How to find causality in practice?

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Introduction to Econometrics using R, Sciences Po

Causality

Causality

- Much of econometrics is concerned with eliminating selection bias, and answering causal "what-if" questions
- This means finding valid counterfactuals, and knowing how to use them
- We will outline the intuition behind a few method.
- Many resources are available online if you want to learn more. Mastering Metrics (Angrist and Pischke, 2014) and Mostly Harmless Econometrics (Angrist and Pischke, 2008) are fantastic books! You can also check out Causal inference, the mixtape by Scott Cunningham.

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So what's a good randomised control trial (RCT)?

- Sufficient sample size (aim at > 30 in each group).
- Correct randomisation (e.g. just taking the month of birth is not enough)
- Give the control group a placebo treatment.
- Avoid desirability effects.

$\Rightarrow$ Depends on the context whether it is feasible for you.

Nice extra: RCTs have won this woman the previous Econ Nobel prize

...Esther Duflo, representative for many others:

- What is the "best" way to spend money on development? Miguel and Kremer (2004)
- Do women on city councils affect policy-making positively? Chattopadhyay et al. (2004)
- What is the effect of the neighbourhood on a child? Chetty et al. (2014)
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... and btw: The tools for causal analysis that follow now won the Nobel prize this year!

DiD

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- **What's the counterfactual?** The control group is assumed to be a good indication for what the treatment group would have been absent the treatment.

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Example: Does a minimum wage increase destroy jobs? (Card et al. (1994))

- **Treatment**: In April 1992, New Jersey (US) increased its minimum wage from \$4.25 to \$5 , whereas neighbouring Pennsylvania did not.

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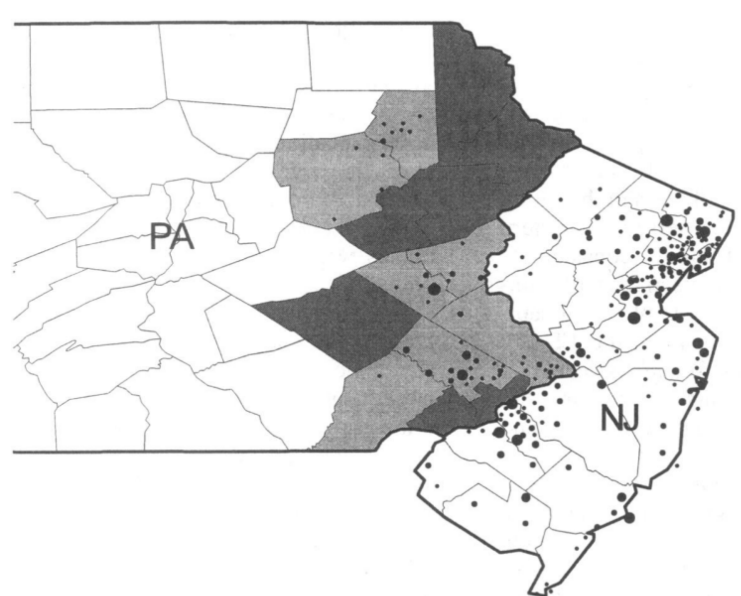
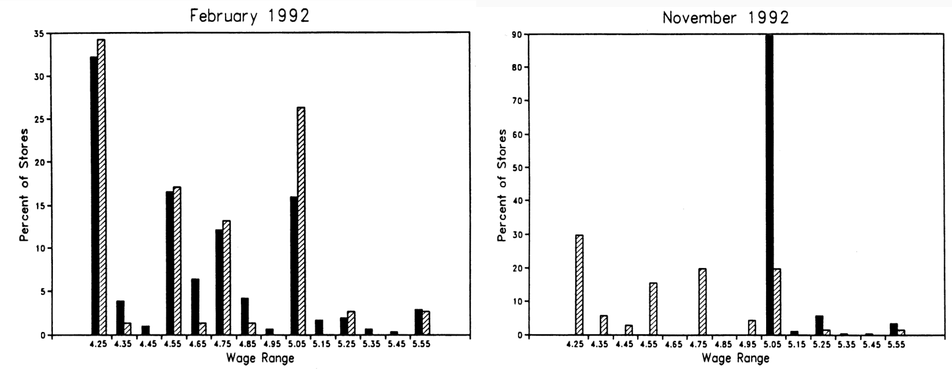
- **Before vs after**: Before the minimum wage introduction in NJ (March 1992) vs after its introduction (November 1992)

