

Building a Robot Judge:  
Data Science for Decision-Making  
5. Machine Learning and Causal Inference

18th October 2020

# Learning Objectives

1. Implement and evaluate machine learning pipelines.
2. **Implement and evaluate causal inference designs.**
3. Understand how (not) to use data science tools (ML and CI) to support expert decision-making.

# Machine Learning vs Causal Inference

Machine Learning (Weeks 2, 4, and 6):

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## ▶ Glossary for machine learning vs causal inference terms:

<https://bit.ly/ML-Econ-Glossary>.

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  - ▶ for example, wearing masks and coronavirus spread.
- ▶ There isn't a machine learning dataset to train a model on.
  - ▶ we can't experimentally force people to wear a mask or not.
- ▶ How do we solve that?

## Zoom Private Chat Activity: Legal Briefs Dataset

- ▶ Let's say we have a dataset of legal briefs with text and metadata, everything you would expect from a case, including information on the actors (litigants, attorneys, judges) and the associated outcomes (e.g. who wins).
- ▶ Chat to me privately on zoom:
  1. A **machine learning task or question** that could be addressed with this dataset.
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- ▶ See padlet link in zoom chat – post your answers there.
  - ▶ Read your classmates' answers – and “like” them liberally.



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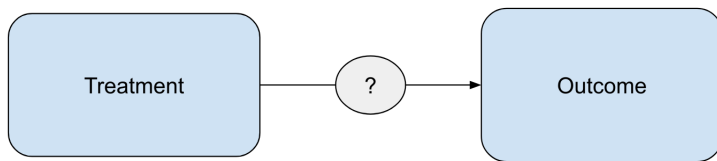
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  - ▶ We need real-world evidence, but we can't experimentally force schools to reopen or not.
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  - ▶ e.g., variation in number of coronavirus cases before/after openings, using differences in the timing of openings (differences-in-differences).

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  - ▶ e.g., variation in number of coronavirus cases before/after openings, using differences in the timing of openings (differences-in-differences).
- ▶ Google/Facebook understand this with A/B testing; social scientists want to use this to assist public policy.

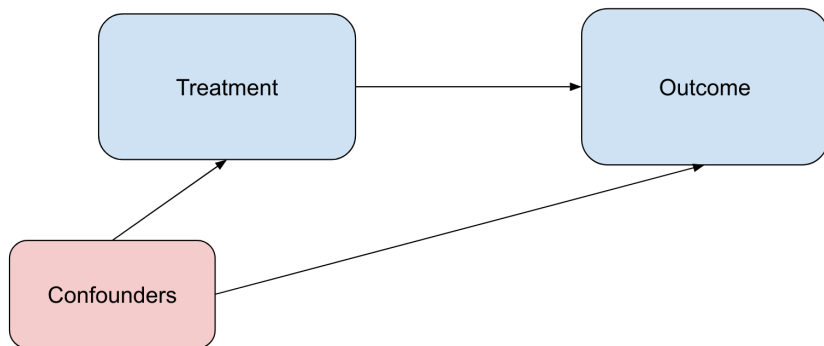
## Review: Causal Graphs



- We are interested in estimating a causal effect (if any) of a “treatment” on an “outcome”.

# Confounders

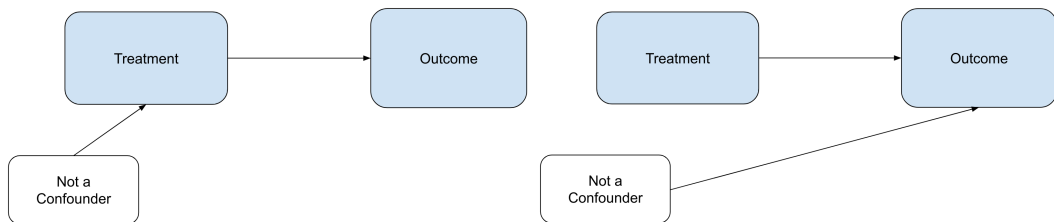
- Confounders affect both the treatment and the outcome:



- Adjusting for confounders (including them in a regression) will reduce bias for estimates of the causal effect of treatment on outcome.
  - Example: ice cream causes heat stroke.

