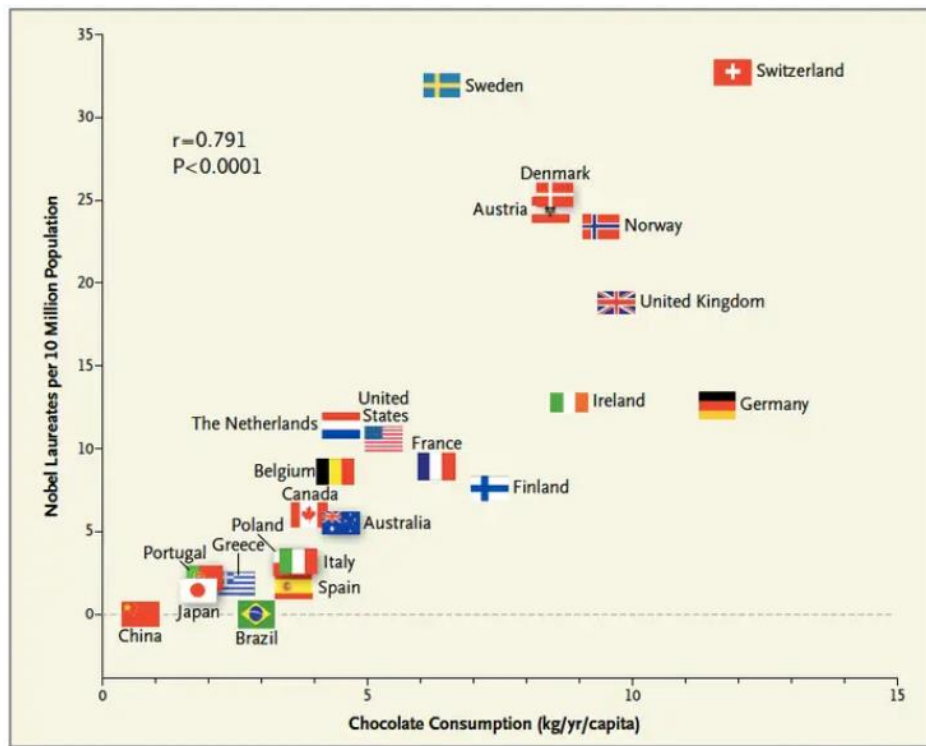


Causal Inference and Quasi- Experimental Research Designs

Prof. Dr. Fabian T. Dehos

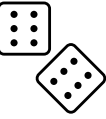
«Correlation does not imply causation»

What do you see in this graph — a correlation or a causal relationship?



If we take this relationship at face value, what policy would you propose to increase Nobel Prize winners in your country?

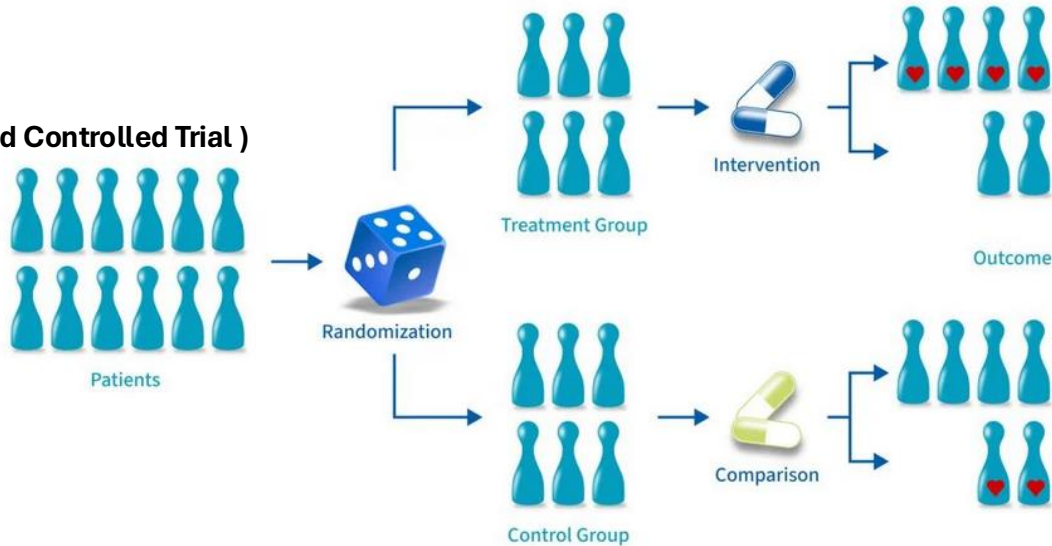
Gold Standard to Detect Causalities: Randomization



Idea

- individuals are **randomly assigned** to **treatment** and **control group** (e.g. flipping a coin or random generator).
- this ensures that groups are as similar as possible in all aspects.
- like a laboratory science, we want to change only one factor to analyze its impact.

