Telescope Matching: A Flexible Approach to Estimating Direct Effects

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International Methods Colloquium

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direct effect

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effect of treatment not due to a particular downstream cause

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why do we care?

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causal mediation

direct effect

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why do we care?

- causal mediation
- causal mechanisms

direct effect

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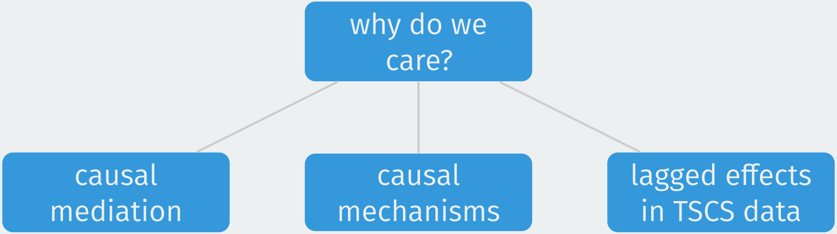
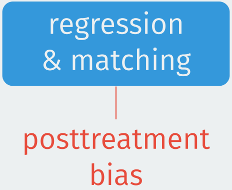


regression
& matching


regression
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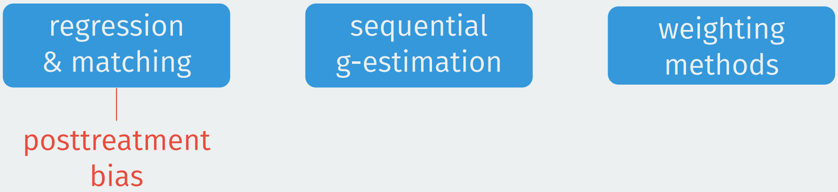
regression & matching
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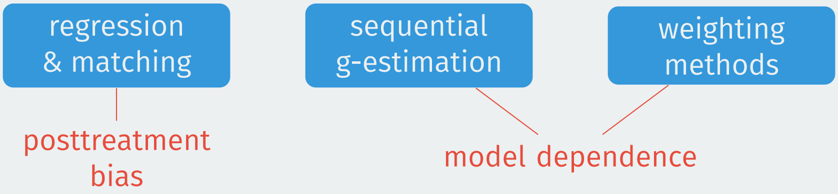
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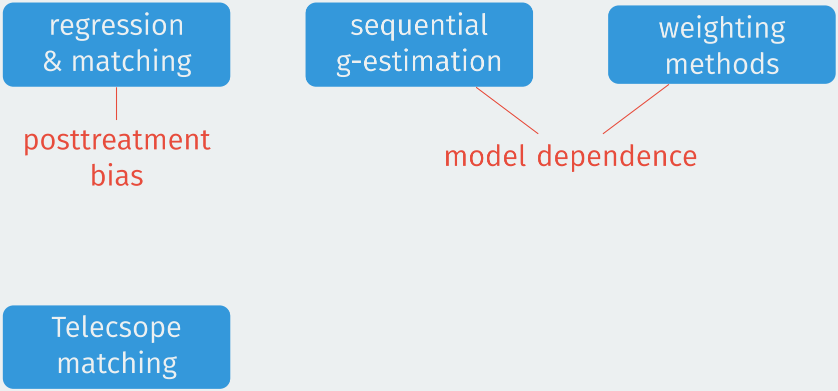
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Telecsope
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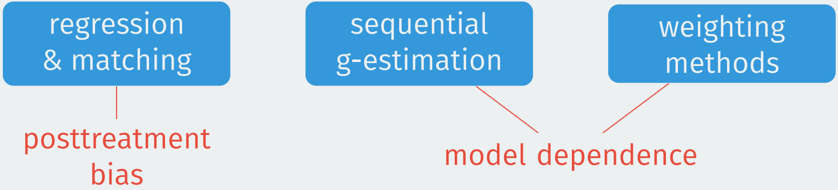
Telescope matching

- consistent for direct effects



Telescope matching

- consistent for direct effects
- avoids post-treatment bias

regression & matching

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Telescope matching

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- avoids post-treatment bias
- robust to (some) model misspecification

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Telecsope matching

- consistent for direct effects
- avoids post-treatment bias
- robust to (some) model misspecification
- carries over logic from standard matching

