A Local Projections Approach to Difference-in-Differences Event Studies

Arindrajit Dube[†] Daniele Girardi[*] Òscar Jordà[‡] Alan M. Taylor[§]

September 2023

[†] University of Massachusetts, Amherst; NBER; and IZA
[*] King's College London and University of Massachusetts, Amherst;
[‡] Federal Reserve Bank of San Francisco; University of California, Davis; and CEPR
[§] Columbia University; NBER; and CEPR

Research question

How to estimate Difference-in-Differences (DiD) with multiple treatment cohorts?

- Recent literature shows that conventional TWFE implementations can be severely biased.
- A new regression-based framework: LP-DiD.
  - Local projections (Jordà 2005) + clean controls (Cengiz et al 2019).
- Montecarlo simulation to assess its performance.
- Empirical applications:
  - The effect of banking deregulation on the wage share.
  - Democracy & growth

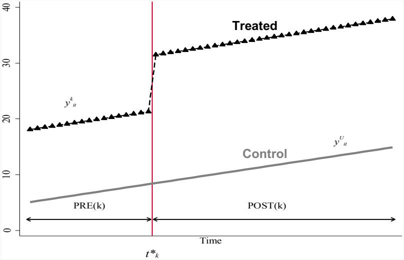
Why do we need yet another DiD estimator?

Advantages of LP-DiD:

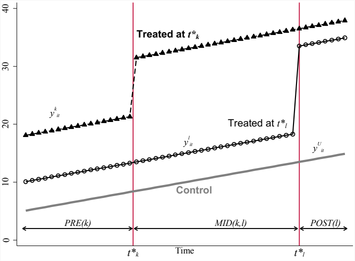
- Simpler, faster and more transparent than other recent DiD estimators.
- Flexible: can easily accommodate different settings, weighting schemes, and target estimands.
- General: encompasses other DiD estimators as specific sub-cases.
- Allows controlling for pre-treatment values of the outcome and of other time-varying covariates.

Difference-in-Differences (DiD)

2x2 Setting



Staggered Setting



(Visual examples from Goodman-Bacon, 2021)

Background

The conventional (until recently) DiD estimator: TWFE

- Static TWFE

$$y_{it} = \alpha_i + \delta_t + \beta^{TWFE} D_{it} + \epsilon_{it}$$

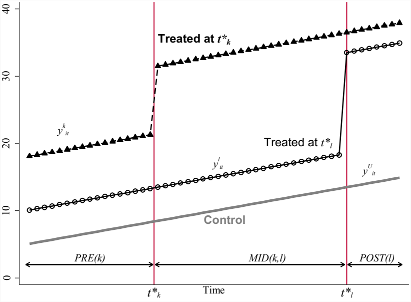
- Event-study (distributed lags) TWFE

$$y_{it} = \alpha_i + \delta_t + \sum_{h=-Q}^{H} \beta_h^{TWFE} D_{it-h} + \epsilon_{it}$$

- OK in the 2x2 setting.
- Biased even under parallel trends with staggered treatment, if treatment effects are dynamic and heterogeneous.

The problems with TWFE in the staggered setting

- TWFE as weighted-average of 2x2 comparisons (Goodman-Bacon 2021)
    1. Newly treated vs Never treated;
    2. Newly treated vs Not-yet treated;
    3. Newly treated vs Earlier treated.



The problems with TWFE in the staggered setting

- TWFE as weighted-average of 2x2 comparisons (Goodman-Bacon 2021)
    1. Newly treated vs Never treated;
    2. Newly treated vs Not-yet treated;
    3. Newly treated vs Earlier treated.

- Bias formula for TWFE (Goodman-Bacon 2021)

$$p\lim_{N\to\infty}\hat{\beta}^{TWFE} = VWATT - \Delta ATT$$

The problems with TWFE in the staggered setting

- TWFE as weighted-average of 2x2 comparisons (Goodman-Bacon 2021)
    1. Newly treated vs Never treated;
    2. Newly treated vs Not-yet treated;
    3. Newly treated vs Earlier treated.