# Not Confounders

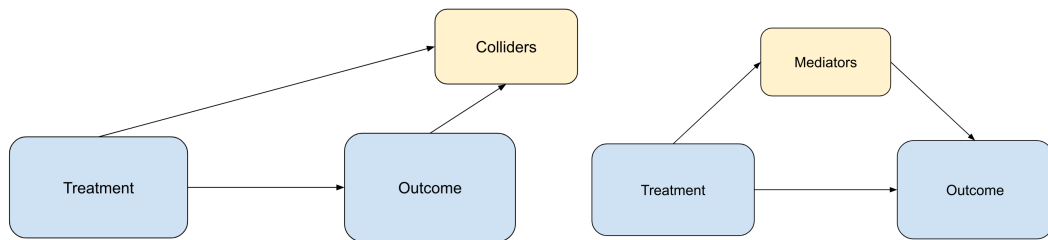
- Variables that affect just the treatment, or just the outcome, are not confounders.



- Adjusting for these variables does not reduce bias, but it might shrink standard errors.

# Colliders and Mediators

- **Colliders** are affected by both the treatment and the outcome.  
**Mediators** are intermediate outcomes / mechanisms.



- Adjusting for colliders or mediators will add bias.



# Reverse Causation or Joint Causation

- ▶ **Reverse causation:** “the outcome” affects “the treatment”.
- Joint causation:** there is bidirectional causation.



- ▶ e.g., effect of tax revenues on economic growth.

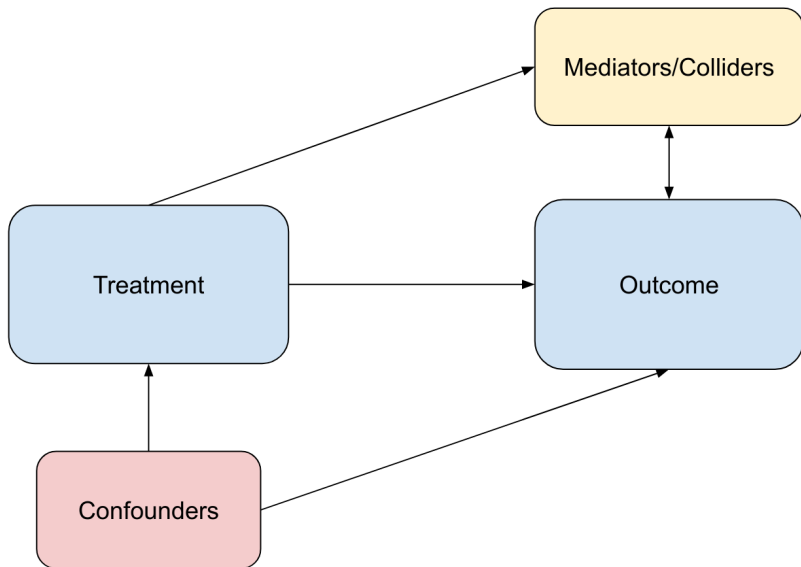
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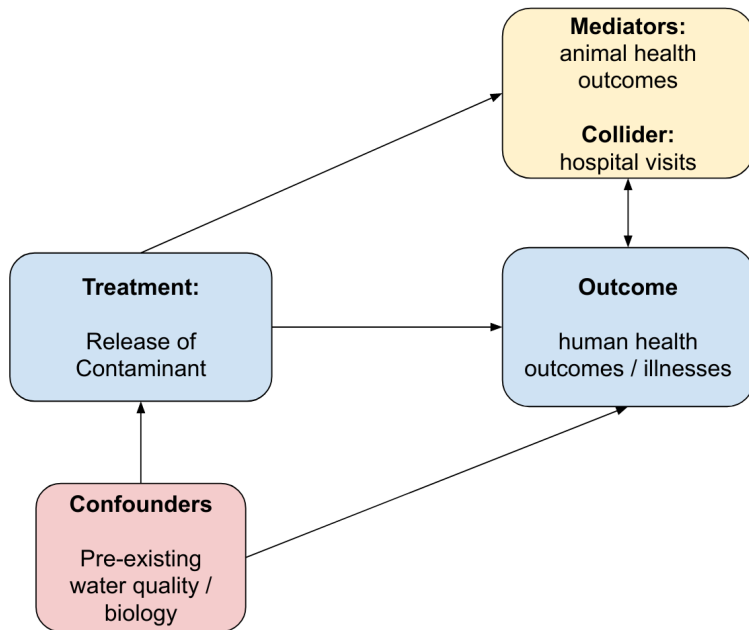


- ▶ e.g., effect of tax revenues on economic growth.
- ▶ Resulting causal estimates are biased, but not adjustable through a confounding variable.
  - ▶ Can only solve through a randomized experiment, or through instrumental variables (next week).

