Project 7: Difference-in-Differences and Synthetic Control

```r
# Install and load packages
if (!require("pacman")) install.packages("pacman")
```

```
## Loading required package: pacman
```

```r
devtools::install_github("ebenmichael/augsynth")
```

```
## Using GitHub PAT from the git credential store.
```

```
## Skipping install of 'augsynth' from a github remote, the SHA1 (0f4f1bcc) has not changed since last i
##   Use `force = TRUE` to force installation
```

```r
pacman::p_load(# Tidyverse packages including dplyr and ggplot2
               tidyverse,
               ggthemes,
               augsynth,
               gsynth)

# set seed
set.seed(44)


# load data
medicaid_expansion <- read_csv('../Downloads/medicaid_expansion.csv')
```

```
## Rows: 663 Columns: 5
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (1): State
## dbl  (3): year, uninsured_rate, population
## date (1): Date_Adopted
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Introduction

For this project, you will explore the question of whether the Affordable Care Act increased health insurance coverage (or conversely, decreased the number of people who are uninsured). The ACA was passed in March 2010, but several of its provisions were phased in over a few years. The ACA instituted the "individual mandate" which required that all Americans must carry health insurance, or else suffer a tax penalty. There are four mechanisms for how the ACA aims to reduce the uninsured population:

- Require companies with more than 50 employees to provide health insurance.
- Build state-run healthcare markets ("exchanges") for individuals to purchase health insurance.
- Provide subsidies to middle income individuals and families who do not qualify for employer based coverage.

- Expand Medicaid to require that states grant eligibility to all citizens and legal residents earning up to 138% of the federal poverty line. The federal government would initially pay 100% of the costs of this expansion, and over a period of 5 years the burden would shift so the federal government would pay 90% and the states would pay 10%.

In 2012, the Supreme Court heard the landmark case NFIB v. Sebelius, which principally challenged the constitutionality of the law under the theory that Congress could not institute an individual mandate. The Supreme Court ultimately upheld the individual mandate under Congress's taxation power, but struck down the requirement that states must expand Medicaid as impermissible subordination of the states to the federal government. Subsequently, several states refused to expand Medicaid when the program began on January 1, 2014. This refusal created the "Medicaid coverage gap" where there are indivudals who earn too much to qualify for Medicaid under the old standards, but too little to qualify for the ACA subsidies targeted at middle-income individuals.

States that refused to expand Medicaid principally cited the cost as the primary factor. Critics pointed out however, that the decision not to expand primarily broke down along partisan lines. In the years since the initial expansion, several states have opted into the program, either because of a change in the governing party, or because voters directly approved expansion via a ballot initiative.

You will explore the question of whether Medicaid expansion reduced the uninsured population in the U.S. in the 7 years since it went into effect. To address this question, you will use difference-in-differences estimation, and synthetic control.

Data

The dataset you will work with has been assembled from a few different sources about Medicaid. The key variables are:

- **State**: Full name of state
- **Medicaid Expansion Adoption**: Date that the state adopted the Medicaid expansion, if it did so.
- **Year**: Year of observation.
- **Uninsured rate**: State uninsured rate in that year.

Exploratory Data Analysis

Create plots and provide 1-2 sentence analyses to answer the following questions:

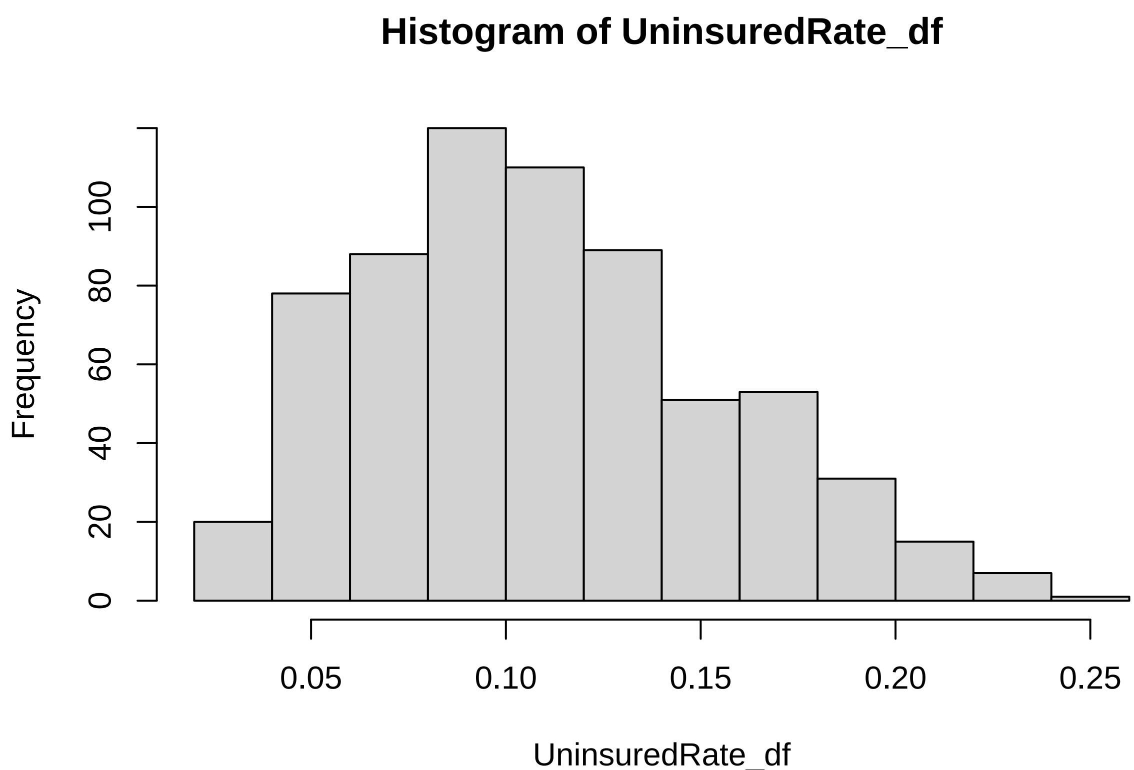
- Which states had the highest uninsured rates prior to 2014? The lowest? Nevada had the most and Mass had the lowest
- Which states were home to most uninsured Americans prior to 2014? How about in the last year in the data set? Texas had the most **Note**: 2010 state population is provided as a variable to answer this question. In an actual study you would likely use population estimates over time, but to simplify you can assume these numbers stay about the same.

```r
# highest and lowest uninsured rates

str(medicaid_expansion)
```

```
## spc_tbl_ [663 x 5] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ State         : chr [1:663] "Alabama" "Alaska" "Arizona" "Arkansas" ...
##  $ Date_Adopted  : Date[1:663], format: NA "2015-09-01" ...
##  $ year          : num [1:663] 2008 2008 2008 2008 2008 ...
##  $ uninsured_rate: num [1:663] 0.14 0.208 0.187 0.179 0.178 ...
##  $ population    : num [1:663] 4849377 737732 6731484 2994079 38802500 ...
##  - attr(*, "spec")=
##   .. cols(
```

```
##   ..   State = col_character(),
##   ..   Date_Adopted = col_date(format = ""),
##   ..   year = col_double(),
##   ..   uninsured_rate = col_double(),
##   ..   population = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
```

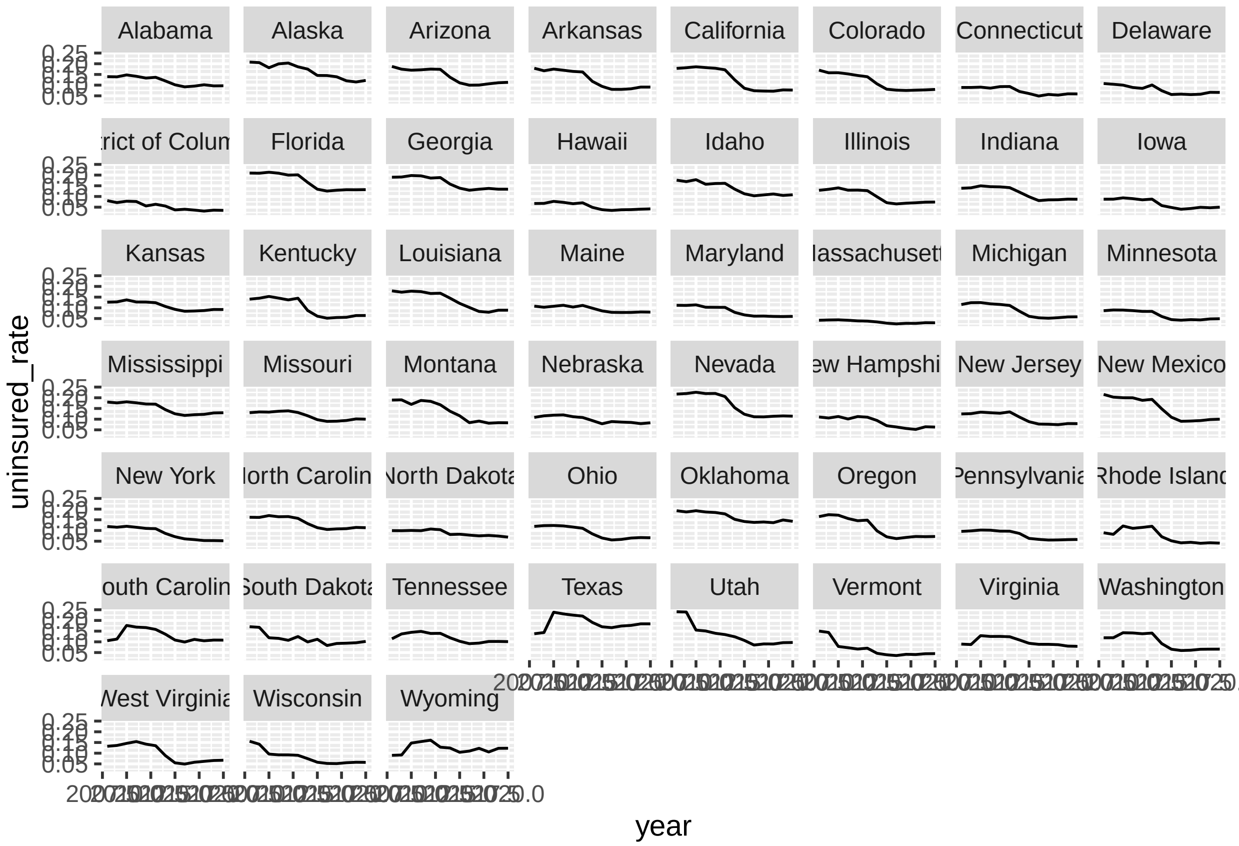
```r
# Using base R to create a density plot
UninsuredRate_df <- medicaid_expansion$uninsured_rate

hist(UninsuredRate_df)
```



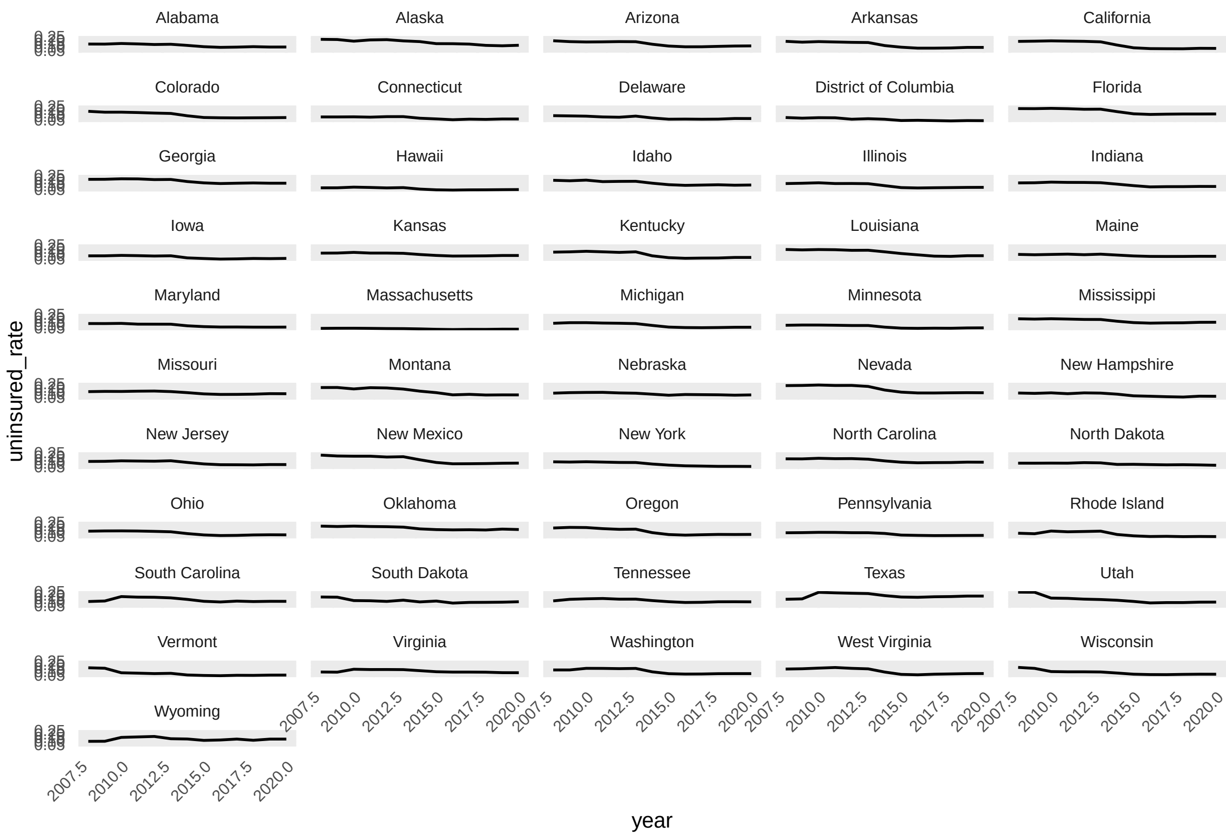

```r
colnames(medicaid_expansion)
```

```
## [1] "State"          "Date_Adopted"   "year"           "uninsured_rate"
## [5] "population"
```

```r
ggplot(data = medicaid_expansion, aes(x = year, y = uninsured_rate)) +
    geom_line() +
    facet_wrap(facets = vars(State))
```




```r
ggplot(data = medicaid_expansion, aes(x = year, y = uninsured_rate)) +
    geom_line() +  # Add lines
    facet_wrap(facets = vars(State), scales = "fixed", ncol = 5) +  # Adjust number of columns
    theme_minimal() +  # Cleaner theme
    theme(text = element_text(size = 8),  # Smaller text size
          axis.text.x = element_text(angle = 45, hjust = 1),  # Rotate x-axis labels
          strip.text = element_text(size = 6))  # Smaller facet labels
```

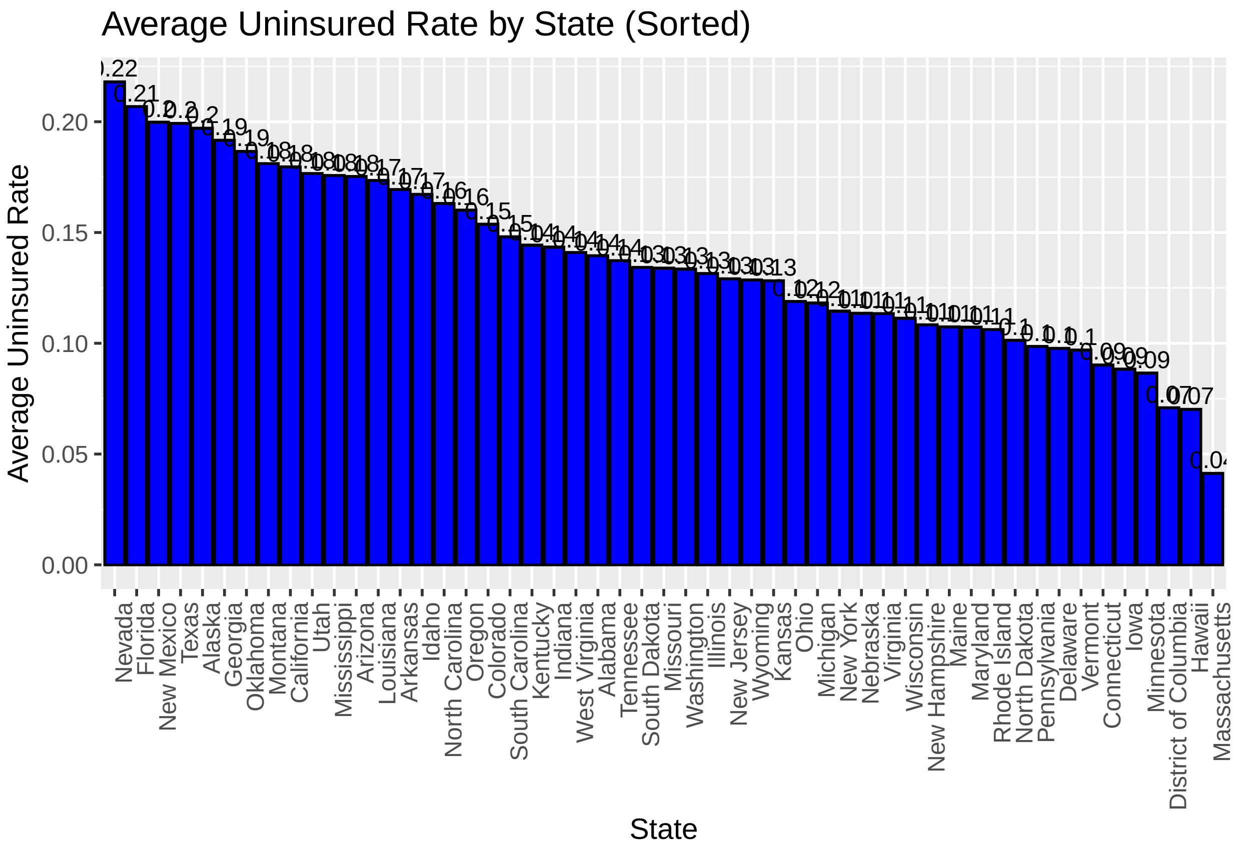



```r
# Filter the data for the years 2008 to 2013, group by state, and calculate the average
average_uninsured_rate_by_state <- medicaid_expansion %>%
  filter(year >= 2008, year <= 2013) %>%  # Filter rows where year is between 2008 and 2013
  group_by(State) %>%  # Group the data by state
  summarise(mean_uninsured_rate = mean(uninsured_rate, na.rm = TRUE))  # Calculate the mean for each gr

