On making causal claims: A review and recommendation

Antonakis et al. (2010) On making causal claims: A Review and recommendations, The Leadership Quarterly 21 (2010), 1086-1120

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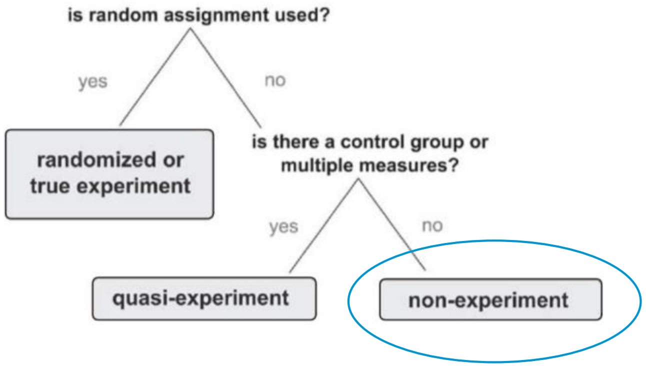
Introduction - Problem Definition

- Social scientist make causal claims like „x causes, predicts, affects, influences y“ or „y depends on x“
- Failsafe way to generate causal evidence –> randomized experiments
- Recent methodological advances are not used by social scientists (or only to estimate causal models in design situations)



Structure of the article:

- Demonstrate the design and estimation conditions that allow or prevent causal interpretation (or even associative interpretation) of estimates
- Examine methods that help researchers test causal claims in the field, especially when randomization isn't possible
- Assess the methodological rigor behind causal claims in leadership research

Source: William M.K. Trochim and James P. Donelli (2007): *The Research Methods Knowledge Base*

Causality and the counterfactual argument

To measure a <u>causal effects</u>, we need an effect (y) and a presumed cause (x)

- x must preced y temporally
- x must be reliably correlated with y (beyond chance)
- the relation between x and y must not explained by other causes

If the relation between x and y is due to other reasons, x is endogenous,
and the coefficient of x cannot be interpreted, not even as a simple correlation.

To test whether a causal relation is real, the model's predictions must be examined from the <u>counterfactual model</u>:

- If the individuals who received the treatment had in fact not received it, what would we observe on y for those individuals? *or*
- If the individuals who did not receive the treatment had in fact received it, what would we have observed on y?

Explanation: randomized experiment vs. non-experimental setting

The randomized field experiment (gold standard)

Randomized field experiment ensures that the origin of the change in the dependent variable stems from no other cause other than that of the manipulated variable.

Example:
The equation is presented as $y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + e_i$
(y is the dependent variable, β_0 is the constant, β_1 and β_2 are regression coefficients, and e_i is the error term.)

- The model includes a binary independent variable, x, representing a randomly assigned treatment (e.g., leadership training, where 1 indicates the subject received the treatment, and 0 otherwise)
- A continuous independent variable, z, is included as a covariate (e.g., IQ of leaders) to help reduce unexplained variance and improve the power of the model

Endogeneity:
- The model assumes that the error term, e, is uncorrelated with the independent variables, especially x
- When x is endogenous (i.e., it correlates with e), it leads to biased and inconsistent estimates of the effects

Endogeneity

Consequences of Endogeneity:
- If x correlates with e, the estimate of $\beta 1$ becomes inaccurate
- This could be due to non-random assignment of treatment, such as the treatment group having more extravert

Impact on Results:
- When x is correlated with e, it becomes challenging to isolate the effect of x on y
- This situation also affects other variables that may correlate with the problematic variable, potentially distorting their estimates

Importance of Random Assignment:
- In randomized field experiments, causal inference is ensured because random assignment makes the treatment and control groups similar in characteristics
- This allows for clearer interpretation of the effect of x on y

Why could estimates become inconsistent? I/II

Validity threat	Explanation
Omitted variables	• Omitting a regressor, that is failing to include important control variables when testing the predictive validity of dispositional or behavioral variables (e.g., testing overall survival of a treatment without including cancer stages or comorbidities) • Omitting fixed effects (e.g. tracking treatment outcomes, overlooking influence of physicians) • Using random-effects without statistical justification (i.e., Hausman test) • In all other cases, independent variables not exogenous (if it's not clear what the controls should be)
Omitted selection	• Comparing a treatment group to other non-equivalent groups (e.g. motivated self-selected intervention group in observational studies) • Comparing entities that are grouped nominally where selection to group is endogenous (e.g. patients outcome, choice of hospitals based on influenced factors like severe conditions) • Sample (participants or survey responses) suffers from self-selection or is non-representative
Simultaneity	• Reverse causality - two variables simultaneously cause each other (e.g. relationship between economic growth and investment, both may reinforce each other)

