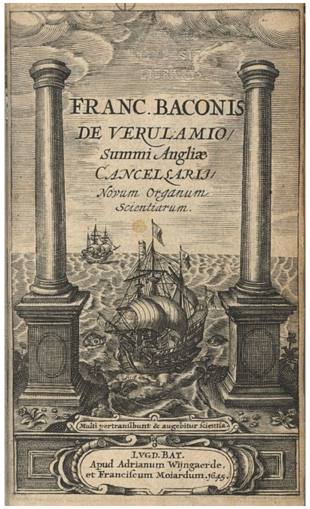
This morning…

Time	Agenda
9:00	Causal inference/statistical modeling
10:00	Regression in R
11:00	Blitz talks

https://cdsbasel.github.io/dataanalytics/

Evidence-based decision making

Francis Bacon
(1561-1626)



1620

In “new instrument of science” Bacon suggests that one can draw up a list of all things in which the phenomenon to explain occurs, as well as a list of things in which it does not occur. Then one can rank the lists according to the degree in which the phenomenon occurs in each one. Then one should be able to deduce what factors match the occurrence of the phenomenon in one list and do not occur in the other list, and also what factors change in accordance with the way the data had been ranked.

1948
Use of placebo control design by Medical Research Council

1980
FDA requires double-blind placebo design

1993
Standardized Reporting of Trials (SORT) and several updates leading to the current Consolidated Standards of Reporting Trials (CONSORT)

1995
Empirically supported treatments (EST) designated by Div. 12 (Clinical Psychology) APA on the basis of RCTs

2001
Institute of Medicine adopts evidence-based practice in medicine

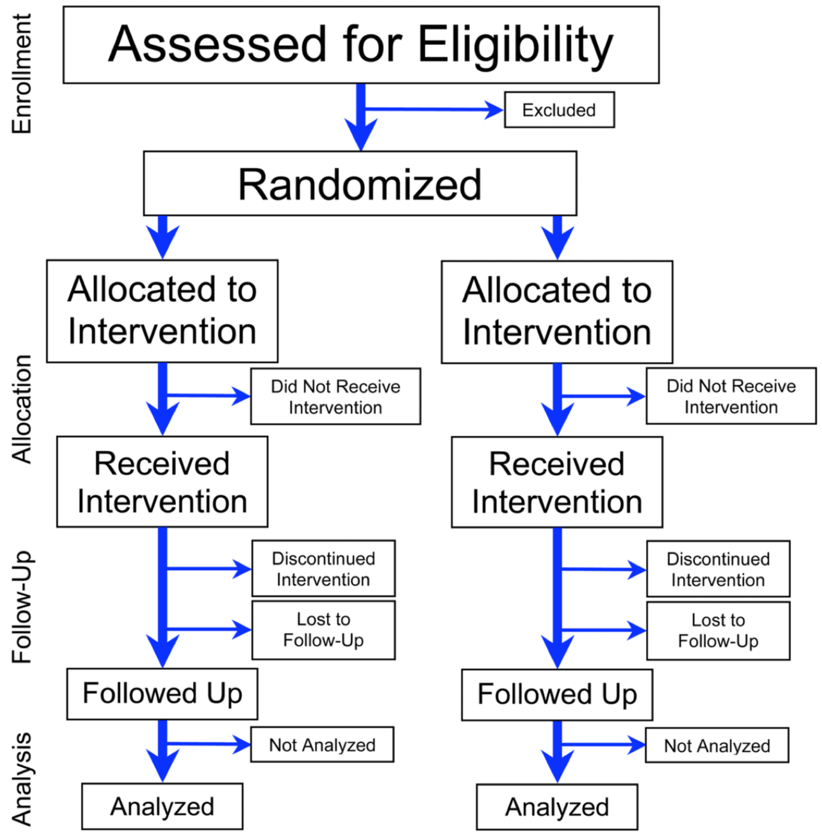
2006
APA adopts evidence-based practice in psychology

Shorter, E. (2011). A brief history of placebos and clinical trials in psychiatry. *Canadian Journal of Psychiatry, 56*(4), 193–197.

