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Causality 1

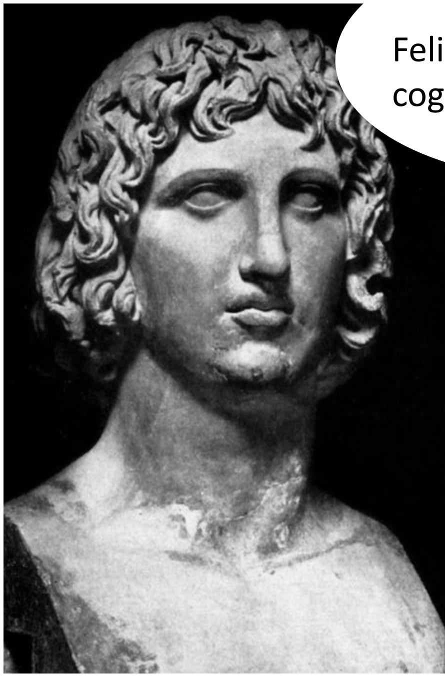
http://users.ox.ac.uk/~sfos0015

1. **Causation**

2. **Causes of Effects**

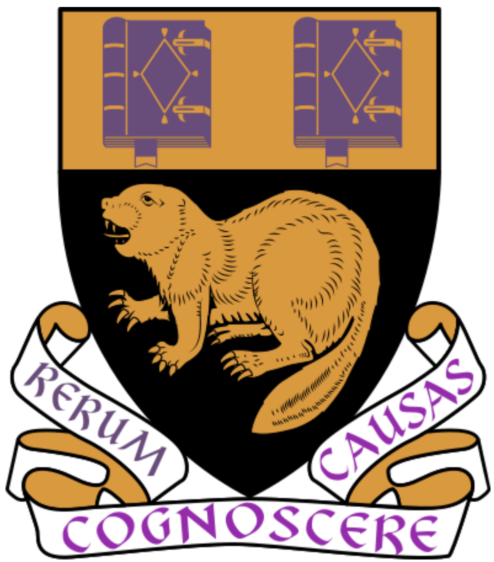
3. **Effects of Causes**

Causation



Felix, qui potuit rerum cognoscere causas.

Virgil 70-19 BC

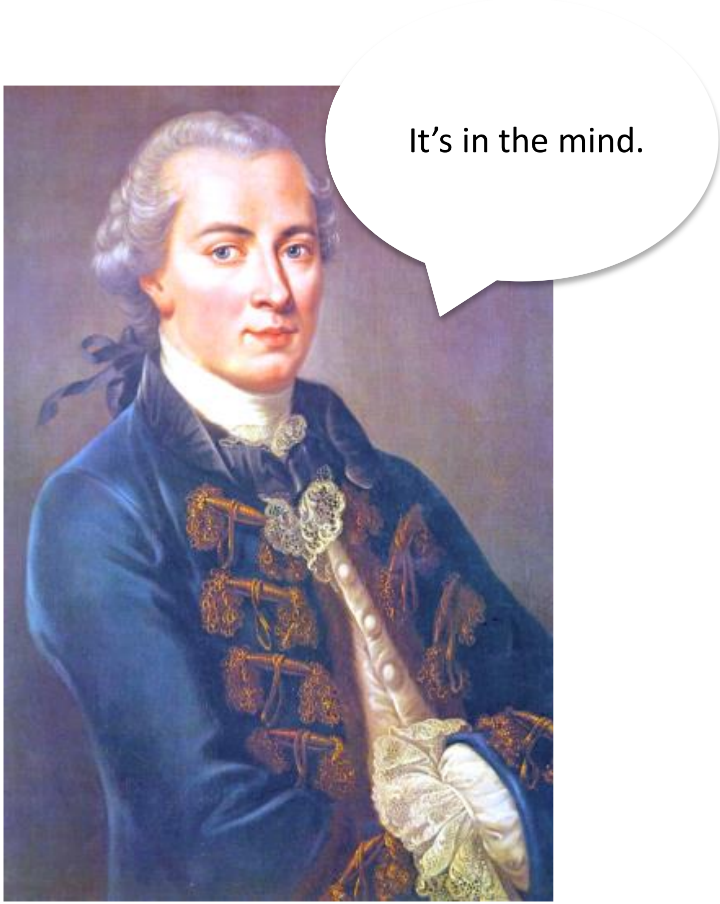


Happy the man, who studying Nature’s Laws,
Thro’ known Effects can trace the secret Cause.

