

Public Economics

Level 2

2020-2021

Conférence de méthode

Session 2

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SciencesPo

Research in economics

Help taking benefits from readings

1. Theoretical models
2. Empirical analysis

1. Theoretical models

Why models?

- ❖ To understand the effects of a given policy, one must comprehend how individuals have responded or will react
- ❖ **Theory** provides an intuition of the direction and sign of the effect
- ❖ **Empirics** estimates its magnitude

Structural modeling (in short)

Principle:

- ❖ **Explicit** economics theory which mathematically describes relations between variables, with "parameters" calibration/setting
- ❖ Models both choices and outcomes as endogenous variables
- ❖ Allows to recover the **fundamental** (policy invariant) parameters (tastes, preferences, technology, discount rates, risk aversion)
- ❖ Distinguishes **causal** from spurious

Structural modeling (in short)

❖ Advantage:

Possible to **simulate** what would happen with an infinity of **policies variants**

❖ Drawbacks:

Requires **many assumptions** rarely verifiable

The range of estimations may be quite large

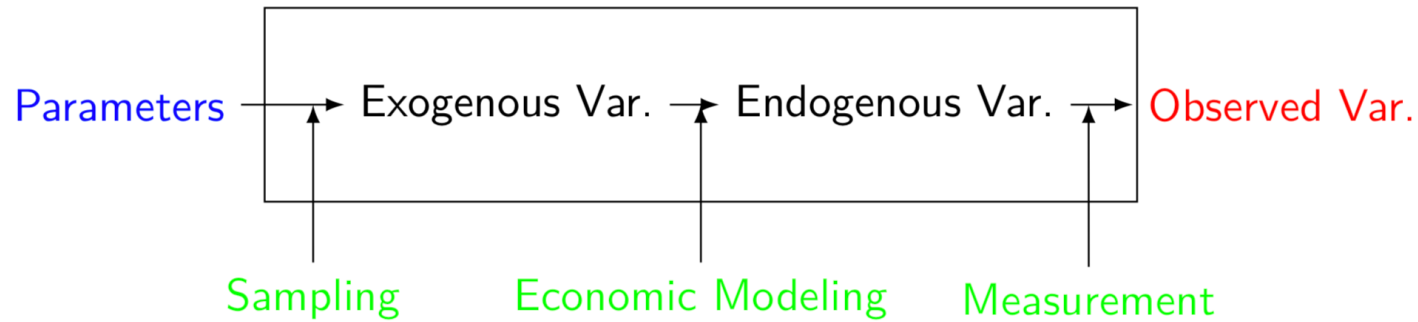


Figure: Structural model

- ❖ **The structural model** is a mapping of parameters to a probability distribution of observed variables in real life.

Parameters are constants or probabilistic distributions (from which we draw).

Observed variables are measured in real life.

What the model does **step by step** is:

- 1/ **sampling**: draw exogenous variables (the input of the model) from the parameters
- 2/ **economic modeling**: economically meaningful mathematical operations transforming exogenous var. into endogenous variables
- 3/ **measurement**: distinguishes the output of the model from what is observed in real life

A model never is truth

- ❖ If a model is misspecified, it will produce wrong simulations
- ❖ The goal is never to constitute truth in its full complexity but to offer the best possible model, which will provide the best possible forecasts...
- ❖ ... with acceptable assumptions
- ❖ Often the prelude to an empirical analysis

2. Empirical methods of public policies' evaluation

- | | |
|--|--|
| 1. Instrumental variables | Angrist & Krueger (1991); Müller & Schwarz (2019) |
| 2. Lab experiments | Prati & Saucet (2019) |
| 3. Random control trials | Miguel & Kremer (2004) |
| 4. Natural experiments | Torche (2018) |
| 5. Difference-in-differences | Card & Krueger (1994) |
| 6. Regression discontinuity design | Eggers & Hainmueller (2009); Angrist & Lavy (1999) |
| 7. Matching – selection on observables | Dehejia & Wahba (1999) |

Concrete example of regression analysis

$$\diamond y = \alpha + \beta X + \gamma T + \epsilon$$

$$y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \gamma T + \epsilon$$

- ❖ with y : **dependent variable** with which we try to evaluate the policy
e.g. number of cigarettes smoked, or dummy variable smoker (1 if smokes, 0 if not)
- ❖ with α : **constant** term
- ❖ with X : observable **controls** that may influence y
e.g. income, age, education level, gender, the smoking behavior of pairs, etc.
- ❖ with T : an indicator of **treatment**, equals 1 when affected by the reform, 0 otherwise
e.g. plain tobacco packaging (*paquet neutre*)
- ❖ with ϵ : the **residuals**, meaning what is unobserved and not included in the equation
e.g. taste for risky attitudes, stress level, and all potential other determinants

We are interested in γ : the **effect of the introduction of the plain tobacco packaging on the number of cigarettes smoked.**

Causality?

- ❖ **Classical risk of endogeneity**, i.e. correlation explanatory variable & residuals
 - ❖ **Reverse causality**: looking at the effect of nb. of policemen on crime, aren't there policemen because there is crime?
 - ❖ **Simultaneity**: X causes Y but Y also causes X (e.g. estimating quantity as a function of price)
 - ❖ **Omitted variable**, which influence both the smoking and the income level (y and X/T)
 - ❖ **Measurement error** of the explanatory variables

- ❖ **How to prove causality and measure an effect?**
 - ❖ **Instrumental variables**
 - ❖ **Lab XP**
 - ❖ **Randomized control trials**
 - ❖ **Natural XP**
 - ❖ **Difference-in-differences**
 - ❖ **Regression discontinuity**
 - ❖ **Matching**

Instrumental variables

- ❖ **Example:** effect of education on health? Biased estimates potentially because:
 - ❖ Childhood health may affect the level of education as well as adulthood health
 - ❖ Discount rates may affect the two: individuals who care less about the future may educate less and care less about their health
 - ❖ Potential reverse causality as a better health implies more time to benefit from returns to education
- ❖ **Principle:** to overcome the endogeneity challenge, we "instrument" (=replace) the explanatory variable with something correlated with it but not influencing the outcome directly
- ❖ In the example, educational reforms influence educ. level but not health directly!
To investigate the effect of education on health, Lleras-Muney (2005) uses the effect of educational reforms on health.

Instrumental variables: an example (i)

Angrist J. & Krueger A. (1991),

"Does Compulsory School Attendance Affect Schooling and Earnings?"

The Quarterly Journal of Economics

<https://www.jstor.org/stable/2937954?seq=1>

Angrist & Krueger (1991)

- ❖ Season of birth is related to educational attainment
 - ❖ Due to start age policy, compulsory school attendance laws.
 - ❖ Individuals **born in the beginning of the year** start school at an older age, and **can therefore drop out after completing less schooling** than individuals born near the end of the year
- ❖ Estimate the impact of compulsory schooling on earnings by **using quarter of birth as an instrument for education.**

