

Difference-in-Differences

Data Science and Causal Inference Workshop 2025

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- The availability of richer datasets and the advances in computational power have changed Social Sciences during the last 40 years.
- Currie, Kleven and Zwiers (2020) show that the fraction of empirical research keeps rising.
- A very common goal of empirical research is to uncover/highlight the causal effect of a given policy intervention.

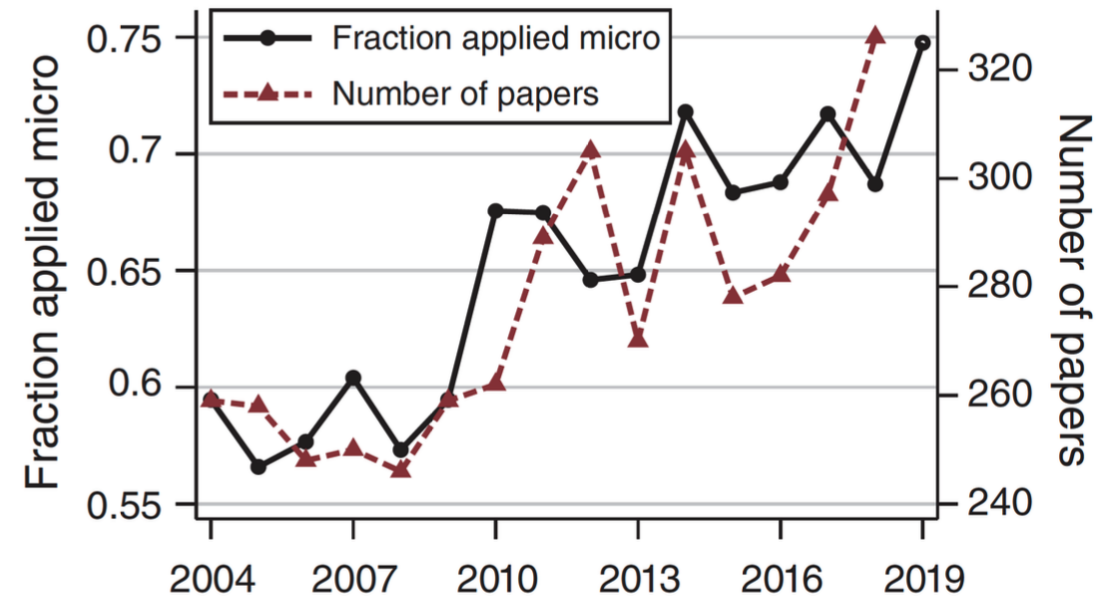


FIGURE 1. APPLIED MICROECONOMICS ARTICLES IN TOP-FIVE JOURNALS

Note: This figure shows the fraction of papers in top-five journals that report an applied microeconomics JEL code (left axis) and the total number of papers in the top-five journals (right axis).

Currie et al. (2020) documented this change well

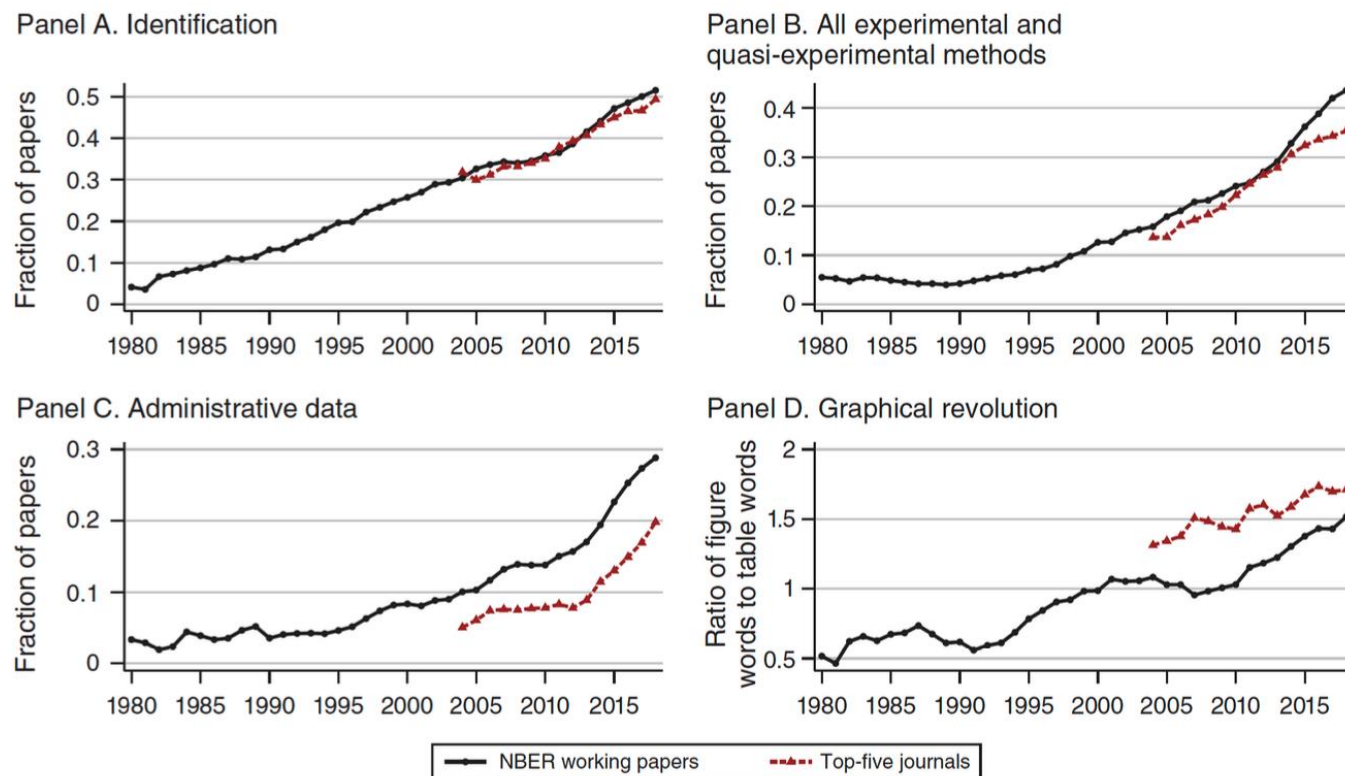


FIGURE 2. THE CREDIBILITY REVOLUTION

Notes: This figure shows different dimensions of the “credibility revolution” in economics: identification (panel A), all experimental and quasi-experimental methods (panel B), administrative data (panel C), and the graphical revolution (panel D). Panel D shows the ratio of the number of “figure” terms to the number of “table” terms mentioned. See Table A.I for a list of terms. The series show five-year moving averages.