## Causal Graphs: Overview



## Causal Graph Example: Pollution of a River



## Activity: Practice with Causal Graphs

- ▶ Think of an example causal inference question:
  - ▶ a research question from your field
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- ▶ Think of an example causal inference question:
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- ▶ Link to causal graph template posted in zoom chat:
  - ▶ make a copy, fill it in
  - ▶ make public and paste link into padlet ([bit.ly/BRJ-W5A2](https://bit.ly/BRJ-W5A2)).
  - ▶ will review these after the break.

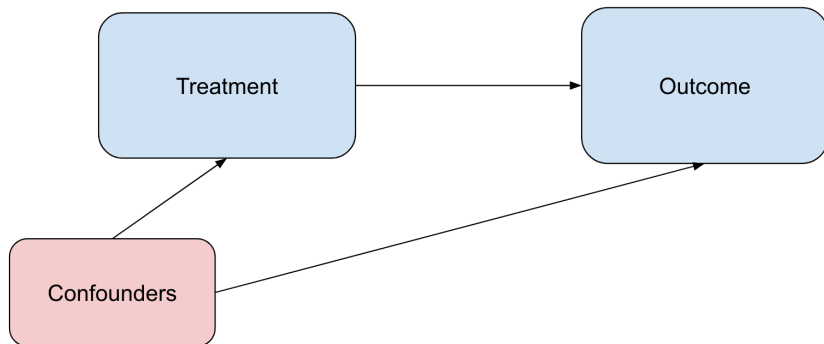
# Outline

Double Machine Learning to Adjust for Confounders

Synthetic Control Methods

Machine Learning for Heterogenous Treatment Effects

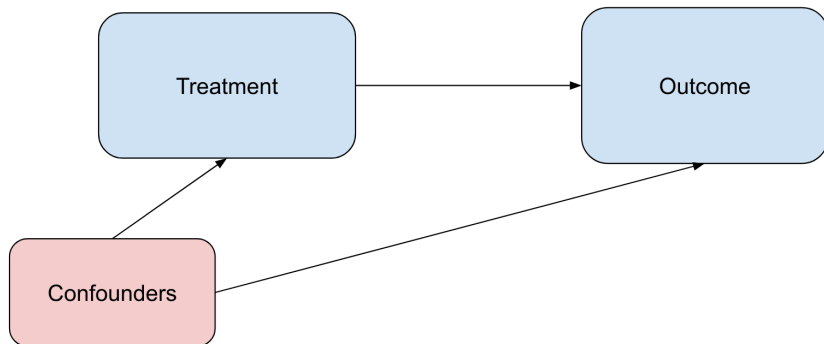
## Adjusting (controlling) for observables



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- ▶ If the treated group and comparison group differ only by a set of observable characteristics, we can “control” or “adjust” for these variables to obtain causal estimates.
- ▶ But what if we have 1000 covariates?
  - ▶ Machine learning can help.

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- ▶ Then include  $\hat{D}(X)$  in the regression as a control.
  - ▶ best practice: include fixed effects for small bins of  $\hat{D}(X)$
  - ▶ then all individuals are compared to other individuals with a similar propensity score.
- ▶ Caveat: PSM is not optimal in terms of efficiency – standard errors can be reduced by including  $X$  rather than  $\hat{D}(X)$ .

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- Consider outcome variable  $Y$  and treatment variable  $D$ . We want to estimate  $\beta$  from

$$Y = \beta D + g(X) + \epsilon$$

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- ▶  $X$  is a high-dimensional set of predictors – some are confounders, most are not.
- ▶ we will use **lasso** to select which predictors to include in our OLS regression.

