

its_synthetic

Bogdan Vasilescu

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Load the smoking data.

```
data(smoking)
head(smoking)
```

```
## # A tibble: 6 x 7
##   state      year cigsale lnincome  beer age15to24 retprice
##   <chr>      <dbl>   <dbl>   <dbl> <dbl>   <dbl>   <dbl>
## 1 Rhode Island 1970    124.     NA    NA     0.183    39.3
## 2 Tennessee    1970    99.8     NA    NA     0.178    39.9
## 3 Indiana      1970   135.     NA    NA     0.177    30.6
## 4 Nevada       1970   190.     NA    NA     0.162    38.9
## 5 Louisiana    1970   116.     NA    NA     0.185    34.3
## 6 Oklahoma     1970   108.     NA    NA     0.175    38.4
```

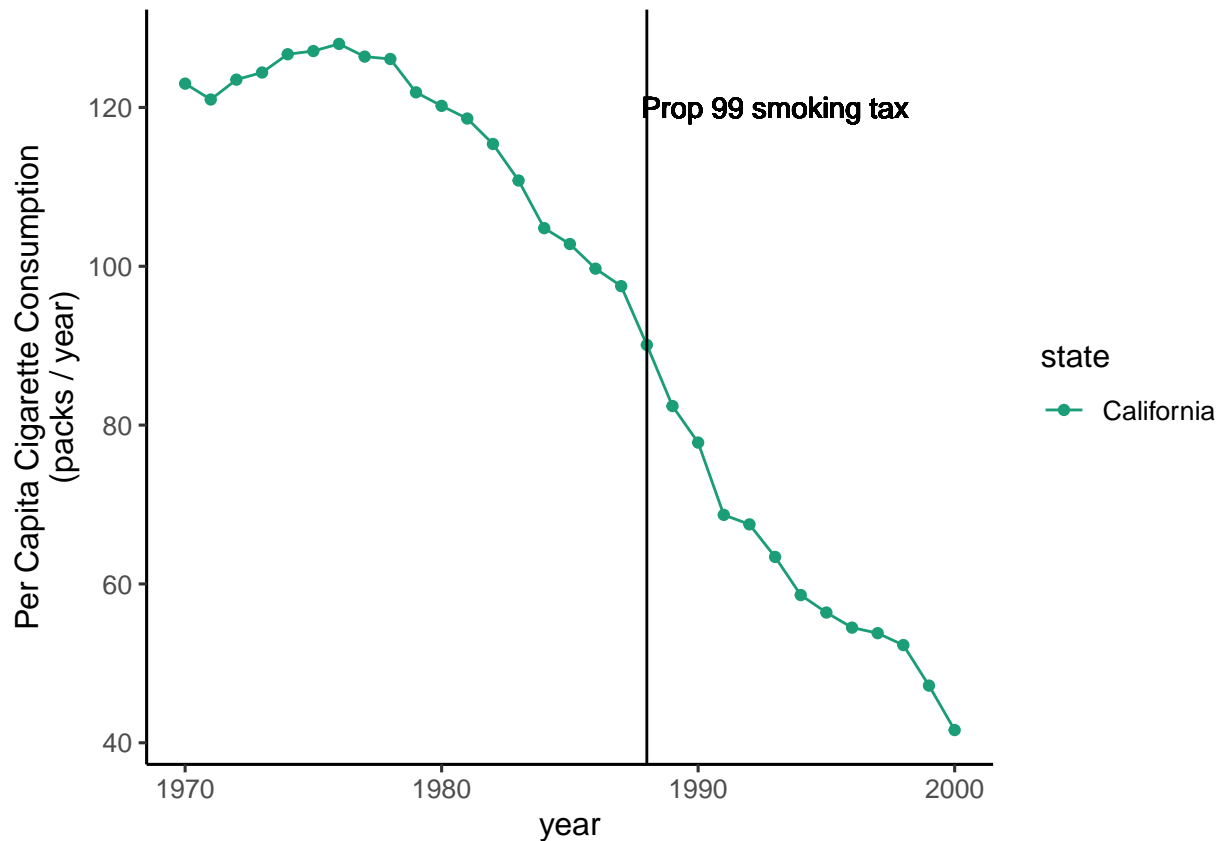
As part of the method's assumptions and requirements, it is important to exclude from the donor pool (this is how the collection of control units is traditionally called) any unit that may not be a true control - i.e. any unit that has implemented a similar intervention. In our case, some states also introduced anti-smoking programs or substantially increased the tax for cigarettes. These have already been excluded:

```
length(unique(smoking$state))
```

```
## [1] 39
```

The trend in California

```
ggplot(data = subset(smoking, state == "California"),
       aes(x = year,
           y = cigsale,
           color = state,
           group = state)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 1988) +
  labs(y = "Per Capita Cigarette Consumption\n(packs / year)") +
  geom_text(aes(x=1993,
                label="Prop 99 smoking tax",
                y=120),
            # angle=90,
            color="black") +
  scale_color_brewer(palette = 'Dark2') +
  theme_classic(base_size = 12)
```