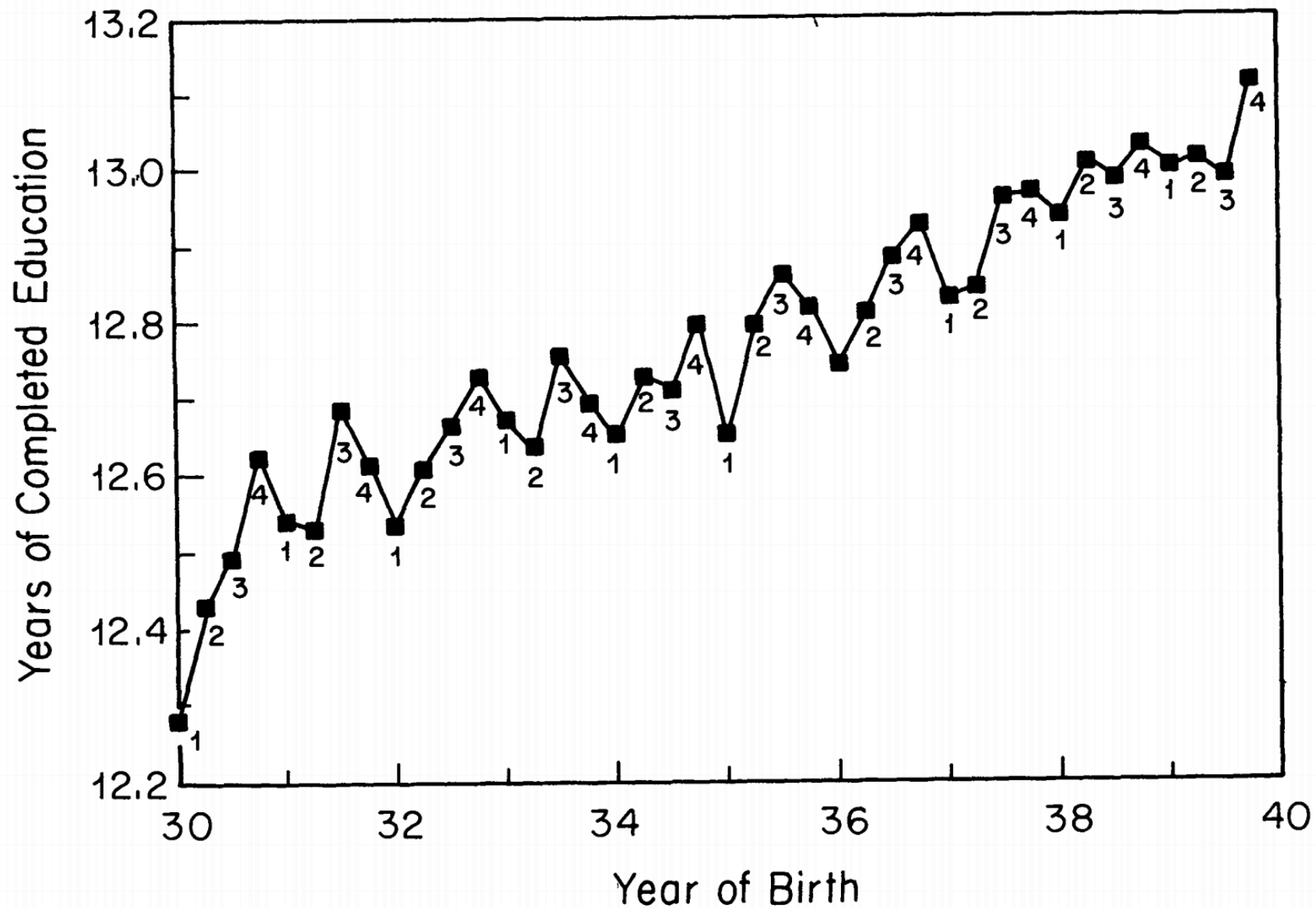
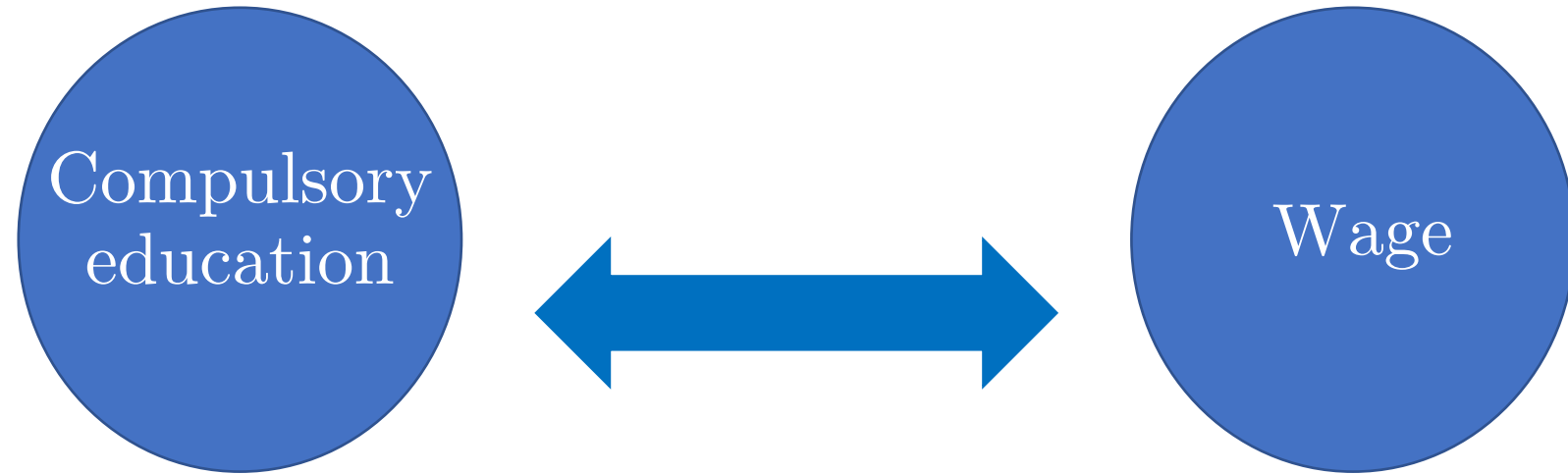


FIGURE I

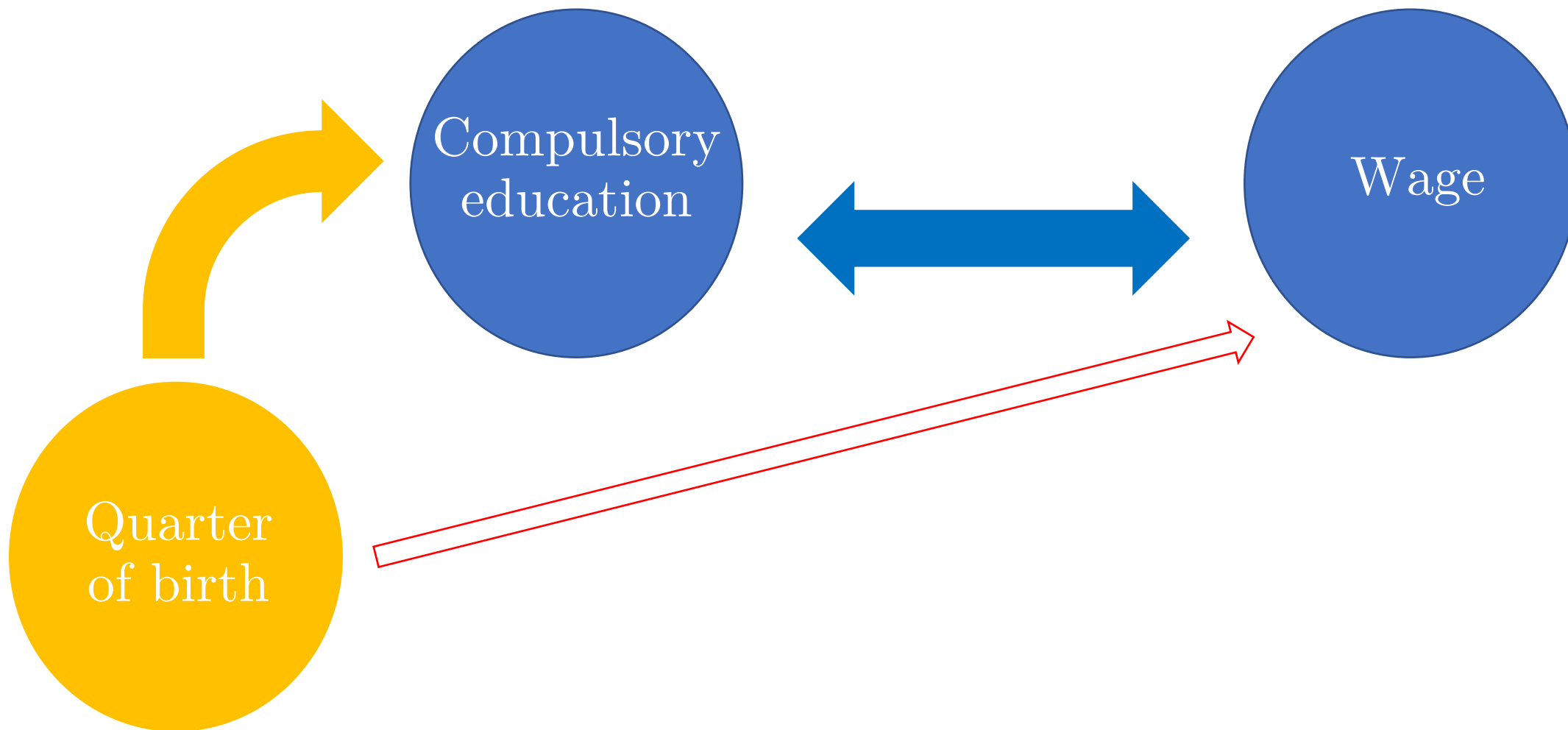
Years of Education and Season of Birth
1980 Census

Note. Quarter of birth is listed below each observation.

