LUND UNIVERSITY

Causal Inference in Environmental & Social Science

Nils Droste

2022 ClimBEco course

Structure of the Course

	time	**Day 1:** May 30, 2022	**Day 2:** May 31, 2022	**Day 3:** June 01, 2022	**Day 4:** June 02, 2022	**Day 5:** June 03, 2022
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*: Card & Krueger (1994) *JAERE*	*Replication*: LaLonde (1986) *PNAS*	*Replication*: Abou-Chadi & Krause (2020) *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

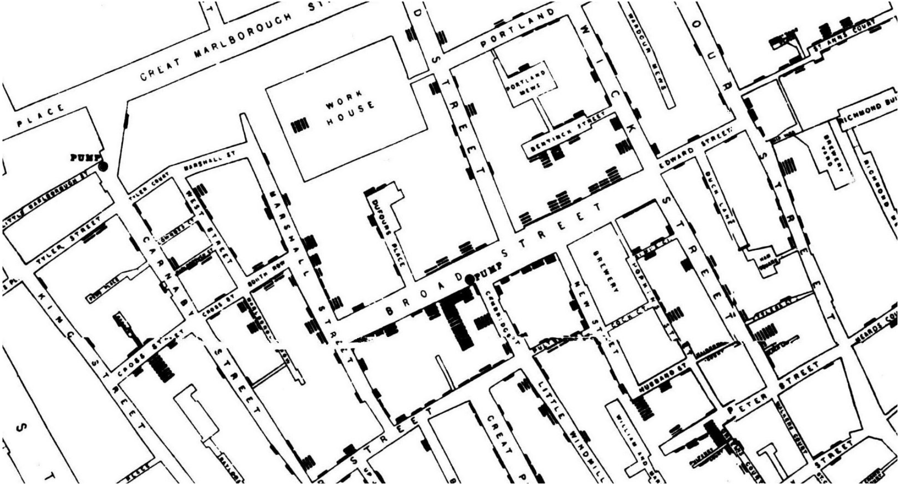
Motivation – My answer

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?

Example I: Epidemiology



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

Motivation – Greater minds' answers

Development of Western science is based on ***two great achievements****:*
the invention of the formal logical system (in Euclidean geometry)
by the Greek philosophers, and the discovery of the possibility to find out
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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?

A short detour into probability

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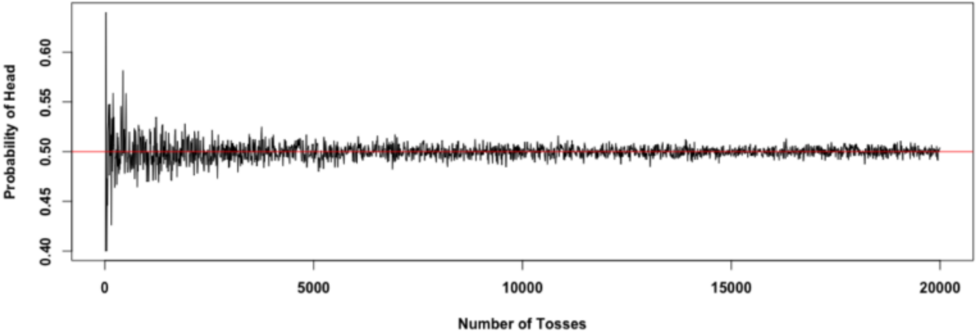

$\rightarrow$ The law of large numbers allows to aproximate "*true*" values.

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 Pischke 2015, (p. xi), own emphasis

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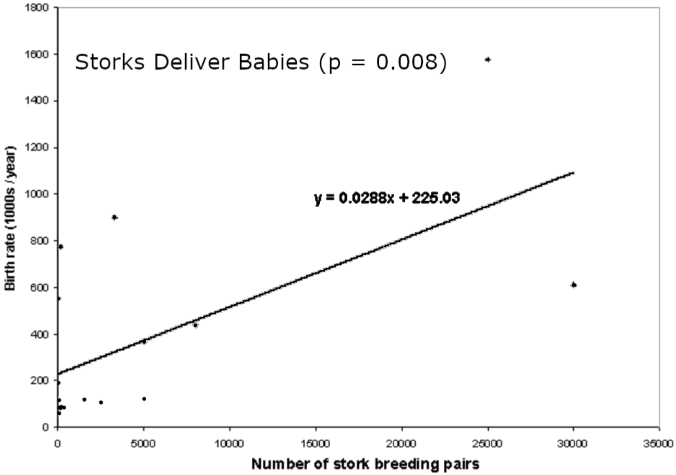
We would like to understand in which circumstances one can conclude from the evidence that D causes Y.

