Jackknife inference for multiway clustering and CSDID in Stata: twowayjack and csdidjack

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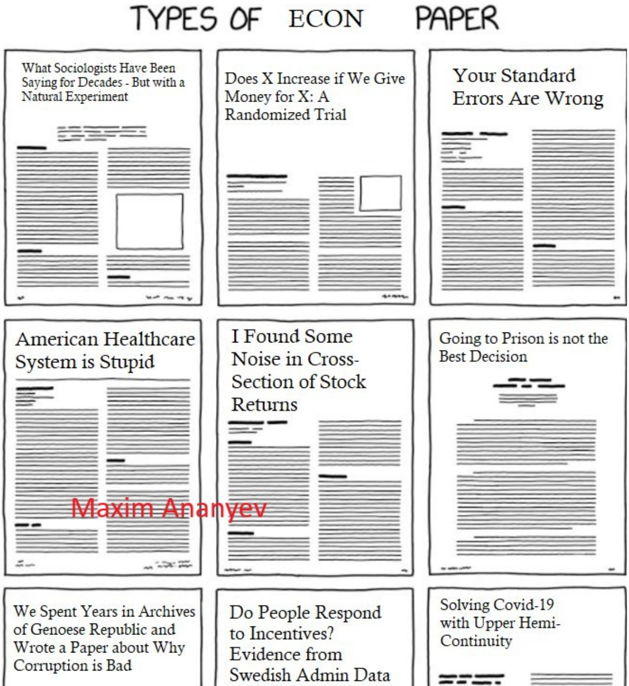
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Overview

This talk will cover:

- Overview of two new `Stata` packages for jackknife clustering
- `csdidjack`
  - Available here Liu (2025)
  - Based on the paper MacKinnon, Nielsen, Webb, and Karim (2025)
  - Jackknife clustering for Callaway and Sant'Anna (2021)
- `twowayjack`
  - Available here Webb (2025)
  - based on the paper MacKinnon, Nielsen, and Webb (2024)
  - two-way cluster jackknife

Staggered Adoption - 6 $\times$ 3 Rollout Matrix

- Setup: 6 regions, 3 time periods
- Each region is either treated or not
- Treatment timing is staggered:

$$\begin{array}{ccccccc} & A & B & C & D & E & F \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 1 & 0 & 0 & 1 & 0 & 0 \\ 3 & 1 & 1 & 0 & 1 & 1 & 0 \end{array} \tag{1}$$

Estimands from 6-Region Rollout

- Follow the setup above
- 6 regions: A, B, C, D, E, F
- Treatment cohorts:
  - Group I: regions A, D (treated at $t = 2$)
  - Group II: regions B, E (treated at $t = 3$)
  - Group III: regions C, F (never treated)
- Define overall ATT:

$$\text{ATT} = \frac{1}{3}(\text{ATT}(\text{I}, 2) + \text{ATT}(\text{I}, 3) + \text{ATT}(\text{II}, 3)) \tag{2}$$

ATT Formulas and CSDID Estimator

- $\text{ATT}(g, t)$ defined via difference-in-differences:

$$\begin{aligned}
\text{ATT}(\text{I}, 2) &= (\mathrm{E}[Y_{\text{I},2}] - \mathrm{E}[Y_{\text{I},1}]) - (\mathrm{E}[Y_{\text{III},2}] - \mathrm{E}[Y_{\text{III},1}]), \\
\text{ATT}(\text{I}, 3) &= (\mathrm{E}[Y_{\text{I},3}] - \mathrm{E}[Y_{\text{I},1}]) - (\mathrm{E}[Y_{\text{III},3}] - \mathrm{E}[Y_{\text{III},1}]), \\
\text{ATT}(\text{II}, 3) &= (\mathrm{E}[Y_{\text{II},3}] - \mathrm{E}[Y_{\text{II},2}]) - (\mathrm{E}[Y_{\text{III},3}] - \mathrm{E}[Y_{\text{III},2}]).
\end{aligned}$$

- CSDID with 'simple' weights estimates:

$$\widehat{\text{ATT}} = \frac{\widehat{\text{ATT}}(\text{I}, 2) + \widehat{\text{ATT}}(\text{I}, 3) + \widehat{\text{ATT}}(\text{II}, 3)}{3}. \tag{3}$$