Roadmap

1. The difficulty of direct effects
2. Our approach: telescope matching
3. Simulating misspecification
4. Application
5. Conclusion

1/ The difficulty of direct effects

Notation

Setting Effect of frame on immigration media accounts

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A_i	Binary treatment $\in \{\texttt{negative frame, positive frame}\}$

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Y_i	Outcome (support for immigration)

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A_i	Binary treatment $\in \{\texttt{negative frame, positive frame}\}$
M_i	Binary mediator $\in \{\texttt{high anxiety, low anxiety}\}$
Y_i	Outcome (support for immigration)
$Y_i(a, m)$	Potential outcome

The Quantity of Interest

Definition (Average Controlled Direct Effect)

$$\tau(m) = E[Y_i(1, m) - Y_i(0, m)]$$

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- Average effect of manipulating A_i while fixing M_i to level m
- Easily identified if A_i and M_i are randomized but...
- Lots of studies are observational in M_i or both.

Confounders

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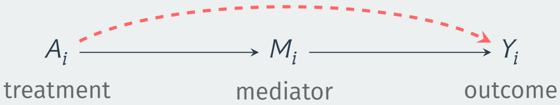

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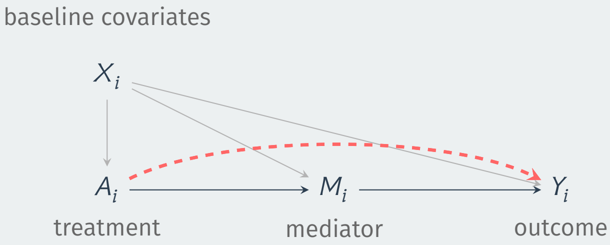

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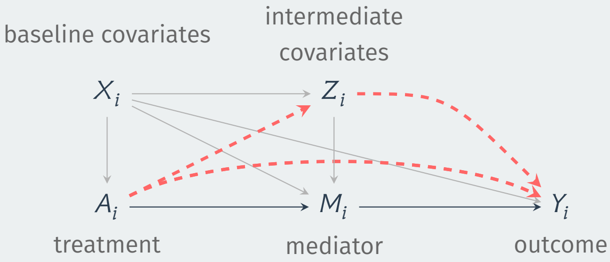

Assumptions

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Assumption (Sequential Ignorability)

$$\{Y_i(a,m), M_i(a), Z_i(a)\} \perp\!\!\!\perp A_i | X_i = x$$
$$Y_i(a,m) \perp\!\!\!\perp M_i | A_i = a, X_i = x, Z_i = z$$

No omitted variables for A_i given X_i.
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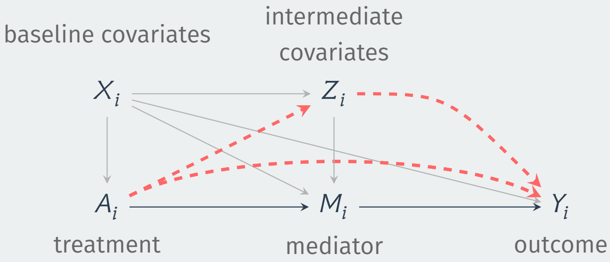
Assumption (Positivity)

$$0 < P(A_i = 1 | X_i = x) < 1$$
$$0 < P(M_i = 1 | X_i = x, Z_i = z, A_i = a) < 1$$

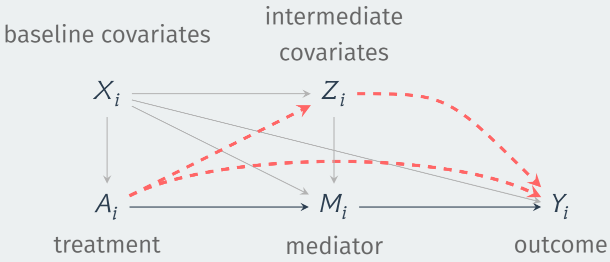
Overlap in the covariate distributions across levels of A_i and M_i

The Problem



baseline covariates
intermediate covariates
X_i
Z_i
A_i
M_i
Y_i
treatment
mediator
outcome

The Problem



naive regression/matching of Y_i on X_i, A_i, M_i, and...