What about experiments (or A/B tests)?

Currie et al. (2020)

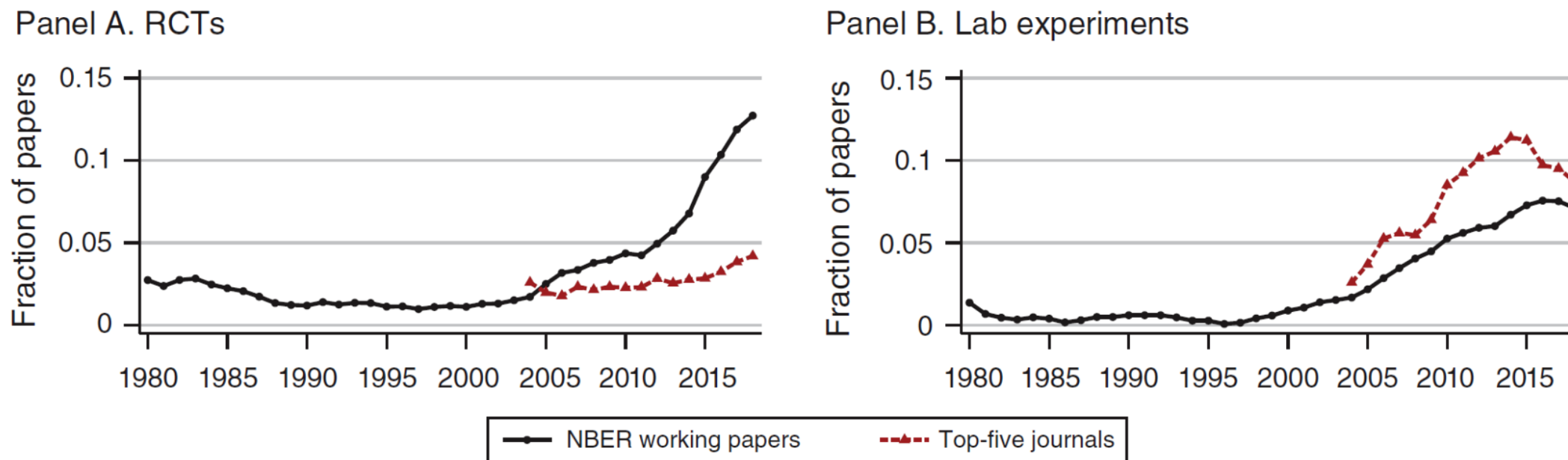
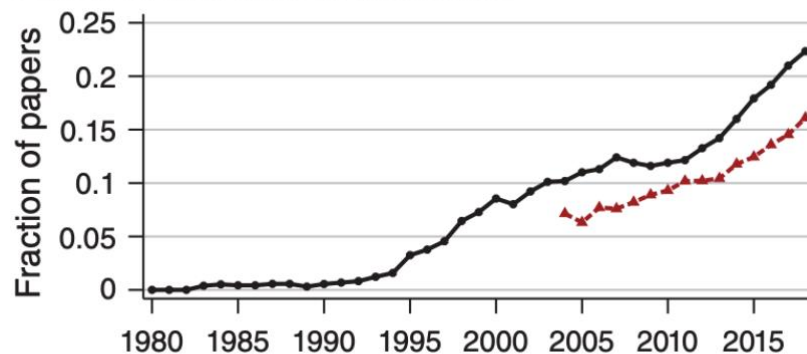


FIGURE 3. EXPERIMENTAL METHODS

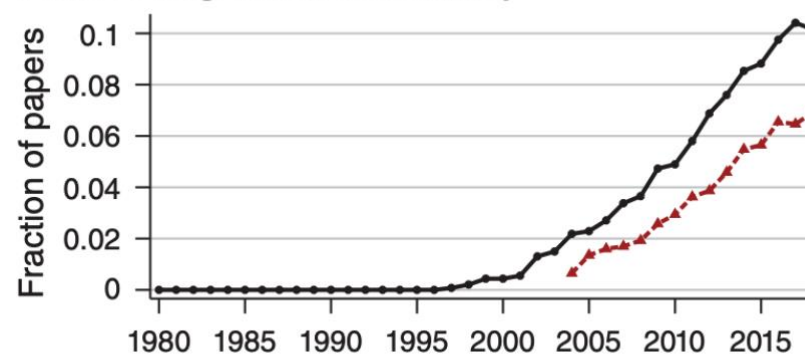
Notes: This figure shows the fraction of papers referring to each type of experiment. See Table A.I for a list of terms. The series show five-year moving averages.