Example: Medical RCT (Randomized Controlled Trial)



Source:
www.simplypsychology.org

Some Problems and Challenges with RCTs

ethical, moral, and legal concerns

- studies on risky behavior.
- development economics.

practical and logistical challenges

- high cost in terms of time and money.
- exception: experiments in computer labs or online experiments.

behavioral adjustments of participants (Hawthorne effect)

- study participants change their behavior as a result of being observed (rather than as a result of the intervention).

The Problem of Identifying Causal Relationships from Observational Data (w/o randomisation)



- **treatment** uptake or exposure is typically **not random**.

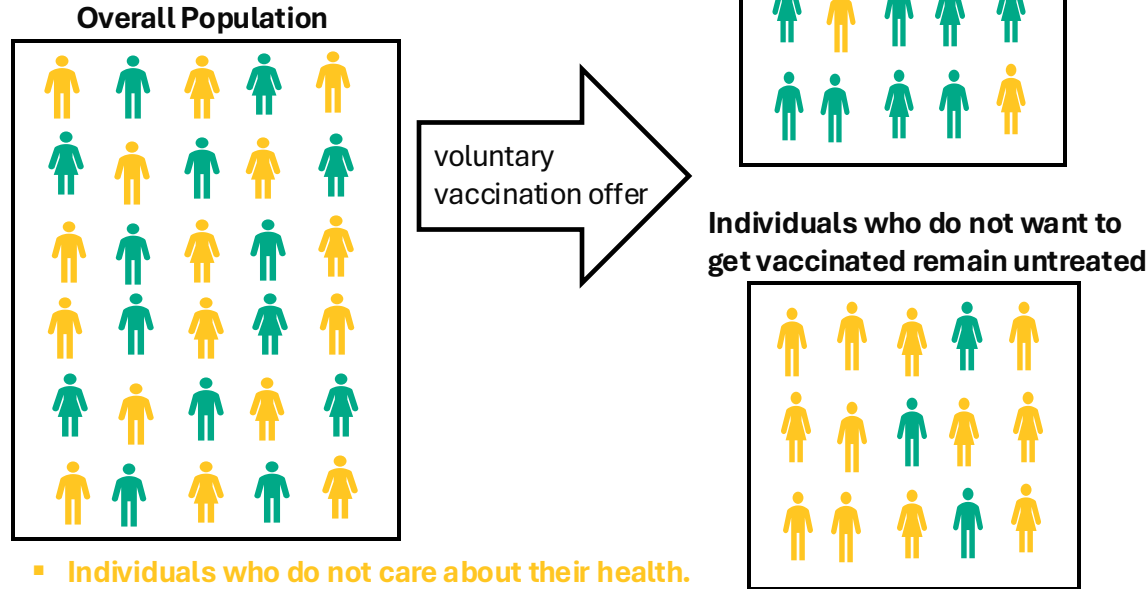
- this leads to **selection bias**!
- **observational data** usually show **correlations**, but not causal relationships.

Why is this problematic?

It leads to **wrong conclusions**, **poor decisions** and ultimately to **inferior outcomes**.



Example: Effectiveness of vaccinations?



- Individuals who do not care about their health.
- Individuals who care about their health.

Problem: selection into treatment based on individual health consciousness.

- a comparison of the two groups would misestimate the effectiveness of vaccinations.

Ways to Overcome Selection Bias

Idea: control for “omitted” factors that drive selection.

- include these drivers as control variables in your regression.
 - but almost always impossible to control for all confounding factors.
 - arbitrary inclusion of control variables can introduce “collider bias” through “bad controls”.

Better solution: use of **quasi-experimental research designs**.

- research methods to detect causalities with observational data.
 - they mimic the experimental idea of random assignment to treatment and control group.

Quasi Experiments

- approximate randomized experiments by using **exogenous variation** from real-world contexts to **infer causality**.
- exploit **naturally occurring** or **policy-induced** variations that mimic **randomization**.
 - situations where units (individuals, regions, firms, etc.) are exposed to a treatment for reasons outside their control.
 - units cannot select into treatment.

Most prominent **quasi-experimental research designs**:

- Regression discontinuity designs (**RDD**).
- Difference-in-Difference (**DiD**) approaches.
- Instrumental Variables (**IV**).

Regression Discontinuity Designs (RDD)

- leverage cutoff regulations or thresholds to assign participants to treatment or control groups.
- **idea:** compare individuals just below and just above the cutoff.
 - at the cutoff, only the treatment changes — other factors remain essentially constant.