# Print rates from largest to smallest.
print(average_uninsured_rate_by_state %>% arrange(desc(mean_uninsured_rate)))
```

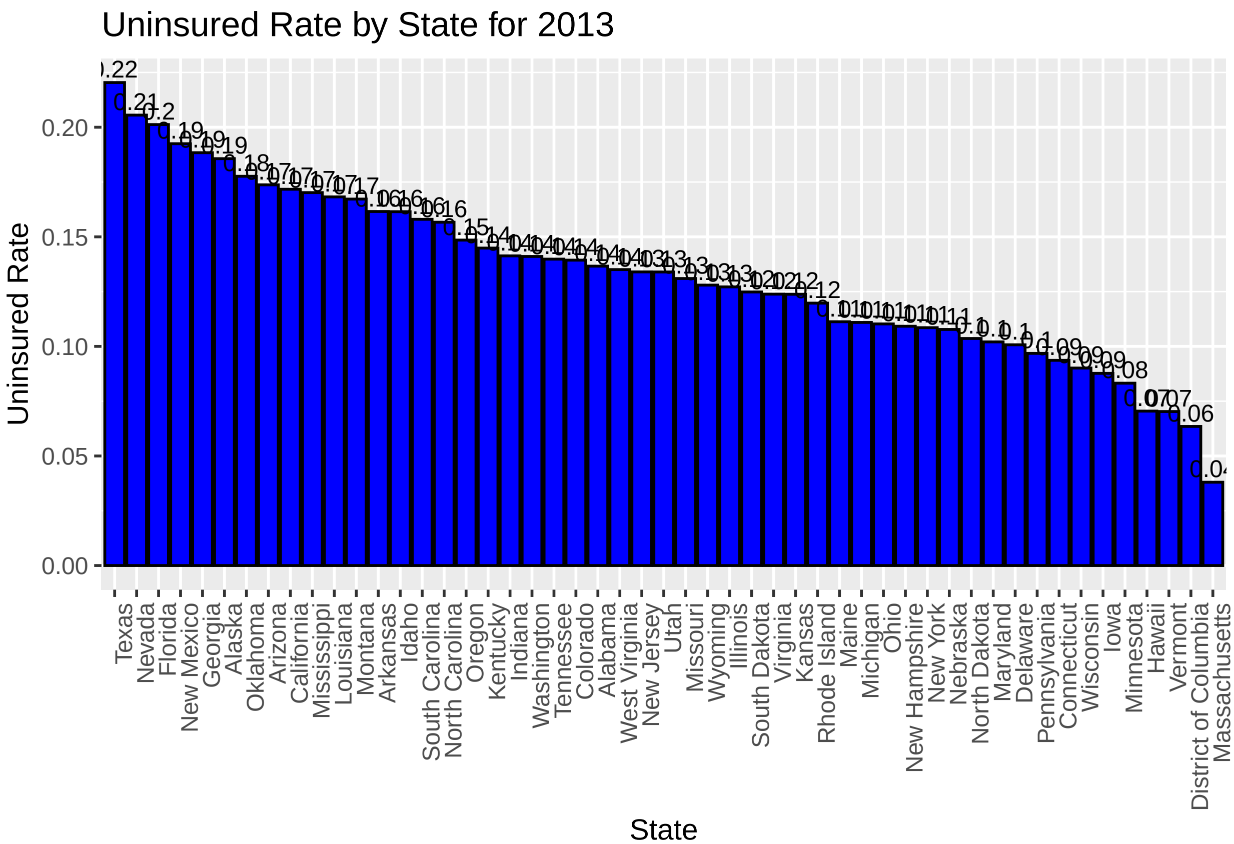
```
## # A tibble: 51 x 2
##    State      mean_uninsured_rate
##    <chr>                    <dbl>
##  1 Nevada                   0.218
##  2 Florida                  0.207
##  3 New Mexico               0.200
##  4 Texas                    0.199
##  5 Alaska                   0.197
##  6 Georgia                  0.192
##  7 Oklahoma                 0.187
##  8 Montana                  0.181
##  9 California               0.180
## 10 Utah                     0.177
## # i 41 more rows
```

```r
# Plot States with larget rates between 2008-2013

ggplot(data = average_uninsured_rate_by_state, aes(x = reorder(State, -mean_uninsured_rate), y = mean_u
    geom_bar(stat = "identity", fill = "blue", color = "black") +
```

```
  geom_text(aes(label = round(mean_uninsured_rate, 2)), vjust = -0.3, color = "black", size = 3) +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  labs(title = "Average Uninsured Rate by State (Sorted)", x = "State", y = "Average Uninsured Rate")
```

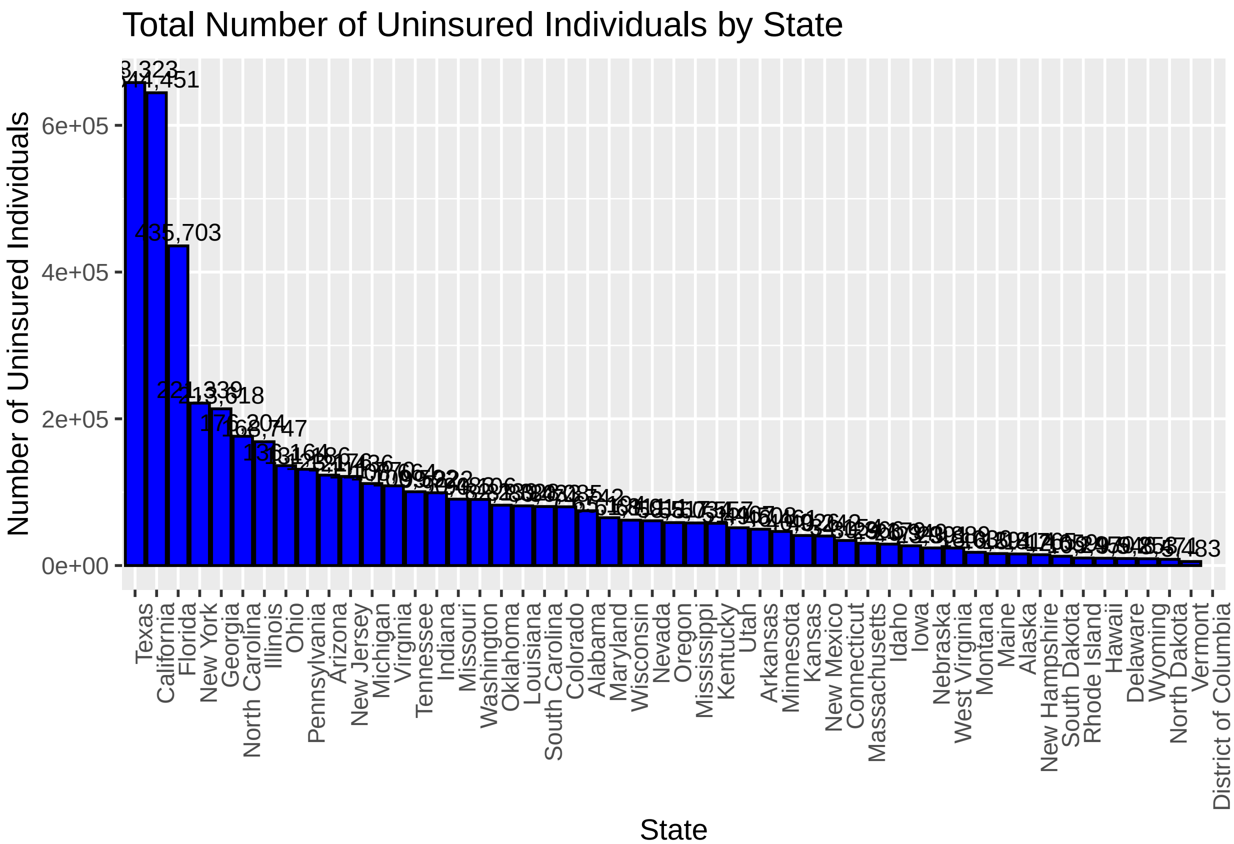



```
# Plot states with  highest uninsured rate in 2013
ggplot(data = medicaid_expansion %>% filter(year == 2013), aes(reorder(State, -uninsured_rate), y = unin
  geom_bar(stat = "identity", fill = "blue", color = "black") +
  geom_text(aes(label = round(uninsured_rate, 2)), vjust = -0.3, color = "black", size = 3) +  # Add te
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +  # Rotate x-axis labels for better readabi
  labs(title = "Uninsured Rate by State for 2013", x = "State", y = "Uninsured Rate")
```




```r
# most uninsured Americans

# Calculate the number of uninsured individuals
medicaid_expansion <- medicaid_expansion %>%
  mutate(uninsured_individuals = uninsured_rate * population / 100)

# Summarize the data by state to get the total number of uninsured individuals per state
total_uninsured_by_state <- medicaid_expansion %>%
  group_by(State) %>%
  summarise(total_uninsured = sum(uninsured_individuals))

# Plot the data with ggplot2
ggplot(data = total_uninsured_by_state, aes(x = reorder(State, -total_uninsured), y = total_uninsured))
  geom_bar(stat = "identity", fill = "blue", color = "black") +
  geom_text(aes(label = scales::comma(total_uninsured)), vjust = -0.3, color = "black", size = 3) +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  labs(title = "Total Number of Uninsured Individuals by State", x = "State", y = "Number of Uninsured 
```

```
## Warning: Removed 1 row containing missing values or values outside the scale range
## (`geom_bar()`).

## Warning: Removed 1 row containing missing values or values outside the scale range
## (`geom_text()`).
```



Difference-in-Differences Estimation

Estimate Model

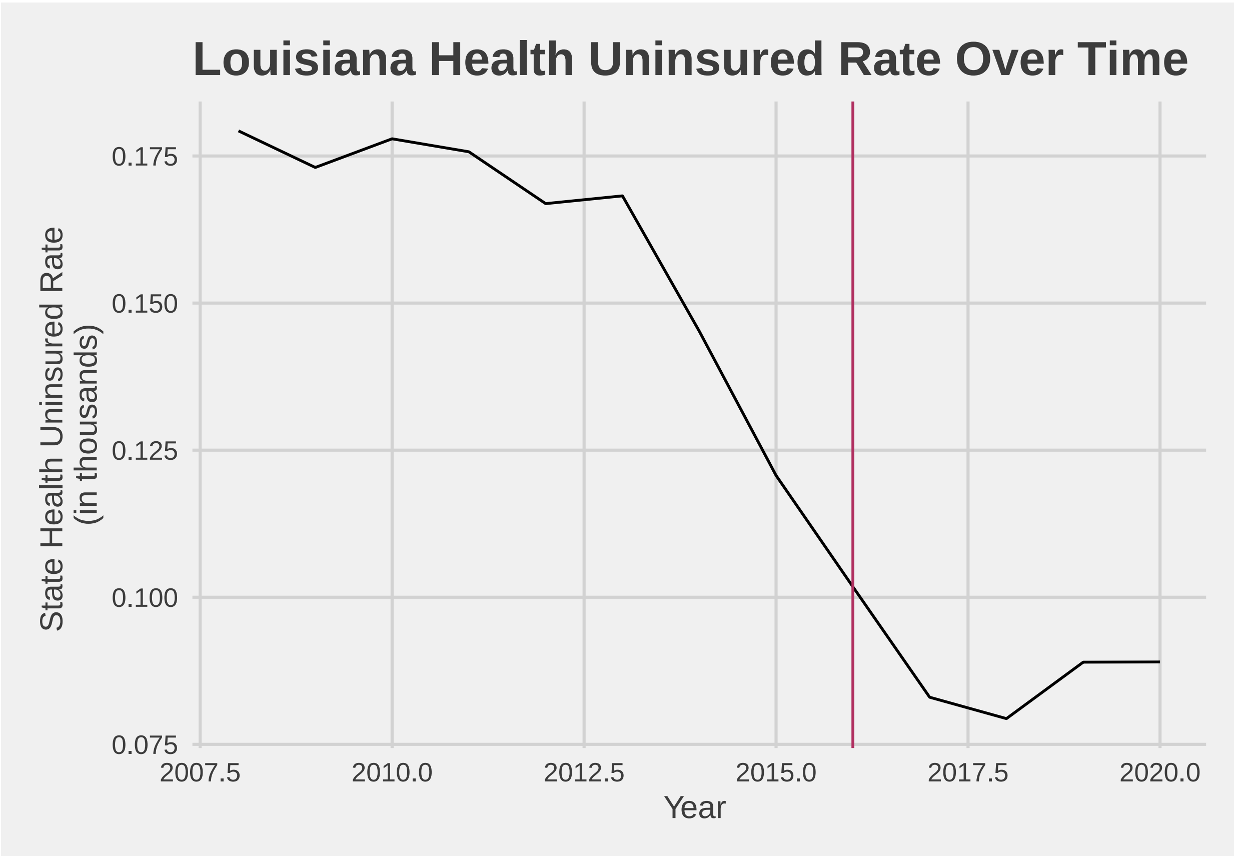
Do the following:

- Choose a state that adopted the Medicaid expansion on January 1, 2014 and a state that did not. **Hint**: Do not pick Massachusetts as it passed a universal healthcare law in 2006, and also avoid picking a state that adopted the Medicaid expansion between 2014 and 2015.
- Assess the parallel trends assumption for your choices using a plot. If you are not satisfied that the assumption has been met, pick another state and try again (but detail the states you tried).

```
# Parallel Trends plot

# Colorado, Nevada Good and Idaho and Utah Later.

medicaid_expansion <-
  medicaid_expansion %>%
  # select subset of variables
  select(year, Date_Adopted, uninsured_rate, State, population) %>%
  # create new treatment flag just to see
  mutate(treatment = case_when(State == "Louisiana" & year >= 2016 ~ 1, # note this adds treatment in 2
                               TRUE ~ 0))


Louisiana_Old <-
  medicaid_expansion %>%
```

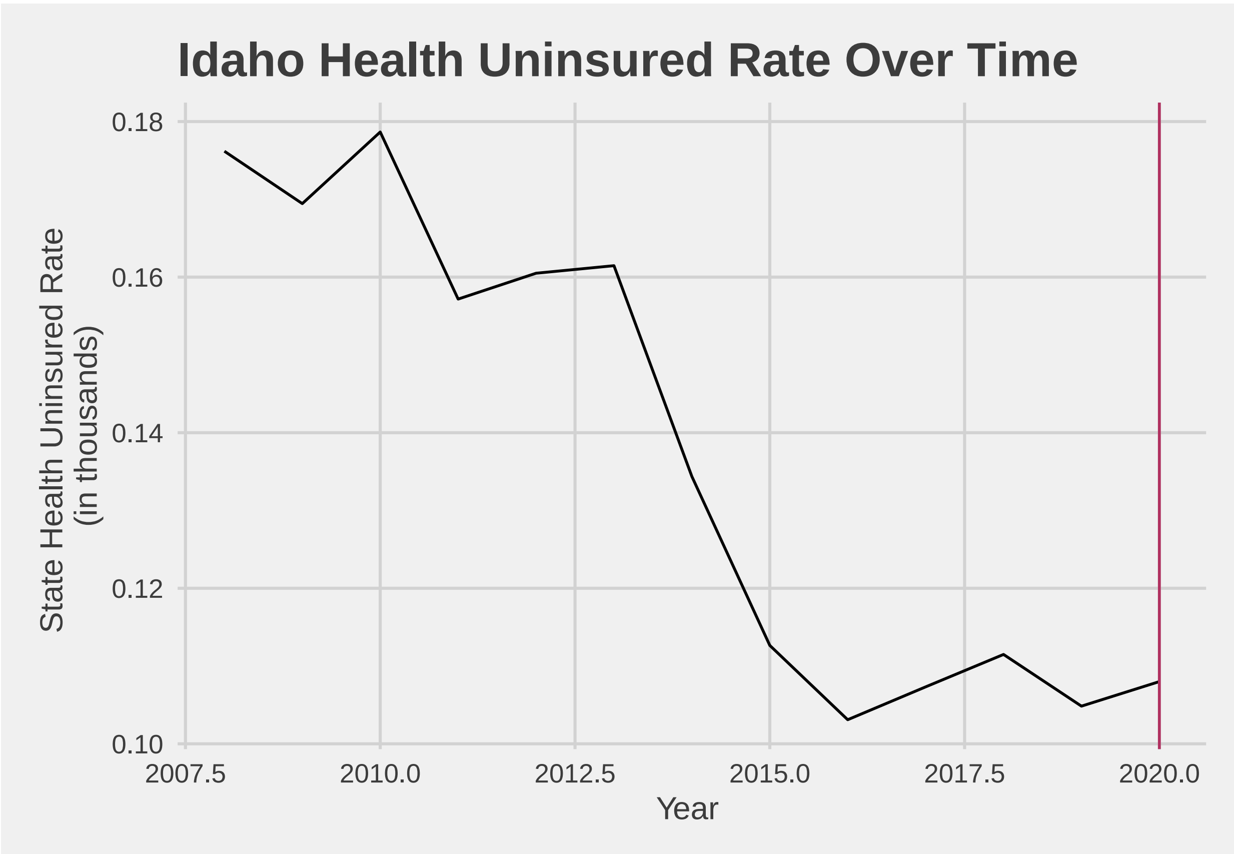
```r
  # Filter to keep only rows for Louisiana
  filter(State == "Louisiana") %>%
  # Select subset of variables
  select(year, Date_Adopted, uninsured_rate, State, population) %>%
  # Create new treatment flag based on the year
  mutate(treatment = case_when(
    year >= 2016 ~ 1,  # Assign '1' from 2016 onward, indicating treatment period
    TRUE ~ 0  # Assign '0' before 2016, indicating control period
  ))

Louisiana_Old <-
  medicaid_expansion %>%
  # Filter to keep only rows for Louisiana
  filter(State == "Louisiana") %>%
  # Select subset of variables
  select(year, Date_Adopted, uninsured_rate, State, population) %>%
  # Create new treatment flag based on the year
  mutate(treatment = case_when(State == "Louisiana" & year >= 2016 ~ 1,  # Assign '1' from 2016 onward
  TRUE ~ 0  # Assign '0' before 2016, indicating control period
  ))
```

```r
Louisiana_Old %>%

  # processing
  # ----------
  filter(State == 'Louisiana') %>%

  # ggplot
  # ----------
  ggplot() +
    # geometries
    geom_line(aes(x = year, y = uninsured_rate)) +
    geom_vline(xintercept = 2016, color = "maroon") + # color vertical line red