The gold standard…

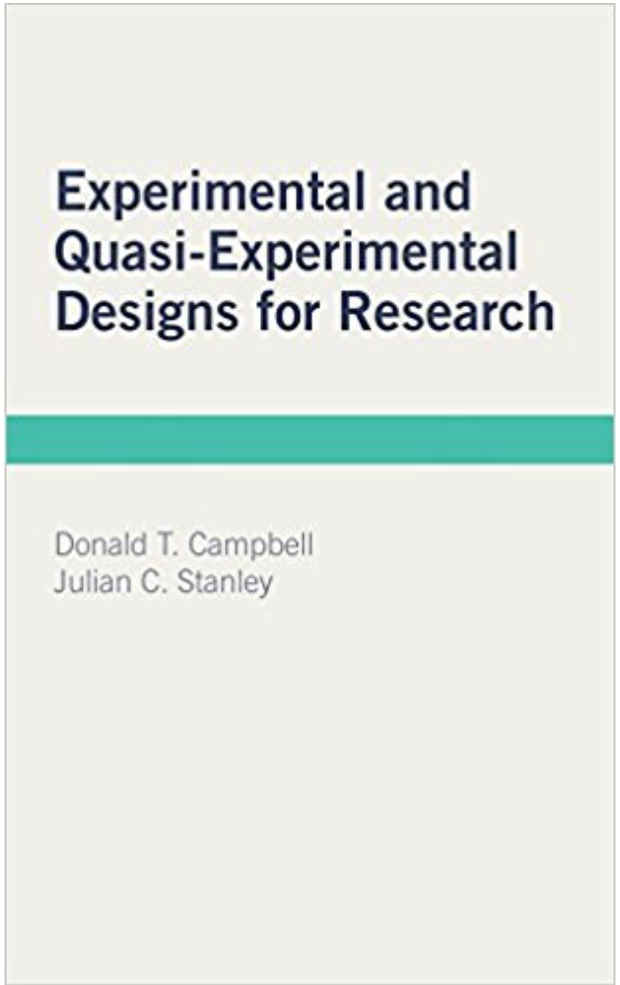
Experiments/Randomised control trials (RCT)

A type of scientific experiment, where the people being studied are randomly allocated one or other of the different treatments under study. RCTs are considered the gold standard for a clinical trial. RCTs are often used to test the efficacy or effectiveness of various types of medical intervention and may provide information about adverse effects, such as drug reactions. Random assignment of intervention is done after subjects have been assessed for eligibility and recruited, but before the intervention to be studied begins.



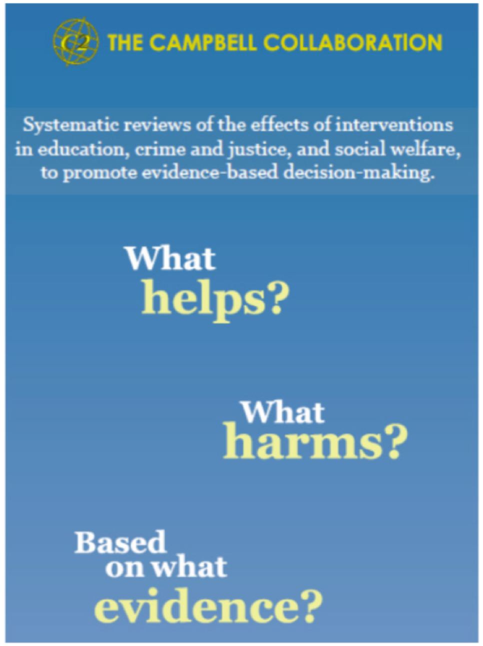
Shorter, E. (2011). A brief history of placebos and clinical trials in psychiatry. *Canadian Journal of Psychiatry, 56*(4), 193–197.

But there are alternatives…



1963

Donald Campbell
1916-1996



THE CAMPBELL COLLABORATION

TABLE 1

SOURCES OF INVALIDITY FOR DESIGNS 1 THROUGH 6

	Sources of Invalidity											
	Internal								External			
	History	Maturation	Testing	Instrumentation	Regression	Selection	Mortality	Interaction of Selection and Maturation, etc.	Interaction of Testing and X	Interaction of Selection and X	Reactive Arrangements	Multiple-X Interference
Pre-Experimental Designs:												
1. One-Shot Case Study *X O*	–	–				–	–			–		
2. One-Group Pretest-Posttest Design *O X O*	–	–	–	–	?	+	+	–	–	–	?	
3. Static-Group Comparison *X O* - - - - - - *O*	+	?	+	+	+	–	–	–		–		
True Experimental Designs:												
4. Pretest-Posttest Control Group Design *R O X O* *R O O*	+	+	+	+	+	+	+	+	–	?	?	
5. Solomon Four-Group Design *R O X O* *R O O* *R X O* *R O*	+	+	+	+	+	+	+	+	+	?	?	
6. Posttest-Only Control Group Design *R X O* *R O*	+	+	+	+	+	+	+	+	+	?	?	

Note: In the tables, a minus indicates a definite weakness, a plus indicates that the factor is controlled, a question mark indicates a possible source of concern, and a blank indicates that the factor is not relevant.

It is with extreme reluctance that these summary tables are presented because they are apt to be "too helpful," and to be depended upon in place of the more complex and qualified presentation in the text. No + or – indicator should be respected unless the reader comprehends why it is placed there. In particular, it is against the spirit of this presentation to create uncomprehended fears of, or confidence in, specific designs.