Adding the average of the other 38 states as a control

```
library(data.table)

## Warning: package 'data.table' was built under R version 4.4.1
##
## Attaching package: 'data.table'
## The following objects are masked from 'package:dplyr':
##
##   between, first, last

smoking.s <- as.data.table(
  smoking[smoking$state != "California", c("state", "year", "cigsale")]

smoking.control <- smoking.s[,
  lapply(.SD,
    mean,
    na.rm=TRUE),
  by=year,
  .SDcols=c("cigsale")]

smoking.control[,
  state := rep("Rest of US", nrow(smoking.control))]

smoking.control <- rbind(
```

```

smoking.control,
as.data.table(smoking[smoking$state == "California", c("state", "year", "cigsale")])
)

smoking.control[, "]="(
  treated = year >= 1988,
  years_after_intervention = ifelse(year < 1988, 0, year - 1988),
  year0 = year - 1988
)]

smoking.control$state <- factor(smoking.control$state,
                               levels = c("Rest of US", "California"))

smoking.means <- smoking.control[,
  lapply(.SD,
    mean,
    na.rm=TRUE),
  by=c("state", "treated"),
  .SDcols=c("cigsale")]
smoking.means

```

```

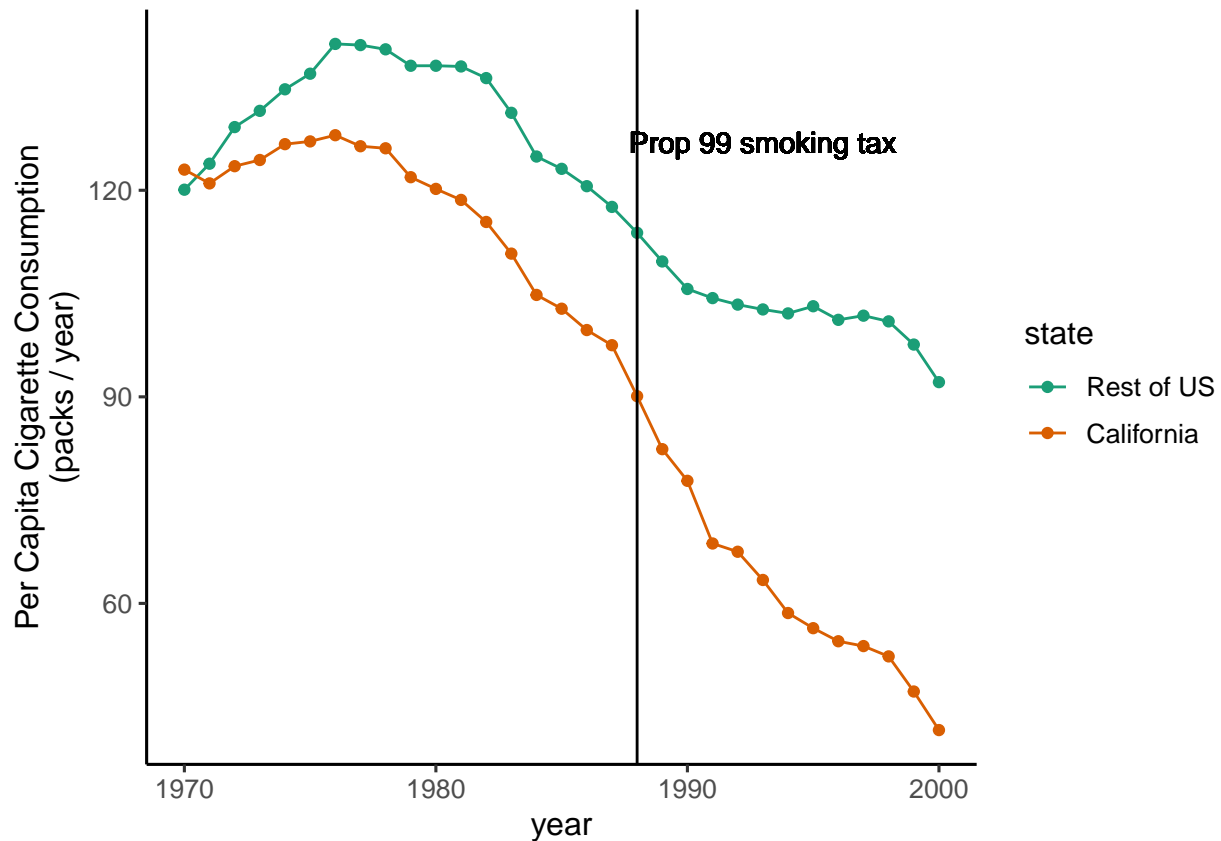
##      state treated  cigsale
##      <fctr>  <lgcl>    <num>
## 1: Rest of US   FALSE 131.49985
## 2: Rest of US   TRUE  102.96316
## 3: California   FALSE 117.66111
## 4: California   TRUE   62.63846

