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policy evaluation concepts and methods

Master in Big Data Analytics for Policy Evaluation
Module VIII - Causal models for decision making

roberto leombruni

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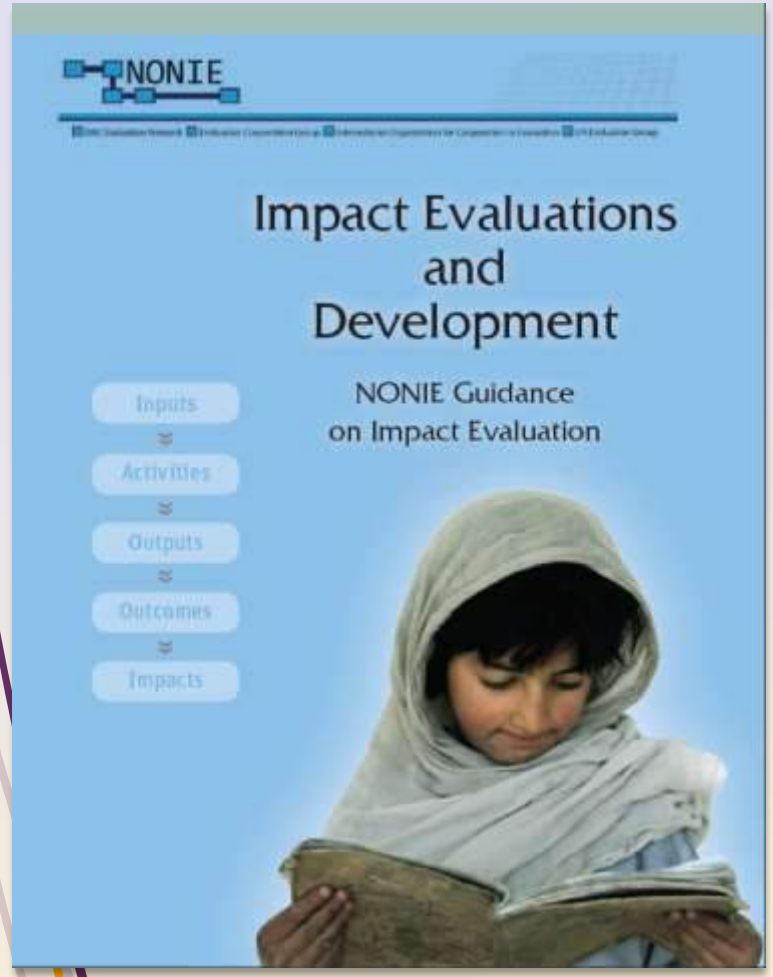

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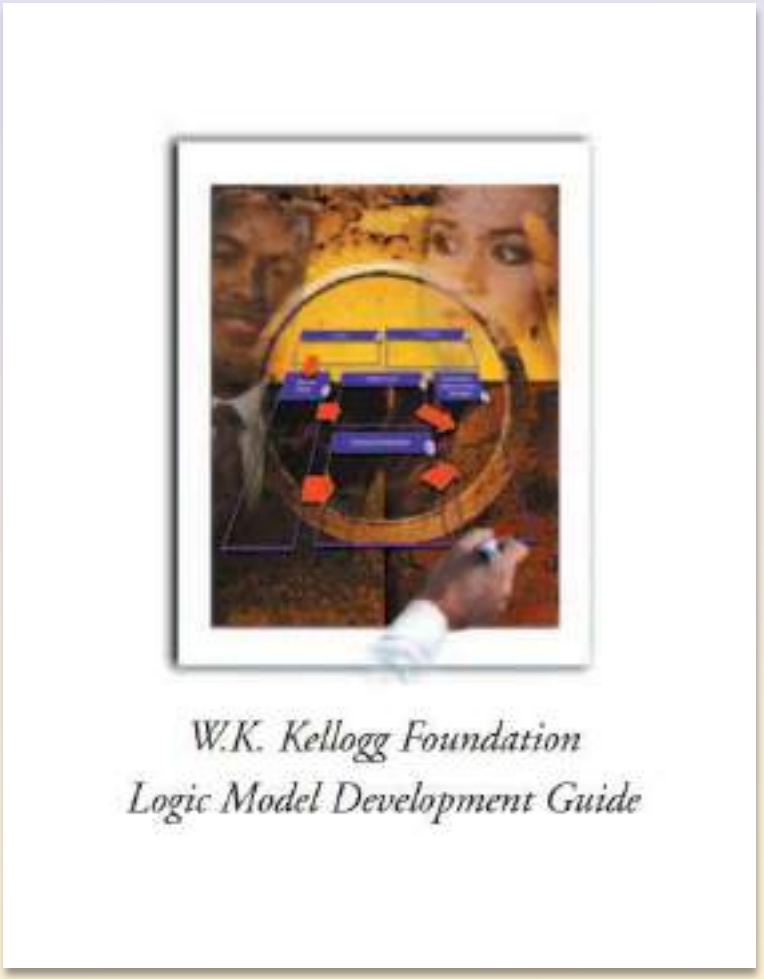
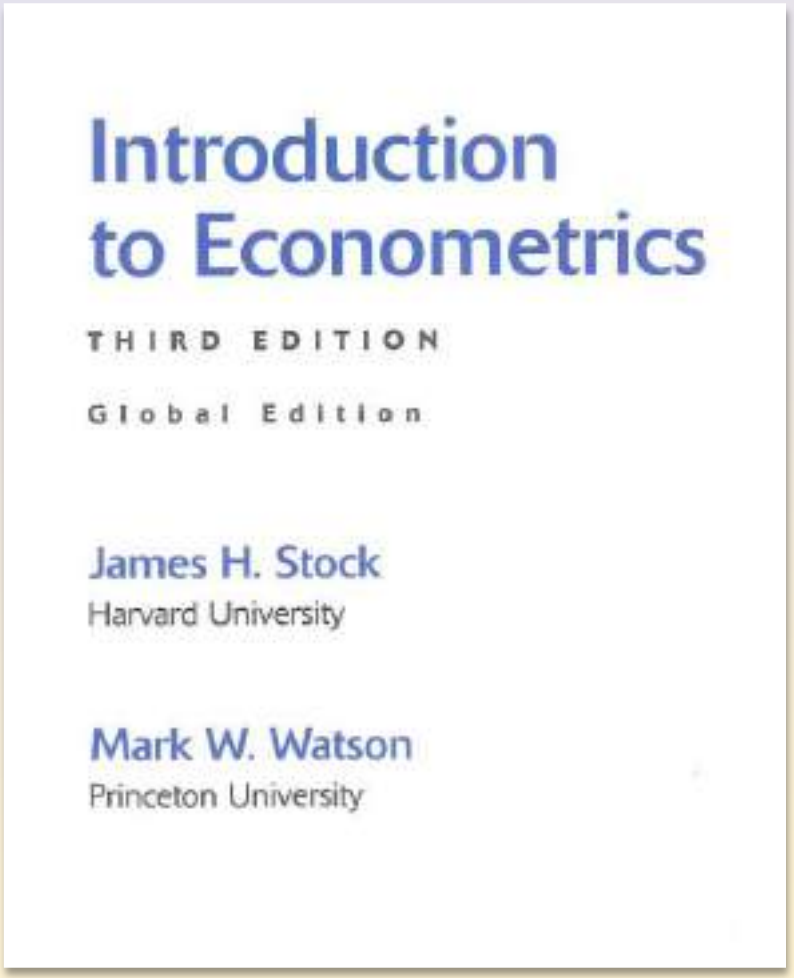


ch 1&2



ch 13

reading suggestions

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menu of the course

0. intro: another look at hypothesis testing
1. policy evaluation: what is, **when** and how
2. before a policy: forecast, forsight and simulations
3. during a policy: monitoring the implementation
4. after a policy: statistical models for causal inference

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intro, from the exam

- Consider the introduction of a minimum wage. From the one side, this may induce a decrease in employment, because firms may decide not to open job positions because their increased costs. From the other side, at higher wages firm can more easily find workers to fill job positions, inducing an increase in employment.
- Consider a country where this policy has been introduced. You have a sample of 1000 firms, about which you know ΔE, the variation in their number of employees after the policy. The average value of ΔE is 2.5, i.e., you register an average increase in employment of 2.5 workers. The standard deviation of ΔE is 1.8.
- Let us first visualize this setting in Excel

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intro, from the exam

- What was the impact of the policy? Which mechanism, if any, prevailed?
- We want to test the hypothesis that the variation in employment induced by the policy is 0, i.e., the hypothesis that the incentives and the disincentives to work are balancing with each other.
- There are two ways of answering this, both hinging on the following:

The shape of the sample mean is that of a Normal, whatever the original distribution

The *Central Limit Theorem* (CLT):

If $(Y_1,\ldots,Y_n)$ are i.i.d. and $0 < \sigma_Y^2 < \infty$, then when n is large the distribution of $\bar{Y}$ is well approximated by a normal distribution.

- $\bar{Y}$ is approximately distributed $N(\mu_Y, \frac{\sigma_Y^2}{n})$ ("normal distribution with mean μ_Y and variance σ_Y^2/n")

