

# Part 8: Policy Evaluation- Matching

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Applied Econometrics

1. Matching
2. Instrumental Variables
3. Difference in Difference and Natural Experiments
4. RCTs
5. Structural Models
  - Key distinction: the treatment effect of some program (a number) from understanding how and why things work (the mechanism).
  - Models let us link numbers to mechanisms.

## Recall the Selection Problem

- Let's start with the easy cases: run OLS and see what happens.
- OLS compares mean of treatment group with mean of control group (possibly controlling for other  $X$ )

$$\begin{aligned}\beta^{OLS} &= E(Y_i|T_i = 1) - E(Y_i|T_i = 0) \\ &= \underbrace{E[\beta_i|T_i = 1]}_{\text{ATT}} + \left( \underbrace{E[u_i|T_i = 1] - E[u_i|T_i = 0]}_{\text{selection bias}} \right)\end{aligned}$$

- Even in absence of heterogeneity  $\beta_i = \beta$  we can still have selection bias.
- $Y_i^0 = \alpha + u_i$  may vary within the population (this is quite common).
- **Unobservables**  $u_i$  are correlated with **treatment**  $T_i$ .

## Suppose we ran a RCT

- Imagine we ran a randomized controlled trial
- Flip a coin and assign  $T_i = 1$  or  $T_i = 0$ 
  - In treated schools we monitor teacher attendance with a camera each day.
  - In control schools we don't.
- By construction it should be that  $E[u_i|T_i = 1] - E[u_i|T_i = 0]$
- But did our randomization work? We might have randomized all of the large classes into the treatment group and the small classes into the control group.
- We want to know if  $f(x|T_i = 1) = f(x|T_i = 0)$ ?

# Checking Covariate Balance

- One easy thing to do is to construct a **covariate balance table**.
  - Not exactly the same as  $f(x|T_i = 1) = f(x|T_i = 0)$ .
  - But if means don't match, we're probably in trouble!
- Compare  $E[x|T_i = 1]$  to  $E[x|T_i = 0]$ .
- Is the difference statistically significant?
- Just look at regression coefficient (and SE) of

$$x_i = \gamma_0 + \gamma_1 T_i + \varepsilon_i$$

# Checking Covariate Balance

TABLE 1—BASELINE DATA

	Treatment (1)	Control (2)	Difference (3)
<i>Panel A. Teacher attendance</i>			
School open	0.66	0.64	0.02
	41	39	(0.11) 80
<i>Panel B. Student participation (random check)</i>			
Number of students present	17.71	15.92	1.78
	27	25	(2.31) 52
<i>Panel C. Teacher qualifications</i>			
Teacher test scores	34.99	33.54	1.44
	53	54	(2.02) 107
<i>Panel D. Teacher performance measures (random check)</i>			
Percentage of children sitting within classroom	0.83	0.84	0.00
	27	25	(0.09) 52
Percent of teachers interacting with students	0.78	0.72	0.06
	27	25	(0.12) 52
Blackboards utilized	0.85	0.89	-0.04
	20	19	(0.11) 39
<i>F-stat (1,110)</i>			1.21
<i>p-value</i>			(0.27)

# Checking Covariate Balance in R

`https://cran.r-project.org/web/packages/cobalt/vignettes/cobalt\_A0\_basic\_use.html`

## Now let's try in R

```
library("cobalt")
data("lalonge", package = "cobalt")
covs0 <- subset(lalonge, select = -c(treat, re78, nodegree, married))
tab<-bal.tab(covs0, treat = lalonge$treat)

# output
print(tab)
love.plot(tab, binary = "std", threshold = .1)
bal.plot(covs0, treat = lalonge$treat, var.name='age')
bal.plot(covs0, treat = lalonge$treat, var.name='educ')
bal.plot(covs0, treat = lalonge$treat, var.name='race')
```



