didint: A Stata package for Intersection Difference-in-differences

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Canadian STATA Conference 2025

What is DID-INT?

- The Stata program was developed to implement Intersection Difference-in-differences (DID-INT).
- DID-INT was introduced by (Karim and Webb, 2024) in the paper *"Good Controls Gone Bad: Difference-in-differences With Covariates."*
- It helps estimate the **Average Treatment Effect on the Treated (ATT)** when the effect of covariates on outcome is different across regions and over time.
- DID-INT is applicable to both common and staggered adoption designs.
- DID-INT allows consistent estimates of the ATT using covariates whose effects on outcomes vary over time and by region.

Why covariates matter I

- Difference-in-differences (DID) is commonly used to evaluate policies/interventions implemented in a region.
- These policies are introduced in some regions (treated regions) and not in others (control regions).
    - Regions could be provinces in Canada, states in the US, cities, municipalities, health authorities, etc.
- DID looks at differences across treated and control regions and over time to measure the impact of policies.
- The method relies on the parallel trends assumption:
    - The trends between treated and control groups would have moved in a similar way (i.e. in parallel) without the policy.
- Parallel trends (without covariates) are unlikely to hold due to differences across regions.

Why covariates matter II

- Researchers use covariates to improve the plausibility of parallel trends, often referred to as the Conditional Parallel Trends (CPT).
- CPT is a relaxed version of the usual parallel trends assumption.
- It is known from DID Literature that time-varying covariates cause **methodological challenges**.
- Without additional assumptions, using time-varying covariates can cause **inconsistent estimates**.
- We introduce an additional assumption, previously implied in the literature called the **Common Causality of Covariates (CCC)** assumption.
    - The effect of covariates (X) on Outcome (Y) is the same across regions and time.
- We show that when the CCC is violated, the estimate of the ATT is inconsistent using traditional and modern DID methods.
- DID-INT uses previously hidden parallel trends when CCC is violated.

Common Causality of Covariates (Setup)

- Assume:
  - Two periods: 1 and 2,
  - Two regions: A and B.
  - B is treated in period 2.
- Also, let the untreated potential outcome of an individual i in region s at time t be:

$$Y_{i,s,t}(0) = \Theta^{\circ}_{s,t} + \gamma^{\circ}_{s,t} X_{i,s,t} + \epsilon_{i,s,t} \tag{1}$$

Common Causality of Covariates Assumption

- Two-way CCC implies:

$$\gamma^{\circ}_{A,1} = \gamma^{\circ}_{A,2} = \gamma^{\circ}_{B,1} = \gamma^{\circ}_{B,2} = \gamma \tag{2}$$

- Region-varying CCC implies:

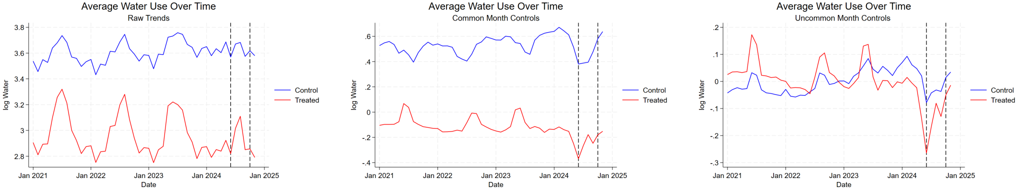
$$\gamma^{\circ}_{A,1} = \gamma^{\circ}_{B,1}; \gamma^{\circ}_{A,2} = \gamma^{\circ}_{B,2} \tag{3}$$

- Time-varying CCC implies:

$$\gamma^{\circ}_{A,1} = \gamma^{\circ}_{A,2}; \gamma^{\circ}_{B,1} = \gamma^{\circ}_{B,2} \tag{4}$$

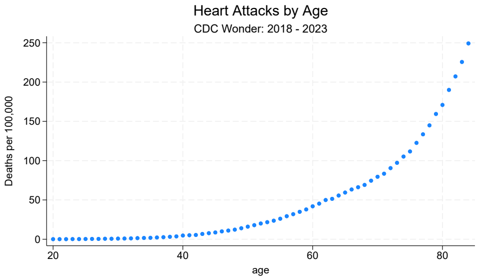
Motivating Example 1 - Uncommon Causality

- Example from Bray (2025) Bray (2025).
- The control group and the treated group have different seasonal trends.