    # themes
    theme_fivethirtyeight() +
    theme(axis.title = element_text()) +

    # labels
    labs(x = "Year ",                               # x-axis label
           y = "State Health Uninsured Rate \n(in thousands)",     # y-axis label
         title = "Louisiana Health Uninsured Rate Over Time")
```



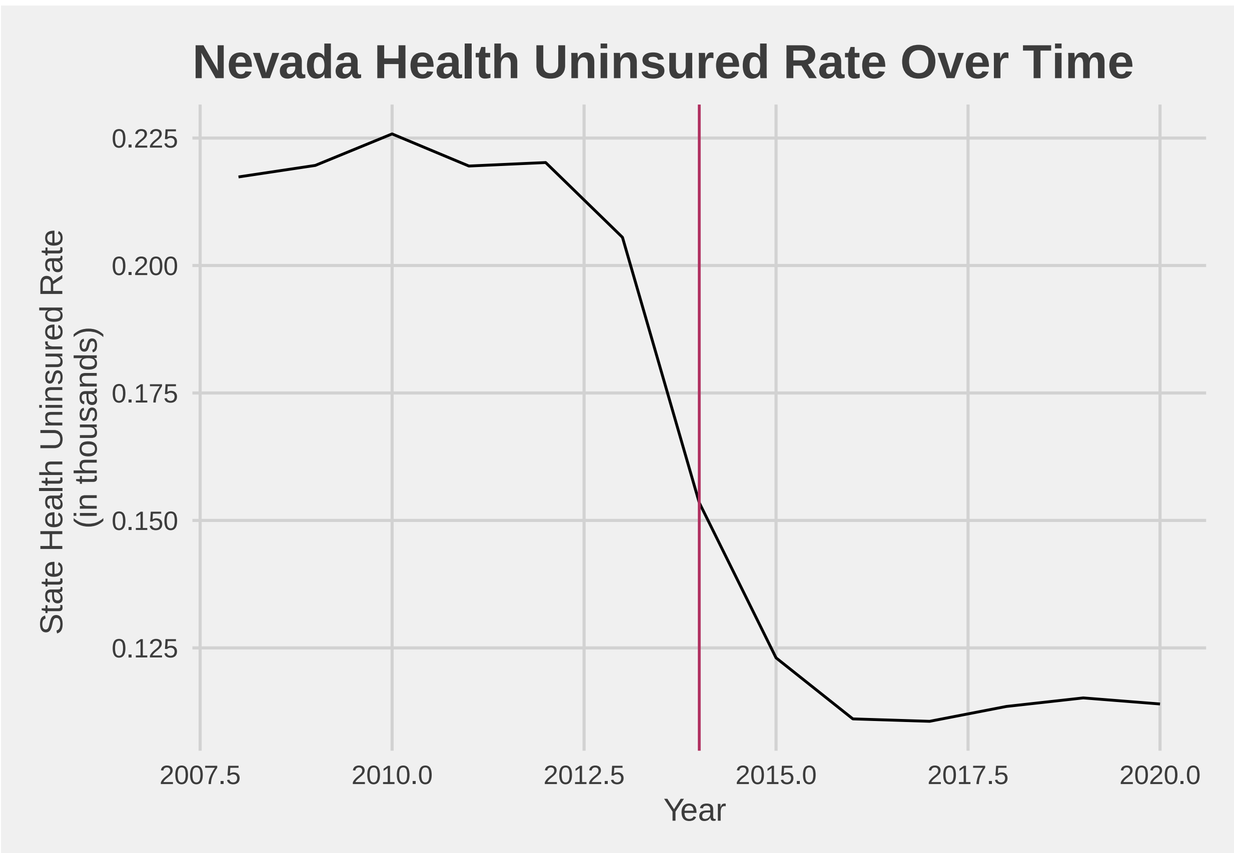

```r
Idaho_Old <-
  medicaid_expansion %>%
  # Filter to keep only rows for Utah
  filter(State == "Idaho") %>%
  # Select subset of variables
  select(year, Date_Adopted, uninsured_rate, State, population) %>%
  # Create new treatment flag based on the year
  mutate(treatment = case_when(State == "Idaho" & year >= 2020 ~ 1,  # Assign '1' from 2016 onward for
  TRUE ~ 0  # Assign '0' before 2020, indicating control period
  ))


Idaho_Old %>%

  # processing
  # ----------
  filter(State == 'Idaho') %>%

  # ggplot
  # ----------
  ggplot() +
    # geometries
    geom_line(aes(x = year, y = uninsured_rate)) +
    geom_vline(xintercept = 2020, color = "maroon") + # color vertical line red

    # themes
```

```r
  theme_fivethirtyeight() +
  theme(axis.title = element_text()) +

  # labels
  labs(x = "Year ",                             # x-axis label
         y = "State Health Uninsured Rate \n(in thousands)",     # y-axis label
       title = "Idaho Health Uninsured Rate Over Time")
```



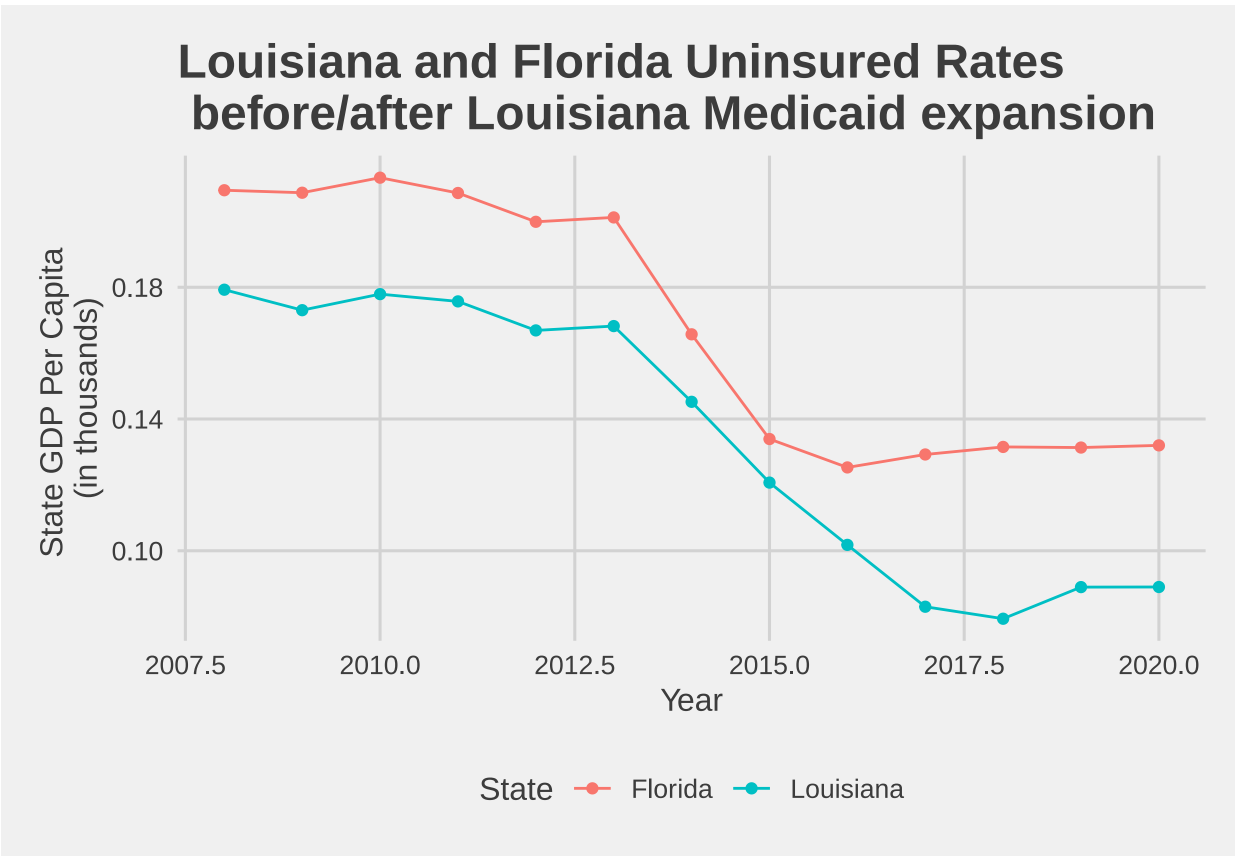

```r
Nevada_Old <-
  medicaid_expansion %>%
  # Filter to keep only rows for Utah
  filter(State == "Nevada") %>%
  # Select subset of variables
  select(year, Date_Adopted, uninsured_rate, State, population) %>%
  # Create new treatment flag based on the year
  mutate(treatment = case_when(State == "Nevada" & year >= 2014 ~ 1,  # Assign '1' from 2016 onward for
  TRUE ~ 0  # Assign '0' before 2014, indicating control period
  ))


Nevada_Old %>%

  # processing
  # ----------
  filter(State == 'Nevada') %>%
```

```
# ggplot
# ----------
ggplot() +
  # geometries
  geom_line(aes(x = year, y = uninsured_rate)) +
  geom_vline(xintercept = 2014, color = "maroon") + # color vertical line red

  # themes
  theme_fivethirtyeight() +
  theme(axis.title = element_text()) +

  # labels
  labs(x = "Year ",                                # x-axis label
         y = "State Health Uninsured Rate \n(in thousands)",       # y-axis label
       title = "Nevada Health Uninsured Rate Over Time")
```




```
medicaid_expansion %>%
  # processing
  # ----------
  filter(State %in% c("Louisiana","Florida")) %>%  # use "%in% to filter values in a vector
  filter(year >= 2008 & year<= 2020) %>%
  #filter(between(year_qtr, 2012.5, 2012.75)) %>%   # same filtering but using between() instead which

  # plot
  # ----------
  ggplot() +
```

```
  # add in point layer
  geom_point(aes(x = year,
                 y = uninsured_rate,
                 color = State)) + # color by state
  # add in line
  geom_line(aes(x = year,
                y = uninsured_rate,
                color = State)) +

  # themes
  theme_fivethirtyeight() +
  theme(axis.title = element_text()) +

  # labels - PREFER TO USE labs() SO THAT IT IS ALL IN ONE ARGUMENT
  ggtitle('Louisiana and Florida Uninsured Rates \n before/after Louisiana Medicaid expansion') +
  xlab('Year') +
  ylab('State GDP Per Capita \n(in thousands)')
```



- Estimates a difference-in-differences estimate of the effect of the Medicaid expansion on the uninsured share of the population. You may follow the lab example where we estimate the differences in one pre-treatment and one post-treatment period, or take an average of the pre-treatment and post-treatment outcomes

```
# Difference-in-Differences estimation

FL <-
  medicaid_expansion %>%
```

```r
  filter(State %in% c("Florida","Louisiana")) %>%
  filter(year >= 2016 & year<= 2017)
view(FL)


# pre-treatment difference
# ----------
pre_diff <-
  FL %>%
  # filter out only the quarter we want
  filter(year == 2016) %>%
  # subset to select only vars we want
  select(State,
         uninsured_rate) %>%
  # make the data wide. Why?
  pivot_wider(names_from = State,
              values_from = uninsured_rate) %>%

  # subtract to make calculation
  summarise(Louisiana - Florida)

# post-treatment difference
# ----------
post_diff <-
  FL %>%
  # filter out only the quarter we want
  filter(year == 2017) %>%
  # subset to select only vars we want
  select(State,
         uninsured_rate) %>%
  # make the data wide
  pivot_wider(names_from = State,
              values_from = uninsured_rate) %>%
  # subtract to make calculation
  summarise(Louisiana - Florida)

# diff-in-diffs
# ----------
diff_in_diffs <- post_diff - pre_diff
diff_in_diffs
```

```
##   Louisiana - Florida
## 1          -0.0227193
```

Discussion Questions

- Card/Krueger's original piece utilized the fact that towns on either side of the Delaware river are likely to be quite similar to one another in terms of demographics, economics, etc. Why is that intuition harder to replicate with this data?
- **Answer**: The logic used by Card & Kruegar is less applicabl (if at all) here due to the level of aggregation. When comparing towns that border there small spatial coverage relative to towns and distance between the town are both minimal. As a results commubnties are more likely to be purous between one another and have similar economic resources. However in our datasets by states are far

more likely to have greater heterogeneity due to diverse cities, communties, resources and histories,

- What are the strengths and weaknesses of using the parallel trends assumption in difference-in-differences estimates?
- **Answer**: First, the parallel trend assumption is flexible in terms of functional form not need to be specifically linear/nonlinear. Secondly it allows for an efficent way to resolve time invarying confounders without needing to gather more data or complicate the model. Furthermore the assumption allows for researchers to exploit the untreated control unit of analysis to have a more robust causal inference as counterfactual. On the otherhand it can be quite difficult to find a control unit that satisfies the parrallel trend and this can be emperically tested.

It might be difficult

Synthetic Control

Estimate Synthetic Control

Although several states did not expand Medicaid on January 1, 2014, many did later on. In some cases, a Democratic governor was elected and pushed for a state budget that included the Medicaid expansion, whereas in others voters approved expansion via a ballot initiative. The 2018 election was a watershed moment where several Republican-leaning states elected Democratic governors and approved Medicaid expansion. In cases with a ballot initiative, the state legislature and governor still must implement the results via legislation. For instance, Idaho voters approved a Medicaid expansion in the 2018 election, but it was not implemented in the state budget until late 2019, with enrollment beginning in 2020.

Do the following:

- Choose a state that adopted the Medicaid expansion after January 1, 2014. Construct a non-augmented synthetic control and plot the results (both pre-treatment fit and post-treatment differences). Also report the average ATT and L2 imbalance.

```
# non-augmented synthetic control


syn <-                              # save object
  augsynth(uninsured_rate ~ treatment, # treatment - use instead of treated bc latter codes 2012.25 as
                         State,      # unit
                         year,  # time
                         medicaid_expansion,    # data
           progfunc = "None",       # plain syn control. Where ridge will come in.
           scm = T)                 # synthetic control
```

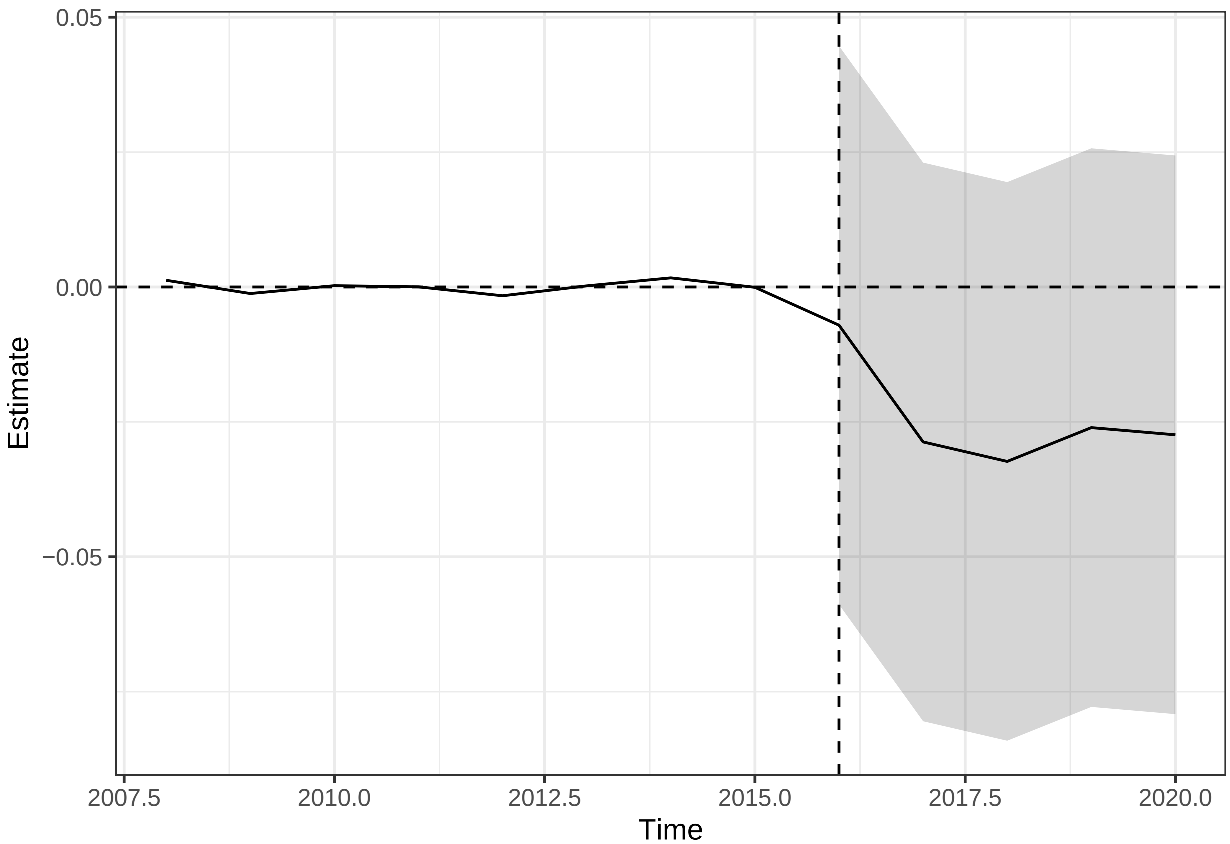
```
## One outcome and one treatment time found. Running single_augsynth.
```