# Why do we care?

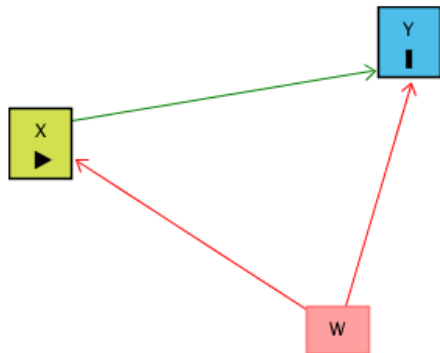
- The same reason we include **controls** in the regression of

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 w_i + u_i$$

- We are interested in effect of  $x_i$  (training) on  $y_i$  (wages).
- But if  $w_i$  (ability, age, race, etc.) is correlated with both  $x_i$  and  $y_i$  then we need to include it our regression.
- Easy to see this as a **Directed Acyclic Graph** (DAG)
  - Think of  $x \rightarrow y$  as “causes”.

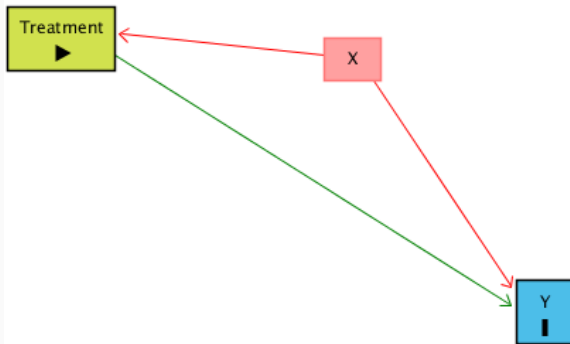
## Control DAG: <http://nickchk.com/causalgraphs.html>

- We want the  $x \rightarrow y$  path
- We do not want the  $x \leftarrow w \rightarrow y$  path (**Backdoor Path**).
- Close the backdoor path by removing part of  $X$  and  $Y$  that depends on  $W$ .



## Matching DAG: <http://nickchk.com/causalgraphs.html>

- We want the  $T \rightarrow y$  path
- We do not want the  $T \leftarrow x \rightarrow y$  path (**Backdoor Path**).
- Same idea as controls in OLS!



# Matching

- Compare treated individuals to un-treated individuals with identical observable characteristics  $X_i$ .
- Key assumption: everything about  $Y_i(1) - Y_i(0)$  is captured in  $X_i$ ; or  $u_i$  is randomly assigned conditional on  $X_i$ .
- Basic idea: The treatment group and the control group don't have the same distribution of observed characteristics as one another.
- **Re-weight** the un-treated population so that it resembles the treated population.
- Once distribution of  $X_i$  is the same for both groups  $X_i|T_i \sim X_i$  then we assume all other differences are irrelevant and can just compare means.
- Matching assumes **all selection is on observables**.

- Formally the key assumption is the **Conditional Independence Assumption (CIA)**

$$\{Y_i(1), Y_i(0)\} \perp T_i | X_i$$

- Once we know  $X_i$  allocation to treatment  $T_i$  is as if it is random.
- The only difference between treatment and control is composition  $f(X_i)$  of the sample.

# Matching

Let  $F^1(x)$  be the distribution of characteristics in the treatment group, we can define the ATE as

$$\begin{aligned} E[Y(1) - Y(0)|T = 1] &= E_{F^1(x)}[E(Y(1) - Y(0)|T = 1, X)] \\ &= E_{F^1(x)}[E(Y(1)|T = 1, X)] - E_{F^1(x)}[E(Y(0)|T = 1, X)] \text{ linearity} \end{aligned}$$

The first part we observe directly:

$$= E_{F^1(x)}[E(Y(1)|T = 1, X)]$$

But the counterfactual mean is not observed!

$$= E_{F^1(x)}[E(Y(0)|T = 1, X)]$$

But conditional independence does this for us:

$$E_{F^1(x)}[E(Y(0)|T = 1, X)] = E_{F^1(x)}[E(Y(0)|T = 0, X)]$$

## Matching in Practice: Caliper Matching

How do we actually do this?