Example from my own research:



Journal of Health Economics

Volume 81, January 2022, 102555



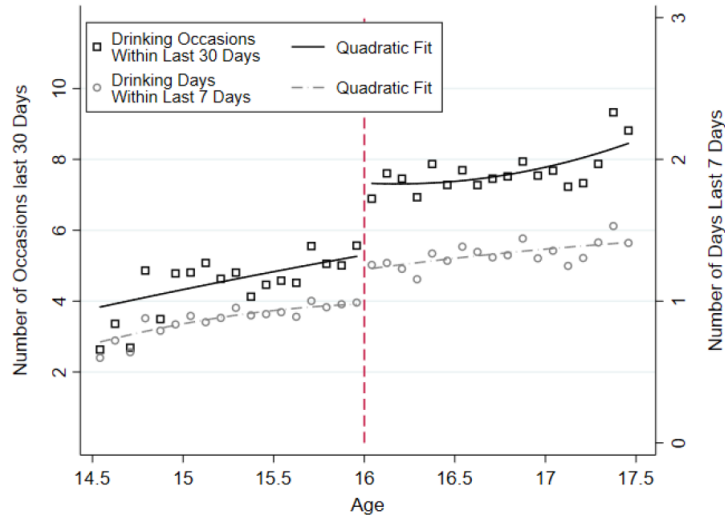
Underage access to alcohol and its impact on teenage drinking and crime ☆

Fabian T. Dehos ✉

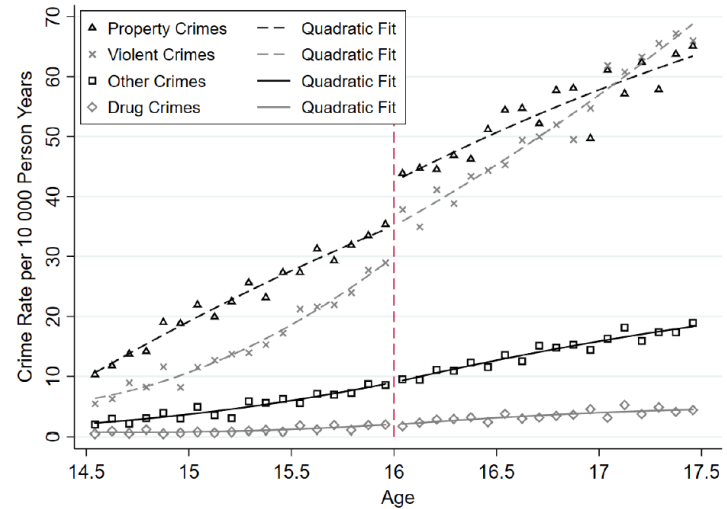
idea: compare drinking and crime behavior around an age-based discontinuity.

- confounding factors remain constant.
- what changes is access to alcohol.
- one obtains causal estimates of the drinking-crime relationship.

Underage Access to Alcohol and Its Impact on Teenage Drinking and Crime



Age profile of **Drinking Frequency** around age 16



Age profile of **Criminal Engagement** around age 16

➤ crimes under the influence of alcohol

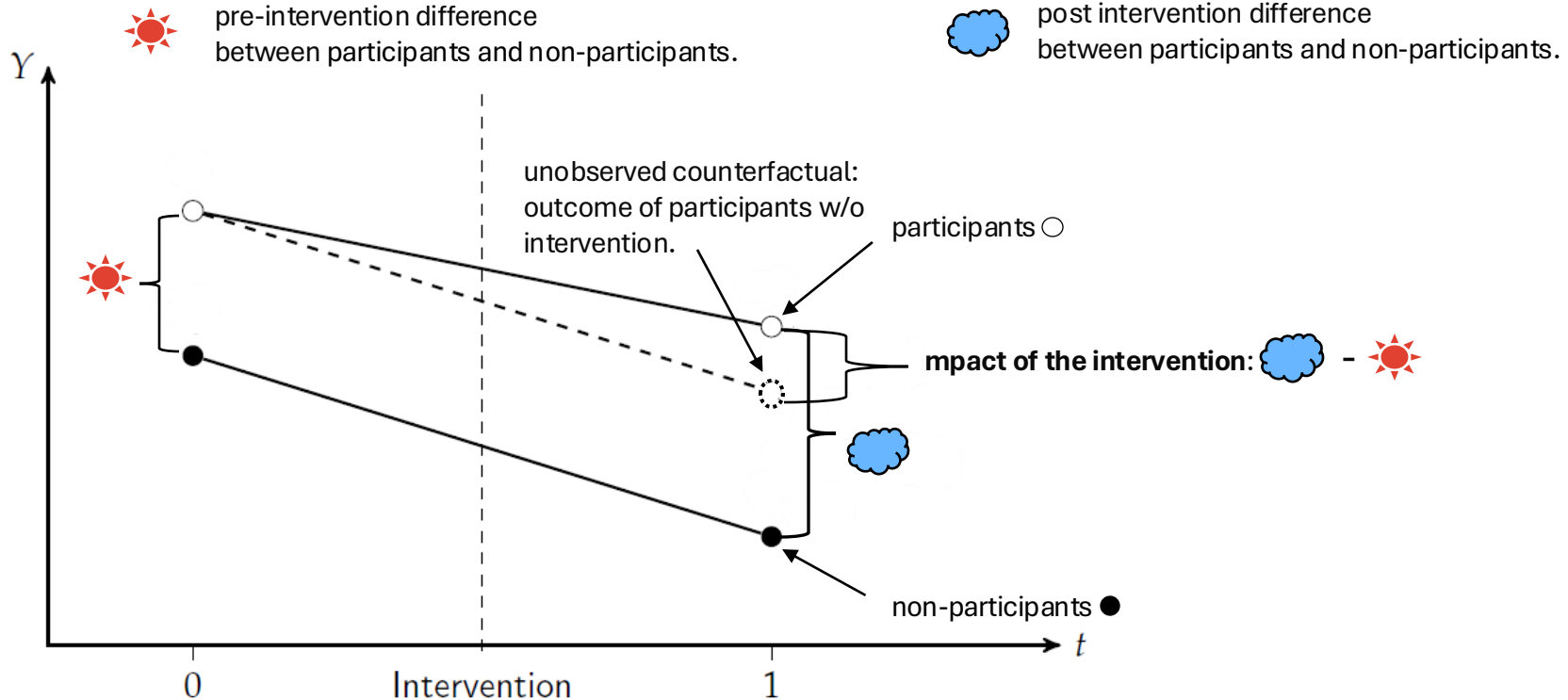
Difference-in-Difference (DiD)