Campbell & Stanley (1963)

TABLE 2

SOURCES OF INVALIDITY FOR QUASI-EXPERIMENTAL DESIGNS 7 THROUGH 12

	Sources of Invalidity											
	Internal								External			
	History	Maturation	Testing	Instrumentation	Regression	Selection	Mortality	Interaction of Selection and Maturation, etc.	Interaction of Testing and X	Interaction of Selection and X	Reactive Arrangements	Multiple-X Interference
Quasi-Experimental Designs:												
7. Time Series O O O OXO O O O	−	+	+	?	+	+	+	+	−	?	?	
8. Equivalent Time Samples Design X_1O X_0O X_1O X_0O, etc.	+	+	+	+	+	+	+	+	−	?	−	−
9. Equivalent Materials Samples Design M_aX_1O M_bX_0O M_cX_1O M_dX_0O, etc.	+	+	+	+	+	+	+	+	−	?	?	−
10. Nonequivalent Control Group Design O X O - - - - - - - - O O	+	+	+	+	?	+	+	−	−	?	?	
11. Counterbalanced Designs X_1O X_2O X_3O X_4O - - - - - - - - X_2O X_4O X_1O X_3O - - - - - - - - X_3O X_1O X_4O X_2O - - - - - - - - X_4O X_3O X_2O X_1O	+	+	+	+	+	+	+	?	?	?	?	−
12. Separate-Sample Pretest-Posttest Design R O (X) R X O	−	−	+	?	+	+	−	−	+	+	+	
12*a*. R O (X) R X O - - - - - - - - R O (X) R X O	+	−	+	?	+	+	−	+	+	+	+	
12*b*. R O_1 (X) R O_2 (X) R X O_3	−	+	+	?	+	+	−	?	+	+	+	
12*c*. R O_1 X O_2 R X O_3	−	−	+	?	+	+	+	−	+	+	+	

Campbell & Stanley (1963)

TABLE 3
Sources of Invalidity for Quasi-Experimental Designs 13 through 16

	Sources of Invalidity											
	Internal								External			
	History	Maturation	Testing	Instrumentation	Regression	Selection	Mortality	Interaction of Selection and Maturation, etc.	Interaction of Testing and X	Interaction of Selection and X	Reactive Arrangements	Multiple-X Interference
Quasi-Experimental Designs Continued:												
13. Separate-Sample Pretest-Posttest Control Group Design $R\ O\ (X)$ $R\ \ X\ O$ - - - - - - $R\ O$ $R\ \ \ O$	+	+	+	+	+	+	+	−	+	+	+	
13a. R' { $R\ O\ (X)$ / $R\ X\ O$ - - - $R\ O\ (X)$ / $R\ X\ O$ - - - $R\ O\ (X)$ / $R\ X\ O$ } R' { $R\ O$ / $R\ O$ - - - $R\ O$ / $R\ O$ - - - $R\ O$ / $R\ O$ }	+	+	+	+	+	+	+	+	+	+	+	
14. Multiple Time-Series $O\ O\ OXO\ O\ O$ - - - - - - $O\ O\ O\ O\ O\ O$	+	+	+	+	+	+	+	+	−	−	?	
15. Institutional Cycle Design Class A X O_1 - - - - - - Class B_1 RO_2 X O_3 Class B_2 R X O_4 - - - - - - Class C O_5 X = = = = = = [a]Gen. Pop. Con. Cl. B O_6 [a]Gen. Pop. Con. Cl. C O_7												
$O_2 < O_1$, $O_5 < O_4$	+	−	+	+	?	−	?		+	?	+	
$O_2 < O_3$	−	−	−	?	?	+	+		−	?	+	
$O_2 < O_4$	−	−	+	?	?	+	?		+	?	?	
$O_6 = O_7$, $O_{2y} = O_{2o}$		+						−				
16. Regression Discontinuity	+	+	+	?	+	+	?	+	+	−	+	+

[a] General Population Controls for Class B, etc.

Campbell & Stanley (1963)

	Sources of Invalidity											
	Internal								External			
	History	Maturation	Testing	Instrumentation	Regression	Selection	Mortality	Interaction of Selection and Maturation, etc.	Interaction of Testing and X	Interaction of Selection and X	Reactive Arrangements	Multiple-X Interference
6. Posttest-Only Control Group Design *R* *X* *O* *R* *O*	+	+	+	+	+	+	+	+	+	?	?	

History	specific events occurring between measurement points
Maturation	"maturation" processes occurring between measurement points (e.g., growing older, hungrier, tired)
Testing	the effects of taking a test on a second testing
Instrumentation	changes in the calibration of measures (e.g, observers)
Regression	regression to the mean (extreme scores are likely less extreme at a second measurement point)
Selection	biases resulting from differential section of respondents for the comparison groups
Mortality	differential loss of respondents from the comparison groups
Interaction selection x maturation	when multiple-group comparisons based on quasi-experimental designs are confounded with the effect of X
Interaction testing x intervention	pretest changes the sensitivity to X
Interaction selection x intervention	biases resulting from the selection of respondents that respond differentially to X
Reactive arrangements	reaction to X may be specific to experimental settings
Multiple-intervention interference	multiple treatments are not independent/erasable

	Sources of Invalidity											
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	History	Maturation	Testing	Instrumentation	Regression	Selection	Mortality	Interaction of Selection and Maturation, etc.	Interaction of Testing and X	Interaction of Selection and X	Reactive Arrangements	Multiple-X Interference
7. Time Series O O O OXO O O O	−	+	+	?	+	+	+	+	−	?	?	
8. Equivalent Time Samples Design X_1O X_0O X_1O X_0O, etc.	+	+	+	+	+	+	+	+	−	?	−	−
9. Equivalent Materials Samples Design M_aX_1O M_bX_0O M_cX_1O M_dX_0O, etc.	+	+	+	+	+	+	+	+	−	?	?	−
10. Nonequivalent Control Group Design O X O / O O	+	+	+	+	?	+	+	−	−	?	?	