- For each entry in the treatment  $(y_t, x_t)$ 
  - Find all  $x_s$  from the control group that is “close enough”  $\|x_s - x_t\| < b_w$ .
  - For each treated observation compute  $\beta(x_t) = y_t - E[y_s | I(\|x_s - x_t\| < b_w)]$ .
  - Compute the mean of  $\beta(x_t)$
- Some pitfalls
  - Variance can be unpredictable: some  $(y_t, x_t)$  have many of matches, others have none
  - For some  $(y_t, x_t)$  may have nothing within  $\|x_s - x_t\| < b_w$ ? Drop these?
- Can also use  $k$ -nearest neighbors instead.

## Matching in Practice: Inverse Probability Weighting

How do we actually do this?

- Calculate a smoothed estimate of the treatment probability  $\pi(x) = Pr(T_i = 1|x)$ .

$$\frac{1}{n} \sum_{t \in \text{Treatment}} \frac{y_t}{\pi(x_t)} - \frac{1}{n} \sum_{s \in \text{Control}} \frac{y_s}{1 - \pi(x_s)}$$

- How to get  $\pi(x)$ ? Run a logit or probit.
- We can stabilize the weights replace  $w(x) = \frac{1}{\pi(x)}$  with:

$$w(x) = \frac{Pr(T = 1)}{\pi(x)} \text{ for } T_i = 1 \quad w(x) = \frac{Pr(T = 0)}{1 - \pi(x)} \text{ for } T_i = 0$$

- This sometimes helps crazy big weights when treated group is small.



## A Matching Example

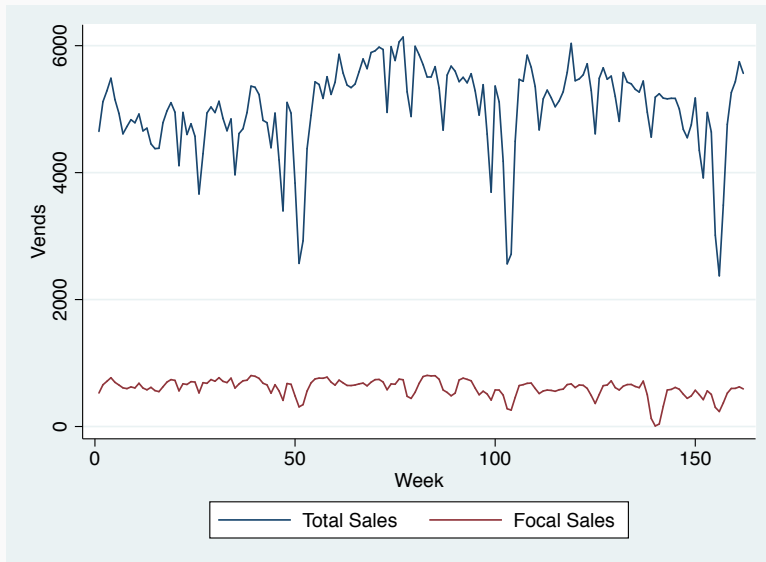
Here is an example where I found that matching was helpful in my own work with Julie Mortimer:

- We ran a randomized experiment where we removed Snickers bars from around 60 vending machines in office buildings in downtown Chicago.
- We have a few possible control groups:
  1. Same vending machine in other weeks (captures heterogeneous tastes in the cross section)
  2. Other vending machines in the same week (might capture aggregate shocks, ad campaigns, etc.)
- We went with #1 as #2 was not particularly helpful.

## A Matching Example

Major problem was that there was a ton of heterogeneity in the overall level of (potential) weekly sales which we call  $M_t$ .

- Main source of heterogeneity is how many people are in the office that week, or how late they work.
- Based on total sales our average over treatment weeks was in the 74th percentile of all weeks.
- This was after removing a product, so we know sales should have gone down!
- How do we fix this without running the experiment for an entire year!
- Can't use shares instead of quantities. Why?