Currie et al. (2020)

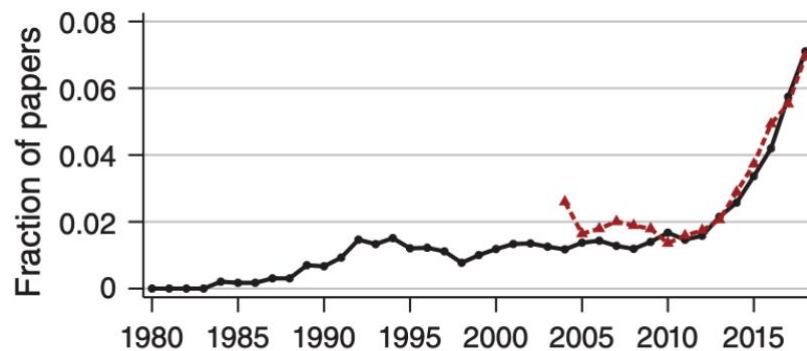
Panel A. Difference-in-differences



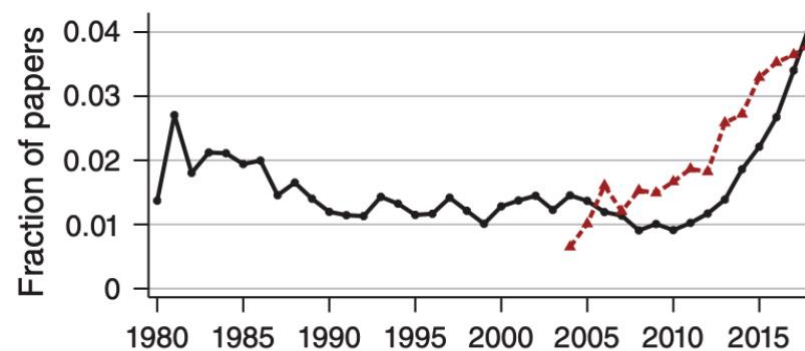
Panel B. Regression discontinuity



Panel C. Event study



Panel D. Bunching



—●— NBER working papers - - -▲- - - Top-five journals