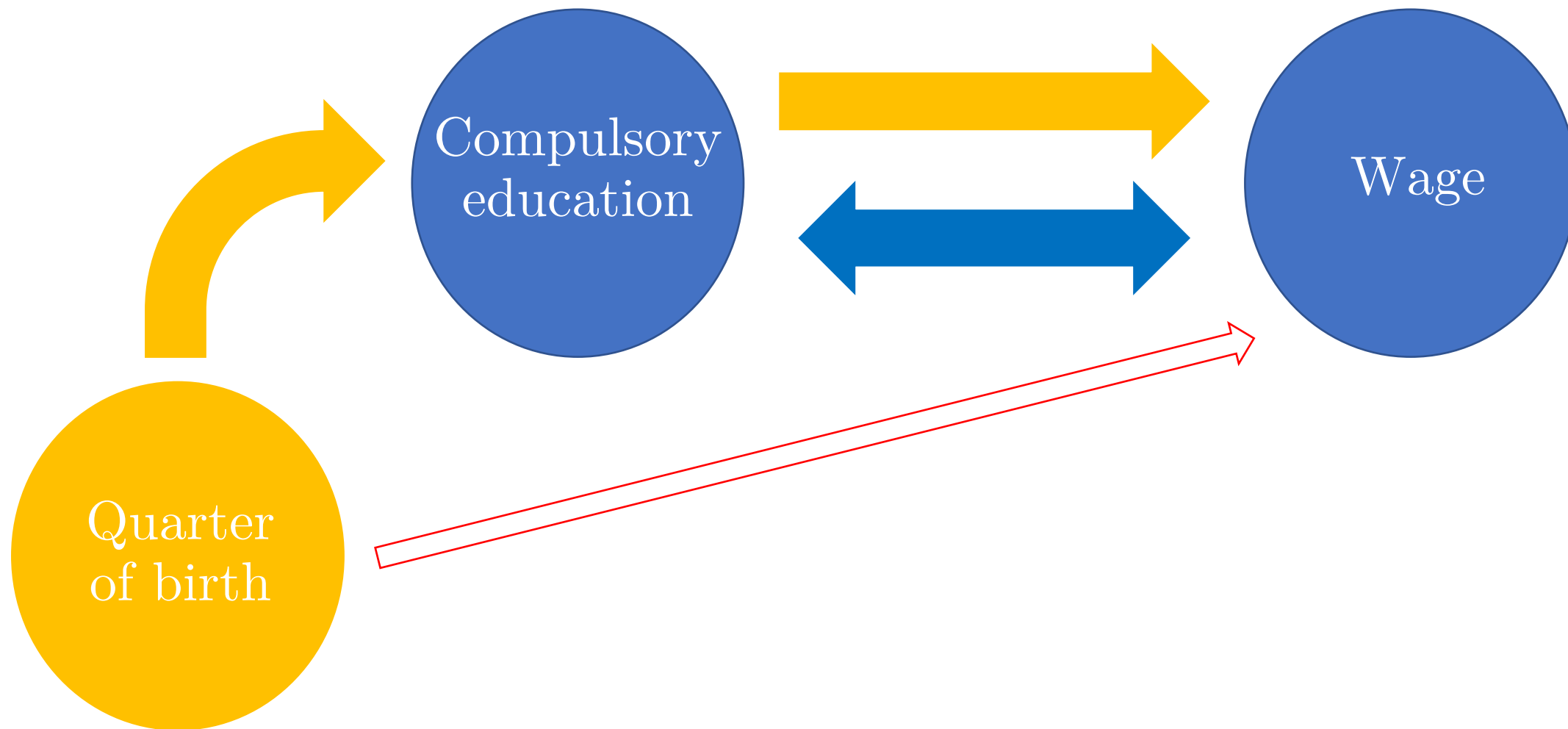
Instrumental variables



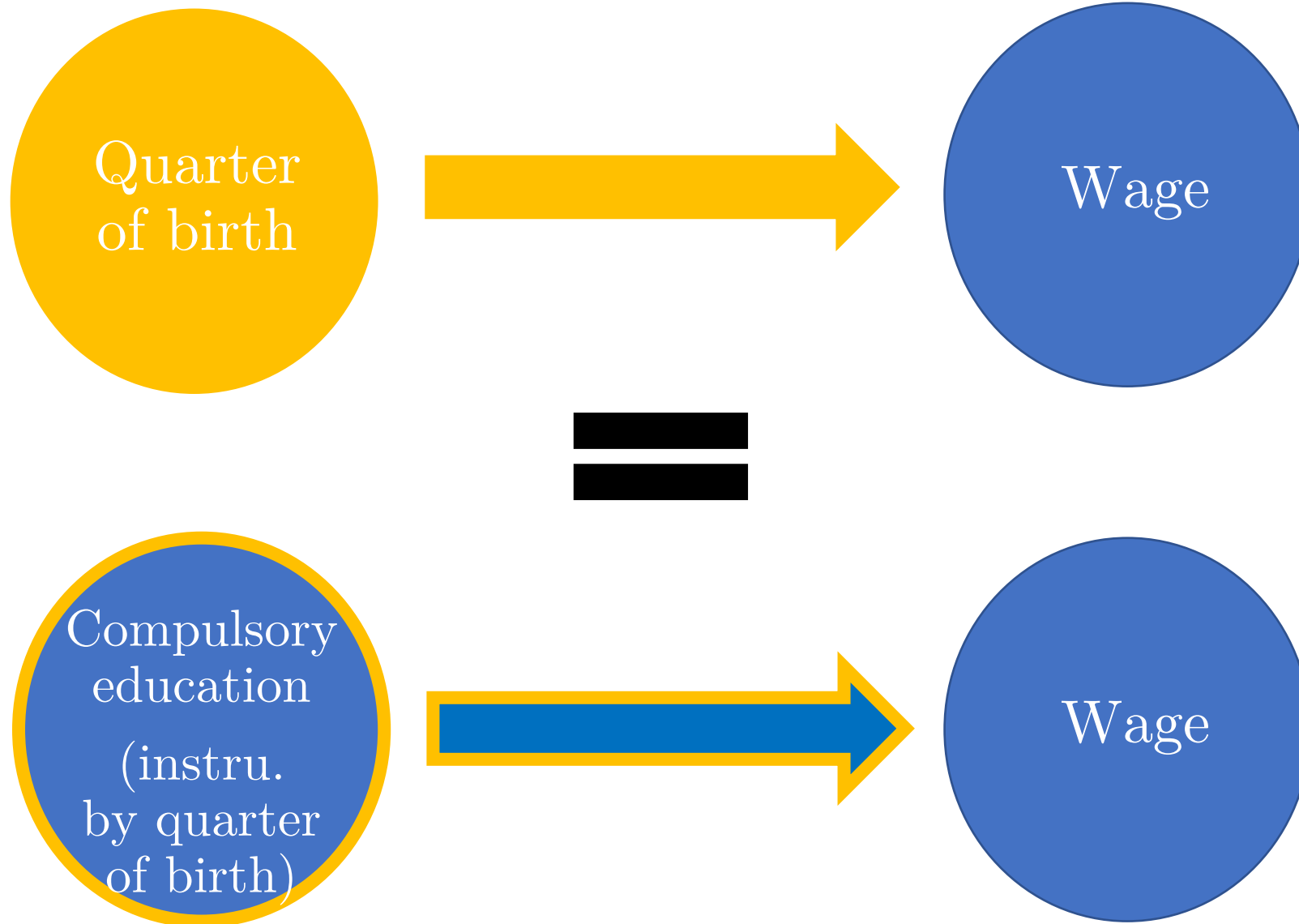
Instrumental variables



Instrumental variables



Instrumental variables



Angrist & Krueger (1991) - conclusion

Results:

- ❖ students who are compelled to attend school longer by compulsory schooling laws **earn higher wages**.
- ❖ **compulsory schooling laws are effective** in compelling some students to attend school.

Always the nuance of results from economic studies:

“Do these results mean that **compulsory schooling laws are necessarily beneficial**? A complete answer to this question would require additional research on the **social and private costs** of compulsory school attendance. For example, compulsory attendance may have the benefit of **reducing crime rates**. And they may impose a social cost because students who are compelled to attend school may **interfere with the learning of other students**.”

