

lwdid: Rolling Difference-in-Differences Estimation for Small and Large Panels

Soo Jeong Lee

School of Analytics, Finance, and Economics
Southern Illinois University

Joint work with **Elizabeth Kayoon Hur** and **Jeffrey M. Wooldridge**,
Michigan State University

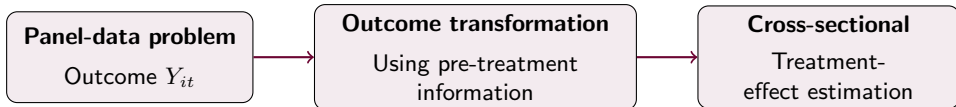
2026 Stata Conference

October 1, 2026

Motivation

- Panel-data DiD applications often involve:
 - **staggered adoption** and **heterogeneous treatment effects**,
 - or **very few treated or control units**.
- These settings create distinct challenges:
 - Static TWFE can be misleading under staggered adoption.
 - With very few units, conventional large- N inference can be unreliable.
- The two papers presented today tackle these challenges using a **single unifying idea**.
⇒ Both are implemented in one Stata command, `lwdid`.

The Common Idea: A Simple Time-Series Transformation



- Transform the outcome using only each unit's own *pre-treatment* observations:

Demeaning

$$\dot{Y}_{itg} = Y_{it} - \frac{1}{g-1} \sum_{q=1}^{g-1} Y_{iq}$$

- removes level differences

Detrending

$$\ddot{Y}_{itg} = Y_{it} - (\hat{A}_{ig} + \hat{B}_{igt})$$

- allows unit-specific linear trends

Deseasonalizing

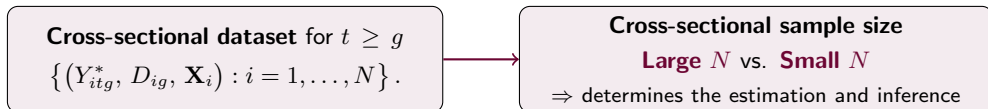
$$\tilde{Y}_{itg} = Y_{it} - \hat{s}_{i,m(t)}$$

- removes quarter/month effects

- For each (g, t) with $t \geq g$, this yields a **cross-sectional dataset**

$$\{(Y_{itg}^*, D_{ig}, \mathbf{X}_i) : i = 1, \dots, N\}.$$

One Transformation, Two Regimes



Large N Lee and Wooldridge (2026a, JBES)

- **Estimation:** For each (g, t) , apply standard treatment-effect estimators to estimate $ATT(g, t)$.
 - `ra`, `ipw`, `ipwra`: such as regression adjustment and doubly robust estimators
- **Inference:** Influence-function-based multiplier bootstrap.

Small N Lee and Wooldridge (2026b, Working paper)

- **Estimation:** aggregate post-treatment transformed outcomes and run a **single cross-sectional regression**.
- **Inference:** t -distribution-based inference under normality, HC3, or randomization inference.

Large- N Rolling DiD

Staggered adoption, group-time effects, and large-sample inference

Setup: Staggered Adoption

- Time periods: $t = 1, \dots, T$.
- Treatment cohorts:

$$g \in G = \{S, \dots, T, \infty\},$$

where $g = \infty$ denotes never-treated units, and treatment is **absorbing**.

- Cohort indicator:

$$D_{ig} = 1 \quad \text{if unit } i \text{ first receives treatment in period } g.$$

- Potential outcomes:

$$Y_{it}(g) : \text{first treated in } g, \quad Y_{it}(\infty) : \text{never treated.}$$

- Parameter of interest:

$$ATT(g, t) \equiv E[Y_{it}(g) - Y_{it}(\infty) \mid D_{ig} = 1], \quad t \geq g.$$

Why Move Beyond Static TWFE?

- With staggered adoption and heterogeneous treatment effects, static TWFE can combine treatment effects with **negative weights**.