John Dryden 1631-1700

Causation

Hume 1711-1776



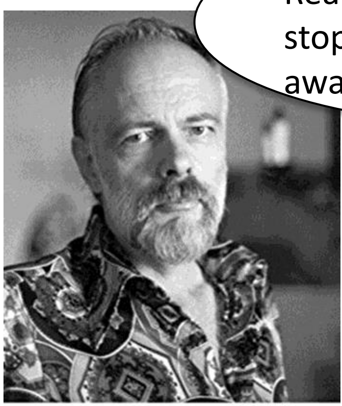
Kant 1724-1804

Causation

1. Distinction between **actual** causal processes and **inferences** about them.
    1. Former is the substantive interest: how to validly make the latter is the methodological interest.

2. Causal inference is in the head but causal processes are in the world and are independent of the observer's mind.

Reality is that which, when you stop believing in it, doesn't go away.



Philip K. Dick

Variation

1. Causal inferences exploit variation in one or more explanatory factors.

2. How is the variation generated?

    1. By the observer?
        1. Random allocation to treatment and control.

    2. By nature?
        1. The outcome of a social process observed by us.
            1. Did nature provide us with exogenous variation?
                1. US draft lottery.
            2. Does nature's variation depend only on observables?
            3. Does nature's variation depend on unobservables?
                1. Missing variables.
                2. Expected outcomes.

3. The meaning of the numbers you estimate depends on the answers.

Broad Views

Causes of effects

What are the causes of…..

wars;
revolutions;
gender discrimination;
social mobility;
ethnic conflict;
social mobility;
recidivism;
voting behaviour;
…….?

Broad Views

Causes of effects

Necessary & sufficient conditions

1. ~ A => ~B
    1. Absence of oxygen implies absence of combustion.
        1. Oxygen is **necessary** for combustion.
1. A => B
    1. A heavy rain shower implies my garden is wet.
        1. A heavy rain shower is **sufficient** for my garden to be wet.
2. A heavy rain shower is **not necessary**. I could have turned the garden hose on.

Broad Views

Causes of effects

INUS conditions

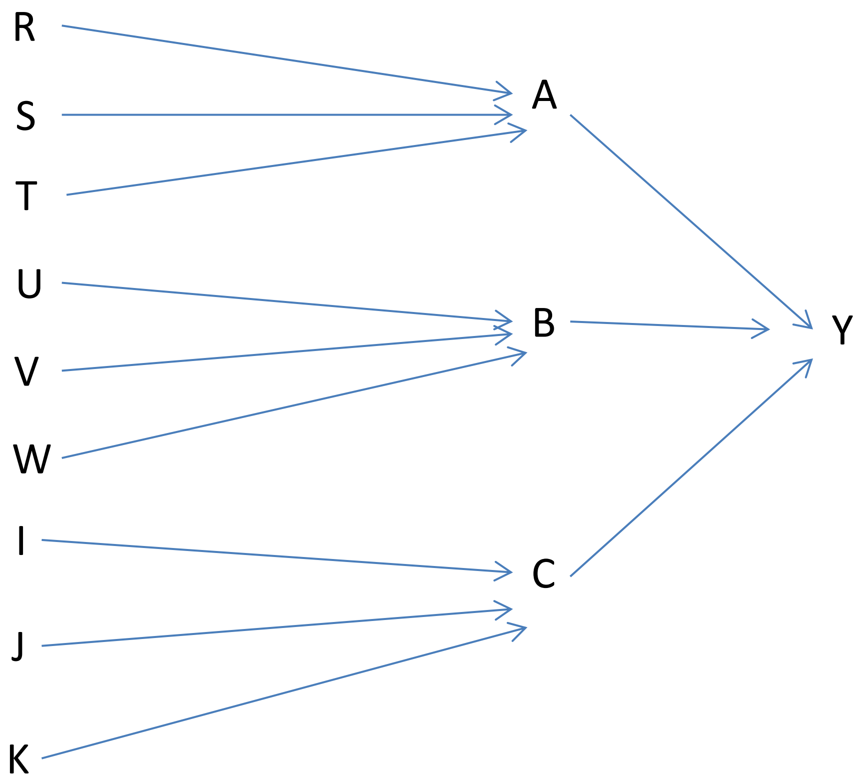
1. ((A^B^C) ᐯ (D^E^F) ᐯ (G^H^I))   <-> Y
2. All A&B&C or D&E&F or G&H&I imply Y
3. And Y implies A&B&C or D&E&F or G&H&I

1. Y is caused by a combinations of conditions.
2. Consider A in (A&B&C).
   1. A is an **insufficient** but **nonredundant** part of an **unnecessary** but **sufficient** condition for Y.

