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

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Research question

How to estimate Difference-in-Differences with multiple treated groups & treatment periods?

- 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).
- Simulation evidence to assess its performance.
- Empirical applications:
  1. The effect of banking deregulation on the wage share.
  2. Democracy & growth.

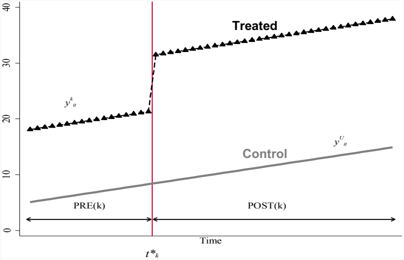
Why do we need yet another DiD estimator?

Advantages of LP-DiD:

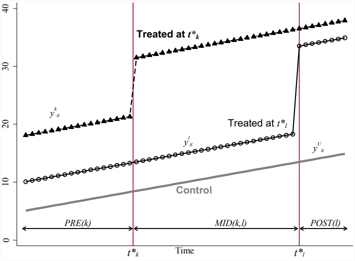
- Simpler, more transparent, easier to code, and faster to compute than other recent DiD estimators.
- Flexible: offers a general framework that can easily accommodate different settings.
- Allows matching on pre-treatment outcomes and other time-varying covariates.

Difference-in-Differences (DiD)

2x2 Setting



Staggered Setting



(Visual examples from Goodman-Bacon, 2021)

Background

The conventional (until recently) DiD estimator: TWFE

- Static TWFE

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

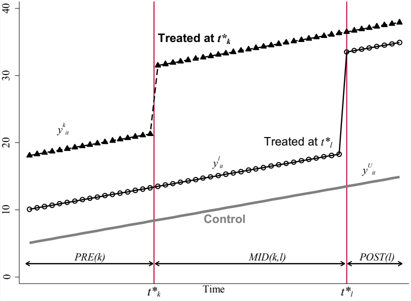
- Event-study (distributed lags) TWFE

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

- 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.



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- Bias formula for TWFE (Goodman-Bacon 2021)

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

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- 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.

LP-DiD: baseline versions

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

Baseline version

Estimating equation:

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

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 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.

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

- Weights are always positive and depend on subsample size & treatment variance

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

  where

  - $CCS_{g,h}$ is a subsample including group g and its 'clean controls'.
  - $n_{g,h} = N_g / N_{CCS_{g,h}}$ is the share of treated units in $CCS_{g,h}$.
  - $n_{c,g,h} = N_{c,g,h} / N_{CCS_{g,h}}$ is the share of control units in $CCS_{g,h}$.

LP-DiD as a ‘swiss knife’

Easy to adapt to different settings

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

Flexibility in choosing a weighting scheme

- Can apply any desired weighting scheme through weighted regression.
- Equally-weighted ATT: reweight observations by $1/(\omega_{g,h}^{LP-DiD}/N_g)$.
- $\omega_{g,h}^{LP-DiD}$ easy to compute from ‘residualized’ treatment indicator.

LP-DiD with covariates and outcome lags

Estimating equation:

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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} \\
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\tag{1}
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\end{cases}
\tag{2}
$$

LP-DiD with covariates

LP-DiD with covariates and outcome lags

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\end{cases} \tag{2}
$$

- Can use p-score methods or weighted regression to preserve the baseline weights or apply any desired weights.

LP-DiD with non-absorbing or continuous treatment

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

LP-DiD with non-absorbing treatment

LP-DiD with non-absorbing or continuous treatment

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- Example for non-absorbing treatment:

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

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- Example for continuous treatment X_{it}:

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

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

Simulation

- N=500 units; T=50 time periods.
- 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.

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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 Evidence

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1 Exogenous treatment

   o Units randomly assigned to 10 groups of size $N/10$
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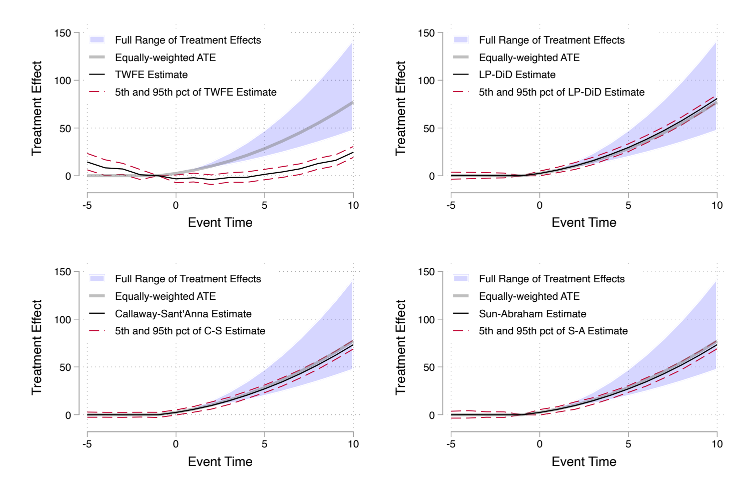
2 Endogenous treatment