FIGURE 4. QUASI-EXPERIMENTAL METHODS

Goldsmith-Pinkham (2024) built on Currie et al. (2020) and updated the analysis using NBER working papers data that ends in May 2024.

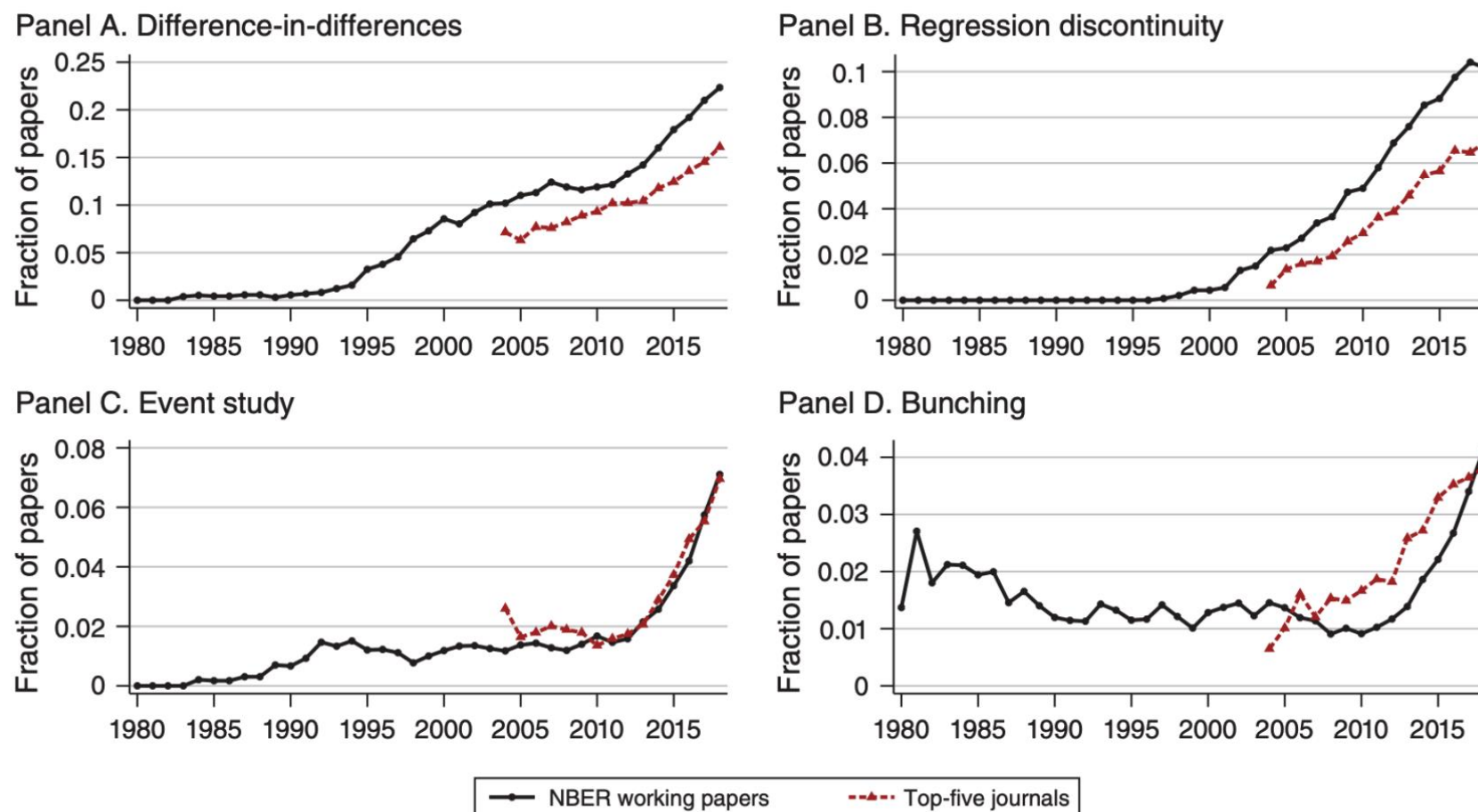
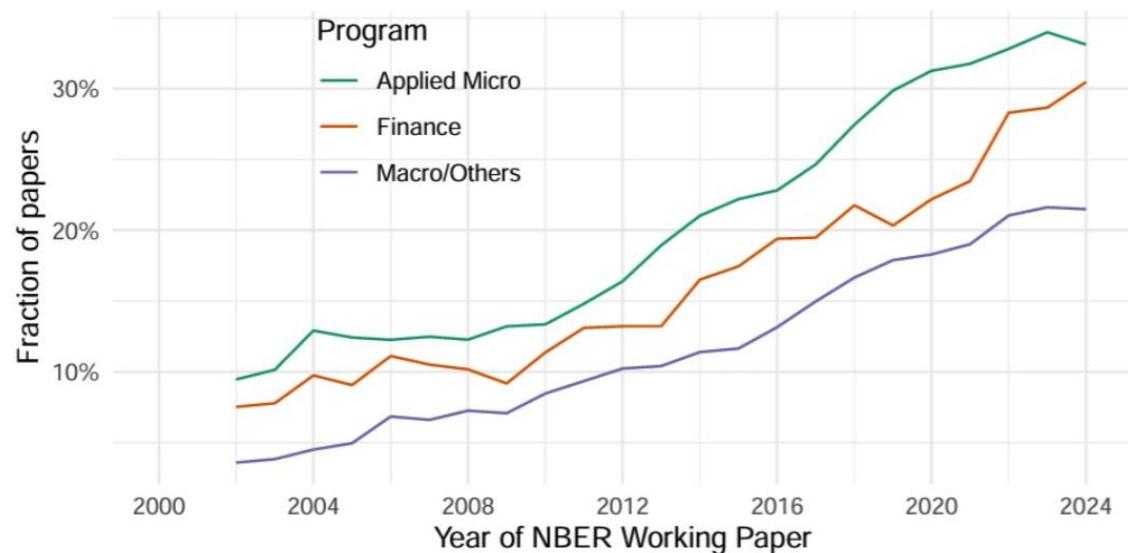
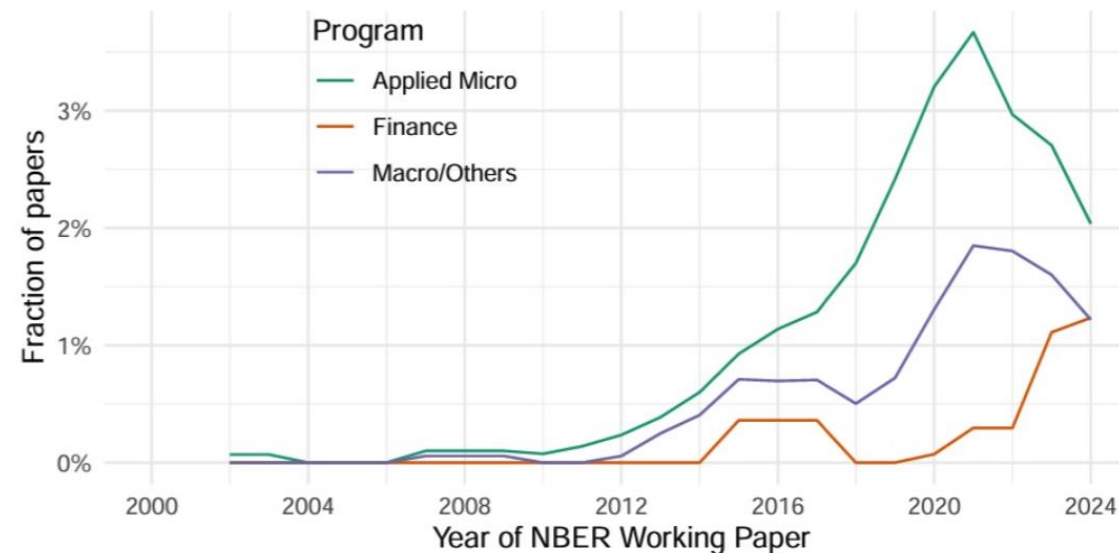