Broad Views

Causes of Effects

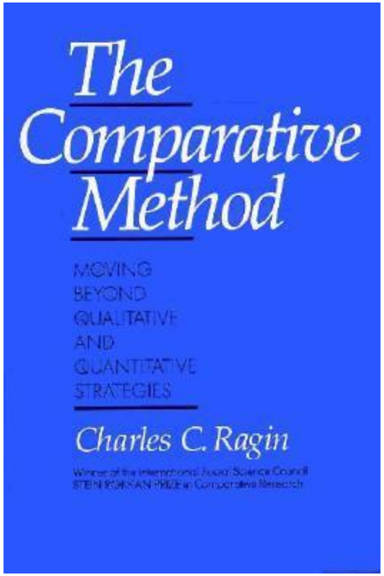
Where to stop?

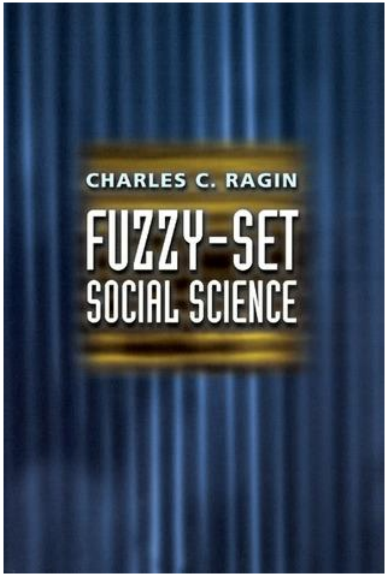


Broad Views

Causes of Effects

Qualitative Comparative Analysis (QCA)





NB. Symposium: Qualitative Comparative Analysis, *Sociological Methodology*, 2014, vol. 44.

Broad views

Effects of causes

1. Interest is in estimating the magnitude of the causal impact or effect of a treatment on an outcome variable.
    1. New drug on five year survival rate
    2. Training program for unemployed on probability of getting a job
    3. Staying in school for an extra year on adult earnings
    4. Going to a religious rather than a secular school on exam success

2. Other factors (observed and unobserved) are nuisance factors to be controlled for (held equal).

3. Intense spotlight on the impact of just one variable.

4. No attempt to provide a complete explanation or evaluate the relative “importance” of many competing explanatory variables.

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Broad views

Effects of causes

Important reading

Holland, Paul W. (1986) 'Statistics and Causal Inference', *Journal of the American Statistical Association*, 81, 396, Dec: 945-960.

Broad views
Effects of causes

1. Important to understand how variation in causal factor generated.
    1. Simplest case is randomization to treatment & control by the investigator.
        1. Classic randomized control trial (RCT).
    2. Causality as consequential manipulation (CACM).

1. Questions
    1. Does “nature” ever mimic this?
    2. What kinds of things can be usefully be regarded as treatments?