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?

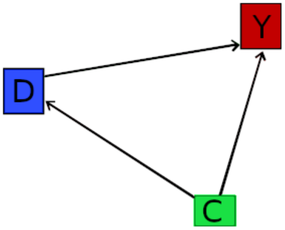
Country	Area (km^2)	Storks (pairs)	Humans (10^6)	Birth rate (10^3/yr)
Albania	28,750	100	3.2	83
Austria	83,860	300	7.6	87
Belgium	30,520	1	9.9	118
Bulgaria	111,000	5000	9.0	117
Denmark	43,100	9	5.1	59
France	544,000	140	56	774
Germany	357,000	3300	78	901

Subset of original data. Source: Matthews (2000)

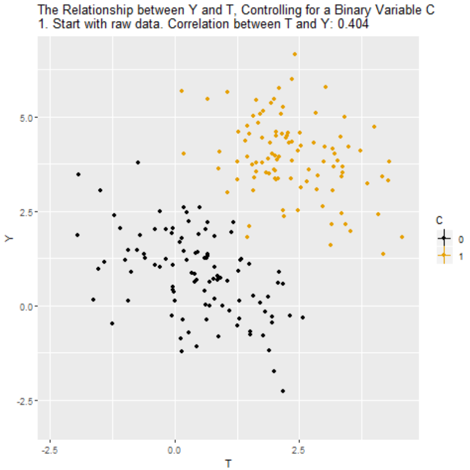
Besides outcome variable and variable of interest, we forgot confounding variables.

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

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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For D we have two possible realizations:

- $D = 1$ 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.

Neyman-Rubin Model II

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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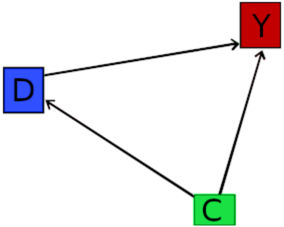

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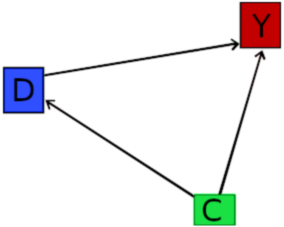

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In the second case we need to close the *back-door path* by controlling for *C*.

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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

Intermediate lessons

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Do you have developed an intuition for the following?

- How large numbers of obervations allow more robust inference?
- That correlation does not imply causation?
- That causal analysis require some form of framework to ...
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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: Pearce and Raman 2014; de Souza Leão and Eyal 2019; Jamison 2019
- Experiments in a broader sense, cf. Wikipedia, Britannica

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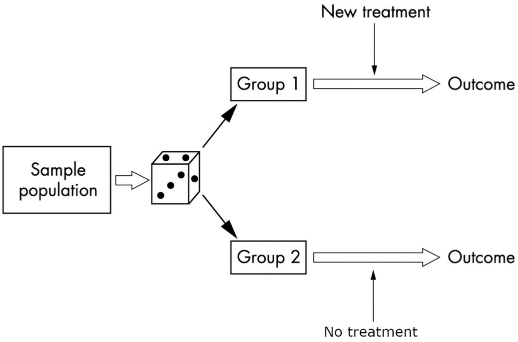

Schematic outline of a randomized controlled trial. Image source: Adapted from Kendall 2003

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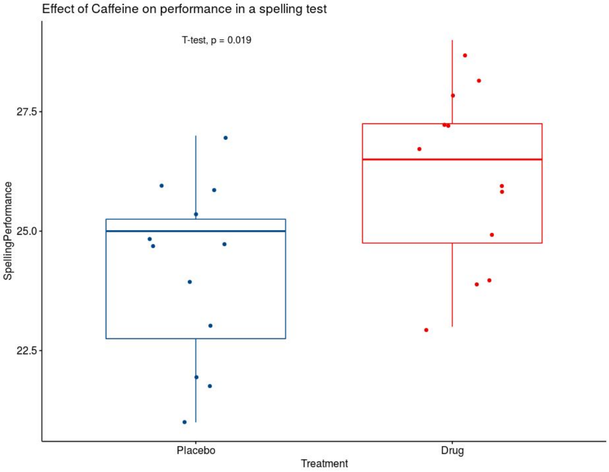
Random chance in sufficiently large samples makes these groups comparable (remember the law of large numbers).