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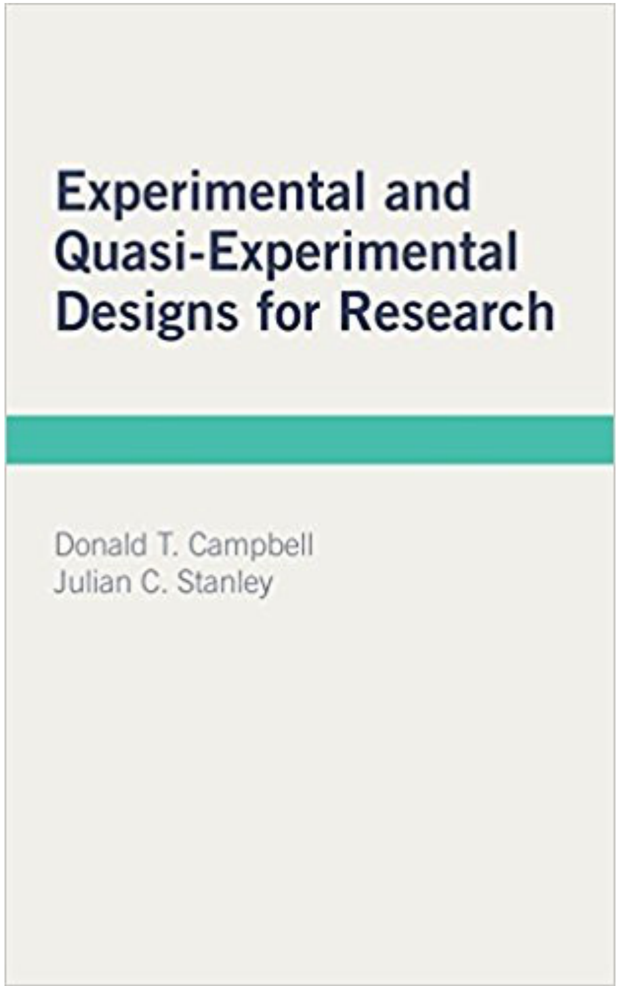
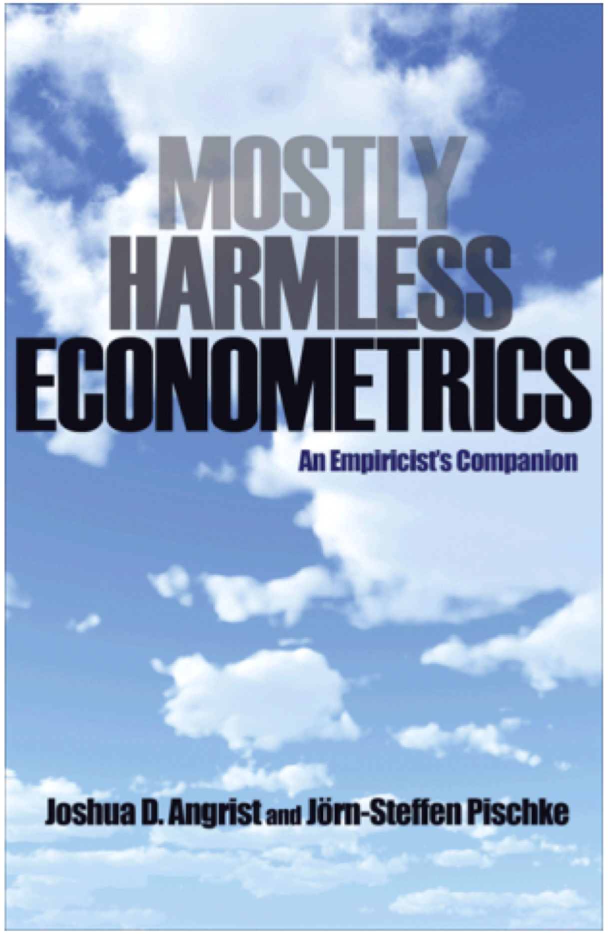
Experimental and Quasi-experimental Designs



1959

“In conclusion, in this chapter we have discussed alternatives in the arrangement or design of experiments, with particular regard to the problems of control of extraneous variables and threats to validity. (…) Through out, attention has been called to the possibility of **creatively** utilizing the idiosyncratic features of any specific research situation in designing unique tests of causal hypotheses.