Broad views

Effects of causes

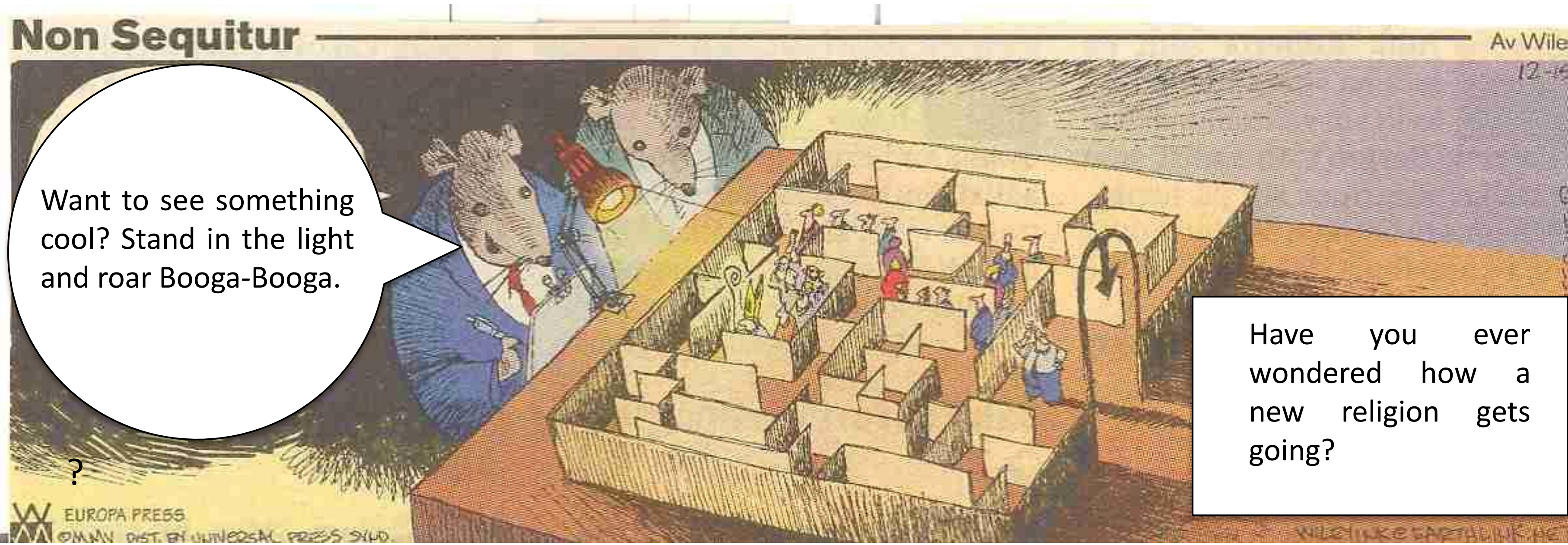
Examples

Holland, P. (2003) ‘Causation and Race’, Educational Testing Service Research Report, RR-03-03.

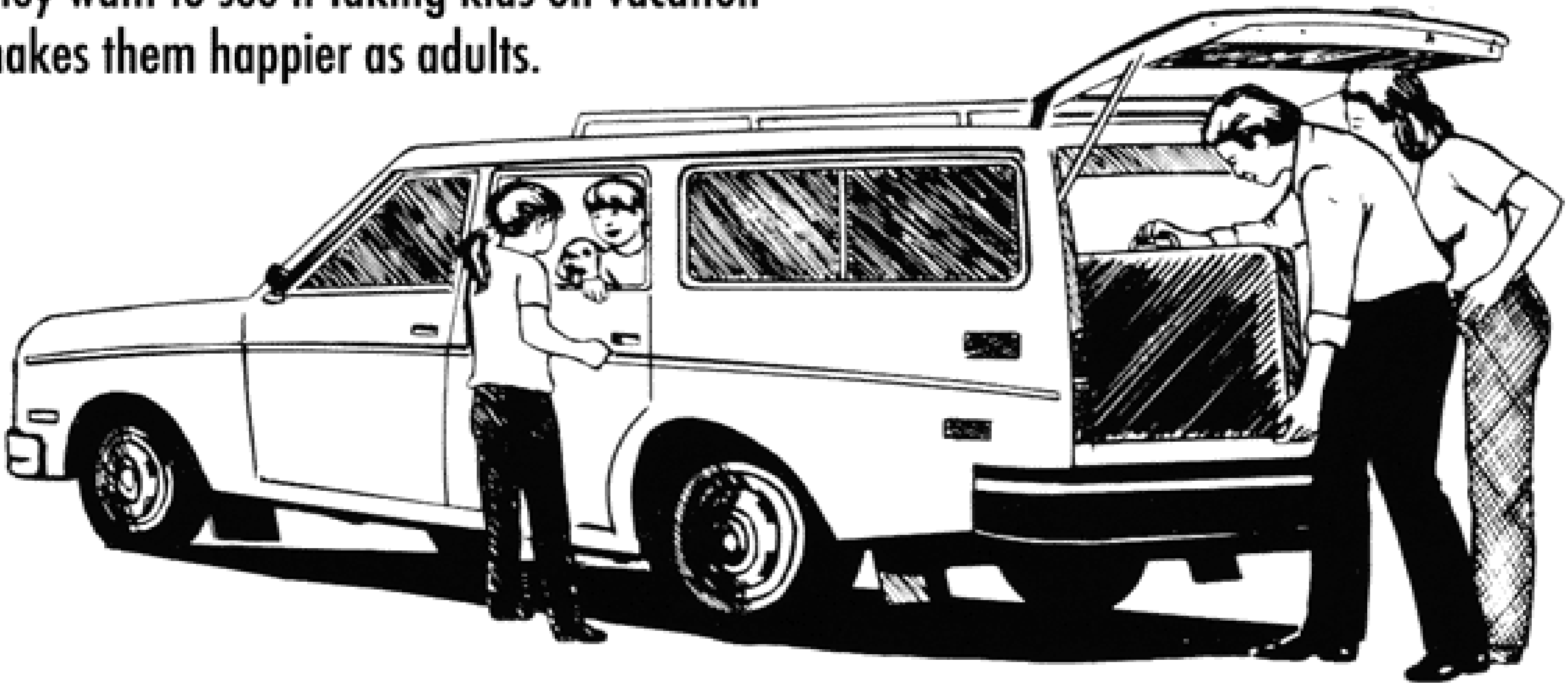
Greiner, D. J. and D. B. Rubin (2011) ‘Causal Effects of Perceived Immutable Characteristics’, *The Review of Economics and Statistics*, 93(3): 775-785.

