Causal Inference in Environmental & Social Science

Nils Droste

2021 ClimBEco course

Structure of the Course

	time	**Day 1:** May 10, 2021	**Day 2:** May 11, 2021	**Day 3:** May 12, 2021	**Day 4:** May 13, 2021	**Day 5:** May 14, 2021
Lectures	10-12h	Greetings, *Introduction to Causal inference*, and randomized controlled trials	*(Semi) Natural Experiments*: Panel data regressions, two-way fixed effects, and recent corrections for staggered treatment	*Simulated Counterfactuals*: matching methods, synthetic controls, and Bayesian Structural time series	*Instruments & Interruptions*: instrumental variables, regression discontinuity design	*Cutting edges* : Structural equation modelling for causal inference (and machine learning techniques?)
Seminars	13-15h	*Replication*: Jayachandran et al. (2017) *Science*	*Replication*: Marcus & Sant'Anna (2020) *JAERE*	*Replication*: Bayer & Aklin (2020) *PNAS*	*Replication*: Kim & Urpelainen (2017) *RPP*	***Student presentations***
Consultations	15-16h					

Learning Contract

My offer

- I will provide you with different *"entry points"* (words, graphs, math) to sharpen your intuition and conceptual understanding of quantitative causal inference
- We will collaboratively replicate exemplary works / causal inference strategies

My ask price

- I want feedback what goes nice and what does not?

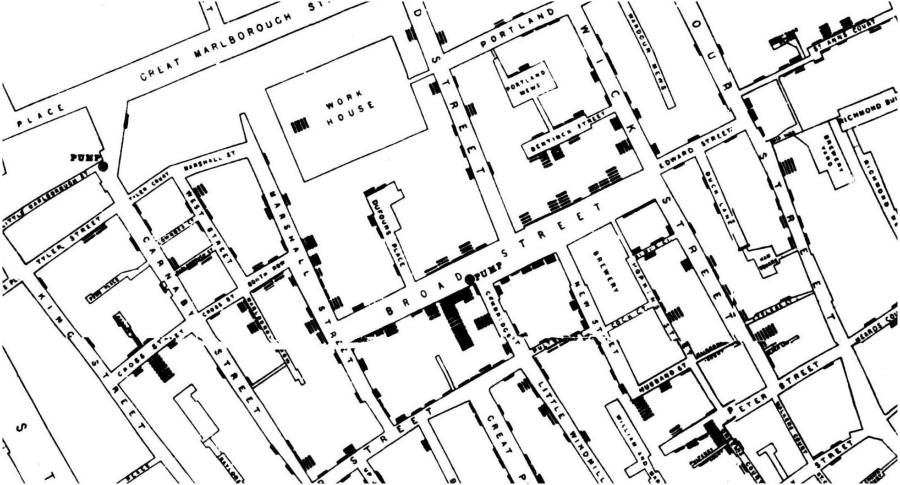
Your task

- You apply one of the methods to a problem of your choice, write a short report and provide replication code

Motivation – Question I

What examples come to mind when you think about ***causality***?

Example I: Epidemiology



John Snow's original dot map of the 1854 Broad street cholera outbreak. Image sources & info: wikipedia

Motivation – My answer

If you think about policies as if

- they were instruments / mechanisms / interventions
- with a potential to fix societal problems

Would you not want to know which ones actually work?

Motivation – Greater minds' answers

Development of Western science is based on ***two great achievements****:*
the invention of the formal logical system (in Euclidean geometry)
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My interpretation:

→ If we want to check our theories about how the world works, we can use systematic obervations (i.e. data) to test our assumptions.

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My interpretation:

→ If we want to check our theories about how the world works, we can use systematic obervations (i.e. data) to test our assumptions.
→ That does not *necessarily* entail quantitative analysis, but large number of observations have benefits for robustness (see next slide).

A short detour into probability

Is the coin fair?

