Heterogeneous Treatment Effects Estimation for Staggered Difference-in-Differences Designs in Repeated Cross-Sections

Partha Deb
Hunter College, CUNY and NBER

March 2026

Coauthors on FLEX Paper

- Edward C. Norton – University of Michigan and NBER
- Jeffrey M. Wooldridge – Michigan State University
- Jeffrey E. Zabel – Tufts University

Thanks

- Anjelica Gangaram – University of Michigan

- IIT Bombay and esp. Souvik Banerjee

Thanks

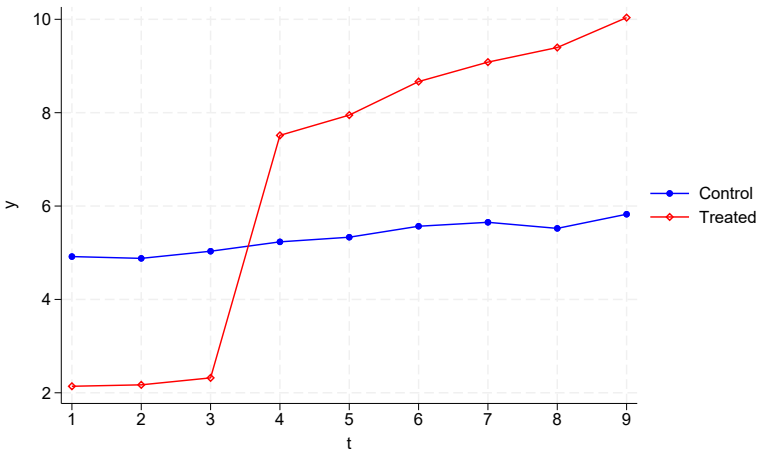
Thanks

Thanks

Thanks

Difference-in-Differences

- The difference-in-differences (DID) study design is an important policy analysis tool.



Two-way Fixed Effects

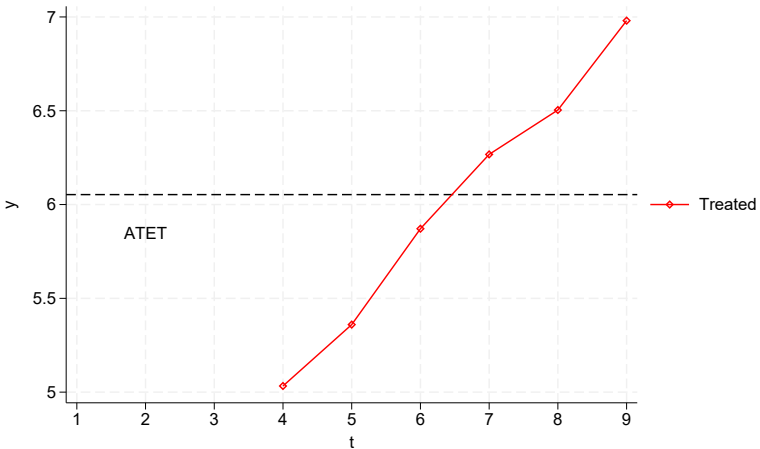
- The workhorse specification assumes a static homogeneous effect (SHo) – inappropriately labeled TWFE:

$$E\left(Y_{it}|R_g, P_t, \boldsymbol{x}_{it}\right) = \tau Z_{it} + \sum_{g=1}^{G} \beta_t R_g + \sum_{t=1}^{T} \eta_t P_t + \boldsymbol{x}_{it}\boldsymbol{\zeta}$$

Z_{it} is an indicator for treatment at the individual level
R_g is the set of group fixed effects
P_t is the set of time (period) fixed effects

