Policy Evaluation - Quasi-Experimental Research Designs

April 2, 2024

Estimating Treatment Effects Review

- $ATE = Avg_n[Y_i^1 - Y_i^0]$
- $ATE_{est} = Avg_n[Y_i^1 | D_i = 1] - Avg_n[Y_i^0 | D_i = 0]$
- When $(Y^1, Y^0) \not\perp\!\!\!\perp D$:

$$ATE_{est} = ATE + \underbrace{\{Avg_n[Y_i^0 | D_i = 1] - Avg_n[Y_i^0 | D_i = 0]\}}_{\text{Selection Bias}} + \underbrace{(1 - \pi)(ATT - ATU)}_{\text{Heterogeneous Treatment Effect Bias}}$$

- $ATE_{est} = \beta_0 + \beta_1 D + \beta_2 X_1 + \beta_3 X_2 + ...\beta_k X_{k-1} + \varepsilon$
- Natural experiment w/randomization (Oregon): $(Y^1, Y^0) \perp\!\!\!\perp D$

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  - ATE $=$
    $(E[Y^1_{treat}|Post] - E[Y^0_{treat}|Pre]) - (E[Y^0_{cont}|Post] - E[Y^0_{cont}|Pre])$

Quasi-Experimental Research Design - Difference-in-Differences

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  - Economic theory suggests that higher employment costs will reduce demand for labor
  - April 1, 1992: New Jersey raises minimum wage from $4.25 to $5.05 per hour
  - Collected data on employment in 400 fast food restaurants in the Philadelphia area in February 1992 (pre-NJ increase) and again in November 1992 (post-increase).

Quasi-Experimental Research Design - Difference-in-Differences

- Card & Kruegar (1994) - Minimum Wages and Employment

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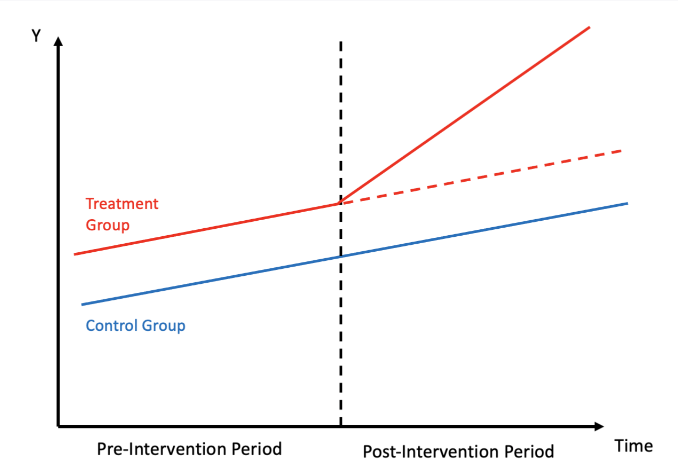

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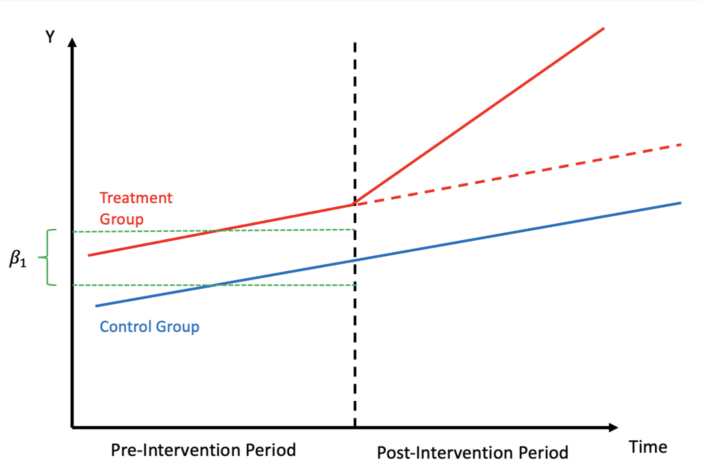

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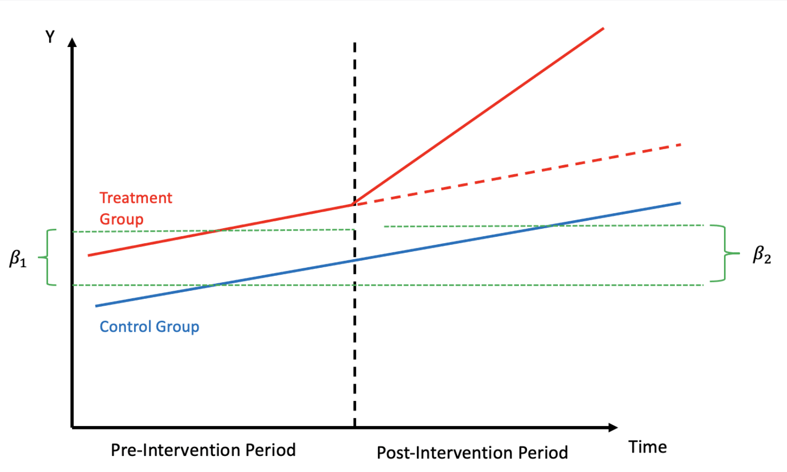