Simple staggered-adoption example

	Group A	Group B
$t = 1$	untreated	untreated
$t = 2$	τ_{A2}	untreated
$t = 3$	τ_{A3}	τ_{B3}

- Static TWFE:**

$$Y_{it} = \alpha_i + \lambda_t + \tau^{\text{TWFE}} D_{it} + u_{it}$$

- Coefficient decomposition (BJS, 2021):**

$$\tau^{\text{TWFE}} = \tau_{A2} + \frac{1}{2}\tau_{B3} - \frac{1}{2}\tau_{A3}$$

⇒ Already-treated units can serve as controls, so static TWFE may not recover a meaningful average of heterogeneous $ATT(g, t)$ effects.

Modern Staggered DiD and Rolling DiD

- Modern staggered-DiD methods seek **cleaner comparisons** while allowing heterogeneous

$$\tau_{gt} \equiv ATT(g, t).$$

- Key idea:** Panel $\Rightarrow$ **Cross section** as in CS (2021).

- CS (2021)**

$$\dot{Y}_{itg} = Y_{it} - Y_{i,g-1}, \quad t \geq g.$$

- RDID** `rolling(demean)`

$$\dot{Y}_{itg} = Y_{it} - \frac{1}{g-1} \sum_{q=1}^{g-1} Y_{iq}, \quad t \geq g.$$

- Potential efficiency gains:** demeaning, detrending, and deseasonalizing use richer pre-treatment information, as in **Wooldridge (2025)**.

Appendix: modern staggered-DiD approaches

Rolling DiD as a Middle Ground

- Which Pre-Treatment Information Is Used to Estimate $ATT(4, 5)$?

CS (2021)			
time	$g = 4$	$g = 5$	$g = 6$
1			
2			
3			
4			
5	★		
6			

Rolling Method			
time	$g = 4$	$g = 5$	$g = 6$
1			
2			
3			
4			
5	★		
6			

Wooldridge (2025)			
time	$g = 4$	$g = 5$	$g = 6$
1			
2			
3			
4			
5	★		
6			



Target: $ATT(4, 5)$



Information used



Pre-period information not used

Note: Default with `rolling(demean)` is shown; `lwdid` with `pre(1)`: one-period baseline as CS(2021).

Comparison Table

Identification of $ATT(g, t)$

- For the **rolling demeaning** case, $ATT(g, t)$ is identified under:

CNA Conditional No Anticipation: no treatment effect before treatment begins.

CPT Conditional Parallel Trends: untreated outcome trends are comparable across treatment cohorts, conditional on $\mathbf{X}$.

OVL Overlap: common support between cohort g and the eligible comparison group.

Identification Result

Under CNA + CPT + OVL, each $ATT(g, t)$ is identified using the transformed outcome $\dot{Y}_{itg}$ and the eligible comparison group.

See Lee and Wooldridge (2026a) for the formal identification conditions and results.

Large-N Rolling method General Estimation Procedure

Step 1. For each cohort g and period $t \geq g$, compute the **selected transformed outcome**,

$$Y_{itg}^*, \quad Y_{itg}^* \in \{\dot{Y}_{itg}, \ddot{Y}_{itg}, \dots\}.$$

Step 2. Choose the eligible *not-yet-treated/never-treated units* as the comparison group.

Step 3. To obtain $\widehat{ATT}(g, t)$, apply a standard cross-sectional treatment-effect estimator—such as RA, IPW, or IPWRA—to

$$(Y_{itg}^*, D_{ig}, \mathbf{X}_i).$$

Step 4. Aggregate the group-time effects at relative time $r = t - g$:

$$\widehat{WATT}(r) = \sum_{g \in G_r} \frac{N_g}{N_{G_r}} \widehat{ATT}(g, g + r),$$

where G_r is the set of cohorts contributing to event time r .

If-based Multiplier Bootstrap

Small- N Rolling DiD

Few treated units, counterfactual construction, and small-sample inference

Small N : Constructing the Counterfactual

- With few treated and control units, finding a good comparison “twin” is difficult.
- Widely used approaches construct a **synthetic counterfactual** by choosing weights:
 - **Synthetic Control (SCM)**: choose **donor-unit weights** to reproduce the treated unit’s pre-treatment path.
 - **Synthetic DiD (SDiD)**: choose **unit and time weights**, then estimate a weighted DiD.
- **Example: California Tobacco Control.** California is the **single treated unit**; SCM constructs “Synthetic California” using positive weights on **only 6 of the 38 donor states**.
- **Inference:** SDiD/SC assume large N_0, T_0, T_1 (with potentially small N_1), normality, and stationarity.