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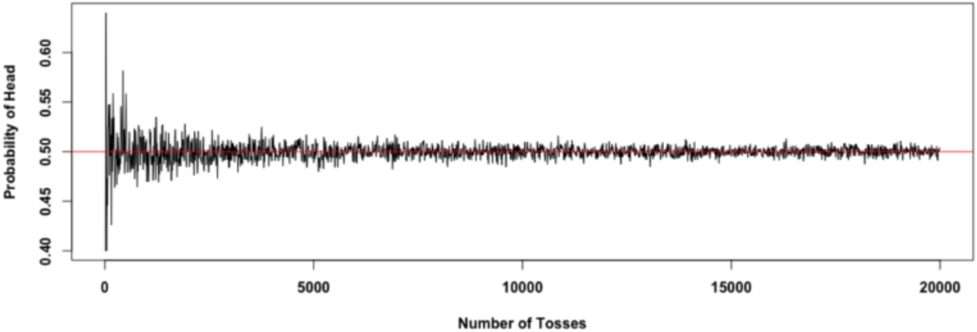

→ The law of large numbers allows to aproximate ”*true*” values.

Epistemological & Ontological Foundations

BLIND MASTER PO: *Close your eyes. What do you hear?*

YOUNG KWAI CHANG CAINE: *I hear the water, I hear the birds.*

MASTER PO: *Do you hear your own heartbeat?*

KWAI CHANG CAINE: *No.*

MASTER PO: *Do you hear the grasshopper that is at your feet?*

KWAI CHANG CAINE: *Old man, how is it that you hear these things?*

MASTER PO: *Young man, **how is it that you do not?***

Kung Fu, Pilot. Cited from Angrist and Jörn-Steffen 2015, (p. xi), own emphasis

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$\rightarrow$ We assume a measurable reality (positivism, empiricism).

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Statistical causal inference is *one* such approach, suitable for

- both inductive and deductive reasoning
- generalizable, reproducible, falsifiable research

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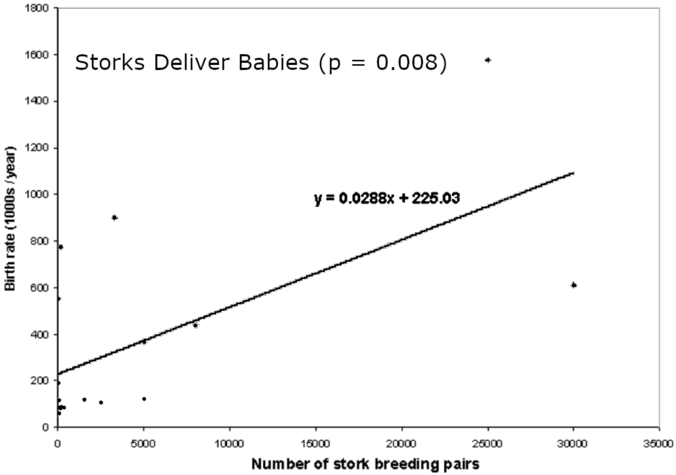
We would like to understand in which circumstances one can conclude from the evidence that D causes Y.

source: lecture notes Sascha Becker 2014

Example II: Storcks & Babies



Do storcks deliver babies? Image source: Matthews (2000)

Example II: Storcks & Babies

What happened, why did we get it so wrong?

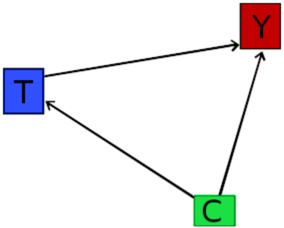
Country	Area (km^2)	Storks (pairs)	Humans (10^6)	Birth rate (10^3/yr)
Albania	28,750	100	3.2	83
Austria	83,860	300	7.6	87
Belgium	30,520	1	9.9	118
Bulgaria	111,000	5000	9.0	117
Denmark	43,100	9	5.1	59
France	544,000	140	56	774
Germany	357,000	3300	78	901

Subset of original data. Source: Matthews (2000)

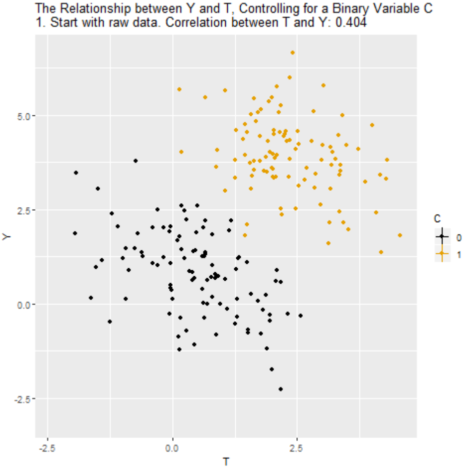
Besides outcome variable and variable of interest, we forgot confounding variables.

$$Y_i = \alpha + \beta_1 D_i + \beta_2 C_i + \epsilon_i \quad (1)$$

Problem I: Confounding variables



Directed acyclic graph where variable C affects both textcolorblueD and Y. Image source: Modified from Huntington-Klein 2018



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- $D = 1$ if i has received treatment;
- $D = 0$ if i has *not* received treatment.