```

```

ggplot(data = smoking.control,
  aes(x = year,
    y = cigsale,
    color = state,
    group = state)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 1988) +
  labs(y = "Per Capita Cigarette Consumption\n(packs / year)") +
  geom_text(aes(x=1993,
    label="\nProp 99 smoking tax",
    y=130),
    # angle=90,
    color="black") +
  scale_color_brewer(palette = 'Dark2') +
  theme_classic(base_size = 12)

```



Simple DID model

Comparing means before and after, by group.

```
m1 <- lm(cigsale ~ state * treated,
          data = smoking.control)
summary(m1)
```

```
##
## Call:
## lm(formula = cigsale ~ state * treated, data = smoking.control)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.0385  -6.7951   0.5966   6.5620  27.4615
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      131.500      2.309  56.944 < 2e-16 ***
## stateCalifornia    -13.839      3.266  -4.237 8.20e-05 ***
## treatedTRUE       -28.537      3.566  -8.002 6.07e-11 ***
## stateCalifornia:treatedTRUE -26.486      5.043  -5.252 2.24e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.797 on 58 degrees of freedom
## Multiple R-squared:  0.8741, Adjusted R-squared:  0.8676
```

```
## F-statistic: 134.2 on 3 and 58 DF, p-value: < 2.2e-16
```

Add trends

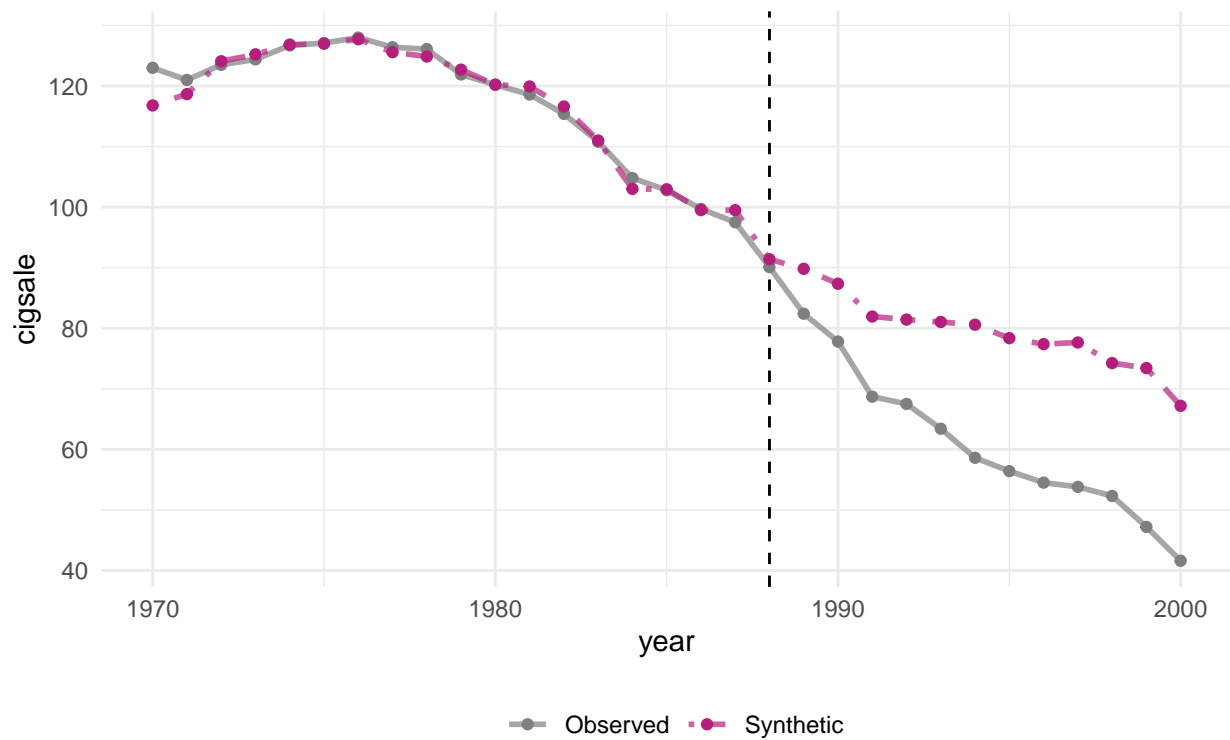
```
m2 <- lm(cigsale ~
  year0
  + treated
  + years_after_intervention
  + state
  + year0:state
  + treated:state
  + years_after_intervention:state
  , data = smoking.control)
summary(m2)

##
## Call:
## lm(formula = cigsale ~ year0 + treated + years_after_intervention +
##     state + year0:state + treated:state + years_after_intervention:state,
##     data = smoking.control)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.1024  -3.9153   0.6397   3.8963   9.1155
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   128.4970     2.7923  46.018 < 2e-16
## year0                        -0.3161     0.2580  -1.225  0.22579
## treatedTRUE                   -18.2506     4.0811  -4.472 4.02e-05
## years_after_intervention      -0.8978     0.4937  -1.819  0.07451
## stateCalifornia               -25.8604     3.9490  -6.549 2.22e-08
## year0:stateCalifornia          -1.2654     0.3648  -3.469  0.00104
## treatedTRUE:stateCalifornia    -0.4278     5.7715  -0.074  0.94119
## years_after_intervention:stateCalifornia -1.0740     0.6981  -1.538  0.12981
##
## (Intercept)                  ***
## year0
## treatedTRUE                  ***
## years_after_intervention      .
## stateCalifornia              ***
## year0:stateCalifornia         **
## treatedTRUE:stateCalifornia
## years_after_intervention:stateCalifornia
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.678 on 54 degrees of freedom
## Multiple R-squared:  0.9606, Adjusted R-squared:  0.9555
## F-statistic: 188.2 on 7 and 54 DF, p-value: < 2.2e-16
```