Clustering in CSDID

- Default SEs in Callaway and Sant'Anna (2021) use influence functions
- Expressions are long (see Theorem 2), but derivation is not our focus
- Key result:

$$\sqrt{n}(\widehat{\mathrm{ATT}}^{dr,nev}_{t\geq(g-\delta)} - \mathrm{ATT}_{t\geq(g-\delta)}) \xrightarrow{d} \mathrm{N}(0, \Sigma), \tag{4}$$

- Where $\Sigma = \mathrm{E}[\Psi(\boldsymbol{W}_i)\Psi(\boldsymbol{W}_i)']$ is from doubly robust estimator
- Normal approximation is used to compute P-values and CIs
- Callaway and Sant'Anna (2021, Remark 13): inference requires many clusters

Problems with Clustering in CSDID

There are three main issues with clustering, by region, in CSDID on account of estimating the $\text{ATT}(g, t)$ terms first

- Observations from the same region can appear in multiple separate $\text{ATT}(g, t)$ estimates, such as region I in $\text{ATT}(\text{I}, 2)$ and $\text{ATT}(\text{I}, 3)$
- Untreated observations from the same region and period can appear in multiple separate $\text{ATT}(g, t)$ estimates, such as region III in $\text{ATT}(\text{I}, 3)$ and $\text{ATT}(\text{II}, 3)$
- When not yet treated control units are specified, treated observations from the same region and period can be used twice as both a pre-period for a treated region, and a post-period for an untreated region

Notation for the Cluster Jackknife

- $\widehat{\text{ATT}}$: full-sample CSDID estimate
- $\widehat{\text{ATT}}^{(h)}$: leave-one-cluster-out estimate
- H: total number of clusters
- CV_3 generalizes HC_3 from MacKinnon and White (1985)
- Attractive feature:
  - No need for $\widehat{\mathrm{Var}}[\widehat{\text{ATT}}(g, t)]$
- Standard error of $\widehat{\text{ATT}}$ remains well-defined

The jackknife has received a lot of attention for clustering recently, see MacKinnon et al. (2023a,b); Hansen (2025a,b); MacKinnon et al. (2025); Hounyo and Lin (2025) among others.

Cluster Jackknife for CSDID

- Alternative to Callaway and Sant'Anna (2021) standard errors
- We use the cluster jackknife for inference on $\widehat{\mathrm{ATT}}$
- Jackknife omits one cluster h at a time:

$$\widehat{\mathrm{ATT}}^{(h)} \text{ omits cluster } h$$

- Resulting SE is:

$$\mathrm{CV}_3(\mathrm{ATT}) = \frac{H-1}{H} \sum_{h=1}^{H} \left(\widehat{\mathrm{ATT}}^{(h)} - \widehat{\mathrm{ATT}}\right)^2 \tag{5}$$

Monte Carlo Design

- Simulations based on CPS MORG data, 1979–1999
- Outcome: log of weekly earnings for women
- Sample: 547,818 observations; earnings $\geq$ \$20
- Placebo laws design inspired by Bertrand, Duflo, and Mullainathan (2004)
  - State-level staggered adoption in 2 cohorts
  - Early cohort (J states): treated in year 4
  - Late cohort (L states): treated in year 6
  - $J = L$; total treated states $= J + L$
- Treatment is absorptive and state-wide
- Each replication samples H states and 8 years
- Recent simulations in Mizushima and Powell (2025)
  - They use state-level unemployment rates
  - We use individual-level earnings
- Inference procedures: `csdid`, `wboot`, `csdidjack`

Monte Carlo Design

Table: Values of H and $J = L$ studied in our experiments

	$H = 8$	$H = 16$	$H = 24$	$H = 32$
$J = L = 1$	✓	✓	✓	✓
$J = L = 2$	✓	✓	✓	✓
$J = L = 3$	✓	✓	✓	✓
$J = L = 4$		✓	✓	✓
$J = L = 6$			✓	✓
$J = L = 8$			✓	✓
$J = L = 10$				✓
$J = L = 12$				✓

Rejection Frequencies: RIF (csdid)

	$H = 8$	$H = 16$	$H = 24$	$H = 32$
$J = L = 1$	0.3046	0.3333	0.3558	0.3800
$J = L = 2$	0.1779	0.1867	0.1750	0.1979
$J = L = 3$	0.2146	0.1245	0.1371	0.1388
$J = L = 4$		0.1132	0.1204	0.1187
$J = L = 6$			0.0829	0.0954
$J = L = 8$			0.0950	0.0850
$J = L = 10$				0.0779
$J = L = 12$				0.0925

Notes: Nominal level is 5%.