Broad views

Effects of causes



I told you that you weren't coming with us, Nicole!
Mom and Dad are using you as the control group.
They want to see if taking kids on vacation
makes them happier as adults.



Effects of causes

Randomisation

1. Key to sound experimental inference.

2. Subjects are allocated by lottery to the different experimental conditions.

3. Usually there is a “control” condition where nothing happens to the subjects (or something that is known to be irrelevant).

4. Sometimes the randomisation is such that neither experimenter nor subject know (at the time) what condition the subject is in (double-blind trials).

5. Randomisation is not the same as random sampling in the social survey sense.
    1. Inference is over the hypothetical population of random allocations of subjects to conditions.
    2. Given some H_0 the likelihood of observing $Y^1 – Y^0$ **for those subjects** assuming randomisation.

Effects of causes

Randomisation

Simple simulation example

R X Y_1

R Y_2

Effects of causes

Randomisation

Simple simulation example

1. 200 subjects participate in an experiment.
2. Randomize 100 to treatment group = 1; 100 to control group = 0.
3. One measured covariate: 100 are female = 1; 100 are male = 0.
4. Outcome values for each case is determined by:
5. $Y = .4 \cdot \text{treatment} + .4 \cdot \text{sex} + \varepsilon$
6. Where ε is drawn from $N(0,1)$
7. So the outcome is influenced by treatment, gender and unmeasured things captured by ε.
8. We want to estimate the treatment effect .

Effects of causes

Randomisation

Simple simulation example

1. Normally we draw an inference about a treatment effect from just 1 of the many randomizations that are possible.

2. We are going to study many randomizations all with the same basic set up.

3. The total number of ways in which 200 subjects can be divided into 2 equal sized groups (ignoring the order in which they are selected) is 200!/ (100! · 100!) which is a very large number - roughly 9 with 58 zeros after it!

4. We will run the experiment just 10,000 times and record on each occasion the treatment effect.

Effects of causes

Randomisation

Simple simulation example

1. Create 200 cases.
2. Assign them a sex: 100 female, 100 male.
3. Generate a random number and sort the cases.
4. First 100 get the treatment, second 100 get the control.
5. Generate the outcome Y = .4 · treatment + .4 · sex + ε.
6. Calculate $\bar{Y}_t - \bar{Y}_c$ and save the result.
7. Go back to 3. and repeat until you have 10000 replications.
8. Calculate some summary statistics for the distribution of $\bar{Y}_t - \bar{Y}_c$ and draw a histogram.

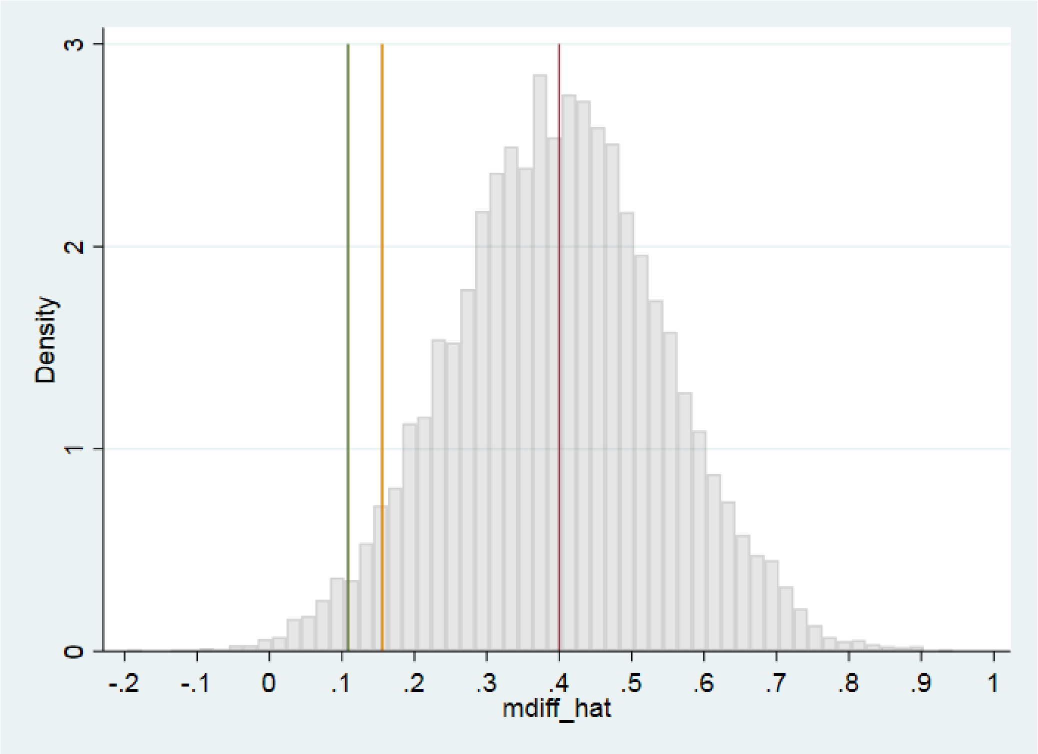
A Stata do file for implementing the simulation can be downloaded from:

http://users.ox.ac.uk/~sfos0015/

Effects of causes

Randomisation

Simple simulation example



True average TE = 0.40.
Mean of averages = 0.40.
SD of averages = 0.15.
Percentile 2.5 = 0.11.
Percentile 5 = 0.16.

Some experiments will give us an estimated average treatment effect of 0 or less. Most won't.

If we construct intervals according to the rule: estimated TE ± 1.96·0.15 approximately 95% of the intervals will include 0.4.

But approximately 23% of the intervals will include 0.

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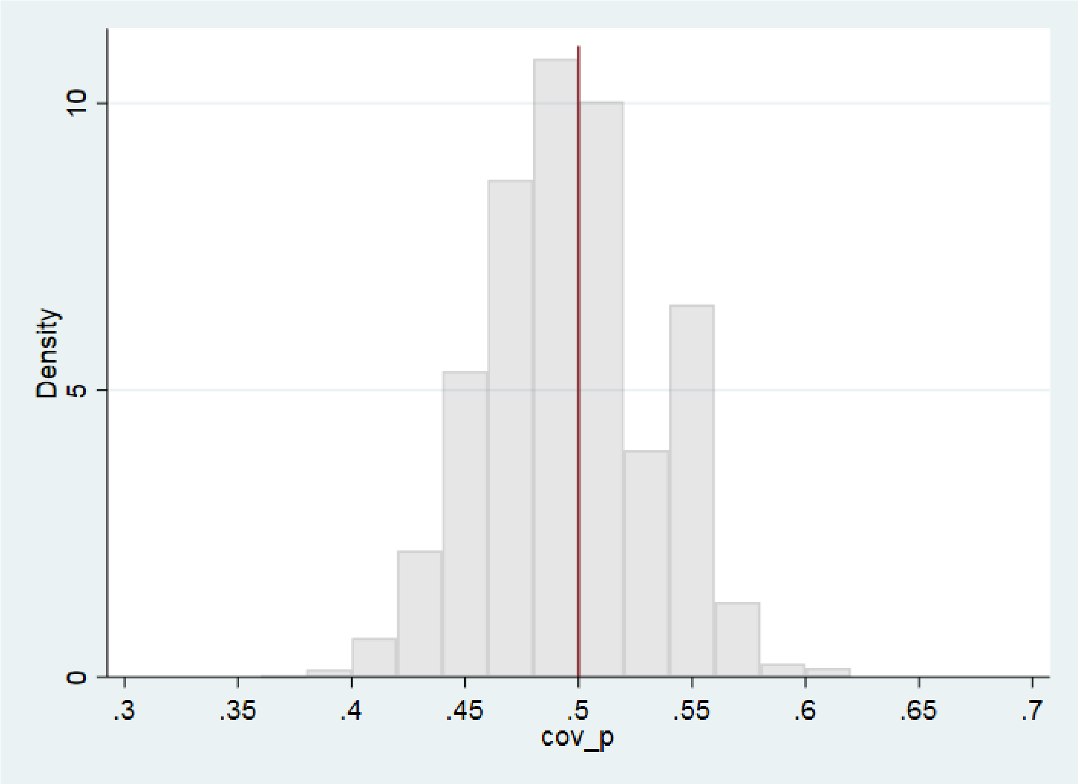
Effects of causes

Randomisation

Simple simulation example



Randomization does not guarantee covariate balance.

Proportion of women in treatment group could be under 0.4 or over 0.6. though the average is 0.5.