- Bias formula for TWFE (Goodman-Bacon 2021)

$$p\lim_{N\to\infty} \hat{\beta}^{TWFE} = VWATT - \Delta ATT$$

- TWFE as a weighted-average of cell-specific ATTs (de Chaisemartin & D'Haultfoeuille 2020)

$$E\left[\hat{\beta}^{TWFE}\right] = E\left[\sum_{(g,t):D_{gt}=1} \frac{N_{g,t}}{N_1} w_{g,t}\Delta_{g,t}\right]$$

    - Weights can be negative!

A Local Projections Diff-in-Diff Estimator (LP-DiD)

Baseline version

Setting & Assumptions:

- Binary absorbing treatment.
- Staggered adoption.
- Treatment effects can be dynamic & heterogeneous.
- No anticipation.
- Parallel trends.

A Local Projections Diff-in-Diff Estimator (LP-DiD)

Baseline version

Estimating equation:

$$y_{i,t+h} - y_{i,t-1} = \begin{array}{ll} \beta_h^{LP-DiD} \Delta D_{it} & \} \text{ treatment indicator} \\ + \delta_t^h & \} \text{ time effects} \\ + e_{it}^h \; ; & \qquad \text{for } h = 0, \ldots, H \, . \end{array}$$

restricting the sample to observations that are either:

$$\begin{cases} \text{newly treated} & \Delta D_{it} = 1 \, , \\ \text{or clean control} & D_{i,t+h} = 0 \end{cases}$$

LP-DiD Estimator

What does LP-DiD identify?

- A variance-weighted average effect:

$$E(\hat{\beta}_h^{LP-DiD}) = \sum_{g \neq 0} \omega_{g,h}^{LP-DiD} \tau_g(h)$$

  - o $\tau_g(h) = h$-periods forward ATT for treatment-cohort g.

- No negative weights.

LP-DiD Estimator

What does LP-DiD identify?

- A variance-weighted average effect:

$$E(\hat{\beta}_h^{LP-DiD}) = \sum_{g \neq 0} \omega_{g,h}^{LP-DiD} \tau_g(h)$$

  - o $\tau_g(h) = h$-periods forward ATT for treatment-cohort g.

- No negative weights.

- Weights depend on subsample size & treatment variance:

$$\omega_{g,h}^{LP-DiD} = \frac{N_{CCS_{g,h}}[n_{gh}(n_{c,g,h})]}{\sum_{g \neq 0} N_{CCS_{g,h}}[n_{g,h}(n_{c,g,h})]},$$

  - o $N_{CCS_{g,h}}$ = size of subsample including group g & its clean controls.
  - o $[n_{gh}(n_{c,g,h})]$ = treatment variance in that subsample.

Flexibility in choosing a weighting scheme

- Can apply any desired weights through weighted regression.
- Equally-weighted ATT:
  - weighted regression with weights $= 1/(\omega_{g,h}^{LP-DiD}/N_g)$
  - can also use regression adjustment.

LP-DiD encompasses other DiD estimators

- Baseline $\leftrightarrow$ stacked estimator (CDLZ, 2019)
  - But no need to stack the data!
- Baseline + reweighting $\leftrightarrow$ CS estimator.
- Baseline + reweighting + alternative base period $\approx$ BJS estimator.
  - LHS: $y_{i,t+h} - \frac{1}{k}\sum_{\tau=t-k}^{t-1} y_{i,\tau}$

LP-DiD as a 'swiss knife'

Easy to adapt to different settings

- Covariates & outcome lags
- Non-absorbing treatment
- Continuous treatment variable

LP-DiD with covariates and outcome lags

Estimating equation:

$$
\begin{aligned}
y_{i,t+h} - y_{i,t-1} = \quad & \beta_h^{LP-DiD} \Delta D_{it} && \} \text{ treatment indicator} \\
& + \textstyle\sum_{p=1}^{P} \gamma_p^h \Delta y_{i,t-p} && \} \text{ outcome lags} \\
& + \textstyle\sum_{m=1}^{M} \sum_{p=0}^{P} \gamma_{m,p}^h \Delta x_{m,i,t-p} && \} \text{ covariates} \\
& + \delta_t^h && \} \text{ time effects} \\
& + e_{it}^h \, ; && \quad \text{for } h = 0, \ldots, H \, ,
\end{aligned}
$$

restricting the sample to observations that are either

$$
\begin{cases}
\text{newly treated} & \Delta D_{it} = 1 \, , \\
\text{or clean control} & D_{i,t+h} = 0
\end{cases}
$$