Small- N Rolling Method: General Estimation Procedure

Step 1. Using the selected transformation, construct the **transformed outcome** for each post-treatment period:

$$Y_{it}^*, \quad Y_{it}^* \in \{\dot{Y}_{it}, \ddot{Y}_{it}, \dots\}, \quad t = S, \dots, T.$$

Step 2. Aggregate the transformed post-treatment outcomes within each unit:

$$\bar{Y}_i^* = \frac{1}{T - S + 1} \sum_{t=S}^T Y_{it}^*.$$

Step 3. Estimate the treatment effect using the resulting **cross-sectional data**

$$\left\{ \left(\bar{Y}_i^*, D_i \right) : i = 1, \dots, N \right\},$$

through

$$\bar{Y}_i^* = \alpha + \tau D_i + U_i.$$

$\Rightarrow$ Use **all available controls**: $D_i = 1$ for **California** and $D_i = 0$ for all other states.

Small- N Inference

- **t -distribution-based inference** — minimum $N \geq 3$ for implementation.

$$\bar{Y}_i^* = \alpha + \tau D_i + U_i, \quad E(U_i \mid D_i) = 0.$$

Under the classical linear model assumptions and **normality**,

$$U_i \mid D_i \sim \text{Normal}(0, \sigma_U^2),$$

so

$$\frac{\hat{\tau} - \tau}{\text{se}(\hat{\tau})} \sim t_{N-2}.$$

- **Alternative inference**
 - **HC3**: allows for heteroskedasticity.
 - **Randomization inference (RI)**: does not require normality; validity comes from the assignment mechanism.
 - **Period-specific effects**: use Y_{it}^* instead of $\bar{Y}_i^*$ to estimate and conduct inference separately for each post-treatment period.

The `lwdid` Command: Main Syntax

```
lwdid varlist [if] [in], ivar(varname) tvar(varlist) gvar(varname)
      rolling(type) [options]
```

- `varlist` : first variable is the outcome; additional variables, if any, are covariates
- `ivar()` : panel identifier
- `tvar()` : time variable
- `gvar()` : cohort variable; first-treated period, 0/missing for never treated; constant within unit
- `rolling(type)` : $\in \{ \text{demean}, \text{detrend}, \text{demeanq}, \text{detrendq}, \text{demeanm}, \text{detrendm} \}$
- `lwdid` **automatically detects** common timing vs. staggered adoption based on `gvar()`.

Required and Key options

Installation

```
ssc install lwdid, replace    // download the latest version
which lwdid                  // check installed version and location
                             // *! version 3.3: 27 September 2026

ssc describe lwdid           // package information
net get lwdid                 // downloads example datasets
                             // -> lw_smoking.dta, lw_walmart.dta
```

- The framework naturally accommodates both **balanced and unbalanced** panels in standard long format (one row per unit-period).
- One command, two engines: supports both small- N and large- N estimation ; use `small` for the small- N routine.

Implementation I: Large N

Walmart Store Openings

Staggered adoption and large-sample inference

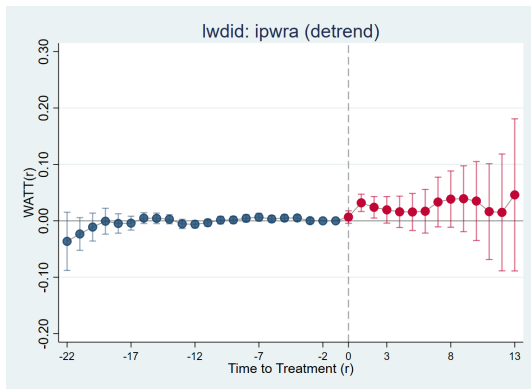
Empirical Application: Walmart Store Openings

Large- N Staggered Adoption Setting

- **County-year panel:** 1977–1999, with **1,277 counties**.
 - **14 treated cohorts:** first Walmart opening in $g \in \{1986, \dots, 1999\}$
 - Never-treated and not-yet-treated counties served as the comparison group.
 - 9 calendar years before the first treatment cohort (1977–1985); cohort-specific pre/post windows vary with g .
- Outcome used here: **log retail employment**.
- **Concern:** county-specific heterogeneous pre-trends may remain even after covariate adjustment. Brown and Butts (2023)
 - ⇒ **Adjustment:** `detrend` removes county-specific linear pre-trends.