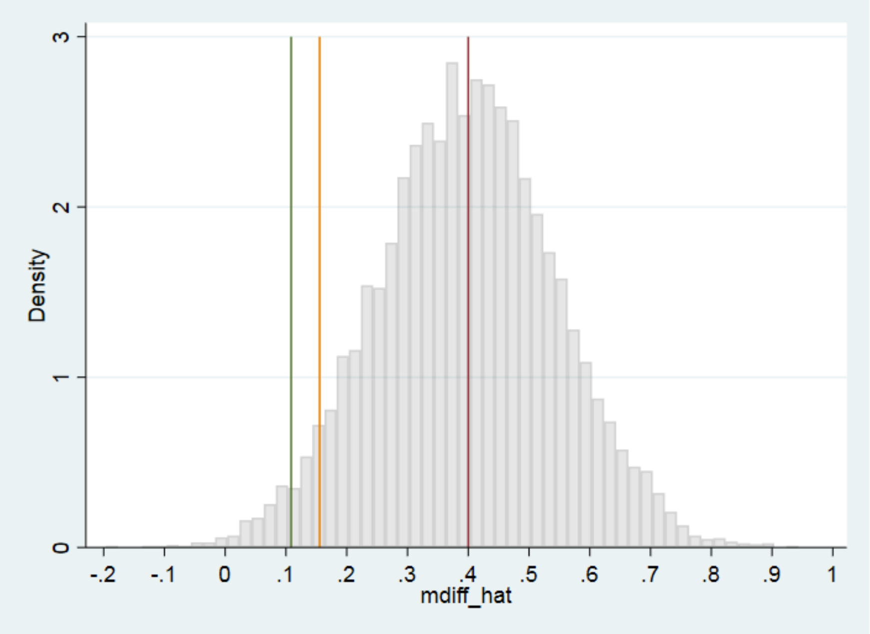
The correlation between the proportion of women in the treatment group and the size of the treatment effect is 0.20

So what can we claim on the basis of a single experiment?

Effects of causes

Randomisation

Simple simulation example



Take experiment 2649.

Estimated average treatment effect = .155, and lies at the 5th percentile.

Using the 'known' standard error gives a 95% confidence interval of: (-0.13 – 0.44) which includes both 0 and the true average.

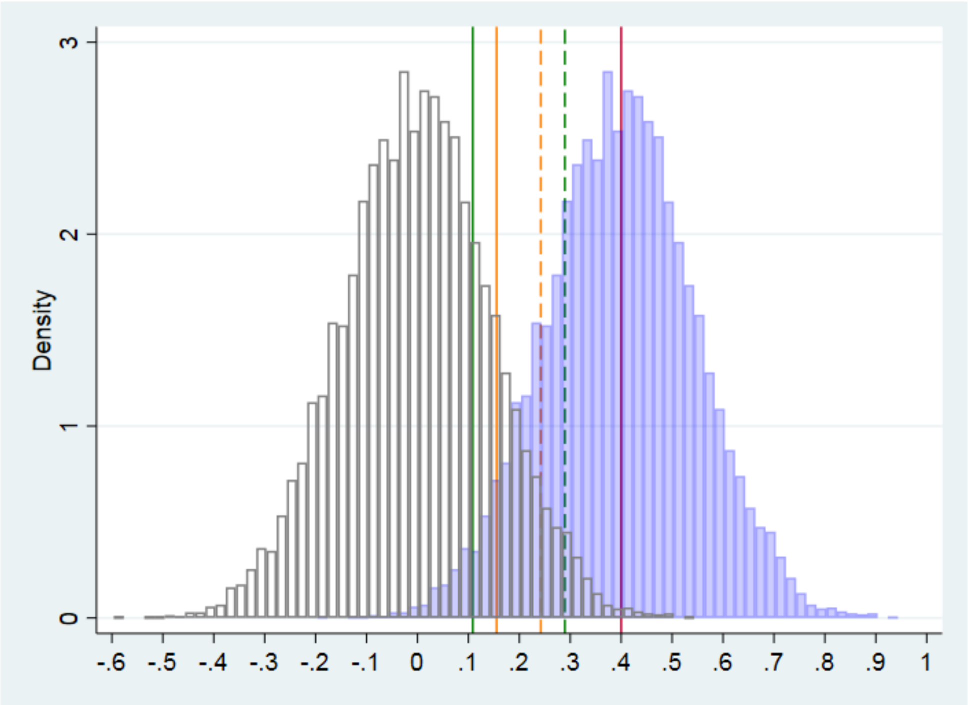
Using the estimated standard error gives an estimated 95% confidence interval of (-0.15 – 0.47)

But what, based on the evidence of experiment 2649 should we conclude about the effect of the treatment on the outcome?

Effects of causes

Randomisation

Simple simulation example



We need the distribution of outcomes assuming the average TE=0.

P value = $P(D|H_0)$.

P (TE >=0.155| H_0) =0.14.

Observing a estimate as large or larger than 0.155 wouldn't be that unusual if TE is really 0. So would be odd to regard the estimate we get from this one experiment as strong evidence against H_0.

When TE=0, 5% of experiments produce estimates >= 0.24 and 2.5% >=0.29.