Instrumental variables: an example (ii)

Müller K. & Schwarz C. (2019),

" From Hashtag to Hate Crime: Twitter and Anti-Minority Sentiment"

Working paper

https://warwick.ac.uk/fac/soc/economics/staff/crschwarz/hashtag_to_hatecrime.pdf

Müller & Schwarz (2019) - abstract

Study whether social media can **activate hatred of minorities**

- ❖ focus on **Donald Trump's** political rise
- ❖ associate **geographical concentration** of Twitter usage and increase in anti-Muslim sentiment

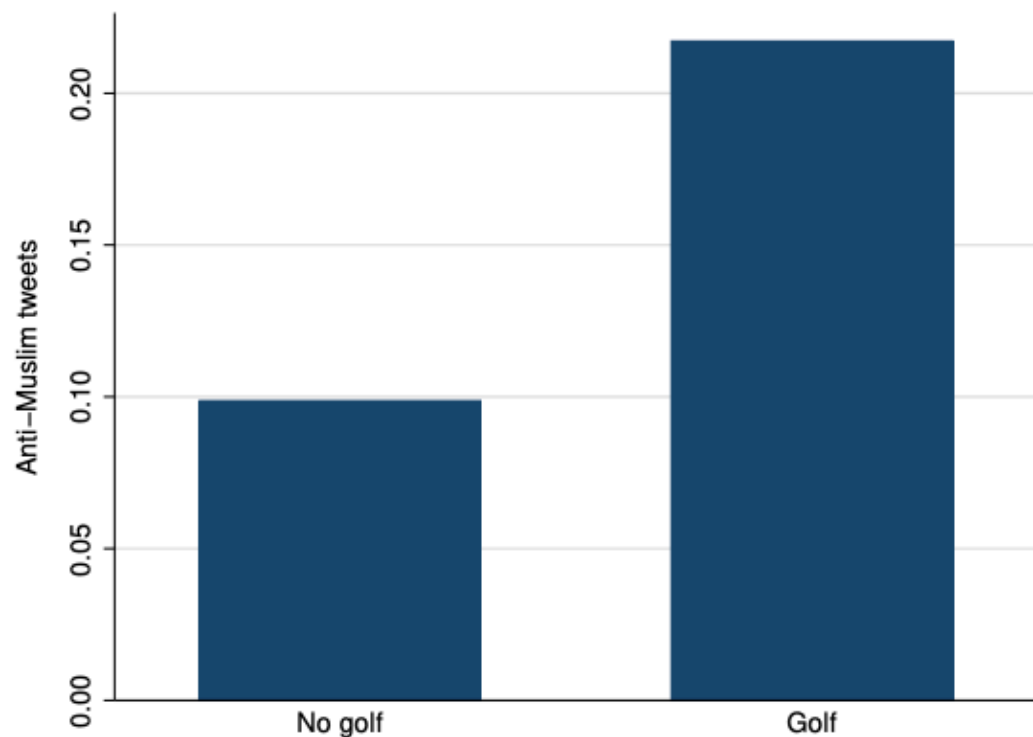
“Instrumenting with the locations of SXSW followers [...], a one standard deviation increase in Twitter usage is associated with a 38% larger increase in anti-Muslim hate crimes.”

”Trump's tweets about Islam-related topics are highly correlated with anti-Muslim hate crimes **after the start of his presidential campaign, but not before**. These correlations persist in an **instrumental variable framework exploiting that Trump is more likely to tweet about Muslims on days when he plays golf**.”

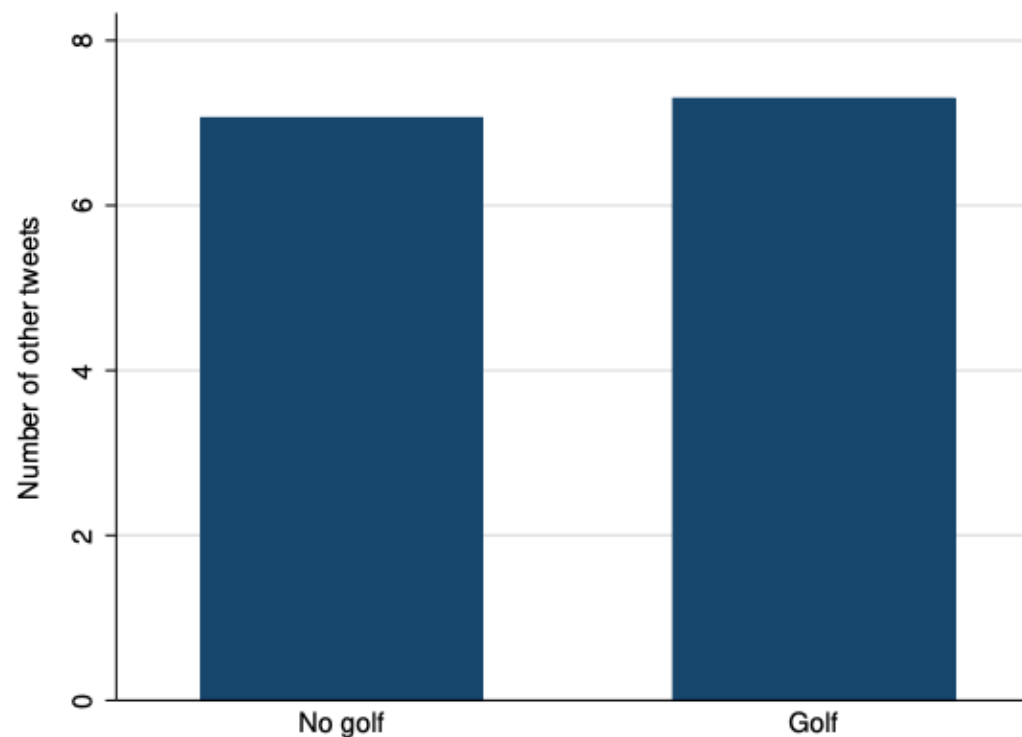
Müller & Schwarz (2019), From Hashtag to Hate Crime: Twitter and Anti-Minority Sentiment, *Working paper*