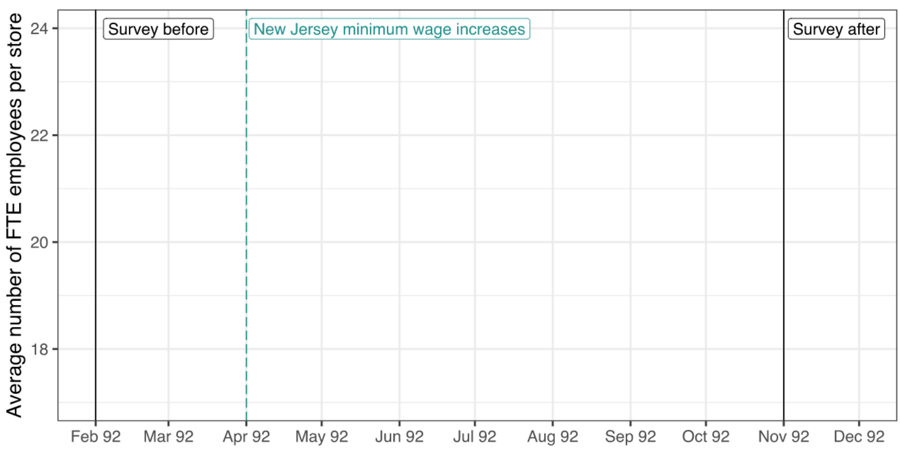
"Difference-in-Difference": Treatment vs control group



"Difference-in-Difference": Minimum wage as treatment



Difference-in-Difference graphically



FTE = Full time employment [1]

[1] Section from this Siences Po Course

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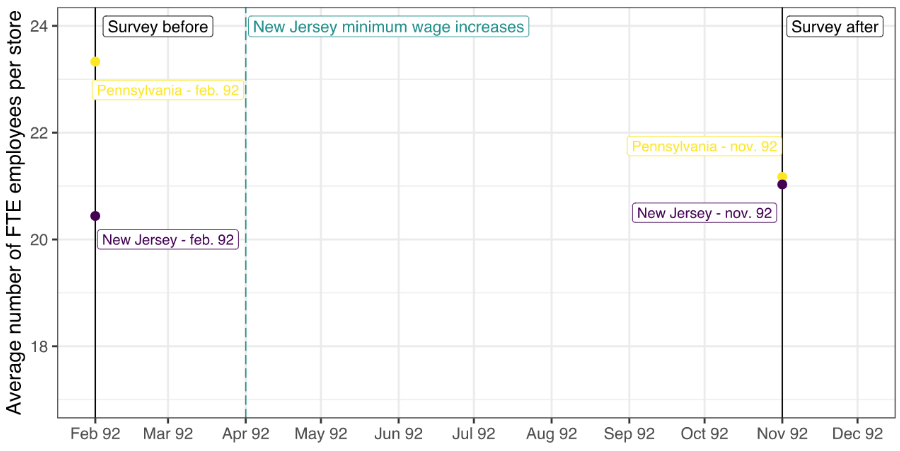

