

Identifying Direct Causal Effects Under Unmeasured Confounding



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Introduction & Motivations

- Developing *mechanistic* understandings of causal effects is a ubiquitous goal across scientific disciplines.
- The natural direct and indirect effects are common target causal parameters since they are nonparametrically identified.
- Identification assumes absence of unmeasured confounders of exposure—mediator, mediator—outcome, and exposure—outcome pathways but this is *not* completely necessary.
- The natural direct and indirect effects arise from a decomposition of the average treatment effect (ATE), and the
 - natural indirect effect (NIE) captures the portion of the ATE passing through the mediators (Z), while the
 - natural direct effect (NDE) captures the remainder of the ATE, through all paths excluding Z.

The Statistical Problem

The average treatment effect may be decomposed as

$$\Psi_{\text{ATE}}^{F}(P_{U,X,0}) = \mathbb{E}_{U,X,0}[Y(1) - Y(0)]$$

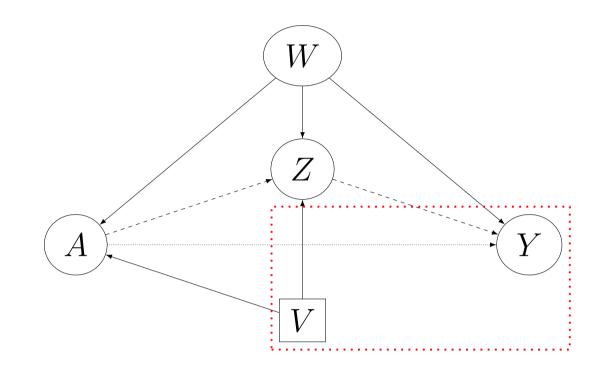
$$= \mathbb{E}_{U,X,0}[Y(1,Z(1)) - Y(1,Z(0))]$$

$$+ \mathbb{E}_{U,X,0}[Y(1,Z(0)) - Y(0,Z(0))],$$
NDE

where Y(1, Z(0)) arises from a *joint* intervention on treatment and mediators (Z), setting them to incompatible values. The NDE is

$$\Psi_{\text{NDE}}^{F}(P_{U,X,0}) = \int_{\mathcal{W},\mathcal{Z}} \mathbb{E}[Y(1,z) - Y(0,z) \mid W = w]$$
$$p_{Z}(z \mid A = 0, w) p_{W}(w) \ d\mu(z) \ d\nu(w) \ .$$

Causal Identification



- (A1) No unmeasured endogenous pathways: $f_Y(Z, A, W, V, U_Y) \equiv f_Y(Z, A, W, U_Y).$
- (A2) Conditional expectation equivalence: $\mathbb{E}(Y \mid Z, A = 1, W, V) \equiv \mathbb{E}(Y \mid Z, A = 1, W)$

Theorem

Under assumptions A1 and A2, $\Psi_{\text{NDE}}^F(P_{U,X,0})$ is identified by

$$\Psi(P_0) = \mathbb{E}_{P_0} \mathbb{E}_{P_0} \{ \mathbb{E}_{P_0} \{ Y \mid W, A = 1, Z \} - \mathbb{E}_{P_0} \{ Y \mid W, A = 0, Z \} \mid A = 0, W \} .$$

Numerical Experiments

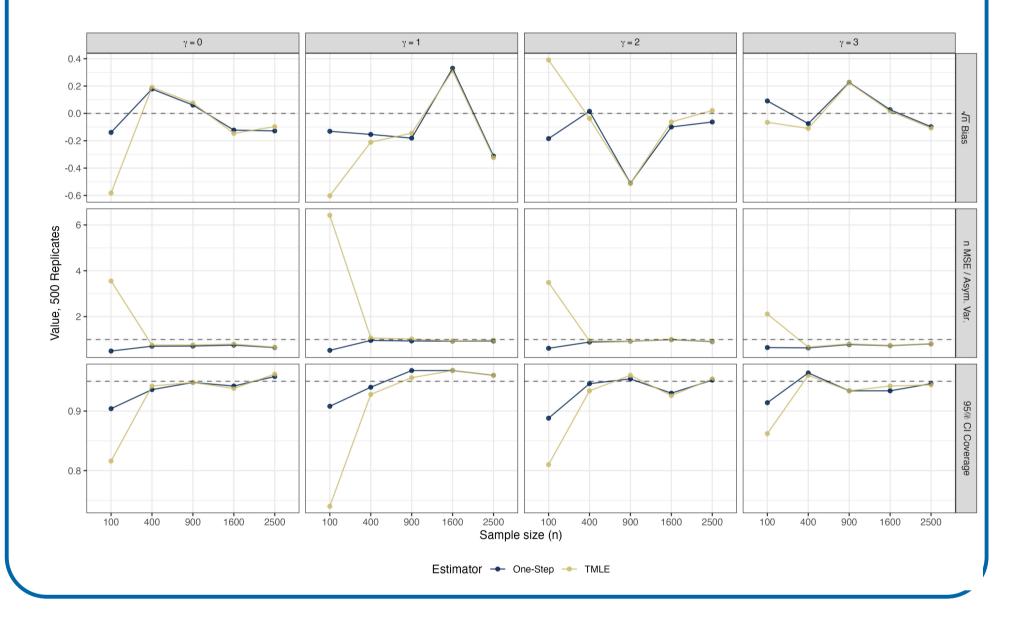
We consider the following data-generating process:

$$W_1 \sim \text{Unif}(-1,1); \ W_2, V \sim \text{Norm}(0,1)$$

$$A|W, V \sim \text{Bern}\left((1 + \exp\{-W_1 - W_2 - V\})^{-1}\right)$$

$$Z|A, W, V \sim \text{Bern}\left((1 + \exp\{-W_1 - W_2 - \gamma V - 3A\})^{-1}\right)$$

$$Y|Z, A, W, V \sim \text{Norm}(3A + W_1 + W_2 + Z, 1).$$



Inference

Existing estimation and testing approaches are compatible with this relaxed identification strategy. For example,

- targeted maximum likelihood estimator of Zheng and van der Laan [2012]
- one-step bias-corrected estimator based on the efficient influence function of Tchetgen Tchetgen and Shpitser [2011].

Both estimators are multiple-robust, asymptotically linear under fairly non-restrictive assumptions, and compatible with cross-fitting. Both estimators are implemented in the **medoutcon R** package.

Conclusions

- The NDE is identifiable under unmeasured exposure—mediator confounding by a *well-studied* statistical functional!
- The NDE has recently been used to study the *proportion of* vaccine effect mediated through candidate immune correlates.
 - Our results strengthen "out-of-the-box" uses of the NDE.
 - Exposure-mediator confounders in vaccine studies: prior infection history, immunocompromised status, genetics.

References

Wenjing Zheng and Mark J. van der Laan. Targeted maximum likelihood estimation of natural direct effects. The International Journal of Biostatistics, 8(1):1-40, 2012. doi: doi:10.2202/1557-4679.1361. URL https://doi.org/10.2202/1557-4679.1361. Eric J Tchetgen Tchetgen and Ilya Shpitser. Semiparametric estimation of models for natural direct and indirect effects. Working Paper 129, Harvard University, 2011. URL https://biostats.bepress.com/harvardbiostat/paper129/.

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