Figure 9: Trump's Twitter Activity, Split by Golf Days

(a) Tweets about Muslims

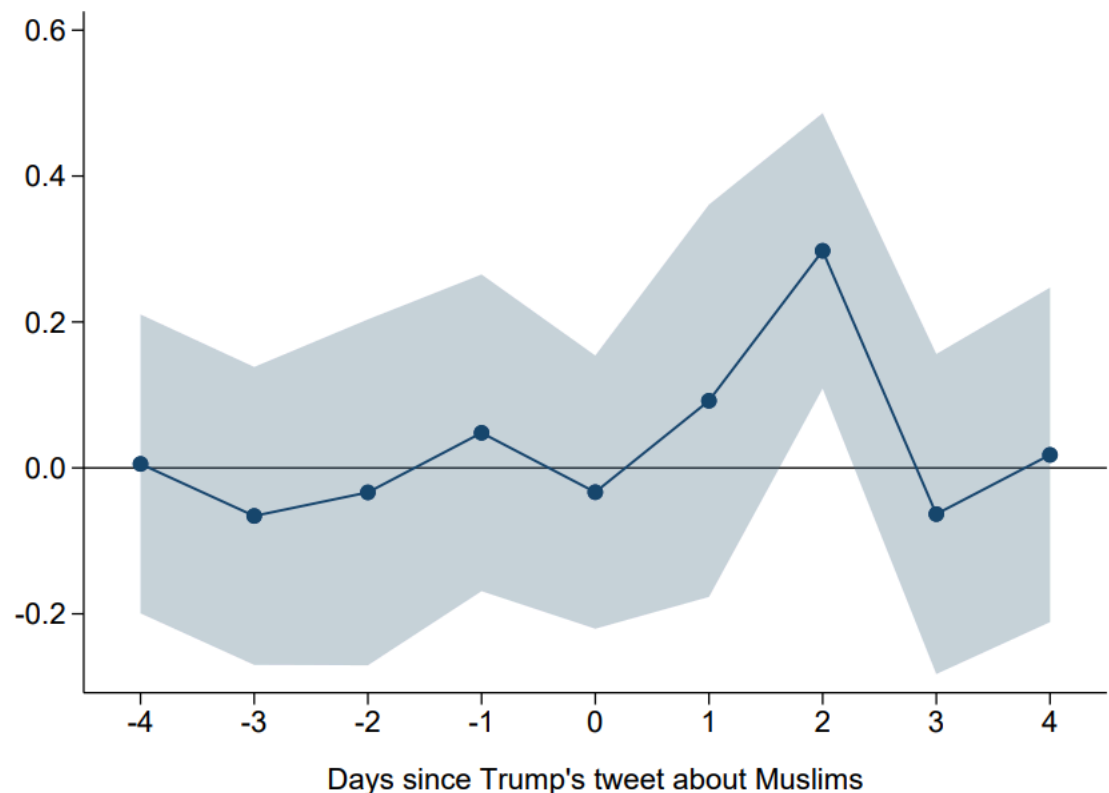


(b) Total tweets

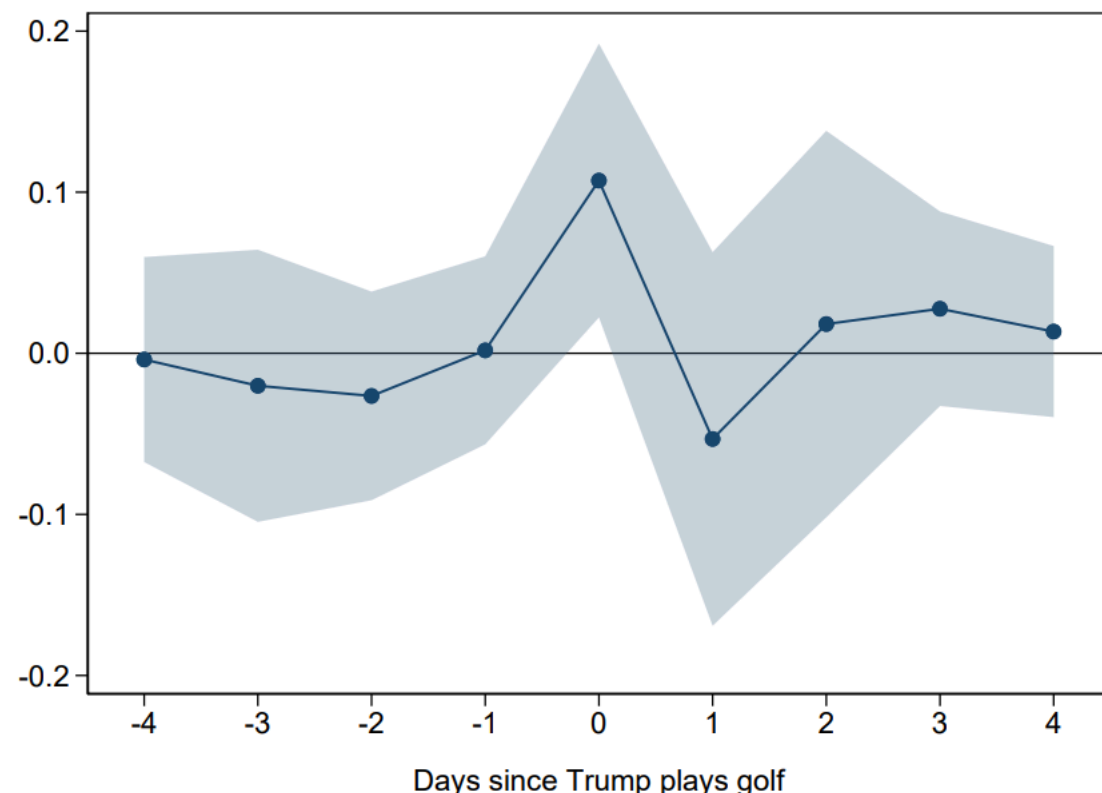


Notes: These figures plot the average daily number of Trump's tweets, split by whether he plays golf on a given day in 2017. Panel (a) reports the average number of tweets about Muslims, panel (b) reports the total number of tweets.

(a) OLS - Trump Tweets about Muslims and Hate Crimes



(b) First Stage - Golf and Trump Tweets about Muslims



Notes: These figures plot the dynamic correlations for equations 4 and 5 for values of h ranging between -4 and 4 . Panel (a) plots the correlation of Trump's tweets about Islam-related topics and anti-Muslim hate crimes (both in natural logarithm). Panel (b) plots the correlation of Trump's golf outings with the log number of his Islam-related tweets. T indicates the date of tweets about Muslims or golfing ($h = 0$). All regressions include time trends; a full set of day of week and year-month dummies; and four lags of dummies for the incidence of terror attacks in the US, Europe, and the rest of the world. The sample is 2017. The shaded areas are 95% confidence intervals based on Newey-West standard errors.

Laboratory experiments

- ❖ **Principle:** set a given framework to study a phenomenon with voluntary participants who must take decisions in this setting
- ❖ **Intuition:** extrapolation of those decisions to situations in real life
- ❖ **Major drawback:**
External validity is sometimes very arguable (selection bias of participants, no major consequence for participants – despite payoffs)

Lab XP: an example, Prati & Saucet (2019)

- ❖ Research question: **effect of mood on memory**
- ❖ First meeting with positive or negative feedbacks
- ❖ Second meeting 3 weeks later with **conditioning through videos** of Gad Elmaleh (French comic) or very sad videos
- ❖ **Ask to recall** how the first meeting went
- ❖ **Differential recall** depending on the conditioning

Randomized control trials (RCT)

- ❖ Comes initially from the medical research
 - ❖ Therefore treatment group and control group
- ❖ Nobel prize 2019: Banerjee, Duflo, Kremer
- ❖ **Principle:** random selection of treatment and control groups
 - Therefore, groups are expected to be similar (if large enough) except the treatment
 - The difference in outcome is then due to treatment
- ❖ Very **useful for an ex-ante analysis**: test on a small scale using RCT

Miguel & Kremer (2004), Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities, *Econometrica*

Intestinal helminths are worms that infect more than one-quarter of the world's population.

Previous studies **randomized** medical treatment **at the individual level** and therefore potentially doubly underestimated their benefits, because of **externalities** benefiting the comparison group (=control group affected by the treatment).

This paper evaluates a treatment project in Kenya with **randomization at the school level** rather than the individual level.

The program **reduced school absenteeism in treated schools by one-quarter**, and was far **cheaper** than alternative ways of boosting school participation.

Deworming substantially improved health and school participation among untreated children in **both treatment schools and neighboring schools**. These externalities are large enough to justify fully subsidizing treatment.

RCT: ideal framework?

- ❖ Risks for the correct identification of the effect:
 - ❖ Non-random attrition between groups (would weaken the XP over time)
 - ❖ Non-observance of the treatment (treated group may imperfectly take pills)
 - ❖ Selection into groups (means both groups may not be truly comparable)
 - ❖ Hawthorne effect (people may behave differently knowing they are monitored)

- ❖ Other limits:
 - ❖ Expensive to run
 - ❖ Questionable external validity
 - ❖ No measure of general equilibrium effects
 - ❖ Ethically ambiguous because social experiments on humans...

Natural experiment

- ❖ **Principle:** a (natural) shock outside the control of investigators and individuals affects a subpopulation
- ❖ **Intuition:** the shock must resemble random assignment
- ❖ **Main hypothesis:** the subpopulation affected by the shock must be comparable to another subpopulation not affected by the shock, in order to causally interpret the effect of the event

Natural experiment: an example

Torche F. (2018),

"Prenatal Exposure to an Acute Stressor and Children's Cognitive Outcomes",

Demography

Torche (2018), abstract

- ❖ **Prenatal stress** may have enduring negative consequences
- ❖ It is highly prevalent and unequally distributed along **socioeconomic characteristics**
- ❖ Use a natural experiment: a strong **earthquake in Chile**
- ❖ Study the effect of prenatal exposure to acute stress on **children's cognitive development**
- ❖ Results:
 - ❖ stress exposure in early pregnancy has no effect among middleclass families, but a **strong negative influence** among **disadvantaged families**
 - ❖ **Mechanisms**: differential exposure, differential sensitivity, parental responses
- ❖ Lessons: intergenerational transmission of disadvantages starts in the prenatal period