FIGURE 4. QUASI-EXPERIMENTAL METHODS

Goldsmith-Pinkham (2024): the popularity of DiD by fields



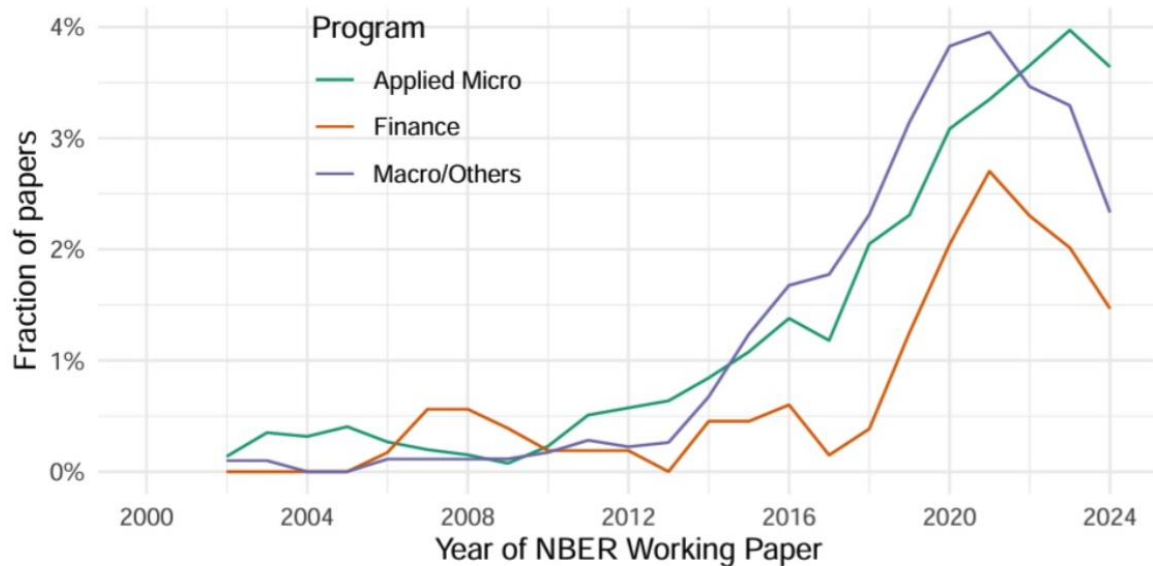
(a) Difference-in-differences



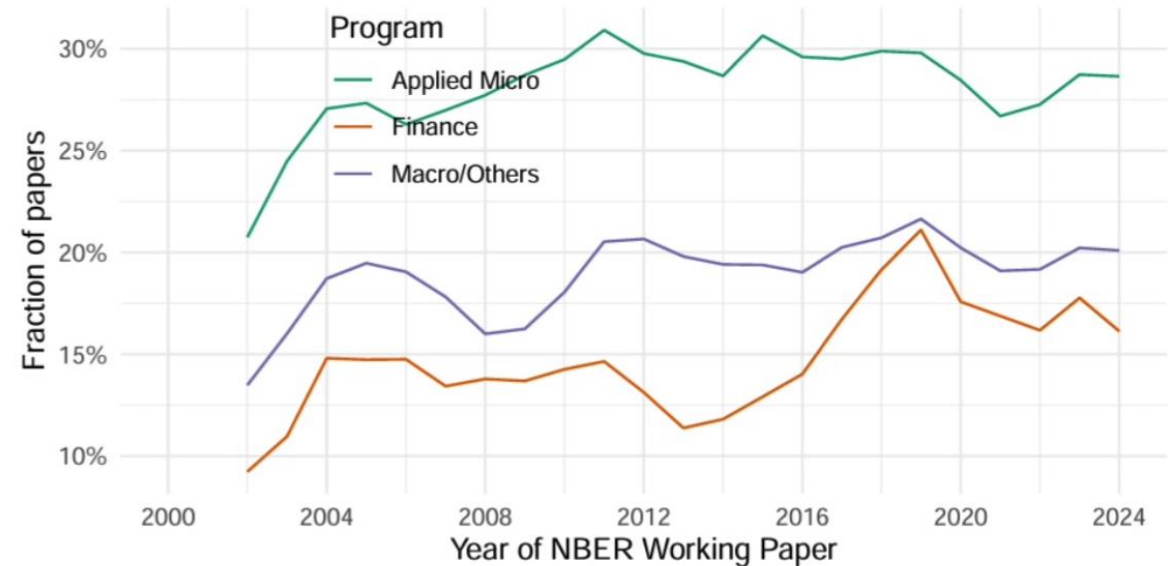
(b) Synthetic controls

Figure 5: Panel (a) reports the share of papers that mention difference-in-differences or event studies. Figure (b) reports the share of papers that mention synthetic controls (this includes both synthetic difference-in-differences and synthetic control methods). See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

Goldsmith-Pinkham (2024): Compare previous plot with IV



(a) Bartik and shift-share instruments



(b) Instrumental variables

Figure 6: Panel (a) reports the share of papers that mention Bartik or shift-share instruments. Figure (b) reports the share of papers that mention instrumental variables. See Table 2 for the breakdown of fields, and the Appendix for definitions on keywords.

- In many applications, we do not have access to experimental data.
- Without an experiment, we will rely on observational data.
- With observational data, we have no choice but rely on assumptions to conduct causal inference.
- Different methods rely on different assumptions.
- Our job as researchers is to assess the pros and cons of each method in their ability to answer the questions we (and the business/policy makers/stakeholders) care about.

- DiD is very popular.
- Why?
- Data requirements, availability of tools to assess the plausibility of assumptions and easy-to-use software.
- What are the main alternatives to DiD?
 1. Rely on unconfoundedness and leverage **regression, matching, re-weighting or double machine learning**.

Drawback: Rule out selection on unobservables.

We need to have data on everything that affects treatment timing and outcome of interest (unconfoundedness assumption).

- What are the main alternatives to DiD?

2. Rely on **Pre-Post analysis**

Drawback: Does not account for potential trends in outcomes.

This is more reasonable if we study very short-run effects, but that is not usually the case.

- DiD methods exploit variation in time (before vs. after) and across groups (treated vs. untreated) to recover causal effects of interest.
 - **DiD combines previous approaches to avoid their pitfalls.**
 - Advantage: Allow for selection on unobservables and time-trends.
- Not magic:** We need to assume that, absent the treatment and conditional on covariates (features), the outcome of interest would evolve similarly across groups/cohorts — **Parallel Trends assumption.**

Parallel Trends needs to be discussed and its plausibility assessed!

- **Data Requirements:** We need data from periods before and after treatment to use DiD (and some periods where no unit is treated).

Beck, Levine and Levkov (2010): **Effect of bank branching deregulation on income distribution in the US.**

- Exploit staggered bank deregulation across states to understand its effect on the Gini index (among other outcomes); see also Baker, Larcker and Wang (2022).

Venkataramani, Shah, O'Brien, Kawachi and Tsai (2017): **Effect of US Deferred Action for Childhood Arrivals (DACA) immigration program on health outcomes.**

- Compared changes in health outcomes among individuals who met key DACA eligibility criteria (based on age at immigration and at the time of policy implementation) before and after program implementation versus changes in outcomes for individuals who did not meet these criteria.

Card and Krueger (1994): **Effect of minimum wage on employment.**

- Compared the changes in wages, employment, and prices at stores in New Jersey (increased minimum wage) relative to stores in Pennsylvania (minimum wage remained fixed).

Dube, Lester and Reich (2010); Dube, William Lester and Reich (2016), Callaway and Sant'Anna (2021) and many others: **Effect of minimum wage on different measures of employment**

- Callaway and Sant'Anna (2021) exploit variation in the timing of state minimum wage changes to understand its effect on teen employment.