LP-DiD with covariates and outcome lags

Estimating equation:

$$
\begin{aligned}
y_{i,t+h} - y_{i,t-1} = \quad & \beta_h^{LP-DiD} \Delta D_{it} && \} \text{ treatment indicator} \\
& + \textstyle\sum_{p=1}^{P} \gamma_p^h \Delta y_{i,t-p} && \} \text{ outcome lags} \\
& + \textstyle\sum_{m=1}^{M} \sum_{p=0}^{P} \gamma_{m,p}^h \Delta x_{m,i,t-p} && \} \text{ covariates} \\
& + \delta_t^h && \} \text{ time effects} \\
& + e_{it}^h \, ; && \qquad \text{for } h = 0, \ldots, H \, ,
\end{aligned}
$$

restricting the sample to observations that are either

$$
\begin{cases}
\text{newly treated} & \Delta D_{it} = 1 \, , \\
\text{or clean control} & D_{i,t+h} = 0
\end{cases}
$$

- Covariates will generally alter the weights.
- Can use p-score methods to make sure weights remain non-negative, or regression adjustment to get equally-weighted ATT.

LP-DiD with non-absorbing or continuous treatment

- In general: Adapt the clean control condition to the specific setting.

Extensions

LP-DiD with non-absorbing or continuous treatment

- In general: Adapt the clean control condition to the specific setting.
- Example for non-absorbing treatment:

$$\begin{cases} \text{treatment} & (\Delta D_{it} = 1) \quad \& \quad (\Delta D_{i,t-j} = 0 \text{ for } -h \leq j \leq L; j \neq 0) \\ \text{clean control} & \Delta D_{i,t-j} = 0 \text{ for } -h \leq j \leq L \end{cases}$$

Extensions

LP-DiD with non-absorbing or continuous treatment

- In general: Adapt the clean control condition to the specific setting.
- Example for non-absorbing treatment:

$$\begin{cases} \text{treatment} & (\Delta D_{it} = 1) \quad \& \quad (\Delta D_{i,t-j} = 0 \text{ for } -h \leq j \leq L; j \neq 0) \\ \text{clean control} & \Delta D_{i,t-j} = 0 \text{ for } -h \leq j \leq L \end{cases}$$

- Example for continuous treatment X_{it}:

$$\begin{cases} \text{movers} & (|\Delta X_{it}| > c) \quad \& \quad (|\Delta X_{i,t-j}| \leq c \text{ for } -h \leq j \leq L; j \neq 0) \\ \text{quasi-stayers} & |\Delta X_{i,t-j}| \leq c \text{ for } -h \leq j \leq L \end{cases}$$

- Underlying assumption: treatment effects *stabilize* after L periods.

Simulation

- N=500; T=50.
- DGP:
  $Y_{0it} = \rho Y_{0,i,t-1} + \lambda_i + \gamma_t + \epsilon_{it}; \quad -1 < \rho < 1; \quad \lambda_i, \gamma_t, \epsilon_{it} \sim N(0, 25)$
- Binary staggered treatment.
- TE grows in time for 20 periods, and is stronger for early adopters.

Simulation

- N=500; T=50.
- DGP:
  $Y_{0it} = \rho Y_{0,i,t-1} + \lambda_i + \gamma_t + \epsilon_{it}; \quad -1 < \rho < 1; \quad \lambda_i, \gamma_t, \epsilon_{it} \sim N(0, 25)$
- Binary staggered treatment.
- TE grows in time for 20 periods, and is stronger for early adopters.

1. Exogenous treatment
   - Units randomly assigned to 10 groups of size $N/10$
   - One group never treated; others treated at $t = 11, 13, 15 \ldots, 27$.