```
# summary
summary(syn)
```

```
##
## Call:
## single_augsynth(form = form, unit = !!enquo(unit), time = !!enquo(time),
##     t_int = t_int, data = data, progfunc = "None", scm = ..2)
##
## Average ATT Estimate (p Value for Joint Null):  -0.0243   ( 0.2 )
## L2 Imbalance: 0.003
## Percent improvement from uniform weights: 97.2%
##
## Avg Estimated Bias: NA
```

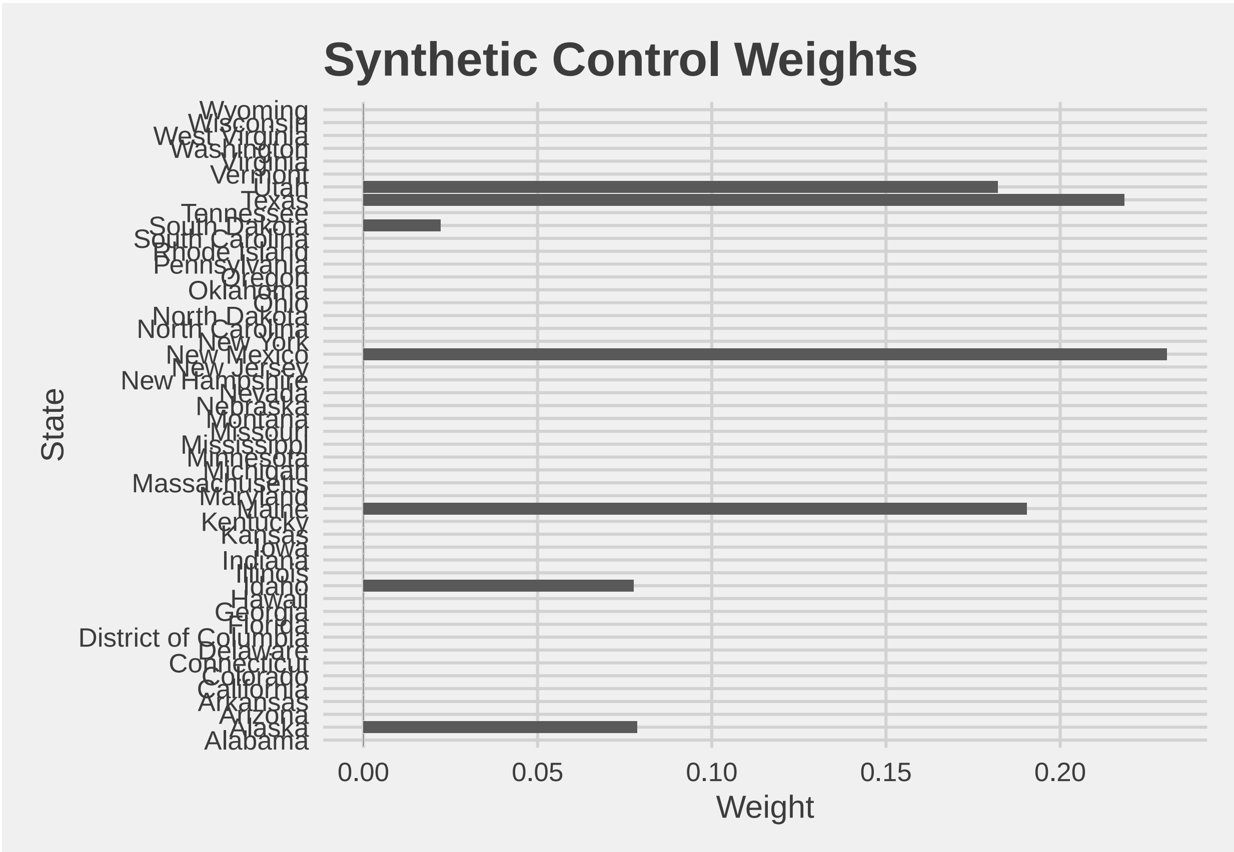
```
##
## Inference type: Conformal inference
##
##  Time Estimate 95% CI Lower Bound 95% CI Upper Bound p Value
##  2016   -0.007             -0.059              0.045   0.217
##  2017   -0.029             -0.080              0.023   0.101
##  2018   -0.032             -0.084              0.019   0.109
##  2019   -0.026             -0.078              0.026   0.113
##  2020   -0.027             -0.079              0.024   0.118
```

```
plot(syn)
```




```
data.frame(syn$weights) %>% # coerce to data frame since it's in vector form
  # process
  # ---------
  # change index to a column
  tibble::rownames_to_column('State') %>% # move index from row to column (similar to index in row as i
  # plot
  # ---------
  ggplot() +
  # stat = identity to take the literal value instead of a count for geom_bar()
  geom_bar(aes(x = State,
               y = syn.weights),
           stat = 'identity') +  # override count() which is default of geom_bar(), could use geom_col(
  coord_flip() +   # flip to make it more readable
  # themes
  theme_fivethirtyeight() +
  theme(axis.title = element_text()) +
```

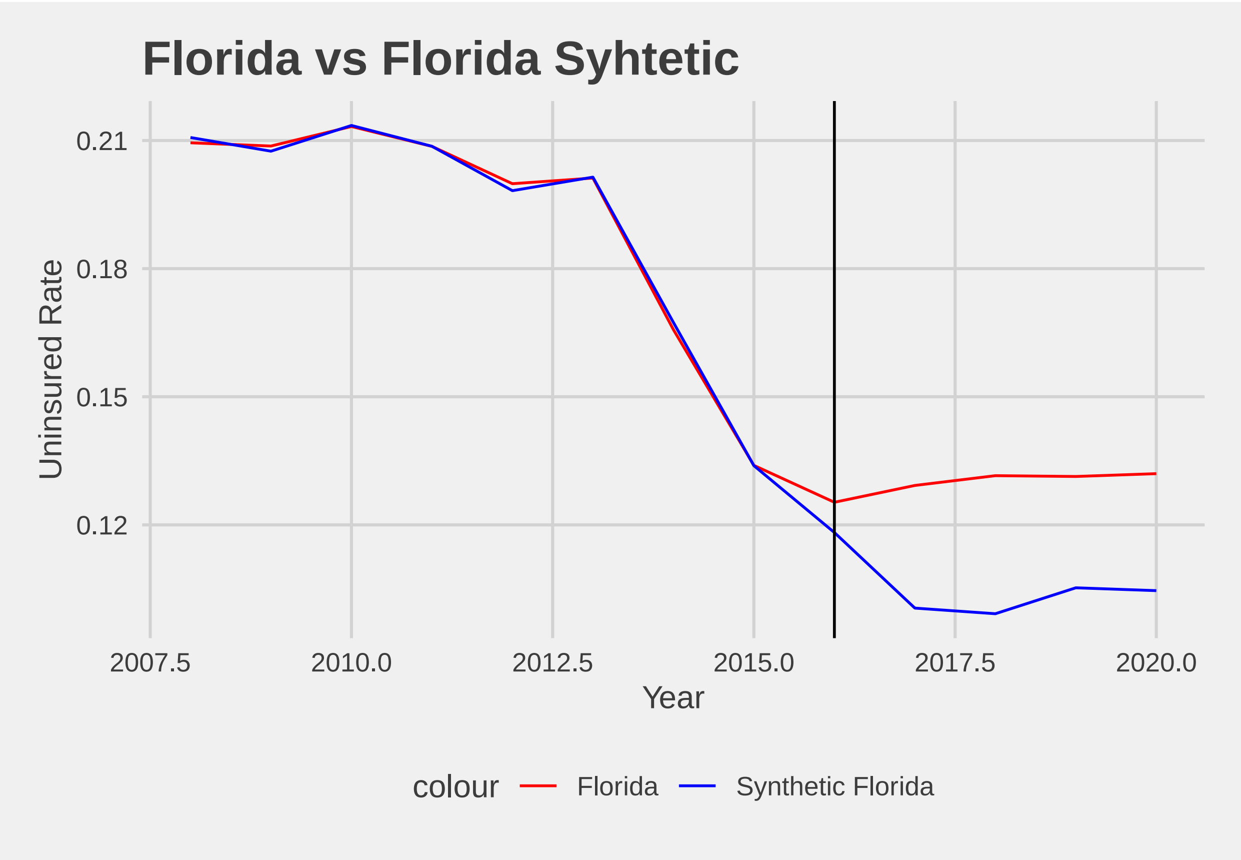
```
  # labels
  ggtitle('Synthetic Control Weights') +
  xlab('State') +
  ylab('Weight')
```



- Re-run the same analysis but this time use an augmentation (default choices are Ridge, Matrix Completion, and GSynth). Create the same plot and report the average ATT and L2 imbalance.

```
# augmented synthetic control

syn_sum <- summary(syn)

# create synthetic Kansas
# ---------
florida_synflorida <-
  # data
  medicaid_expansion %>%
  # filter just Florida
  filter(State == "Florida") %>%
  # bind columns
  bind_cols(difference = syn_sum$att$Estimate) %>%     # add in estimate
  # calculate synthetic Kansas
  mutate(synthetic_florida = uninsured_rate + difference) # adds the estimate to the observed Kansas to



# plot
```

```r
# ---------
florida_synflorida %>%
  ggplot() +
  # kansas
  # ---------
  geom_line(aes(x = year,
                y = uninsured_rate,
                color = 'Florida')) +
  # synthetic kansas
  # ---------
  geom_line(aes(x = year,
                y = synthetic_florida,
                color = 'Synthetic Florida')) +
  scale_color_manual(values = c('Florida' = 'red', 'Synthetic Florida' = 'blue')) +
  geom_vline(aes(xintercept = 2016)) +
  theme_fivethirtyeight() +
  theme(axis.title = element_text()) +
  ggtitle('Florida vs Florida Syhtetic') +
  xlab('Year') +
  ylab('Uninsured Rate')
```




```r
ridge_syn <-
  augsynth(uninsured_rate ~ treatment,
                         State,
                         year,
                         medicaid_expansion,
```

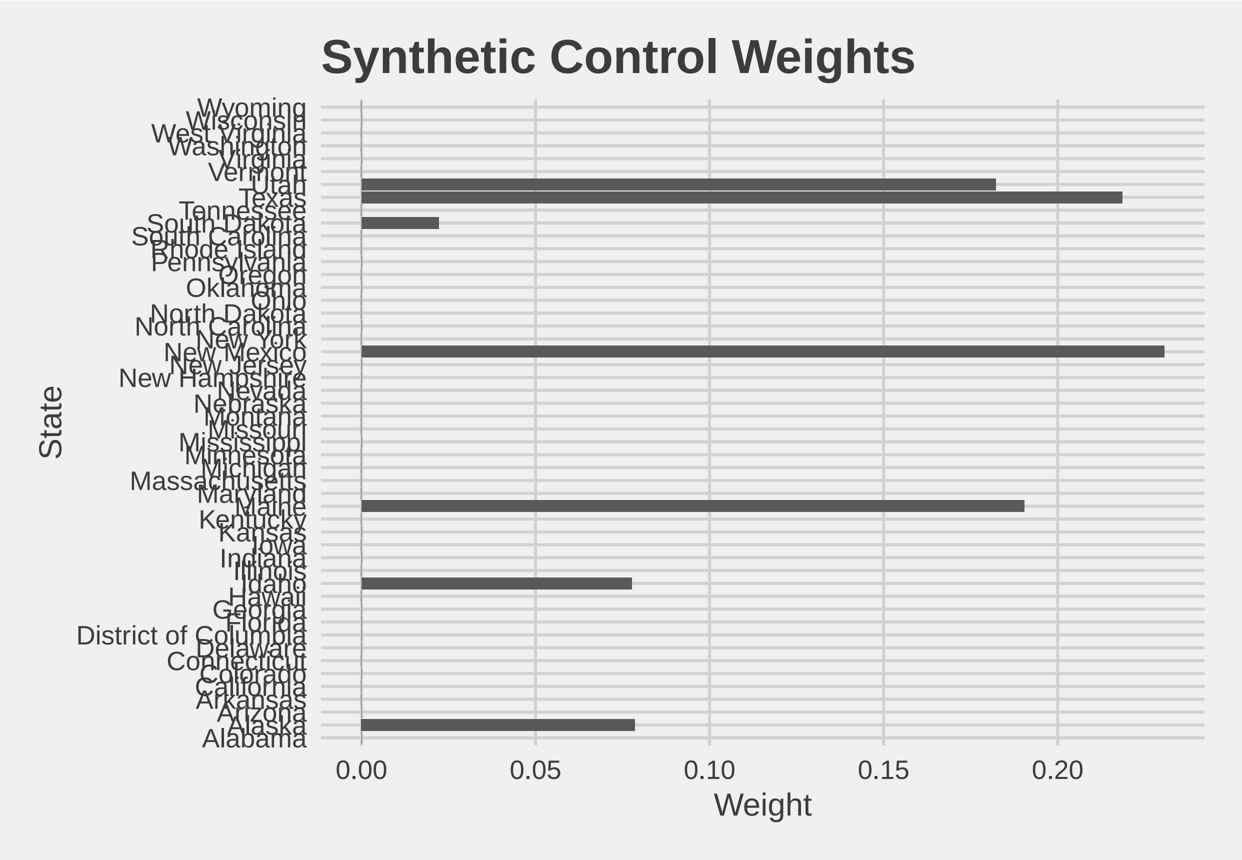
```r
          progfunc = "ridge",  # specify
          scm = T)
```

```
## One outcome and one treatment time found. Running single_augsynth.
```

```r
summary(ridge_syn)
```

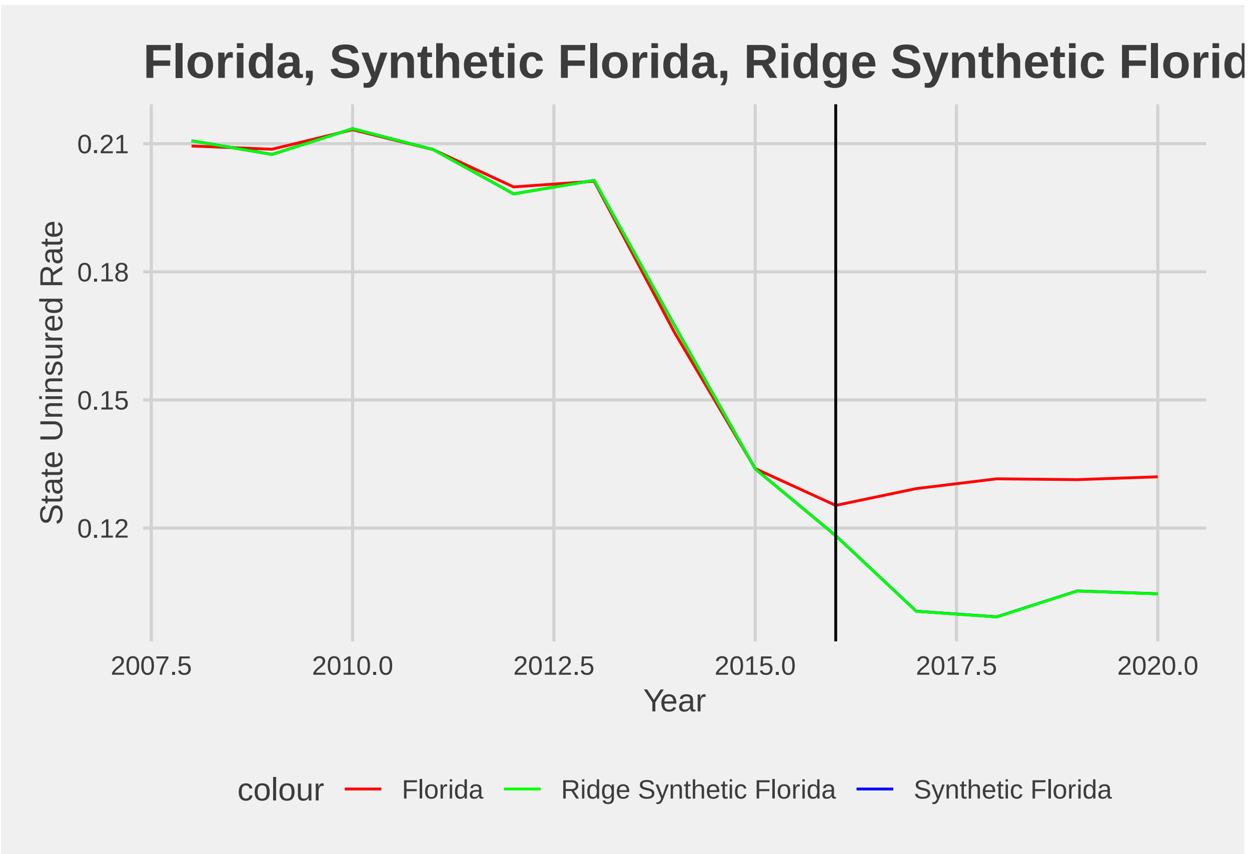
```
##
## Call:
## single_augsynth(form = form, unit = !!enquo(unit), time = !!enquo(time),
##     t_int = t_int, data = data, progfunc = "ridge", scm = ..2)
##
## Average ATT Estimate (p Value for Joint Null):  -0.0243   ( 0.16 )
## L2 Imbalance: 0.003
## Percent improvement from uniform weights: 97.2%
##
## Avg Estimated Bias: 0.000
##
## Inference type: Conformal inference
##
##  Time Estimate 95% CI Lower Bound 95% CI Upper Bound p Value
##  2016   -0.007             -0.059              0.045   0.200
##  2017   -0.029             -0.081              0.023   0.098
##  2018   -0.032             -0.084              0.019   0.096
##  2019   -0.026             -0.078              0.026   0.117
##  2020   -0.027             -0.079              0.024   0.101
```

```r
data.frame(ridge_syn$weights) %>%
  tibble::rownames_to_column('State') %>%
  ggplot() +
  geom_bar(aes(x = State, y = ridge_syn.weights),
           stat = 'identity') +
  coord_flip() + # coord flip
  theme_fivethirtyeight() +
  theme(axis.title = element_text()) +
  ggtitle('Synthetic Control Weights') +
  xlab('State') +
  ylab('Weight')
```




```
ridge_sum <- summary(ridge_syn)

# create synthetic Kansas
# ---------
florida_synflorida_ridgesynflorida <- florida_synflorida %>%
  bind_cols(ridge_difference = ridge_sum$att$Estimate) %>%
  mutate(ridge_synthetic_florida = uninsured_rate + ridge_difference)

# plot
# ---------
florida_synflorida_ridgesynflorida %>%
  ggplot() +

  # kansas
  # ---------
  geom_line(aes(x = year,
                y = uninsured_rate,
                color = 'Florida')) +
  # synthetic kansas
  # ---------
  geom_line(aes(x = year,
                y = synthetic_florida,
                color = 'Synthetic Florida')) +
  # ridge kansas
  # ---------
  geom_line(aes(x = year,
```

```r
               y = ridge_synthetic_florida,
               color = 'Ridge Synthetic Florida')) +
  # use scale color manual to assign color values
  scale_color_manual(values = c('Florida' = 'red',
                                'Synthetic Florida' = 'blue',
                                'Ridge Synthetic Florida' = 'green')) +
  geom_vline(aes(xintercept = 2016)) +
  # themes
  theme_fivethirtyeight() +
  theme(axis.title = element_text()) +
  # labels
  ggtitle('Florida, Synthetic Florida, Ridge Synthetic Florida') +
  xlab('Year') +
  ylab('State Uninsured Rate')
```



- Plot barplots to visualize the weights of the donors.