Thus, $Y_i(D_i)$ indicates the *potential outcome* according to treatment:

- $Y_i(1)$ is the outcome in case of treatment;
- $Y_i(0)$ is the outcome in case of *no* treatment.

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The hypothetical outcome for each unit can be written as

$$\Delta Y_i = Y_i(1) - Y_i(0) \tag{2}$$

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- While theoretically ideal, the identification and the measurement of a pure counterfactual is logically impossible:
- We can only observe one state of the world, i.e. we cannot *directly* measure what would have happened in the counterfactual case (cf. Holland 1986).

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In this case we exploit *random chance* within sufficiently large samples that makes these groups comparable. Such a setting can be generated by randomized controlled experiments.

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Another approach is to specify the assumed causal relation within a system by directed acyclic graphs (DAG). For example:

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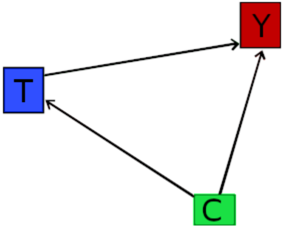

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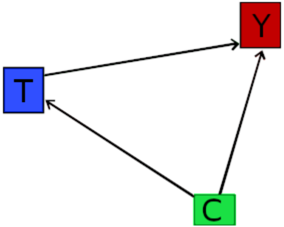

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In the second case we need to close the *back-door path* by controlling for *C*.

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$$P(Y|do(D)) = \sum_C P(Y|D, C)P(C) \tag{5}$$

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My take: $\rightarrow$ ***We need theory!*** Theory can be developed (and tested) through many (inductive & deductive) methods.

Ontology - Epistemology - Theory

Plato's allegory of the cave. Image source: Studio Binder 2020

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- How large numbers of obervations allow more robust inference?
- That correlation does not imply causation?
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- That quantitative causal inference needs theory / an understanding of the causal mechanism to work?

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References and further reading

- RCTs: **DeSouzaLeao2019**; **Jamison2019**; Pearce and Raman 2014
- Experiments in a broader sense, cf. Wikipedia, Britannica

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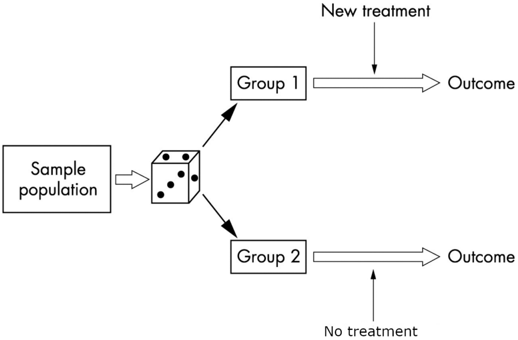

Schematic outline of a randomized controlled trial. Image source: Adapted from Kendall 2003

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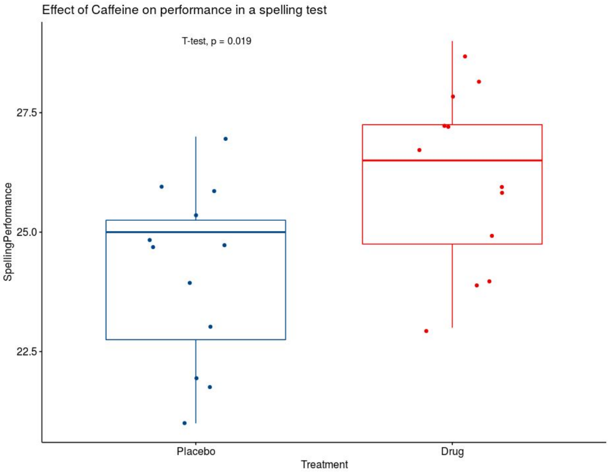
Random chance in sufficiently large samples makes these groups comparable (remember the law of large numbers).

Experiments – graphical approach



A hypothetical experiment. Image source: Adapted from personality-project

Experiments – methodological note of caution

When designing an experiment we need a **big enough sample size**.