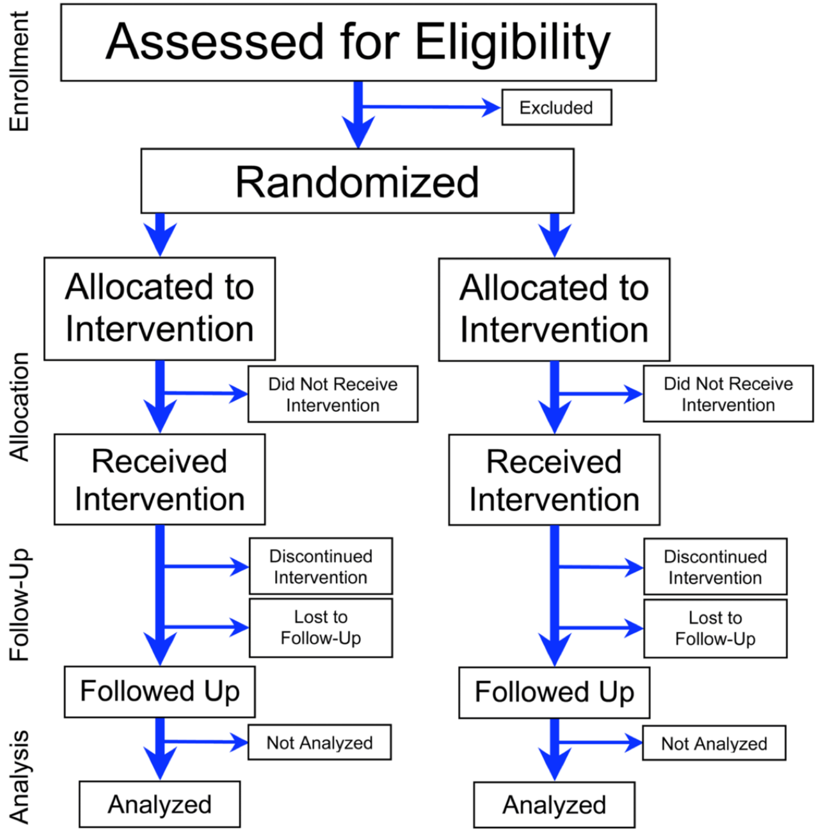
"Furious Five" statistical methods for causal inference



- Randomisation
- Regression
- Instrumental variables
- Difference in differences
- Regression discontinuity

Angrist, J. D., & Pischke, J.-S. (2010). The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics. *Journal of Economic Perspectives, 24*(2), 3–30. http://doi.org/10.1257/jep.24.2.3

Randomisation



Full randomisation is seldom available in practice…

The "ideal" data, from the viewpoint of the analyst, would be data from an incompetent advertiser who allocated expenditures randomly across cities. If ad expenditure is truly random, then we do not have to worry about confounding variables because the predictors will automatically be orthogonal to the error term. However, statisticians are seldom lucky enough to have a totally incompetent client.

Varian, H. R. (2016). Causal inference in economics and marketing. *Proceedings of the National Academy of Sciences of the United States of America, 113*(27), 7310–7315. http://doi.org/10.1073/pnas.1510479113

Regression

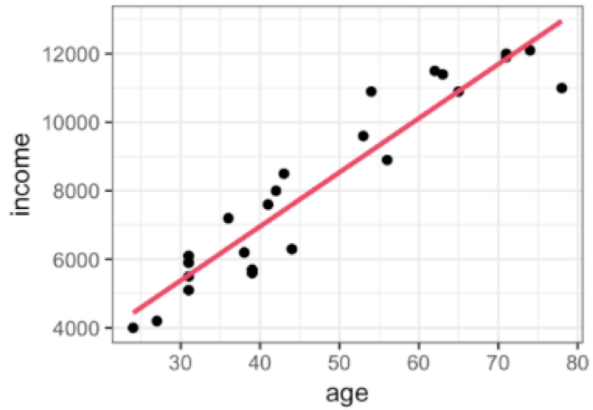
Regression analysis is a set of statistical processes for estimating the relationships among variables. It includes many techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable (criterion) and one or more independent variables (predictors). More specifically, regression analysis helps one understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are fixed.

Regression

Simple Linear Regression

Definition: Simple linear regression is a linear model with one predictor x, and where the error term ϵ is Normally distributed.

$$y = \beta_0 + \beta_1 x + \epsilon$$



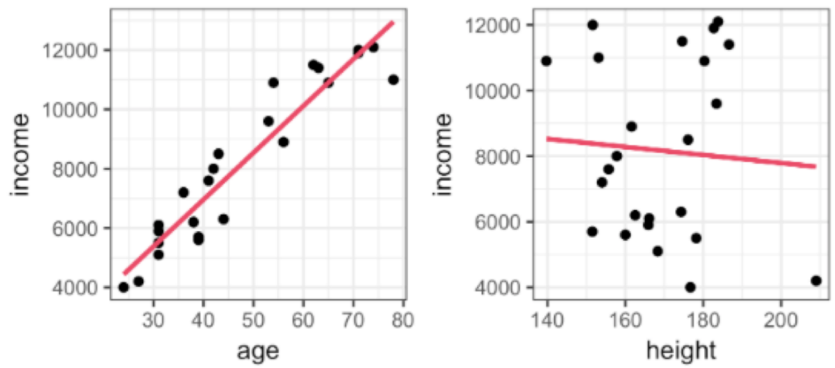
Regression

Multiple Linear Regression

Definition: Multiple linear regression is a linear model with many predictors $x_1, x_2, \ldots, x_n$, and where the error term ϵ is Normally distributed.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon$$