- In this example:
  - Unconditional parallel trends do not hold
  - Conditional parallel trends do not hold, with a common covariate adjustment
  - Parallel trends seem plausible with group specific adjustment
  - *Research Question: Which estimators can accommodate this situation?*
  - **Answer:** Many existing estimators can't adapt to this.

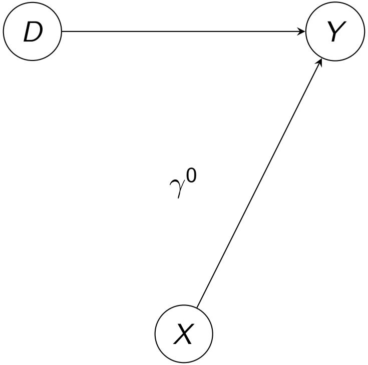
Example 2 - Time Varying Covariates



- Consider an intervention to reduce deaths from heart attacks

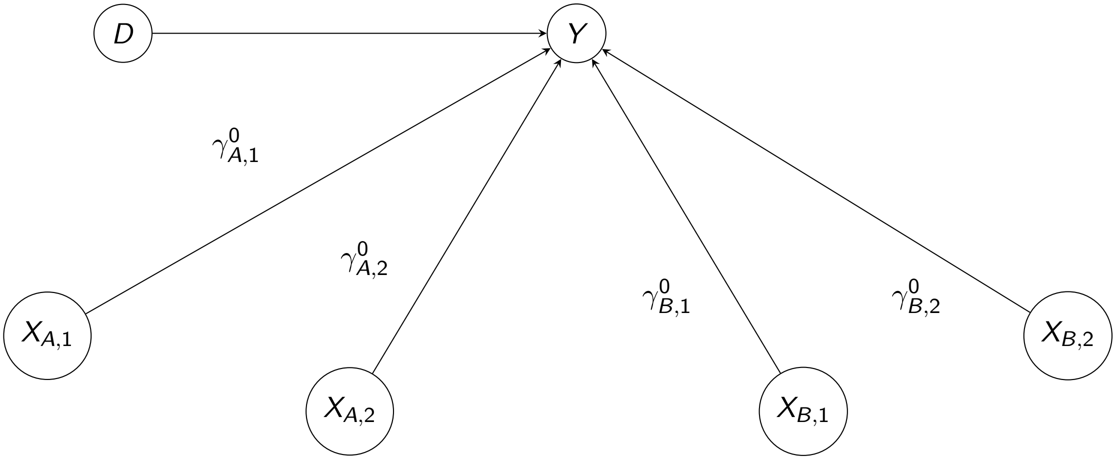
- We have a panel of individuals, say from 2018–2023
- Given the above, we want to include the age of the individual
    - **Problem:** Age is time varying
    - **Current Practice:** Use pre-treatment value of covariate
    - **Additional Problem:** This assumes that the relationship between the covariate and outcome is stable over time, clearly violated here
    - Age in 2010 is not the same as age in 2020

Illustration of Covariate Types: Good Controls



Good controls

Illustration of Covariate Types: Good Controls Gone Bad



Good controls gone bad

Intersection Difference-in-differences (DID-INT) I

- DID-INT is a multi-step semi-parametric method.
- Assume there are S regions and T periods.
- **Step 1:** We run the following regression:

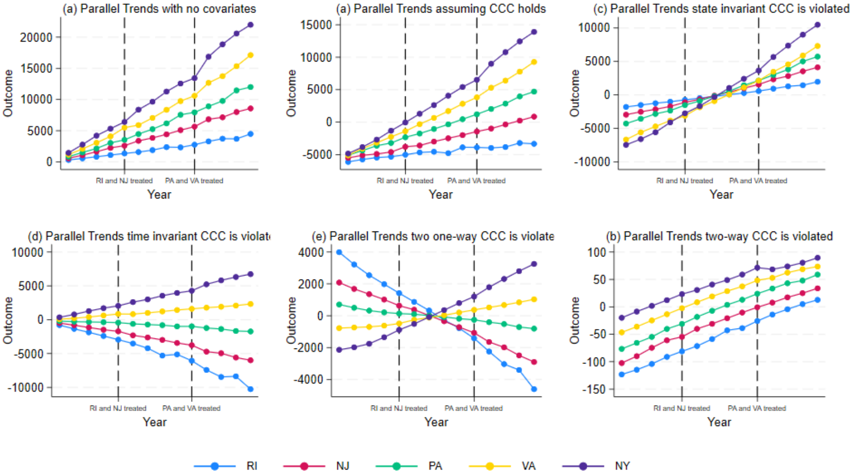
$$Y_{i,s,t} = \sum_{s \in S} \sum_{t=2}^{T} \lambda_{s,t} I(s,t) + f(X^k_{i,s,t}) + \epsilon_{i,s,t} \tag{5}$$

  - $I(s,t)$ is the group-by-time dummy (i.e. 1 if unit is in region s at time t).
  - $I(s)$ is a region dummy.
  - $I(t)$ is a time dummy.
  - k indexes covariates (K total).
- **Step 2:** Several "2×2" $ATT(s,t)$'s are estimated using the $\lambda_{s,t}$ terms.
  - DID-INT estimates ATTs **for each region**, rather than pooling regions by treatment timing (as in Callaway and Sant'Anna (2021) Callaway and Sant'Anna (2021)).

Intersection Difference-in-differences (DID-INT) II

  - Benefits of doing this is explored in more details in Karim et. al (2025) Karim et al. (2025a).
- **Step 3:** Overall ATT is calculated using a weighted average.
- Depending on the type of CCC violation, $f(X_{i,s,t}^{k})$ can take the following forms:
  - **Case 1:** $f(X_{i,s,t}^{k}) = \sum_{k=1}^{K} \gamma^{k} X_{i,s,t}^{k}$ if two-way CCC holds.
  - **Case 2:** $f(X_{i,s,t}^{k}) = \sum_{s=1}^{S^{T}} \sum_{k=1}^{K} \gamma_{s}^{k} I(s) X_{i,s,t}^{k}$ if region-varying CCC is violated.
  - **Case 3:** $f(X_{i,s,t}^{k}) = \sum_{t=1}^{T} \sum_{k=1}^{K} \gamma_{t}^{k} I(t) X_{i,s,t}^{k}$ if time-varying CCC is violated.
  - **Case 4:** $f(X_{i,s,t}) = \sum_{t=1}^{T} \sum_{s=1}^{S^{T}} \sum_{k=1}^{K} \gamma_{s,t}^{k} I(s) I(t) X_{i,s,t}^{k}$ if two-way CCC is violated.
  - **Case 5:** $f(X_{i,s,t}) = \sum_{s=1}^{S^{T}} \sum_{k=1}^{K} \gamma_{s,t}^{k} I(s) X_{i,s,t}^{k} + \sum_{t=1}^{T} \sum_{t=2}^{T} \sum_{k=1}^{K} \gamma_{s,t}^{k} I(t) X_{i,s,t}^{k}$ if two-way CCC is violated (but it enters linearly).
- Inference is done using Jackknife/Randomization Inference