Meyer, Viscusi and Durbin (1995): **Effect of weekly benefit amount on time out of work due to injury.**

- They compared high-earnings (affected by the policy change) and low-earnings (not affected by the policy change) individuals injured before and after increases in the maximum weekly benefit amount. Estimated effects in Kentucky and Michigan.

Malesky, Nguyen and Tran (2014): **Effect of government re-centralization in Vietnam on public services.**

- They compared provinces (and districts) that abolished elected councils in Vietnam to other provinces that did not abolish them, before and after the re-centralization. Analyzed 30 outcomes.

Carey, Miller and Wherry (2020): **Effect of Medicaid expansion on access to care and utilization for those who are already insured.**

- They compare different insurance coverage and health care utilization measures among states that opted to expand Medicaid eligibility in 2014 or 2015 with those that did not expand by 2015, before and after the expansion.

Assunção, Gandour, Rocha and Rocha (2020): **Effect of rural credit on deforestation.**

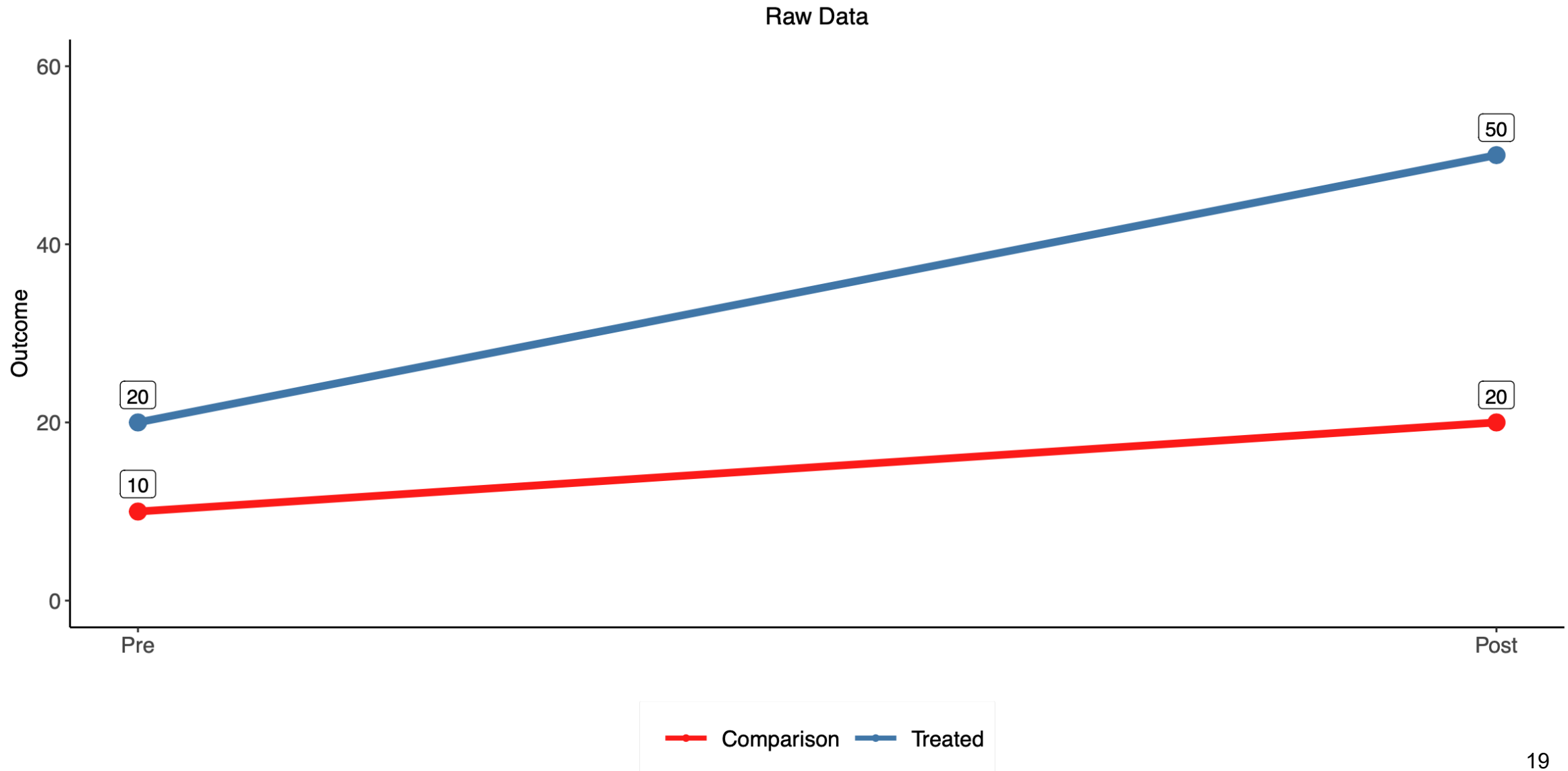
- Compared municipalities within the Amazon biome (concession of subsidized rural credit for them are conditional on stricter requirements since 2008), with municipalities outside the border of the Amazon biome (not affected by the policy change), before and after the policy.