```r
# barplots of weights
```

HINT: Is there any preprocessing you need to do before you allow the program to automatically find weights for donor states?

Discussion Questions

- What are the advantages and disadvantages of synthetic control compared to difference-in-differences estimators?
- **Answer**: When using a synthetic control we are much more likely to produce a satisfactory control

group and satisfy a parrelel trends assumption. However there may be a bit od trade off in terms of external valdiity in our results. Essentially we while we have greater interal validity our results may be only relative to the specfic case we are testsing rather than what other real life units of analysis experience in the true universe.

- One of the benefits of synthetic control is that the weights are bounded between [0,1] and the weights must sum to 1. Augmentation might relax this assumption by allowing for negative weights. Does this create an interpretation problem, and how should we balance this consideration against the improvements augmentation offers in terms of imbalance in the pre-treatment period?
- **Answer**: When using augmentation we gain several key benefits. First due to the penality term we use in say a ridge approach to ridge we reduce the chance of over fitting our model and we end reducing the variance of the weights used. Secodnly it allows for less sensitivity in our synthetic control by reducing the chance that one weight is overly influential in the composite synthetic control. However when using augmentation soem coefficents can not only be reduced to zero but actually become negative which is a little against the logic of the weights summing to one and may be difficult to explain in the context the empirical question asked. When considering on choosing synthetic control the primary consideration may likely be when you are unable to find pre-treatment balances or there may be a clear over fit in the model (which can be hard because these pull in diffeent directions.). Similarly the size of your syhtetic control donors may be a consideration but also not as clear cut. For example if we have limited numbers of donors this may lead to one or few donors playing an over extensive contribution. Yet on the other hand having many donors may allow for a ebtter fit but lead to a situation where youa re more likely to have donors that more related to one another producing multicolliniarity.

Staggered Adoption Synthetic Control

Estimate Multisynth

Do the following:

- Estimate a multisynth model that treats each state individually. Choose a fraction of states that you can fit on a plot and examine their treatment effects.

turn adoption column into date object then creaate a year of adoption column.

```
# multisynth model states



  medicaid_expansion_clean <- medicaid_expansion %>%
  # Filter out Massachusetts
  filter(!State %in% c("Massachusetts")) %>%
  # Create a new column `year_adopted` by extracting year from `Date_Adopted`
  mutate(year_adopted = as.numeric(format(as.Date(Date_Adopted, format = "%Y-%m-%d"), "%Y")),
         # Create an `adopted` column that is 1 if `year` >= `year_adopted`, 0 otherwise
         adopted = as.integer(year >= year_adopted))

medicaid_expansion_clean <- medicaid_expansion_clean %>%
  mutate(adopted = ifelse(is.na(adopted), 0, adopted))
```

```
non_ppool_syn <- multisynth(uninsured_rate ~ adopted,
                            State,                          # unit
                            year,                           # time
                            nu = 0,                        # varying degree of pooling
                            medicaid_expansion_clean, # data
                            n_leads = 2)                   # post-treatment periods to estimate
```

```r
# view results
print(non_ppool_syn$nu)
```

```
## [1] 0
```

```r
non_ppool_synsum<- summary(non_ppool_syn)
```

```r
non_ppool_synsum$att
```

```
##     Time           Level      Estimate   Std.Error   lower_bound
## 1    -12         Average  1.025101e-02 0.039271594 -0.0647664152
## 2    -11         Average  1.160478e-02 0.027308948 -0.0417780986
## 3    -10         Average  3.432105e-03 0.011849364 -0.0180847454
## 4     -9         Average -5.185198e-04 0.007390945 -0.0158242221
## 5     -8         Average -1.848474e-03 0.008247531 -0.0164663496
## 6     -7         Average -1.163056e-03 0.007119267 -0.0131376233
## 7     -6         Average -1.136448e-04 0.007104484 -0.0124154940
## 8     -5         Average -7.142314e-04 0.006054753 -0.0117522118
## 9     -4         Average  2.720578e-04 0.003358312 -0.0064935468
## 10    -3         Average -3.903377e-04 0.003536491 -0.0075040009
## 11    -2         Average -8.841279e-04 0.003869246 -0.0085709176
## 12    -1         Average -9.166283e-05 0.003473674 -0.0074667558
## 13     0         Average -1.173916e-02 0.004735153 -0.0209972950
## 14     1         Average -1.817259e-02 0.006573750 -0.0309759456
## 15    NA         Average -1.440935e-02 0.005167987 -0.0243962259
## 16   -12          Alaska            NA         NaN            NA
## 17   -11          Alaska            NA         NaN            NA
## 18   -10          Alaska            NA         NaN            NA
## 19    -9          Alaska            NA         NaN            NA
## 20    -8          Alaska            NA         NaN            NA
## 21    -7          Alaska  1.027723e-03 0.022481769 -0.0409719153
## 22    -6          Alaska  7.243849e-04 0.017427003 -0.0343835332
## 23    -5          Alaska -1.195273e-02 0.023984472 -0.0461080795
## 24    -4          Alaska  4.610996e-03 0.007685761 -0.0108831379
## 25    -3          Alaska  6.778125e-03 0.008730414 -0.0126445973
## 26    -2          Alaska -2.317406e-03 0.010460116 -0.0181322092
## 27    -1          Alaska  1.128911e-03 0.005098997 -0.0090646399
## 28     0          Alaska -1.065096e-02 0.011804917 -0.0271727861
## 29     1          Alaska -4.996361e-03 0.005640353 -0.0156595156
## 30    NA          Alaska -7.823663e-03 0.008405806 -0.0212206821
## 31   -12         Arizona            NA         NaN            NA
## 32   -11         Arizona            NA         NaN            NA
## 33   -10         Arizona            NA         NaN            NA
## 34    -9         Arizona            NA         NaN            NA
## 35    -8         Arizona            NA         NaN            NA
## 36    -7         Arizona            NA         NaN            NA
## 37    -6         Arizona  2.625765e-03 0.024764222 -0.0409360312
## 38    -5         Arizona -2.946809e-03 0.013846812 -0.0219373805
## 39    -4         Arizona -3.901417e-03 0.015269473 -0.0300861721
## 40    -3         Arizona -2.336919e-03 0.011769788 -0.0228414918
## 41    -2         Arizona  3.943136e-03 0.007815743 -0.0114451857
## 42    -1         Arizona  2.616243e-03 0.007694863 -0.0118801415
## 43     0         Arizona -2.067609e-02 0.016431985 -0.0466208607
```

```
## 44    1            Arizona -3.170106e-02 0.025056830 -0.0661154843
## 45   NA            Arizona -2.618858e-02 0.020687031 -0.0564431651
## 46  -12           Arkansas           NA         NaN            NA
## 47  -11           Arkansas           NA         NaN            NA
## 48  -10           Arkansas           NA         NaN            NA
## 49   -9           Arkansas           NA         NaN            NA
## 50   -8           Arkansas           NA         NaN            NA
## 51   -7           Arkansas           NA         NaN            NA
## 52   -6           Arkansas  2.488362e-03 0.026412732 -0.0523441903
## 53   -5           Arkansas -2.706397e-03 0.016669255 -0.0319936452
## 54   -4           Arkansas  9.865953e-04 0.010583994 -0.0184227801
## 55   -3           Arkansas  1.429651e-03 0.011213991 -0.0215578826
## 56   -2           Arkansas -1.852202e-03 0.010515267 -0.0222671383
## 57   -1           Arkansas -3.460092e-04 0.010392528 -0.0222635633
## 58    0           Arkansas -2.147545e-02 0.029081039 -0.0572074369
## 59    1           Arkansas -2.998838e-02 0.035415774 -0.0685532823
## 60   NA           Arkansas -2.573191e-02 0.032198473 -0.0627751342
## 61  -12         California           NA         NaN            NA
## 62  -11         California           NA         NaN            NA
## 63  -10         California           NA         NaN            NA
## 64   -9         California           NA         NaN            NA
## 65   -8         California           NA         NaN            NA
## 66   -7         California           NA         NaN            NA
## 67   -6         California -6.332163e-11 0.014658915 -0.0240700866
## 68   -5         California  7.062909e-11 0.014819450 -0.0252338250
## 69   -4         California  1.736669e-11 0.006161963 -0.0122959284
## 70   -3         California -1.434475e-10 0.006933572 -0.0139245272
## 71   -2         California  9.116377e-11 0.008007722 -0.0157791313
## 72   -1         California  2.760953e-11 0.009347783 -0.0174025544
## 73    0         California -2.939468e-02 0.031903158 -0.0647015559
## 74    1         California -5.028501e-02 0.054409554 -0.1048238062
## 75   NA         California -3.983985e-02 0.043117481 -0.0842553962
## 76  -12           Colorado           NA         NaN            NA
## 77  -11           Colorado           NA         NaN            NA
## 78  -10           Colorado           NA         NaN            NA
## 79   -9           Colorado           NA         NaN            NA
## 80   -8           Colorado           NA         NaN            NA
## 81   -7           Colorado           NA         NaN            NA
## 82   -6           Colorado  3.411354e-03 0.025391384 -0.0437230447
## 83   -5           Colorado -3.552840e-03 0.012030566 -0.0254625172
## 84   -4           Colorado  1.924324e-03 0.004577450 -0.0063698723
## 85   -3           Colorado  1.918107e-03 0.008017365 -0.0127857295
## 86   -2           Colorado -2.129560e-03 0.010527900 -0.0182534981
## 87   -1           Colorado -1.571385e-03 0.014376684 -0.0251218886
## 88    0           Colorado -1.172853e-02 0.026710319 -0.0473271697
## 89    1           Colorado -2.533451e-02 0.033117488 -0.0595221535
## 90   NA           Colorado -1.853152e-02 0.029691996 -0.0534965002
## 91  -12        Connecticut           NA         NaN            NA
## 92  -11        Connecticut           NA         NaN            NA
## 93  -10        Connecticut           NA         NaN            NA
## 94   -9        Connecticut           NA         NaN            NA
## 95   -8        Connecticut           NA         NaN            NA
## 96   -7        Connecticut           NA         NaN            NA
## 97   -6        Connecticut -1.263251e-04 0.012106536 -0.0237074002
```

```
## 98    -5          Connecticut  6.919339e-05 0.012023108 -0.0241253199
## 99    -4          Connecticut -1.432031e-03 0.009685315 -0.0212986201
## 100   -3          Connecticut -5.046973e-03 0.010626239 -0.0217832928
## 101   -2          Connecticut  3.190982e-03 0.007896485 -0.0140109989
## 102   -1          Connecticut  3.345153e-03 0.007392641 -0.0110993811
## 103    0          Connecticut -2.165019e-03 0.008205622 -0.0173944441
## 104    1          Connecticut -1.438232e-03 0.013534933 -0.0273310439
## 105   NA          Connecticut -1.801626e-03 0.010104170 -0.0198054741
## 106  -12             Delaware            NA         NaN            NA
## 107  -11             Delaware            NA         NaN            NA
## 108  -10             Delaware            NA         NaN            NA
## 109   -9             Delaware            NA         NaN            NA
## 110   -8             Delaware            NA         NaN            NA
## 111   -7             Delaware            NA         NaN            NA
## 112   -6             Delaware  4.698354e-04 0.029499530 -0.0586771407
## 113   -5             Delaware -1.178458e-03 0.025853605 -0.0500084306
## 114   -4             Delaware  6.165954e-04 0.014971976 -0.0282647471
## 115   -3             Delaware -3.182807e-03 0.018695953 -0.0396755198
## 116   -2             Delaware -1.628232e-03 0.020606240 -0.0404686624
## 117   -1             Delaware  4.903066e-03 0.008179468 -0.0126685176
## 118    0             Delaware  4.390070e-03 0.006956644 -0.0098149870
## 119    1             Delaware -1.210016e-02 0.011024743 -0.0263470609
## 120   NA             Delaware -3.855047e-03 0.004134846 -0.0113649240
## 121  -12 District of Columbia            NA         NaN            NA
## 122  -11 District of Columbia            NA         NaN            NA
## 123  -10 District of Columbia            NA         NaN            NA
## 124   -9 District of Columbia            NA         NaN            NA
## 125   -8 District of Columbia            NA         NaN            NA
## 126   -7 District of Columbia            NA         NaN            NA
## 127   -6 District of Columbia  4.078235e-03 0.016082141 -0.0272521001
## 128   -5 District of Columbia -4.334165e-03 0.007642776 -0.0189161501
## 129   -4 District of Columbia  1.799168e-03 0.002089748 -0.0023365219
## 130   -3 District of Columbia  5.574322e-03 0.002846918 -0.0004596855
## 131   -2 District of Columbia -6.438455e-03 0.016382848 -0.0271592155
## 132   -1 District of Columbia -6.791057e-04 0.005992486 -0.0105282636
## 133    0 District of Columbia  1.517938e-02 0.010520671 -0.0088488921
## 134    1 District of Columbia  2.024933e-02 0.013673158 -0.0102339887
## 135   NA District of Columbia  1.771435e-02 0.011864735 -0.0095414000
## 136  -12               Hawaii            NA         NaN            NA
## 137  -11               Hawaii            NA         NaN            NA
## 138  -10               Hawaii            NA         NaN            NA
## 139   -9               Hawaii            NA         NaN            NA
## 140   -8               Hawaii            NA         NaN            NA
## 141   -7               Hawaii            NA         NaN            NA
## 142   -6               Hawaii  8.876372e-12 0.013570442 -0.0236986342
## 143   -5               Hawaii -9.900775e-12 0.012400881 -0.0214329451
## 144   -4               Hawaii -2.434455e-12 0.007460427 -0.0138255562
## 145   -3               Hawaii  2.010841e-11 0.007277200 -0.0144332836
## 146   -2               Hawaii -1.277931e-11 0.008980039 -0.0179891372
## 147   -1               Hawaii -3.870293e-12 0.004867173 -0.0088771458
## 148    0               Hawaii  2.364820e-03 0.004996020 -0.0073420097
## 149    1               Hawaii  2.551249e-03 0.010296614 -0.0180065262
## 150   NA               Hawaii  2.458034e-03 0.006558859 -0.0109230631
## 151  -12                Idaho  2.304296e-03 0.025554689 -0.0450970463
```

```
## 152  -11              Idaho -2.183838e-03 0.018586888 -0.0358393315
## 153  -10              Idaho  7.250498e-03 0.013442481 -0.0188150272
## 154   -9              Idaho -8.595266e-03 0.009154344 -0.0225507428
## 155   -8              Idaho  1.218516e-03 0.004618009 -0.0075147115
## 156   -7              Idaho  1.150191e-03 0.006871412 -0.0113212189
## 157   -6              Idaho -8.992386e-04 0.002453435 -0.0056468254
## 158   -5              Idaho  9.360247e-04 0.010428778 -0.0174712089
## 159   -4              Idaho -9.584729e-05 0.011320075 -0.0187943022
## 160   -3              Idaho  1.291580e-03 0.011631087 -0.0185581827
## 161   -2              Idaho  1.776667e-03 0.008933456 -0.0148592633
## 162   -1              Idaho -4.153583e-03 0.018187041 -0.0312051419
## 163    0              Idaho -1.308111e-03 0.015209802 -0.0246980149
## 164    1              Idaho            NA         NaN            NA
## 165   NA              Idaho -1.308111e-03 0.015209802 -0.0246980149
## 166  -12           Illinois            NA         NaN            NA
## 167  -11           Illinois            NA         NaN            NA
## 168  -10           Illinois            NA         NaN            NA
## 169   -9           Illinois            NA         NaN            NA
## 170   -8           Illinois            NA         NaN            NA
## 171   -7           Illinois            NA         NaN            NA
## 172   -6           Illinois -5.280943e-04 0.009070725 -0.0178660749
## 173   -5           Illinois  6.320909e-04 0.008081867 -0.0156521663
## 174   -4           Illinois  1.955541e-04 0.002614010 -0.0050594475
## 175   -3           Illinois -9.334521e-04 0.009847912 -0.0188279634
## 176   -2           Illinois  8.370655e-04 0.004356491 -0.0082750664
## 177   -1           Illinois -2.031641e-04 0.003258644 -0.0069196283
## 178    0           Illinois -6.831126e-03 0.010481245 -0.0219540465
## 179    1           Illinois -1.585249e-02 0.021544821 -0.0432901558
## 180   NA           Illinois -1.134181e-02 0.015972931 -0.0326578902
## 181  -12            Indiana            NA         NaN            NA
## 182  -11            Indiana            NA         NaN            NA
## 183  -10            Indiana            NA         NaN            NA
## 184   -9            Indiana            NA         NaN            NA
## 185   -8            Indiana            NA         NaN            NA
## 186   -7            Indiana -4.746103e-06 0.005159338 -0.0099760349
## 187   -6            Indiana  4.391358e-06 0.004453526 -0.0092199602
## 188   -5            Indiana -1.361134e-05 0.003187270 -0.0071352240
## 189   -4            Indiana -2.374178e-05 0.003501687 -0.0064195866
## 190   -3            Indiana  2.861172e-05 0.002751568 -0.0058399050
## 191   -2            Indiana  2.471800e-05 0.001373596 -0.0025496941
## 192   -1            Indiana -1.562186e-05 0.002611840 -0.0047470294
## 193    0            Indiana -4.896250e-03 0.005384833 -0.0137327302
## 194    1            Indiana -1.351991e-02 0.014096223 -0.0292392340
## 195   NA            Indiana -9.208082e-03 0.009531406 -0.0212251738
## 196  -12               Iowa            NA         NaN            NA
## 197  -11               Iowa            NA         NaN            NA
## 198  -10               Iowa            NA         NaN            NA
## 199   -9               Iowa            NA         NaN            NA
## 200   -8               Iowa            NA         NaN            NA
## 201   -7               Iowa            NA         NaN            NA
## 202   -6               Iowa -8.297807e-12 0.011908516 -0.0214110041
## 203   -5               Iowa  9.255346e-12 0.010933388 -0.0189089354
## 204   -4               Iowa  2.275749e-12 0.006505534 -0.0129743911
## 205   -3               Iowa -1.879763e-11 0.006555214 -0.0132314877
```