Example 1: Walmart Store Openings — Retail Employment

- What is the effect of Walmart entry on **log retail employment**?



Implementation

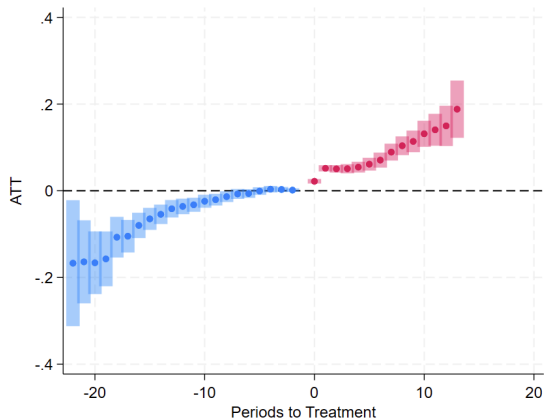
```
lwdid log_retail_emp x1 x2 x3, ///  
ivar(cid) tvar(year) gvar(first_year) ///  
rolling(detrnd) method(ipwra) ///  
graph cb
```

- `gvar()` :first Walmart opening year
- `detrnd` :allows for county-specific linear trends
- `ipwra` :doubly robust estimator
inverse-probability-weighted regression adjustment
- `cb` :simultaneous confidence bands

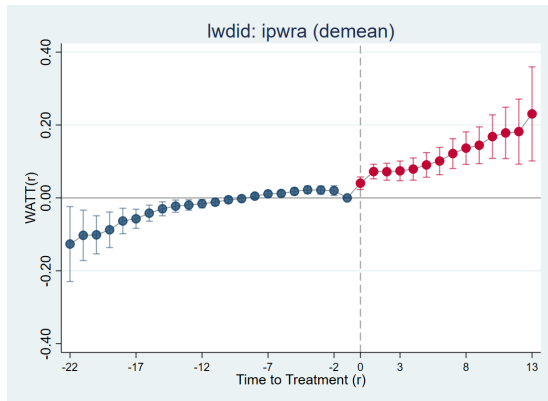
Example 1: Walmart Store Openings — Retail Employment

Parallel-Trend Violation (Event-Study Comparison: CS (2021) vs. Rolling DiD with demeaning)

CS (2021) `csdid`



Rolling IPWRA `rolling(demean)`



Equivalence with Existing Commands I — Regression-based estimators

- Under **common timing**, with a balanced panel and no covariates, the rolling RA estimator with demeaning corresponds to several lags-only regression-based estimators.

lwdid

```
lwdid y, ///  
  ivar(cid) tvar(year) ///  
  gvar(first_year) ///  
  rolling(demean) method(ra)
```

jwddid and did_imputation

```
jwddid y, ///  
  ivar(cid) tvar(year) ///  
  gvar(first_year) ///  
  
did_imputation y id year ///  
cohort, allhorizons
```

⇒ This comparison is useful for checking that `lwdid` recovers the familiar lags-only path before adding detrending, covariates, or doubly robust estimator IPWRA.

Equivalence with Existing Commands II — Last Pre-period Baseline

- With `pre(1)`, use **only** $g - 1$ as the pre-treatment baseline.

lwdid

```
use lw_walmart, clear
gen y = log_retail_emp
gen w = (year >= first_year)
replace w = 0 if first_year == 0

lwdid y, ///
    ivar(cid) tvar(year) ///
    gvar(first_year) ///
    rolling(demean) method(ra) pre(1)
```

csdid and lpdid

```
csdid y, ivar(cid) time(year) ///
    gvar(first_year) ///
    method(reg) agg(event) ///
    notyet long2

lpdid y, unit(cid) time(year) ///
    treat(w) ///
    pre-window(22) post_window(13) rw
```

- Without covariates, these produce the same point estimates in the balanced-panel case.
- With covariates, `csdid` remains comparable in `lwdid, method(ra)`, but `lpdid` is no longer equivalent.

