Quantitative Research Design

Design

Johanna Gruber

Nathanael Paterno

Establishing Cause and Effect

Temporal precedence

- Establishing that the hypothesized cause occurs earlier in time than the effect

Covariation of the cause and effect

- A criterion for establishing a causal relationship that holds that the cause and effect must be related or co-vary.

No plausible alternative explanations

- It is possible, that some other variable or factor is causing the outcome
- Referres to the thrid-carible or missing-varible problem

Single-Group Threats

- **History threat:** a threat to internal validity that occurs when some historical event affects your study outcome. Hypothesis A specific statement of prediction.

- **Maturation threat:** a threat to validity that is a result of natural maturation that occurs between pre- and postmeasurement.

- **Testing threat:** a threat to internal validity that occurs when taking the pretest affects how participants do on the posttest.

- **Instrumentation threat:** a threat to internal validity that arises when the instruments (or observers) used on the posttest and the pretest differ.

- **Mortality threat:** a threat to validity that occurs because a significant number of participants drop out

- **Regression threat:** a statistical phenomenon that causes a group's average performance on one measure to regress toward or appear closer to the mean of that measure than anticipated or predicted. Regression occurs whenever you have a nonrandom sample from a population and two measures that are imperfectly correlated. A regression threat will bias your estimate of the group's posttest performance and can lead to incorrect causal inferences.

Regression to the Mean

= a statistical phenomenon that occurs whenever you have a nonrandom sample from a population and two measures that are imperfectly correlated

- The regression to the mean in statistics refers to the tendency for extreme values to move closer to the average or mean upon subsequent measurements or observations. This phenomenon occurs because extreme values are often influenced by random or temporary factors that are unlikely to persist over time.

Example: If a student performs exceptionally well on one exam due to luck or unusual circumstances, it is likely that their performance on the next exam will regress towards the class average.

Regression to the Mean

Here are a few things you need to know about the regression to the mean phenomenon:

- It is a **statistical** phenomenon.
- It is a **group** phenomenon.
- It happens between **any two variables**.
- It is a **relative** **phenomenon**.
- You can have regression up or down.
- The more extreme the sample group, the greater the regression to the mean.
- The less correlated the two variables, the greater the regression to the mean.

Regression to the Mean – The Formular for the Percent of Regression to the Mean

- You can estimate exactly the percent of regression to the mean in any given situation. The formula is:

$$Prm = 100(1-r)$$

- where:
  - Prm = the percent of regression to the mean
  - r = the correlation between the two measures

- Consider the following four cases:
  - if r = 1, there is no (i.e. 0%) regression to the mean
  - if r = .5, there is 50% regression to the mean
  - if r = .2, there is 80% regression to the mean
  - if r = 0, there is 100% regression to the mean

Multiple-Group Threats

- **Selection history threat:** a threat to internal validity that results from any other event that occurs between pretest and posttest that the groups experience differently.

- **Selection-maturation threat:** a threat to internal validity that arises from any differential rates of normal growth between pretest and posttest for the groups.

- **Selection-testing threat:** a threat to internal validity that occurs when a differential effect of taking the pretest exists between groups on the posttest.

- **Selection-instrumentation:** a threat to internal validity that results from differential changes in the test used for each group from pretest to posttest.

- **Selection-mortality:** a threat to internal validity that arises when there is differential nonrandom dropout between pretest and posttest.

- **Selection-regression:** a threat to internal validity that occurs when there are different rates of regression to the mean in the two groups.

Social Interaction Threats

- **Social interaction threats:** threats to internal validity that arise because social research is conducted in real-world human contexts where people react to not only what affects them, but also to what is happening to others around them.

- **External validity:** the degree to which the conclusions in your study would hold for other persons in other places and at other times.

- **Diffusion or imitation of treatment:** a social threat to internal validity that occurs because a comparison group learns about the program either directly or indirectly from program group participants.

- **Compensatory rivalry:** a social threat to internal validity that occurs when one group knows the program another group is getting and, because of that, develops a competitive attitude with the other group.

- **Resentful demoralization:** a social threat to internal validity that occurs when the comparison group knows what the program group is getting and becomes discouraged or angry and gives up.

- **Compensatory equalization of treatment:** a social threat to internal validity that occurs when the control group is given a program or treatment (usually, by a well-meaning third party) designed to make up for or "compensate" for the treatment the program group gets.