```
## 206   -2                   Iowa  1.194625e-11 0.008270472 -0.0161532822
## 207   -1                   Iowa  3.617995e-12 0.003458553 -0.0066972290
## 208    0                   Iowa -8.208280e-03 0.008148107 -0.0204109011
## 209    1                   Iowa -6.110681e-03 0.005518208 -0.0150092909
## 210   NA                   Iowa -7.159481e-03 0.004615565 -0.0146967148
## 211  -12               Kentucky            NA         NaN            NA
## 212  -11               Kentucky            NA         NaN            NA
## 213  -10               Kentucky            NA         NaN            NA
## 214   -9               Kentucky            NA         NaN            NA
## 215   -8               Kentucky            NA         NaN            NA
## 216   -7               Kentucky            NA         NaN            NA
## 217   -6               Kentucky -7.023438e-04 0.016062577 -0.0313755519
## 218   -5               Kentucky  6.916848e-04 0.015126352 -0.0299333344
## 219   -4               Kentucky  1.579115e-03 0.009003872 -0.0156869417
## 220   -3               Kentucky  5.145222e-06 0.009032226 -0.0188185148
## 221   -2               Kentucky -2.042224e-03 0.011859724 -0.0243631904
## 222   -1               Kentucky  4.686232e-04 0.005686138 -0.0102803875
## 223    0               Kentucky -3.270426e-02 0.033973925 -0.0673206862
## 224    1               Kentucky -4.939311e-02 0.044404094 -0.0952422278
## 225   NA               Kentucky -4.104869e-02 0.038968080 -0.0791593458
## 226  -12              Louisiana            NA         NaN            NA
## 227  -11              Louisiana            NA         NaN            NA
## 228  -10              Louisiana            NA         NaN            NA
## 229   -9              Louisiana            NA         NaN            NA
## 230   -8              Louisiana  1.401961e-03 0.017867558 -0.0343786879
## 231   -7              Louisiana -1.546136e-03 0.011581882 -0.0235402036
## 232   -6              Louisiana  3.544046e-04 0.004601756 -0.0106344284
## 233   -5              Louisiana  1.164666e-03 0.003944345 -0.0069374187
## 234   -4              Louisiana -9.895302e-04 0.006176768 -0.0112130282
## 235   -3              Louisiana -7.468527e-04 0.003147299 -0.0072158805
## 236   -2              Louisiana  8.391783e-04 0.006341788 -0.0127365118
## 237   -1              Louisiana -4.776909e-04 0.015994519 -0.0300539088
## 238    0              Louisiana -1.205470e-02 0.024270152 -0.0492615953
## 239    1              Louisiana -3.358185e-02 0.045653651 -0.0905281854
## 240   NA              Louisiana -2.281828e-02 0.034707901 -0.0702162084
## 241  -12               Maryland            NA         NaN            NA
## 242  -11               Maryland            NA         NaN            NA
## 243  -10               Maryland            NA         NaN            NA
## 244   -9               Maryland            NA         NaN            NA
## 245   -8               Maryland            NA         NaN            NA
## 246   -7               Maryland            NA         NaN            NA
## 247   -6               Maryland -4.145015e-07 0.012396607 -0.0248738116
## 248   -5               Maryland  4.968849e-07 0.009745892 -0.0194147310
## 249   -4               Maryland  5.656665e-08 0.002946714 -0.0056730448
## 250   -3               Maryland -9.219880e-07 0.011530763 -0.0191978772
## 251   -2               Maryland  7.423690e-07 0.006758509 -0.0117873699
## 252   -1               Maryland  4.066901e-08 0.003605293 -0.0059418731
## 253    0               Maryland -4.179886e-04 0.006494708 -0.0118009369
## 254    1               Maryland  3.877541e-03 0.006699014 -0.0090824857
## 255   NA               Maryland  1.729776e-03 0.005988446 -0.0099304466
## 256  -12               Michigan            NA         NaN            NA
## 257  -11               Michigan            NA         NaN            NA
## 258  -10               Michigan            NA         NaN            NA
## 259   -9               Michigan            NA         NaN            NA
```

