Closing Comments, Logic of Causal Order

Remember that variables can be correlated for a number of reasons:

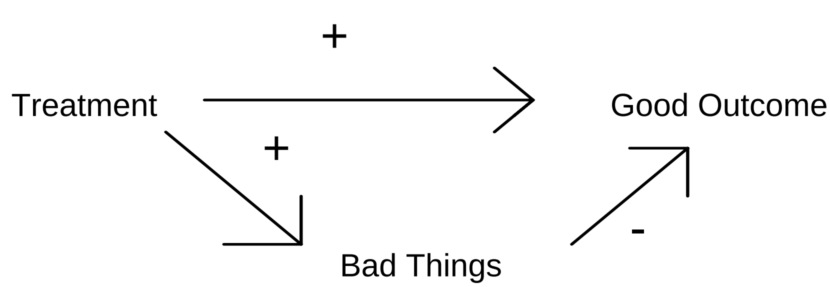
- One variable can have a direct effect on the other
- One variable can indirectly affect the other
- Variables can have reciprocal effects on each other
- Variables can share a common cause
- One variable can be correlated with the cause of another

CAUTION I: In a *properly* specified model, only the direct effect of one variable on another will be reflected in the regression coefficient. All other effects will be partialled out, i.e. controlled for. Correlation does not prove causation, because a correlation reflects all the sources of association reflected above.

CAUTION II: In an *improperly* specified model, the direct causal effect of one variable can get confounded with all the other sources of association between variables. That is, in an improperly specified model, the regression coefficients can reflect something other than the direct causal effect of one variable on another. For example, association due to a common cause could erroneously get attributed to a direct causal effect.

- In our Head Start example, if we do not take into account association produced by poverty being a common cause of both Head Start participation and Achievement, it appears that Head Start is harmful rather than beneficial, i.e. the positive direct effect of Head Start on Achievement gets confounded with the negative association produced by the common cause of poverty.

CAUTION III: It is often unwise to simply ignore indirect effects. Example:



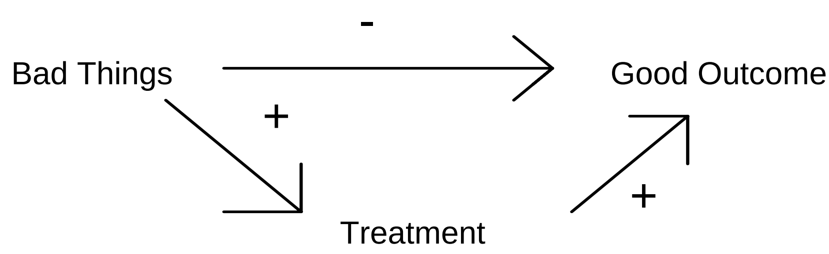
Suppose that the correlation between "treatment" and "good outcome" is negative. According to this model, this would be because of suppressor effects. The treatment increases the likelihood of "bad things" happening. However, once you control for these "bad things", the effect of treatment is positive. Does this therefore mean the treatment is good?

No, it does not. If you administer the treatment, the "bad things" are likely to happen, and if this model is correct, the negative indirect effect of treatment working through bad things will be greater than the positive direct effect. Hence, if you only look at the positive direct effect and not the total effect (direct + indirect) of treatment, you can get a misleading picture.

Remember, the regression coefficient for X1 tells you how much Y would change if X1 increased by 1 *and the values of all other IVs stayed the same.* The problem is that if X1 changes, other IVs may not stay the same. This would occur if, say, X1 was also a cause of X2.

The moral is that we should consider both the direct and indirect effects of variables. In order to do this, however, we need to have a model of how variables are inter-related. Unfortunately, this is not a simple matter.

Referring to the above example, suppose this was the true model:



Note that, in this model, you would conclude that the treatment was desirable. Treatment is not a cause of bad things, but rather, a consequence of it. This leads us to

CAUTION IV: Multiple models can be consistent with the data. The data can't tell you which models are correct, but they can tell you that a model appears to be incorrect.

- The correlation matrix would be the same regardless of which model represents the truth, i.e. a correlation matrix can't tell you what the correct ordering of variables is. Indeed, as Duncan notes, "one can never infer the causal ordering of two or more variables knowing only the values of the correlations." The researcher has to somehow decide which causal ordering is most reasonable. This decision might be based on theory. Or, it might be based on the way in which the data were collected, e.g. some sort of longitudinal design could make it clear what order the variables should be in.

- As Duncan also notes, "knowing the causal ordering or, more precisely, the causal model linking the variables, we can sometimes infer something about the correlations...we can ...(sometimes) find one or more conditions that must hold if the model is true but that are potentially subject to refutation by empirical evidence."

    - For example, signs of estimated effects must be consistent with the model; estimated values of parameters hypothesized to be non-zero must significantly differ from zero.

    - Thus, models can be rejected if "their estimated values do not come close to satisfying the condition noted in the figure. Failure to reject a model, however, does not require one to accept it, for the reason...that some other models will always be consistent with the same set of data. Only if one's theory is comprehensive and robust enough to rule out all these alternatives would the inference be justified."