## Selecting Controls with Double Lasso (2)

- ▶ Data prep:
  - ▶ drop from  $X$  any potential colliders.
  - ▶ can add interactions and transformations, e.g.  $x_7x_9$ ,  $x_7^2$ .
  - ▶ standardize each variable in  $X$  to variance one

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- ▶ Train two lasso models,  $Y \sim \text{Lasso}(X)$  and  $D \sim \text{Lasso}(X)$ :
  1. use CV grid search across the whole dataset to select best penalties  $\lambda_Y$  and  $\lambda_D$ .
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  2. Run both lasso models with whole dataset, get subsets of non-zero predictors,  $X_Y$  and  $X_D$
- ▶ Regress

$$Y = \beta D + X'_{YD} \gamma + \epsilon$$

where  $X_{YD} = X_Y \cup X_D$  is the union of the lasso-selected covariates.

- ▶ this is the optimal set of covariates for confounder adjustment (Belloni et al 2014).

## Zoom Poll: Which line(s) have a problem?

```
# python
param_grid = {'alpha': [.01, .1, 1, 10]}
lasso = Lasso()
grid = GridSearchCV(lasso, param_grid)

01 grid.fit(X, Y)
02 alpha_Y = grid.best_params_['alpha']
03 lasso_Y = Lasso(alpha=alpha_Y)
04 lasso_Y.fit(X,Y)
05 selected_Y = lasso_Y.coef_ != 0

06 grid.fit(X, D)
07 alpha_D = grid.best_params_['alpha']
08 lasso_D = Lasso(alpha=alpha_D)
09 lasso_D.fit(X,D)
10 selected_D = lasso_D.coef_ != 0

11 X_YD = X[(selected_Y and selected_D)]

* stata
12 reghdfe Y D , absorb(one#c.('X_YD')) robust
```

## What if $g(\cdot)$ is not linear?

- ▶ Lasso assumes that  $g(X)$  is linear in  $X$ .
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  - ▶ but how do we know what interactions/transformations to add?
- ▶ Can use a non-linear model, e.g. xgboost, to approximate and adjust for  $g(X)$ .
  - Double Machine Learning, also called Debiased machine Learning (Chernozhukov et al 2018)

## Double ML: Setup

$$Y = \beta D + g(X) + \epsilon$$

- ▶ low-dimensional treatment  $D$ , high-dimensional set of (observed) confounders  $X$ .
  - ▶ OLS regression without adjusting for confounders will be biased for  $\hat{\beta}$
  - ▶ can we just include them in the regression as linear covariates?
    - ▶ will not adjust correctly due to potential non-linearities.
    - ▶ will probably fail to converge due to high dimensionality / collinearity / overfitting



## Double ML method

1. Learn  $Y$  given  $X$ ,  $\hat{Y}(X)$ , using any ML method
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**Sample split** (samples A and B, 50% of data each) to prevent overfitting:

- ▶ Fit (1) and (2) on sample A, then predict (3) and regress (4) on sample B, to estimate  $\hat{\beta}_A$
- ▶ vice versa: fit (1)/(2) on sample B, and predict/regress (3)/(4) on sample A, to learn a second estimate for  $\hat{\beta}_B$ .
- ▶ average them to get a more efficient estimator:  $\hat{\beta} = \frac{1}{2}(\hat{\beta}_A + \hat{\beta}_B)$ .

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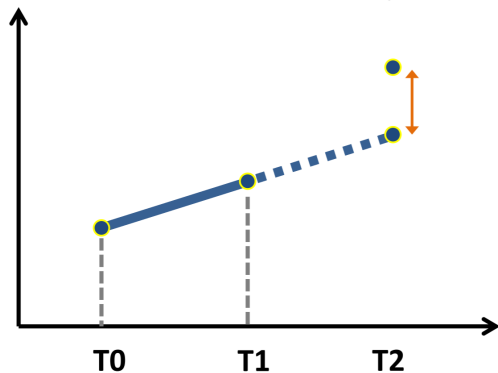
## Recap: Panel Data

Panel data, or longitudinal data, is data over time.

- ▶ our goal is to use this data to construct counterfactuals and learn causal effects, for example due to changes in government policies.