```
## 260   -8              Michigan            NA         NaN            NA
## 261   -7              Michigan            NA         NaN            NA
## 262   -6              Michigan -4.896385e-04 0.013556839 -0.0252626372
## 263   -5              Michigan  5.485453e-04 0.014963359 -0.0288835230
## 264   -4              Michigan  4.250109e-04 0.004712684 -0.0089972521
## 265   -3              Michigan -6.605248e-04 0.007900198 -0.0161838255
## 266   -2              Michigan  5.226093e-04 0.007247113 -0.0144326810
## 267   -1              Michigan -3.460021e-04 0.007922636 -0.0156663420
## 268    0              Michigan -8.025371e-03 0.011422530 -0.0256272138
## 269    1              Michigan -1.369117e-02 0.017957653 -0.0378145523
## 270   NA              Michigan -1.085827e-02 0.014630584 -0.0319486249
## 271  -12             Minnesota            NA         NaN            NA
## 272  -11             Minnesota            NA         NaN            NA
## 273  -10             Minnesota            NA         NaN            NA
## 274   -9             Minnesota            NA         NaN            NA
## 275   -8             Minnesota            NA         NaN            NA
## 276   -7             Minnesota            NA         NaN            NA
## 277   -6             Minnesota -4.920693e-11 0.009562874 -0.0181608257
## 278   -5             Minnesota  5.488555e-11 0.010452459 -0.0203108458
## 279   -4             Minnesota  1.349559e-11 0.005864478 -0.0106352282
## 280   -3             Minnesota -1.114724e-10 0.005887295 -0.0105393108
## 281   -2             Minnesota  7.084297e-11 0.005906039 -0.0107440788
## 282   -1             Minnesota  2.145525e-11 0.002363238 -0.0043701761
## 283    0             Minnesota -3.542872e-03 0.004401268 -0.0107997243
## 284    1             Minnesota -5.321175e-03 0.003885860 -0.0120886910
## 285   NA             Minnesota -4.432024e-03 0.003366959 -0.0100920407
## 286  -12               Montana            NA         NaN            NA
## 287  -11               Montana            NA         NaN            NA
## 288  -10               Montana            NA         NaN            NA
## 289   -9               Montana            NA         NaN            NA
## 290   -8               Montana  4.453454e-04 0.029012509 -0.0601861821
## 291   -7               Montana  1.703790e-03 0.028518313 -0.0579397392
## 292   -6               Montana -1.267496e-02 0.014575123 -0.0342975599
## 293   -5               Montana  7.908725e-03 0.010311417 -0.0152700766
## 294   -4               Montana  9.668764e-03 0.012053999 -0.0171816507
## 295   -3               Montana  1.325011e-03 0.009994623 -0.0173875686
## 296   -2               Montana -6.278959e-03 0.016845832 -0.0360358385
## 297   -1               Montana -2.097720e-03 0.024551799 -0.0475031003
## 298    0               Montana -2.522622e-02 0.045777793 -0.0929795576
## 299    1               Montana -2.396532e-02 0.043302729 -0.0910401284
## 300   NA               Montana -2.459577e-02 0.044521775 -0.0920098430
## 301  -12              Nebraska -3.667427e-03 0.016975342 -0.0354883435
## 302  -11              Nebraska  5.059002e-03 0.014103950 -0.0223955567
## 303  -10              Nebraska  2.174985e-03 0.010074810 -0.0159426516
## 304   -9              Nebraska  8.734972e-04 0.006110759 -0.0108263463
## 305   -8              Nebraska -4.222909e-03 0.010698258 -0.0217825336
## 306   -7              Nebraska -3.552310e-03 0.010075929 -0.0178965855
## 307   -6              Nebraska -4.880591e-03 0.003858202 -0.0115228910
## 308   -5              Nebraska -5.260393e-03 0.004208810 -0.0111950432
## 309   -4              Nebraska  1.049622e-02 0.019295789 -0.0261212583
## 310   -3              Nebraska  4.305912e-03 0.013563508 -0.0217422147
## 311   -2              Nebraska  4.564940e-03 0.009643457 -0.0141248143
## 312   -1              Nebraska -5.890924e-03 0.005491509 -0.0135453452
## 313    0              Nebraska -2.017920e-03 0.006637692 -0.0140998043
```

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## 314    1            Nebraska            NA         NaN            NA
## 315   NA            Nebraska -2.017920e-03 0.006637692 -0.0140998043
## 316  -12              Nevada            NA         NaN            NA
## 317  -11              Nevada            NA         NaN            NA
## 318  -10              Nevada            NA         NaN            NA
## 319   -9              Nevada            NA         NaN            NA
## 320   -8              Nevada            NA         NaN            NA
## 321   -7              Nevada            NA         NaN            NA
## 322   -6              Nevada -7.968625e-04 0.024601990 -0.0403406565
## 323   -5              Nevada  8.873256e-04 0.023973556 -0.0354586869
## 324   -4              Nevada  7.379966e-04 0.009889712 -0.0184500513
## 325   -3              Nevada -1.008670e-03 0.012402748 -0.0273289877
## 326   -2              Nevada  7.938569e-04 0.015204795 -0.0265006316
## 327   -1              Nevada -6.136469e-04 0.016091928 -0.0284073621
## 328    0              Nevada -3.877113e-02 0.043376537 -0.0886619265
## 329    1              Nevada -4.845291e-02 0.056864472 -0.1097983657
## 330   NA              Nevada -4.361202e-02 0.050078481 -0.0984570109
## 331  -12       New Hampshire            NA         NaN            NA
## 332  -11       New Hampshire            NA         NaN            NA
## 333  -10       New Hampshire            NA         NaN            NA
## 334   -9       New Hampshire            NA         NaN            NA
## 335   -8       New Hampshire            NA         NaN            NA
## 336   -7       New Hampshire            NA         NaN            NA
## 337   -6       New Hampshire  6.607513e-04 0.011622121 -0.0252808109
## 338   -5       New Hampshire -7.057918e-04 0.007566461 -0.0167499935
## 339   -4       New Hampshire -1.860400e-03 0.005468093 -0.0108872731
## 340   -3       New Hampshire -5.562685e-03 0.013748477 -0.0263649903
## 341   -2       New Hampshire  3.964452e-03 0.005855277 -0.0071841445
## 342   -1       New Hampshire  3.503674e-03 0.005213696 -0.0064604670
## 343    0       New Hampshire  7.535342e-03 0.011347273 -0.0158254333
## 344    1       New Hampshire  1.736218e-03 0.007727458 -0.0120234308
## 345   NA       New Hampshire  4.635780e-03 0.008849786 -0.0137564145
## 346  -12          New Jersey            NA         NaN            NA
## 347  -11          New Jersey            NA         NaN            NA
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## 349   -9          New Jersey            NA         NaN            NA
## 350   -8          New Jersey            NA         NaN            NA
## 351   -7          New Jersey            NA         NaN            NA
## 352   -6          New Jersey -5.790568e-04 0.017173421 -0.0289202400
## 353   -5          New Jersey  4.180303e-04 0.017306866 -0.0291972452
## 354   -4          New Jersey -9.176344e-04 0.009393860 -0.0181476219
## 355   -3          New Jersey -1.113657e-03 0.009159325 -0.0184405642
## 356   -2          New Jersey  4.185996e-04 0.011168963 -0.0194704895
## 357   -1          New Jersey  1.773718e-03 0.010569814 -0.0181320010
## 358    0          New Jersey -3.417452e-03 0.012325646 -0.0233459274
## 359    1          New Jersey -1.862684e-02 0.012827869 -0.0339235654
## 360   NA          New Jersey -1.102215e-02 0.011470813 -0.0243348373
## 361  -12          New Mexico            NA         NaN            NA
## 362  -11          New Mexico            NA         NaN            NA
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## 364   -9          New Mexico            NA         NaN            NA
## 365   -8          New Mexico            NA         NaN            NA
## 366   -7          New Mexico            NA         NaN            NA
## 367   -6          New Mexico  3.267756e-03 0.025188576 -0.0417373715
```

```
## 368   -5           New Mexico -3.495510e-03 0.012245219 -0.0234306222
## 369   -4           New Mexico  1.055547e-03 0.009462265 -0.0155090540
## 370   -3           New Mexico  2.933805e-03 0.007743997 -0.0104917727
## 371   -2           New Mexico -3.047410e-03 0.013621123 -0.0211202242
## 372   -1           New Mexico -7.141884e-04 0.007397770 -0.0133251100
## 373    0           New Mexico -2.495741e-02 0.029021070 -0.0576070439
## 374    1           New Mexico -4.559683e-02 0.051623917 -0.1014023615
## 375   NA           New Mexico -3.527712e-02 0.040301314 -0.0794801953
## 376  -12             New York            NA         NaN            NA
## 377  -11             New York            NA         NaN            NA
## 378  -10             New York            NA         NaN            NA
## 379   -9             New York            NA         NaN            NA
## 380   -8             New York            NA         NaN            NA
## 381   -7             New York            NA         NaN            NA
## 382   -6             New York  1.598151e-05 0.013657765 -0.0302721719
## 383   -5             New York -1.726374e-05 0.009987665 -0.0227909834
## 384   -4             New York  4.526955e-06 0.005161625 -0.0106160074
## 385   -3             New York  1.177596e-05 0.006083543 -0.0119150118
## 386   -2             New York -8.287400e-06 0.007026323 -0.0129285713
## 387   -1             New York -6.733288e-06 0.005838456 -0.0117121765
## 388    0             New York  4.465051e-04 0.006268400 -0.0104301102
## 389    1             New York  3.426964e-03 0.005998095 -0.0080022830
## 390   NA             New York  1.936735e-03 0.006021257 -0.0091083494
## 391  -12         North Dakota            NA         NaN            NA
## 392  -11         North Dakota            NA         NaN            NA
## 393  -10         North Dakota            NA         NaN            NA
## 394   -9         North Dakota            NA         NaN            NA
## 395   -8         North Dakota            NA         NaN            NA
## 396   -7         North Dakota            NA         NaN            NA
## 397   -6         North Dakota  7.365070e-04 0.007258239 -0.0137707134
## 398   -5         North Dakota -7.978633e-04 0.007554046 -0.0160940155
## 399   -4         North Dakota -1.998166e-03 0.010554955 -0.0210851849
## 400   -3         North Dakota -4.367890e-03 0.007491875 -0.0157710231
## 401   -2         North Dakota  3.184796e-03 0.007322662 -0.0133362159
## 402   -1         North Dakota  3.242616e-03 0.005568244 -0.0068852902
## 403    0         North Dakota -2.870206e-03 0.006913222 -0.0154670754
## 404    1         North Dakota  1.265383e-02 0.022643677 -0.0300751516
## 405   NA         North Dakota  4.891811e-03 0.014012170 -0.0210987182
## 406  -12                 Ohio            NA         NaN            NA
## 407  -11                 Ohio            NA         NaN            NA
## 408  -10                 Ohio            NA         NaN            NA
## 409   -9                 Ohio            NA         NaN            NA
## 410   -8                 Ohio            NA         NaN            NA
## 411   -7                 Ohio            NA         NaN            NA
## 412   -6                 Ohio -3.226225e-12 0.016342870 -0.0252008791
## 413   -5                 Ohio  3.598524e-12 0.016873543 -0.0290461480
## 414   -4                 Ohio  8.848200e-13 0.007018763 -0.0143330122
## 415   -3                 Ohio -7.308612e-12 0.007243794 -0.0149180815
## 416   -2                 Ohio  4.644771e-12 0.009033874 -0.0179783133
## 417   -1                 Ohio  1.406694e-12 0.010383926 -0.0193806106
## 418    0                 Ohio -8.337684e-03 0.012624058 -0.0284643757
## 419    1                 Ohio -9.242049e-03 0.014692094 -0.0311486318
## 420   NA                 Ohio -8.789867e-03 0.013633766 -0.0296397177
## 421  -12               Oregon            NA         NaN            NA
```

```
## 422  -11          Oregon            NA         NaN            NA
## 423  -10          Oregon            NA         NaN            NA
## 424   -9          Oregon            NA         NaN            NA
## 425   -8          Oregon            NA         NaN            NA
## 426   -7          Oregon            NA         NaN            NA
## 427   -6          Oregon -3.095536e-03 0.026489451 -0.0499193694
## 428   -5          Oregon  3.177208e-03 0.030190035 -0.0556878514
## 429   -4          Oregon  6.465552e-03 0.011335080 -0.0183613607
## 430   -3          Oregon -4.548286e-04 0.014788434 -0.0295533029
## 431   -2          Oregon -5.597237e-03 0.020186103 -0.0389935837
## 432   -1          Oregon -4.951587e-04 0.016511885 -0.0295705099
## 433    0          Oregon -2.984363e-02 0.041341890 -0.0772337109
## 434    1          Oregon -3.869174e-02 0.052746923 -0.0961138891
## 435   NA          Oregon -3.426769e-02 0.047026732 -0.0867832437
## 436  -12    Pennsylvania            NA         NaN            NA
## 437  -11    Pennsylvania            NA         NaN            NA
## 438  -10    Pennsylvania            NA         NaN            NA
## 439   -9    Pennsylvania            NA         NaN            NA
## 440   -8    Pennsylvania            NA         NaN            NA
## 441   -7    Pennsylvania -9.303645e-04 0.010990835 -0.0188733785
## 442   -6    Pennsylvania  9.710774e-04 0.011083423 -0.0176412197
## 443   -5    Pennsylvania  3.626142e-04 0.007593324 -0.0150089595
## 444   -4    Pennsylvania -1.502775e-03 0.005065575 -0.0105193116
## 445   -3    Pennsylvania  1.319086e-04 0.006576188 -0.0129528602
## 446   -2    Pennsylvania -1.228539e-03 0.005567318 -0.0124418767
## 447   -1    Pennsylvania  2.196078e-03 0.012648311 -0.0238461573
## 448    0    Pennsylvania -6.346238e-03 0.009763512 -0.0233287787
## 449    1    Pennsylvania -2.522150e-03 0.013096807 -0.0296937399
## 450   NA    Pennsylvania -4.434194e-03 0.011344840 -0.0265412671
## 451  -12    Rhode Island            NA         NaN            NA
## 452  -11    Rhode Island            NA         NaN            NA
## 453  -10    Rhode Island            NA         NaN            NA
## 454   -9    Rhode Island            NA         NaN            NA
## 455   -8    Rhode Island            NA         NaN            NA
## 456   -7    Rhode Island            NA         NaN            NA
## 457   -6    Rhode Island  1.873017e-03 0.019497330 -0.0321179540
## 458   -5    Rhode Island -2.649163e-03 0.026302142 -0.0446870073
## 459   -4    Rhode Island  1.767065e-05 0.010416009 -0.0172825527
## 460   -3    Rhode Island -4.244557e-03 0.006632602 -0.0127563841
## 461   -2    Rhode Island -7.050353e-04 0.012478808 -0.0212488325
## 462   -1    Rhode Island  5.708068e-03 0.019073736 -0.0277030706
## 463    0    Rhode Island -2.607626e-02 0.020194185 -0.0508241568
## 464    1    Rhode Island -2.878355e-02 0.022653257 -0.0575354280
## 465   NA    Rhode Island -2.742990e-02 0.021413019 -0.0541797924
## 466  -12            Utah  3.211616e-02 0.103607286 -0.1496361435
## 467  -11            Utah  4.427464e-02 0.094472276 -0.1265444246
## 468  -10            Utah  6.203015e-03 0.019056152 -0.0276382074
## 469   -9            Utah  5.657675e-03 0.020640344 -0.0305047518
## 470   -8            Utah -5.031201e-03 0.022201248 -0.0388728862
## 471   -7            Utah -9.093646e-03 0.024410786 -0.0447591893
## 472   -6            Utah -3.626450e-03 0.012120153 -0.0217460773
## 473   -5            Utah -3.927796e-03 0.012312494 -0.0222282459
## 474   -4            Utah -1.989720e-02 0.023660545 -0.0463830920
## 475   -3            Utah -1.404148e-02 0.024368774 -0.0467217586
```

```
## 476   -2                Utah -1.840027e-02 0.024188478 -0.0473240328
## 477   -1                Utah -1.423345e-02 0.022676304 -0.0438112512
## 478    0                Utah -1.293536e-02 0.022031364 -0.0423144065
## 479    1                Utah           NA         NaN            NA
## 480   NA                Utah -1.293536e-02 0.022031364 -0.0423144065
## 481  -12             Vermont           NA         NaN            NA
## 482  -11             Vermont           NA         NaN            NA
## 483  -10             Vermont           NA         NaN            NA
## 484   -9             Vermont           NA         NaN            NA
## 485   -8             Vermont           NA         NaN            NA
## 486   -7             Vermont           NA         NaN            NA
## 487   -6             Vermont  1.644172e-03 0.072193718 -0.1288309351
## 488   -5             Vermont -5.973458e-04 0.065090348 -0.1165918316
## 489   -4             Vermont -8.107928e-05 0.031710802 -0.0486580536
## 490   -3             Vermont -2.335120e-03 0.034869439 -0.0542943339
## 491   -2             Vermont -6.393527e-05 0.038476780 -0.0613536214
## 492   -1             Vermont  1.433308e-03 0.032878126 -0.0504490745
## 493    0             Vermont -6.342753e-03 0.031783380 -0.0516571372
## 494    1             Vermont -5.839137e-03 0.023983502 -0.0477688279
## 495   NA             Vermont -6.090945e-03 0.027318050 -0.0481642988
## 496  -12            Virginia           NA         NaN            NA
## 497  -11            Virginia -7.306868e-04 0.035161025 -0.0592227126
## 498  -10            Virginia -1.900077e-03 0.036816584 -0.0578367209
## 499   -9            Virginia -9.985294e-06 0.011096808 -0.0184414382
## 500   -8            Virginia -4.902555e-03 0.007627085 -0.0179465797
## 501   -7            Virginia  7.779925e-04 0.009270805 -0.0187839299
## 502   -6            Virginia  8.975205e-04 0.006321903 -0.0098601509
## 503   -5            Virginia  2.685063e-03 0.011152991 -0.0184499273
## 504   -4            Virginia  3.326303e-03 0.012958631 -0.0203855880
## 505   -3            Virginia  2.600563e-03 0.016911761 -0.0291294865
## 506   -2            Virginia -1.284143e-03 0.012592012 -0.0253742488
## 507   -1            Virginia -1.459996e-03 0.010214276 -0.0207692028
## 508    0            Virginia -1.401384e-02 0.007173062 -0.0255222585
## 509    1            Virginia -1.472141e-02 0.007489213 -0.0268109006
## 510   NA            Virginia -1.436762e-02 0.007319777 -0.0261665795
## 511  -12          Washington           NA         NaN            NA
## 512  -11          Washington           NA         NaN            NA
## 513  -10          Washington           NA         NaN            NA
## 514   -9          Washington           NA         NaN            NA
## 515   -8          Washington           NA         NaN            NA
## 516   -7          Washington           NA         NaN            NA
## 517   -6          Washington -2.101208e-04 0.013957583 -0.0263272459
## 518   -5          Washington  1.225242e-04 0.014989186 -0.0280588271
## 519   -4          Washington -1.670990e-04 0.005421840 -0.0085424591
## 520   -3          Washington -3.650552e-04 0.005359345 -0.0113238511
## 521   -2          Washington -6.773906e-05 0.007558101 -0.0128393768
## 522   -1          Washington  6.874899e-04 0.011995051 -0.0209374236
## 523    0          Washington -3.232985e-02 0.021023884 -0.0608107421
## 524    1          Washington -4.561742e-02 0.030023519 -0.0833924791
## 525   NA          Washington -3.897364e-02 0.025447790 -0.0721385622
## 526  -12       West Virginia           NA         NaN            NA
## 527  -11       West Virginia           NA         NaN            NA
## 528  -10       West Virginia           NA         NaN            NA
## 529   -9       West Virginia           NA         NaN            NA
```

```
## 530   -8        West Virginia            NA         NaN            NA
## 531   -7        West Virginia            NA         NaN            NA
## 532   -6        West Virginia  4.085459e-04 0.009416417 -0.0188968761
## 533   -5        West Virginia -4.661518e-04 0.008989865 -0.0170719889
## 534   -4        West Virginia -1.521051e-03 0.004017840 -0.0086009169
## 535   -3        West Virginia  4.406058e-03 0.010039586 -0.0150312845
## 536   -2        West Virginia -1.916591e-03 0.007766978 -0.0117820446
## 537   -1        West Virginia -9.108102e-04 0.004554985 -0.0096498890
## 538    0        West Virginia -3.322117e-02 0.028111141 -0.0657915841
## 539    1        West Virginia -5.064441e-02 0.044829315 -0.0992142117
## 540   NA        West Virginia -4.193279e-02 0.036442316 -0.0827762329
##       upper_bound
## 1    0.0787193044
## 2    0.0635928434
## 3    0.0268853632
## 4    0.0120484905
## 5    0.0157968329
## 6    0.0144224477
## 7    0.0141147808
## 8    0.0115098215
## 9    0.0062780406
## 10   0.0059641723
## 11   0.0062267493
## 12   0.0062848723
## 13  -0.0026093903
## 14  -0.0050136843
## 15  -0.0043445715
## 16             NA
## 17             NA
## 18             NA
## 19             NA
## 20             NA
## 21   0.0414757933
## 22   0.0321198566
## 23   0.0349907691
## 24   0.0161850092
## 25   0.0219357958
## 26   0.0173598122
## 27   0.0112816805
## 28   0.0128693802
## 29   0.0064673573
## 30   0.0098279713
## 31             NA
## 32             NA
## 33             NA
## 34             NA
## 35             NA
## 36             NA
## 37   0.0445441770
## 38   0.0234448895
## 39   0.0250164625
## 40   0.0176902260
## 41   0.0154791720
## 42   0.0147237925
```

```
## 43   0.0145396601
## 44   0.0212404977
## 45   0.0182200041
## 46             NA
## 47             NA
## 48             NA
## 49             NA
## 50             NA
## 51             NA
## 52   0.0554851839
## 53   0.0290709463
## 54   0.0193270943
## 55   0.0230926733
## 56   0.0200181141
## 57   0.0218505117
## 58   0.0327986411
## 59   0.0361314549
## 60   0.0344342062
## 61             NA
## 62             NA
## 63             NA
## 64             NA
## 65             NA
## 66             NA
## 67   0.0294985423
## 68   0.0294984839
## 69   0.0101947997
## 70   0.0121822179
## 71   0.0135467948
## 72   0.0161124090
## 73   0.0304579333
## 74   0.0497085391
## 75   0.0402378983
## 76             NA
## 77             NA
## 78             NA
## 79             NA
## 80             NA
## 81             NA
## 82   0.0437068434
## 83   0.0188057185
## 84   0.0102124166
## 85   0.0166832398
## 86   0.0175156421
## 87   0.0248669796
## 88   0.0377002473
## 89   0.0360965267
## 90   0.0368984194
## 91             NA
## 92             NA
## 93             NA
## 94             NA
## 95             NA
## 96             NA
```

```
## 97   0.0225911336
## 98   0.0237380987
## 99   0.0194696916
## 100  0.0167322104
## 101  0.0175668346
## 102  0.0156147595
## 103  0.0156741467
## 104  0.0225000089
## 105  0.0164552456
## 106            NA
## 107            NA
## 108            NA
## 109            NA
## 110            NA
## 111            NA
## 112  0.0592185842
## 113  0.0484263683
## 114  0.0266719263
## 115  0.0364857283
## 116  0.0387543436
## 117  0.0195932250
## 118  0.0154739297
## 119  0.0097599961
## 120  0.0051651734
## 121            NA
## 122            NA
## 123            NA
## 124            NA
## 125            NA
## 126            NA
## 127  0.0257174853
## 128  0.0096014716
## 129  0.0044333456
## 130  0.0101532471
## 131  0.0254914059
## 132  0.0105023983
## 133  0.0311713224
## 134  0.0396378628
## 135  0.0356583002
## 136            NA
## 137            NA
## 138            NA
## 139            NA
## 140            NA
## 141            NA
## 142  0.0265892250
## 143  0.0240604799
## 144  0.0126601043
## 145  0.0130420086
## 146  0.0165697301
## 147  0.0095601053
## 148  0.0115948079
## 149  0.0195655856
## 150  0.0126982304
```

```
## 151  0.0443323347
## 152  0.0310426336
## 153  0.0276175185
## 154  0.0129403978
## 155  0.0098853911
## 156  0.0137942015
## 157  0.0045252244
## 158  0.0177482369
## 159  0.0184618279
## 160  0.0204292519
## 161  0.0165605254
## 162  0.0284580574
## 163  0.0252146937
## 164            NA
## 165  0.0252146937
## 166            NA
## 167            NA
## 168            NA
## 169            NA
## 170            NA
## 171            NA
## 172  0.0188042787
## 173  0.0134878510
## 174  0.0055061171
## 175  0.0179185443
## 176  0.0088903522
## 177  0.0072597133
## 178  0.0138734573
## 179  0.0251007069
## 180  0.0195278372
## 181            NA
## 182            NA
## 183            NA
## 184            NA
## 185            NA
## 186  0.0102292339
## 187  0.0089216151
## 188  0.0054650370
## 189  0.0073302611
## 190  0.0050784041
## 191  0.0027103823
## 192  0.0052927770
## 193  0.0065688658
## 194  0.0141544485
## 195  0.0100094909
## 196            NA
## 197            NA
## 198            NA
## 199            NA
## 200            NA
## 201            NA
## 202  0.0243918617
## 203  0.0218830351
## 204  0.0112596253
```

```
## 205  0.0122321499
## 206  0.0153476543
## 207  0.0068528075
## 208  0.0082570519
## 209  0.0052008000
## 210  0.0024414031
## 211            NA
## 212            NA
## 213            NA
## 214            NA
## 215            NA
## 216            NA
## 217  0.0305100033
## 218  0.0291274708
## 219  0.0173827554
## 220  0.0187757841
## 221  0.0238371747
## 222  0.0109886185
## 223  0.0306901903
## 224  0.0338497781
## 225  0.0297743754
## 226            NA
## 227            NA
## 228            NA
## 229            NA
## 230  0.0358508463
## 231  0.0242387301
## 232  0.0093802866
## 233  0.0073030091
## 234  0.0111784767
## 235  0.0040314138
## 236  0.0113039038
## 237  0.0279299530
## 238  0.0333494832
## 239  0.0521195425
## 240  0.0426054496
## 241            NA
## 242            NA
## 243            NA
## 244            NA
## 245            NA
## 246            NA
## 247  0.0213951403
## 248  0.0149357634
## 249  0.0057173492
## 250  0.0212417394
## 251  0.0132037234
## 252  0.0072435432
## 253  0.0114046329
## 254  0.0125062892
## 255  0.0108477546
## 256            NA
## 257            NA
## 258            NA
```

```
## 259           NA
## 260           NA
## 261           NA
## 262  0.0254999650
## 263  0.0278274592
## 264  0.0069652595
## 265  0.0142602879
## 266  0.0140794127
## 267  0.0148483904
## 268  0.0148401464
## 269  0.0219214291
## 270  0.0182360783
## 271           NA
## 272           NA
## 273           NA
## 274           NA
## 275           NA
## 276           NA
## 277  0.0185117183
## 278  0.0176856653
## 279  0.0111798217
## 280  0.0113542322
## 281  0.0108844033
## 282  0.0045073488
## 283  0.0056772688
## 284  0.0032463004
## 285  0.0026536948
## 286           NA
## 287           NA
## 288           NA
## 289           NA
## 290  0.0606986937
## 291  0.0599004920
## 292  0.0163967139
## 293  0.0258747603
## 294  0.0301617849
## 295  0.0188298804
## 296  0.0288098977
## 297  0.0450890062
## 298  0.0648569319
## 299  0.0634603947
## 300  0.0637045776
## 301  0.0291461124
## 302  0.0284586665
## 303  0.0214737083
## 304  0.0141358340
## 305  0.0206513696
## 306  0.0156433996
## 307  0.0033152997
## 308  0.0030734690
## 309  0.0361465938
## 310  0.0264966657
## 311  0.0172700464
## 312  0.0052753939
```

```
## 313  0.0112903443
## 314            NA
## 315  0.0112903443
## 316            NA
## 317            NA
## 318            NA
## 319            NA
## 320            NA
## 321            NA
## 322  0.0488217564
## 323  0.0479203059
## 324  0.0176790673
## 325  0.0201546950
## 326  0.0303023974
## 327  0.0267221644
## 328  0.0440956987
## 329  0.0574799614
## 330  0.0506113637
## 331            NA
## 332            NA
## 333            NA
## 334            NA
## 335            NA
## 336            NA
## 337  0.0249318960
## 338  0.0132881447
## 339  0.0088651419
## 340  0.0216871818
## 341  0.0149314554
## 342  0.0132725348
## 343  0.0254686723
## 344  0.0163418891
## 345  0.0206410935
## 346            NA
## 347            NA
## 348            NA
## 349            NA
## 350            NA
## 351            NA
## 352  0.0295137782
## 353  0.0296241834
## 354  0.0170818378
## 355  0.0157514068
## 356  0.0195910347
## 357  0.0199466080
## 358  0.0196237336
## 359  0.0098055061
## 360  0.0104698134
## 361            NA
## 362            NA
## 363            NA
## 364            NA
## 365            NA
## 366            NA
```

```
## 367  0.0397640352
## 368  0.0173619706
## 369  0.0176142972
## 370  0.0152366165
## 371  0.0222964682
## 372  0.0136775261
## 373  0.0306807144
## 374  0.0496624058
## 375  0.0400502128
## 376            NA
## 377            NA
## 378            NA
## 379            NA
## 380            NA
## 381            NA
## 382  0.0265305380
## 383  0.0208376479
## 384  0.0111421004
## 385  0.0133791727
## 386  0.0151089268
## 387  0.0126096138
## 388  0.0131410548
## 389  0.0149458180
## 390  0.0140484990
## 391            NA
## 392            NA
## 393            NA
## 394            NA
## 395            NA
## 396            NA
## 397  0.0145241921
## 398  0.0150726003
## 399  0.0191014946
## 400  0.0107413620
## 401  0.0169871204
## 402  0.0122006955
## 403  0.0123475295
## 404  0.0406891421
## 405  0.0254840749
## 406            NA
## 407            NA
## 408            NA
## 409            NA
## 410            NA
## 411            NA
## 412  0.0332873818
## 413  0.0331116625
## 414  0.0118049440
## 415  0.0114013519
## 416  0.0147157157
## 417  0.0175796639
## 418  0.0169106514
## 419  0.0194260304
## 420  0.0181882098
```

```
## 421            NA
## 422            NA
## 423            NA
## 424            NA
## 425            NA
## 426            NA
## 427  0.0461641477
## 428  0.0567995936
## 429  0.0256404472
## 430  0.0290879937
## 431  0.0339075252
## 432  0.0290639413
## 433  0.0451454349
## 434  0.0572906430
## 435  0.0509967493
## 436            NA
## 437            NA
## 438            NA
## 439            NA
## 440            NA
## 441  0.0197208526
## 442  0.0222970342
## 443  0.0155536073
## 444  0.0080349548
## 445  0.0131430971
## 446  0.0080564150
## 447  0.0256351947
## 448  0.0156978711
## 449  0.0255346571
## 450  0.0209062486
## 451            NA
## 452            NA
## 453            NA
## 454            NA
## 455            NA
## 456            NA
## 457  0.0339144602
## 458  0.0412955695
## 459  0.0172961178
## 460  0.0078716713
## 461  0.0205725983
## 462  0.0344774907
## 463  0.0191491741
## 464  0.0225718811
## 465  0.0208605276
## 466  0.1865241626
## 467  0.1774083341
## 468  0.0339884393
## 469  0.0362961123
## 470  0.0330965539
## 471  0.0343118224
## 472  0.0175819782
## 473  0.0177161145
## 474  0.0235202219
```