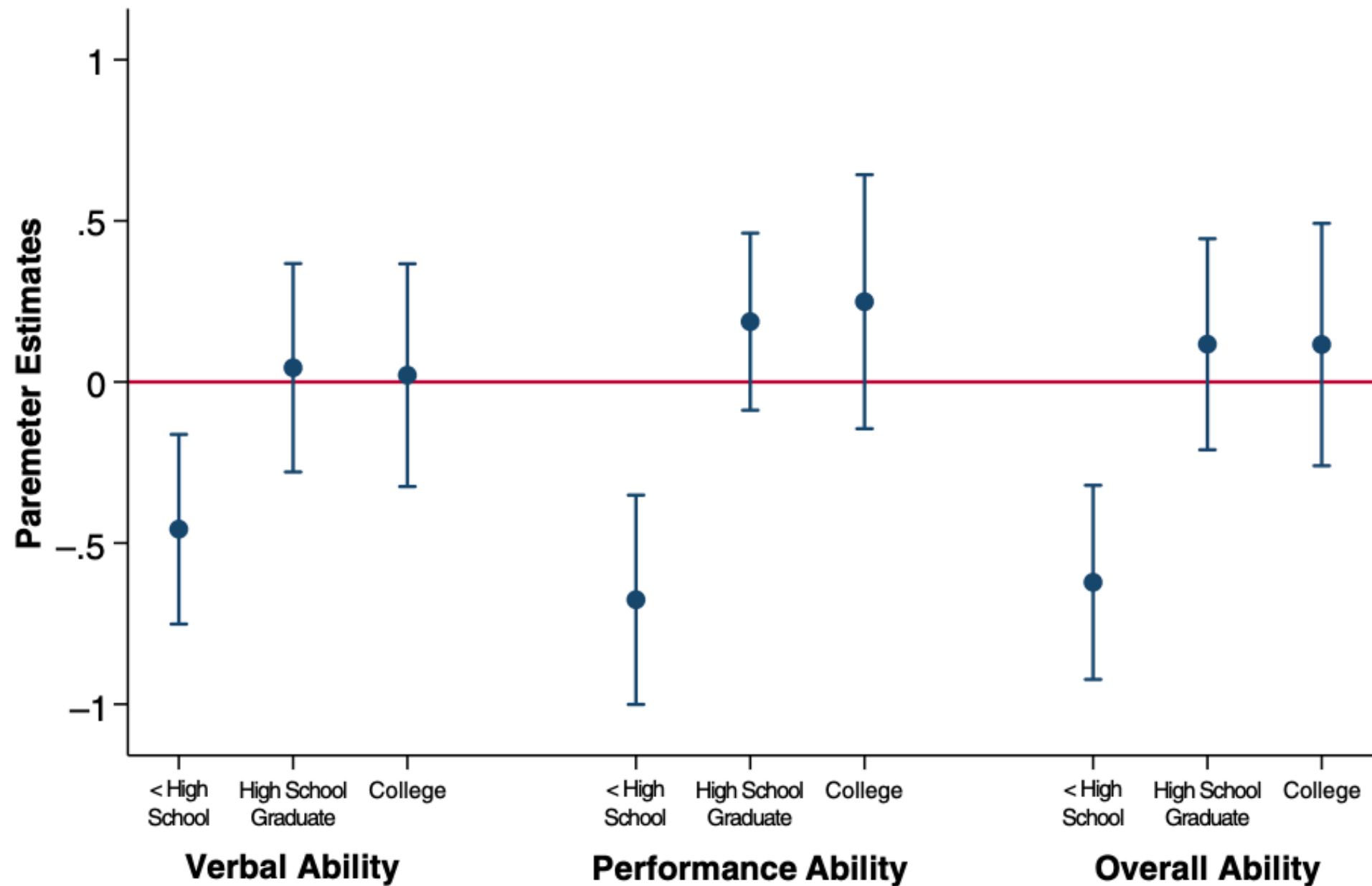


Fig. 2 Effect of prenatal exposure to earthquake in first trimester of gestation on children’s cognitive ability at age 7 by family SES. Solid dots are parameter estimates; vertical bars are 95 % confidence intervals based on tests for the null hypothesis that the difference in parameter estimates across SEs is different from 0 at the .05

Difference-in-differences (or double difference)

❖ **Principle:** compare changes in the outcomes of treated and control groups after and before the treatment

How did the treated group evolve after the treatment?

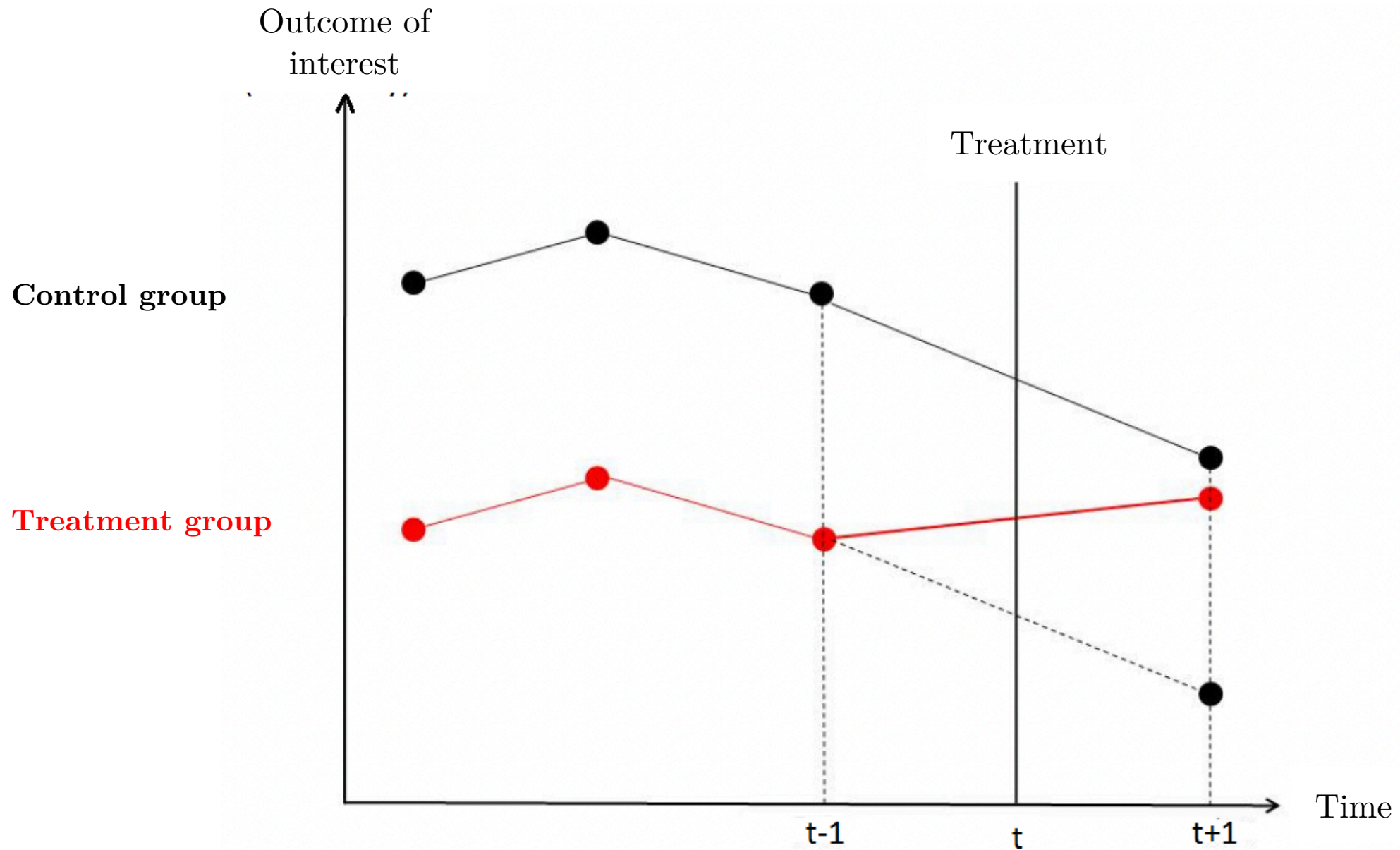
VS

How did the control group evolve?

❖ Two main **hypothesis:**

1. Without the treatment, both groups would have evolved similarly
Parallel trends are required before the treatment but a similar level is not required
2. No other shock must affect any of the groups at the same time
Otherwise, it would not be all other things being equal (*ceteris paribus*)

Difference-in-differences (or double difference)



Difference-in-differences: an example

Card D. & Krueger A. (1994),

"Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania",

The American Economic Review

Context

Increase of the minimum wage in NJ \$4.25 to \$5.05

April 1992

New Jersey (NJ)

Pennsylvania (PA)

Phone interviews
Feb – March 1992

Phone interviews
Nov – Dec 1992



❖ Fast food industry

- ❖ Many low wages jobs
- ❖ Respect of minimum law rules
- ❖ Not the *tips* remuneration system
- ❖ Homogeneous products

TABLE 3—AVERAGE EMPLOYMENT PER STORE BEFORE AND AFTER THE RISE
IN NEW JERSEY MINIMUM WAGE

Variable	Stores by state			Stores in New Jersey ^a			Differences within NJ ^b	
	PA (i)	NJ (ii)	Difference, NJ – PA (iii)	Wage = \$4.25 (iv)	Wage = \$4.26–\$4.99 (v)	Wage ≥ \$5.00 (vi)	Low– high (vii)	Midrange– high (viii)
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	–2.89 (1.44)	19.56 (0.77)	20.08 (0.84)	22.25 (1.14)	–2.69 (1.37)	–2.17 (1.41)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	–0.14 (1.07)	20.88 (1.01)	20.96 (0.76)	20.21 (1.03)	0.67 (1.44)	0.75 (1.27)
3. Change in mean FTE employment	–2.16 (1.25)	0.59 (0.54)	2.76 (1.36)	1.32 (0.95)	0.87 (0.84)	–2.04 (1.14)	3.36 (1.48)	2.91 (1.41)
4. Change in mean FTE employment, balanced sample of stores ^c	–2.28 (1.25)	0.47 (0.48)	2.75 (1.34)	1.21 (0.82)	0.71 (0.69)	–2.16 (1.01)	3.36 (1.30)	2.87 (1.22)
5. Change in mean FTE employment, setting FTE at temporarily closed stores to 0 ^d	–2.28 (1.25)	0.23 (0.49)	2.51 (1.35)	0.90 (0.87)	0.49 (0.69)	–2.39 (1.02)	3.29 (1.34)	2.88 (1.23)

Notes: Standard errors are shown in parentheses. The sample consists of all stores with available data on employment. FTE (full-time-equivalent) employment counts each part-time worker as half a full-time worker. Employment at six closed stores is set to zero. Employment at four temporarily closed stores is treated as missing.