Synthetic control

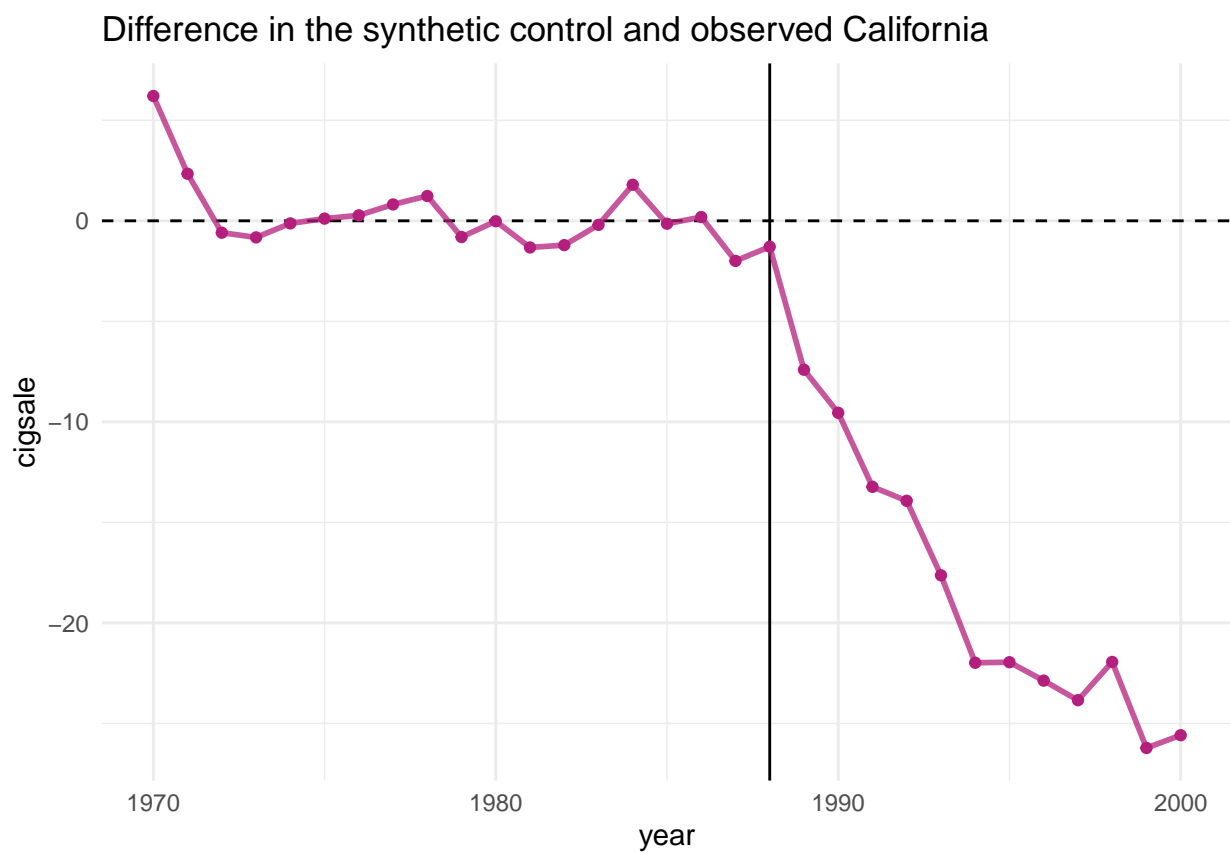
```
smoking_out <-  
  
smoking %>%  
  
# initial the synthetic control object  
synthetic_control(outcome = cigsale, # outcome  
                  unit = state, # unit index in the panel data  
                  time = year, # time index in the panel data  
                  i_unit = "California", # unit where the intervention occurred  
                  i_time = 1988, # time period when the intervention occurred  
                  generate_placebos=T # generate placebo synthetic controls (for inference)  
                  ) %>%  
  
# Generate the aggregate predictors used to fit the weights  
  
# average log income, retail price of cigarettes, and proportion of the  
# population between 15 and 24 years of age from 1980 - 1988  
generate_predictor(time_window = 1980:1988,  
                  ln_income = mean(lnincome, na.rm = T),  
                  ret_price = mean(retprice, na.rm = T),  
                  youth = mean(age15to24, na.rm = T)) %>%  
  
# average beer consumption in the donor pool from 1984 - 1988  
generate_predictor(time_window = 1984:1988,  
                  beer_sales = mean(beer, na.rm = T)) %>%  
  
# Lagged cigarette sales  
generate_predictor(time_window = 1975,  
                  cigsale_1975 = cigsale) %>%  
generate_predictor(time_window = 1980,  
                  cigsale_1980 = cigsale) %>%  
generate_predictor(time_window = 1988,  
                  cigsale_1988 = cigsale) %>%  
  
# Generate the fitted weights for the synthetic control  
generate_weights(optimization_window = 1970:1988, # time to use in the optimization task  
                margin_ipop = .02, sigf_ipop = 7, bound_ipop = 6 # optimizer options  
                ) %>%  
  
# Generate the synthetic control  
generate_control()  
  
plot_trends(smoking_out)
```