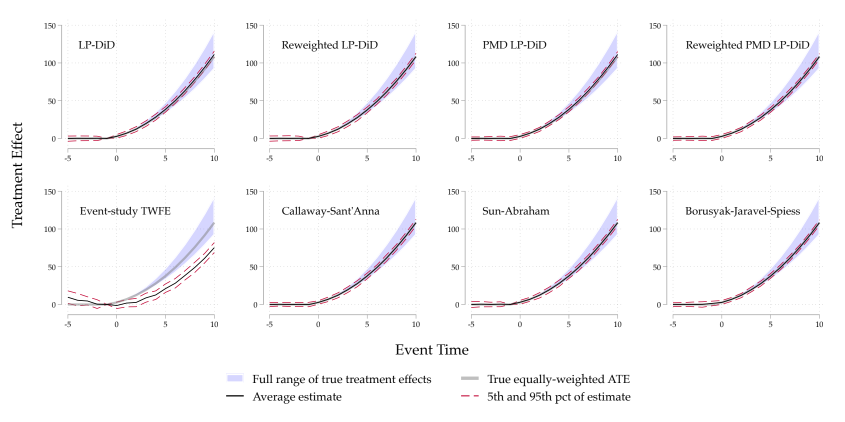
Simulation

- N=500; T=50.
- DGP:
  $Y_{0it} = \rho Y_{0,i,t-1} + \lambda_i + \gamma_t + \epsilon_{it}; \quad -1 < \rho < 1; \quad \lambda_i, \gamma_t, \epsilon_{it} \sim N(0, 25)$
- Binary staggered treatment.
- TE grows in time for 20 periods, and is stronger for early adopters.

1. Exogenous treatment
   - Units randomly assigned to 10 groups of size $N/10$
   - One group never treated; others treated at $t = 11, 13, 15 \ldots, 27$.
2. Endogenous treatment
   - Probability of treatment depends on past outcome dynamics.
   - Negative shocks increase probability of treatment.
   - Parallel trends holds only conditional on outcome lag.

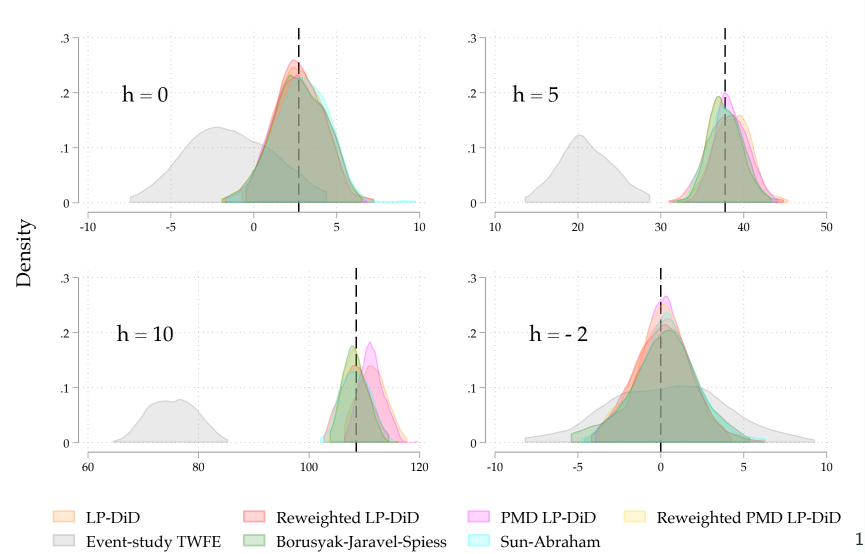
Simulation 1 – exogenous treatment scenario