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

”This study also adds to the literature on PES [by]”

- ”satellite images with very high resolution, which enables us to detect selective tree-cutting in addition to clear-cutting”

Jayachandran et al. 2017, p. 6

Paying households for conservation

Results

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

"This study also adds to the literature on PES [by]"

- "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

Paying households for conservation

A note on methods

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

- number of PFOs

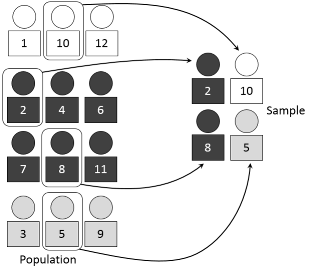

Image source: wikipedia

Paying households for conservation

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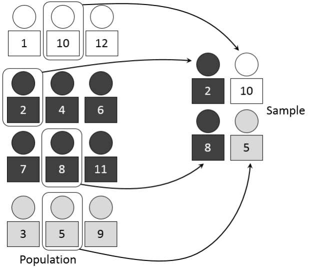

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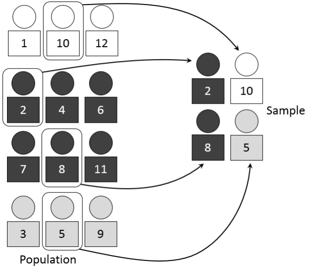

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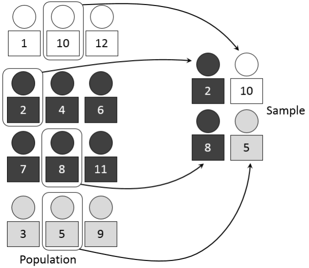


Image source: wikipedia

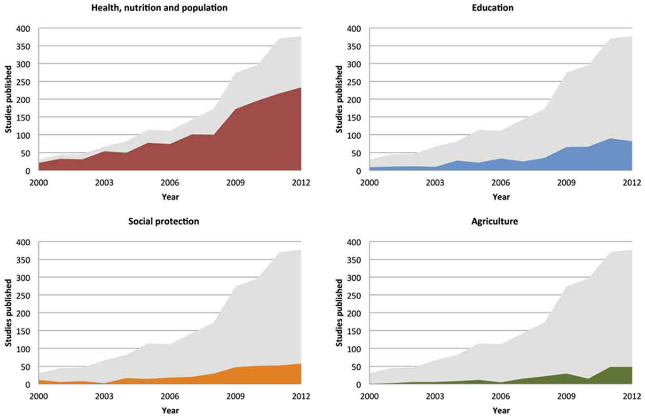
Paying households for conservation

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?

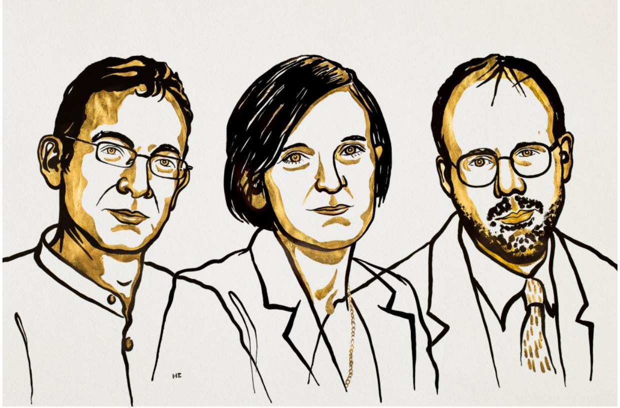
Randomistas on a roll

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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- Some treatments cause ethical concern.
- RCTs target individuals not structural causes.
- 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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→ *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 Pischke 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

- Behaghel, L., Macours, K., & Subervie, J. (2019). How can randomised controlled trials help improve the design of the common agricultural policy? *European Review of Agricultural Economics*, 46(3), 473-493. doi: 10.1093/erae/jbz021
- Beaman, L., Duflo, E., Pande, R., & Topalova, P. (2012). Female leadership raises aspirations and educational attainment for girls: A policy experiment in India. *Science, 335*(6068), 582-586. doi: 10.1126/science.1212382
- Braga, A. A., & Bond, B. J. (2008). Policing crime and disorder hot spots: A randomized controlled trial. *Criminology*, 46(3), 577-607. doi: 10.1111/j.1745-9125.2008.00124.x

References I

Angrist, Joshua D and Jörn-Steffen Pischke (2015). *Mastering 'Metrics*. Princeton: Princeton University Press.