Increasing N, the variability of the sample mean is decreasing

$$Var(\bar{Y}) = \frac{\sigma^2_Y}{N}$$

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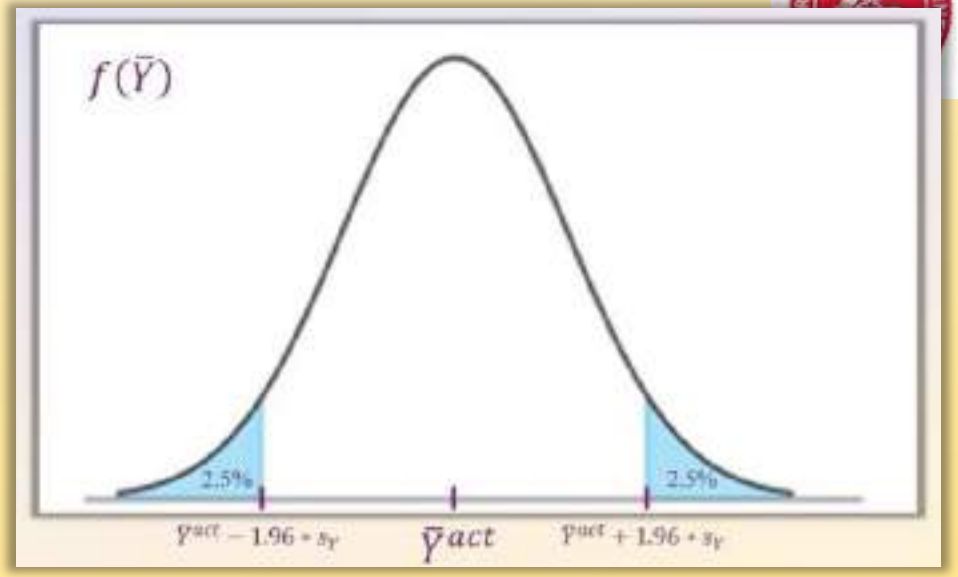
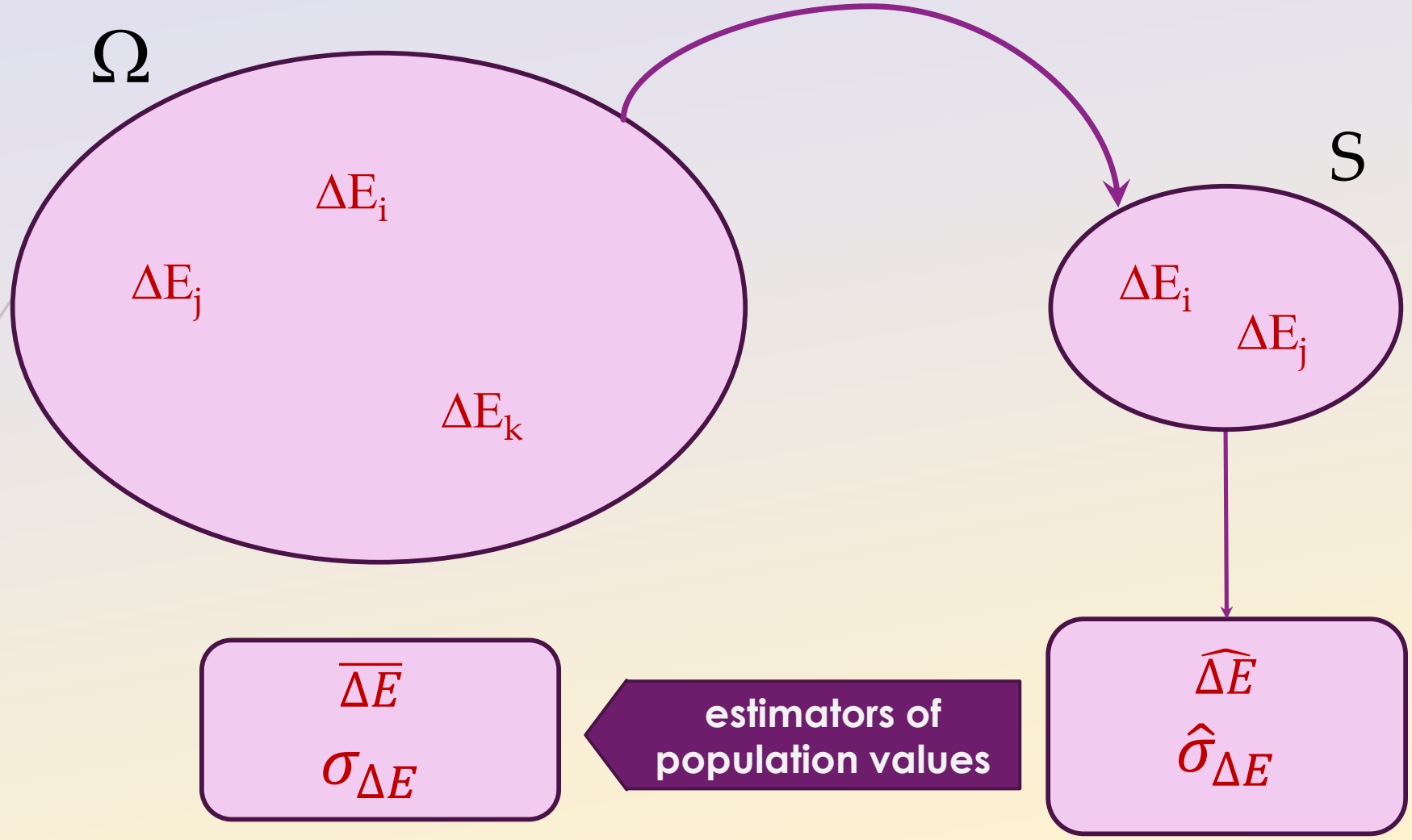
intro, from the exam



- You know that 2.8 is not a sure answer. Build a confidence interval for your estimate, and check whether it comprises 0, the "no harm for employment" hypothesis.
- Express your theory as the following assumption: the policy, on average, will do no harm to the level of employment. Build a "statistic" (a random variable) that under the assumption will have a known distribution, and check weather it's realization is plausible under the null.

Some terminology for testing statistical hypotheses:

p-value = probability of drawing a statistic (e.g. $\bar{Y}$) at least as adverse to the null as the value actually computed with your data, assuming that the null hypothesis is true.

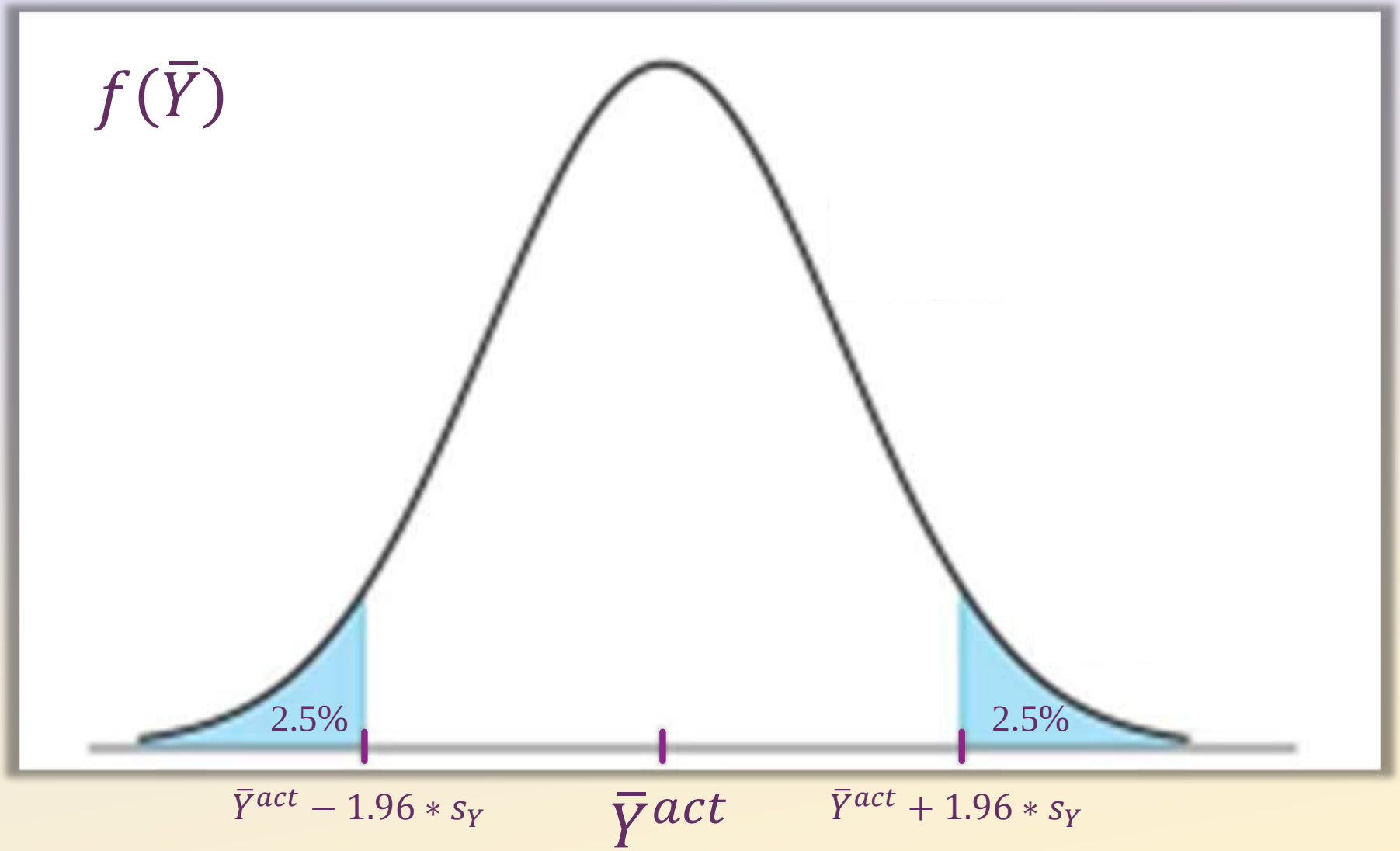


intro, from the exam

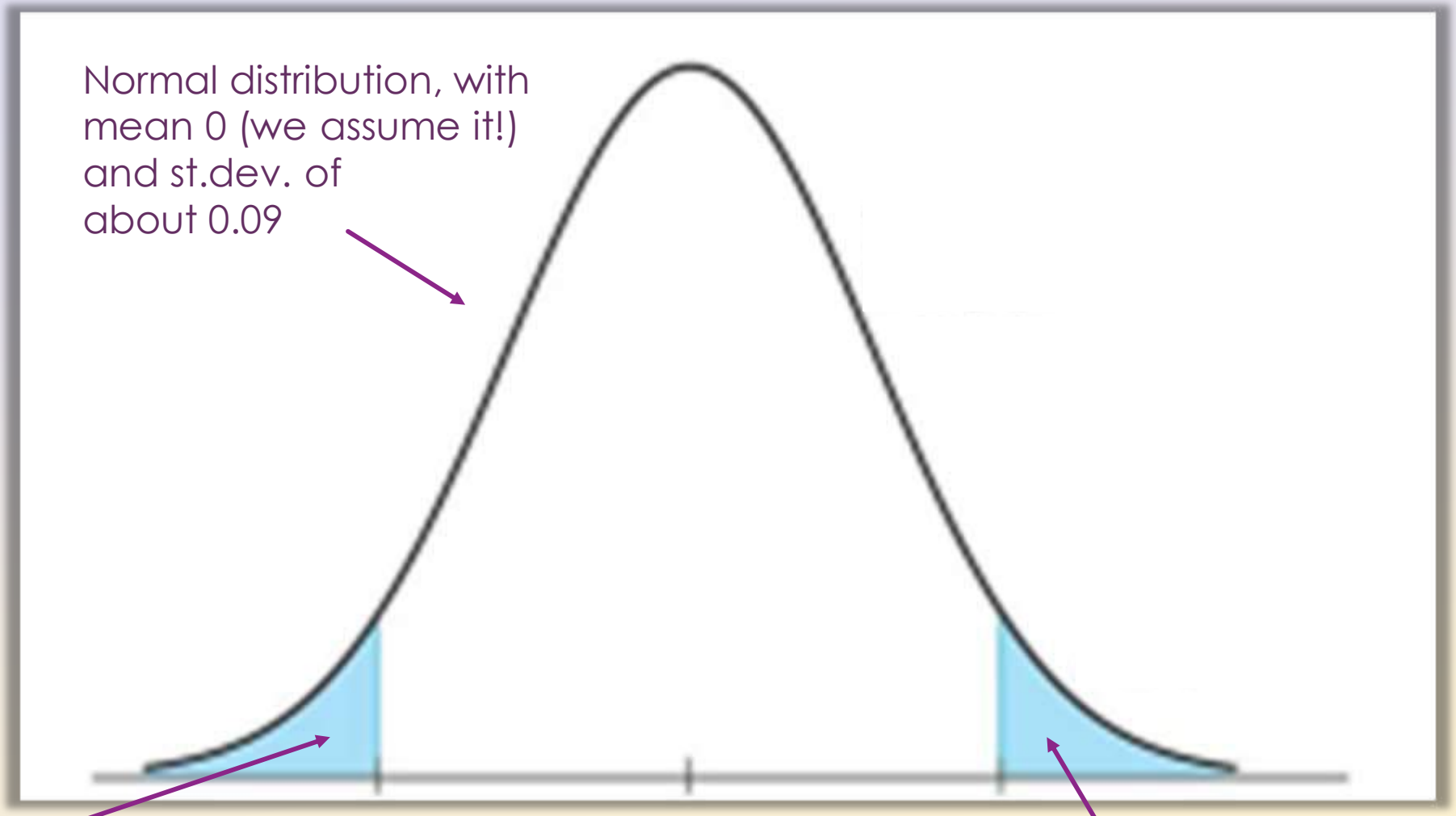
Properties of the sample mean

If S is a random sample (peek *N* firms at random), then the sample mean of the change in employment recorded on them is a nice guess of it, because:

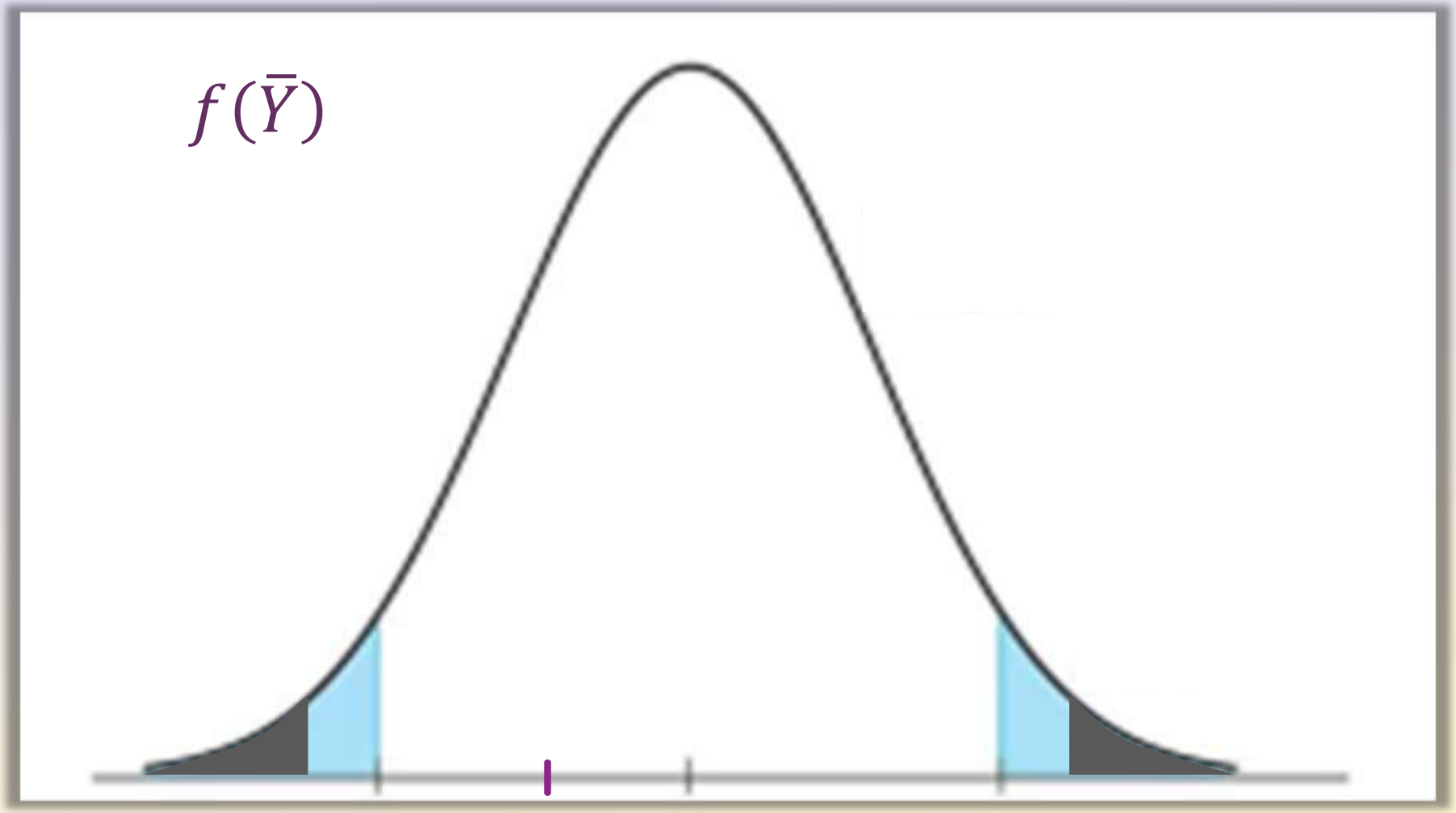
- It is **correct**: E(sample mean) = Average income in the population.
- It is also **consistent**: as N goes big, the sample mean converge to P.
- We know its distribution (if N is large, it is normal), so we know how uncertain is our guess.



1. C.I. → $2.5 \pm 1.96*2.8/\sqrt{1000} \cong 2.5 \pm 0.17$



2. the p-value



We reject the null: the probability of getting an average income this far from the null is negligible.

WIKIPEDIA
The Free Encyclopedia

Evidence-based policy

Evidence-based policy is a concept in public policy that advocates for policy decisions to be grounded on, or influenced by, rigorously established objective evidence. This concept presents a stark contrast to policymaking predicated on ideology, 'common sense,' anecdotes, or personal intuitions. The approach mirrors the effective altruism movement's philosophy within governmental circles. The methodology employed in evidence-based policy often includes comprehensive research methods such as randomized controlled trials (RCT).[1] Good data, analytical skills, and political support to the use of scientific information are typically seen as the crucial elements of an evidence-based approach.[2]

The effectiveness of evidence-based policy hinges upon the presence of quality data, proficient analytical skills, and political backing for the utilization of scientific information.[3]

What is policy evaluation

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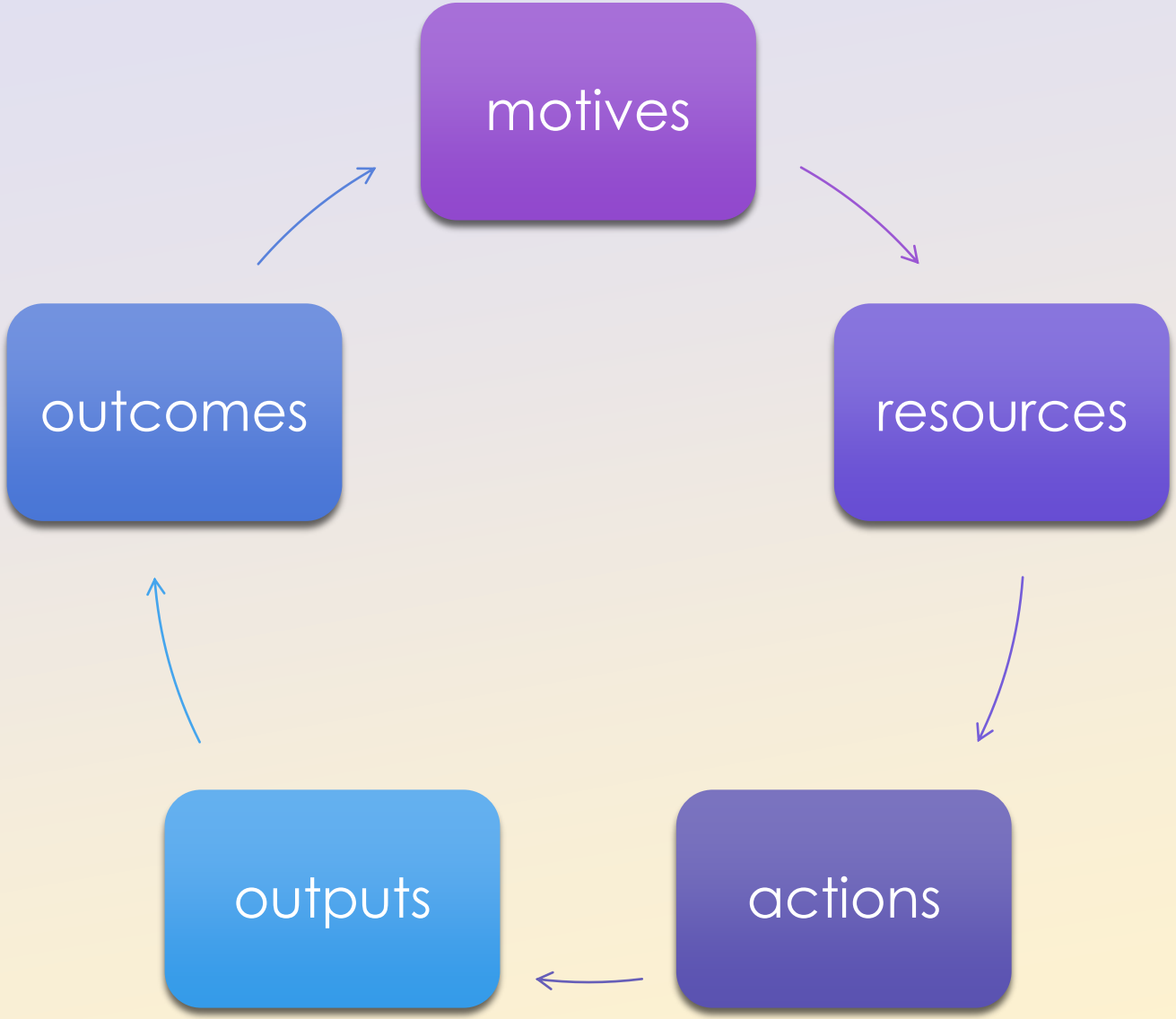
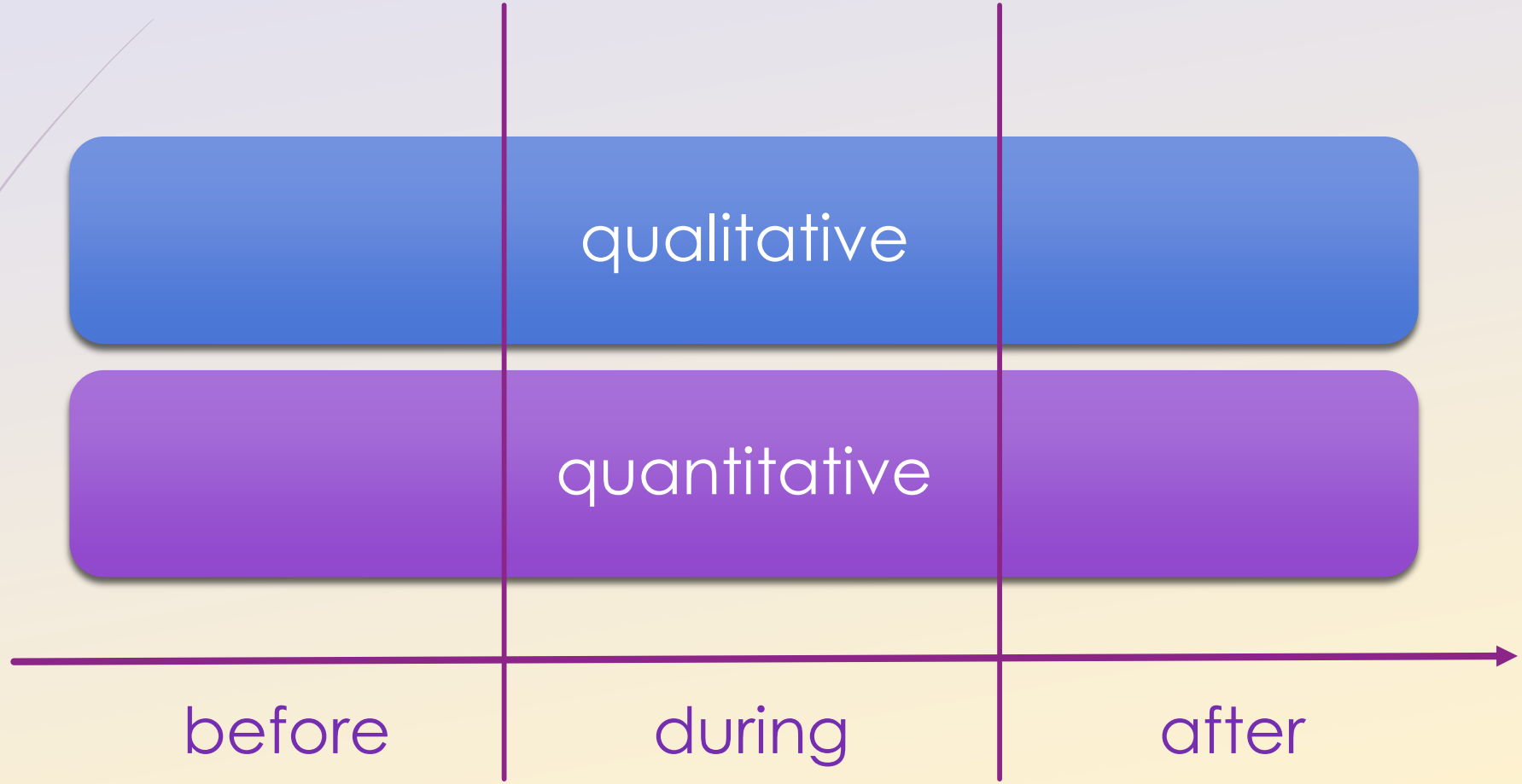


