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Comments on Neuberg's Review of Causality

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I am grateful to Professor Neuberg for taking the time to study my book *Causality*, and for summarizing its main ideas in a language familiar to readers of Econometric Theory. I would like to comment on several issues that I believe warrant further discussion. First, I will summarize in my own style what economists can learn from "Causality" and, second, I will correct several inaccuracies in the summary of Professor Neuberg.

1 What economists can learn from "Causality"

Economists have had a long and treacherous encounter with the notion of causation. While the standard econometric literature prefers to skirt the issue and relegates causal relationships to the province of human intuition, the more foundation-inspired economics literature admits the importance of capturing such relationships mathematically and usually concludes by lamenting the "controversial" and "illusive" nature of causation,

The first benefit readers of Causality should gain is the recognition that causation is not controversial or illusive; rather, it is a well-defined concept that is amiable to mathematical analysis. There is hardly any causal concept that does not lend itself to a formal analysis through the framework developed in Causality.

Neuberg mentions several economics issues whose analysis seem to escape the structural framework introduced in Causality, among them, problems connected with equilibrium constraints (e.g. that supply and demand quantities are equal at equilibrium) and behavior emanating from rational expectations. However, as mentioned on page 137 of Causality, the analysis of these issues can well be managed within the proposed framework, albeit one that invokes deeper, more refined levels of structural equations. For example, the equilibrium condition $q_D = q_S$ need not be taken as a constraint but can be formulated as a consequence of cause-effect processes involving inventory costs. The concepts and tools developed in Causality are basic to causal analysis at all levels of analysis. If intervention occurs only at the utility production level, as suggested by Neuberg, then the variables under direct manipulation can be made explicit in a deeper level of analysis, and the results would illuminate the coarser analysis. Additionally, Section 4.2 (page 113) of Causality shows how problems involving function-modification interventions can be reduced to those involving variable-fixing interventions.

To let readers judge whether Causality would merit one's investment of time and thought, I will now list a set of problems that a typical economist will find hard or impossible to solve, and for which Causality offers simple mathematical solutions.

We start by assuming that one is given an economic model M in the form of a set of linear equations with undetermined parameters and stochastic disturbances with unknown correlation matrix C. The only information available to us is the set of zero correlation entries in C (i.e., the set of disturbance pairs that are uncorrelated.)

1. Identifying independence in linear models
Given model M and an arbitrary pair of variables X and Y, determine if X and Y are correlated (for some possible values of the parameters, and for some matrix C with same zero entries.)

2. identifying conditional independence in linear models
Given model M as in problem 1, and a set of three variable, X, Y and Z. Determine if X and Y are correlated given observations on Z (again, for some possible values of the parameters, and for some matrix C with same zero entries.)

3. Identifying conditional independence in nonlinear models
Assume that the model M above is composed of a set of recursive (i.e. feedback free) nonlinear equations, with unknown parameters, and a set of disturbances having arbitrary statistics. Given model M and three subsets of variables, X, Y and Z determine if X and Y are independent given observations on Z (again, for all possible values of the parameters.)

4. Conditional independence in nonparametric models
Same as problems 3, except that model M is now composed of a set of arbitrary functions, the form of which is unknown, and the disturbance statistics is, likewise, unknown. The only information available is a set of subsets of disturbances that are mutually independent.

5. Causal effects in linear systems
Given a fully specified economic model M as in problem 1 (i.e., all parameters, including matrix C are known), and let X and Y be two arbitrary variables. Determine the causal effect of variable X on variable Y namely, the increase in $E(Y)$ due to unit increase in X.

6. Counterfactuals in linear systems
Given a fully specified economic model M as in problem 5 (i.e., all parameters,

including matrix C are known), and let X and Y be two arbitrary variables. Determine what $E(Y)$ would be if X were equal to x, given that, in reality, $X = x'$ and $Y = y'$.

7. Causal effects in nonlinear systems

Same as problem 5, but model M is composed of nonlinear set of functions (with unique equilibrium) with known parameters and known distribution of disturbances.

8. Counterfactuals in nonlinear systems

Same as problem 6, but model M is composed of nonlinear set of functions (with unique equilibrium) with known parameters and known distribution of disturbances.

9. Identification of causal effects

Given a nonparametric economic model M as in problem 4, and let X and Y be two arbitrary variables. Let the causal effect of X on Y be defined as the probability $P(Y = y)$ that would ensue if we were to intervene and hold X constant, at x. Determine whether the causal effect of X on Y can be estimated consistently from nonexperimental data. If the answer is positive, determine whether there exists a set Z of variable that can be adjusted for, to yield the desired causal effect.

10. Identification of counterfactual claims

Given a nonparametric economic model M as in problem 4, and let X and Y be two arbitrary variables.

a. Determine whether the following quantity, Q, can be estimated consistently from nonexperimental data: Q is the probability of $Y = y$ that would prevail had X been equal to x, given that, in reality, X is equal to x'.

b. Determine whether Q can be estimated consistently from experimental data.

2 Corrections to Neuberg's review

2.1

Throughout his review, Neuberg refers to my framework as "the theory of inferred causation." This is not accurate. I have used the phrase "theory of inferred causation" when dealing with one task only, that of inferring the structure of a model from nonexperimental data (Chapter 2). The reader would do well to replace this phrase with "the Structural Model Approach."

2.2

Neuberg asserts that "Pearl ...takes third variable common causes as the only source of confounding bias." This is not the case. Any association between two disturbances can lead to confounding bias, whether or not the association is created by a common cause. For example, an association can be caused by the two disturbances having a common effect E, when the data are selected such that all samples satisfy $E = 0$. This leads to the Berkson paradox (see Causality page 17).

Graphically, associated disturbances are represented by curved arcs connecting the corresponding variables. Thus, the approach in Causality does not "rule out a priori" the problem of multicollinearity, or "two associated causes of an effect." It in fact offers effective solution to such problems, elaborated in chapters 3, 4 and 5 (e.g,. Figure 3.8, page 92). If the association emanates from selection bias on a common effect, as in the Berkson paradox, the approach offers a formal graphical method of managing such associations as well.

2.3

Referring to Figure 1 (iii), the caption reads "Don't adjust for Z when finding the causal effect of x on Y." A more accurate caption would read: "There is no need to adjust for Z when finding the causal effect of X on Y." The reason is as follows. The absence of curved arc between X and Z conveys the assumption that X and Z are not associated and, under such assumption, adjusting for Z is superfluous (i.e., it may improve power, but not gain consistency). Adding a curved arc between X and Z would qualify Z for adjustment by the back-door criterion. Thus, to answer Neuberg's question, if Z and X are collinear, adjustment for Z is warranted by the back-door criterion, which coincides with econometric intuitions.

2.4

In the Conclusion section, Neuberg asks "If there are situations where the graph theory approach says to adjust for intermediate effects but statisticians say do not do so, how can we decide who is right?" The answer is simple. Conclusions based the graphical approach are mathematically proven, while those based on statistical tradition are folklore. The choice is clear. Fortunately, however, the clash that Neuberg alludes to does not occur in the model of Figure 2. Statistical intuition warns us against adjusting for T, and so does the graph-theoretic approach; simple adjustment for T would introduce bias. What graph-theoretical analysis provides, that statistical intuition does not, is the realization that the causal effect of X on Y can be estimated by a two-stage adjustment for T, as given by the front-door formula (Causality, page 83).