True effect path and estimates from 200 replications



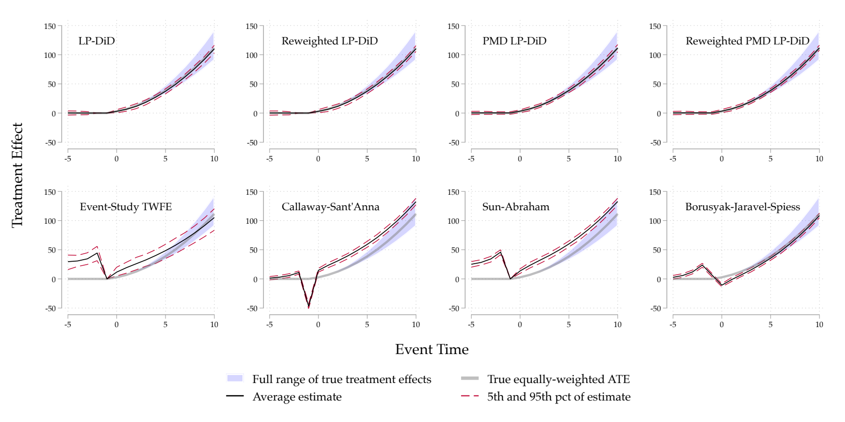
Simulation 1 – exogenous treatment scenario

Distribution of estimates from 200 replications.



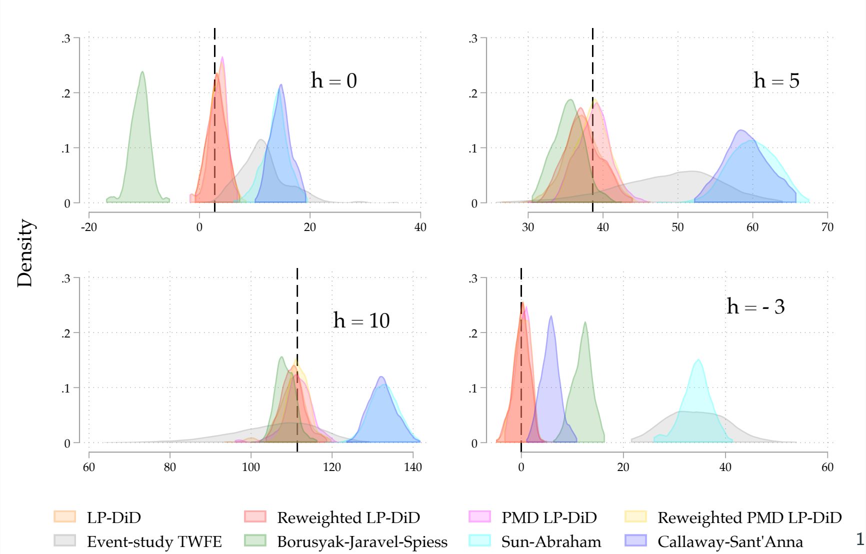
Simulation 2 – endogenous treatment scenario

True effect path and estimates from 200 replications



Simulation 2 – endogenous treatment scenario

Distribution of estimates from 200 replications.



Computational speed

Estimating the treatment effect path in a single repetition of the simulations (seconds):

Simulation 1 (exogenous treatment scenario)							
ES TWFE	LP-DiD	PMD LP-DiD	Rw LP-DiD	Rw PMD LP-DiD	CS	SA	BJS
.59	.74	.80	1.59	1.64	79.25	177.71	7.08
Simulation 2 (endogenous treatment scenario)							
ES TWFE	LP-DiD	PMD LP-DiD	Rw LP-DiD	Rw PMD LP-DiD	CS	SA	BJS
.61	.74	.82	16.27	19.03	177.5	902.78	7.48

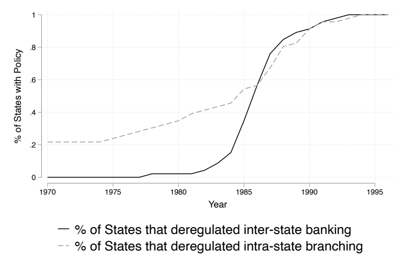
(using a laptop with 2.80 GHz Quad-core Intel i7 Processor and 16 GB of Ram)

Empirical Applications (1)

Application: Banking Deregulation and the Labor Share

1970-1996: US states deregulate banking in a staggered fashion.

