The Authors Respond

To the Editor:

We read with keen interest Cinelli and Pearl's[1] response to our letter.[2] A key difference in our approaches can be appreciated by examining the first line of each of our derivations. In our derivation, the quantity we begin with is $E[Y(a)]$, but Cinelli and Pearl[1] begin with $E[Y \mid do(A=a)]$. Thus, a fundamental distinction, previously highlighted by Pearl,[3] is that our approach introduces new variables (in particular, the counterfactuals or potential outcomes $Y(a)$, $W(a)$, and $S(a)$), whereas Cinelli and Pearl[1] introduce a new operator (the *do* operator). Because these counterfactuals appear on the single world intervention graph in Figure B of our letter, the counterfactual independencies used in our derivation can be determined immediately using standard graphical criteria such as Pearl's d-separation. However, the causal diagram in Figure A of our letter only includes the observed factual random variables A, S, W, Y and the unobserved factual U, so it seems impossible to determine counterfactual independencies without additional context. In particular, if we equate $E[Y(a)]$ with $E[Y|do(A=a)]$ (Richardson and Robins,[4] page 7), then the first step in Cinelli and Pearl's[1] derivation becomes $E[Y(a)] = E[Y \mid A=a]$. However, because $Y(a)$ does not appear on the causal diagram, this step does not seem to be justified from the causal graph alone and requires knowledge that is not reflected by the causal diagram.

We appreciate the simplicity of Cinelli and Pearl's[1] derivation based on the causal diagram, but our intuition and insight are improved by working directly with counterfactuals. Before the introduction of single world intervention graphs, a shortcoming of the counterfactual approach was the conceptual difficulty of mapping knowledge of the factual variables to unobserved counterfactuals.[3] A key utility of single world intervention graphs is that they remove this difficulty. The first step in constructing a single world intervention graph is to construct a causal diagram based only on assumptions regarding the causal relationships between factuals.[4] This is then followed by applying an algorithm to map the causal relationships from the causal diagram to the single world intervention graph and thus the counterfactuals.[4] The construction of the single world intervention graph, therefore, explicitly links our assumptions regarding factuals to assumptions regarding counterfactuals.

We are pleased by the dialogue our letter has initiated. Causal inference holds a unique place at the intersection of many diverse fields, including epidemiology, statistics, philosophy, computer science, and economics, to name a few. Cross-disciplinary conversations like this provide valuable opportunities for us to learn alternate perspectives, minimize ambiguities, and enrich our understanding.

Alexander Breskin
Stephen R. Cole
Department of Epidemiology
University of North Carolina at Chapel Hill
Chapel Hill, NC
abreskin@unc.edu

Michael G. Hudgens
Department of Biostatistics
University of North Carolina at Chapel Hill
Chapel Hill, NC

Supported by the National Institutes of Health grants DP2HD084070 (A.B.), R01AI100654 (S.R.C.), and R01AI085073 (M.G.H.).
The authors report no conflicts of interest.

REFERENCES

1. Cinelli C, Pearl J. On the utility of causal diagrams in modeling attrition: a practical example. *Epidemiology*. 2018;29:e50–e51.
2. Breskin A, Cole SR, Hudgens MG. A practical example demonstrating the utility of single-world intervention graphs. *Epidemiology*. 2018;29:e20–e21.
3. Pearl J. Causal inference in statistics: an overview. *Stat Surv*. 2009;3:96–146.
4. Richardson TS, Robins JM. Single world intervention graphs (SWIGs): a unification of the counterfactual and graphical approaches to causality. *Cent Stat Soc Sci Univ Washingt Ser Work Pap*. 2013;128:2013.