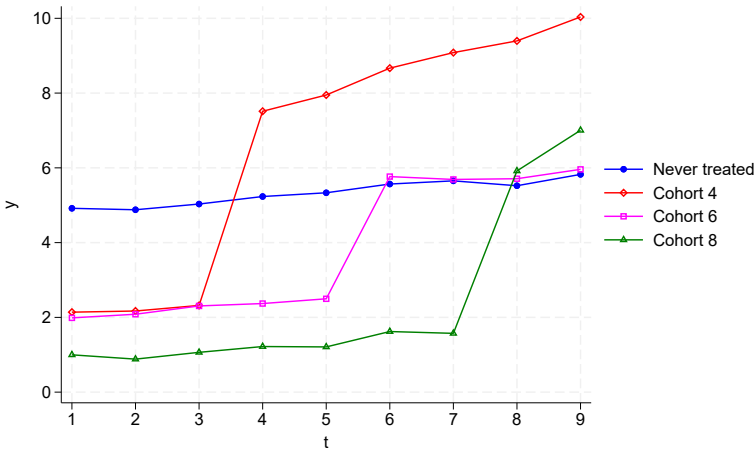
SHo

- The SHo estimator produces consistent ATET.



Staggered Difference-in-Differences

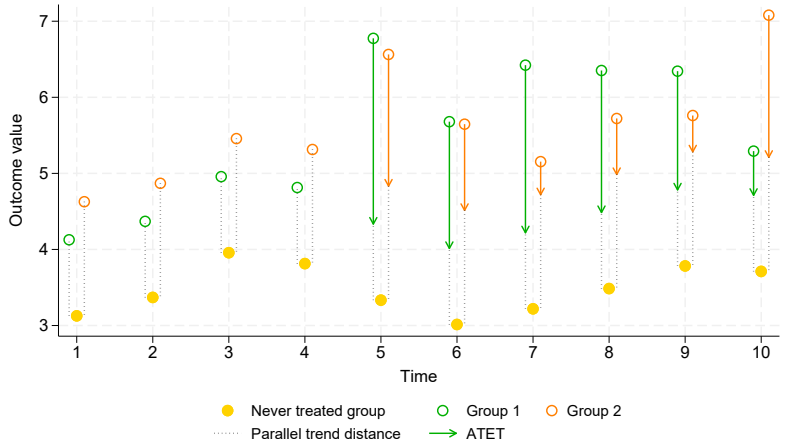
- The staggered difference-in-differences study design is common.



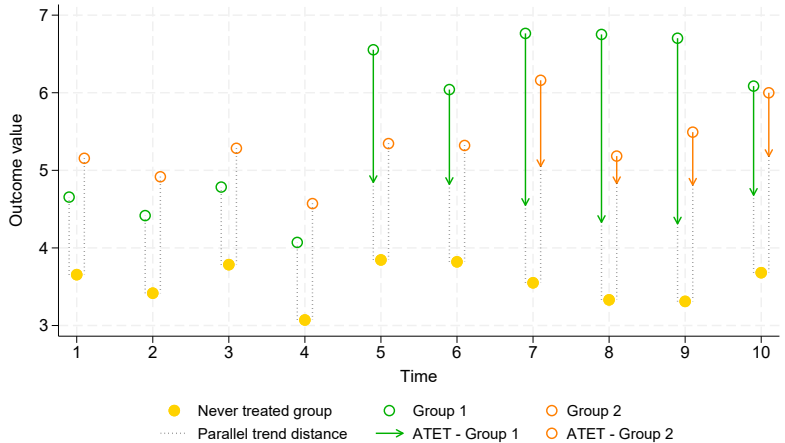
Staggered Difference-in-Differences

- SHo produces biased estimates of treatment effects when treatment is staggered over time and treatment effects are heterogeneous (e.g., de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021).
- Most approaches to resolve this issue require complex computation (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Cengiz et al., 2019; de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021).
- They all involve estimators for heterogeneous treatment effects τ_{ct}
- They all involve an estimation step to produce estimates at the cohort $\times$ time level and an aggregation step to calculate ATETs