Main points



Main dimensions

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menu of the day

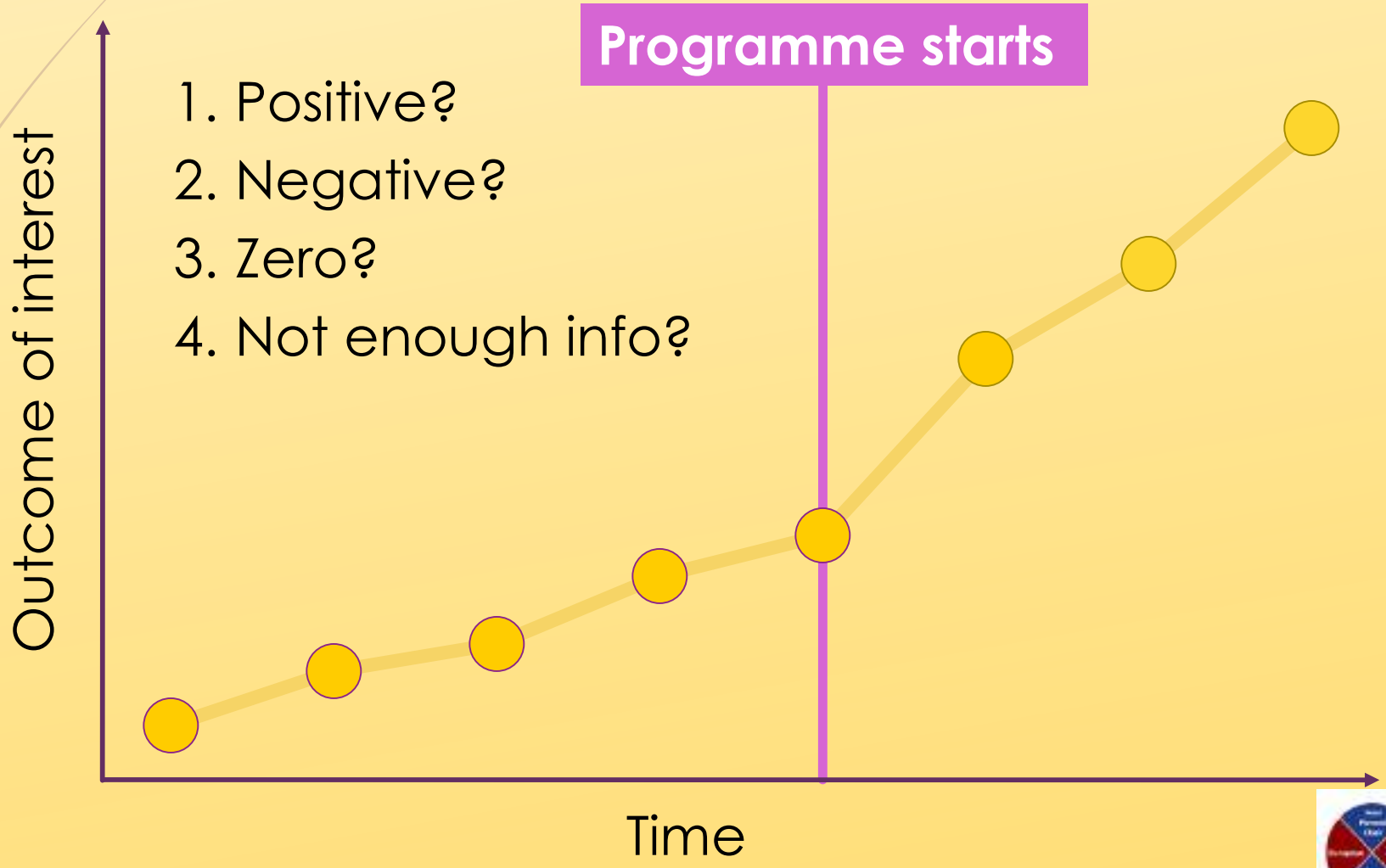
0. intro: another look at… the GDP
1. short an illustrative history of randomized trials for causal explanation
2. experiments and univariate OLS

another look at… the GDP

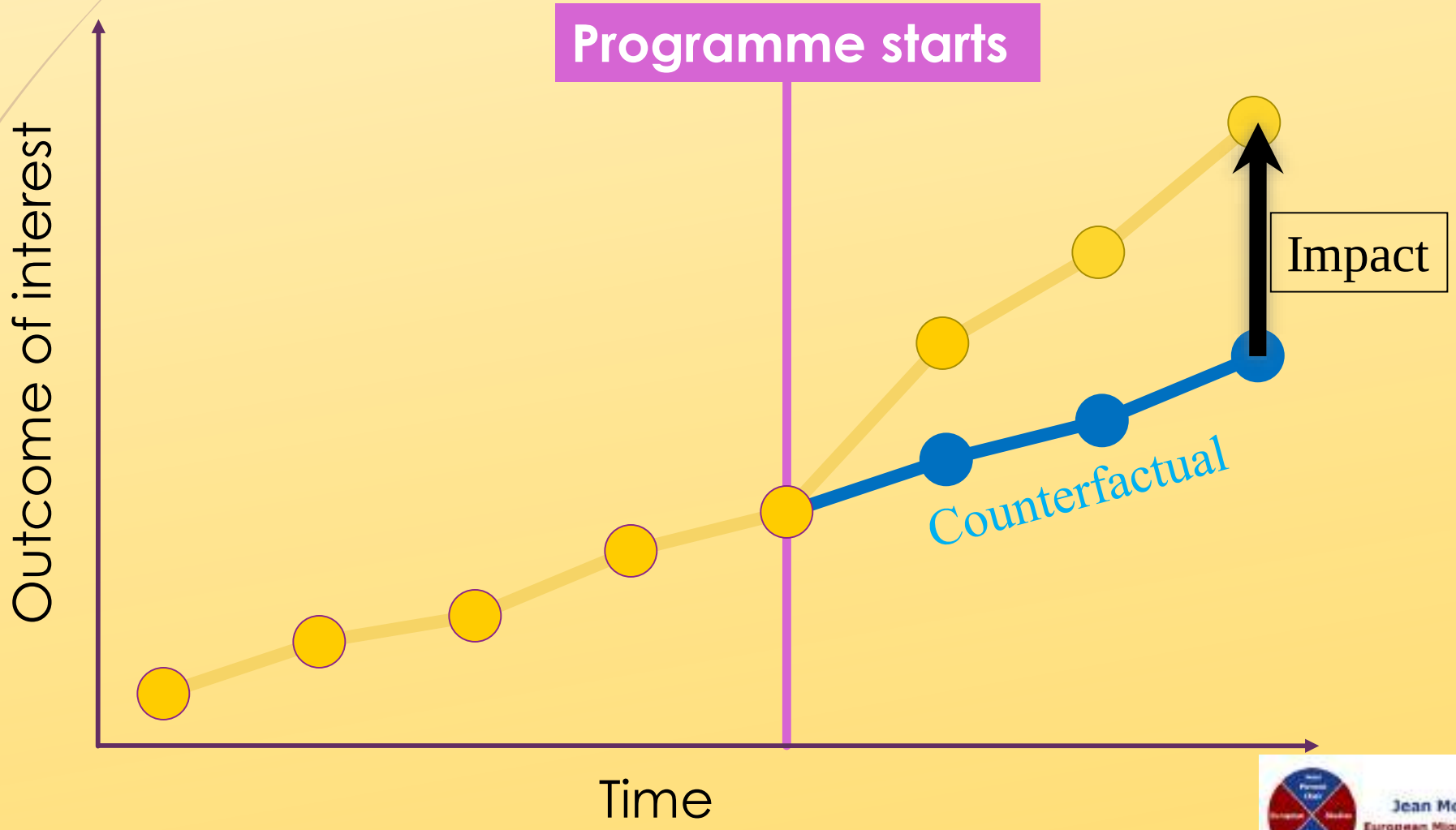
With a little help of my friend… Excel, do the following:

- take again yesterday's example
- «explode» ΔE
- discuss why average ΔE is not a good statistic about the causal effect of minimum wage, writing down a possible GDP illustrating the point