# Time Series Analysis

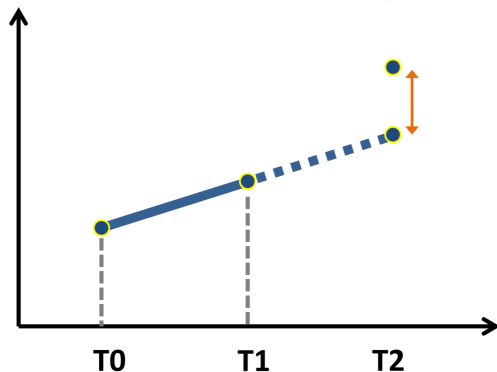
Solution 1: Time Series Analysis



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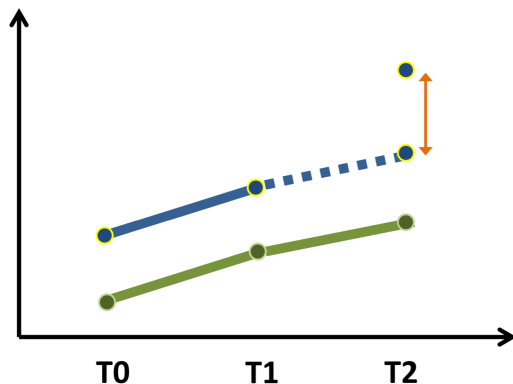
Solution 1: Time Series Analysis



- ▶ In macroeconomics (analysis of the whole economy), you only observe one individual/group (the economy).
  - ▶ How to estimate causal effect of a macroeconomic policy like changing interest rates?
- ▶ “time series analysis” assumes economy continues on current trend in absence of intervention.
  - ▶ macro is wrong most of the time.

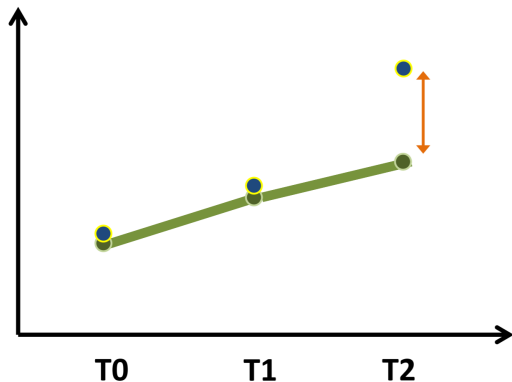


## Differences-in-Differences (last week)



- Differences-in-differences (or fixed effects) estimation assumes that the treated group (in blue) would evolve the same way as the control group (in green)

# Matching



- ▶ Matching searches over the control group and finds an individual with similar pre-trends.
  - ▶ can also match on covariates
  - ▶ can use any distance metric, e.g. cosine similarity.
- ▶ Estimate causal effect as the difference between the treated unit and the matched unit.

# Synthetic Control

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- ▶ Statistically comparable to fixed effects or matching, but **powered up with ML**.

# Setup

- ▶ *Dataset:*
  - ▶  $j \in \{1, \dots, J+1\}$  units,  $t = 1, 2, \dots, T$  periods.
  - ▶ Outcome  $Y_{jt}$ , characteristics  $X_j$

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- ▶ *Control group:*
  - ▶ Remaining  $J$  units are potential controls (“donor pool”)
- ▶ *Objective:*
  - ▶ find combination of untreated units that best approximates treated unit

## Formalization

- Define weights  $w_2, \dots, w_{J+1} \geq 0$  where  $\sum_{i=2}^{J+1} w_i = 1$ .

$$\text{Synthetic Control Treatment Effect} = \underbrace{Y_{1t}}_{\text{treated}} - \underbrace{\sum_{j=2}^{J+1} w_j^* Y_{jt}}_{\text{synthetic}}$$

where  $t \geq T_0$  is the post-intervention period



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where  $t \geq T_0$  is the post-intervention period

- Synthetic control vector  $(w_2^*, \dots, w_{J+1}^*)$  is chosen to minimize

$$\sum_{m=1}^k v_m \left( x_{1m} - \sum_{j=2}^{J+1} w_j x_{jm} \right)^2$$

- $v_m$  = weight on  $m$ -th variable, chosen to minimize pre-reform MSE for  $Y$ , that is, match on pre-trends.