Implementation II: Small N

California Tobacco Program

Single treated unit, donor-pool comparisons, and small-sample inference

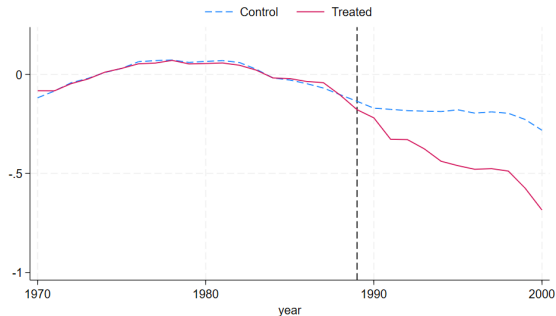
Empirical Application: California Tobacco Control Program

Small-*N* Setting (Abadie, Diamond, and Hainmueller 2010)

- In **1989**, California raised its cigarette tax by **\$0.25 per pack** under Proposition 99.
- Outcome: **log per-capita cigarette sales**.
- State-year panel: 1970–2000, with **California** as the single treated state.
- **Full donor pool**: 38 potential control states.
- **Restricted donor pool**: Alabama, Arkansas, Louisiana, and Mississippi only.
 - Mimics a setting with limited control-unit availability.
 - Compare with SC and Synthetic DiD under a restricted donor pool.
- **Adjustment**: `detrend` removes state-specific linear pre-trends

Example 2: California Tobacco Control Program — 38 Donor States

- Effect of California's tobacco control program on **log per-capita cigarette sales**.



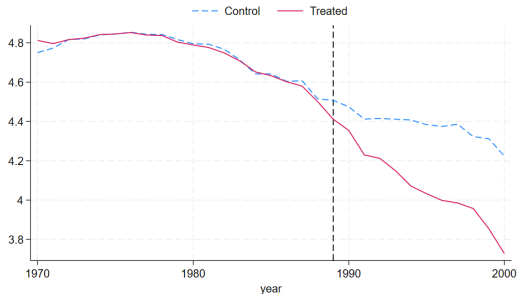
Implementation

```
lwdid lcigsale, small ///  
    ivar(state) tvar(year) ///  
    gvar(first_year) ///  
    rolling(detrend) graph
```

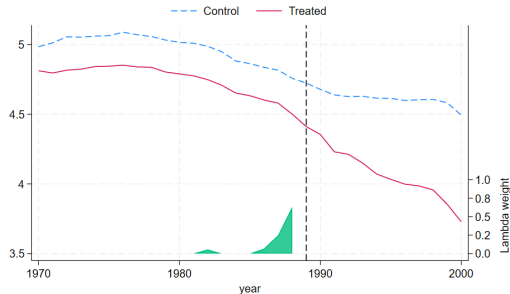
- `small` : small- N routine
- `gvar()` : first-treatment year
- `detrend` : state-specific linear detrending

Example 2: California Tobacco Control Program — 38 Donor States

Synthetic Control



Synthetic DiD



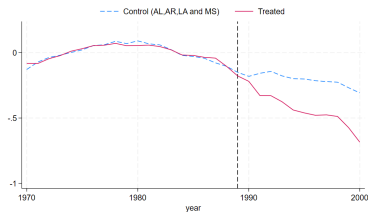
```
sdid lcigsale state year treat, method(sc) vce(placebo) graph  
sdid lcigsale state year treat, method(sdid) vce(placebo) graph
```

- SC and SDiD have a rich donor pool (38 states) and achieve good pre-treatment fit.

