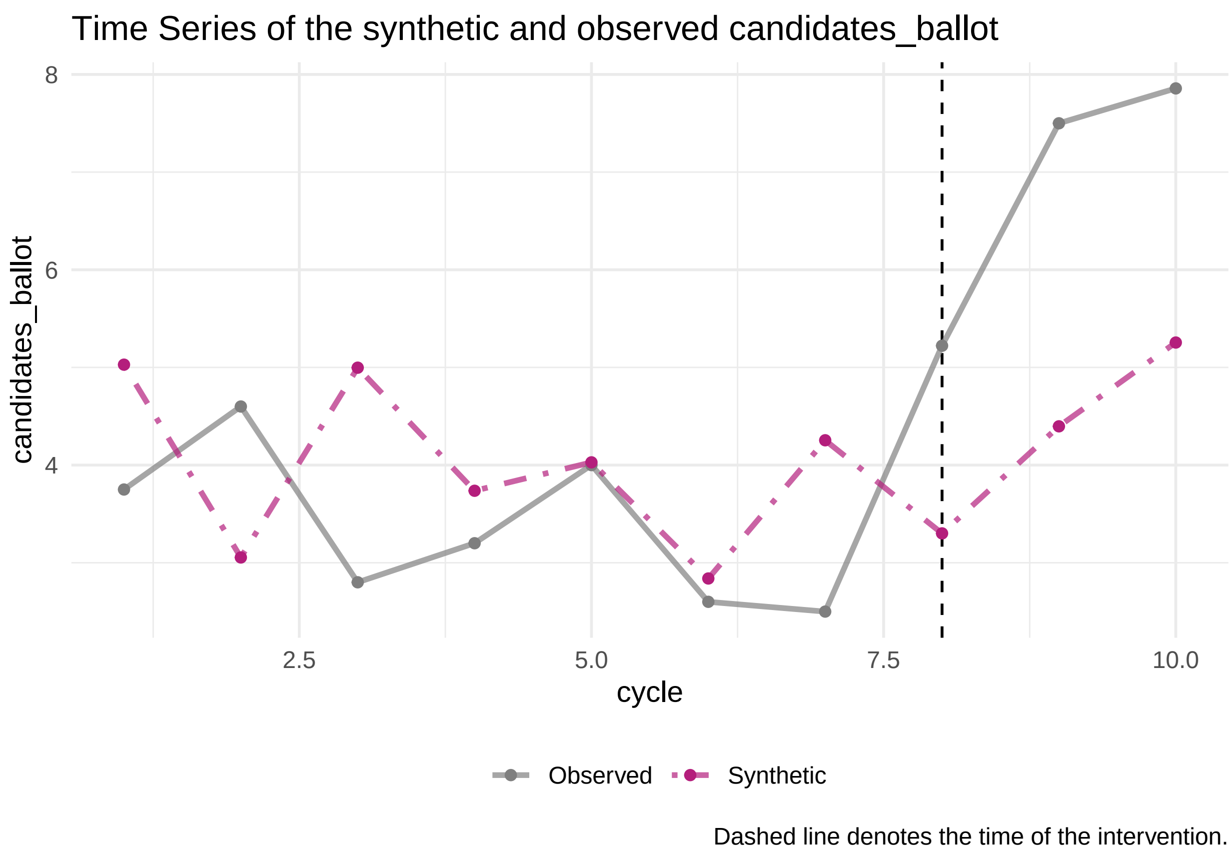


e)

```
grab_unit_weights(california_synth) |> arrange(desc(weight))
```

```
## # A tibble: 8 x 2
##   unit               weight
##   <chr>               <dbl>
## 1 San Diego     0.456
## 2 Long Beach    0.338
## 3 Fresno        0.107
## 4 Sacramento    0.0338
## 5 Oakland       0.0270
## 6 Los Angeles   0.0243
## 7 San Francisco 0.0145
## 8 San Jose      0.0000237
```

```
plot_trends(california_synth)
```

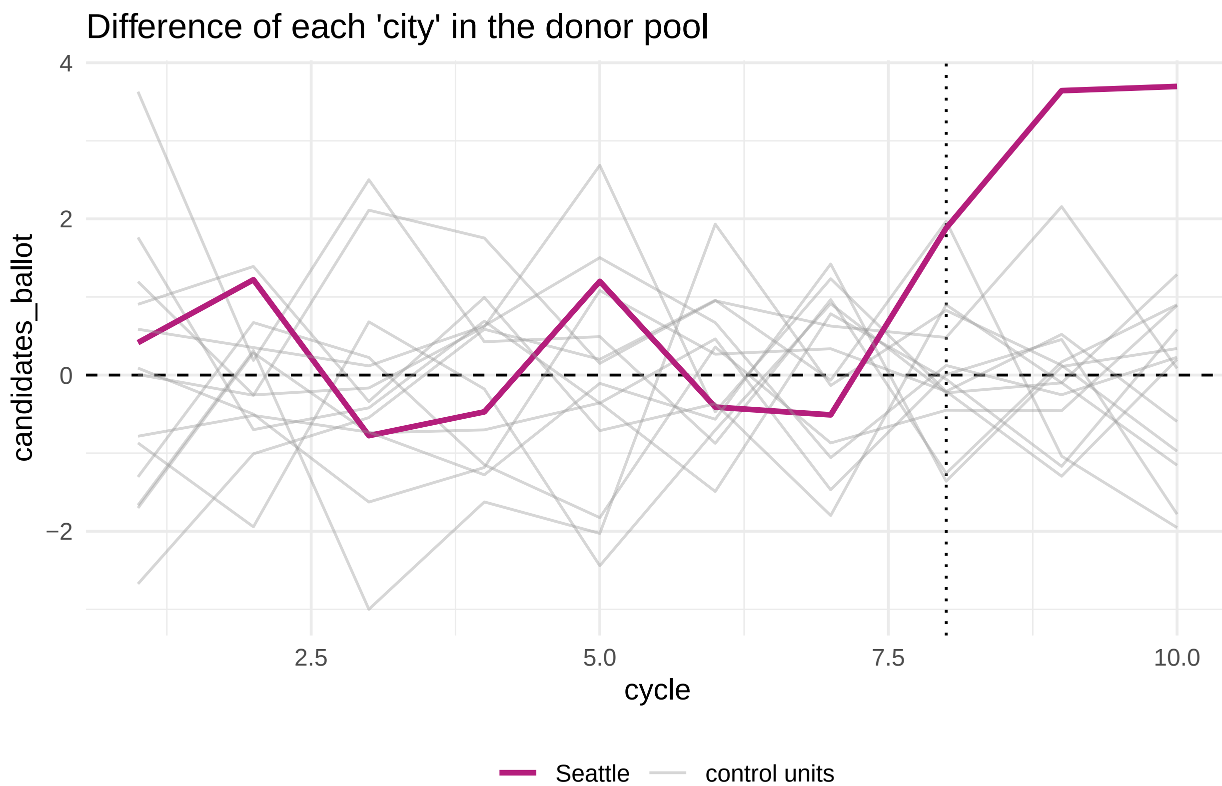



```r
# Different approach first because its built into the package. This generates placebos and plots them
placebos_synth = balanced_df |>
  synthetic_control(outcome = candidates_ballot,
                    unit = city,
                    time = cycle,
                    i_unit = 'Seattle',
                    i_time = 8,
                    generate_placebos = T) |>

  generate_predictor(At_Large = At_Large,
                     Pct_general = Pct_general,
                     inc_run = inc_run,
                     inc_win = inc_win,
                     inc_pct_general = inc_pct_general,
                     pop = pop,
                     pop100k = pop100k) |>

  generate_weights() |>
  generate_control()
```

```r
# Plot placebo trends vs seattle trend
plot_placebos(placebos_synth)
```



f) Pruned all placebo cases with a pre−period RMSPE exceeding two times the treated unit's pre−period RMSPE.

