Final exercise

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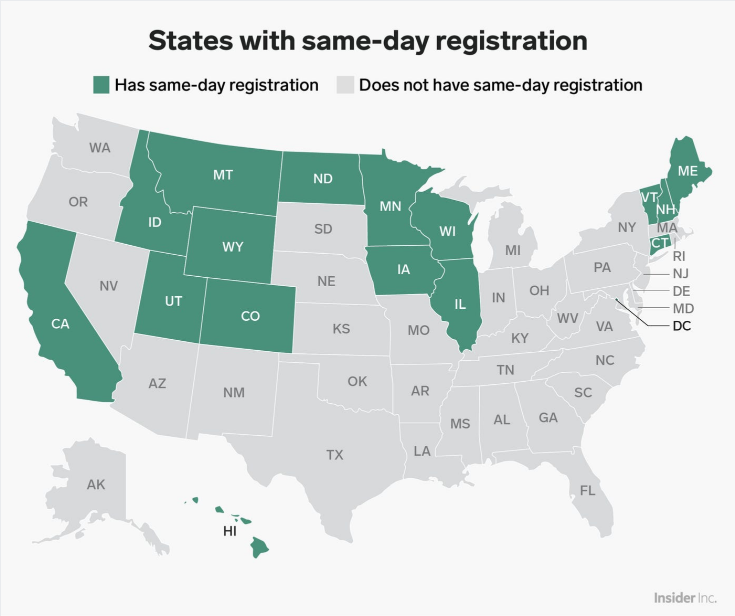
10.09.2020

Election day registration & voter turnout in the US

- The majority of states require voters to *register two to four weeks before an election*. (Wikipedia)
- "There is *strong evidence that same day and Election Day registration increases voter turnout*, but the extent of the impact is difficult to conclude.
- Multiple studies place the *effect between an increase of 3 to 7 percent*, with an **average of a 5 percent increase**." (NCLS)



(Source: businessinsider.com, November 2018.)

Research question

We want to examine ourselves **if introducing election day registration has an impact on voter turnout**.

We will try to understand the **effect of EDR upon voter turnout** in the state of Maine.

If time allows, we will go one step further and ask:

What is the **causal effect** of EDR upon voter turnout in the US, and is our estimate in the *range of values provided in the literature*, i.e., **5% on average**?

(Source: Andertoons)

(Acknowledgment: this exercise is based on an assignment created by our former Statistics I lecturer Liam Beiser-McGreith. Thanks, Liam!)

The data set

We use data on **US states** for all **presidential elections from 1920 to 2012**.

```r
# load data set
library(gsynth)
data(gsynth)
rm(list = c("simdata"))
```

Reference: *Melanie Jean Springer. 2014. How the States Shaped the Nation: American Electoral Institutions and Voter Turnout, 1920-2000. University of Chicago Press.*

```r
# inspect data
str(turnout)
```

```
## 'data.frame':	1128 obs. of  6 variables:
##  $ abb           : chr  "AL" "AL" "AL" "AL" ...
##  $ year          : int  1920 1924 1928 1932 1936 1940 1944 1948 1952 1956 .
##  $ turnout       : num  21 13.6 19 17.6 18.7 ...
##  $ policy_edr    : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ policy_mail_in: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ policy_motor  : num  0 0 0 0 0 0 0 0 0 0 ...
```

```r
# unique states
length(unique(turnout$abb))
```

```
## [1] 47
```

```r
# unique years
length(unique(turnout$year))
```

```
## [1] 24
```

Exercise

We first focus on the state **Maine** (abb = "ME"). Maine introduced *election day registration (EDR)* in the year **1976**.

1) **Plot turnout in Maine over the 1920-2012 time period.**

Hint: First, you need to *filter* for Maine (abb = "ME"). For the plot *geom_line* and *geom_point* might be suitable functions. Note that years should be on the x-axis, while turnout should be on the y-axis.

2) **Distinguish between the period before and after EDR was introduced in Maine**.

These are commonly called the *"pre-" and "post-treatment"* periods respectively, where the term "treatment" specifically refers to the introduction of EDR. After you have done so, split the pre- and post-treatment data and assign them to two new variables *pre* and *post*, respectively.

Hint: Use *mutate* to add another column called *treatment* to the data set that consists out of 0 and 1 values, where 1 should be assigned to all rows starting 1976 and 0 to all rows before that (an *ifelse* clause might be handy). Use *filter* to split the pre- and post-treatment data.

Exercise

3) **Update your plot further**.