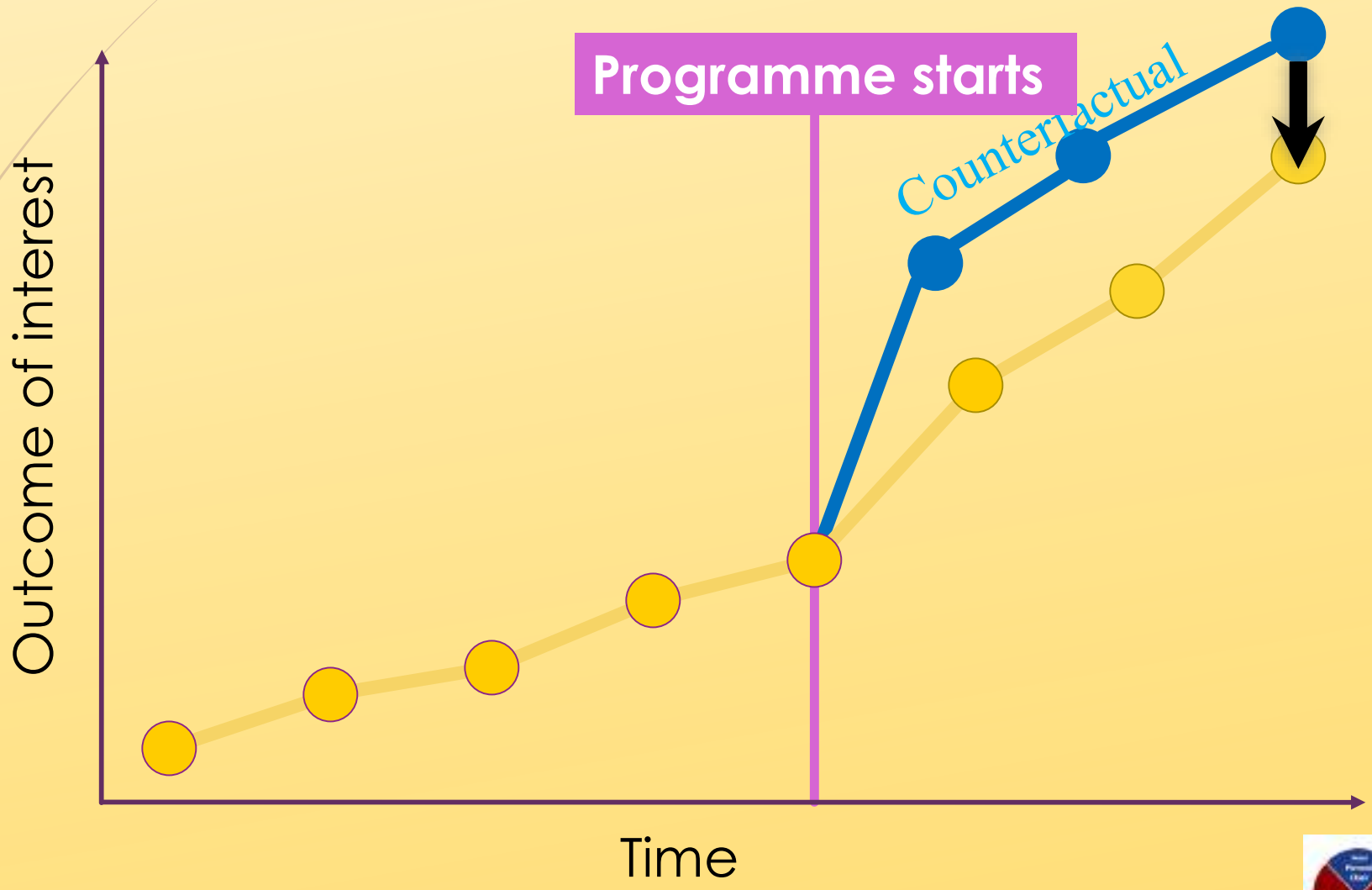
What is the impact of the programme?



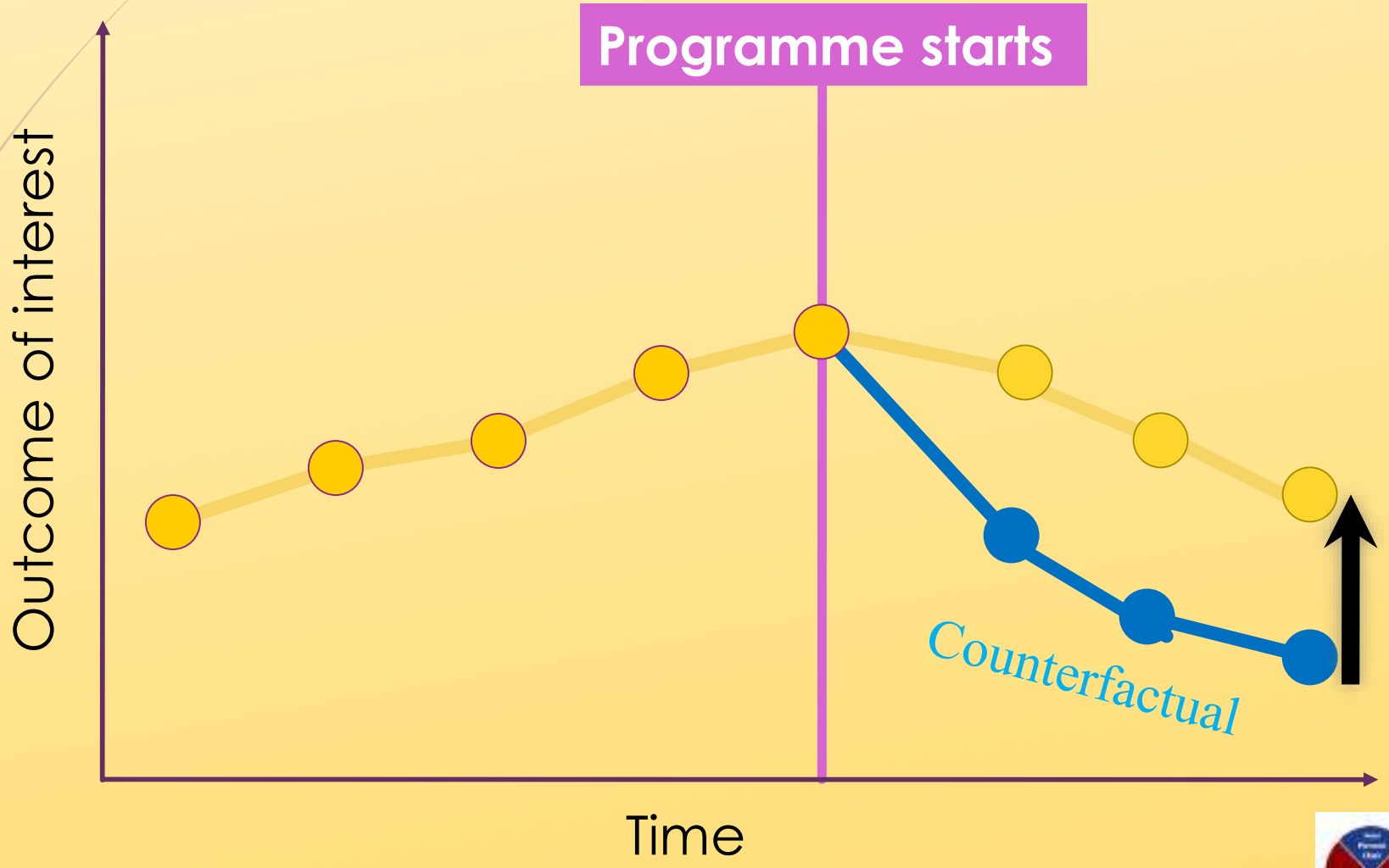
What is the impact of the programme?



What is the impact of the programme?



What is the impact of the programme?



Galileo Galilei
(1564–1642)

experiments in science, a brief history

Is the veggy diet bad for your health?

Daniel Taken to Babylon, 1-13

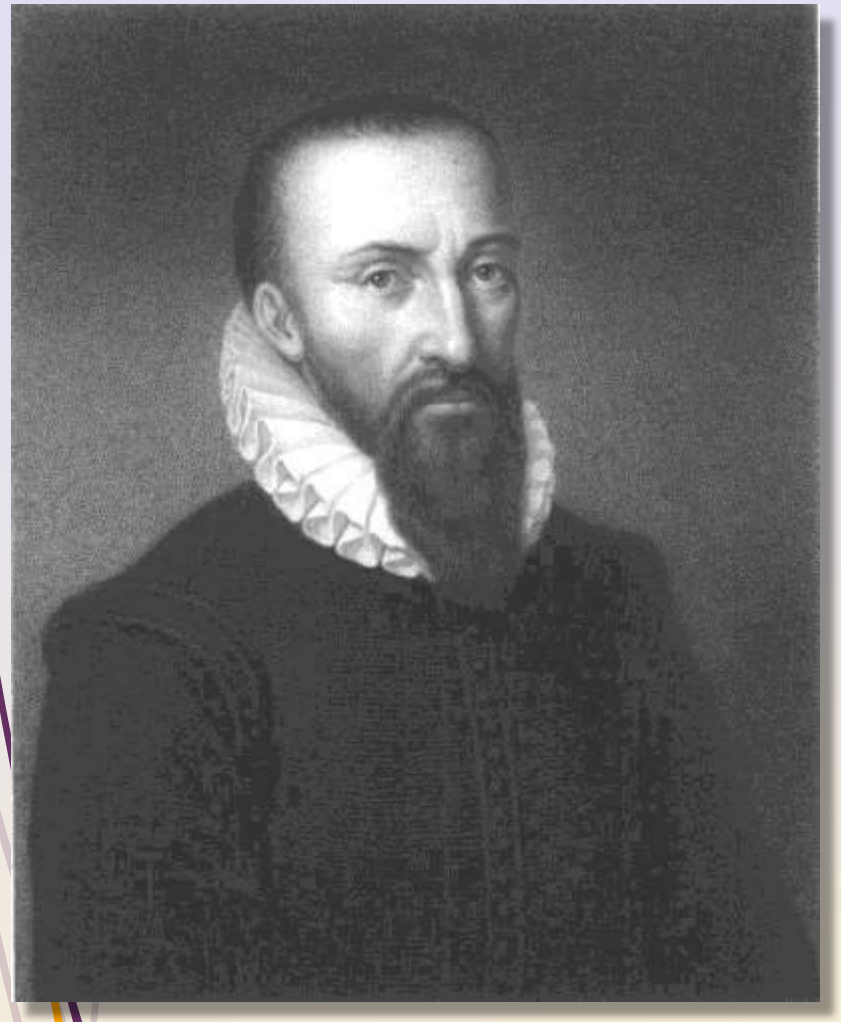
- During the third year that Jehoiakim was king of Judah, Nebuchadnezzar king of Babylon came to Jerusalem and surrounded it with his army.
- Then King Nebuchadnezzar ordered Ashpenaz, his chief officer, to bring some of the men of Judah into his palace. […] They were to be handsome and well educated, capable of learning and understanding, and able to serve in his palace. […] The king gave the young men a certain amount of food and wine every day, just like the food he ate.
- Daniel decided not to eat the king's food or drink his wine because that would make him unclean. So he asked Ashpenaz for permission not to make himself unclean in this way. […] but Ashpenaz said to Daniel, "I am afraid of my master, the king. He ordered me to give you this food and drink. If you begin to look worse than other young men your age, the king will see this. Then he will cut off my head because of you."

the simplest (and older!) idea

Daniel said to the guard, “Please give us this test for ten days: Don’t give us anything but vegetables to eat and water to drink. After ten days compare how we look with how the other young men look who eat the king’s food. See for yourself and then decide how you want to treat us, your servants.”

just try!