Banerjee, Abhijit and Esther Duflo (2011). *Poor economics: A radical rethinking of the way to fight global poverty*. PublicAffairs.

Blok, Anders and Morten Axel Pedersen (2014). 'Complementary social science? Quali-quantitative experiments in a Big Data world'. In: *Big Data and Society* 1.2, pp. 1–6. DOI: 10.1177/2053951714543908.

Cameron, Drew B, Anjini Mishra and Annette N Brown (2016). 'The growth of impact evaluation for international development: how much have we learned?' In: *Journal of Development Effectiveness* 8.1, pp. 1–21. DOI: 10.1080/19439342.2015.1034156.

Coleman, Renita (2018). *Designing Experiments for the Social Sciences: How to Plan, Create, and Execute Research Using Experiments*. Sage.

de Souza Leão, Luciana and Gil Eyal (2019). 'The rise of randomized controlled trials (RCTs) in international development in historical perspective'. In: *Theory and Society* 48.3, pp. 383–418. DOI: 10.1007/s11186-019-09352-6.

Gelman, Andrew (2014). 'Experimental Reasoning in Social Science'. In: *Field Experiments and Their Critics: Essays on the Uses and Abuses of Experimentation in the Social Sciences*, p. 185.

Holland, Paul W (1986). 'Statistics and causal inference'. In: *Journal of the American Statistical Association* 81.396, pp. 945–960. DOI: 10.1080/01621459.1986.10478354.

References II

Howe, Kenneth R (2004). 'A critique of experimentalism'. In: *Qualitative Inquiry* 10.1, pp. 42–61. DOI: 10.1177/1077800403259491.

Imai, Kosuke et al. (2011). 'Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational studies'. In: *American Political Science Review* 105.4, pp. 765–789. DOI: 10.1017/S0003055411000414.

Jamison, Julian C (2019). 'The Entry of Randomized Assignment into the Social Sciences'. In: *Journal of Causal Inference* 7.1. DOI: 10.1515/jci-2017-0025.

Jayachandran, Seema et al. (2017). 'Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation'. In: *Science* 357.6348, pp. 267–273. DOI: 10.1126/science.aan0568.

Kendall, J M (2003). 'Designing a research project: randomised controlled trials and their principles'. In: *Emergency Medicine Journal* 20.2, pp. 164–168. DOI: 10.1136/emj.20.2.164.

Latour, Bruno et al. (2012). ''The whole is always smaller than its parts' - a digital test of Gabriel Tardes' monads'. In: *British Journal of Sociology* 63.4, pp. 590–615. DOI: 10.1111/j.1468-4446.2012.01428.x.

Matthews, Robert (2000). 'Storks deliver babies (p= 0.008)'. In: *Teaching Statistics* 22.2, pp. 36–38. DOI: 10.1111/1467-9639.00013.

References III

Pearce, Warren and Sujatha Raman (2014). ‘The new randomised controlled trials (RCT) movement in public policy: challenges of epistemic governance’. In: *Policy Sciences* 47.4, pp. 387–402. DOI: 10.1007/s11077-014-9208-3.

Pearl, Judea (2009). *Causality - Models, Reasoning, and Inference*. 2nd editio. Cambridge University Press.

Pearl, Judea, Madelyn Glymour and Nicholas P Jewell (2016). *Causal inference in statistics: A primer*. Wiley. URL: http://bayes.cs.ucla.edu/PRIMER/.

Salmon, Wesley C (1984). *Scientific explanation and the causal structure of the world*. Princeton University Press.

Tollefson, Jeff (2015). ‘Revolt of the Randomistas: a new generation of economists is trying to transform global development policy through the power of randomized controlled trials’. In: *Nature* 524.7564, pp. 150–154. DOI: 10.1038/524150a.