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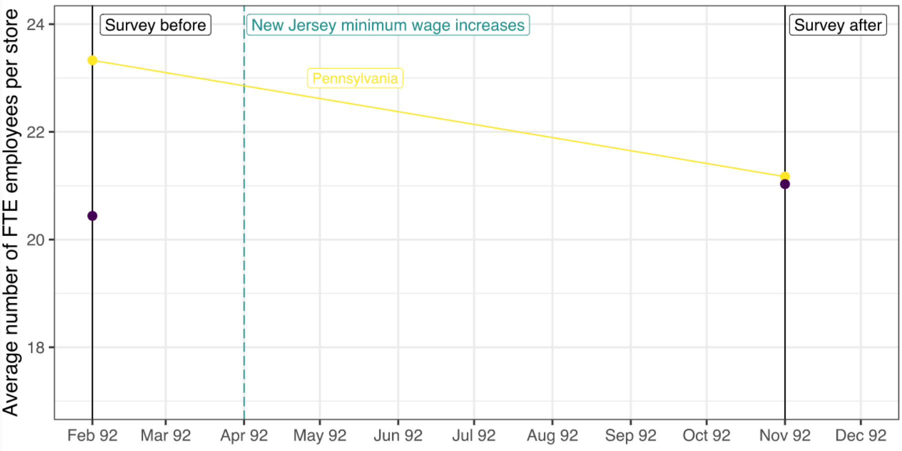

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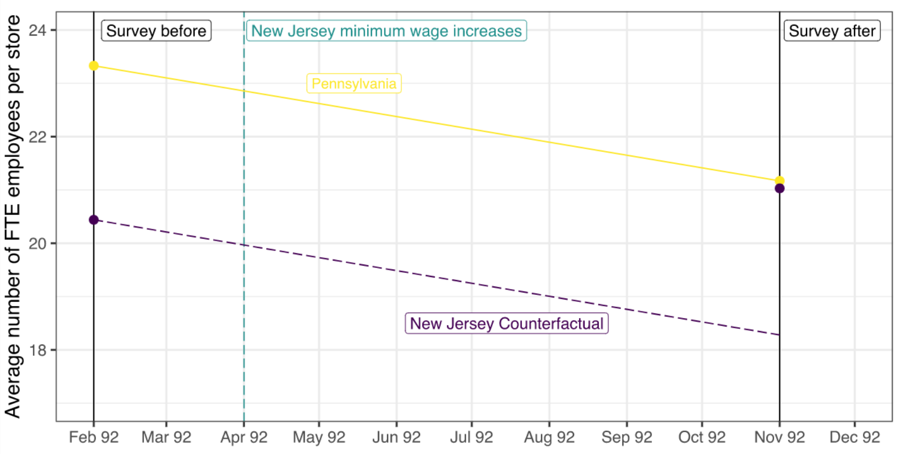

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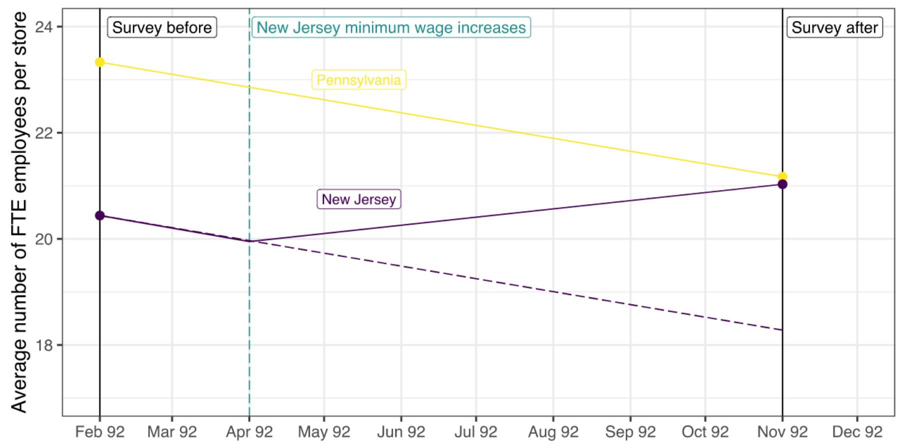

