Generalized Nonlinear Difference-in-Difference-in-Differences

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Introduction

CiC and NOC Procedures

NOCNOC

Simulation Results

DiD and DiDiD primer

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- Difference-in-Difference-in-Differences (DiDiD) adds a 3rd D to check/correct for violations of the DiD assumptions. (e.g., 3rd D might be min wage jobs vs non-min wage jobs)

Issues and previous work

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Previous work addressing issues:

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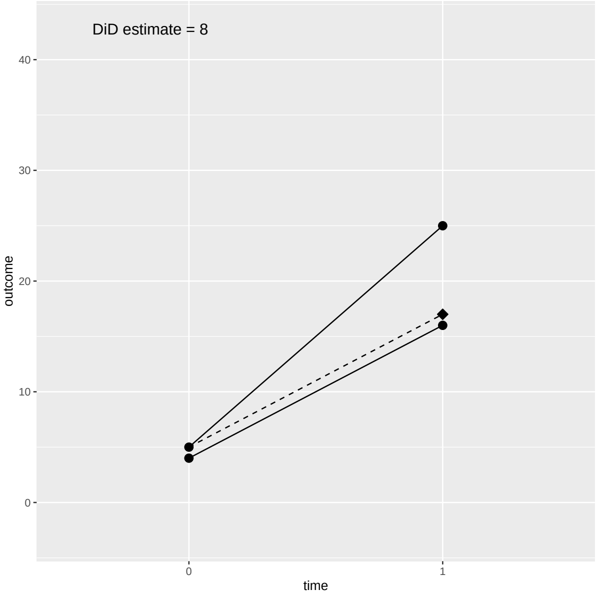
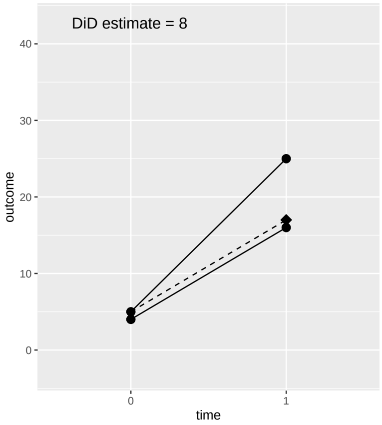
Let's work through the intuition behind CiC and NOC.

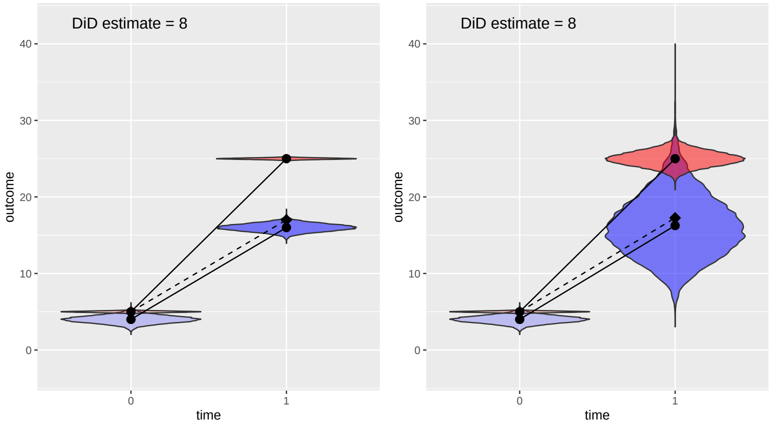
Traditional DiD with one pre-treatment period