^aStores in New Jersey were classified by whether starting wage in wave 1 equals \$4.25 per hour ($N = 101$), is between \$4.26 and \$4.99 per hour ($N = 140$), or is \$5.00 per hour or higher ($N = 73$).

^bDifference in employment between low-wage (\$4.25 per hour) and high-wage (\geq \$5.00 per hour) stores; and difference in employment between midrange (\$4.26–\$4.99 per hour) and high-wage stores.

^cSubset of stores with available employment data in wave 1 and wave 2.

^dIn this row only, wave-2 employment at four temporarily closed stores is set to 0. Employment changes are based on the subset of stores with available employment data in wave 1 and wave 2.

Back to “How can the State intervene?”

Is minimum wage properly addressing the objectives

❖ Poverty reduction

- ❖ In practice, many companies have market power (massive unemployment), minimum wage is addressing a market failure
- ❖ The overlap between poverty and poor workers is much higher in countries without a minimum wage policy
- ❖ Obviously doesn't tackle poverty of the elderly, the youth, or the unemployed

❖ Favor equality

- ❖ Bunching around the minimum wage, although the whole scale of wages adjusts
- ❖ If unemployment ↑, the lower the safety net the more problematic

❖ Improve social cohesion

- ❖ Reduce poverty without social benefits stigma, unless unemp. ↑

❖ The main issue is setting an efficient **amount** for the minimum wage

- ❖ Very challenging to have a decisive academic answer, at least w/o a given context (15\$?)

Regression discontinuity

❖ **Principle:** use a **discontinuity in the access** to the treatment to define comparable groups on both side of a **threshold**

❖ **Intuition:**

Some individuals benefit narrowly from a treatment, whereas others narrowly don't
Imagine I offer a specific job market application training to everyone in the room with at least 15 at the final exam, we can think that those who obtained 14.5 are quite comparable to those who get 15.
We then can compare their entry on the job market at the end of the master... (sample size too small but idea here)

❖ **Main hypothesis:**

Groups on both side of the threshold are comparable (arbitrary aspect of the threshold)
The perimeter around the threshold must be sufficiently small

Regression discontinuity: an example (i)

Eggers A. & Hainmueller J. (2009),

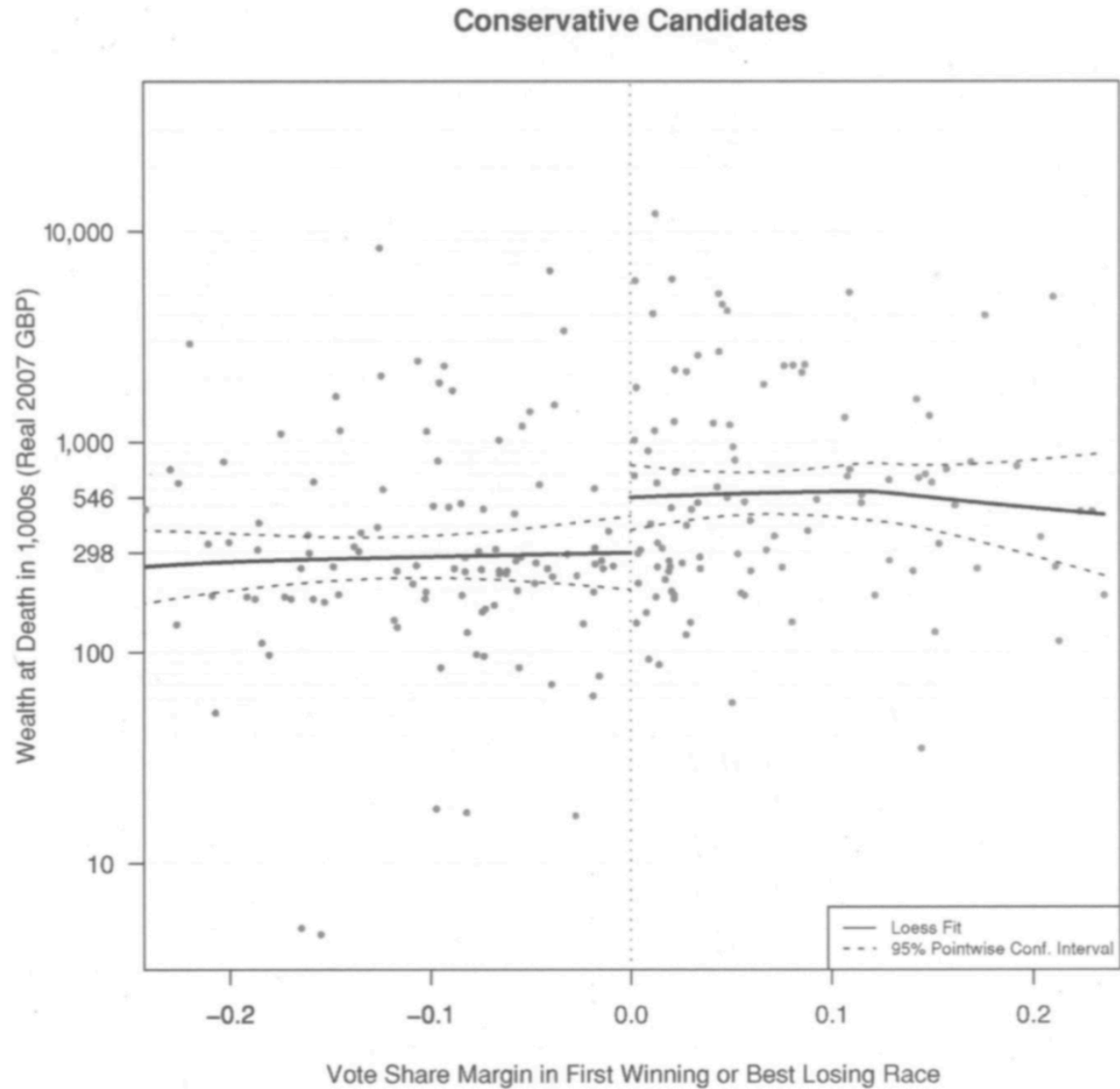
"MPs for Sale? Returns to Office in Post war British Politics"