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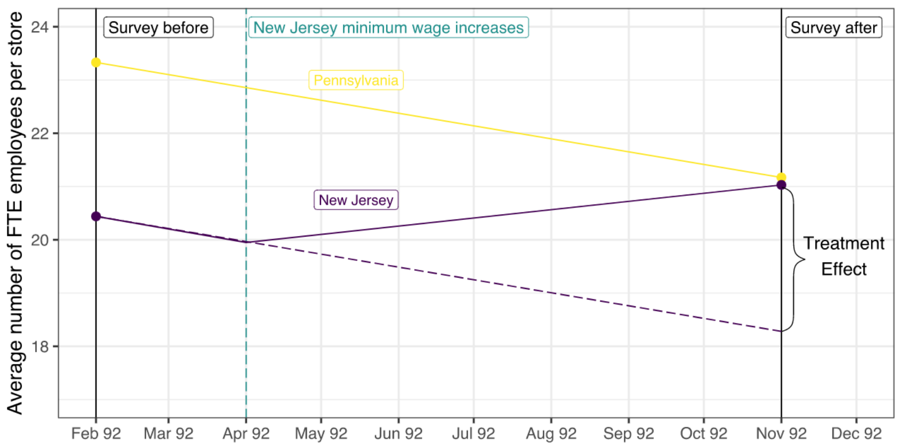

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Difference-in-Difference: What's the counterfactual?

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- This is equivalent to assuming that they **would have followed parallel trends** absent the treatment.

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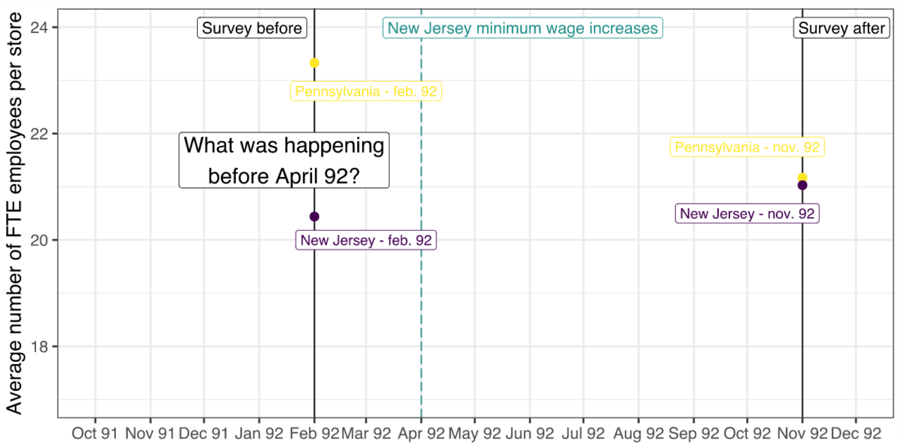
- Obviously, we cannot observe this. But we can do two things:
  - Check if they **were similar before**
  - Check if the followed **parallel trends before treatment**
- **Ultimately, the credibility of the difference-in-differences approach rests on the assumption of parallel trends.**

Difference-in-Difference: Pre-treatment trends



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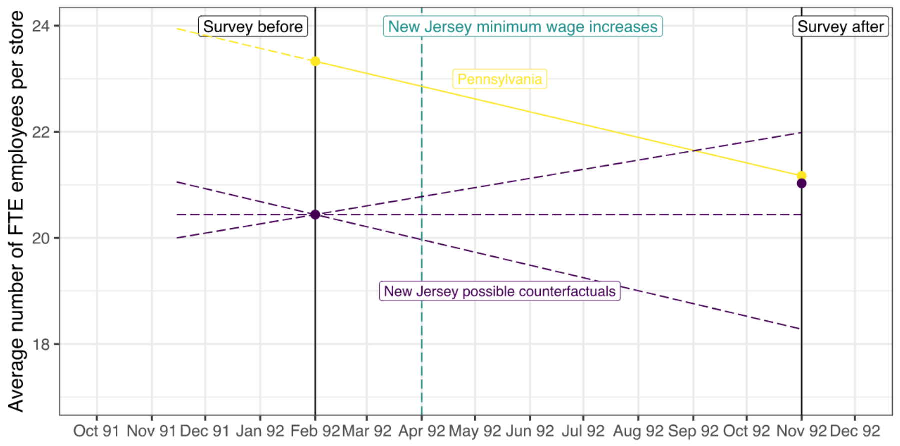