Why could estimates become inconsistent? II/II

Validity threat	Explanation
Measurement error	Including imperfectly measured variables as independent variables and not modelling measurement error (e.g. inaccurate assessment of health outcomes)
Common-method variance	Independent and dependent variables are gathered from the same rating source (e.g. self-reported measures, clinicians subjectively evaluating treatment response)
Inconsistent inference	Using normal standard errors without examining for non-constant variance (different errors across different levels of the independent variable)
Model misspecification	• Not correlating disturbances of potentially endogenous regressors in mediation models (and not testing for endogeneity using a Hausman test or augmented regression) • Using a full information estimator (e.g., maximum likelihood, three-stage least squares) without comparing estimates to a limited information estimator (e.g., two stage-least squares)

Methods for inferring causality in non-experimental settings

Method	Brief description
Statistical adjustment	Measure and control for all causes of y (impractical and not recommended!)
Propensity score analysis	Compare individuals who were selected to treatment to statistically similar controls using a matching algorithm (e.g. adjust for differences in baseline characteristics)
Simultaneous-equation models	Using “instruments” (exogenous sources of variance that do not correlate with the error term) to purge the endogenous x variable from bias (e.g. disentangle causal pathways between treatment and survival outcomes in studies)
Regression discontinuity	Select individuals to treatment using a modelled cut-off
Difference-in-differences models	Compare a group who received an exogenous treatment to a similar control group over time (pre versus post intervention between treated and control group)
Heckman selection models	Predict selection to treatment (where treatment is endogenous) and then control for unmodeled selection to treatment in predicting y

Review of robustness of causal inference in management & applied psychology I/II

Objective:

- The study focused on leadership research defined as the influencing process between a leader and followers, examining dispositional or behavioral perspectives where leadership could be either an independent or dependent variable

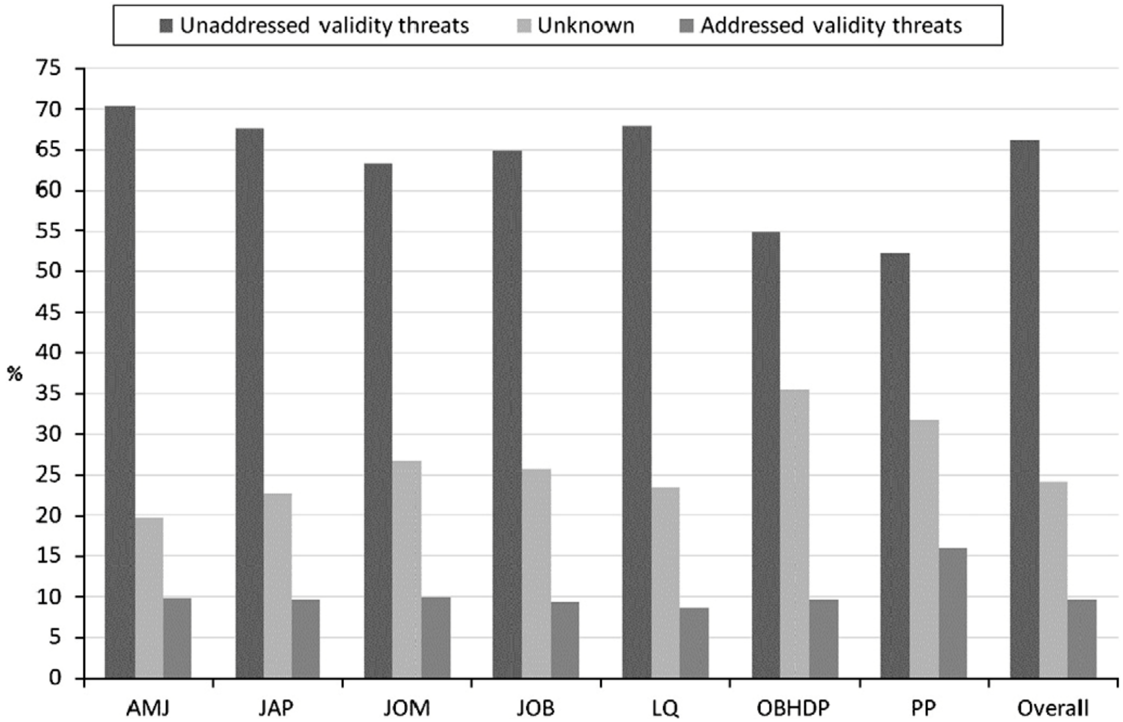
Methodology:

- Random sample of articles from top management and applied psychology journals to gauge whether leadership research is dealing with central threats to causal inference:
  - The initial sample was large (n=120) and covered the last 10 years (1999-2008); final sample (n=110)
  - Only empirical non-experimental papers and field experiments were coded
- Studies were evaluated on 14 criteria using a categorical scale, and the coding was undertaken by two coders with high agreement

Result:

- The results indicated unsatisfactory methodological practices regarding causal modeling in the domain of leadership, with most validity threats not adequately handled

Review of robustness of causal inference in management & applied psychology II/II



Reasons unsatisfactory methodological practices:

- inadequate doctoral training in field research and quantitative methods
- slow adoption of appropriate software for causal analysis
- use of simplified statistical programs

The study also highlighted concerns about the limitations of certain statistical and structural-equation modeling software in handling complex models.