you often see the acronyms **DD**, **Diff-in-diff**, or even **DnD**.

- combines two approaches/comparisons:
 - **before vs. after** the intervention.
 - **participants vs. non-participants** (treatment vs. control group).
- **idea**: compare changes in outcomes over time between participants and non-participants.

DiD: Basic Setup

- idea: compare changes in outcomes over time between participants and non-participants.



Seminal Example: Card and Krueger (1994, AER)



Setting

- in February 1992 **NJ** increased the state minimum wage from \$4.25 to \$5.05.
- Pennsylvania's (**PA**) minimum wage stayed at \$ 4.25.
- the authors surveyed about 400 fast food stores in NJ and PA both before and after the minimum wage increase in NJ.
- the DID-strategy compares the change in employment in NJ to the change in employment in PA.

Result: impact on full-time employment (FTE)

Variable	Stores by state		
	PA (i)	NJ (ii)	Difference, NJ – PA (iii)
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	-2.89 (1.44)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	-0.14 (1.07)
3. Change in mean FTE employment	-2.16 (1.25)	0.59 (0.54)	2.76 (1.36)

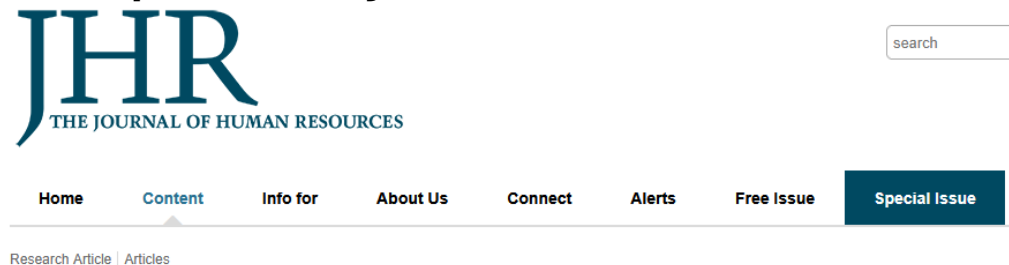


➤ minimum wage increase **did not lead to job losses.**

Instrumental Variables (IV) Approach

- events or factors that influence whether someone receives treatment, which is beyond the individuals' control.
- like a lottery, this approach aims to mimic random assignment.

Example from my own research



The Effects of After-School Programs on Maternal Employment

Fabian T. Dehos and Marie Paul

Published online before print July 12, 2021, 0120-10651R1; DOI: <https://doi.org/10.3368/jhr.58.5.0120-10651R1>

problem:

attendance in After-School Programs (ASPs) is highly selective.

Idea: exploit expansion of ASPs after the PISA-shock 2021.

- ASP expansion grants were “quasi-randomly” assigned across time and space to schools.
- we use ASP grants as in instrument for ASP attendance.
- instrument changes the probability to attend an ASP, but grants are out of maternal control.

My Contact Details



Do you have any **further questions**?

Do you like to learn more about **quasi experiments**?

Do you like to write an **empirical (data-based) thesis** with me?

👉 **Feel free to reach out!**

Email Address: fdehos@constructor.university

Office: Campus Ring 1, Research IV, Office 91