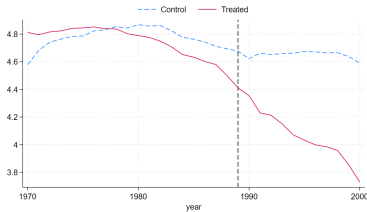
Example 2: California Tobacco Control Program

Restricted Donor Pool: Alabama, Arkansas, Louisiana, and Mississippi

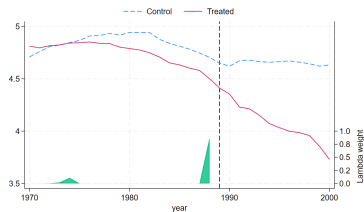
Rolling DiD



SC



Synthetic DiD



- Only **4 donor states**; pre-trends do not match well.
- Rolling DiD uses **all available controls after transformation** and achieves a **strong pre-treatment fit**, comparable to the 38-donor-state case.

Example 2: California Tobacco Control Program

ATT Estimates: 38 Donor States vs. 4 Donor States

	Rolling DiD demean	Rolling DiD detrend	SC	Synthetic DiD
<i>Panel A: 38 donor states</i>				
Average effect	-0.422*** (0.121)	-0.227** (0.0941)	-0.304*** (0.112)	-0.286*** (0.0974)
<i>Panel B: AL, AR, LA, MS only</i>				
Average effect	-0.556*** (0.0800)	-0.215** (0.0392)	-0.571*** (0.0342)	-0.392*** (0.0299)

- With a rich donor pool, all three approaches deliver similar estimates.
- With a thin donor pool, Rolling DiD still performs well and remains a useful **complement**.

Implementation III: Small N

Arizona Medicaid Freeze

Common treatment timing and small-sample inference

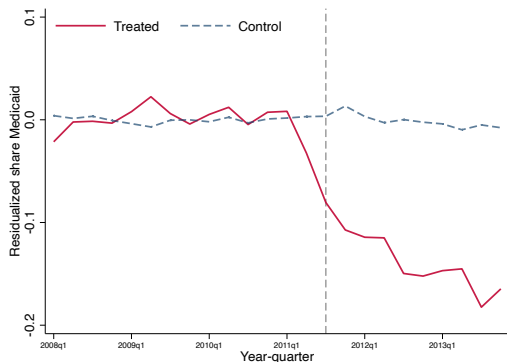
Empirical Application: Arizona's 2011 Medicaid Freeze

Small- N Setting (Hur 2026)

- Arizona froze new Medicaid enrollment for low-income adults without dependent children on July 8, 2011.
- Outcomes: share of hospital discharges with **Medicaid** as primary payer; share **self-pay** (uninsured).
- **Why small N ? 4 states** (AZ treated; AR, MD, NJ controls)
- State-quarter panel: 2008q1–2013q4.
- **Adjustment:** `detrendq`
 - State-specific linear pre-trends
 - Quarter-of-year seasonal effects

Example 3: Medicaid Enrollment Freeze

- What's the effect of Arizona's Medicaid freeze on the **Medicaid share of hospital discharges**?



Implementation

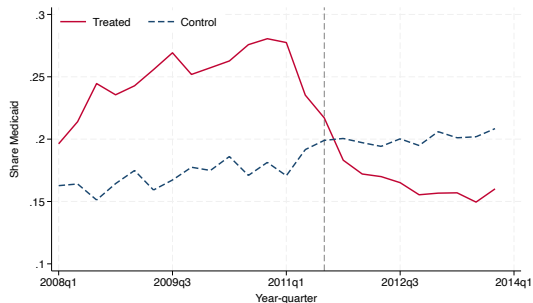
```
lwdid medicaid, small ///  
    ivar(id) tvar(tq) ///  
    gvar(first_treat_q) ///  
    rolling(detrendq) ///  
    graph gopts( ... )
```

- `small` :small- N routine
- `gvar()` :first-treatment period
- `gopts()` :optional graph customization

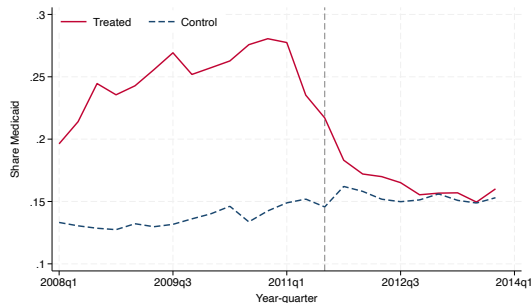
Example 3: Medicaid Enrollment Freeze

Benchmarking against SC and Synthetic DiD

Synthetic Control



Synthetic DiD



- With only **3 donor states**, both SC and SDiD exhibit **poor pre-treatment fit**.