Visualise the *time EDR was introduced* to distinguish *pre- and post-treatment periods* and the *mean values of pre- and post-treatment turnout* in Maine. In the end, *label* your plot.

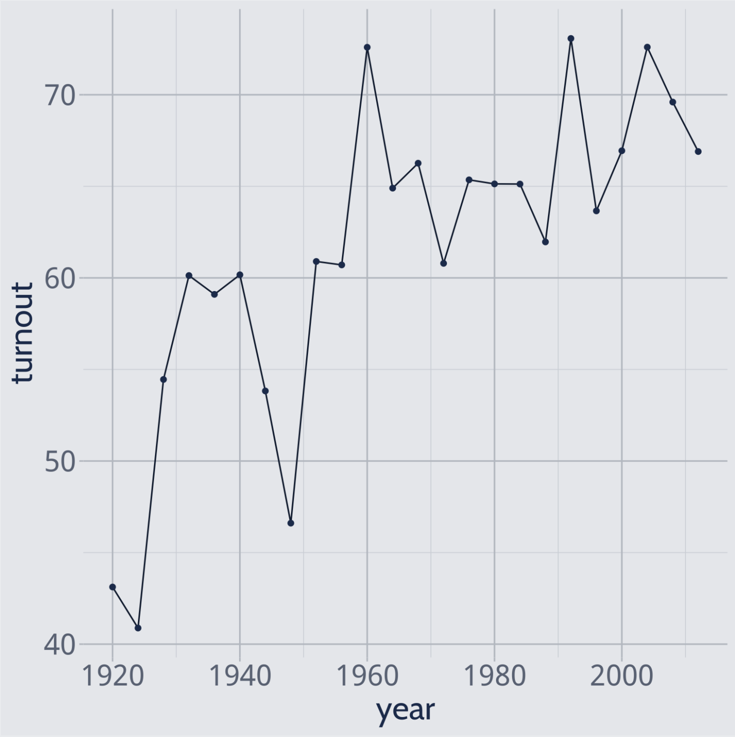
--> *Do you observe a notable difference in pre- and post-treatment mean turnout?*

Hint: use *geom_vline* to visualise the EDR introduction time and *geom_segment* to indicate pre- and post-treatment period mean turnout. Use *labs* to assign x/y labels and a title.

Go for it!

1) Plot turnout in Maine over 1920 - 2012.

```
turnout_maine <- turnout %>%
  filter(abb == 'ME')

ggplot(turnout_maine) +
  aes(y=turnout, x=year) +
  geom_line() +
  geom_point() +
  theme_xaringan()
```

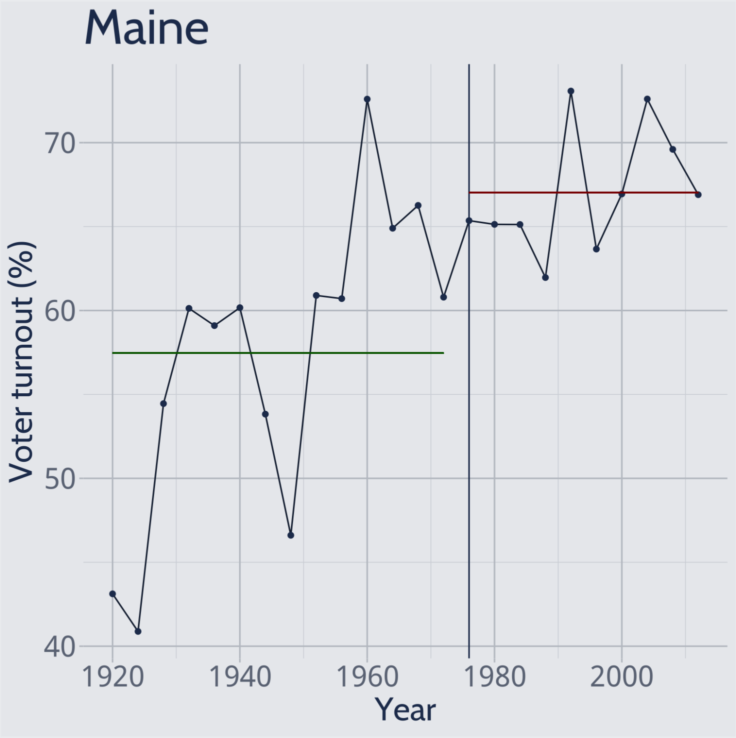


2) Distinguish between pre- and post-EDR periods

```r
# filter and mutate
turnout_maine <- turnout_maine %>%
  mutate(treatment=ifelse(year >= 1976, 1, 0))

# disentangle treatment groups
pre <- turnout_maine %>%
  filter(treatment == 0)
post <- turnout_maine %>%
  filter(treatment == 1)
```