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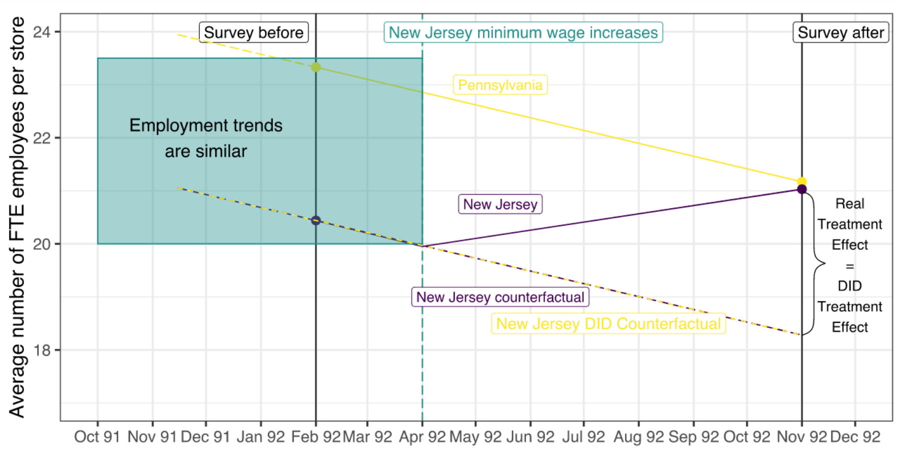

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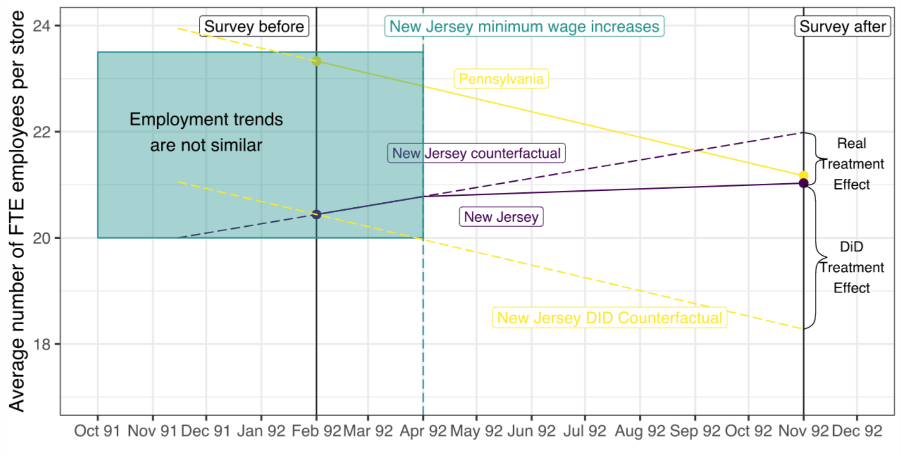

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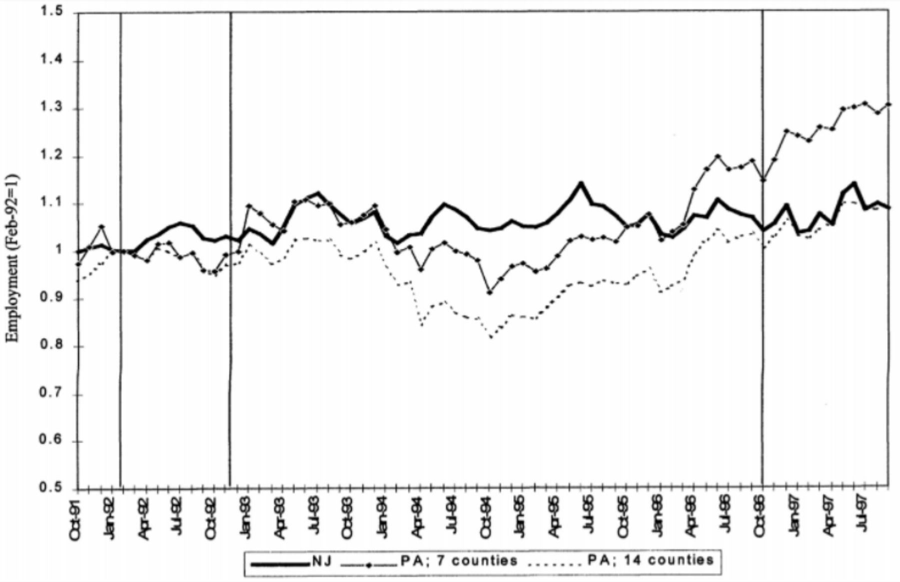

RDD

Regression Discontinuity Design (RDD)

- **Intuition:** Arbitrary rules in the "real world" can create wonderful natural experiments[3]
- For instance, children can start school if they are five years old before January 31st; people are eligible for microfinance loan if they own less than 0.5 acre of land, students get scholarships above a certain GPA...
- But how different are people just above and below those thresholds?