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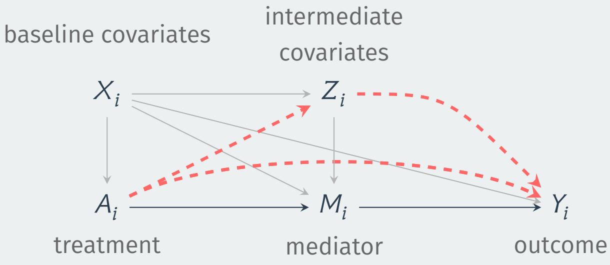

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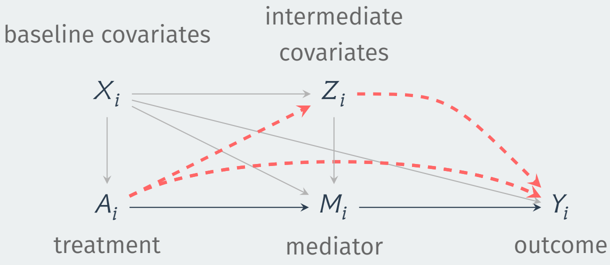
Omit Z_i

The Problem



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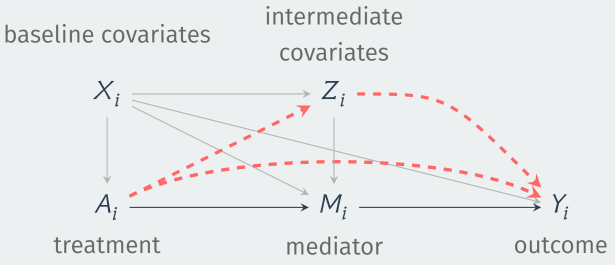

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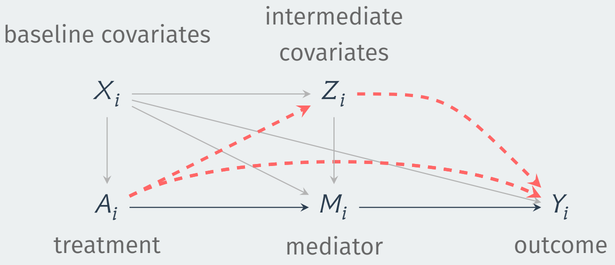

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Omit Z_i

omitted variable bias for M_i

Control for Z_i

post-treatment bias for A_i

Extant solutions are model dependent

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Structural Nested Mean Models (SNMMs)

Need the correct model for $\mathbb{E}[Y_i | X_i, A_i, Z_i, M_i]$ and $\mathbb{E}[Y_i | X_i, A_i]$

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Structural Nested Mean Models (SNMMs)

Need the correct model for $\mathbb{E}[Y_i | X_i, A_i, Z_i, M_i]$ and $\mathbb{E}[Y_i | X_i, A_i]$

Inverse probability of treatment weighting (IPTW)

Need the correct model for $\mathbb{P}[M_i | X_i, A_i, Z_i]$ and $\mathbb{P}[A_i | X_i]$