Means don't tell us everything



Useful information in the distributions



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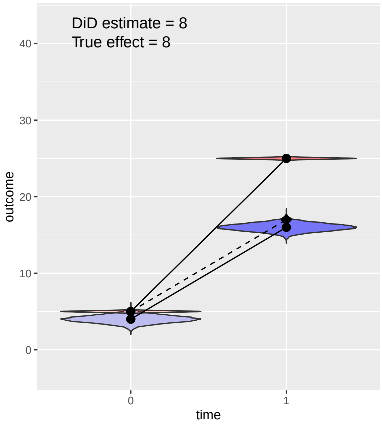
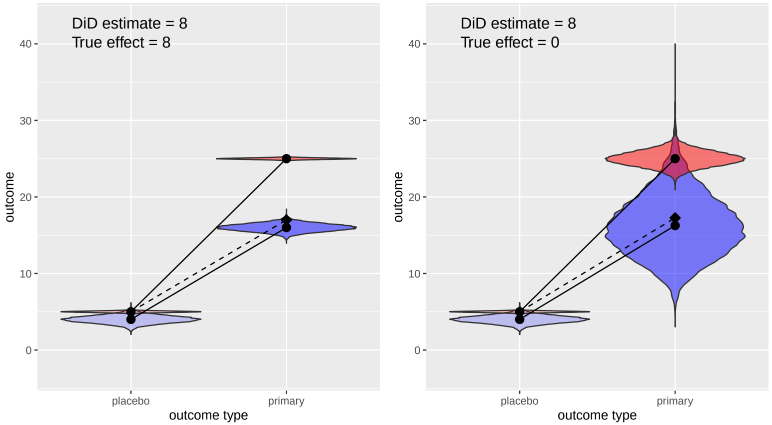


X-axis doesn't have to be time



Our approach to solving issues 1 and 2

We generalize DiDiD by extending the CiC procedure and the NOC procedure to a NOCNOC procedure.

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- nonlinear DiDiD that uses all the information
- generalized nonlinear DiDiD to accommodate placebo outcomes

Running example: effects of debate attendance on political efficacy in a 2017 transitional election in Nepal

Treatment (A): attendance at debate screening ($\approx$ 50 min)

- Samriddhi Foundation organized candidate debates for each of 3 SMD seats in House of Representatives (parliament).
- Combinations of debate/discussions were randomly assigned among attendees of the debates.
- Here, we focus on the effects of attendance, which was not randomized.

Sample

- Constituencies within Kanchanpur, Jhapa, Sunsari districts
- Random sample of adults in each constituency were invited to sign up for an event date of their choice.
- Reinterview rate of 90.7% of 777 baseline respondents.
- We analyze $n = 705$ complete cases among those who signed up for Nov 21 - Nov 27.
- $A = 1$ for 30.4% of these cases.

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Y: Political Efficacy - the sense that one can influence politics and government (external) and that one can understand politics and government (internal)

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Parameter of Interest (ATT): $E[Y_{11}] - E[Y_{11}(0)]$ is the average effect of attendance on those that attended.

Classic DiD approach

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Difference-in-differences:

$$(\widehat{E}[Y_{11}] - \widehat{E}[Y_{10}]) - (\widehat{E}[Y_{01}] - \widehat{E}[Y_{00}]) =$$
$$(\widehat{E}[Y_{11}] - \widehat{E}[Y_{01}]) - (\widehat{E}[Y_{10}] - \widehat{E}[Y_{00}]) = .041\ (.023)$$

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Appears to show effect (90% CI), but relies on parallel trends assumption, or time-invariant bias assumption, which are not scale invariant. So try CiC.

CiC procedure

Athey and Imbens (2006) presents a generalization of DiD using cdfs and inverse cdfs.

- DiD average estimate (re-written):

$$\widehat{E}[Y_{11}] - (\widehat{E}[Y_{01}] + (\widehat{E}[Y_{10}] - \widehat{E}[Y_{00}]))$$

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- CiC average estimate:

$$\frac{1}{n_{11}} \sum_{i=1}^{n_{11}} Y_{11,i} - \frac{1}{n_{10}} \sum_{i=1}^{n_{10}} \hat{F}_{Y_{01}}^{-1}(\hat{F}_{Y_{00}}(Y_{10,i}))$$