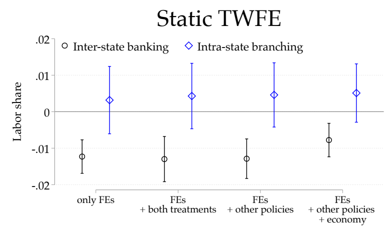
- Inter-state banking deregulation
- Intra-state branching deregulation

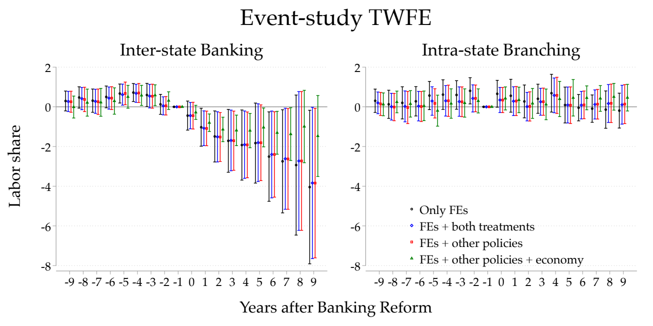


- Leblebicioglu & Weinberger (EJ, 2020) use static & event-study TWFE to estimate effects on the labor share.

TWFE estimates

- Negative effect of *inter-state* bank deregulation (≈ -1pp).
- No effect of *intra-state* branching deregulation.





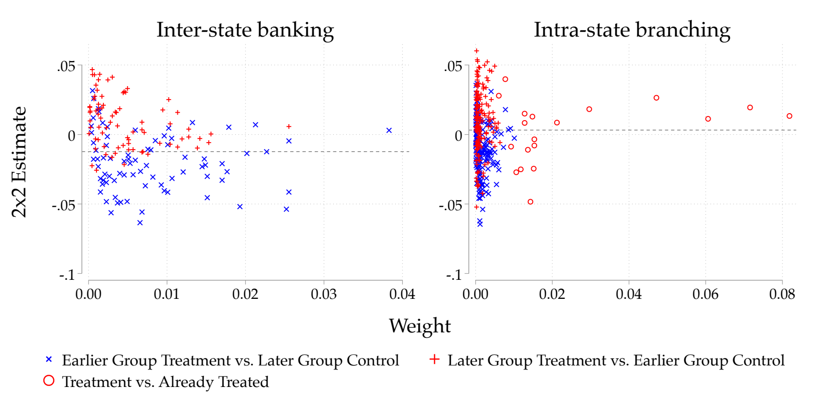
Empirical Applications (1)

Forbidden comparisons in the TWFE specification

- TWFE uses 'forbidden' comparisons: earlier liberalizers are controls for later liberalizers.
- Goodman-Bacon (2021) decomposition to quantify their influence.
- Contribution of unclean comparisons to TWFE estimates:
  - 36% for inter-state banking deregulation;
  - 70% for intra-state branching deregulation.

Empirical Applications (1)

Goodman-Bacon (2021) decomposition diagnostic for the static TWFE estimate

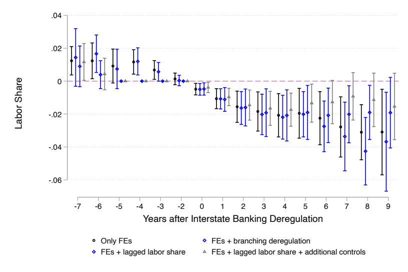


Empirical Applications (1)

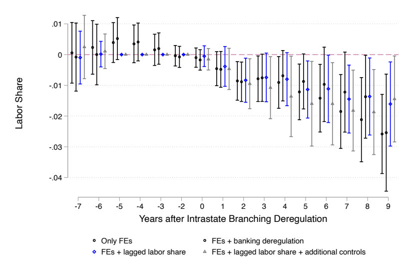
Effect of banking deregulation on the labor share:

LP-DiD estimates

(a) Inter-state banking deregulation



(b) Intra-state branching deregulation



Empirical Applications (2)

Application: Democracy and economic growth

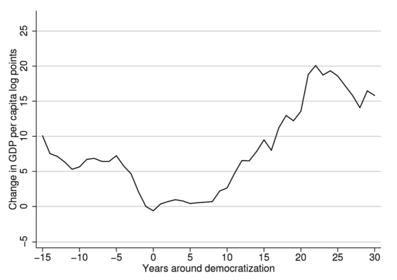
- Acemoglu, Naidu, Restrepo and Robinson (2019).
- 1960-2010 panel on 175 countries & binary measure of democracy.
- Potential for negative weights.
- Non-absorbing treatment.
- Selection based on pre-treatment GDP dynamics.