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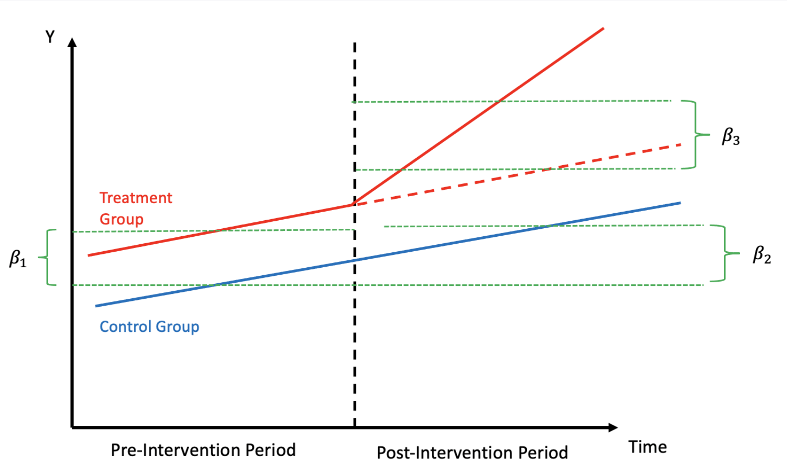

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  - Parallel trends assumption

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- Note that Diff 1 assumes that $T_{NJ} = T_{PA}$

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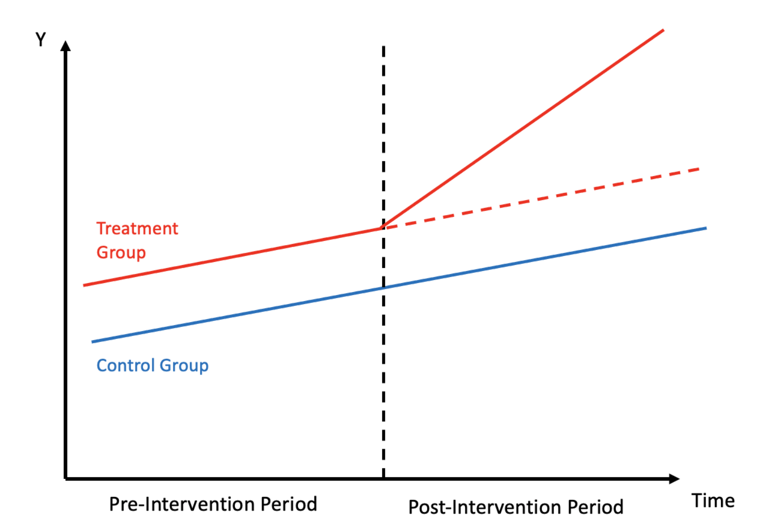

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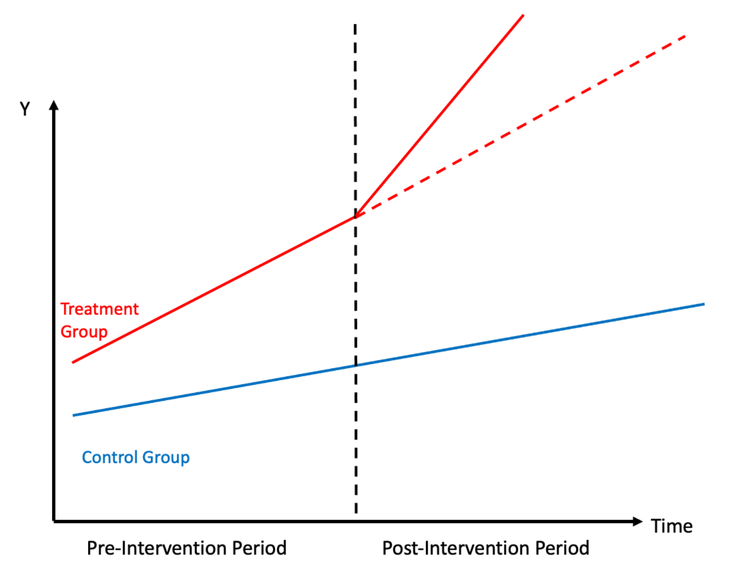