Rejection Frequencies: Multiplier Bootstrap (`csdid`)

	$H = 8$	$H = 16$	$H = 24$	$H = 32$
$J = L = 1$	0.3079	0.3458	0.3725	0.3950
$J = L = 2$	0.1808	0.1887	0.1762	0.2004
$J = L = 3$	0.2125	0.1233	0.1408	0.1388
$J = L = 4$		0.1161	0.1200	0.1204
$J = L = 6$			0.0846	0.0967
$J = L = 8$			0.0929	0.0842
$J = L = 10$				0.0787
$J = L = 12$				0.0938

Notes: Nominal level is 5%.

Rejection Frequencies: Jackknife (`csdidjack`)

	$H = 8$	$H = 16$	$H = 24$	$H = 32$
$J = L = 1$	0.0938	0.1279	0.1450	0.1642
$J = L = 2$	0.0379	0.0763	0.0796	0.0929
$J = L = 3$	0.0533	0.0488	0.0600	0.0688
$J = L = 4$		0.0505	0.0621	0.0571
$J = L = 6$			0.0450	0.0571
$J = L = 8$			0.0425	0.0483
$J = L = 10$				0.0450
$J = L = 12$				0.0500

Notes: Nominal level is 5%.

Minimum Wage and Teen Employment

- Adapted from Callaway and Sant'Anna (2021)
- County-level QWI data (2001–2007), 29 states
- Outcome: log of teen employment (`lemp`)
- Covariates: demographics + economics
  - Region dummies, % white, % HS diploma, poverty rate
  - County pop. and median income (quadratics)
- Estimation via `csdid`, calendar aggregation

Table: Effect of minimum wage on teen employment

Method	ATT	Std. error	P value	CI lower	CI upper
`csdid`	-0.0309	0.0076	0.000	-0.0457	-0.0160
`csdidjack`	-0.0309	0.0166	0.073	-0.0649	0.0031

Software Packages

- Open-source implementations of CV_3 jackknife inference
- Available for both `Stata` and `R` users

`Stata`: `csdidjack` **(post-estimation for `csdid`)**

- Supports `agg(simple)`, `agg(group)`, and `agg(calendar)`
- Install via:
```
net install csdidjack,
from("https://raw.githubusercontent.com/liu-yunhan/csdidjac
replace
```
- After estimating a model with `csdid` (Rios-Avila, Callaway, and Sant'Anna, 2021), run:
```
csdidjack
```
- Returns CV_3 SEs, t-stats, P values, and CIs
- Docs: `help csdidjack`
- Source code: `https://github.com/liu-yunhan/csdidjack`

Two-Way Cluster Jackknife

- Multiway clustering is very popular, introduced by Cameron et al. (2011) and Thompson (2011)
- Shown to be over-sized with few clusters in either dimension in MacKinnon et al. (2021)
- A (sort of) two-way version of the wild cluster bootstrap is proposed in that paper
- MacKinnon et al. (2024) proposes a two-way jackknife
- The paper also proposes a max(se) alternative to eigen-value corrections
- The paper describes `twowayjack` which will be the focus here
- That package basically makes three calls to `summclust` described in MacKinnon et al. (2023c)

Two-Way Cluster-Robust Variance

- OLS estimator: $\hat{\beta} = (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \boldsymbol{X}^\top \boldsymbol{y}$
- Residuals: $\hat{\boldsymbol{u}}$, with cluster slices $\hat{\boldsymbol{u}}_g$, $\hat{\boldsymbol{u}}_h$, $\hat{\boldsymbol{u}}_{gh}$
- From sandwich formula:

$$\mathrm{Var}(\hat{\beta}) = (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \Sigma (\boldsymbol{X}^\top \boldsymbol{X})^{-1} = \boldsymbol{V}_G + \boldsymbol{V}_H - \boldsymbol{V}_I \tag{6}$$

$$\boldsymbol{V}_G = (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \left(\sum_{g=1}^{G} \Sigma_g \right) (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \tag{7}$$

$$\boldsymbol{V}_H = (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \left(\sum_{h=1}^{H} \Sigma_h \right) (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \tag{8}$$

$$\boldsymbol{V}_I = (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \left(\sum_{g=1}^{G} \sum_{h=1}^{H} \Sigma_{gh} \right) (\boldsymbol{X}^\top \boldsymbol{X})^{-1} \tag{9}$$