The **canonical DiD** estimator is given by:

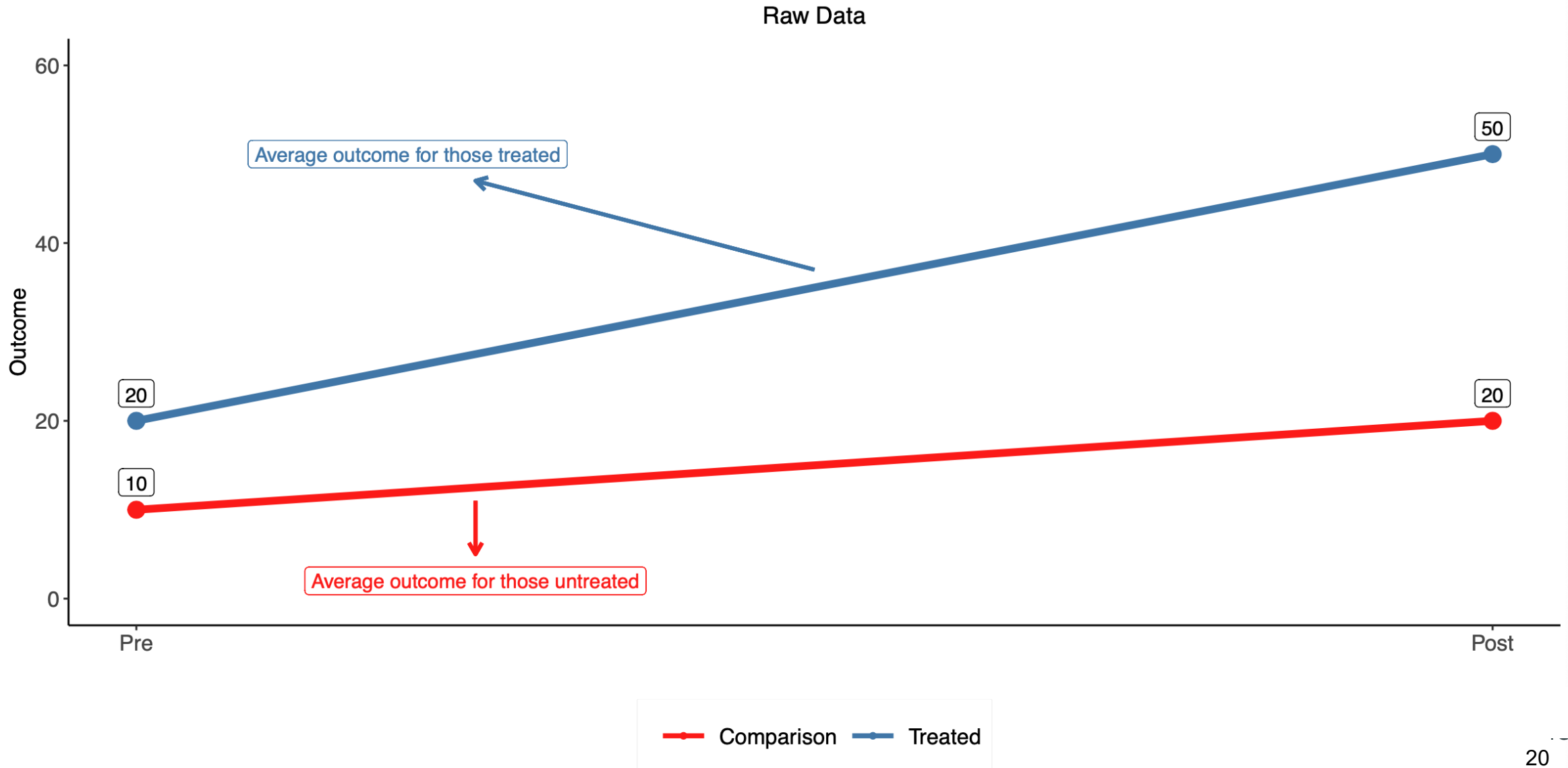
$$\hat{\theta}^{DiD} = (\bar{Y}_{Treated,Post} - \bar{Y}_{Treated,Pre}) - (\bar{Y}_{Untreated,Post} - \bar{Y}_{Untreated,Pre})$$

where the subscripts refer to:

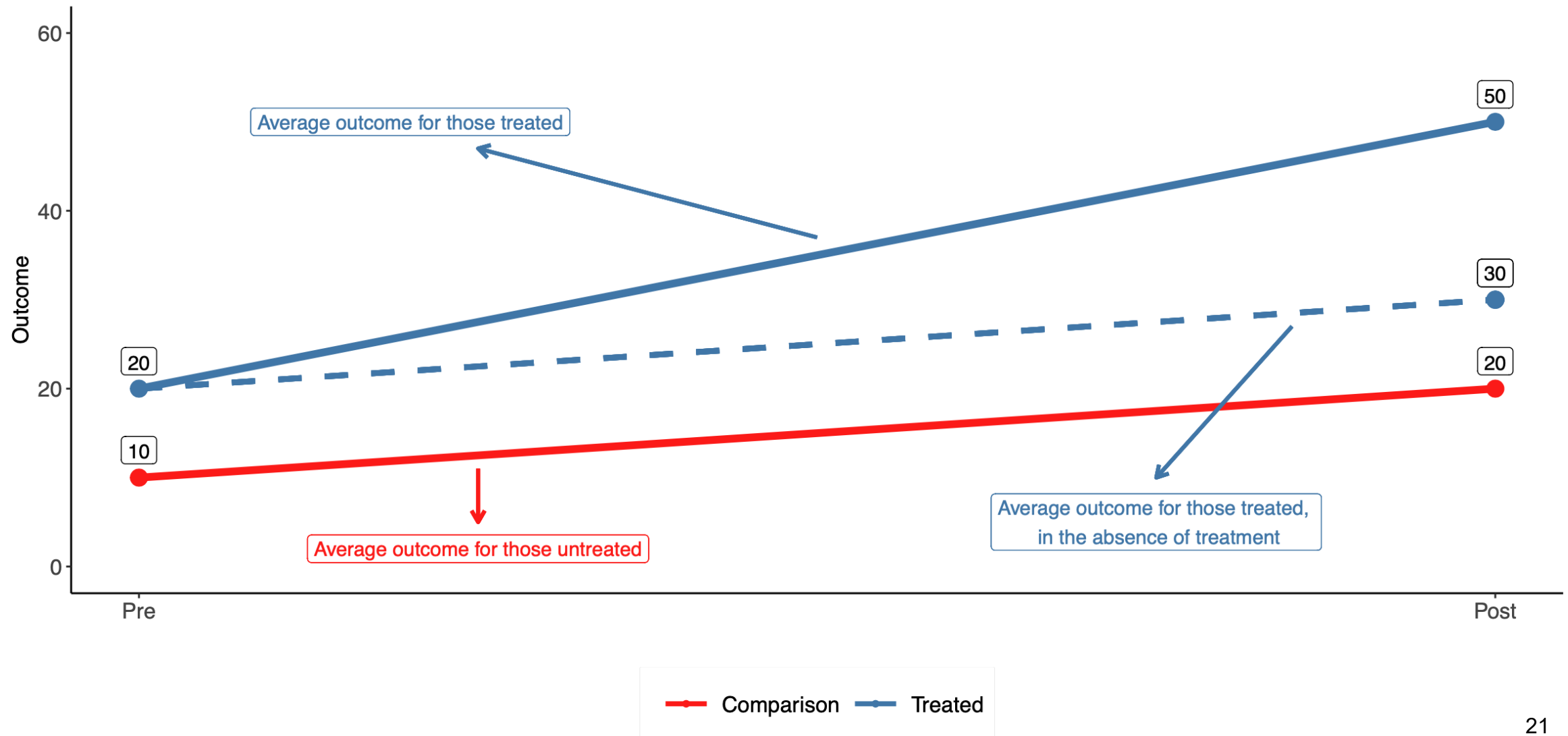
- Treated, Post = average outcome for the group that received the treatment after it happened
- Treated, Pre = average outcome for the group treated group before the treatment
- Untreated, Post = average outcome for the group that did not receive the treatment after the time that the treatment happened
- Untreated, Pre = average outcome for the group that did not receive the treatment before the treatment happened