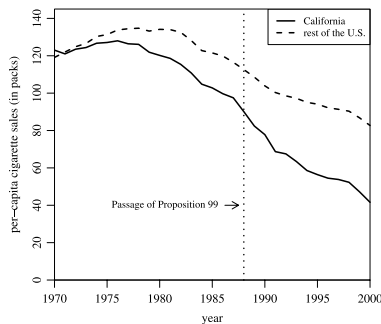
## Application: Tobacco Laws in CA

In 1988, California passed anti-tobacco legislation (Proposition 99)

- ▶ Increased tax by \$0.25/pack
- ▶ Extra tax revenues earmarked to health budget
- ▶ Funded anti-smoking campaigns
- ▶ Clean-air signs in closed spaces

```
// stata  
use http://fmwww.bc.edu/repec/bocode/s/synth\_smoking.dta
```

# Trends in cigarette sales: Parallel trends fails



Rest of US is not a good comparison group for California

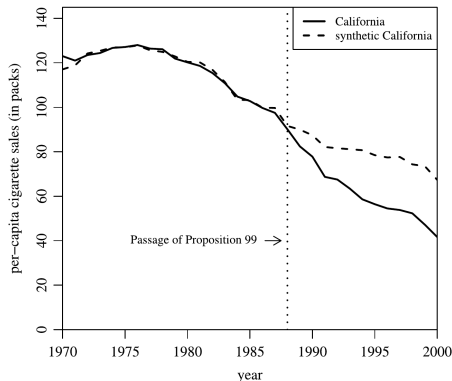
- ▶ Trends start diverging in 1970s, before the reform
- ▶ Parallel trends assumption fails  $\Rightarrow$  Cannot apply diff-in-diff

Source: Abadie, Diamond and Hainmueller (2010)

# Synthetic California

Table 2. State weights in the synthetic California

State	Weight	State	Weight
Alabama	0	Montana	0.199
Alaska	—	Nebraska	0
Arizona	—	Nevada	0.234
Arkansas	0	New Hampshire	0
Colorado	0.164	New Jersey	—
Connecticut	0.069	New Mexico	0
Delaware	0	New York	—
District of Columbia	—	North Carolina	0
Florida	—	North Dakota	0
Georgia	0	Ohio	0
Hawaii	—	Oklahoma	0
Idaho	0	Oregon	—
Illinois	0	Pennsylvania	0
Indiana	0	Rhode Island	0
Iowa	0	South Carolina	0
Kansas	0	South Dakota	0
Kentucky	0	Tennessee	0
Louisiana	0	Texas	0
Maine	0	Utah	0.334
Maryland	—	Vermont	0
Massachusetts	—	Virginia	0
Michigan	—	Washington	—
Minnesota	0	West Virginia	0
Mississippi	0	Wisconsin	0
Missouri	0	Wyoming	0



Source: Abadie, Diamond and Hainmueller (2010)

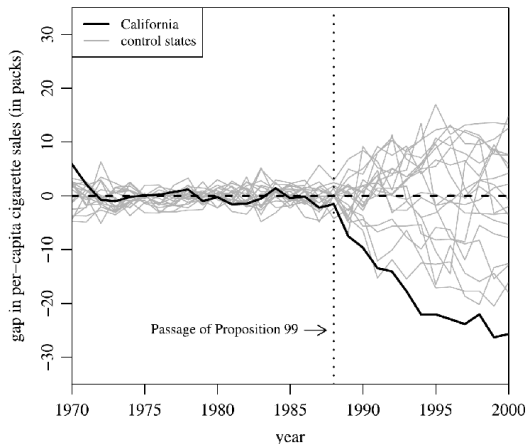
```
// stata
tsset state year
synth y x1 x2 x3 y(1980) y(1988), trunit(3) trperiod(1989)
// trunit = 3 is the state # for california
// trperiod = 1989 is the first post-reform year
```

# Inference

- ▶ Synthetic control does not give standard errors. Instead, use bootstrap approach:
  - ▶ Compare estimated synthetic control effect for california to distribution of placebo effects where treated unit is picked at random from donor pool.

# Inference

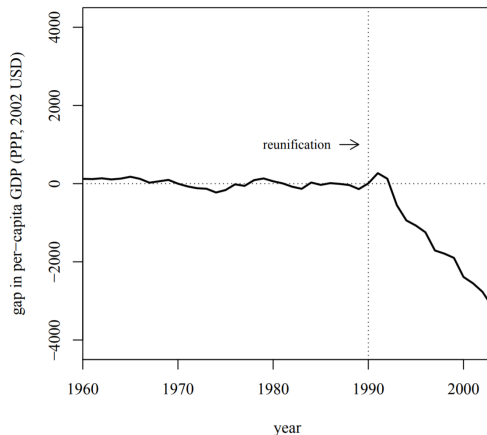
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  - ▶ Compare estimated synthetic control effect for California to distribution of placebo effects where treated unit is picked at random from donor pool.