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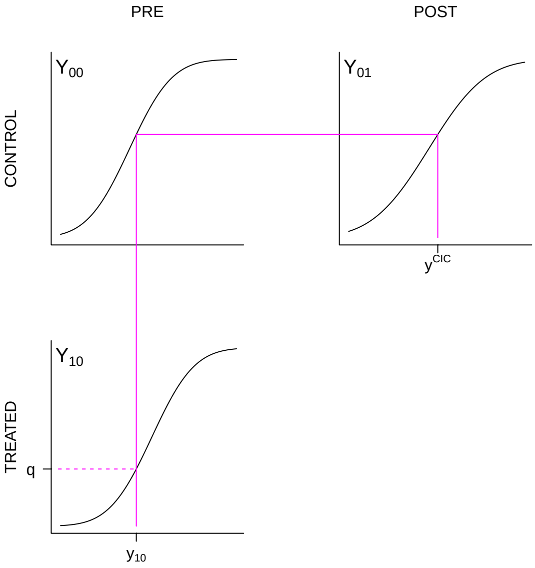
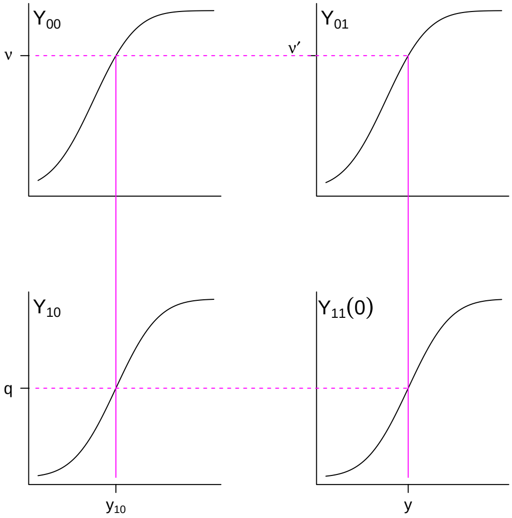
- Imputation can be done for each quantile ($\hat{F}^{-1}_{Y_{11}(0)}(q)$).

CiC procedure for imputing $Y(0)$ for quantile q



Relies on time-invariant confounding on the quantile scale.

CiC equi-confounding assumption for quantile q



Nepal CiC estimate

CiC estimate of ATT:

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Effect is robust, but maybe assumptions don't hold. Can't find 3rd D group, but can find placebo outcome.

Placebo (negative) outcome: knowledge

N: Knowledge of government not presented in the debate (max possible score of 18)

- How many levels of government under the new constitution
- How many assemblies at the federal level
- Name responsibilities/powers of local government under the new constitution

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Should not be affected (much) by debate attendance, but may be affected by similar confounding factors.

NOC procedure

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$$\frac{1}{n_{11}}\sum_{i=1}^{n_{11}} Y_{11,i} - \frac{1}{n_{11}}\sum_{i=1}^{n_{11}} \hat{F}_{Y_{01}}^{-1}(\hat{F}_{N_{01}}(N_{11,i}))$$

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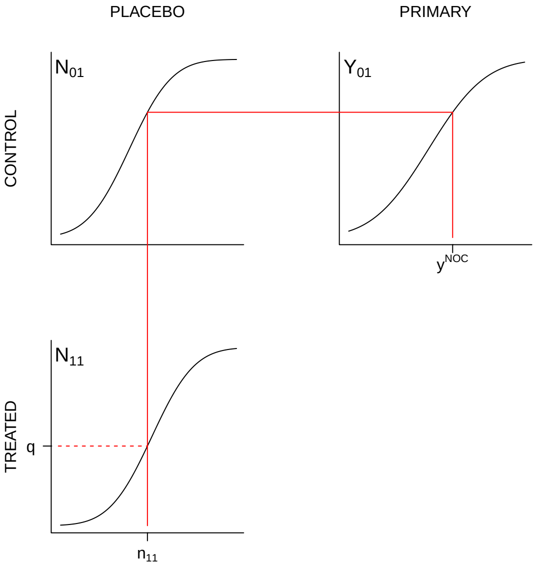
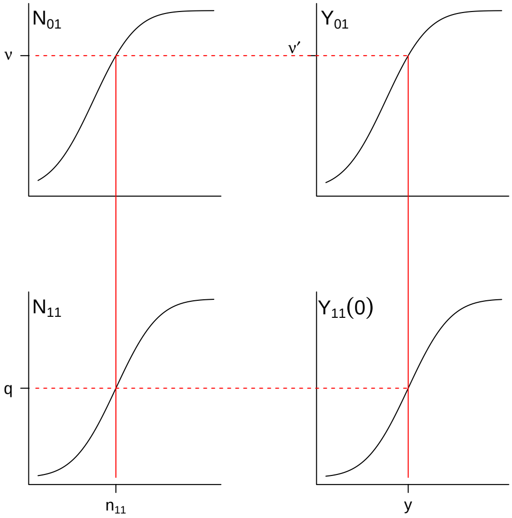
- Imputation can again be done for each quantile ($\hat{F}^{-1}_{Y_{11}(0)}(q)$).

NOC procedure for imputing $Y(0)$ for quantile q



Relies on variable-invariant confounding on the quantile scale.