Recommendations – 10 commandments of causal analysis – best practice for causal inference I/II

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Recommendations

- **To avoid omitted variable bias include adequate control variables.** If adequate control variables cannot be identified or measured obtain panel data and use exogenous sources of variance (i.e., instruments) to identify consistent effects.
- With panel (multilevel) data, always model the fixed effects using dummy variables or cluster means of level 1 variables. Do not estimate random-effects models without ensuring that the estimator is consistent with respect to the fixed-effects estimator (using a Hausman test).
- **Ensure that independent variables are exogenous**. If they are endogenous (and this for whatever reason) obtain instruments to estimate effects consistently.
- **If treatment has not been randomly assigned to individuals in groups**, if membership to a group is endogenous, or samples are not representative between-group estimates must be corrected **using the appropriate selection model** or other procedures (difference-in-differences, propensity scores).
- Use overidentification tests (chi-square tests of fit) in simultaneous equations models to determine if the model is tenable. Models that fail overidentification tests have untrustworthy estimates that cannot be interpreted.

Recommendations – 10 commandments of causal analysis – best practice for causal inference II/II

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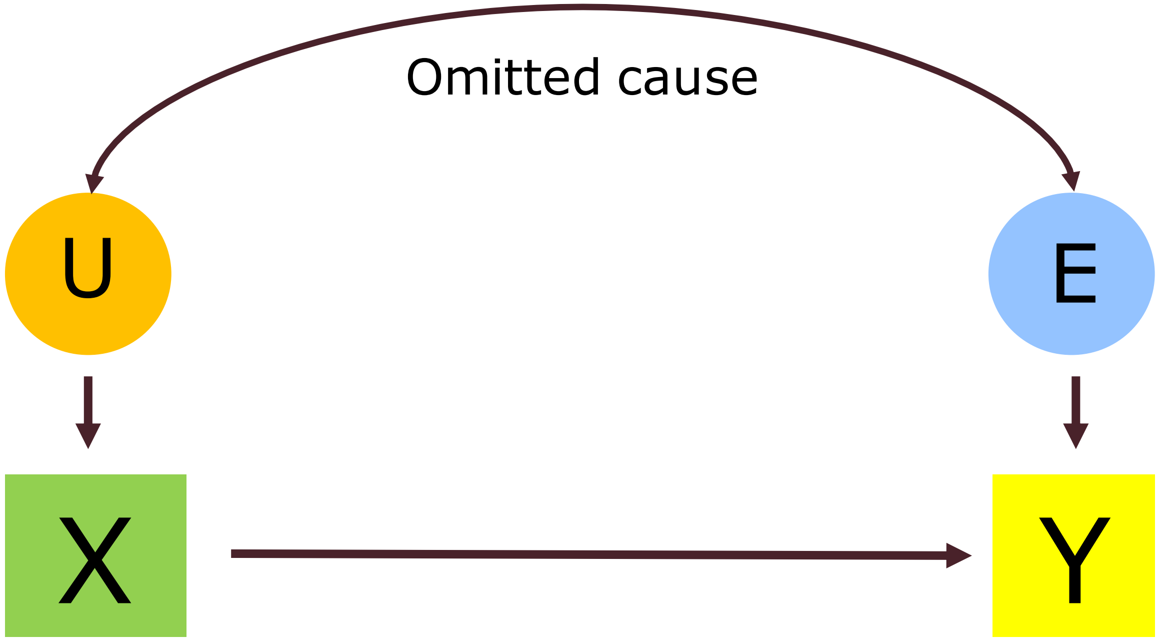
Recommendations
• When independent variables are measured with error, estimate models using errors-in-variables or use instruments (well-measured, of course, in the context of 2SLS models) to correct estimates for measurement bias.
• **Avoid common-method bias**; if it is unavoidable use instruments (in the context of 2SLS models) to obtain consistent estimates.
• **To ensure consistency of inference, check if residuals are i.i.d. (identically and independently distributed).** Use robust variance estimators as the default (unless residuals can be demonstrated to be i.i.d.). Use cluster-robust variance estimators with panel data (or group-specific regressors).
• Correlate disturbances of potentially endogenous regressors in mediation models (and use a Hausman test to determine if mediators are endogenous or not).
• Do not use a full-information estimator (i.e., maximum likelihood) unless estimates are not different to that of limited information (2SLS) estimator (based on the Hausman test). Never use PLS.

Endogeneity



Endogeneity – Adding Covariate