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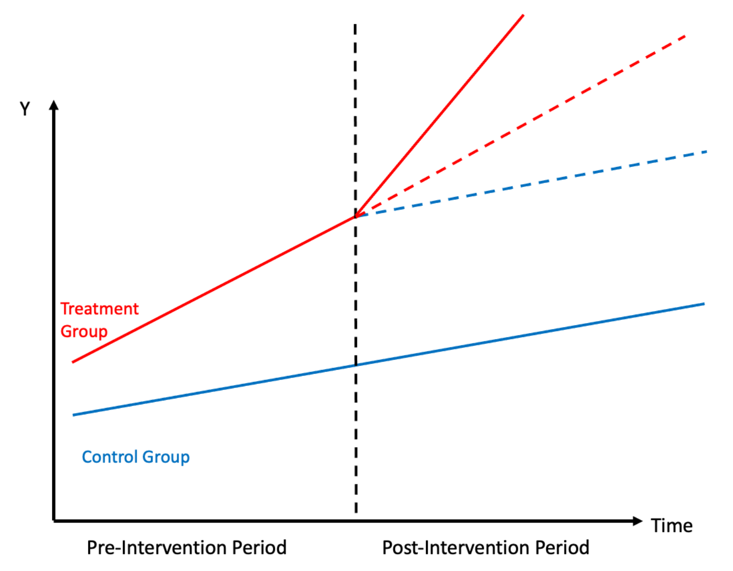

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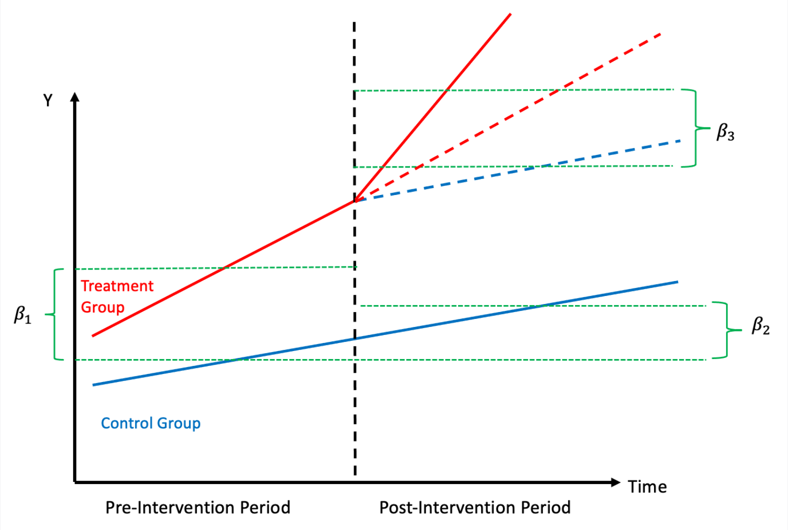

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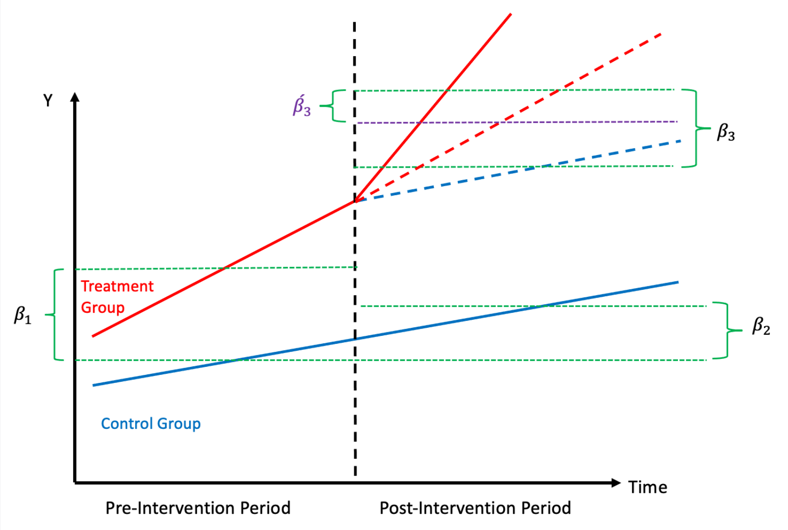