Equi-confounding assumption



NOC procedure

NOC estimate of ATT:

$$\widehat{NOC} = .004\ (.029)$$

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Lack of effect contradicts previous findings, but is the variable-invariant confounding assumption reasonable?

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$$
\begin{aligned}
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&- \{(\widehat{E}[Y_{10}] - \widehat{E}[Y_{00}]) - (\widehat{E}[N_{10}] - \widehat{E}[N_{00}])\} \\
&= \widehat{E}[Y_{11}] \\
&- \left[\widehat{E}[Y_{01}] - (\widehat{E}[N_{11}] - \widehat{E}[N_{01}]) - \{(\widehat{E}[N_{10}] - \widehat{E}[N_{00}]) - (\widehat{E}[Y_{10}] - \widehat{E}[Y_{00}])\}\right]
\end{aligned}
$$

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- no treatment effect in pre-treatment period, so figure out q' of N_{10} that would have produced q of Y_{10} for NOC in the pre-treatment period
- use q' instead of q in the posttreatment NOC procedure
- relies on time-invariant, variable-variant confounding assumption
- NOCNOC average estimate:

$$\frac{1}{k_{11}}\sum_{i=1}^{k_{11}} Y_{11,i} - \frac{1}{k_{10}}\sum_{i=1}^{k_{10}} \hat{F}^{-1}_{Y_{01}}(\hat{F}_{N_{01}}(\hat{F}^{-1}_{N_{11}}(\hat{F}_{N_{10}}(\hat{F}^{-1}_{N_{00}}(\hat{F}_{Y_{00}}(Y_{10,i}))))))$$

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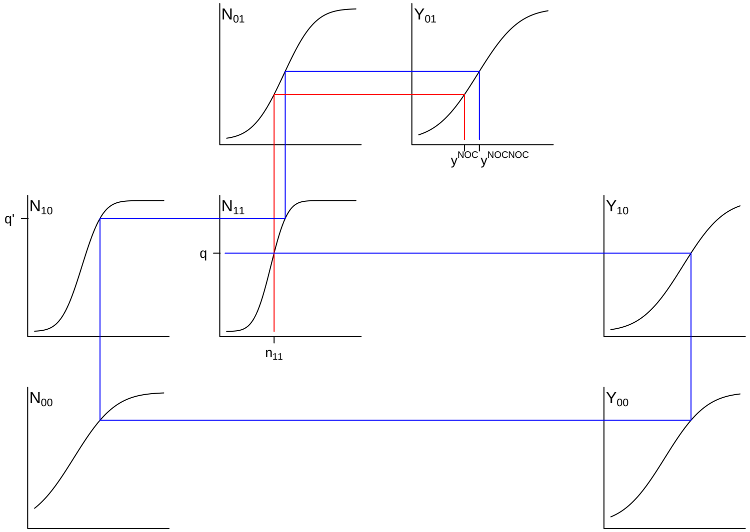

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Reduced effect so less confidence in finding.