Model Selection Algorithm



STATA Package

- **Requirements:**
  - `STATA` version 14.1 or later, `Julia` version 1.1.6 or later and David Roodman's `Julia` Package for STATA (v1.1.10).
- The wrapper uses the `julia` package (Roodman, 2025) which integrates the Julia programming language into `STATA`.
- The command help file can be accessed using: `help didintjl`
- DID-INT can be implemented using the following command:

```
didintjl outcome(string) state(string) time(string) treated_states(string) treatment_times(string) date
_format(string) [covariates(string) ccc(string) ref_column(string) ref_group(string) freq(string) freq_
multiplier(int 1) start_date(string) end_date(string) nperm(int 1000) verbose(int 1) seed(int 0) use_pr
e_controls(int 0)]
```

Syntax I

- `outcome` - Declares the dependent variable or the outcome of interest.
- `state` - Variable identifying region of observation.
- `time` - Variable identifying date of observation.
- `treated_states` A list of strings which lists the treated states.
  - Example: `treated_states` - should be entered as ("ON QC MN SK NL").
  - Other `states` - in variable state are treated as controls.
- `treated_times` - A list of strings of treatment time corresponding to the treated states.
  - Example: `treated_times` - should be entered as ("2001 2002 2003 2004 2005").
  - There is a one-to-one correspondence between the ordered lists.
  - So, ON is first treated in 2001, QC is first treated in 2002, and so on.
  - 2001 corresponds to ON, 2002 corresponds to QC.
- `date_format` - Variable used to define the date format used in the data.
  - Options include: yyyy, yyyy/mm/dd, ddmonyyyy, etc.

Syntax II

- `covariates` (optional) - lists covariates to be used. If omitted, covariates are not used
- `ccc` (optional) - Specifies which version of DID-INT to use.
  - Options include: hom for Case 1, state for Case 2, time for Case 3, int for Case 4 (default) and add for Case 5.
- agg (optional) - Used to specify the aggregation scheme to be used in Step 3.
  - Options include: cohort (default), state, simple, sgt, time, none.

Example Output

```
. use "MeritExampleDataDiDIntjl.dta", clear
. didintjl, outcome("coll") state("state") time("year") ///
 treated_states("34 57 58 59 61 64 71 72 85 88") ///
 treatment_times("2000 1998 1993 1997 1999 1996 1991 1998 1997 2000") ///
 date_format("yyyy") covariates("asian male black") ccc("int")
```

DiDInt.jl Results

Cohort	ATT	SE	p-val	JKNIFE SE	JKNIFE p-val	RI p-val
1991-01-01	0.0044675	0.040	0.911	0.044	0.920	0.947
1993-01-01	0.0414129	0.039	0.284	0.044	0.344	0.676
1996-01-01	0.0637732	0.047	0.172	0.058	0.272	0.442
1997-01-01	0.0883183	0.034	0.010	0.040	0.027	0.333
1998-01-01	0.0301035	0.056	0.593	0.067	0.654	0.711
1999-01-01	0.1940669	0.022	0.000	0.035	0.000	0.300
2000-01-01	-0.0161931	0.034	0.638	0.095	0.865	0.893

```
Aggregation Method: Cohort

Aggregate Results:
Aggregate ATT: .05110589
Standard error: .01691945
p-value: .02338082
Jackknife SE: .02094461
Jackknife p-value: .05046831
RI p-value: .1911912
```

Code

- Code and example dataset can be found at: https://github.com/ebjamieson97/didintjl
- The Julia package can be found at: https://github.com/ebjamieson97/DiDInt.jl

Related Papers

- DID-INT is fully described in Karim and Webb (2024)
- Karim et al. (2025b) describes a related procedure for unpoolable data
- Cluster robust inference for DID-INT, and state level treatment effects are considering in Karim et al. (2025a)
  - Cluster robust inference is done using either randomization inference (RI β) (MacKinnon and Webb, 2020) or the jackknife (MacKinnon et al., 2023; MacKinnon et al., 2025)

References I

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References II

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MacKinnon, J. G. and Webb, M. D. (2020). Randomization inference for difference-in-differences with few treated clusters. *Journal of Econometrics*, 218(2):435–450.

Roodman, D. (2025). Julia as a universal platform for statistical software development. *The Stata Journal*, 25(2):255–284.