2/ Our approach: telescope matching

Telescope matching

Telescope matching

Two-stage matching procedure

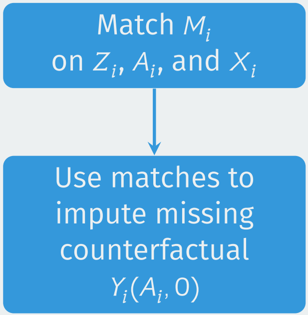
Telescope matching

Two-stage matching procedure

Match M_i
on Z_i, A_i, and X_i

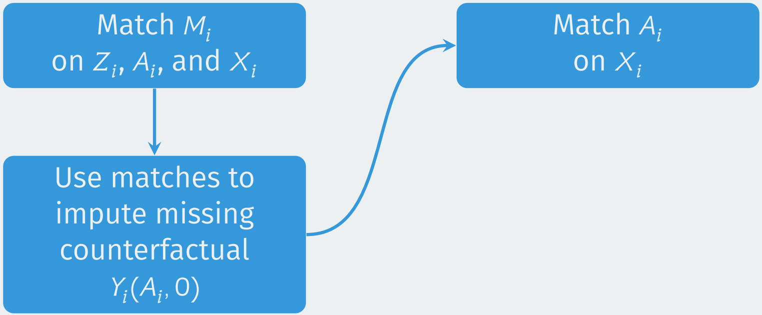
Telescope matching

Two-stage matching procedure



Telescope matching

Two-stage matching procedure



Telescope matching

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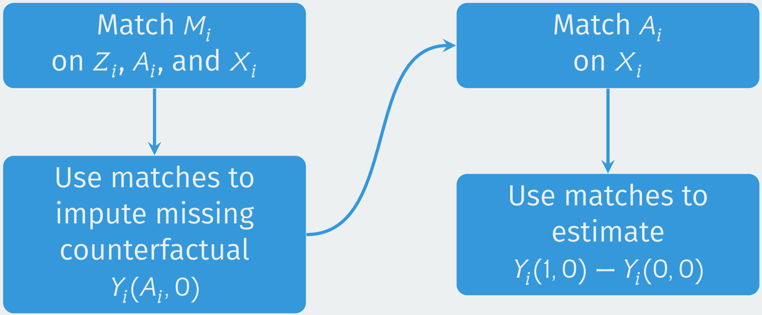

An imputation problem

Unit	Observed				Potential Outcomes			
	A_i	M_i	X_i	Z_i	$Y_i(1,1)$	$Y_i(1,0)$	$Y_i(0,1)$	$Y_i(0,0)$

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$$\tau(0) = E[Y_i(1,0) - Y_i(0,0)]$$

First stage

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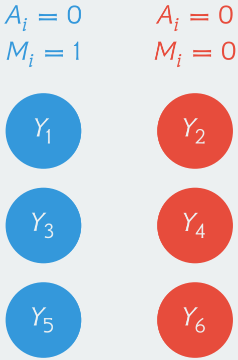


First stage

1. Subset to a particular level of A_i

$A_i = 0$ $M_i = 1$

Y_1

Y_3

Y_5

$A_i = 0$ $M_i = 0$

Y_2

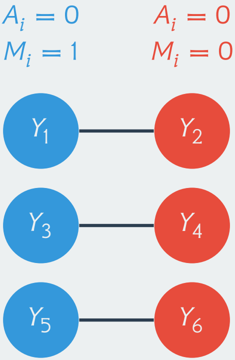
Y_4

Y_6

First stage

1. Subset to a particular level of A_i

2. Match each $M_i = 1$ to closest $M_i = 0$ unit in $\{X_i, Z_i\}$



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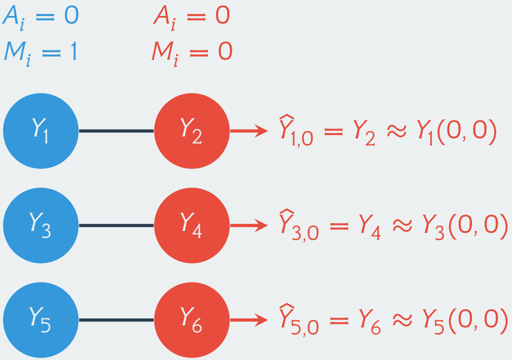

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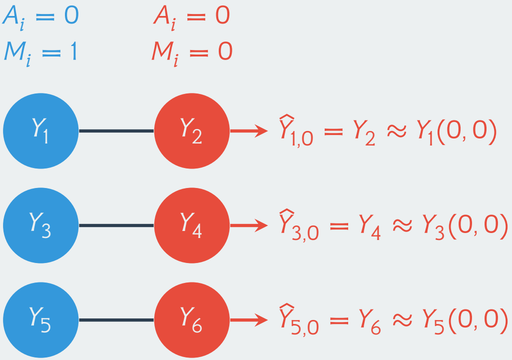

$$\widehat{Y}_{i0} = \begin{cases} Y_i & \text{if } M_i = 0 \\ Y_\ell & \text{if } M_i = 1, M_\ell = 0 \text{ and } \ell \text{ is matched to } i \end{cases}$$

1:1 matching example

Unit	Observed				Potential Outcomes			
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Standard matching using $\widehat{Y}_{i0}$ as outcome completely ignoring M_i and Z_i

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3. Take difference in means to estimate ACDE

$$\widehat{\tau} = \frac{1}{N}\sum_{i=1}^{N} \widehat{Y}_i(1,0) - \widehat{Y}_i(0,0)$$