3) Update plot

```
ggplot(turnout_maine) +
  aes(y=turnout, x=year) +
  geom_line() +
  geom_point() +
  geom_vline(xintercept=1976) +
  geom_segment(
    x=first(pre$year),
    xend=last(pre$year),
    y=mean(pre$turnout),
    yend=mean(pre$turnout),
    color='darkgreen') +
  geom_segment(
    x=first(post$year),
    xend=last(post$year),
    y=mean(post$turnout),
    yend=mean(post$turnout),
    color='darkred') +
  labs(
    title = "Maine",
    x = "Year",
    y = "Voter turnout (%)") +
  theme_xaringan()
```



Pre-treatment mean turnout: 57.46%

Post-treatment mean turnout: 67.04%

Difference: 9.58%

Bonus exercise (to be continued at home (-:)

- We now go one step further and ask a more general question: **what is the causal effect of EDR upon voter turnout in the US** as a whole?
- This means that we not only need to distinguish between **pre- and post-treatment periods** (i.e., the time EDR was introduced in a state, e.g., in Maine), but also between **treatment and control group states**. *Treatment group states* are those where EDR was introduced, while *control group states* are those where it was not introduced over the observed time period. The *control group states* provide what is called the **counterfactual** in policy jargon, i.e., "what would have happened if no policy was introduced?".

Bonus exercise

- Essentially, you will work with a combination of **4 subsets of the original data**:

  1. the **pre-treatment subset**
  2. the **post-treatment subset**
  3. the **treatment subset**
  4. the **control subset**

- We will only **focus on those states that introduced EDR in 1976**. There are *6 states that introduced EDR at other points in time* throughout our observation period, but we will *neglect* them for the time being in order to *simplify the analysis*. Note that since we do not exploit the full range of information availabe, our *estimates will be somewhat biased*. There are techniques for addressing this and you will (probably) learn about them in the future.

Bonus exercise: steps and hints

1) Find the treatment group states (subset 3): use *filter* with conditions to find all states that introduced EDR in 1976 (Hint: ME, MN, WI). Assign to a new variable called *states_E1*.

2) Find the control group states (subset 4): use *group_by*, *summarise*, *filter* and *select* to find all states that didn't introduce EDR within our observation period. Assign to a new variable called *states_E0*.

3) Now, focus on the time dimension in the control group subset: use *filter* to distinguish between pre- and post-treatment subsets within the control group. Assign the resulting data frames to variables called *E0T0* and *E0T1*, respectively. Calculate the mean $\mu_{turnout}$ (over the time dimension) for both variables.

4) Next, focus on the time dimension in the treatment group subset: use *filter* to distinguish between pre- and post-treatment subsets within the treatment group. Assign the resulting data frames to variables called *E1T0* and *E1T1*, respectively. Calculate the mean $\mu_{turnout}$ (over the time dimension) for both variables.

Bonus exercise: steps and hints

… continued …

5) **Plot** turnout across all states over time, distinguishing between election day registration states and non-election day registration states, as well as pre- and post-treatment periods.

6) Lastly, estimate the **average effect of EDR on voter turnout** through double-differencing of mean turnout within each of the 4 subsets:

$$DID = (\mu_{E1T1} - \mu_{E1T0}) - (\mu_{E0T1} - \mu_{E0T0})$$

Solution to Exercise 2: steps 1 and 2

```
yrs <- unique(turnout$year) # years
states <- unique(turnout$abb) # states

# treatment group data
states_E1 <- unique(
  filter(
    turnout, (policy_edr == 1 & year == 1976))$abb
  )

# control group data
states_E0 <- turnout %>%
  group_by(abb) %>%
  summarise(sum_policy_edr = sum(policy_edr)) %>%
  filter(sum_policy_edr == 0) %>%
  select(abb)
states_E0 <- states_E0$abb
```

Solution to Exercise 2: step 3

```r
# Control group elements: E0T0, E0T1
E0 <- turnout %>% filter(abb %in% states_E0)
E0T0 <- E0 %>% filter(year < 1976)
E0T1 <- E0 %>% filter(year >= 1976)

E0T0_mean <- E0T0 %>%
  group_by(year) %>%
  summarise(mean_turnout = mean(turnout))

E0T1_mean <- E0T1 %>%
  group_by(year) %>%
  summarise(mean_turnout = mean(turnout))
```