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- But how different are people just above and below those thresholds? Not much: allocation is as good as random.
- The essence of RDD is to compare people just above the cut-off to others just below
- **Identifying assumption**: assignment variable cannot be manipulated
- **Our example**: Do generous welfare payments reduce the incentive to work (Lemieux et al., 2008)?

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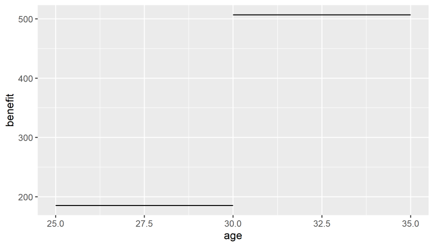
Regression Discontinuity Design

- Arbitrary discontinuity in welfare rules in Québec: Until 1989 unemployed individuals without children under the age of 30 received substantially lower welfare benefits than those of age 30 and over



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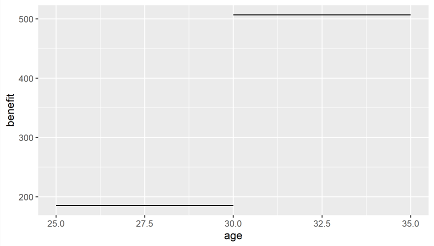

- Those over age 30 received \$507 per month in 1989; compared to \$185 for those under age 30.
- How do people just above 30 compare to people just below 30 in their labour behaviour?
- Outcome variable: whether a person worked in the week before the census

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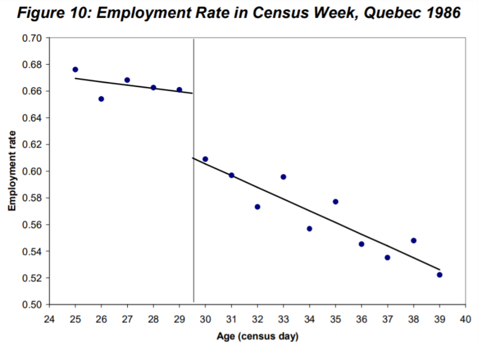

- Results: there is a clear discontinuity at age 30.
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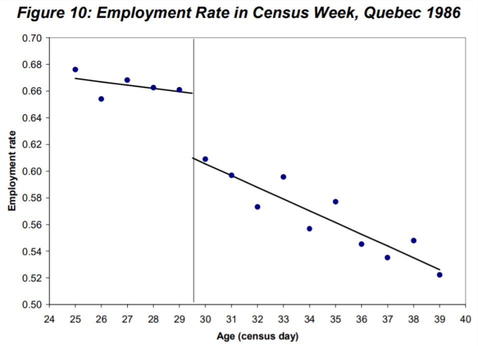

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- **Assuming that all other factors remained constant or changed smoothly**, this is the causal effect of an increase in welfare benefits: people work less.
- Is it a big assumption?
- There is no reason to expect labour outcomes to change sharply at age 30.
- Another concern could be manipulation (some specific people lying about their age). But unlikely to happen: age is easy to check for the administration.