## Application 2: Effect of Reunification on West Germany GDP

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Country	Weight	Country	Weight
Australia	0	Netherlands	0.11
Austria	0.47	New Zealand	0.11
Belgium	0	Norway	0
Canada	0	Portugal	0
Denmark	0	Spain	0
France	0	Sweden	0
Greece	0	Switzerland	0
Ireland	0	United Kingdom	0.17
Italy	0	United States	0
Japan	0		0.14





## Practicalities

- ▶ Easiest way to get going with synthetic control: the synth package in stata.
- ▶ In python, can use microsoft's SparseSC package.

```
# python
from numpy import hstack
from SparseSC import fit

# Let X be the features plus some of the targets
X = hstack([features, targets[:,t:]])

# And let Y be the remaining targets
Y = targets[:,t:]

# fit the model:
sc = fit(X=X, Y=Y, model_type="full")
```

# Summary: Synthetic Control

## Advantages:

1. Works with a single treated unit.
2. Makes explicit the contribution of each comparison unit to the synthetic control
3. Quantitative and qualitative ways to analyze similarities and differences of treatment and synthetic control
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3. Cannot estimate effect of a single reform when multiple reforms passed at once

# Outline

Double Machine Learning to Adjust for Confounders

Synthetic Control Methods

Machine Learning for Heterogenous Treatment Effects

# Heterogeneous Treatment Effects

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# Heterogeneous Treatment Effects

- ▶ Treatments don't affect every individual equally.
  - ▶ for example, effect of covid social distancing will depend on the age distribution.
- ▶ The simplest way to estimate these is to interact treatment with another covariate (the “**moderator**”):

$$Y_i = \beta_1 D_i + \beta_2 \text{Age}_i + \beta_3 D_i \text{Age}_i + \epsilon_i$$

- ▶ here,  $\beta_3$  summarizes heterogeneous impact by age ( $\frac{\partial Y_i}{\partial D_i} = \beta_1 + \beta_3 \text{Age}_i$ )

## Activity: Brainstorming about Moderators

Revisit your customized causal graph:

- ▶ Add a new “bubble” with the header “Moderators”, and list some potential variables/characteristics that you expect to have a larger or smaller treatment effect.



# Conditional Treatment Effects

- ▶ Consider the model

$$Y = \underbrace{\beta(X)}_{\text{CTE}} D + g(X) + \epsilon$$

- ▶ the causal estimate  $\beta(X)$  is a function of  $X$ .
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- ▶ the causal estimate  $\beta(X)$  is a function of  $X$ .
  - ▶ this is the conditional treatment effect (CTE) – that is, the effect conditional on  $X$ .
- ▶ Can learn flexible representation of  $\hat{\beta}(X)$  using machine learning.

## T-Learner Method

- ▶ Residualize  $Y$  on the fixed effects and controls to get rid of  $g(X)$ :

$$Y = \beta(X)D + \epsilon$$

- ▶ if  $D$  is randomly assigned (e.g. RCT), this is not necessary.
- ▶ Note that the standard (non-conditional) treatment effect is then immediately obtainable by OLS:  $\hat{\beta}_{OLS} = \text{Cov}(Y, D)/\text{Var}(D)$ .

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### T-Learner Method:

- ▶ Using any machine learning method:
  - ▶ Learn  $\mu_0(X) = \mathbb{E}(Y|X, D = 0)$
  - ▶ Learn  $\mu_1(X) = \mathbb{E}(Y|X, D = 1)$
- ▶ Tune parameters in whole dataset using cross-validation.
- ▶ The conditional treatment effect estimate is  $\hat{\beta}(X) = \mu_1(X) - \mu_0(X)$ .

See Knaus, Lechner, and Strittmatter (2020) for a review of different methods/extensions.

# Homework Note

- ▶ Next homework is due Tuesday October 27th before 8am.

Two parts:

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2. Peer review of response essays:
  - ▶ You will be randomly assigned two anonymized essays from one of your classmates.
  - ▶ Write one paragraph (5-10 sentences) about each essay, providing constructive feedback/suggestions.
  - ▶ Follow the rubric on the homework assignments page.