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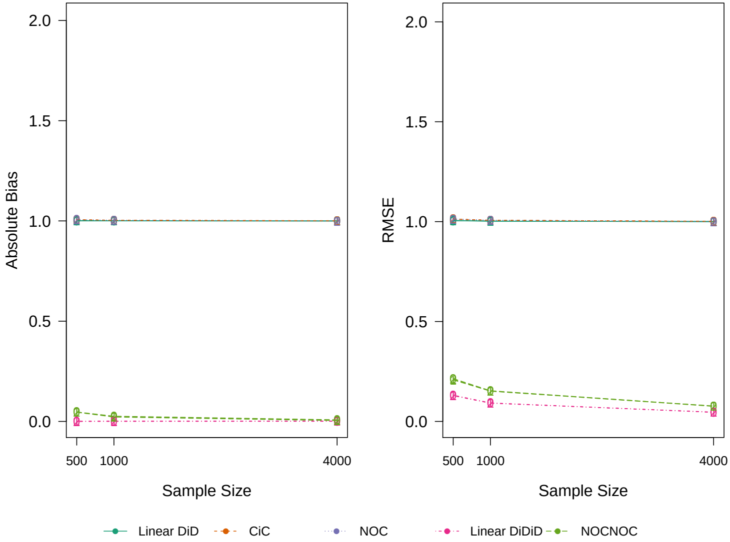
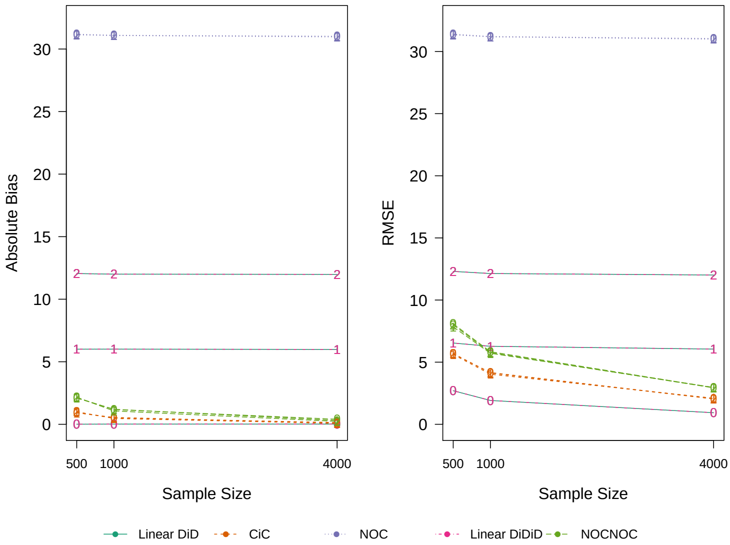
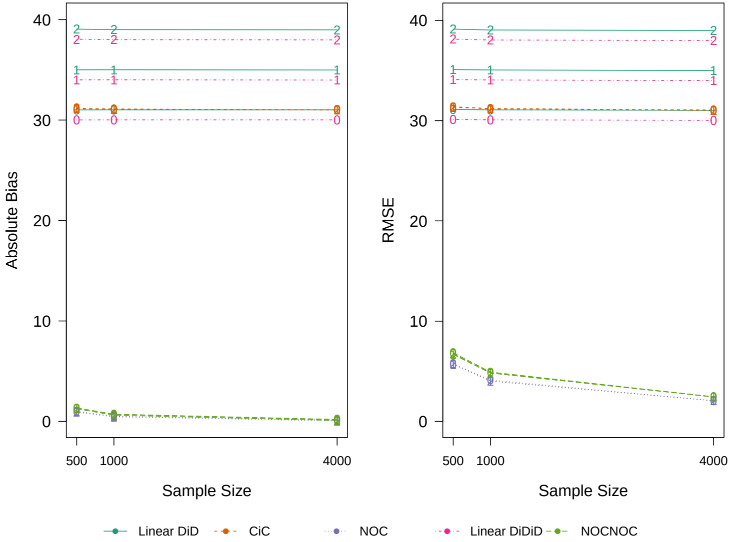
Simulation with linear DiDiD Model



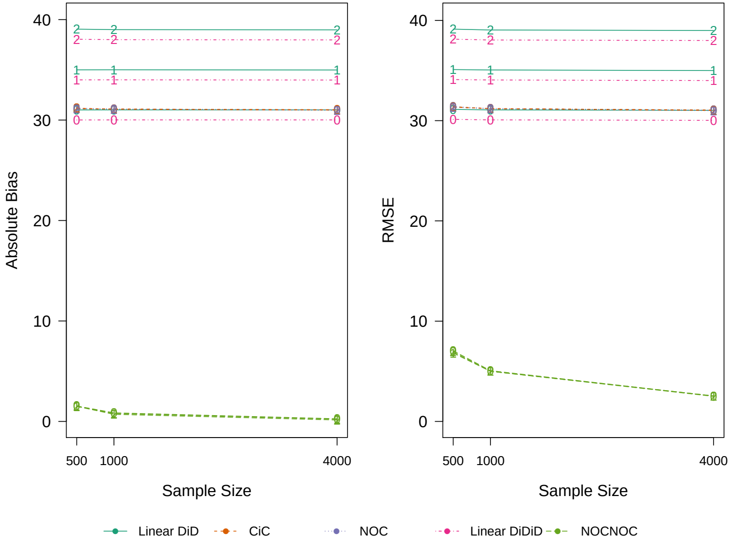
Simulation with CiC Model



Simulation with NOC Model



Simulation with NOCNOC Model



Conclusion and Future Work

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- Genearlized nonlinear DiDiD allows:
  - robustness check of linear DiDiD
  - use of placebo outcomes in lieu of third differencing group
- Inclusion of covariates almost done
- Nonparametric analysis almost done (outcomes need only be ranked, not fully measured)