Time Series of the synthetic and observed cigsale

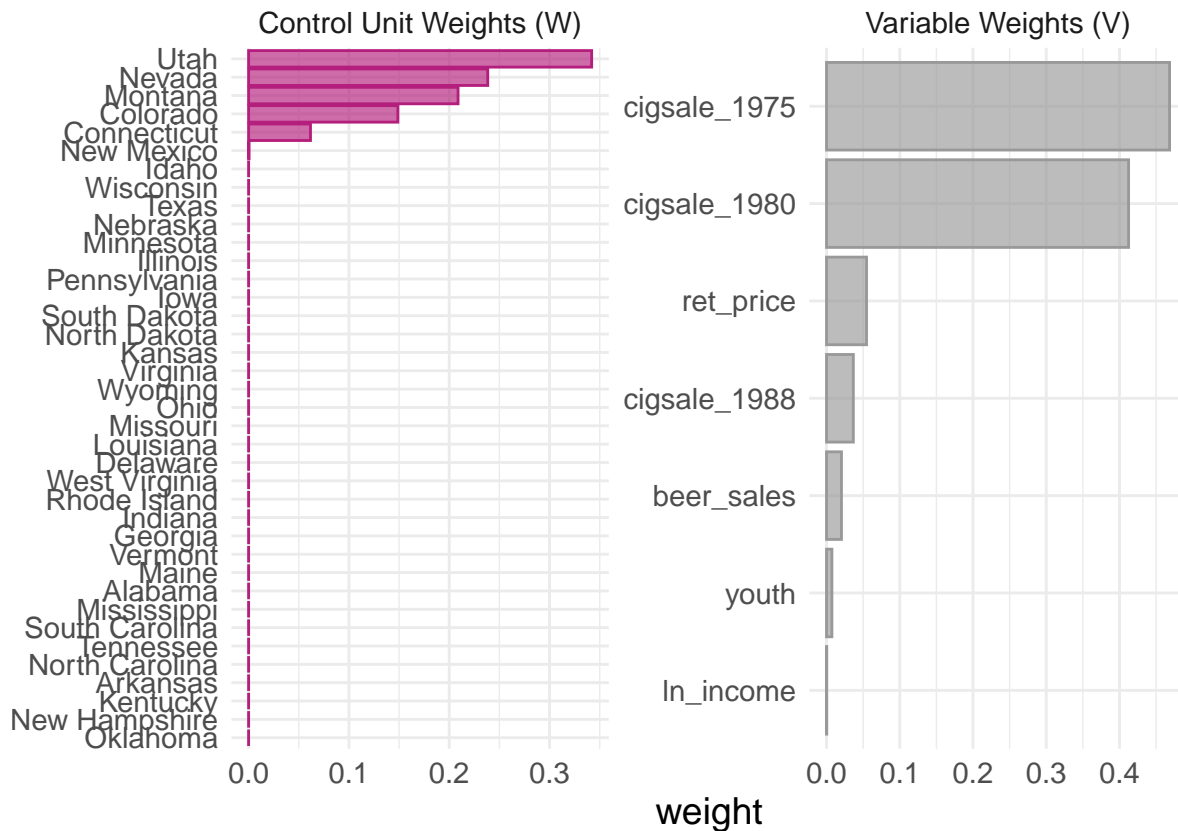


Dashed line denotes the time of the intervention.

```
plot_differences(smoking_out)
```



```
plot_weights(smoking_out)
```