Inference caveat: SDiD theory assumes large N_0 , T_0 , and T_1 . Here, $N_0 = 3$, $T_0 = 14$, and $T_1 = 10$.

Estimated ATTs: Rolling vs. SC vs. Synthetic DiD

	Rolling (<code>detrendq</code>)	SC	Synthetic DiD
<i>Panel A: Share Medicaid</i>			
Average effect	-0.135*** (0.011)	-0.032 (0.043)	-0.074*** (0.016)
<i>Panel B: Share Self-Pay</i>			
Average effect	0.101*** (0.018)	0.066*** (0.022)	0.104*** (0.015)

- SC and SDiD rely on a sufficiently rich donor pool to construct a credible synthetic counterfactual. With only **3 donor states**, that flexibility is limited
- Rolling DiD can therefore serve as a useful **complementary approach** in very small- N settings.

→ See Hur, Lee, and Wooldridge (2026) for additional results, including Share Self-Pay.

Conclusion

- `lwdid` provides one command for rolling DiD in both **large- N** and **small- N** settings.
- `rolling(demean|detrend|detrendq|detrendm)` flexible transformation, including detrending and quarterly/monthly seasonal adjustment.
- **Large N** : nests several existing DiD commands as **special cases**, while allowing additional flexibility for covariates and unbalanced panels.
- **Small N** : provides simple inference for single- or few-treated-unit settings and serves as a useful **complement to SC/SDiD** when the donor pool is limited.

```
ssc install lwdid, replace
```

Thank you!

ssc install lwdid, replace

Questions and comments welcome.

References I

- Abadie, A., Diamond, A., Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies. *Journal of the American Statistical Association*, 105, 493–505.
- Arkhangelsky, D., Athey, S., Hirshberg, D., Imbens, G., Wager, S. (2021). Synthetic Difference-in-Differences. *American Economic Review*, 111, 4088–4118.
- Borusyak, K., Jaravel, X., Spiess, J. (2024). Revisiting Event Study Designs. *Review of Economic Studies*, 91, 3253–3285.
- Brown, N.L., Butts, K. (2025). Dynamic Treatment Effect Estimation with Interactive Fixed Effects and Short Panels. *Journal of Econometrics*, 250, 106013.
- Busch, A., Girardi, D. (2023). `lpdid`: Stata module implementing LP-DiD. SSC S459273.
- Callaway, B., Sant'Anna, P.H. (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics*, 225, 200–230.
- Hur, E.K. (2026). Where Do Patients Go? Medicaid Coverage Loss and Hospital Discharge Destinations. Working Paper.
- Hur, E.K., Lee, S.J., Wooldridge, J.M. (2026). Rolling Difference-in-Differences Estimation for Small and Large Panels. SSRN 6502558. doi:10.2139/ssrn.6502558.

References II

Lee, S.J., Wooldridge, J.M. (2026a). A Simple Transformation Approach to DiD Estimation for Panel Data. *Journal of Business & Economic Statistics*, forthcoming.

Lee, S.J., Wooldridge, J.M. (2026b). Simple Approaches to Inference with DiD Estimators with Small Cross-Sectional Sample Sizes.
SSRN 5325686.

Lee, S.J., Wooldridge, J.M. (2026c). `lwdid`: Stata module to implement rolling DiD for small- N and large- N panel data.
SSC S459672.

Rios-Avila, F., Nagengast, A.J., Yotov, Y.V. (2022). `jwdid`.
SSC S459114.

Rios-Avila, F., Sant'Anna, P.H.C., Callaway, B. (2021). `csdid`.
SSC S458976.

Wooldridge, J.M. (2025). Two-Way Fixed Effects and Difference-in-Differences Estimators. *Empirical Economics*, 69, 2545–2587.