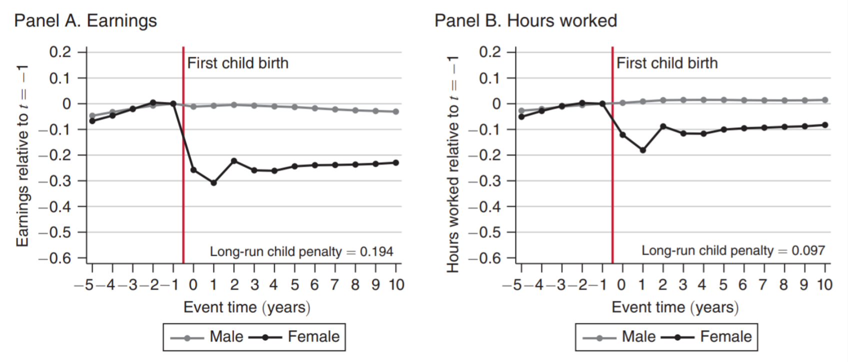
Event studies

Event Studies

- **Intuition:** Core results rely on within person variation: how does person i change at date t?[4]
- **Identifying assumptions**: at threshold t, treatment switches discretely to on; other factors evolve smoothly.
- **Example**: Effect of children on (female) careers (Kleven et al., 2019)
- Children are not randomly allocated, and it is not possible to randomize fertility $\Rightarrow$ exogeneity is not achievable
- However, the event of having a first child generates sharp changes in labor market outcomes.
- If other unobserved determinants of those outcomes evolve smoothly over time, the changes can arguably be attributed to the event of having children.

[4] Section inspired by slides by Florian Oswald

Event Studies



- Plotted coefficients measure the impact of children relative to the year just before the first childbirth. Lifecycle trend (age) and time trend (year) are controlled for.
- Earnings of men and women are parallel until parenthood; diverge exactly as first child arrives: women experience an immediate drop in gross earnings of almost 30 percent and never converge back.

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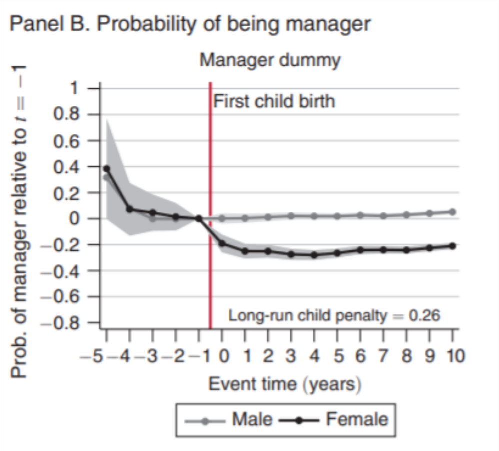

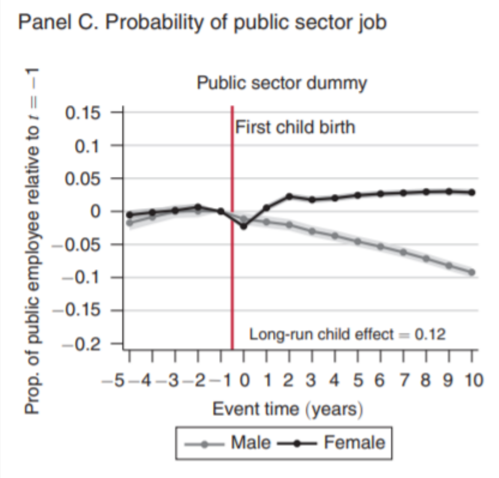

- After childbirth, women are also less likely to be a manager, and more likely to work in the public sector. **Check paper for more results!**

IV

Instrumental variable

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- But the techniques behind it can be used in different settings.

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  - Outcome: Modern-day economic performance.
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  - Instrument: **Early European settler mortality rates**.
    - ✓ **Relevant**: Where Europeans could not settle, they did not establish their institutions.
    - ? **Exogenous**: Is settler mortality not related to other factors that matter for economic performance?
    - ? **Exclusive**: Is there any other way how the settler mortality rate could affect ?

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  - Outcome: Test scores of students in national exam in the US.

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  - ... here those whose decision to go to a private school is changed by the lottery.

Conclusion

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- Exogeneity is hard to come by!
- But economists have developed interesting tools to try to get to it. You only saw the intuitions today, there are many resources to learn the maths behind!
- In general, it's important to know the **context**: not all relies on the maths, you need to convince people that the assumptions for causality are met
- We don't expect you to use these methods in the final project! (you can breathe now)

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