## A Matching Example

Ideally we could just observe  $M_t$  directly and use that as our matching variable  $X$

- We didn't observe it directly and tried a few different measures:
  - Sales at the soda machine next to the snack machine
  - Sales of salty snacks at the same machine (not substitutes for candy bars).
  - We used k-NN with  $k = 4$  to select control weeks – notice we re-weight so that overall sales are approximately same (minus the removed product).
- We also tried a more structured approach:
  - Define controls weeks as valid IFF
  - Overall sales were weakly lower
  - Overall sales were not less than Overall Sales less expected sales less Snickers Sales.

Product	Control Mean	Control %ile	Treatment Mean	Treatment %ile	Mean Difference	% $\Delta$
<i>Vends</i>						
Peanut M&Ms	359.9	73.6	478.3*	99.4	118.4*	32.9
Twix Caramel	187.6	55.3	297.1*	100.0	109.5*	58.4
Assorted Chocolate	334.8	66.7	398.0*	95.0	63.2*	18.9
Assorted Energy	571.9	63.5	616.2	76.7	44.3	7.8
Zoo Animal Cracker	209.1	78.6	243.7*	98.1	34.6*	16.5
Salted Peanuts	187.9	70.4	216.3*	93.7	28.4	15.1
Choc Chip Famous Amos	171.6	71.7	193.1*	95.0	21.5*	12.5
Ruger Vanilla Wafer	107.3	59.7	127.9	78.6	20.6*	19.1
Assorted Candy	215.8	43.4	229.6	60.4	13.7	6.4
Assorted Potato Chips	279.6	64.2	292.4*	66.7	12.8	4.6
Assorted Pretzels	548.3	87.4	557.7*	88.7	9.4	1.7
Raisinets	133.3	66.0	139.4	74.2	6.1	4.6
Cheetos	262.2	60.1	260.5	58.2	-1.8	-0.7
Grandmas Choc Chip	77.9	51.3	72.5	37.8	-5.4	-7.0
Doritos	215.4	54.1	203.1	39.6	-12.3*	-5.7
Assorted Cookie	180.3	61.0	162.4	48.4	-17.9	-10.0
Skittles	100.1	62.9	75.1*	30.2	-25.1*	-25.0
Assorted Salty Snack	1382.8	56.0	1276.2*	23.3	-106.7*	-7.7
Snickers	323.4	50.3	2.0*	1.3	-321.4*	-99.4
Total	5849.6	74.2	5841.3	73.0	-8.3	-0.1

Notes: Control weeks are selected through the-neighbor matching using four control observations for each treatment week. Percentiles are relative to the full distribution of control weeks.

# Higher Dimensions

So matching works great in dimension 1. But what if  $\dim(X) > 1$ ?

- True high-dimensional matching may be infeasible. There may be no set of weights such that:  $f(X_i|T_i = 1) \equiv \int w_i f(X_i|T_i = 0) \partial w_i$ .
- One solution is the nearest-neighbor approach in Abadie Imbens (2006).
- This is still cursed in that our nearest neighbors get further away as the dimension grows.
- Suppose instead we had a **sufficient statistic**

# Propensity Score

- Rosenbaum and Rubin propose the **propensity score**

$$P(T_i = 1|X_i) \equiv P(X_i)$$

- They prove that the propensity score and any function of  $X$ ,  $b(X)$  which is finer serves as a **balancing score**.
- Finer implies that:

$$\begin{aligned} b(X^1) = b(X^2) &\implies P(X^1) = P(X^2) \\ P(X^1) = P(X^2) &\not\implies b(X^1) = b(X^2) \end{aligned}$$

# Propensity Score

- Main result: If treatment assignment is strongly ignorable conditional on  $X$  (CIA) then it is strongly ignorable  $Y(1), Y(0) \perp T|X$  given any balancing score  $b(X)$  including the propensity score:

$$\begin{aligned}Pr(T = 1|Y(1), Y(0), P(X)) &= E[Pr(T = 1|Y(1), Y(0), X)|P(X)] \\ &= E[Pr(T = 1|x)|P(X)] = P(X)\end{aligned}$$

- Also we require that  $0 < P(X) < 1$  at each  $X$  which is known as the **support condition**.
- The theorem implies that given  $P(X)$  we have as if random assignment.