the simplest (and older!) idea

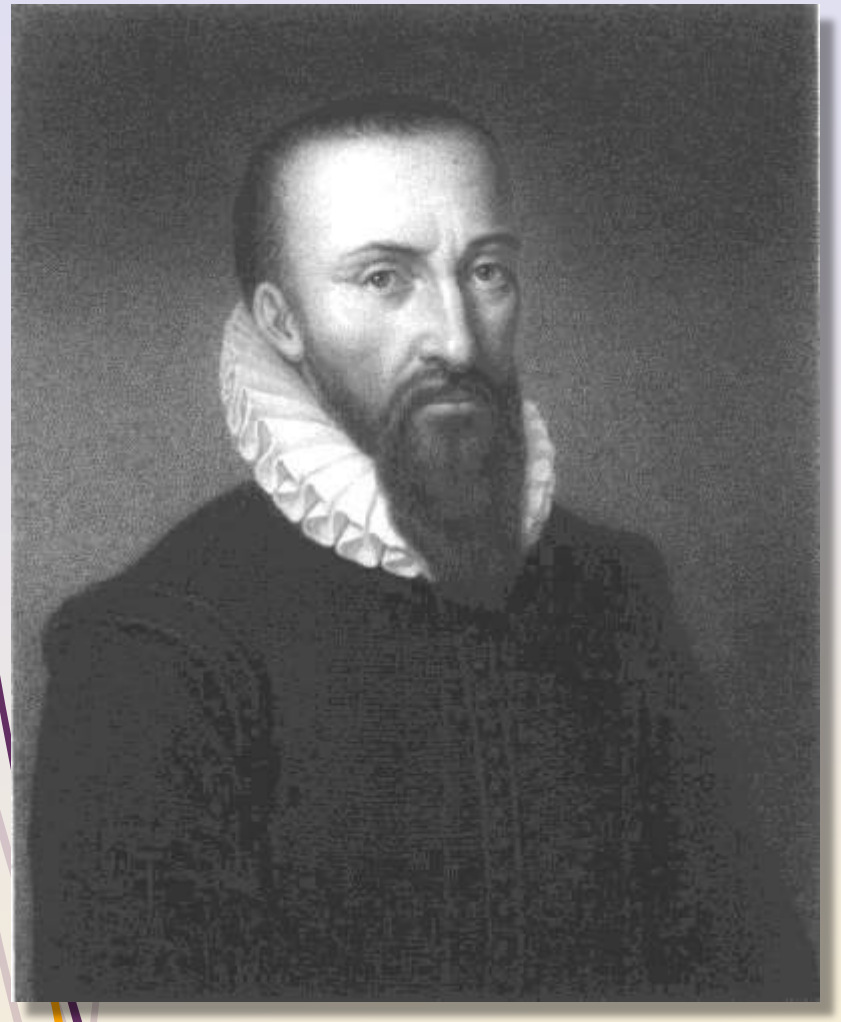


Ambroise Paré (1510 1590)

- In 1567, Ambroise Paré described an experiment to test the properties of bezoar stones. At the time, the stones were commonly believed to be able to cure the effects of any poison, but Paré believed this to be impossible.
- It happened that a cook at Paré's court was caught stealing fine silver cutlery, and was condemned to be hanged. The cook agreed to be poisoned, on the conditions that he would be given a bezoar straight after the poison and go free in case he survived. The stone did not cure him, and he died in agony seven hours after being poisoned. Thus Paré had proved that bezoars could not cure all poisons.

just try!

first modern examples (1.1)



Ambroise Paré (1510 1590)

- In 1537 he was responsible for the treatment of the wounded, after the capture of the castle of Villaine. They were so numerous that, he says, ‘at length my oil lacked and I was constrained to apply in its place a digestive made of yolks of eggs, oil of roses and turpentine. That night I could not sleep at any ease […]
- I raised myself early to visit them, when beyond my hope I found those to whom I had applied the digestive medicament feeling but little pain, their wounds neither swollen nor inflamed, and having slept through the night. The others to whom I had applied the boiling oil were feverish with much pain and swelling about their wounds’. (Bull, 1951)

the comparison group

first modern examples (1.2)

Jan Baptist van Helmont
(1580-1644)

- He engaged in the new learning based on experimentation that was producing men like William Harvey, Galileo Galilei and Francis Bacon. Van Helmont was a careful observer of nature; his analysis of data gathered in his experiments suggests that he had a concept of the conservation of mass.
- He performed an experiment to determine where plants get their mass. He grew a willow tree and measured the amount of soil, the weight of the tree and the water he added. After five years the plant had gained about 164 lbs (74 kg). Since the amount of soil was basically the same as it had been when he started his experiment (it lost only 57 grams), he deduced that the tree's weight gain had come from water.

controlled conditions

first modern examples (2.1)

Jan Baptist van Helmont
(1580-1644)

- He participated to a fiercy debate about the use of **bloodletting**, as an all-purpose cure for desperate situations.
- "Let us take out of the Hospitals, out of the Camps, or from elsewhere, 200 or 500 poor People, that have Fevers, Pleurisies, etc. Let us divide them in halfes, **let us cast lots**, that one half of them may fall to my share, and the other to yours; I will cure them without bloodletting… we shall see how many Funerals both of us shall have", Ortus medicinæ: Id est Initia physicæ inaudita, 1648 pp 526-527

`randomization!`

first modern examples (2.2)

Lady Mary Wortley Montagu
(1689-1762)

- She defied convention most memorably with her pioneering of a **smallpox inoculation**, a course of action unparalleled in medical advance up to that point. Lady Mary's own brother had died of smallpox and her own famous beauty had been marred by a bout with the disease in 1715. In 1717, she went to live in Turkey with her husband, the British ambassador to that country, and stayed for two years. In the Ottoman Empire, she visited the women in their segregated zenanas, learning Turkish, making friends and learning about Turkish customs. There she witnessed the practice of inoculation against smallpox—variolation—which she called engrafting, and wrote home about it.

first modern examples (3.1)

Lady Mary Wortley Montagu (1689-1762)

- Lady Mary was eager to spare her children, and had her son inoculated while in Turkey. On her return to London, she enthusiastically promoted the procedure, but encountered a great deal of resistance from the medical establishment.
- She finally persuaded Princess Caroline to **test the treatment**. Seven prisoners awaiting execution were offered the chance to undergo variolation instead of execution: they all survived and were released. Then six orphan children were inoculated: they all survived. In 1722 King George I allowed to inoculate two of his grandchildren, children of the Princess. They recovered, too.

a pilot!

first modern examples (3.2)

James Lind
(1716-1794)

- **Scurvy** is a disease caused by a vitamin C deficiency, but in Lind's day, the concept of vitamins was unknown.
- Since antiquity in some parts of the world, and since the 17th century in England, it had been known that citrus fruit had an antiscorbutic effect. John Woodall, an English military surgeon recommended them but their use did not become widespread.
- Although Lind was not the first to suggest citrus as a cure for scurvy, he was the first to study its effect by a systematic experiment in 1747. It was one of the first reported, **controlled, clinical experiments** in history.

first modern examples (4.1)

James Lind
(1716-1794)

- He divided twelve scorbutic sailors into six groups of two. They all received the same diet, but in addition group one was given a quart of cider daily, group two twenty-five drops of elixir of vitriol (sulfuric acid), group three six spoonfuls of vinegar, group four half a pint of seawater, group five two oranges and one lemon, and the last group a spicy paste plus a drink of barley water. The treatment of group five stopped after six days when they ran out of fruit, but by that time one sailor was fit for duty while the other had almost recovered.
- "I took twelve patients in the scurvy, on board the Salisbury at sea. The cases were as similar as I could have them….they lay together in one place…. and had one diet common to all."

first modern examples (4.2)

balancing

Further points

- The importance of being… blind
  Part 1: don't tell the patients

Experiment on Mesmerism, 1784

Further points

- The importance of being… blind
  Part 2: don't tell the doctors, too!

Allgemeine Zeitung
von und für Bayern.
Tagsblatt für Politik, Literatur, Kunst und Unterhaltung.
(Zweiter Jahrgang.)

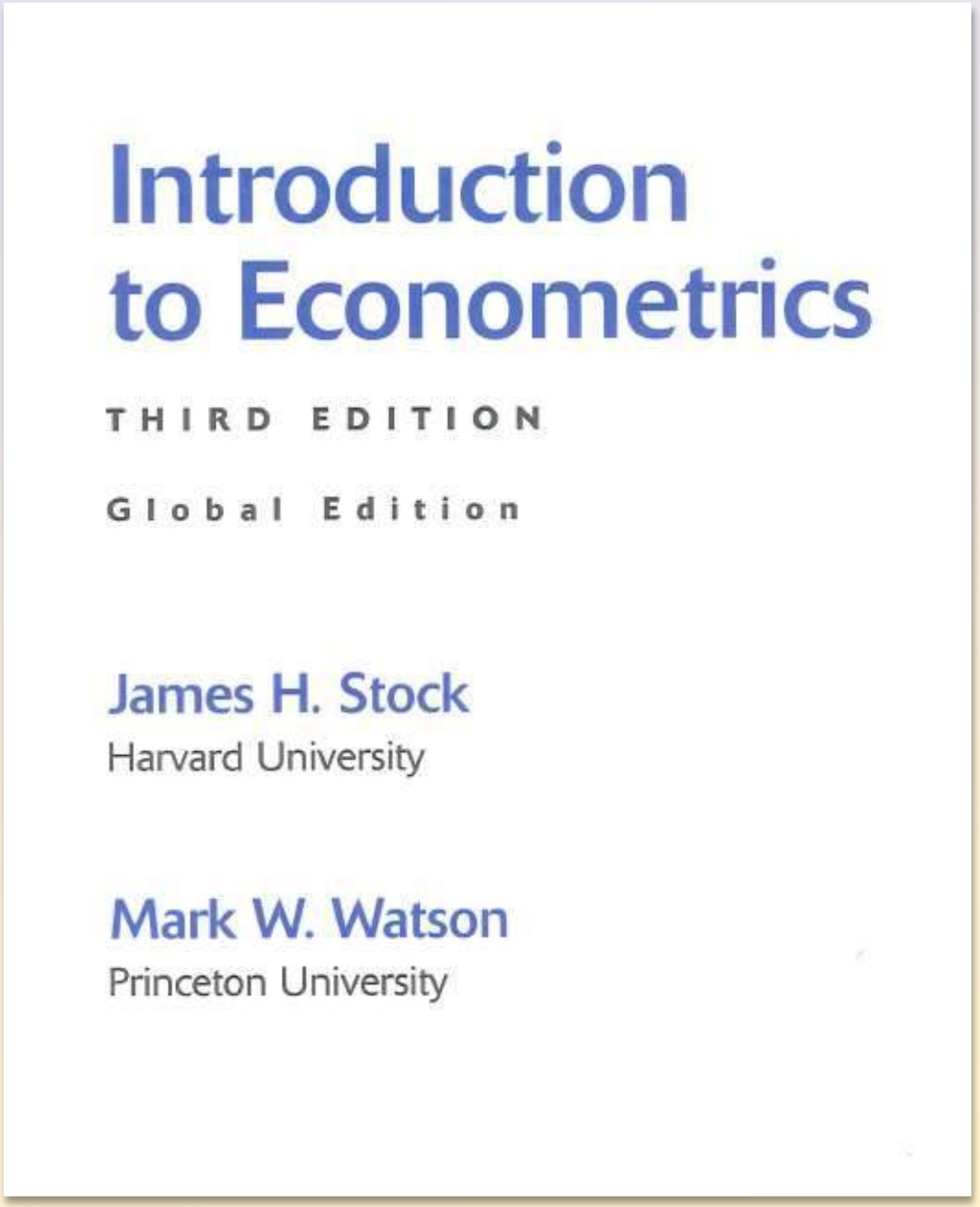
Nr. 35. Mittwoch. Nürnberg, den 4. Februar 1835.

Ausland.

[the Nuremberg salt test on Omeopathy,1835]

Chapter 13

- Experiments and Quasi-Experiments



Experiments and Quasi-Experiments

Why study experiments?

- Ideal randomized controlled experiments provide a benchmark for assessing observational studies.
- Actual experiments are rare ($$$) but influential.
- Experiments can solve the threats to internal validity of observational studies, but they have their own threats to internal validity.
- Thinking about experiments helps us to understand quasi-experiments, or “natural experiments,” in which there some variation is “as if” randomly assigned.

Terminology: experiments and quasi-experiments

- An ***experiment*** is designed and implemented consciously by human researchers. An experiment entails conscious use of a treatment and control group with random assignment (e.g. clinical trials of a drug)
- A ***quasi-experiment*** or ***natural experiment*** has a source of randomization that is "as if" randomly assigned, but this variation was not part of a conscious randomized treatment and control design.
- ***Program evaluation*** is the field of statistics aimed at evaluating the effect of a program or policy, for example, an ad campaign to cut smoking.