Introduction to Design

The research design tells you how all the elements in a research project fit together. A design includes the following elements:
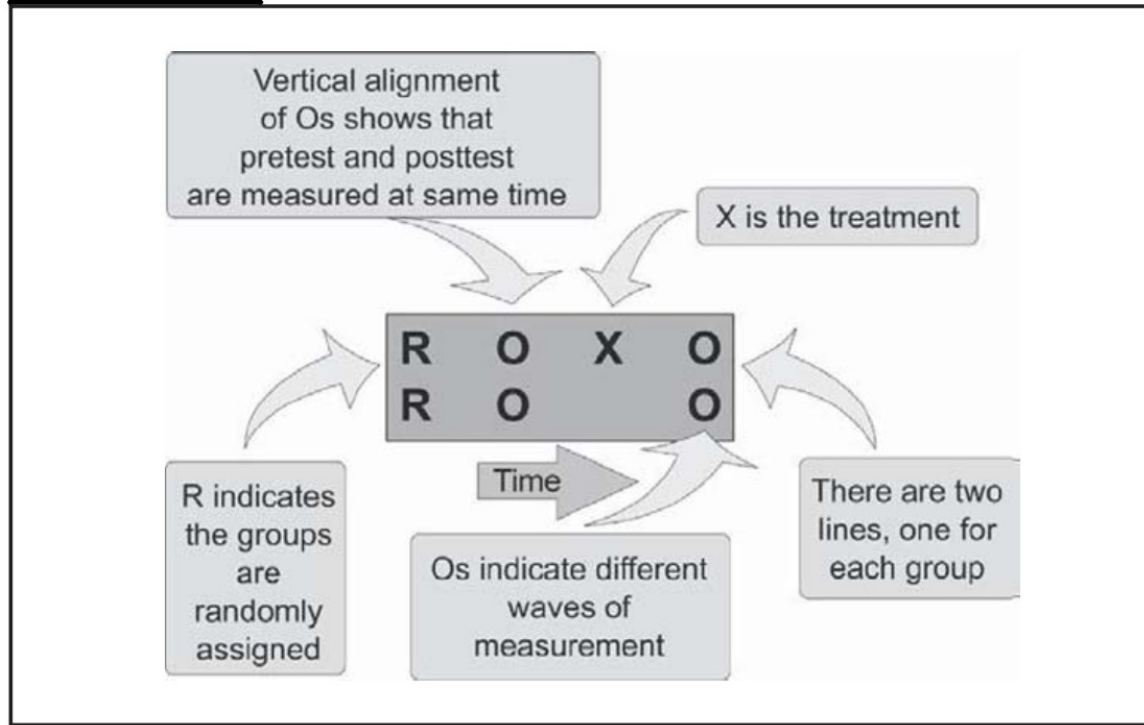
Observation or measures	Treatments or programs	Groups

Assignment to group	Time

A detailed example of Design notation

FIGURE 7–7 — A detailed example of design notation

Vertical alignment of Os shows that pretest and posttest are measured at same time

X is the treatment

R O X O
R O   O

R indicates the groups are randomly assigned

Time

Os indicate different waves of measurement

There are two lines, one for each group

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

Types of Designs

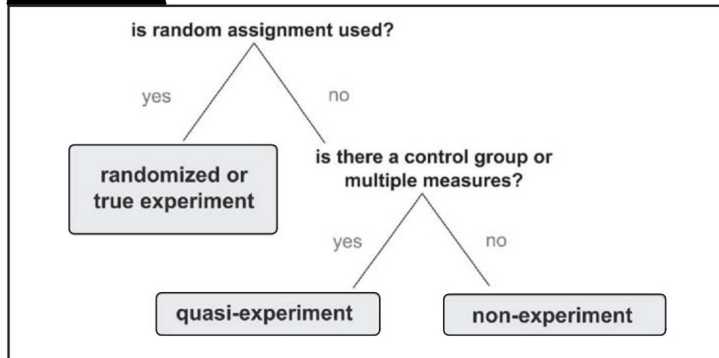**FIGURE 7–9**   Basic questions that distinguish the major types of designs

is random assignment used?

yes   no

randomized or true experiment

is there a control group or multiple measures?

yes   no

quasi-experiment   non-experiment

FIGURE 7–10   Notational for examples of each of the three major classes of research design

Posttest Only Randomized Experiment	R X O
	R O
Pretest-Posttest Nonequivalent Groups Quasi-Experiment	N O X O
	N O O
Posttest Only Non-Experiment	X O

- **Posttest-only randomized experiment:** an experiment in which the groups are randomly assigned and receive only a posttest.