Empirical Applications (2)

Application: Democracy and economic growth

- Acemoglu, Naidu, Restrepo and Robinson (2019).
- 1960-2010 panel on 175 countries & binary measure of democracy.
- Potential for negative weights.
- Non-absorbing treatment.
- Selection based on pre-treatment GDP dynamics.

GDP per capita around democratization



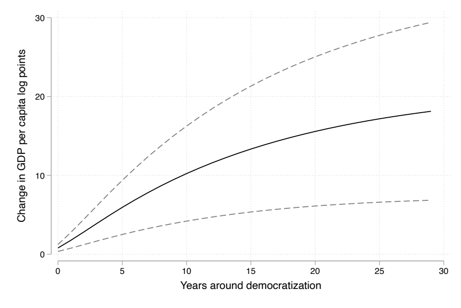
Effect of democracy on growth: dynamic panel estimates

- Dynamic fixed effects specification:

$$y_{ct} = \beta D_{ct} + \sum_{j=1}^{p} \gamma_j y_{c,t-j} + \alpha_c + \delta_t + \epsilon_{ct} \,,$$

- Long-run effect: $\frac{\hat{\beta}}{1-\sum_{j=1}^{p} \hat{\gamma}_j} = 21pp$ (s.e. 7pp)

IRF from the dynamic panel estimates



Effect of democracy on growth: LP-DiD specification

$$y_{c,t+h} - y_{c,t-1} = \beta_h^{LP\ DiD} \Delta D_{ct} + \delta_t^h + \sum_{j=1}^{p} \gamma_j^h y_{c,t-j} + \epsilon_{ct}^h \, .$$

restricting the estimation sample to:

$$\begin{cases} \text{democratizations} & D_{it} = 1; D_{i,t-j} = 0 \text{ for } 1 \leq j \leq L \\ \text{clean controls} & D_{i,t-j} = 0 \text{ for } 0 \leq j \leq L \, . \end{cases}$$

Effect of democracy on growth: LP-DiD specification

$$y_{c,t+h} - y_{c,t-1} = \beta_h^{LP\ DiD} \Delta D_{ct} + \delta_t^h + \sum_{j=1}^{p} \gamma_j^h y_{c,t-j} + \epsilon_{ct}^h \,.$$

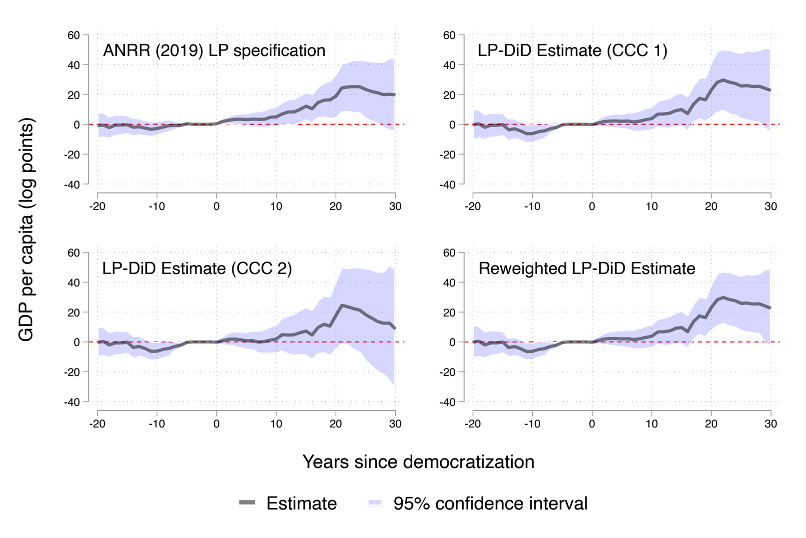
restricting the estimation sample to:

$$\begin{cases} \text{democratizations} & D_{it} = 1; D_{i,t-j} = 0 \text{ for } 1 \leq j \leq L \\ \text{clean controls} & D_{i,t-j} = 0 \text{ for } 0 \leq j \leq L \,. \end{cases}$$