Thank You

Extension: ATC with Placebo Outcomes N

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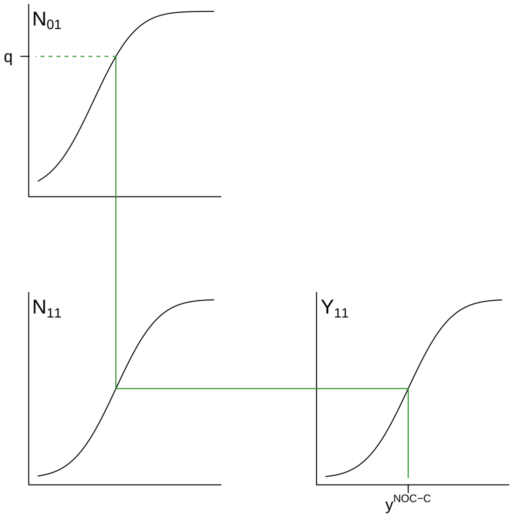
NOC estimator for ATC:

$$\frac{1}{k_{01}} \sum_{i=1}^{k_{01}} \hat{F}_{Y_{11}}^{-1}(\hat{F}_{N_{11}}(N_{01,i})) - \widehat{E}[Y_{01}]$$

where k_{01} is the number of control units in the post-treatment period for the placebo outcome.

NOC procedure for imputing $Y_{01}(1)$ for quantile q

Imputation can be done at each quantile $\hat{F}^{-1}_{Y_{01}(1)}(q)$



Extension: ATT with Surrogate Outcomes

Proxy/surrogate: no confounding, but effect on S is the same as the effect on Y on the quantile scale.

Surrogate estimator for ATT:

$$\widehat{E}[Y_{11}] - \frac{1}{n_{01}} \sum_{i=1}^{n_{01}} \hat{F}_{Y_{11}}^{-1}(\hat{F}_{S_{11}}(S_{01,i}))$$

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1. Compare with NOC estimator for ATC:

$$\frac{1}{k_{01}} \sum_{i=1}^{k_{01}} \hat{F}^{-1}_{Y_{11}}(\hat{F}_{N_{11}}(N_{01,i})) - \widehat{E}[Y_{01}]$$

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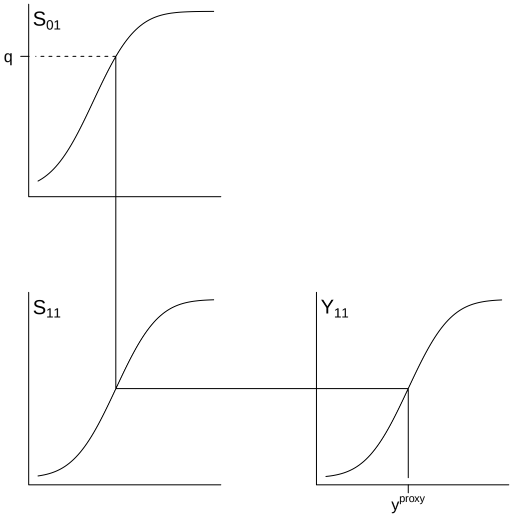
2. No primary outcome measures on the control used; neither Y_{01} nor Y_{00} are included in the formula.

Surrogate ATT estimator for imputing $Y(0)$ for quantile q

Imputation can be done at each quantile $\hat{F}^{-1}_{Y_{11}(0)}(q)$



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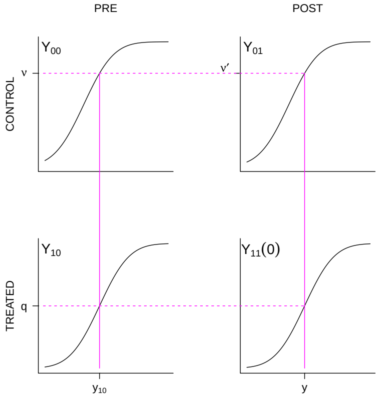

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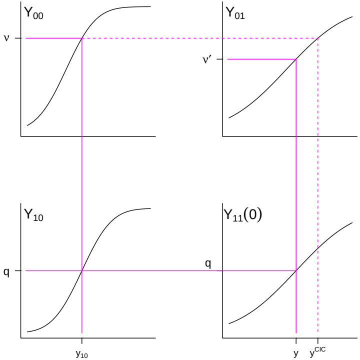
2. for ATT, only need equi-confounding to hold on average $(E_q[y - y^{CiC}] = 0)$