Two-Way Cluster-Jackknife CRVEs

- Standard CRVEs (e.g., $\hat{\boldsymbol{V}}_G$) follow CV_1 form
- Jackknife estimators improve performance in small samples
- For $J \in \{G, H, I\}$, define leave-one-out estimator:

$$\hat{\beta}^{(j)} = (\boldsymbol{X}^\top \boldsymbol{X} - \boldsymbol{X}_j^\top \boldsymbol{X}_j)^{-1}(\boldsymbol{X}^\top \boldsymbol{y} - \boldsymbol{X}_j^\top \boldsymbol{y}_j) \tag{10}$$

- Cluster-jackknife variance for dimension J:

$$\hat{\boldsymbol{V}}_J^{\mathrm{JK}} = \frac{J-1}{J} \sum_{j=1}^{J} (\hat{\beta}^{(j)} - \hat{\beta})(\hat{\beta}^{(j)} - \hat{\beta})^\top \tag{11}$$

- Three-term jackknife CRVE:

$$\hat{\boldsymbol{V}}_3^{(3)} = \hat{\boldsymbol{V}}_G^{\mathrm{JK}} + \hat{\boldsymbol{V}}_H^{\mathrm{JK}} - \hat{\boldsymbol{V}}_I^{\mathrm{JK}} \tag{12}$$

- Related CRVEs: $\text{CV}_3^{(2)}$, $\text{CV}_3^{(3)}$, $\text{CV}_3^{(\text{max})}$

Modified Wald Statistic: $W_{\min}$

- Problem: $\hat{\boldsymbol{V}}_1^{(3)}$ may not be positive definite
- We propose:
  - Compute 3 Wald statistics: W_3, W_G, W_H
  - Use smallest valid one: $W_{\min}$

$$
\begin{aligned}
W_3 &= (\boldsymbol{R}\hat{\beta} - \boldsymbol{r})^\top (\boldsymbol{R}\hat{\boldsymbol{V}}_1^{(3)}\boldsymbol{R}^\top)^{-1}(\boldsymbol{R}\hat{\beta} - \boldsymbol{r}) \\
W_G &= (\boldsymbol{R}\hat{\beta} - \boldsymbol{r})^\top (\boldsymbol{R}\hat{\boldsymbol{V}}_G\boldsymbol{R}^\top)^{-1}(\boldsymbol{R}\hat{\beta} - \boldsymbol{r}) \\
W_H &= (\boldsymbol{R}\hat{\beta} - \boldsymbol{r})^\top (\boldsymbol{R}\hat{\boldsymbol{V}}_H\boldsymbol{R}^\top)^{-1}(\boldsymbol{R}\hat{\beta} - \boldsymbol{r})
\end{aligned} \tag{13}
$$

$$
W_{\min} = \min\{\max(W_3, 0),\ W_G,\ W_H\} \tag{14}
$$

Tsetse Fly and African Development

- Alsan (2015) examines long-run effects of tsetse fly exposure
- Dependent variables: agricultural + technological outcomes
- Two-Way clustered inference using multiple CRVEs

Table: Selected P-values for Conventional and Jackknife CRVEs

Dependent Var.	$\hat{\beta}$	HC_1	$\text{CV}_{(1)}^{(I)}$	$\text{CV}_{(1)}^{(G)}$	$\text{CV}_{(3)}$	$\text{CV}_{(3)}^{(3)}$	$\text{CV}_{(3)}^{(\max)}$
Panel A: Conventional							
Large animals	−0.231	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intensive agriculture	−0.090	0.0080	0.0087	0.0020	0.0321	0.0003	0.0045
Plow use	−0.057	0.0096	0.0171	0.0149	0.1496	0.0715	0.0791
Panel B: Jackknife							
Large animals	−0.231	0.0000	0.0000	0.0000	0.0007	0.0000	0.0000
Intensive agriculture	−0.090	0.0092	0.0130	0.0044	0.0549	0.0027	0.0123
Plow use	−0.057	0.0124	0.0220	0.0207	0.2112	0.1365	0.1422

Syntax: `twowayjack` Command

```
twowayjack depvar indepvar controls,
    cluster(var1 var2) [fevar(varlist) sample(cond)]
```

- `depvar`: dependent variable
- `indepvar`: main regressor of interest
- `controls`: other covariates (binary or continuous)
- `cluster(varlist)` (required): exactly two cluster vars
- `fevar(varlist)`: fixed effects (like `i.var`)
  - Uses a generalized inverse (works with singular subsamples)
- `sample(string)`: subset selection, e.g., `sample(female==1)`

More info:
`http://qed.econ.queensu.ca/pub/faculty/mackinnon/twowayjack/`

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