1:1 matching, second stage

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$$\widehat{\tau} = \frac{1}{6}\Big[(Y_2 - Y_6) + (Y_2 - Y_5) + (Y_3 - Y_5) + (Y_3 - Y_5) + (Y_2 - Y_5) + (Y_2 - Y_6)\Big]$$

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Robust

- more robust to model misspecification

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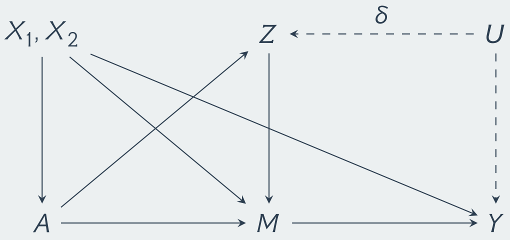
- we follow Otsu and Rai (2017) and resample each contribution to the estimator

3/ Simulating misspecification

Simulation set-up



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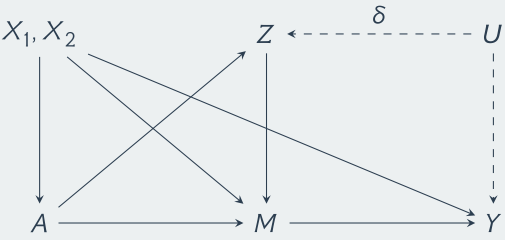

- All variables observed except U $\rightsquigarrow$ sequential ignorability holds

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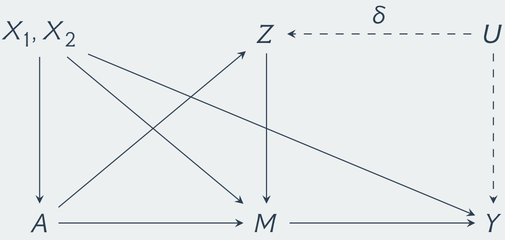

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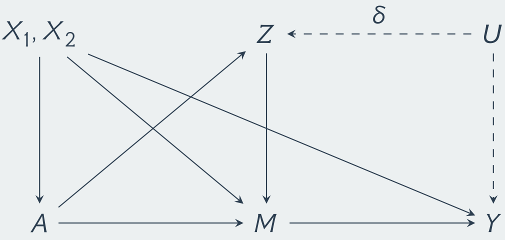

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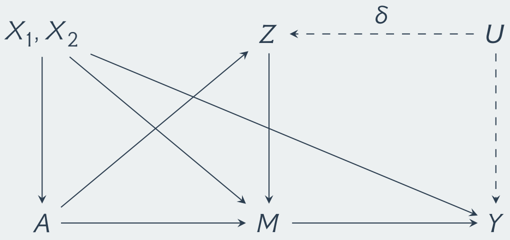

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- δ controls magnitude of post-treatment confounding
  - when $\delta \neq 0$, controlling for Z in a naive regression will induce post-treatment bias.

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  Number of matches per stage = 3

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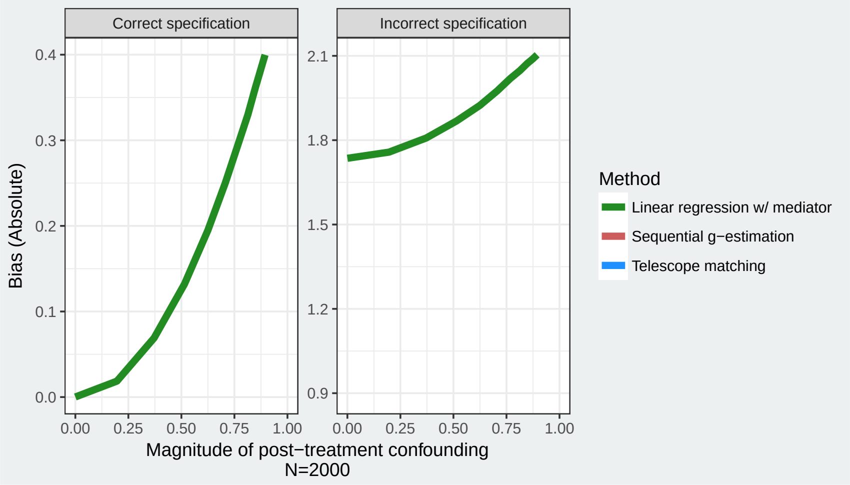