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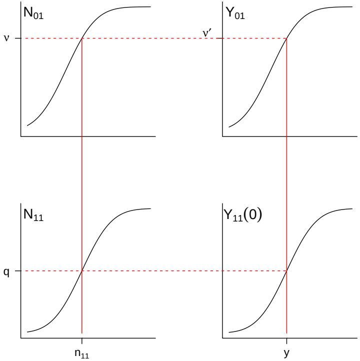

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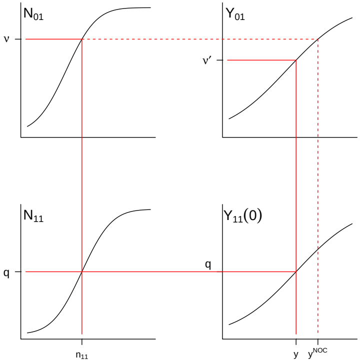
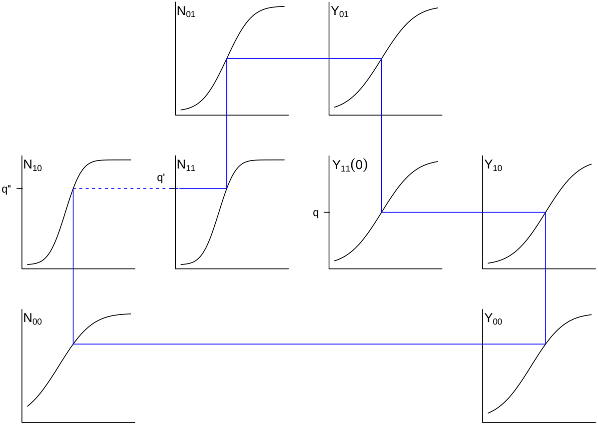


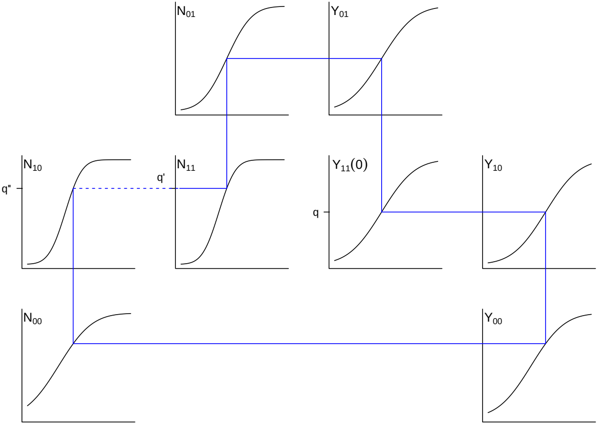
Key assumption of NOCNOC

1. assume the q" that leads to $F_{Y_{10}}(q)$ in pre-treatment period equals the q' that leads to $F_{Y_{11}(0)}(q)$ in post-treatment period



Key assumption of NOCNOC

1. assume the q" that leads to $F_{Y_{10}}(q)$ in pre-treatment period equals the q' that leads to $F_{Y_{11}(0)}(q)$ in post-treatment period
2. for ATT only need to hold on average $E_q[y_{11}(0) - y^{NOCNOC}] = 0$



Reduced form NOCNOC assumptions

Time-invariant variable-variant confounding:

$$F_{N_{11}}(F^{-1}_{N_{01}}(F_{Y_{01}}(F^{-1}_{Y_{11}(0)}(q)))) = F_{N_{10}}(F^{-1}_{N_{00}}(F_{Y_{00}}(F^{-1}_{Y_{10}}(q)))), q \in [0, 1]$$

Support condition:

$$\begin{aligned}
\text{if } 0 < f_{Y_{10}}(y_{10}),\ \text{then } & 0 < F_{Y_{00}}(y_{10}) < 1, \\
& 0 < F_{N_{10}}(F^{-1}_{N_{00}}(F_{Y_{00}}(y_{10}))) < 1,\ \text{and} \\
& 0 < F_{N_{01}}(F^{-1}_{N_{11}}(F_{N_{10}}(F^{-1}_{N_{00}}(F_{Y_{00}}(y_{10}))))) < 1
\end{aligned}$$