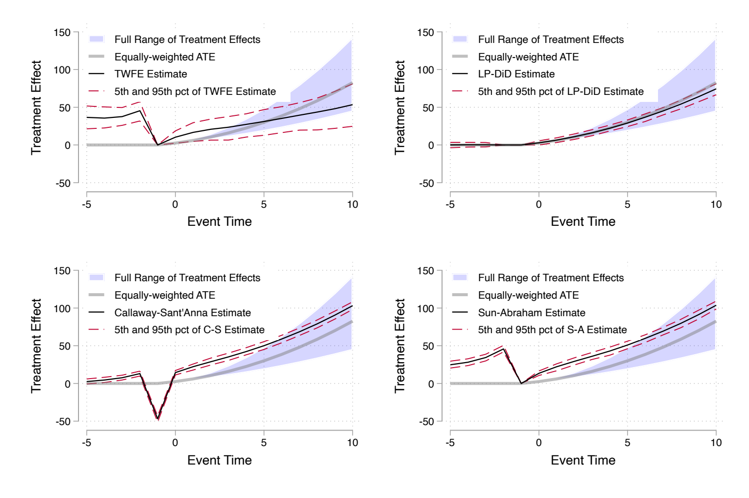
   o Probability of treatment depends on past outcome dynamics.
   o Negative shocks increase probability of treatment.
   o Parallel trends holds only conditional on outcome lag.

Simulation results – exogenous treatment scenario



Average estimates and 95% and 5% percentiles from 200 replications.

Simulation results – endogenous treatment scenario



Average estimates and 95% and 5% percentiles from 200 replications.

Simulation Evidence

Computational speed

Estimating the treatment effect path in a single simulation of the synthetic dataset with exogenous treatment timing:

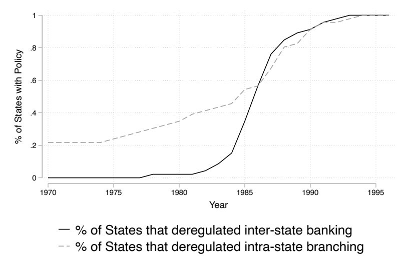
- **TWFE**: 1.04 seconds
- **LP-DiD**: 1.2 seconds
- **Callaway-Sant'Anna (2020)**: 144.6 seconds
- **Sun-Abraham (2020)**: 198.5 seconds

(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: staggered introduction of (inter-state & intra-state) banking deregulation in US states.

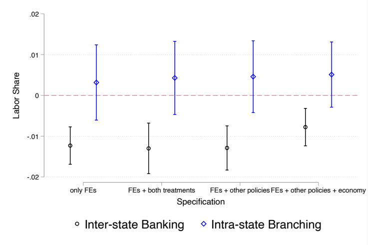


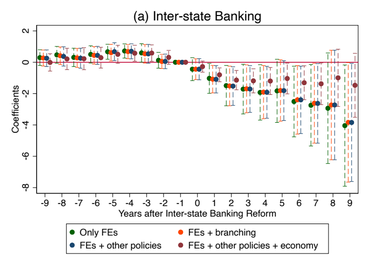
- Leblebicioglu & Weinberger (2020) use static & event-study TWFE to estimate effects on the labor share.
- Negative effect of *inter-state* banking deregulation (≈ -1p.p.).
- No effect of *intra-state* branching deregulation.

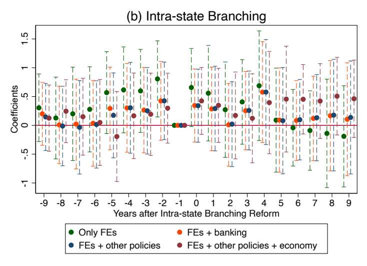
Empirical Applications (1)

Effect of banking deregulation on the labor share:

TWFE estimates







Empirical Applications (1)

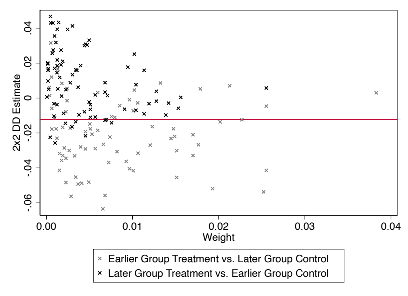
Forbidden comparisons in the TWFE specification