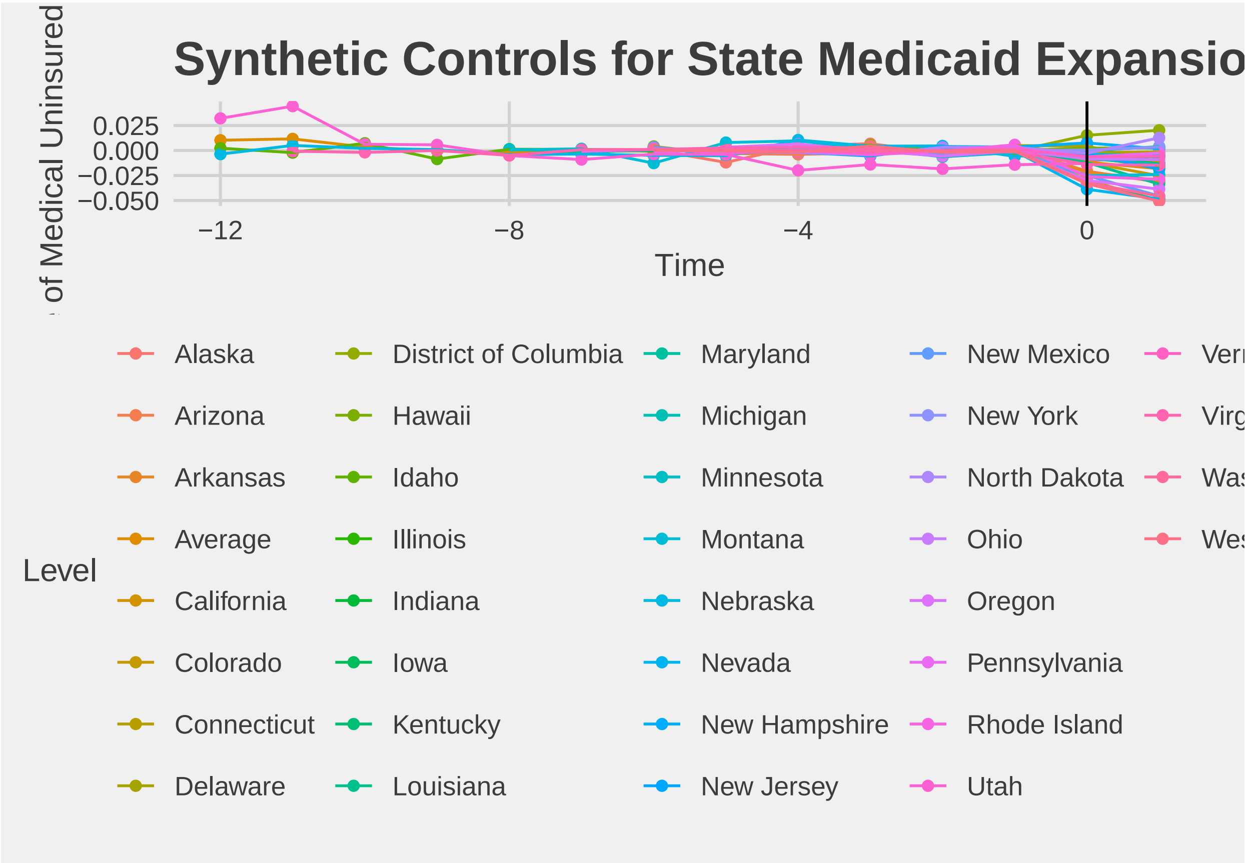
```
## 475  0.0305908121
## 476  0.0261816764
## 477  0.0274592247
## 478  0.0274539188
## 479            NA
## 480  0.0274539188
## 481            NA
## 482            NA
## 483            NA
## 484            NA
## 485            NA
## 486            NA
## 487  0.1104114591
## 488  0.1016641789
## 489  0.0577334278
## 490  0.0615845710
## 491  0.0692270197
## 492  0.0571461028
## 493  0.0508952231
## 494  0.0410397010
## 495  0.0414140044
## 496            NA
## 497  0.0607126600
## 498  0.0650499522
## 499  0.0183885464
## 500  0.0102342742
## 501  0.0196780153
## 502  0.0125330104
## 503  0.0187543134
## 504  0.0223546886
## 505  0.0262260489
## 506  0.0159665259
## 507  0.0161883870
## 508  0.0011809462
## 509  0.0012119354
## 510  0.0008420151
## 511            NA
## 512            NA
## 513            NA
## 514            NA
## 515            NA
## 516            NA
## 517  0.0260979510
## 518  0.0271439597
## 519  0.0115959398
## 520  0.0095523520
## 521  0.0150339052
## 522  0.0201686990
## 523  0.0141922490
## 524  0.0174219970
## 525  0.0158071868
## 526            NA
## 527            NA
## 528            NA
```

```
## 529            NA
## 530            NA
## 531            NA
## 532  0.0172360733
## 533  0.0146950865
## 534  0.0079727102
## 535  0.0200886523
## 536  0.0129862295
## 537  0.0079549658
## 538  0.0214704972
## 539  0.0347033791
## 540  0.0283336017
```

```
# plot actual estimates not values of synthetic controls
# ---------
non_ppool_synsum$att %>%
  ggplot(aes(x = Time, y = Estimate, color = Level)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 0) +
  theme_fivethirtyeight() +
  theme(axis.title = element_text(),
        legend.position = "bottom") +
  ggtitle('Synthetic Controls for State Medicaid Expansion') +
  xlab('Time') +
  ylab('Rate of Medical Uninsured Rate')
```

```
## Warning: Removed 219 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

```
## Warning: Removed 219 rows containing missing values or values outside the scale range
## (`geom_line()`).
```

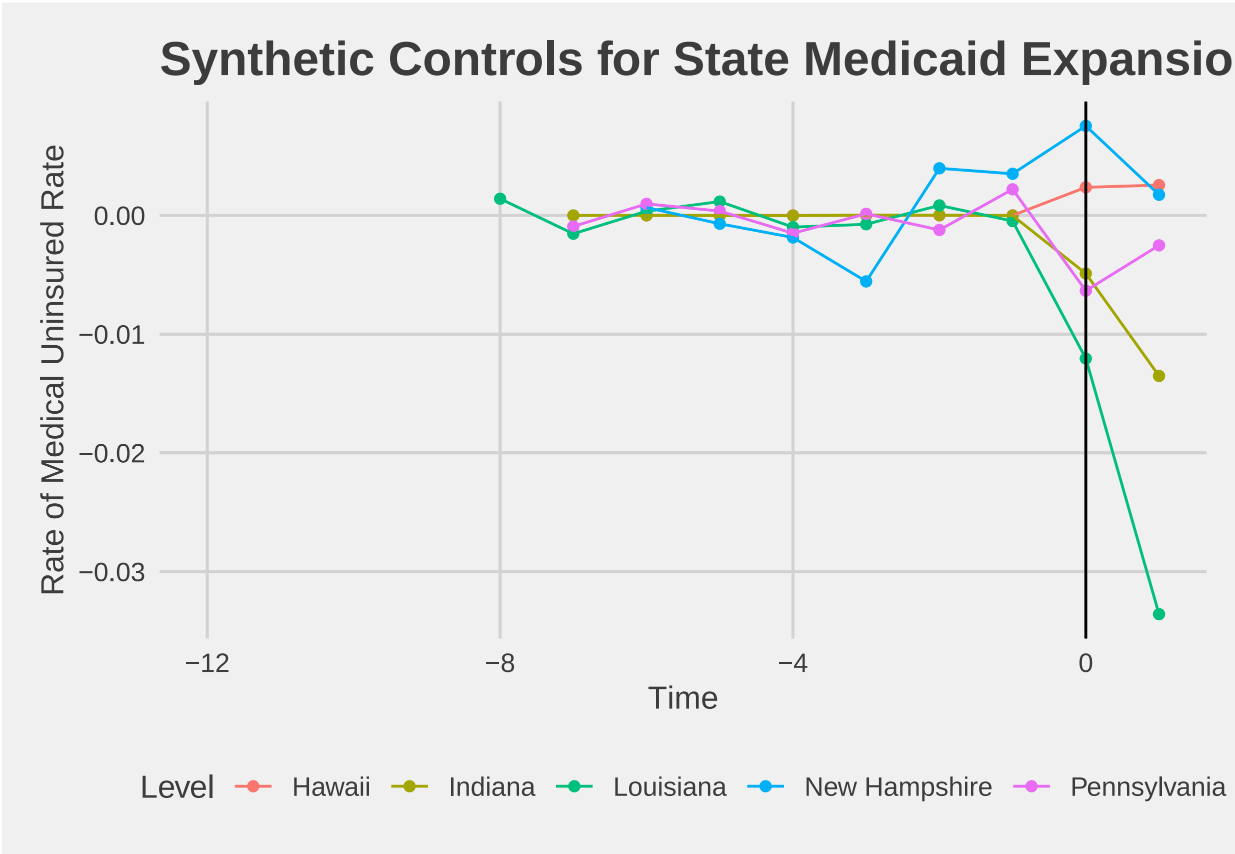



```r
non_ppool_synsum_sub_att<- as.data.frame(non_ppool_synsum$att) %>% filter(Level %in% c("Hawaii", "Calif

non_ppool_synsum_sub_att %>%
  ggplot(aes(x = Time, y = Estimate, color = Level)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 0) +
  theme_fivethirtyeight() +
  theme(axis.title = element_text(),
        legend.position = "bottom") +
  ggtitle('Synthetic Controls for State Medicaid Expansion') +
  xlab('Time') +
  ylab('Rate of Medical Uninsured Rate')
```

```
## Warning: Removed 31 rows containing missing values or values outside the scale range
## (`geom_point()`).

## Warning: Removed 31 rows containing missing values or values outside the scale range
## (`geom_line()`).
```



- Estimate a multisynth model using time cohorts. For the purpose of this exercise, you can simplify the treatment time so that states that adopted Medicaid expansion within the same year (i.e. all states that adopted epxansion in 2016) count for the same cohort. Plot the treatment effects for these time cohorts.

```
# multisynth model time cohorts

ppool_syn_time <- multisynth(uninsured_rate ~ adopted,
                        State,                          # unit
                        year,                           # time
                        medicaid_expansion_clean,   # data
                        n_leads = 10,
                        time_cohort = TRUE)                  # post-treatment periods to estimate

# save summary
ppool_syn_time_summ <- summary(ppool_syn_time)

# view
ppool_syn_time_summ
```

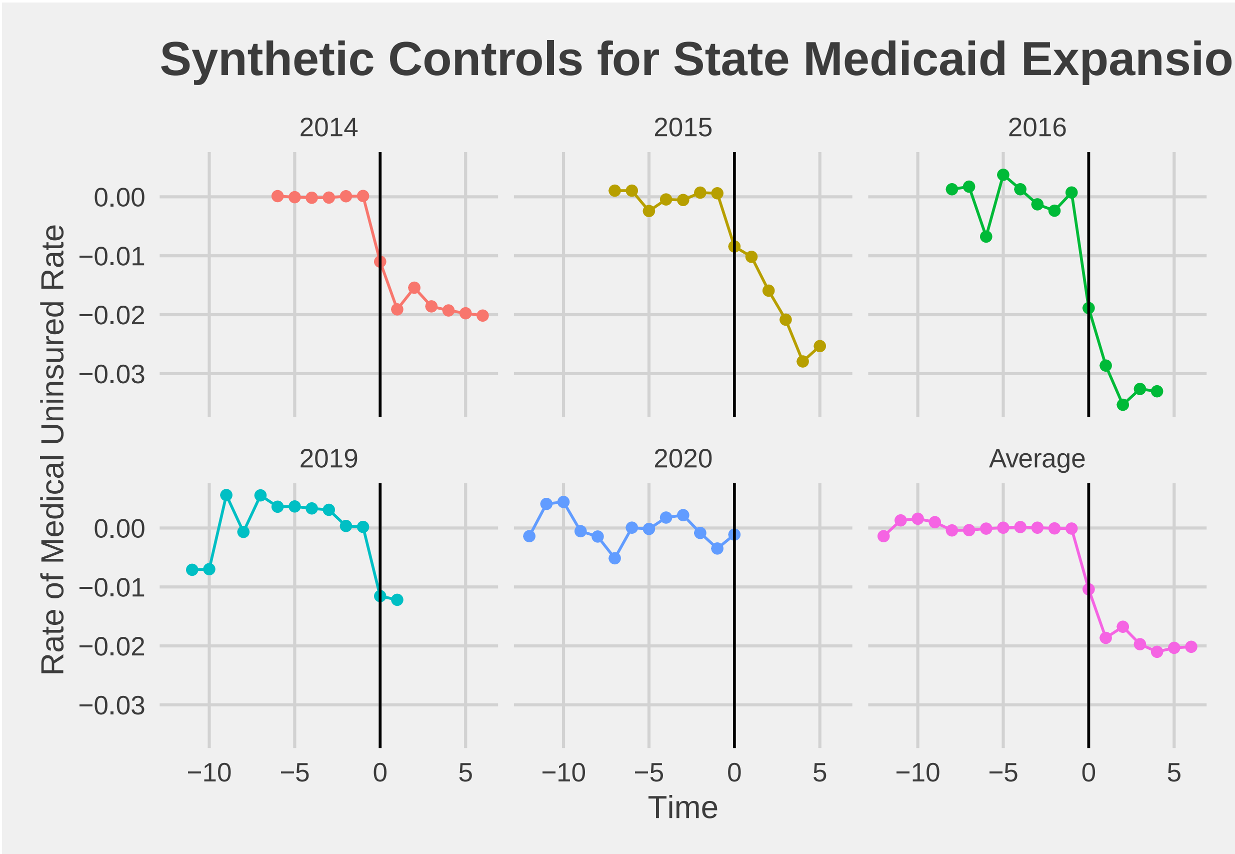
```
##
## Call:
## multisynth(form = uninsured_rate ~ adopted, unit = State, time = year,
##     data = medicaid_expansion_clean, n_leads = 10, time_cohort = TRUE)
##
## Average ATT Estimate (Std. Error): -0.017  (0.006)
##
## Global L2 Imbalance: 0.001
```

```
## Scaled Global L2 Imbalance: 0.008
## Percent improvement from uniform global weights: 99.2
##
## Individual L2 Imbalance: 0.005
## Scaled Individual L2 Imbalance: 0.018
## Percent improvement from uniform individual weights: 98.2
##
##  Time Since Treatment   Level    Estimate   Std.Error lower_bound  upper_bound
##                     0 Average -0.01039793 0.004815381 -0.02072180 -0.002118507
##                     1 Average -0.01864128 0.005947491 -0.03048110 -0.007653855
##                     2 Average -0.01674715 0.006065281 -0.02936776 -0.004963693
##                     3 Average -0.01971271 0.006321548 -0.03271252 -0.007651756
##                     4 Average -0.02100310 0.006175154 -0.03331766 -0.009265066
##                     5 Average -0.02033303 0.005618902 -0.03130448 -0.009657738
##                     6 Average -0.02015002 0.006201813 -0.03227776 -0.008279763
```

```r
# plot effect for each time period (local treatment effects)
# ---------
ppool_syn_time_summ$att %>%
  ggplot(aes(x = Time, y = Estimate, color = Level)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 0) +
  theme_fivethirtyeight() +
  theme(axis.title = element_text(),
        legend.position = 'None') +
  ggtitle('Synthetic Controls for State Medicaid Expansion') +
  xlab('Time') +
  ylab('Rate of Medical Uninsured Rate') +
  facet_wrap(~Level)
```

```
## Warning: Removed 36 rows containing missing values or values outside the scale range
## (`geom_point()`).
```

```
## Warning: Removed 36 rows containing missing values or values outside the scale range
## (`geom_line()`).
```



Discussion Questions

- One feature of Medicaid is that it is jointly administered by the federal government and the states, and states have some flexibility in how they implement Medicaid. For example, during the Trump administration, several states applied for waivers where they could add work requirements to the eligibility standards (i.e. an individual needed to work for 80 hours/month to qualify for Medicaid). Given these differences, do you see evidence for the idea that different states had different treatment effect sizes?
- **Answer**: Yes, when plotting individual states even when considering the differences in pre treatment trends there are dramtic different effect sizes as observed by the highly varied slopes in the post treatment periods.
- Do you see evidence for the idea that early adopters of Medicaid expansion enjoyed a larger decrease in the uninsured population?
- **Answer**: Yes indeed there is. For example when observing the trendes in time cohorts we do see that for example the 2014 cohort had a much larger effect on the decrease in uninsured rates than the 2019 cohorts. Yet it seems this trends may not be purely about early expansion as we can also see that the 2015 cohort had much larger decreases relative to the 2014 cohort.

General Discussion Questions

- Why are DiD and synthetic control estimates well suited to studies of aggregated units like cities, states, countries, etc?
- **Answer**: Difference-in-Differencess and synthetic control methods are suited to studies involving aggregated units such as cities, states, and countries for several reasons. Firstly, these methods excel

in situations where a clear comparison between treated and untreated units over time can elucidate the impact of policy or intervention. In the case of DiD, the technique relies on comparing changes in outcomes over time between a group that experiences some intervention (the treatment group) and a group that does not (the control group). Many policies are implemented at a regional or national level, directly affecting aggregated units. DiD and Synthetic Control are adept at analyzing these situations because they can directly measure the impact of policy changes on the entire populations of these units. This is especially relevant when assessing interventions like economic stimulus packages, healthcare reforms, or education system overhauls, where the unit of treatment isn't individuals but rather whole regions or countries.

Synthetic Control further refines this approach by constructing a weighted combination of control units that best replicate the characteristics of the treated unit prior to the intervention. This method is particularly useful when dealing with heterogeneous units like states or countries, where no single control unit perfectly matches the treated unit. The use of a synthetic control allows for a more precise estimation of what the outcome would have been in the absence of the treatment, accounting for both observed and unobserved pre-treatment characteristics. The synthetic control method is robust to cases where there might be many potential confounders and where the treatment effect needs to be isolated in a context of complex social and economic dynamics typical of aggregated data.

- What role does selection into treatment play in DiD/synthetic control versus regression discontinuity? When would we want to use either method?
- **Answer**: The role of selection into treatment differs quite a bit between DiD/Synthetic Control and RD). In DiD and Synthetic Control, the selection into treatment can be non-random and may depend on characteristics observable to the researcher as well as unobservable factors. DiD in particular assumes that any unobserved differences between treatment and control groups remain constant over time, which might not hold if the treatment is endogenous (e.g., if cities adopt a policy due to rising crime rates). Synthetic Control attempts to mitigate this issue by explicitly constructing a control group that closely matches the treated unit's pre-treatment characteristics, thereby controlling for both observed and unobserved factors that might lead to selection into treatment.

Dissimialrly, RD provides a quasi-experimental design that precisely exploits a cutoff in an assignment variable (e.g., age, income) to identify causal effects. RD is particularly powerful when the treatment is assigned based on an observable and continuous variable that has a clear cutoff point. The choice between DiD/Synthetic Control and RD should be guided by the nature of the treatment assignment and the research question. DiD and Synthetic Control are preferable when the treatment assignment is more arbitrary or influenced by factors not easily controlled for, especially when longitudinal data is available and when there are no clear cutoffs defining treatment eligibility. These methods are ideal for assessing the impact of policy changes, economic interventions, or other treatments spread across different times or regions.

RD should be chosen when the treatment assignment is strictly determined by a cutoff value on an observable variable, and there is a need to precisely estimate local treatment effects at the cutoff.