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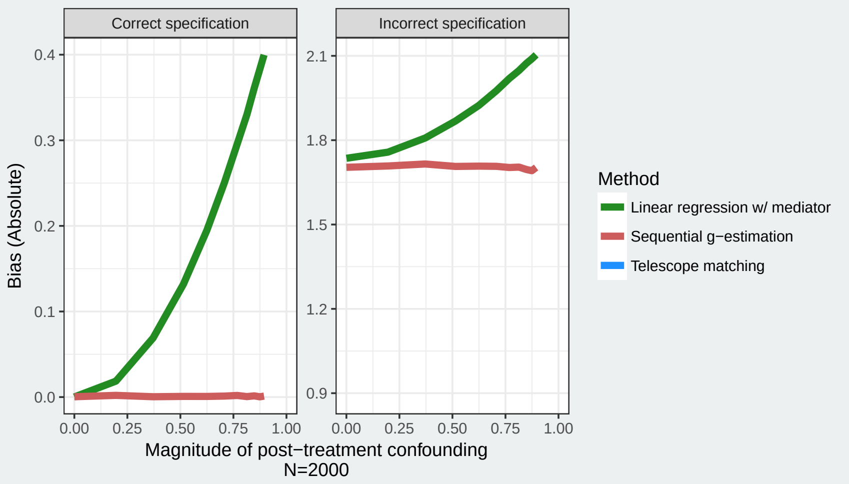

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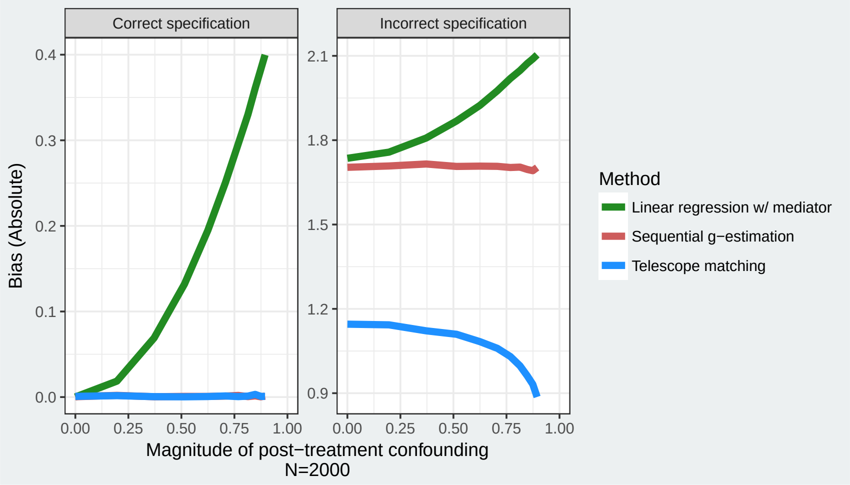
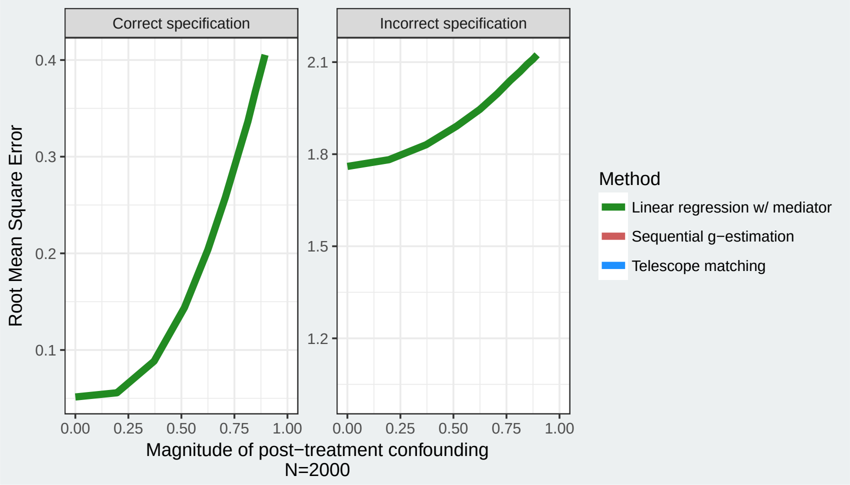