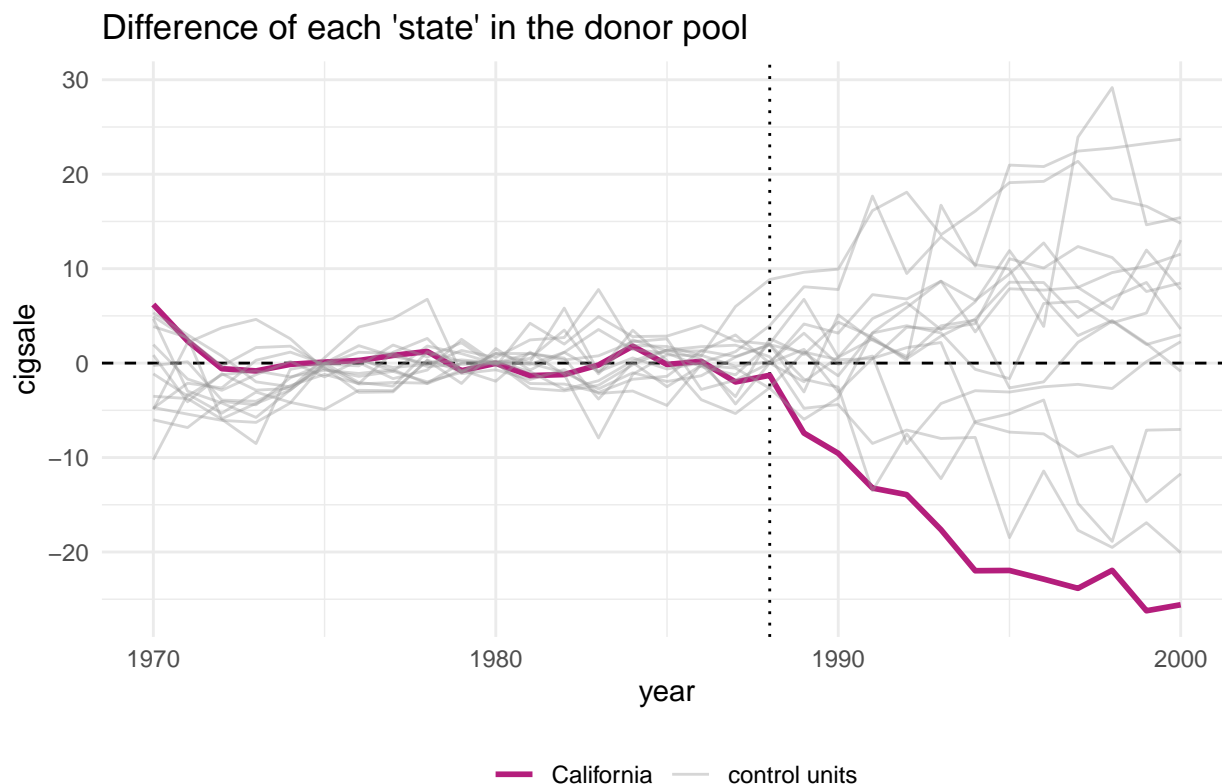



Inference

For inference, the method relies on repeating the method for every donor in the donor pool exactly as was done for the treated unit — i.e. generating placebo synthetic controls). By setting `generate_placebos = TRUE` when initializing the synth pipeline with `synthetic_control()`, placebo cases are automatically generated when constructing the synthetic control of interest. This makes it easy to explore how unique difference between the observed and synthetic unit is when compared to the placebos.

Note that the `plot_placebos()` function automatically prunes any placebos that poorly fit the data in the pre-intervention period. The reason for doing so is purely visual: those units tend to throw off the scale when plotting the placebos. To prune, the function looks at the pre-intervention period mean squared prediction error (MSPE) (i.e. a metric that reflects how well the synthetic control maps to the observed outcome time series in pre-intervention period). If a placebo control has a MSPE that is two times beyond the target case (e.g. “California”), then it’s dropped. To turn off this behavior, set `prune = FALSE`.

```
plot_placebos(smoking_out)
```