What is big enough can be calculated based on

- false positive probability (e.g. no more than 5%)
- minimum detectable effect (MDE)
- the power required at MDE (e.g. 80%)

Reference: cf. Coleman 2018 or Ramesh Johari MS&E 226 lecture 18

Paying households for conservation

RESEARCH ARTICLE

ECONOMICS

Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation

Seema Jayachandran,[1*] Joost de Laat,[2] Eric F. Lambin,[3,4] Charlotte Y. Stanton,[5] Robin Audy,[6] Nancy E. Thomas[7]

We evaluated a program of payments for ecosystem services in Uganda that offered forest-owning households annual payments of 70,000 Ugandan shillings per hectare if they conserved their forest. The program was implemented as a randomized controlled trial in 121 villages, 60 of which received the program for 2 years. The primary outcome was the change in land area covered by trees, measured by classifying high-resolution satellite imagery. We found that tree cover declined by 4.2% during the study period in treatment villages, compared to 9.1% in control villages. We found no evidence that enrollees shifted their deforestation to nearby land. We valued the delayed carbon dioxide emissions and found that this program benefit is 2.4 times as large as the program costs.

Paying households for conservation

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  - pay 563 private forest owners (PFO) in 60 treated villages (there are 535 PFO in 61 control villages), and
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- Jayachandran et al. (2017) analyse the effect on tree cover.

Paying households for conservation

Results

Primary outcomes

	Village boundaries		
	ΔTree cover (ha)	**ΔTree cover (ha)**	**ΔLog of tree cover**
	(1)	(2)	(3)
Treatment group	5.549*	5.478**	0.0521**
	[2.888]	[2.652]	[0.021]
Control group	–13.371	–13.371	–0.095
Control variables	No	Yes	Yes
Observations	121	121	121

Paying households for conservation

Results

Secondary outcomes

	Cut any trees in the past year	Allow others to gather firewood from own forest	Increased patrolling of the forest in last 2 years	Has any fence around land with natural forest	IHS of food expend. in past 30 days	IHS of nonfood expend. in past 30 days
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	−0.140***	−0.170***	0.109***	0.036	0.065	0.156**
	[0.034]	[0.033]	[0.039]	[0.033]	[0.074]	[0.066]
Lee bound (lower)	−0.161***	−0.185***	0.094**	0.007	−0.029	0.053
	[0.034]	[0.033]	[0.039]	[0.033]	[0.070]	[0.064]
Lee bound (upper)	−0.104***	−0.148***	0.132***	0.055	0.144*	0.215***
	[0.033]	[0.032]	[0.039]	[0.034]	[0.075]	[0.064]
Control group mean	0.453	0.427	0.378	0.667	2.524	4.363
Control group SD	[0.498]	[0.495]	[0.485]	[0.472]	[1.177]	[1.354]
Observations	1018	9767	984	1020	1020	1020
Observations (Lee bounds)	994	957	965	998	998	998

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Results

Paying forest owners for conservation reduces deforestation rates
$\rightarrow$ No afforestation is observable at that payment level.

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$\rightarrow$ No afforestation is observable at that payment level.

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Paying households for conservation

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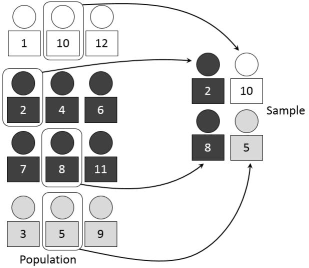
- ”satellite images with very high resolution, which enables us to detect selective tree-cutting in addition to clear-cutting”
- ”cost-benefit analysis allows policy-makers to assess the cost-effectiveness of the PES program in comparison to other options for reducing global carbon emissions”

Jayachandran et al. 2017, p. 6

A note on methods

The authors used a *stratification* strategy to ensure balanced randomization:

- number of PFOs



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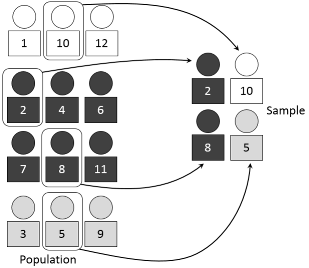

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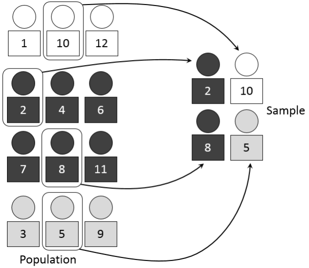