- We set L=20 years.
- Acemoglu et al. LP analysis: a version of this, but (implicitly) L=1.

Empirical Applications (2)

Effect of democracy on growth: LP-DiD estimates



Conclusions

Khoa Vu
@KhoaVuUmn

Arin Dube @arindube · May 1

🚨 Difference-in-differences working paper alert 🚨

Our Local-Projections DiD offers a unified approach that encompasses many popular alternatives as specific instances; allows for extensions; and does it all using an OLS regression.

nber.org/papers/w31184

🧵

Additional Slides

Identification Assumptions (baseline specification)

No anticipation

$$E\left[y_{it}(p) - y_{it}(0)\right] = 0, \text{ for all } p \text{ and } t \text{ such that } t < p.$$

Units do not respond in anticipation of a future treatment.

Parallel trends

$$E\left[y_{it}(0) - y_{i1}(0) | p_i = p\right] = E\left[y_{it}(0) - y_{i1}(0)\right],$$
$$\text{for all } t \in \{2, ..., T\} \text{ and for all } p \in \{1, ..., T, \infty\}.$$

Average trends in untreated potential outcomes do not depend on treatment status.

Obtaining an equally-weighted ATT

- Baseline weights $\omega_{g,h}^{LP-DiD}$ depend on cohort size & treatment variance.
- But you can apply any desired weights using weighted regression.
- Equally-weighted ATE: Reweight by

$$1/(\omega_{g,h}^{LP-DiD}/N_g).$$

- $\omega_{g,h}^{LP-DiD}$ easy to compute from 'residualized' treatment indicator $\Delta\tilde{D}$.
- Can also use regression adjustment.

A1 - Other new DiD estimators

Alternative estimators: de Chaisemartin & D'Haultfoeiulle

de Chaisemartin & D'Haultfoeiulle estimator

- For a given time-horizon ℓ, it estimates the average effect of having switched in or out of treatment ℓ periods ago.
- A weighted average, across time periods t and possible values of treatment d, of 2x2 DiD estimators.
- The constituent 2x2 DiDs compare the $t - \ell - 1$ to t outcome change, in groups with a treatment equal to d at the start of the panel and whose treatment changed for the first time in $t - \ell$ (the first-time switchers) and in control groups with a treatment equal to d from period 1 to t (not-yet switchers).

Alternative estimators: Callaway-Sant'Anna

Callaway-Sant'Anna estimator

- Estimates each group specific effect at the selected time horizon.
- Take long-differences in the outcome variable, and compare each treatment group g with its control group.
- To control for covariates, re-weight observations based on outcome regression (OR), inverse-probability weighting (IPW) or doubly-robust (DR) estimation.
- Aggregate group-time effects into a single overall ATT using some weights.

Alternative estimators: Sun-Abraham

Sun-Abraham interaction-weighted estimator

- Event-study DiD specification, with leads and lags of the treatment variable.
- Includes a full set of interaction terms between relative time indicators D_{it}^{k} (ie, leads and lags of the treatment variable) and treatment cohort indicators $1\{G_g = g\}$ (dummies for when a unit switches into treatment).
- Then calculates a weighted average over cohorts g for each time horizon, in order to obtain a standard event-study plot.

Alternative estimators: Borusyak-Jaravel-Spiess

Borusyak-Jaravel-Spiess imputation estimator

- Estimate unit and time FEs only using untreated sample.
- Take them out from Y to form counterfactual Y'.
- Then for any treatment group, just compare Y and Y' for treated units around event time.
- Average these across events to get an average effect.