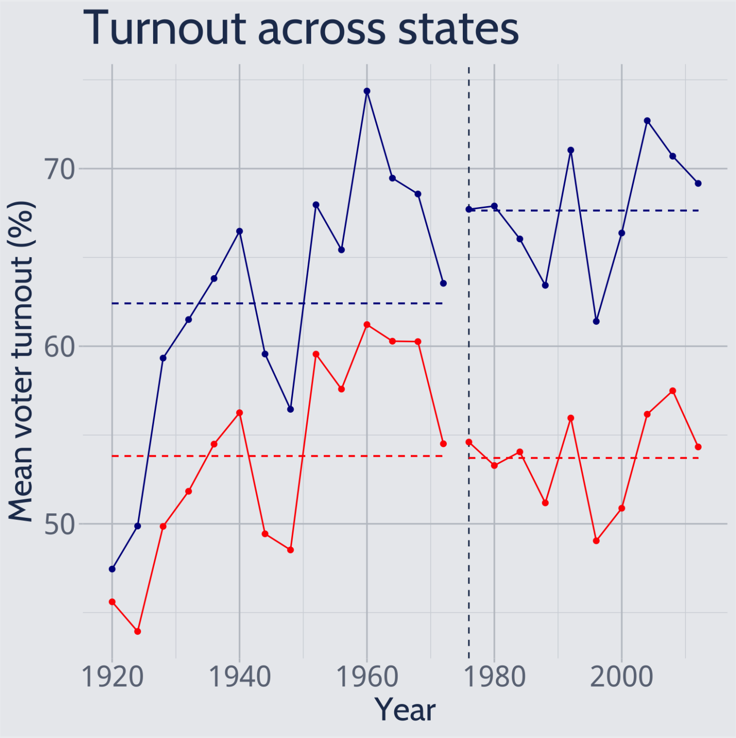
Solution to Exercise 2: step 4

```r
# Treatment group elements: E1T0, E1T1
E1 <- turnout %>% filter(abb %in% states_E1)
E1T0 <- E1 %>% filter(year < 1976)
E1T1 <- E1 %>% filter(year >= 1976)

E1T0_mean <- E1T0 %>%
  group_by(year) %>%
  summarise(mean_turnout = mean(turnout))

E1T1_mean <- E1T1 %>%
  group_by(year) %>%
  summarise(mean_turnout = mean(turnout))
```

Solution to Exercise 2: step 5

```
# plot
ggplot() +
  geom_vline(xintercept=1976,
             linetype='dashed') +
  # E0T0
  geom_point(data = E0T0_mean,
             aes(x=year, y=mean_turnout),
             colour='red') +
  geom_line(data = E0T0_mean, aes(x=year, y=mean_turnout),
            colour='red') +
  geom_segment(data = E0T0_mean,
               x=first(E0T0_mean$year),
               xend=last(E0T0_mean$year),
               y=mean(E0T0_mean$mean_turnout),
               yend=mean(E0T0_mean$mean_turnout),
               color='red',
               linetype='dashed') +
  # labeling
  labs(title = "Turnout across states",
       x = "Year", y = "Mean voter turnout (%)") +
  theme_xaringan()
```

Solution to Exercise 2: step 5



The figure shows group-aggregated mean voter turnout over time. It can easily be seen that the treatment-group mean increased between pre- and post-treatment, while the control-group mean did not change a lot.

But: is the change in treatment-group mean turnout really in response to the introduction of EDR?

Solution to Exercise 2: step 6

```r
# treatment group difference
diff_treatment <-
  mean(E1T1$turnout) -
  mean(E1T0$turnout)

# control group difference
diff_control <-
  mean(E0T1$turnout) -
  mean(E0T0$turnout)

# treatment - control
DID <- diff_treatment -
  diff_control
```

The average **causal effect** of EDR on voter turnout is **5.34%**.

Congratulations!

Without knowing so, you have completed your first causal inference using a quasi-experimental technique called **Difference in Differences**, in short **DID**. You will learn more about this and other related methods in your studies.

Thanks for being part of the very first edition of the **MACIS-STP R Crash Course** (-:

Now it's time for a **final 20 min break** and **giving feeback**.

Please take the time and fill out the feedback form **by following this link (click)** during the break. Your feedback is invaluable for improving the **MACIS-STP R Crash Course** for next year.

We **reconvene at 15:20** for a final wrap up and end at **15:45**.