# Propensity Score

- Instead of matching on  $K$  dimensional  $X$  we can now match on a one-dimensional propensity score
- Thus the propensity score provides **dimension reduction**
- We still have to estimate the propensity score which is a high dimensional problem without *ad-hoc* parametric restrictions.
- Let us begin by assuming a can-opener.
- An easy way would be to use  $\pi(x)$  from logit or probit.

## Propensity Score

Just like in the matching case the problem arises because we do not observe the counterfactual mean:

$$E_{F^1(x)}[E(Y(0)|T = 1, X)]$$

With conditional independence and the propensity score:

$$\begin{aligned} E_{F^1(x)}[E(Y(0)|T = 1, X)] &= E_{F^1(x)}[E(Y(0)|T = 0, X)] \\ &= E_{F^1(x)}[E(Y(0)|T = 0, P(X))] \end{aligned}$$

How do we implement?

- Kernels are an obvious choice

$$\widehat{ATT} = \frac{1}{N_1} \sum_{i \in T=1} \left[ Y_i - \frac{\sum_{j \in T=0} Y_j K(P(X_i) - P(X_j))}{\sum_{s \in T=0} K(P(X_i) - P(X_s))} \right]$$

where  $N_1$  is the sample size of the treatment group

and  $K(u)$  is a valid Kernel weight (people tend to use Gaussian Kernels here)

- As your propensity score gets further away from observation  $i$  you get less weight
- As  $h \rightarrow 0$  (or  $\sigma_h$ ) the window gets smaller and we use fewer neighbors.

# Kernel Matching

- The usual caveats apply:  $h$  determines the **bias-variance** tradeoff
- Choice of Kernel effects finite-sample properties
- Here the **common support** is important. We can only learn about cases where  $P(X) \neq 1$  and  $P(X) \neq 0$ . If you always get treated (or not-treated) we cannot learn from this observation.
- We also have to be careful in choosing  $X$  so as not to violate CIA (too many  $X$ 's , too few  $X$ 's)  $\rightarrow$  have to think carefully!
- If you use propensity scores you will need a slide convincing us you have thought about why CIA holds for you!

# Gotcha!

Under CIA we know

$$G(Y(1), Y(0)|X, T) = G(Y(1), Y(0)|X)$$

Suppose we add in  $Z$ , then we require that:

$$G(Y(1), Y(0)|X, Z, T) = G(Y(1), Y(0)|X, Z)$$

$$\begin{aligned} G(Y(1), Y(0)|X, T) &= \int G(Y(1), Y(0)|X, Z, T) dF(Z|X, T) \\ &= G(Y(1), Y(0)|X) \end{aligned}$$

where the last part follows by CIA.

- Thus each element can depend on  $T$  conditional on  $Z, X$  but the average may not.
- Mindless applications of matching can give you biased results!

## Matching and OLS

- Recall that OLS is a special case of Kernel regression (and hence matching!)
- Think about

$$Y = \alpha + \beta T_i + u$$

- Assume that  $E(u|T, X) = E(u|X)$  which is a conditional mean independence assumption
- Then we can get  $\beta$  consistently (but not other variables) by running the following:

$$Y = \alpha + \beta T_i + \gamma X + v$$

- Again we are in the homogenous treatment world

- This would be a good time to work through the vignette for cobalt [https://cran.r-project.org/web/packages/cobalt/vignettes/cobalt\\_A0\\_basic\\_use.html](https://cran.r-project.org/web/packages/cobalt/vignettes/cobalt_A0_basic_use.html)
- Compare the ATE for the Lalonde data with the IPW, Nearest Neighbor, and Propensity Score estimates.
- Then start the homework

Up next...

Local Average Treatment Effects.