Effects of causes

Randomisation

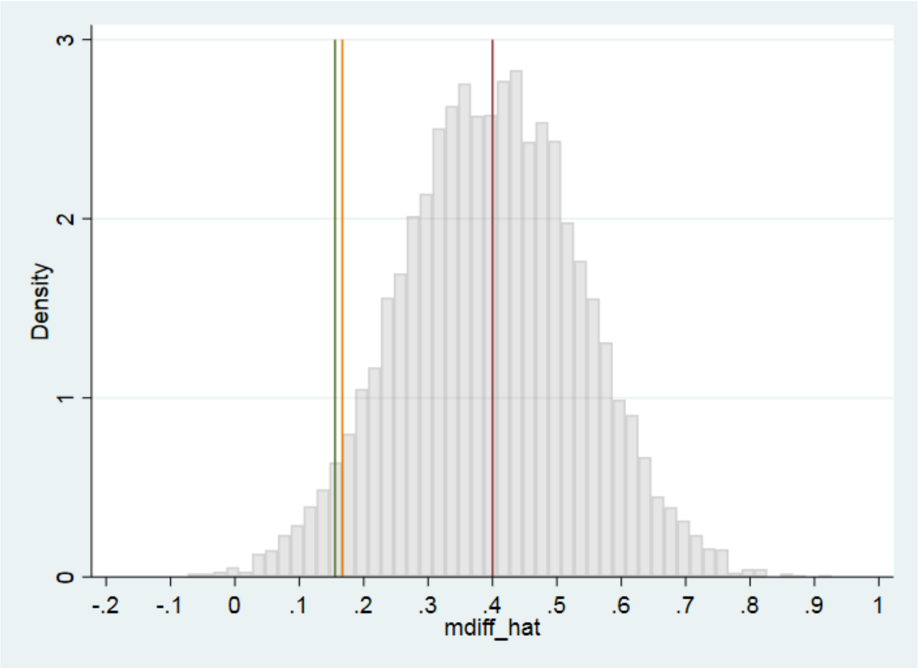
Simple simulation example

1. Is H_0 that the average treatment effect = 0 especially interesting?
2. Don't we know a priori that the average treatment effect is not literally zero?
3. So why construct a test for that?
4. "There may be no special reason for thinking the null hypothesis to be even approximately true. Its importance stems from the implication that, so long as H_0 is reasonably consistent with the data, the sign or direction of the effect under study has not been securely established." Cox and Donnelly, *Principles of Applied Statistics*, pp 145.

Effects of causes

Randomisation

Simple simulation example



Can we do better?

Balance covariate across treatment and control.

New simulation. Randomize within sex. First 50 males to treatment, second 50 to control etc.

True average TE = 0.40.
Mean of averages = 0.40.
SD of averages = 0.14.
Percentile 2.5 = 0.12.
Percentile 5 = 0.17.

Effects of causes

Randomisation

Simple simulation example

"My view is that randomisation should not be used as an excuse for ignoring what is known and observed but that it does deal validly with hidden confounders. It does not do this by delivering answers that are guaranteed to be correct; nothing can deliver that. It delivers answers about which valid probability statements can be made and, in an imperfect world, this has to be good enough."

Stephen Senn, Head of Competence Center for Methodology and Statistics, Luxembourg Institute of Heath.

Effects of causes

Before-After Two-Group Design

R	Y_1	X	Y_2
R	Y_3		Y_4

$$H_0:\ (\bar{Y}_2 - \bar{Y}_1) - (\bar{Y}_4 - \bar{Y}_3) = 0$$

Effects of causes

Internal Validity

1. Internally valid designs are resistant to rival explanations that claim the treatment is not the **cause** of an observed effect.

2. Good experimental design seeks to maximize internal validity against a number of threats, in other words weaknesses of design, that call into doubt the attribution of changes in values of the response to the experimental manipulation.
    1. In an observational context this kind of idea is usually discussed in terms of having a good **identification strategy**.

Effects of causes

Threats to Internal Validity

1. Maturation.
2. Selection.
3. History.
4. Testing.
5. Instrumentation.
6. Regression to the mean.
7. For more detail see Shadish, W. R., Cook, T. D. and D. T. Campbell (2001) *Experimental and Quasi-Experimental Designs for Generalized Causal Inference* , Boston: Houghton Mifflin. Especially Chapter 2.

Effects of causes

External Validity

1. Generalizability beyond the experimental setting.
2. We know it works there, but how do we know it will work here?
3. Central question for any evidence-based policy implementation.
4. Have the right causal principles been identified?
5. At the right level of abstraction?
6. Are all the supporting conditions in place?
7. Will there be any negative unintended consequences?
8. For more details see Cartwright, N. and J. Hardie (2012) *Evidence-Based Policy: A Practical Guide to Doing it Better*, Oxford: OUP.