```
# Drop seattle and generate weights for each different city as a placebo
noseattle_df = balanced_df |> filter(city != 'Seattle')

placebo_weights = lapply(unique(noseattle_df$city),
                         function(x) {
                           synthetic_control(
                             noseattle_df,
                             outcome = candidates_ballot,
                             unit = city,
                             time = cycle,
                             i_unit = x,
                             i_time = 8
                           ) |>
                             generate_predictor(
                               At_Large = At_Large,
                               Pct_general = Pct_general,
                               inc_run = inc_run,
                               inc_win = inc_win,
                               inc_pct_general = inc_pct_general,
                               pop = pop,
                               pop100k = pop100k
                             ) |>
                             generate_weights() |>
                             generate_control()
```

```
                          }
)
```

```
lapply(1:length(placebo_weights), function(i){
  placebo_weights = placebo_weights[[i]]
  plot_weights(placebo_weights)
  grab_unit_weights(placebo_weights)
})
```

```
## [[1]]
## # A tibble: 13 x 2
##    unit                 weight
##    <chr>                 <dbl>
##  1 Everett       0.927
##  2 Fresno        0.00000112
##  3 Kent          0.000000324
##  4 Long Beach    0.00000590
##  5 Los Angeles   0.00000524
##  6 Oakland       0.00000262
##  7 Sacramento    0.00000220
##  8 San Diego     0.000000892
##  9 San Francisco 0.00000239
## 10 San Jose      0.0000000213
## 11 Spokane       0.000113
## 12 Tacoma        0.00000417
## 13 Vancouver     0.0731
##
## [[2]]
## # A tibble: 13 x 2
##    unit               weight
##    <chr>               <dbl>
##  1 Bellevue      0.995
##  2 Fresno        0.0000754
##  3 Kent          0.00202
##  4 Long Beach    0.00000532
##  5 Los Angeles   0.0000243
##  6 Oakland       0.00154
##  7 Sacramento    0.00112
##  8 San Diego     0.00000757
##  9 San Francisco 0.00000834
## 10 San Jose      0.00000369
## 11 Spokane       0.00000488
## 12 Tacoma        0.0000143
## 13 Vancouver     0.00000566
##
## [[3]]
## # A tibble: 13 x 2
##    unit                weight
##    <chr>                <dbl>
##  1 Bellevue      0.00000222
##  2 Everett       0.00000110
##  3 Kent          0.684
##  4 Long Beach    0.00000148
```

```
##  5 Los Angeles   0.0739
##  6 Oakland       0.000000465
##  7 Sacramento    0.000000449
##  8 San Diego     0.00000318
##  9 San Francisco 0.00000225
## 10 San Jose      0.0447
## 11 Spokane       0.00000228
## 12 Tacoma        0.00000353
## 13 Vancouver     0.197
##
## [[4]]
## # A tibble: 13 x 2
##    unit                 weight
##    <chr>                 <dbl>
##  1 Bellevue      0.00000246
##  2 Everett       0.0100
##  3 Fresno        0.139
##  4 Long Beach    0.000000377
##  5 Los Angeles   0.00000000292
##  6 Oakland       0.0000000319
##  7 Sacramento    0.851
##  8 San Diego     0.0000000986
##  9 San Francisco 0.000000187
## 10 San Jose      0.000000172
## 11 Spokane       0.000000834
## 12 Tacoma        0.0000597
## 13 Vancouver     0.00000342
##
## [[5]]
## # A tibble: 13 x 2
##    unit                 weight
##    <chr>                 <dbl>
##  1 Bellevue      0.00000586
##  2 Everett       0.00000466
##  3 Fresno        0.00000352
##  4 Kent          0.00000249
##  5 Los Angeles   0.0112
##  6 Oakland       0.0000334
##  7 Sacramento    0.00000659
##  8 San Diego     0.0000698
##  9 San Francisco 0.100
## 10 San Jose      0.0420
## 11 Spokane       0.847
## 12 Tacoma        0.00000634
## 13 Vancouver     0.00000000616
##
## [[6]]
## # A tibble: 13 x 2
##    unit            weight
##    <chr>            <dbl>
##  1 Bellevue      6.31e- 9
##  2 Everett       5.66e- 9
##  3 Fresno        2.67e- 8
##  4 Kent          8.09e- 9
```

```