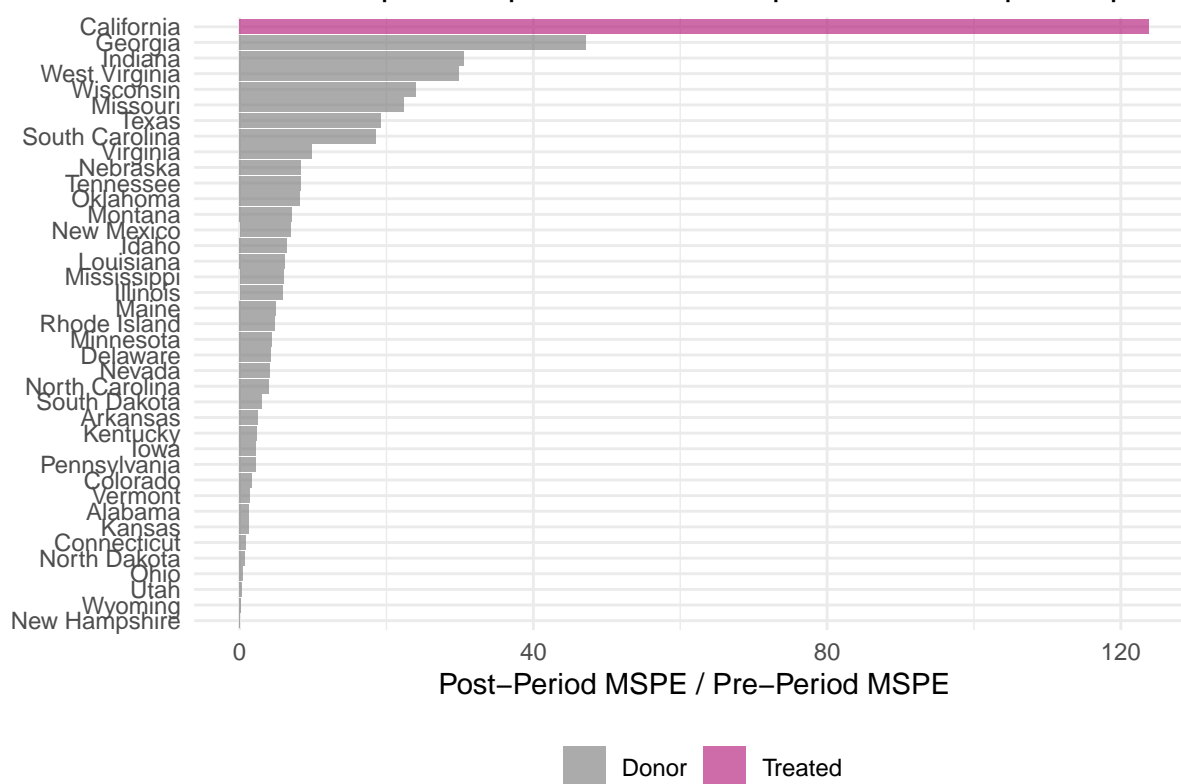
Pruned all placebo cases with a pre-period RMSPE exceeding two times the treated unit's pre-period RMSPE.

Finally, Adabie et al. 2010 outline a way of constructing Fisher's Exact P-values by dividing the post-intervention MSPE by the pre-intervention MSPE and then ranking all the cases by this ratio in descending order. A p-value is then constructed by taking the rank/total.¹ The idea is that if the synthetic control fits the observed time series well (low MSPE in the pre-period) and diverges in the post-period (high MSPE in the post-period) then there is a meaningful effect due to the intervention. If the intervention had no effect, then the post-period and pre-period should continue to map onto one another fairly well, yielding a ratio close to 1. If the placebo units fit the data similarly, then we can't reject the null hypothesis that there is no effect brought about by the intervention.

This ratio can be easily plotted using `plot_mspe_ratio()`, offering insight into the rarity of the case where the intervention actually occurred.

```
plot_mspe_ratio(smoking_out)
```