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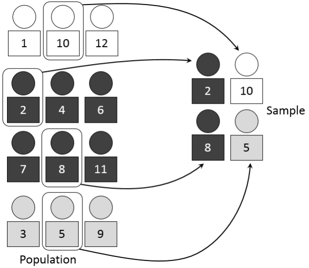

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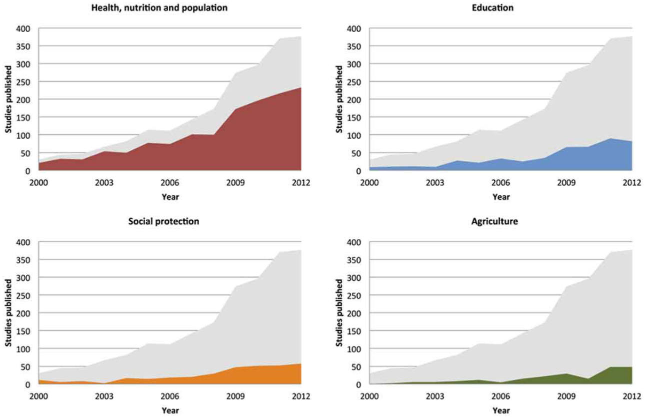
Paying households for conservation

Discussion questions

- Do you think it is a good idea to pay private land owners for the provision of public goods ecosystem services?
- Do you think it is a market-based approach if the government pays it? If so why?
- What could be alternative approaches to ensure provision of public (environmental) goods?

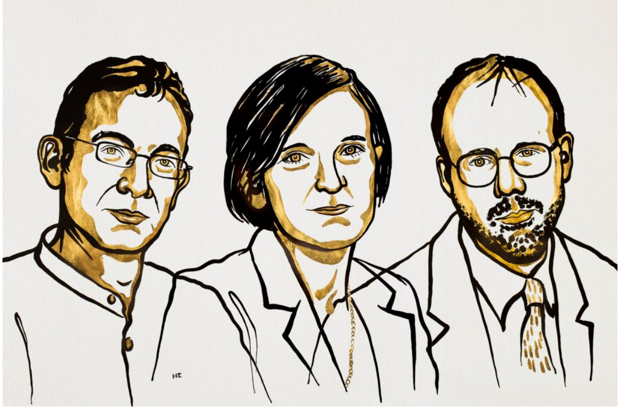
Randomistas on a roll

Increased use of development policy evaluation studies (or RCTs)



Share of quasi-experimental studies in color. Image source: Cameron et al. 2016, cf. Tollefson 2015

Randomistas on a roll



Banerjee, Duflo & Kremer win the 2019 Nobel Prize in Economics.
Image source: Sverige Riksbank

Not all that glitters is gold

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- A solid design is needed for internal and external validity.
- There is / was a replication crisis and p-hacking.
- There can be secondary, unintended outcomes.
- Experiments can be costly.

A rejoinder

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$\rightarrow$ *My own take*: I believe more systematical experiments in the implementation of policies can increase effectiveness (compared to trial-and-error)

Econometricians

MASTER JOSHWAY: *In a nutshell, please, Grasshopper.*

GRASSHOPPER: *Causal inference compares potential outcomes, descriptions of the world when alternative roads are taken.*

MASTER JOSHWAY: *Do we compare those who took one road with those who took another?*

GRASSHOPPER: *Such comparisons are often contaminated by selection bias, that is, differences between treated and control subjects that exist even in the absence of a treatment effect.*

MASTER JOSHWAY: *Can selection bias be eliminated?*

GRASSHOPPER: *Random assignment to treatment and control conditions eliminates selection bias. Yet even in randomized trials, we check for balance.*

MASTER JOSHWAY: *Is there a* ***single causal truth****, which all randomized investigations are sure to reveal?*

GRASSHOPPER: *I see now that there can be* ***many truths****, Master, some compatible, some in contradiction. We therefore take special note when findings from two or more experiments are similar.*

Angrist and Jörn-Steffen 2015, (p. 30), own emphasis

Experiment lessons

- The design of the experiments matter for it's
  - (internal and external) validity
  - ethical implications
- Interpretation of the results is a big part of the story / political recommendation.

Further readings

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