##  5 Long Beach    1.18e-10
##  6 Oakland       2.90e- 8
##  7 Sacramento    1.38e- 7
##  8 San Diego     1.00e+ 0
##  9 San Francisco 2.37e-10
## 10 San Jose      1.09e-11
## 11 Spokane       2.23e-10
## 12 Tacoma        6.00e-10
## 13 Vancouver     1.99e-10
##
## [[7]]
## # A tibble: 13 x 2
##    unit                weight
##    <chr>                <dbl>
##  1 Bellevue      0.000000457
##  2 Everett       0.478
##  3 Fresno        0.00000697
##  4 Kent          0.00000971
##  5 Long Beach    0.487
##  6 Los Angeles   0.0290
##  7 Sacramento    0.00598
##  8 San Diego     0.000330
##  9 San Francisco 0.0000671
## 10 San Jose      0.0000123
## 11 Spokane       0.0000000199
## 12 Tacoma        0.0000170
## 13 Vancouver     0.00000901
##
## [[8]]
## # A tibble: 13 x 2
##    unit                weight
##    <chr>                <dbl>
##  1 Bellevue      0.0000000982
##  2 Everett       0.0000000247
##  3 Fresno        0.0000178
##  4 Kent          0.732
##  5 Long Beach    0.0000361
##  6 Los Angeles   0.0808
##  7 Oakland       0.187
##  8 San Diego     0.0000385
##  9 San Francisco 0.0000362
## 10 San Jose      0.0000189
## 11 Spokane       0.00000904
## 12 Tacoma        0.0000300
## 13 Vancouver     0.0000204
##
## [[9]]
## # A tibble: 13 x 2
##    unit                 weight
##    <chr>                 <dbl>
##  1 Bellevue      0.000000141
##  2 Everett       0.380
##  3 Fresno        0.000000577
##  4 Kent          0.000000448
```

```
##  5 Long Beach    0.00000000214
##  6 Los Angeles   0.00000483
##  7 Oakland       0.00000000855
##  8 Sacramento    0.000000480
##  9 San Francisco 0.620
## 10 San Jose      0.00000167
## 11 Spokane       0.000000156
## 12 Tacoma        0.000000567
## 13 Vancouver     0.000000500
##
## [[10]]
## # A tibble: 13 x 2
##    unit          weight
##    <chr>          <dbl>
##  1 Bellevue    0.000766
##  2 Everett     0.000371
##  3 Fresno      0.000636
##  4 Kent        0.000582
##  5 Long Beach  0.111
##  6 Los Angeles 0.0200
##  7 Oakland     0.253
##  8 Sacramento  0.000793
##  9 San Diego   0.00213
## 10 San Jose    0.606
## 11 Spokane     0.00228
## 12 Tacoma      0.000979
## 13 Vancouver   0.000901
##
## [[11]]
## # A tibble: 13 x 2
##    unit               weight
##    <chr>               <dbl>
##  1 Bellevue      0.000000987
##  2 Everett       0.000000657
##  3 Fresno        0.00000153
##  4 Kent          0.000000514
##  5 Long Beach    0.0000735
##  6 Los Angeles   0.0426
##  7 Oakland       0.000000169
##  8 Sacramento    0.000000442
##  9 San Diego     0.000965
## 10 San Francisco 0.954
## 11 Spokane       0.00000600
## 12 Tacoma        0.00000304
## 13 Vancouver     0.00201
##
## [[12]]
## # A tibble: 13 x 2
##    unit               weight
##    <chr>               <dbl>
##  1 Bellevue      0.152
##  2 Everett       0.0000108
##  3 Fresno        0.000000859
##  4 Kent          0.000000197
```

```
##  5 Long Beach    0.660
##  6 Los Angeles   0.00000120
##  7 Oakland       0.000000461
##  8 Sacramento    0.000000535
##  9 San Diego     0.0000185
## 10 San Francisco 0.0000142
## 11 San Jose      0.0263
## 12 Tacoma        0.00000221
## 13 Vancouver     0.161
##
## [[13]]
## # A tibble: 13 x 2
##    unit            weight
##    <chr>            <dbl>
##  1 Bellevue      0.000919
##  2 Everett       0.000854
##  3 Fresno        0.00141
##  4 Kent          0.347
##  5 Long Beach    0.416
##  6 Los Angeles   0.000424
##  7 Oakland       0.00253
##  8 Sacramento    0.00142
##  9 San Diego     0.00201
## 10 San Francisco 0.00273
## 11 San Jose      0.000110
## 12 Spokane       0.00195
## 13 Vancouver     0.222
##
## [[14]]
## # A tibble: 13 x 2
##    unit                 weight
##    <chr>                 <dbl>
##  1 Bellevue      0.0000000688
##  2 Everett       0.0000000547
##  3 Fresno        0.000000153
##  4 Kent          0.000000115
##  5 Long Beach    0.0612
##  6 Los Angeles   0.0000000400
##  7 Oakland       0.0000000612
##  8 Sacramento    0.0000000814
##  9 San Diego     0.000000121
## 10 San Francisco 0.000000157
## 11 San Jose      0.00000387
## 12 Spokane       0.939
## 13 Tacoma        0.000000250
```