Generative model NOCNOC assumptions

No effect of treatment on placebo outcome:

$$N_{at}(a) = N_{at} \text{ for } a = 0, 1$$
$$Y_{at}(a) = Y_{at} \text{ if } A = a$$

Unconfounded conditional on unmeasured U_t and W_t:

$$A_t \perp\!\!\!\perp Y_t(0) | U_t \text{ for } t = 0, 1$$
$$A_t \perp\!\!\!\perp N_t | W_t \text{ for } t = 0, 1$$

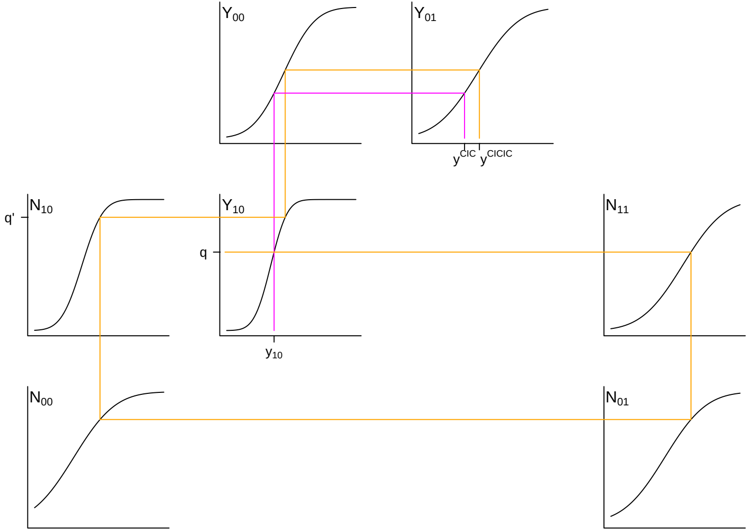
Control potential outcomes monotone in U_t and W_t:

$$Y_{at}(0) = h_{yt}(U_{at}) \text{ where } h_{yt}(U_{at}) \text{ is monotone increasing}$$
$$N_{at} = h_{nt}(W_{at}) \text{ where } h_{nt}(W_{at}) \text{ is monotone increasing}$$

Time-invariant unobserved variable-variant confounding:

$$F_{W_{11}}(F^{-1}_{W_{01}}(F_{U_{01}}(F^{-1}_{U_{11}(0)}(q)))) = F_{W_{10}}(F^{-1}_{W_{00}}(F_{U_{00}}(F^{-1}_{U_{10}}(q)))), q \in [0, 1]$$

CiCiC procedure

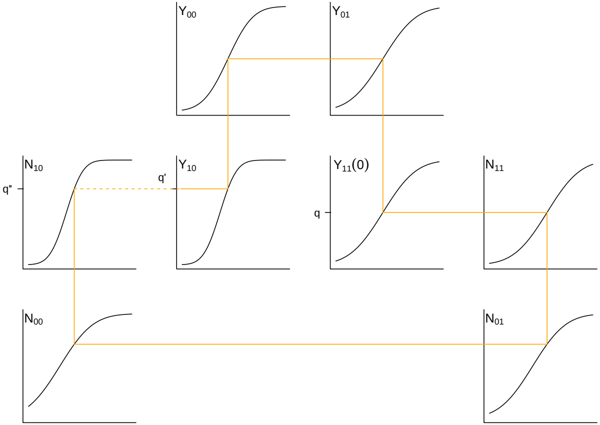


Key assumption of CICIC

1. assume that if q' leads to $F_{N_{11}(q)}$ for the negative outcome, then q' leads to $F_{Y_{11}(q)}(0)$ for the outcome

Key assumption of CICIC

1. assume that if q' leads to $F_{N_{11}(q)}$ for the negative outcome, then q' leads to $F_{Y_{11}(q)}(0)$ for the outcome
2. for ATT only need to hold on average $E_q[y_{11}(0) - y^{CiCiC}] = 0$



Efficacy Measure

1. I feel I can influence political decisions that affect my life. (Strongly agree to strongly disagree, 5 point scale)
2. I feel I am as well-informed about politics and government as most people. (Strongly agree to strongly disagree, 5 point scale)
3. Which of the following is closer to your view? (a) Politics is complicated and I usually do not understand what politicians are doing, (b) Most of the time I understand what politicians are doing