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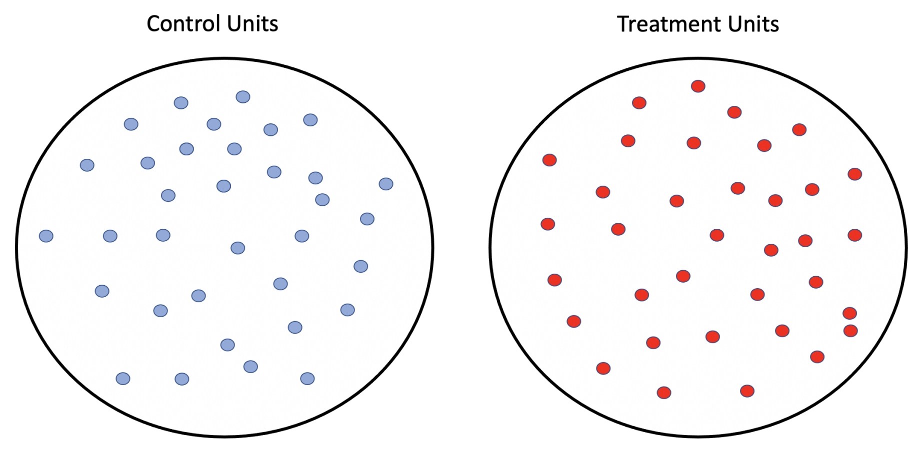
  - Intuition: control units that more closely resemble treatment units on *observables* will also more closely resemble treatment units on *unobservables*.

Quasi-Experimental Research Design - Propensity Score Matching



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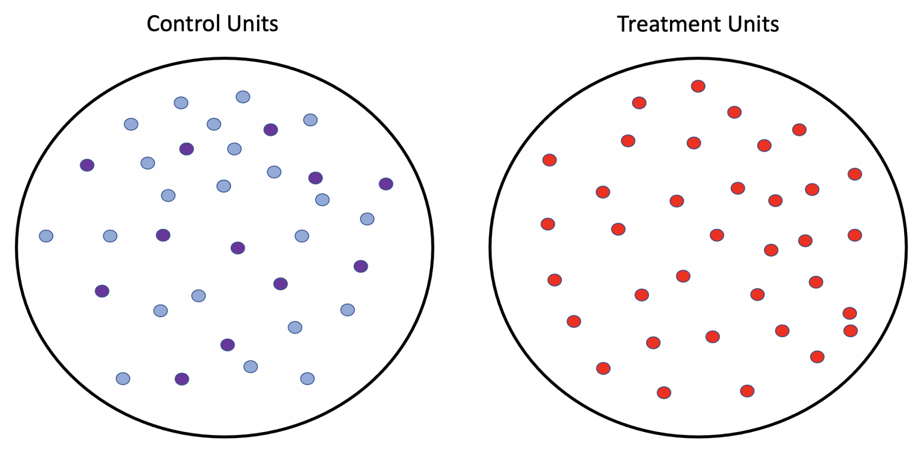

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  6. Estimate the ATE.

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- Downsides:
    - Lots of (ad hoc) decision making required.
    - Discard unmatched control units.

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- Remember: regardless of matching technique, PSM assumes that matching on observables removes confounding from unobservables.
- We have no definitive way to test this assumption.

Quasi-Experimental Research Design - Propensity Score Matching

- Balance Test: *Shau et al. (2018) - Medicaid is Associated with Increased Readmission and Resource Utilization after Primary Total Knee Arthroplasty*

Table 1
Characteristics of the TKA (ICD-9 code 8154) patients from the 2013 NRD.

Risk factors	Before propensity matching				After propensity matching			
	Medicaid, N = 8372	Other insurance, n = 268,261	*P* Value	Standardized difference	Medicaid, n = 8372	Other insurance, n = 8372	*P* value[a]	Standardized difference[b]
Age, years (mean ± SD)	56.7 ± 9.4	66.7 ± 9.7	<.0001	1.055	56.7 ± 9.4	56.5 ± 9.6	<.001	0.014
Female sex	6072 (72.5%)	165,227 (61.6%)	<.0001	0.234	6071 (72.5%)	6129 (73.2%)	.004	0.016
Severity of illness (major/extreme loss vs other)	549 (6.6%)	13,685 (5.1%)	<.0001	0.062	547 (6.5%)	477 (5.7%)	<.001	0.035
Discharged to skilled facility	2118 (25.3%)	75,028 (28.0%)	<.0001	0.061	2118 (25.3%)	2142 (25.6%)	.261	0.007
Smoking	2711 (32.4%)	59,997 (22.4%)	<.0001	0.226	2710 (32.4%)	2664 (31.8%)	.038	0.012