Parameter	Description	In words
β_0	Intercept	When all x values are 0, what is the predicted value for y?
$\beta_1, \beta_2, \ldots$	Coefficient for $x_1, x_2, \ldots$	For every increase of 1 in coefficient for $x_1, x_2, \ldots$ how does y change?



Formula

$$income = 1628 + 147 \times age - 4.1 \times height + \epsilon$$

Coefficients

$$\beta_0 = 1628, \beta_{age} = 147, \beta_{weight} = -4.1$$

Instrumental variables

The method of instrumental variables (IV) is used to estimate causal relationships when controlled experiments are not feasible or when a treatment is not successfully delivered to every unit in a randomized experiment. Intuitively, IV is used when an explanatory variable of interest is correlated with the error term, in which case ordinary least squares gives biased results. A valid instrument (***z***) induces changes in the explanatory variable but has no independent effect on the dependent variable, allowing a researcher to uncover the causal effect of the explanatory variable on the dependent variable.

$$
\begin{tikzcd}
z \arrow[r] & x \arrow[r] & y \\
& u \arrow[u] \arrow[ur] &
\end{tikzcd}
$$

Angrist, J. D., & Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives, 15*(4), 69–85.

Instrumental variables

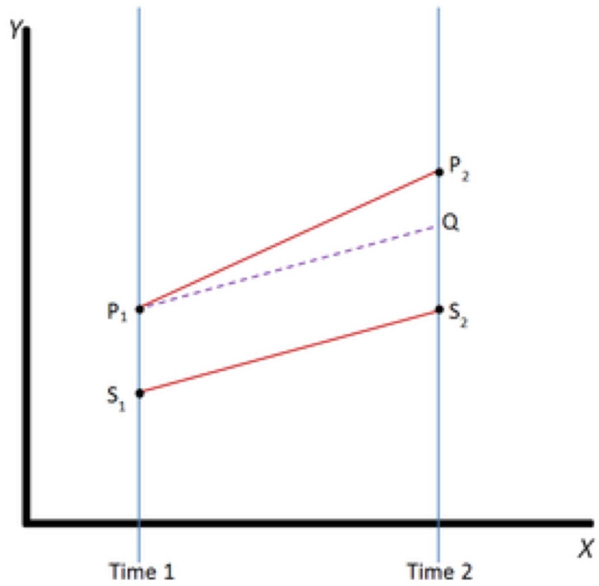
Table 1
Examples of Studies That Use Instrumental Variables to Analyze Data From Natural and Randomized Experiments

Outcome Variable	*Endogenous Variable*	*Source of Instrumental Variable(s)*	*Reference*
		1. Natural Experiments	
Labor supply	Disability insurance replacement rates	Region and time variation in benefit rules	Gruber (2000)
Labor supply	Fertility	Sibling-Sex composition	Angrist and Evans (1998)
Education, Labor supply	Out-of-wedlock fertility	Occurrence of twin births	Bronars and Grogger (1994)
Wages	Unemployment insurance tax rate	State laws	Anderson and Meyer (2000)
Earnings	Years of schooling	Region and time variation in school construction	Duflo (2001)
Earnings	Years of schooling	Proximity to college	Card (1995)
Earnings	Years of schooling	Quarter of birth	Angrist and Krueger (1991)
Earnings	Veteran status	Cohort dummies	Imbens and van der Klaauw (1995)
Earnings	Veteran status	Draft lottery number	Angrist (1990)
Achievement test scores	Class size	Discontinuities in class size due to maximum class-size rule	Angrist and Lavy (1999)
College enrollment	Financial aid	Discontinuities in financial aid formula	van der Klaauw (1996)
Health	Heart attack surgery	Proximity to cardiac care centers	McClellan, McNeil and Newhouse (1994)
Crime	Police	Electoral cycles	Levitt (1997)
Employment and Earnings	Length of prison sentence	Randomly assigned federal judges	Kling (1999)
Birth weight	Maternal smoking	State cigarette taxes	Evans and Ringel (1999)

Angrist, J. D., & Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives, 15*(4), 69–85.

Difference in differences

Difference in differences (DID or DD) is a statistical technique used in the social sciences that attempts to mimic an experimental research design using observational study data, by studying the differential effect of a treatment on a 'treatment group' versus a 'control group' in a natural experiment. It calculates the effect of a treatment on an outcome by comparing the average change over time in the outcome variable for the treatment group, compared to the average change over time for the control group. Although it is intended to mitigate the effects of extraneous factors and selection bias, depending on how the treatment group is chosen, this method may still be subject to certain biases (e.g., mean regression, reverse causality and omitted variable bias).



Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? The Quarterly Journal of Economics, 119(1), 249–275.

Regression discontinuity

A regression discontinuity design (RDD) is a quasi-experimental pretest-posttest design that elicits the causal effects of interventions by assigning a cutoff or threshold above or below which an intervention is assigned. By comparing observations lying closely on either side of the threshold, it is possible to estimate the average treatment effect in environments in which randomization is unfeasible. RDD was first applied by Donald Thistlethwaite and Donald Campbell to the evaluation of scholarship programs.

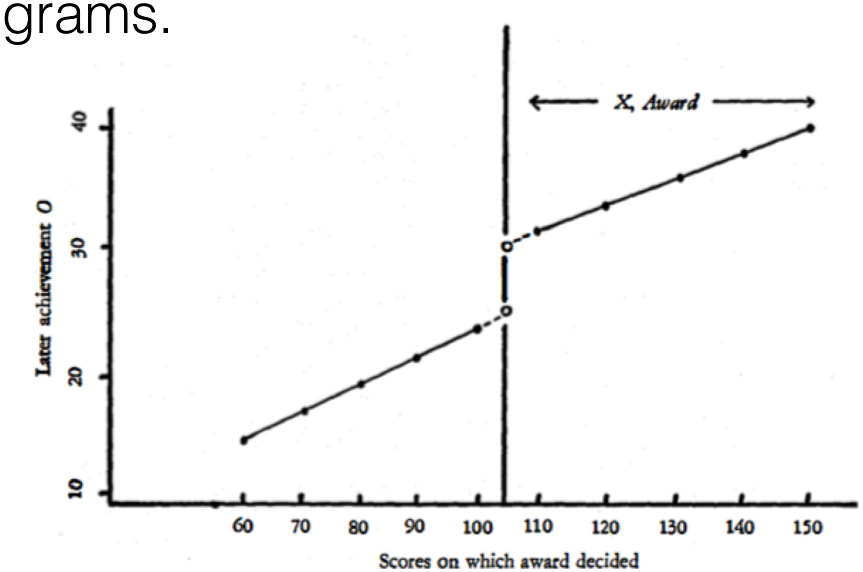
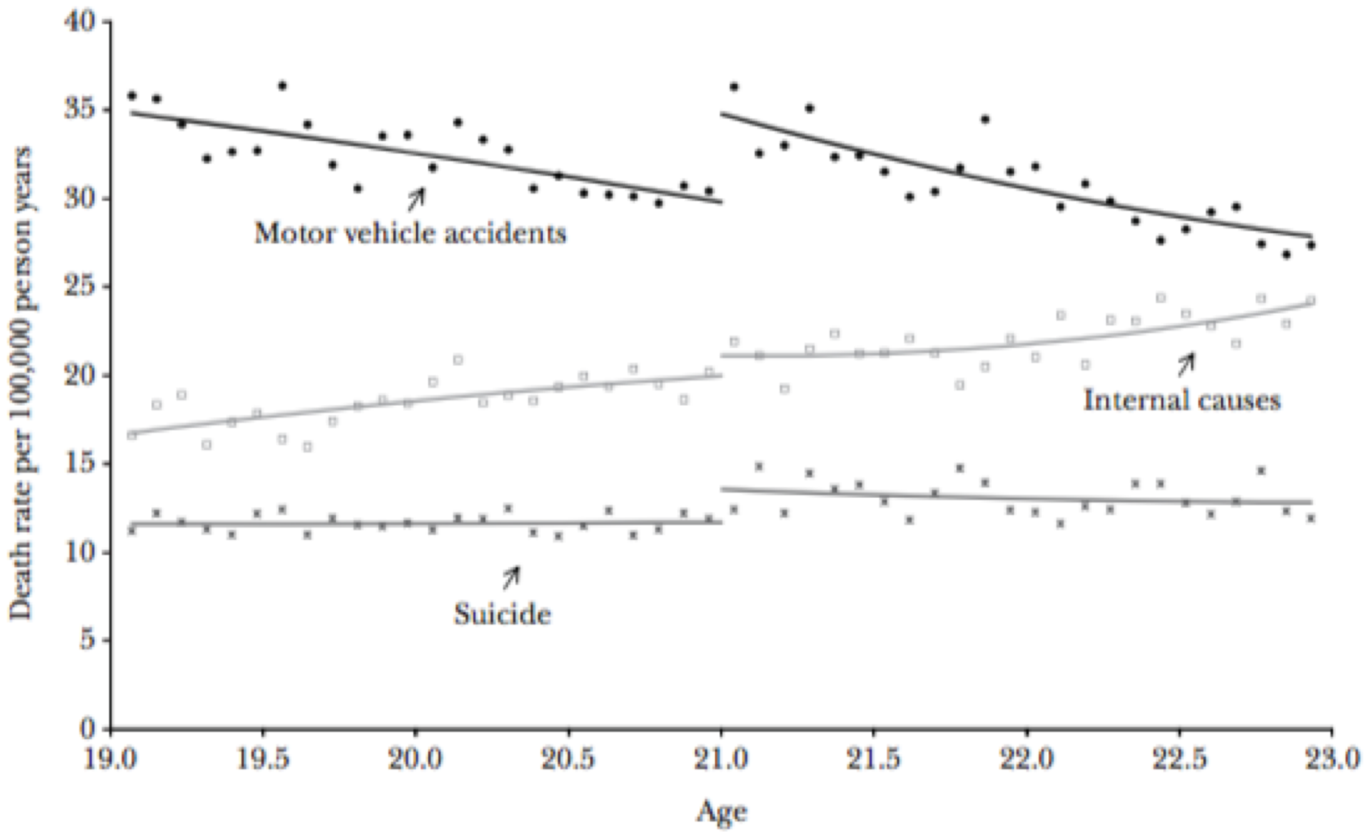