Different types of experiments: three examples

- Clinical drug trial: does a proposed drug lower cholesterol?
  - Y = cholesterol level
  - X = treatment or control group (or dose of drug)

- Job training program (Job Training Partnership Act)
  - Y = has a job, or not (or Y = wage income)
  - X = went through experimental program, or not

- Class size effect (Tennessee class size experiment)
  - Y = test score (Stanford Achievement Test)
  - X = class size treatment group (regular, regular + aide, small)

Our treatment of experiments: a brief outline

- Why (precisely) do ideal randomized controlled experiments provide estimates of causal effects?
- What are the main threats to the validity (internal and external) of actual experiments – that is, experiments actually conducted with human subjects?
- Flaws in actual experiments can result in X and u being correlated (threats to internal validity).
- Some of these threats can be addressed using the regression estimation methods we have used so far: multiple regression, panel data, IV regression.

Idealized Experiments and Causal Effects

- An ideal randomized controlled experiment randomly assigns subjects to treatment and control groups.
- More generally, the treatment level X is randomly assigned:

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

- If X is randomly assigned (for example by computer) then u and X are independently distributed, so $E(u_i|X_i) = 0$, so OLS yields an unbiased estimator of β_1.
- The ***causal effect*** is the population value of β_1 in an ideal randomized controlled experiment

Estimation of causal effects in an ideal randomized controlled experiment

- Random assignment of X implies that $E(u_i|X_i) = 0$.
- Thus the OLS estimator $\hat{\beta}_1$ is unbiased.
- When the treatment is binary, $\hat{\beta}_1$ is just the difference in mean outcome (Y) in the treatment vs. control group ($\bar{Y}^{treated} - \bar{Y}^{control}$).
- This difference in means is sometimes called the ***differences estimator*.**

Potential Problems with Experiments in Practice

Threats to Internal Validity

1. ***Failure to randomize*** (or imperfect randomization)
   - for example, openings in job treatment program are filled on first-come, first-serve basis; latecomers are controls
   - result is correlation between X and u

Threats to internal validity, ctd.

1. ***Failure to follow treatment protocol*** (or "***partial compliance***")
   - some controls get the treatment
   - some "treated" get controls
   - "errors-in-variables" bias: $\text{corr}(X,u) \neq 0$
   - Attrition (some subjects drop out)
   - suppose the controls who get jobs move out of town; then $\text{corr}(X,u) \neq 0$

Threats to internal validity, ctd.

1. ***Experimental effects***
   - experimenter bias (conscious or subconscious): treatment X is associated with "extra effort" or "extra care," so corr(X,u) $\neq$ 0
   - subject behavior might be affected by being in an experiment, so corr(X,u) $\neq$ 0 (Hawthorne effect)

Just as in regression analysis with observational data, threats to the internal validity of regression with experimental data implies that corr(X,u) $\neq$ 0 so OLS (the differences estimator) is biased.

George Elton Mayo and the Hawthorne Experiment

Subjects in the Hawthorne plant experiments, 1924 – 1932

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policy evaluation concepts and methods, day III

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menu of the day

0. prologue: the potential outcomes notation
1. from PON to RCT to naïve estimators
2. another look at the OLS hypothesis, and to the omitted variable bias

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what did we see yesterday…

	A	B	C	D	E
1	minimum wage	1			
2	Employment in t=1	"natural" Δ Employment	Δ Employment due to the policy	Employment in t=2	observed Δ Employment
3	51	4	-2	53	2
4	99	-3	0	96	-3
5	67	8	-1	74	7
6	55	-2	-2	51	-4
7	71	5	-2	74	3

These are what we call POTENTIAL OUTCOMES

	A	B	C	D	E
1	minimum wage	0			
2	Employment in t=1	"natural" Δ Employment	Δ Employment due to the policy	Employment in t=2	observed Δ Employment
3	51	4	-2	55	4
4	99	-3	0	96	-3
5	67	8	-1	75	8
6	55	-2	-2	53	-2
7	71	5	-2	76	5

The potential outcomes notation (1/2)

Y^0 ≡ the outcome that we would observe in case the unit **received** the treatment

Y^1 ≡ the outcome that we would observe in case the unit **would not receive** the treatment

The outcome that we actually observe, Y, is the **factual**.

The outcome that we would have observed in the opposite treatment state is the **counterfactual**.

→ *get back to excel: can you write a formula to compute the counterfactual??*

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The potential outcomes notation (2/2)

With this simple notation we can clarify many different things.

First, what is the effect of a treatment:

$$\beta \equiv Y^1 - Y^0$$

Second, what is the difference betwee experimental and observational data… so, let's get back to the RCT!

NB → If we consider a particular sub-population A, the effect of the treatment in A is:

$$\beta_A \equiv Y_A - Y_A$$

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the «toolbox» of an experimenter

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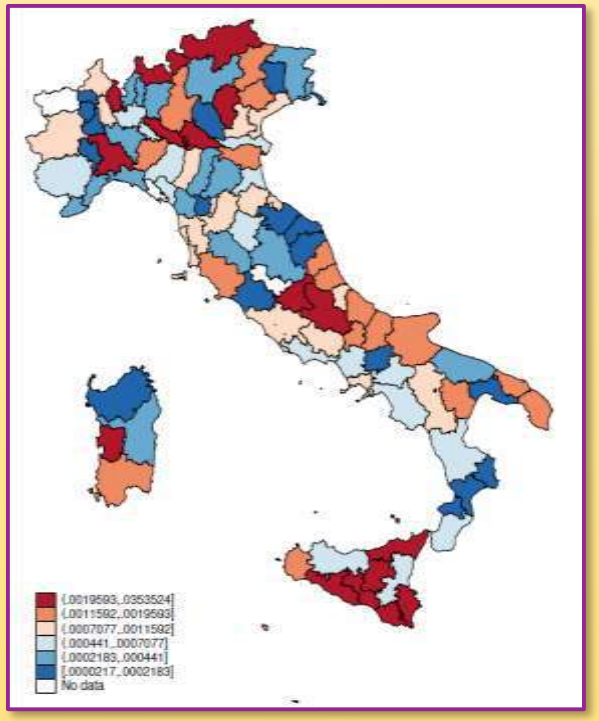
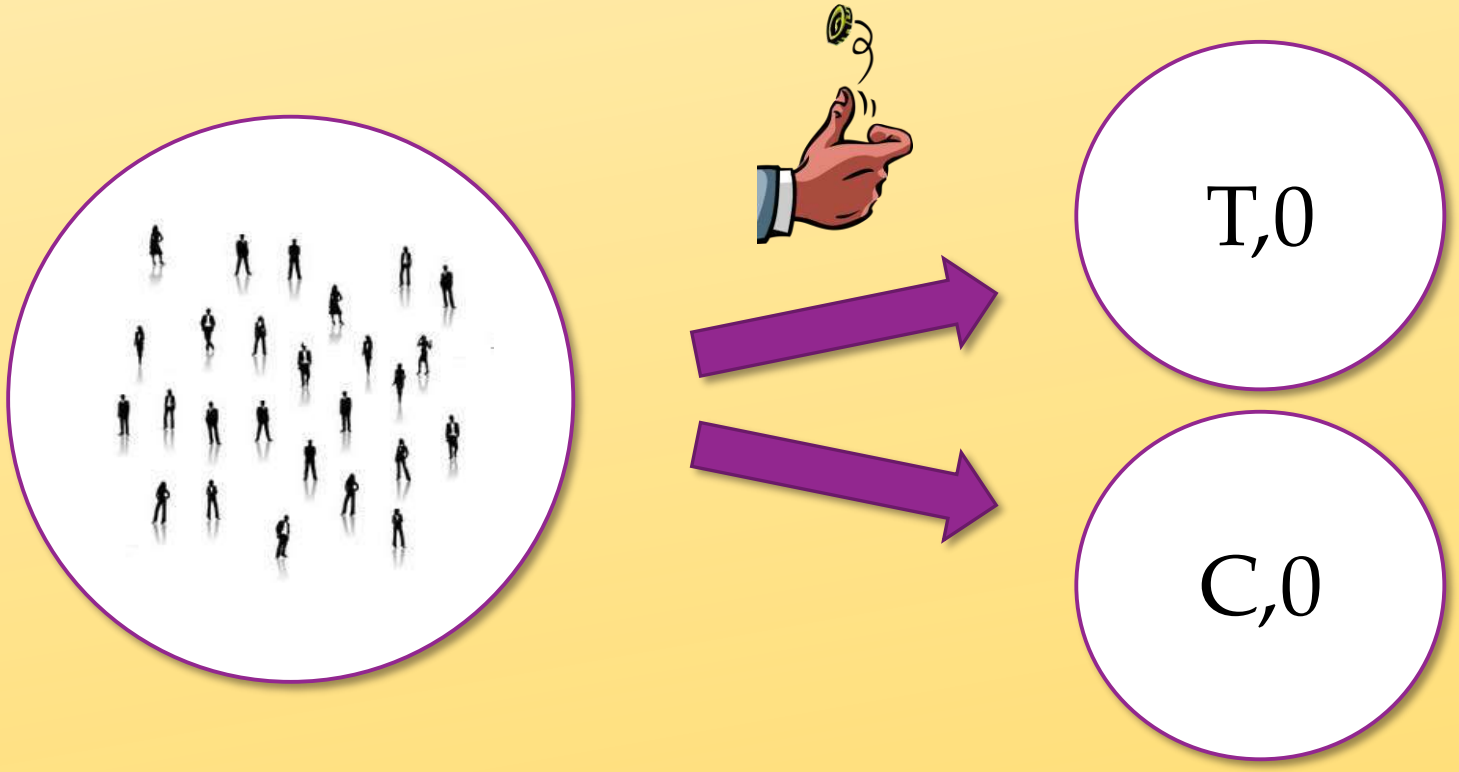
Step 0: randomize the reference population