Difference-in-Differences via graphs



Raw Data + Counterfactuals via PT



Difference-in-Differences via graphs

Raw Data + Counterfactuals via PT + ATT

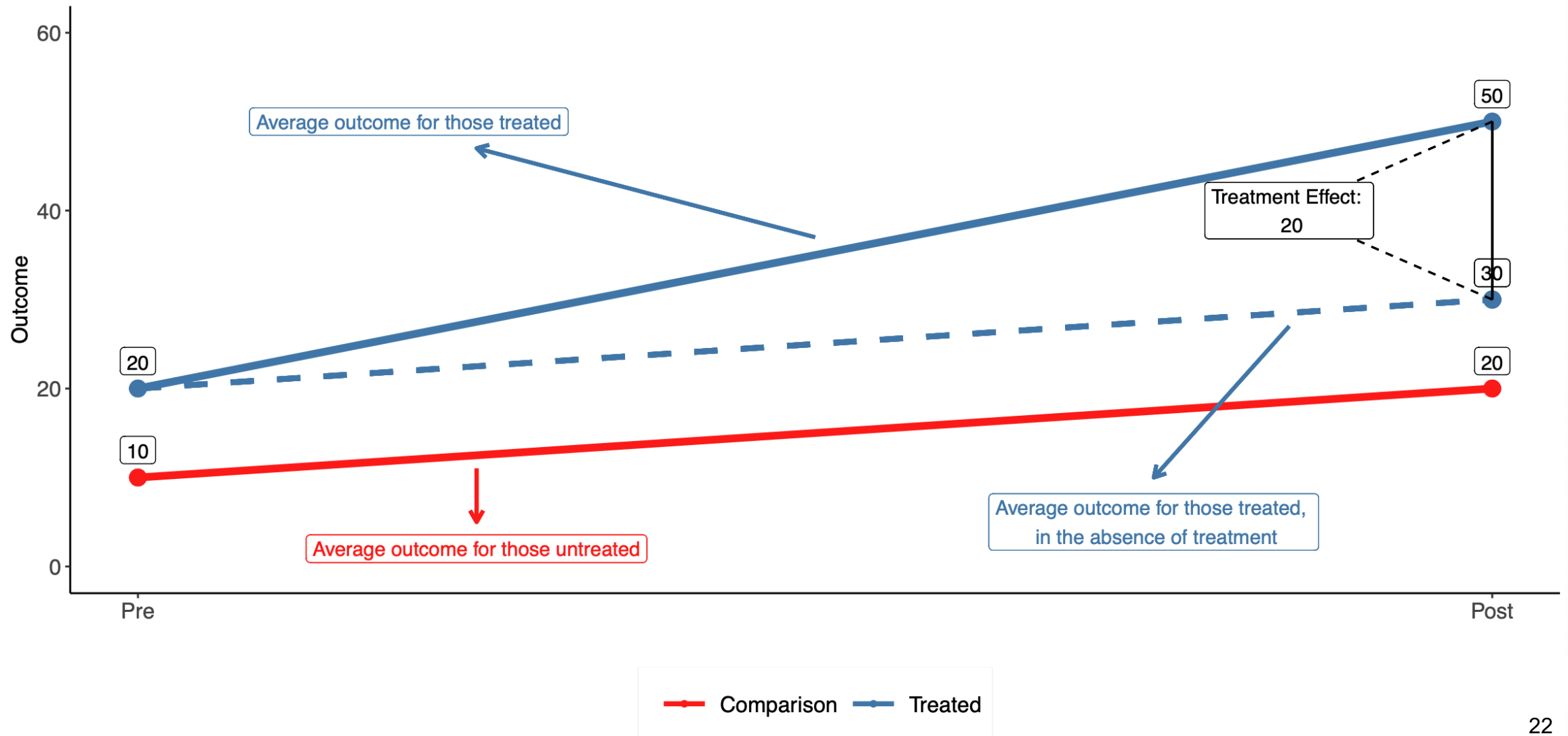


Illustration with R

Staggered difference-in-differences

https://github.com/borusyak/did_imputation
https://github.com/andrewchbaker/JFE_DID

On Codespaces, create a new folder called “repos”
and use “git clone” to download the above repos

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