Fig. 4. Regression-Discontinuity Analysis.

Lee, D. S., & Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature, 48*(2), 281–355.

Regression discontinuity

Figure 2
Age Profiles for Death Rates in the United States

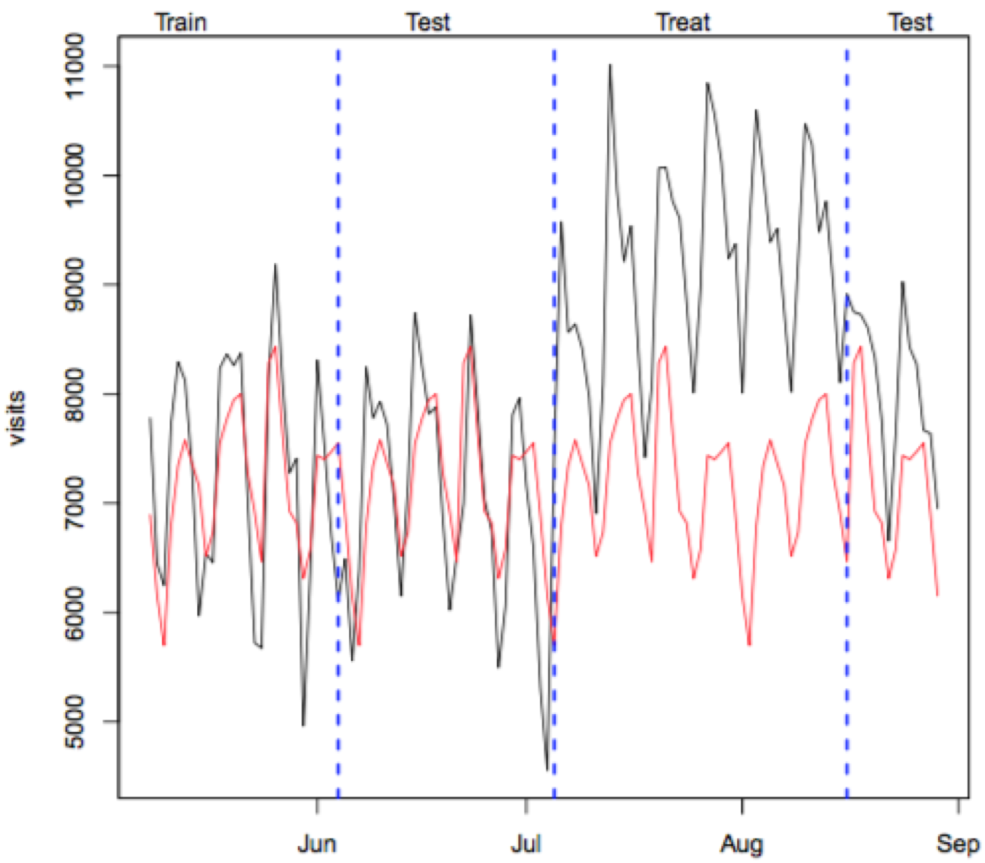


Notes: The death rates are estimated by combining the National Vital Statistics records with population estimates from the U.S. Census.

Carpenter, C., & Dobkin, C. (2011). The Minimum Legal Drinking Age and Public Health. *Journal of Economic Perspectives*, *25*(2), 133–156.

New developments…

Using models as the control group (Train-test-treat-compare)



An online advertiser might ask "if I increase my ad expenditure by some amount, how many extra sales do I generate?"

A predictive statistical model (based on number of "searches" about topics related to the subject matter of the website) is estimated during the training period and its predictive performance is assessed during the test period. The extrapolation of the model during the treat period (red line) serves as a counterfactual. This counterfactual is compared with the actual outcome (black line), and the difference is the estimated treatment effect. When the treatment is ended, the outcome returns to something close to the original level.

Varian, H. R. (2016). Causal inference in economics and marketing. *Proceedings of the National Academy of Sciences of the United States of America, 113*(27), 7310–7315. http://doi.org/10.1073/pnas.1510479113