- important for **external validity**



Step 1: randomize the population under study

- important for **internal validity**



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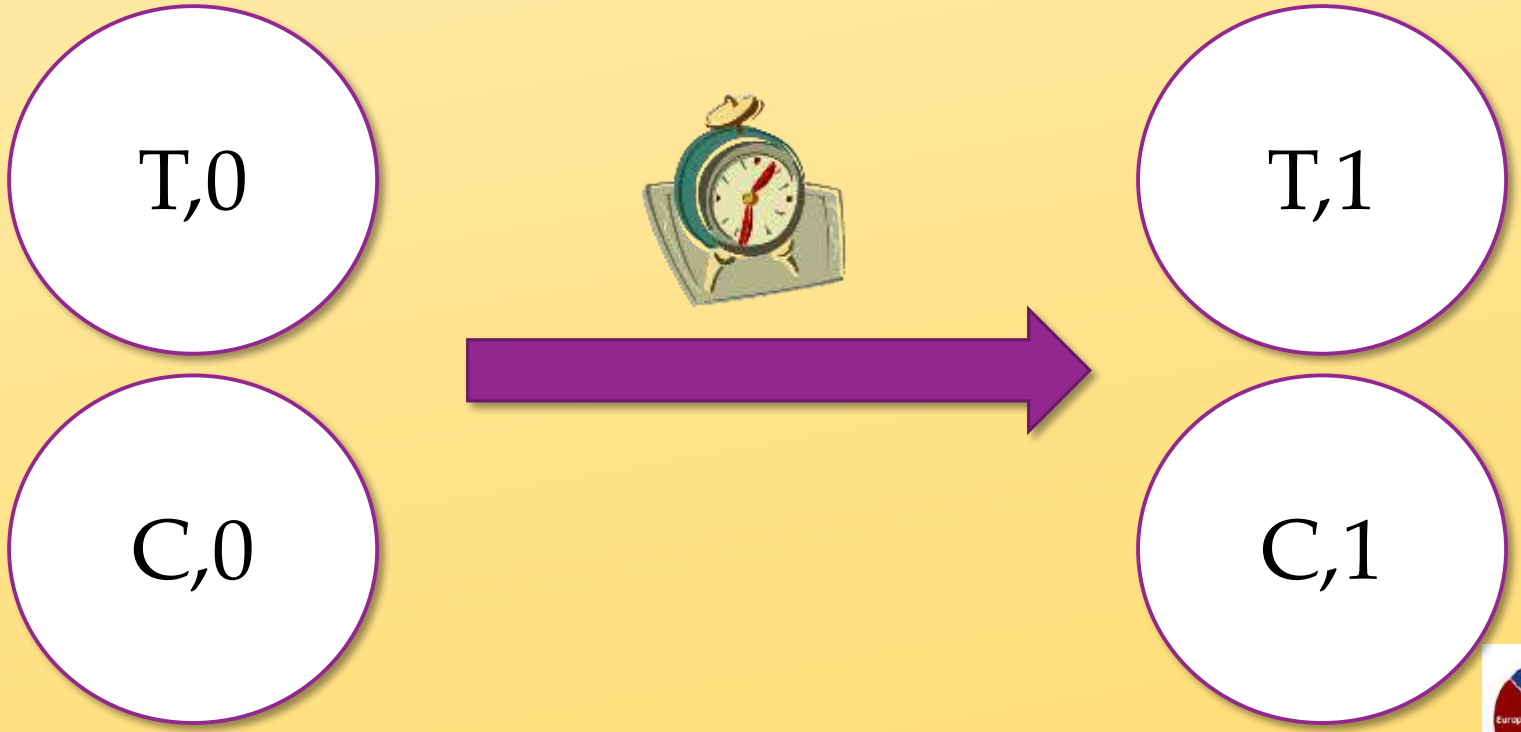
Step 2: assign the treatment, and take your time

- Assign treatment to individuals in group T;
- When possible, assign a placebo (or a different treatment) to group C.
- Wait the time you expect is necessary to see whether there are the effects you are interested in



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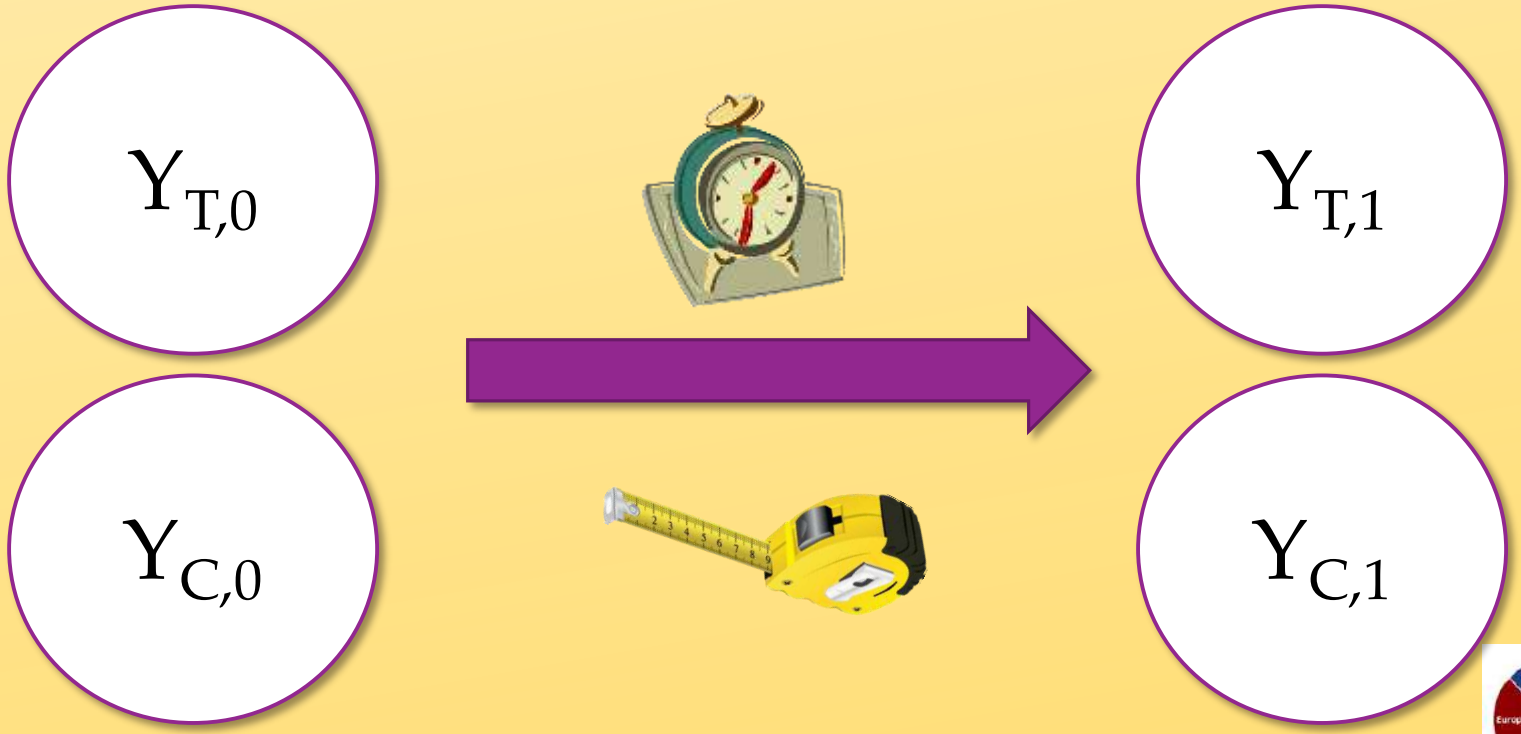
Step 3: control & measure everything

- Consider in particular your outcome of interest, and call it $Y_{g,t}$, where g is the group and t is the time



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…and at the end of the day…

- After the experiment, we can produce our estimates. The experimental estimator of the effect of treatment T is:

$$\hat{\beta}^{e} = \bar{Y}_{T,1} - \bar{Y}_{C,1}$$

- When feasible, **THIS** is the **GOLD STANDARD** for causal estimation.

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THE PUBLIC ENEMY #1 OF POLICY EVALUATION

the naïve estimators

https://www.pinterest.it/pin/524528687824558978/

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naïve estimator #1

- This is really **DANGEROUS**, because it is a very natural way of looking at economic data*. Like in this sentence, drawing conclusions from our example.

We introduced a minimum wage to grant to all individuals a decent pay for their work. Many were afraid of a disincentive effect on employment, but the statistics say that there was a positive net job creation, with an average 2.8 employment increase in all firms.

* And not only economic data: it's the meaning of the latin *Post hoc ergo propter hoc*.

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before-after naïve comparison

- This is the formula:

$$\hat{\beta}^{\mathrm{ba}} = \overline{\mathrm{Y}}_{T,1} - \overline{\mathrm{Y}}_{T,0}$$

- Try to write down the formula using the PON. What is $\overline{\mathrm{Y}}_{T,1}$? What is $\overline{\mathrm{Y}}_{T,0}$? They are both factual → we observe them! But are they outcomes in the presence of the treatment or not??

you add the superscript

$$\hat{\beta}^{\mathrm{ba}} = \overline{\mathrm{Y}}_{T,1} - \overline{\mathrm{Y}}_{T,0}$$

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before-after naïve comparison

- Now we can use the PON to clarify what is the big flaw of a naïve before-after comparison. Let us manipulate the formula adding and subctracting the same quantity, $\bar{Y}^0_{T,1}$:

$$\hat{\beta}^{ba} = \bar{Y}^1_{T,1} - \bar{Y}^0_{T,0} \quad \rightarrow \text{add and subtract } \bar{Y}^0_{T,1}$$

$$= \bar{Y}^1_{T,1} - \bar{Y}^0_{T,1}$$

$$+ \bar{Y}^0_{T,1} - \bar{Y}^0_{T,0}$$

this is the ATT (ATET)

this is the natural trend

before-after naïve comparison

1. How would have changed the outcome from 0 to 1…
2. …in the treated group…
3. …in case they did not receive the treatment

$$\bar{Y}^0_{T,1} - \bar{Y}^0_{T,0}$$

In our example: Also without the treatment, may be employment would have increased by 2.8. Or even more!

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naïve estimator #2

- This is **EVEN MORE DANGEROUS**, because it's formula is exactly the same of the experimental estimator.
- Also the idea is a natural one. Like in this sentence:

We offered to innovative start-ups support for their digital marketing strategies. In the first year of the policy, 480 start-ups where selected: their performance in the market was 24% better than their competitors.

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treated-control naïve comparison

- This is the formula:

$$\hat{\beta}^{\text{tc}} = \overline{\text{Y}}_{T,1} - \overline{\text{Y}}_{C,0}$$

- Try to write down the formula using the PON. What is $\overline{\text{Y}}_{T,1}$? What is $\overline{\text{Y}}_{C,0}$? They are both factual → we observe them! But are they outcomes in the presence of the treatment or not??

you add the superscript

$$\hat{\beta}^{\text{tc}} = \overline{\text{Y}}_{T,1} - \overline{\text{Y}}_{C,0}$$

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treated-control naïve comparison

- Again, we can use the PON to clarify what is the big flaw of a naïve comparison of treated and controls. Let us again add and subctrac $\overline{Y}^0_{T,1}$:

$$\hat{\beta}^{\text{ba}} = \overline{Y}^1_{T,1} - \overline{Y}^0_{C,1} \quad \rightarrow \text{add and subtract } \overline{Y}^0_{T,1}$$

$$= \overline{Y}^1_{T,1} - \overline{Y}^0_{T,1}$$

$$+ \overline{Y}^0_{T,1} - \overline{Y}^0_{C,1}$$

this is again the ATT

this is the selection bias

treated-control naïve comparison

1. After the policy…
2. …also in absence of the tratment…
3. …treated and controls would have been different

$$\bar{Y}^0_{T,1} - \bar{Y}^0_{C,1}$$

In our example: Also without the policy, the start-up who where selected for the policy were the best ones. → Very often, incentives are offered to the best ones!

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Do experiments provide correct estimates?

Why is it that the same formula behave differently in case of experimental and observational data?

$$\mathrm{E}[\hat{\beta}^{\mathrm{e}}] = \mathrm{E}[\bar{\mathrm{Y}}^{1}{}_{T,1} - \bar{\mathrm{Y}}^{0}{}_{C,1}] = \mathrm{E}[\bar{\mathrm{Y}}^{1}{}_{T,1}] - \mathrm{E}[\bar{\mathrm{Y}}^{0}{}_{C,1}]$$

Thanks to randomization, both the control group and the treatment group are random sample of the population of interest! Hence:

$$\mathrm{E}[\hat{\beta}^{\mathrm{e}}] = \mathrm{E}[\bar{\mathrm{Y}}^{1}{}_{T,1}] - \mathrm{E}[\bar{\mathrm{Y}}^{0}{}_{T,1}] = \beta_{T,1}$$

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