Modern Staggered DiD: Two Starting Points

- **Lags-only / regression-based approaches (Wooldridge, 2025)**

- Examples: Wooldridge's extended TWFE and the Borusyak–Jaravel–Spiess imputation estimator.
- Use **multiple pre-treatment periods** to construct the untreated counterfactual.
- + Richer pre-treatment information may improve efficiency.
- Regression-based estimators can be sensitive to outcome-model misspecification.

- **Group-Time ATT Estimation (Callaway–Sant'Anna, 2021)**

- Estimates each $ATT(g, t)$ using clean treated–comparison-group contrasts.
- Typically uses the **last pre-treatment period**, $g - 1$, as the baseline.
- + Supports flexible treatment-effect estimation, including doubly robust methods.
- Earlier pre-treatment information is not used in the baseline transformation.

Back

Inference: IF-Based Multiplier Bootstrap

Algorithm

- 1 Estimate each group-time effect $\widehat{ATT}(g, t)$ and store the corresponding **observation-level influence functions**.
- 2 Aggregate both estimates and influence functions to the event-time level:

$$\widehat{WATT}(r) = \sum_g \omega_{g,r} \widehat{ATT}(g, g+r), \quad \widehat{IF}_{i,r} = \sum_g \omega_{g,r} \widehat{IF}_{i,g,g+r}.$$

- 3 Apply multiplier weights to the aggregated influence functions and repeat over bootstrap draws.
- 4 Use the bootstrap distribution to construct **pointwise confidence intervals** for each r by default; with `cb`, construct **simultaneous confidence bands across event times** r .

⇒ **Computational advantage:** no model re-estimation is required across bootstrap draws.

How Rolling DiD Differs from Existing Methods

	Wooldridge (2021) Extended TWFE	Callaway and Sant'Anna (2021)	Rolling Method lwdid
Cross-sectional procedure	Regression-based	✓ Baseline: $Y_{i,g-1}$	✓ Baseline: $\frac{1}{g-1} \sum_{q=1}^{g-1} Y_{iq}$
Common Timing $E(Y X)$ correctly specified	✓ BLUE	✓ less efficient	✓ BLUE (RA)
Staggered Adoption $E(Y X)$ correctly specified	✓ Most Efficient	✓	✓ More Efficient than CS
$E(Y X)$ misspecified	—	✓ Doubly robust	✓ IPWRA
Parallel Trends May Not Hold Heterogeneous linear trends	✓	—	✓ Detrending

Note: Efficiency comparisons are under the classical assumptions: homoskedasticity, no serial correlation, and parallel trends.

Back

Required and Key Options

Required: choose the implementation

Option	Description
<code>small</code>	Small-N : required for the small- N implementation
<code>method(ra ipw ipwra)</code>	Large-N : required for the large- N implementation

Key options (optional)

Option	Description
<code>pre(#)</code>	Large- N : number of pre-periods used for transformation (e.g., <code>pre(1)</code> $\Rightarrow$ “leads-and-lags” style)
<code>never</code>	Large- N : use only never-treated units as controls
<code>attgt</code>	Large- N : report $ATT(g, t)$ before aggregation
<code>ri</code> / <code>ri reps(#)</code> / <code>riseed(#)</code>	Small- N : randomization inference
<code>vce()</code>	Small- N : e.g., <code>vce(hc3)</code> , <code>vce(cluster id)</code>
<code>graph</code> / <code>gopts()</code> / <code>save()</code>	Event-study plot, plot customization, and saving results

[Back](#)

Large- N Syntax Options

```
lwdid log_retail_emp x1 x2 x3, ivar(cid) tvar(year) gvar(first_year) ///  
    rolling(detrend) method(ipwra) ///  
    attgt pre(1) graph save( walmart_retail)
```

- `method(ipwra)` : selects the estimator; alternatives are `ra` or `ipw`
- `attgt` : displays all $\widehat{ATT}(g, t)$ estimates
- `pre(1)` : uses only the last pre-treatment period, $g - 1$, as the baseline

$$\dot{Y}_{itg} = Y_{it} - Y_{i,g-1}.$$

- `save(result)` : saves estimates, CIs, and CBs to a `result.dta` file

Back