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

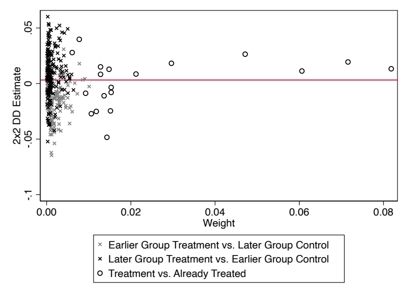
Empirical Applications (1)

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

(a) Inter-state banking deregulation



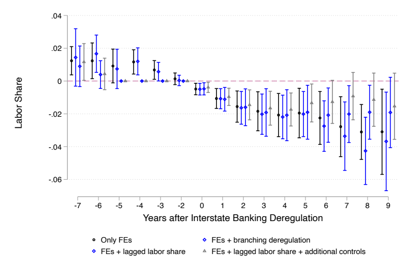
(b) Intra-state branching deregulation



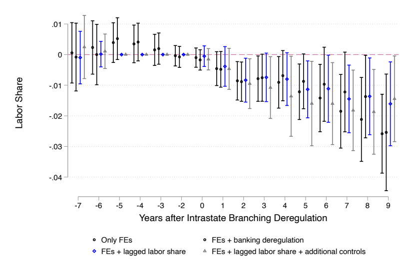
Empirical Applications (1)

Effect of banking deregulation on the labor share: LP-DiD estimates

(a) Inter-state banking deregulation



(b) Intra-state branching deregulation



- LP-DiD avoids unclean comparisons & allows controlling for y lags.
- Negative effect of inter-state branking deregulation is confirmed.
- But also intra-state branching deregulation has negative effect.

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)

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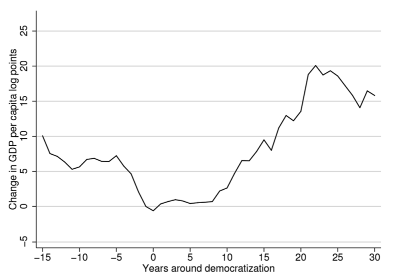
GDP per capita around democratization



Empirical Applications (2)

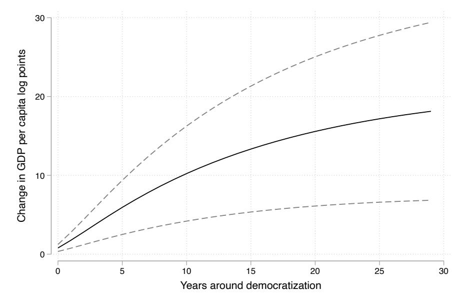
Effect of democracy on growth: dynamic panel estimates

- 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 sample to:

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

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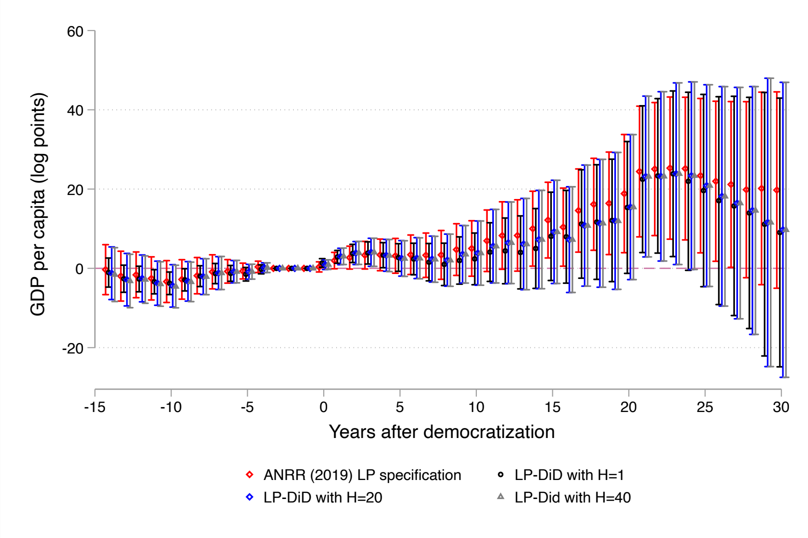
- Acemoglu et al. LP analysis: a version of this, but controls defined by $D_{it} = D_{i,t-1} = 0$.
- They still include countries that slide into autocracy at or before $t-1$, and countries that transition between t and $t+h$.

Empirical Applications (2)

Effect of democracy on growth: LP-DiD estimates



Conclusions

- LP-DiD offers a flexible overarching framework for DiD settings.
- Simpler and less computationally intensive than estimators that aggregate many group-specific averages.
- Flexibility in defining the treatment and ('clean') control units based on the setting.
- Allows matching on pre-treatment outcomes and other time-varying covariates.

Additional Slides

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.