- **Pre-post nonequivalent groups quasi-experiment:** a research design in which groups receive both a pre- and posttest, and group assignment is not randomized, and there-fore, the groups may be nonequivalent, making it a quasi-experiment.

- **Posttest-only nonexperimental design:** a research design in which only a posttest is given. It is referred to as nonexperimental because no control group exists.

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

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

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 β_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 predictive validity of „emotional intelligence" without including IQ or personality; not controlling for competing leadership styles)
	• Omitting fixed effects
	• Using random-effects without statistical justification (i.e., Hausman test)
	• In all other cases, independent variables not exogenous (if it'snot clear what the controls should be)
Omitted selection	• Comparing a treatment group to other non-equivalent groups (i.e., where the treatment group is not the same as the other groups)
	• Comparing entities that are grouped nominally where selection to group is endogenous (e.g., comparing men and women leaders on leadership effectiveness where the selection process to leadership is not equivalent)
	• Sample (participants or survey responses) suffers from self-selection or is non-representative
Simultaneity	• Reverse causality (i.e., an independent variable is potential caused by the dependent variable)

Why could estimates become inconsistent? II/II

Validity threat	Explanation
Measurement error	Including imperfectly measured variables as independent variables and not modelling measurement error
Common-method variance	Independent and dependent variables are gathered from the same rating source
Inconsistent inference	Using normal standard errors without examining for heteroscedasticity
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
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
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
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
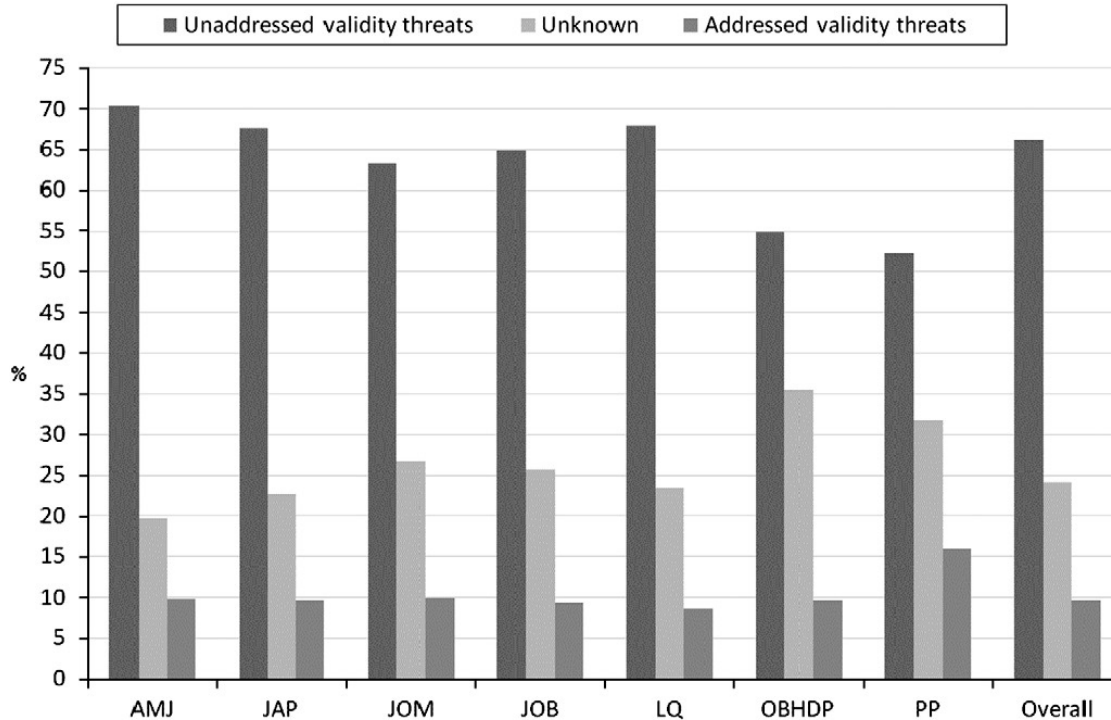
Methodology:

- 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

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

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.