American Political Science Review

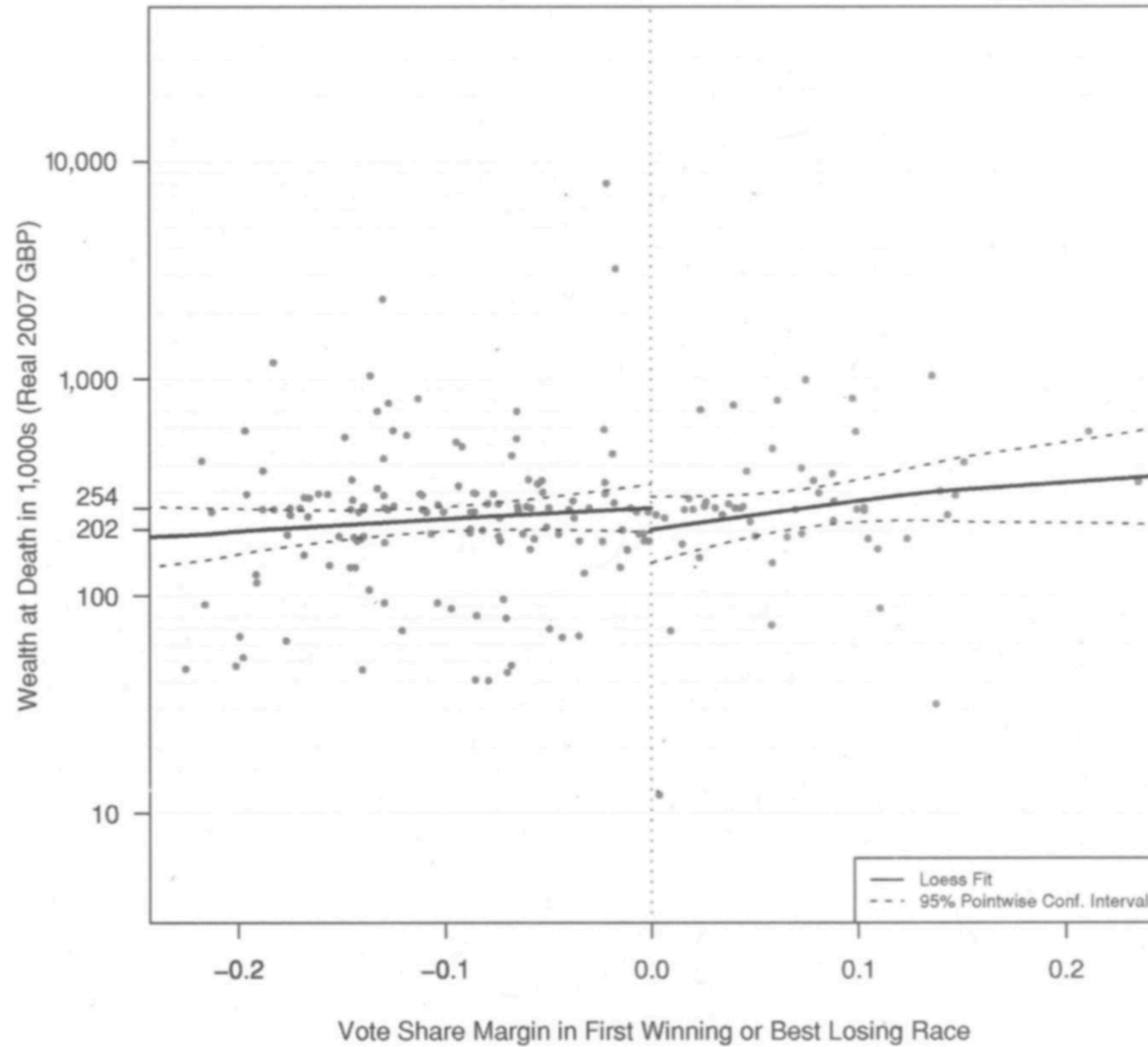
Paper in a nutshell

- ❖ Compare MPs to candidates who **narrowly lost elections**
- ❖ Almost **doubled wealth of Conservative MPs** but no discernible financial benefits for Labour MPs
- ❖ Conservative MPs: largely through lucrative outside employment they acquired as a result of their political positions
- ❖ Tripled the probability that a Conservative politician would later serve as a director of a publicly traded firm

FIGURE 4. Regression Discontinuity Design: Effect of Serving in House of Commons on Wealth at Death



Labour Candidates



Regression discontinuity: an example (i)

Angrist J. & Lavy V. (1999),

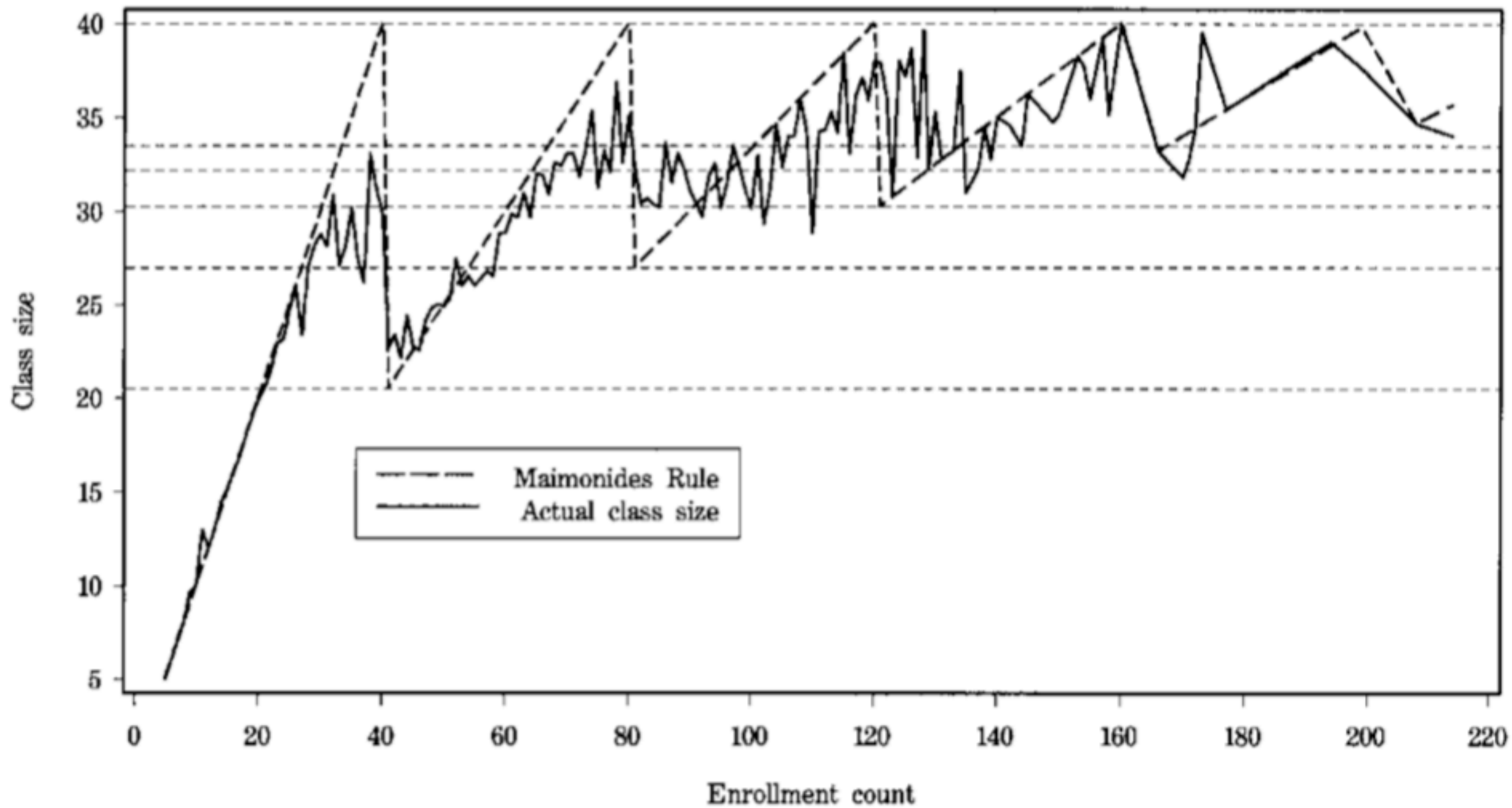
"Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement"

The Quarterly Journal of Economics

Context

- ❖ Study the effect of class sizes on students' outcomes
- ❖ Maimonide (rabbinic scholar, 12th Century) rule:
 - ❖ **Max 40 students** per class
 - ❖ Implying thresholds' effects
a school with 39 students = 1 class of 39; a school with 42 students = 2 classes of 21
 - ❖ Use this discontinuity by looking at school sizes around multiples of 40
[35;45], [75;85], [115;125], [155;165], etc.

a. Fifth Grade



Results

- ❖ When not taking into account **social background** of students (control), it seems that increased class sizes is associated with better results
But there is **sorting** (low SES students are in smaller classes because more rural and targeted policies)
- ❖ When controlling for **proportion of disadvantaged** students (place of birth, level of educ. of parents, family size, etc.)
 - ❖ A **reduced class size implies better reading and math scores**
 - ❖ The effect is higher for 5th graders (*CM2*) than 4th graders (*CM1*)
This might be a cumulated effect

Matching – selection on observables

❖ Principle:

build a **counterfactual**, a control group purged from **selection bias**

❖ Intuition:

We **select in the sample** individuals from the control group similar to those treated (or part of them)

❖ Main **assumption**:

Unobserved variables are not key determinants of the probability to be treated

Matching – selection on observables

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❖ **3 steps**:

- ❖ 1/ estimate what variables determine participation to the program
- ❖ 2/ select similar individuals among non-participants
- ❖ 3/ estimate the effect of the program

Matching – selection on observables: example

- ❖ Dehejia & Wahba (1999)
- ❖ Effect of a **training program** on **earnings** in the US
- ❖ Data from the NSH (National Supported Work)
 - ❖ 185 treated individuals; 2 490 untreated
 - ❖ Variables: age, years of education, marital status

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