Simulation results: Root Mean Square Error



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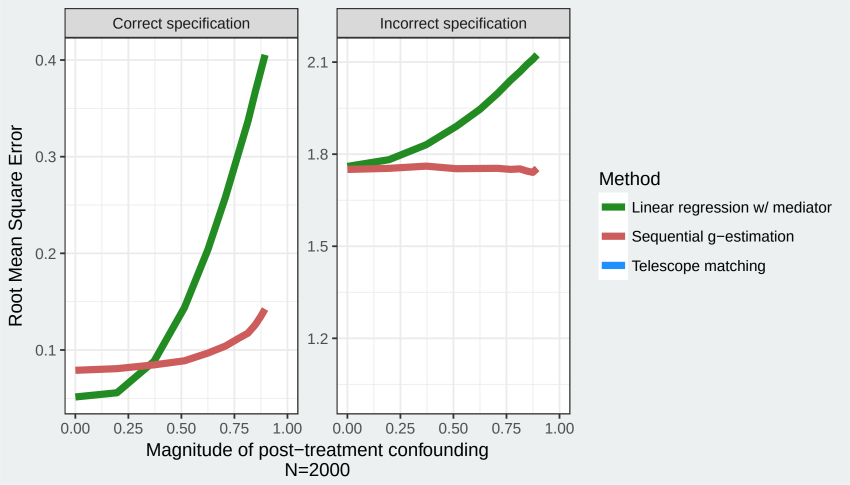

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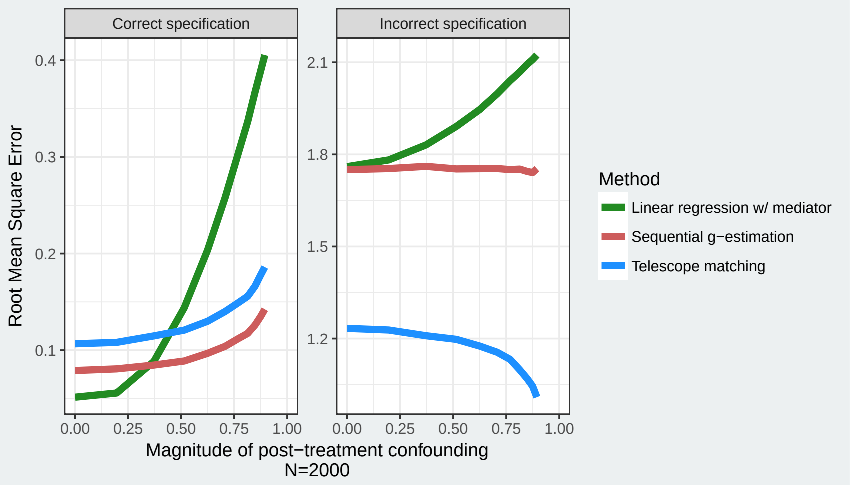

4/ Application

Brader, Suhay, Valentino (2008)

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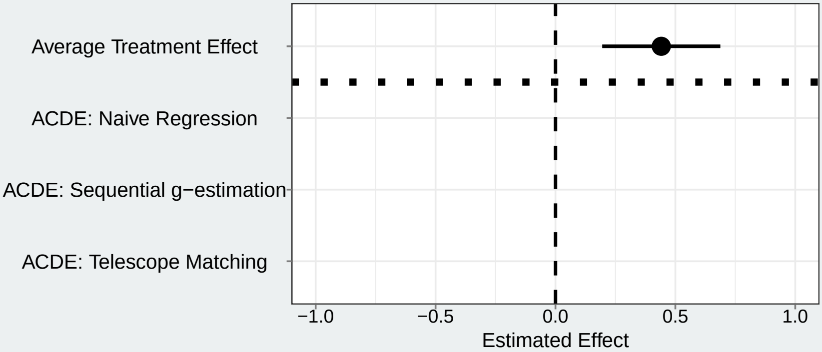