Ratio of the pre and post intervention period mean squared prediction error



Prep data and rerun ITS model

```
sc <- grab_synthetic_control(smoking_out)

dreal <- sc[c("time_unit", "real_y")]
dreal$state = rep("California", nrow(dreal))
names(dreal) <- c("year", "cigsale", "state")
dsynth <- sc[c("time_unit", "synth_y")]
dsynth$state = rep("Rest of US", nrow(dsynth))
names(dsynth) <- c("year", "cigsale", "state")
ds <- as.data.table(rbind(dreal, dsynth))

ds[, "treated" := (
  treated = year >= 1988,
  years_after_intervention = ifelse(year < 1988, 0, year - 1988),
  year0 = year - 1988
)]

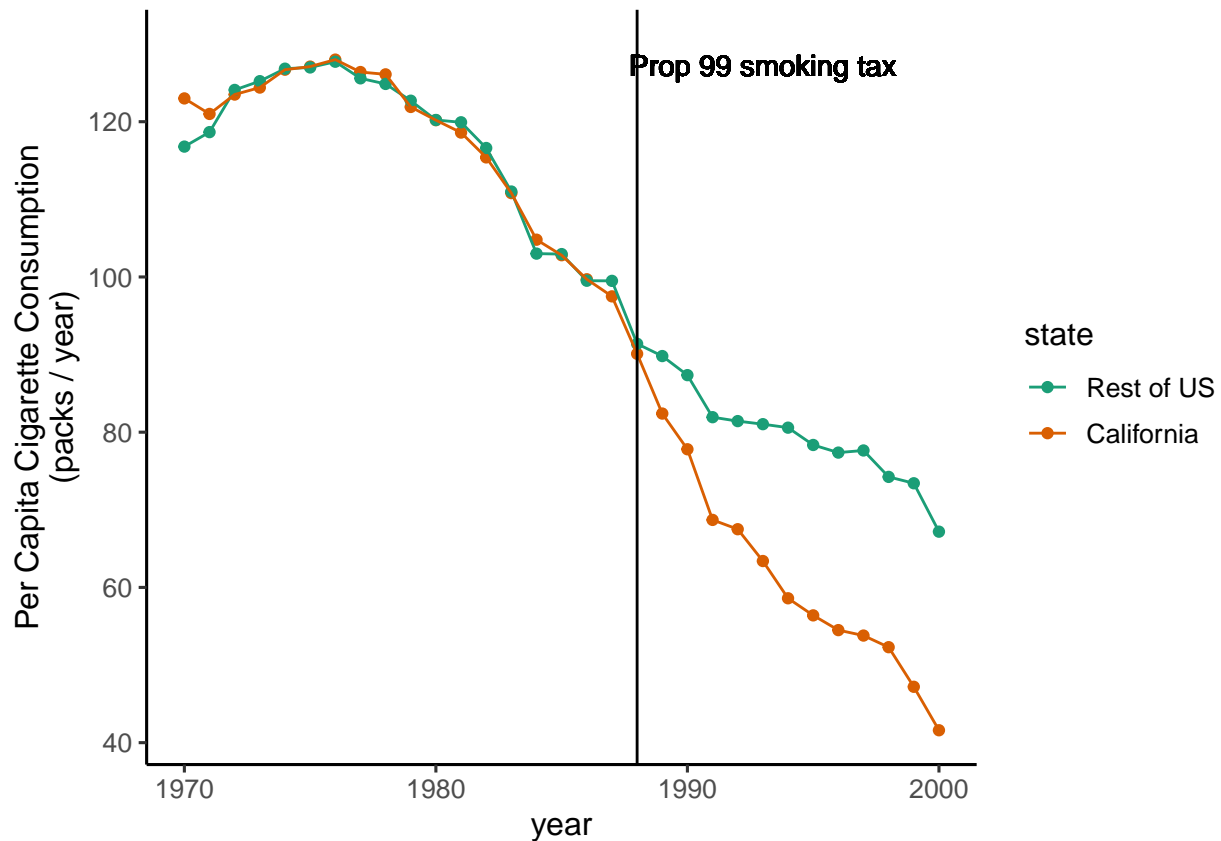
ds$state <- factor(ds$state, levels = c("Rest of US", "California"))

smoking.ds.means <- ds[,
  lapply(.SD,
    mean,
    na.rm=TRUE),
  by=c("state", "treated"),
  .SDcols=c("cigsale")]
```

```
smoking.ds.means
```

```
##      state treated  cigsale
##      <fctr> <lgcl>    <num>
## 1: California  FALSE 117.66111
## 2: California   TRUE  62.63846
## 3: Rest of US   FALSE 117.34447
## 4: Rest of US   TRUE  80.13355
```

```
ggplot(data = ds,
       aes(x = year,
           y = cigsale,
           color = state,
           group = state)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 1988) +
  labs(y = "Per Capita Cigarette Consumption\n(packs / year)") +
  geom_text(aes(x=1993,
                label="\nProp 99 smoking tax",
                y=130),
            # angle=90,
            color="black") +
  scale_color_brewer(palette = 'Dark2') +
  theme_classic(base_size = 12)
```



```
m3 <- lm(cigsale ~
         year0
```

```

+ treated
+ years_after_intervention
+ state
+ year0:state
+ treated:state
+ years_after_intervention:state
, data = ds)
summary(m3)

```

```

##
## Call:
## lm(formula = cigsale ~ year0 + treated + years_after_intervention +
##      state + year0:state + treated:state + years_after_intervention:state,
##      data = ds)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.5947  -3.1379   0.5003   3.8963   7.6481
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    103.8843     2.4807  41.878 < 2e-16
## year0          -1.4169     0.2292  -6.182 8.68e-08
## treatedTRUE    -13.7535     3.6255  -3.794 0.000377
## years_after_intervention -0.2494     0.4386  -0.569 0.572007
## stateCalifornia -1.2477     3.5082  -0.356 0.723487
## year0:stateCalifornia -0.1647     0.3241  -0.508 0.613472
## treatedTRUE:stateCalifornia -4.9249     5.1273  -0.961 0.341069
## years_after_intervention:stateCalifornia -1.7224     0.6202  -2.777 0.007524
##
## (Intercept)          ***
## year0                 ***
## treatedTRUE           ***
## years_after_intervention
## stateCalifornia
## year0:stateCalifornia
## treatedTRUE:stateCalifornia
## years_after_intervention:stateCalifornia **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.044 on 54 degrees of freedom
## Multiple R-squared:  0.966, Adjusted R-squared:  0.9616
## F-statistic: 219.4 on 7 and 54 DF,  p-value: < 2.2e-16

```