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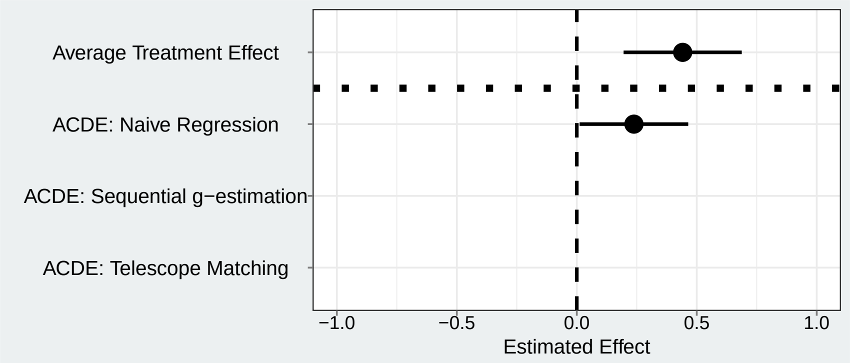

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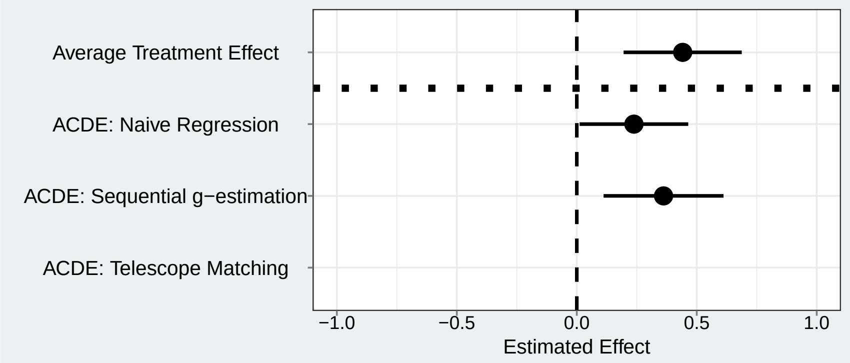

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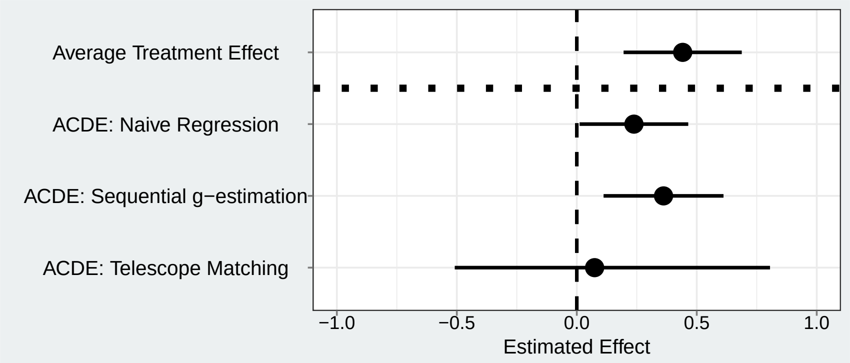

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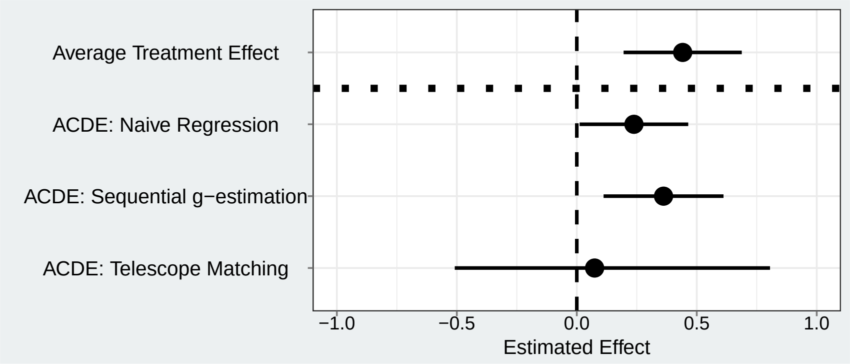

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- Apply ideas to mediation analysis where there are no Z_i.
- How to handle dropping units in the first stage since it induces post-treatment bias?

Thanks!

- For more information, see:
- http://www.mattblackwell.org/files/papers/telescope_matchin
- http://www.mattblackwell.org
- https://www.antonstrezhnev.com/

SNMMs as imputation estimators

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