Logic of Estimators for Heterogeneous Treatment Effects

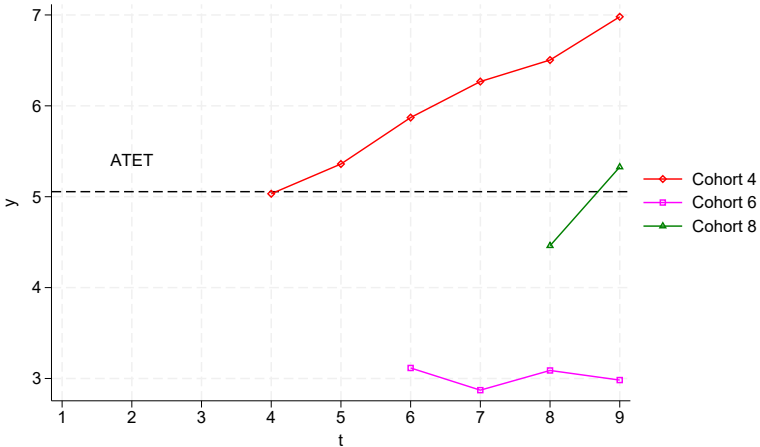


Logic of Estimators for Heterogeneous Treatment Effects



Estimators for Heterogeneous Treatment Effects

- Estimators that allow for heterogeneous treatment effects produce consistent ATET.



Research Agenda

- Deb et al. (2025) derive a Flexible Linear model with covariates (X) [FLEX] for DID designs.
- Like others, it estimates heterogeneous treatment effects and allows for staggered entry.
- Unlike most others, FLEX formally applies to repeated cross-sectional data.
- The linear-in-parameters specification can be estimated using one OLS regression.
- It delivers consistent estimates, allows for considerable functional form flexibility, and provides access to the OLS toolbox for inference and specification testing.

Research Agenda

- We prove that consistent estimates of group-time heterogeneous treatment effects can be obtained in the repeated cross-section setting using FLEX.

- First, we extend the imputation estimators approaches of Borusyak et al. (2024) and Wooldridge (2021) to allow for "event study" designs and repeated cross-sections.

- Second, we show that the estimates from this imputation estimator are identical to those from a flexible linear regression specification (FLEX).

Population Setting

- Fixed T time periods, indexed by $t = 1, 2, ..., T$.
- The data contain never-treated population units.
- Treatment assignment is absorbing.
- Interventions occur at the group level: $g = 1, 2, ..., G$.
- Let $c(g)$ denote the cohort: a subset of groups that is first treated at the same point in time.
- Each group belongs to only one cohort, while a cohort will often have more than one group.

Population Setting

- Let $\bar{g}$ groups receive treatment by time period by time period T.
- Without loss of generality, let groups $g = 1, 2, ..., \bar{g}$ index the treated groups ordered by their cohort membership.
- $c(1)$ denotes the first treated cohort and $c(\bar{g})$ denotes the last treated cohort.
- Never-treated groups are denoted as being "treated" at ∞, i.e., $c(g) = \infty$ for $g = \bar{g} + 1, ..., G$.

Assumption: SUTVA

Assumption (Stable Unit Treatment Value Assumption, SUTVA)

$$Y_{it}\left(g_1, ..., g_{i-1}, g_i, g_{i+1}, ...\right) = Y_{it}\left(g_i\right),\ t = 1, ..., T,$$

where g_j is the group assignment for unit j.

- For each unit i in the population, the potential outcome depends only on unit i's assignment and not on the assignment of the other units.
- SUTVA ensures that we observe one potential outcome for each unit i corresponding to i's treatment assignment.
- It rules out spillover effects.

Assumption: NBC

Assumption (No Bad Controls, NBC)

For a $1 \times K$ vector of covariates $\{\mathbf{X}_t(g) : t = 1, ..., T; g = 1, ..., G\}$, which may be time-varying, the covariates are the same across all potential treatment assignments: $\mathbf{X}_t(g) = \mathbf{X}_t(\infty) = \mathbf{X}_t$ for all $g \in \{1, ..., G\}$ and $t = 1, ..., T$.

- NBC implies that the covariates vary exogeneously from the treatment status.
- Covariates do not change with the treatment assignment.
- We can include time-varying predictors of the outcome whose paths are not influenced by treatment.

Assumption: CNA

Assumption (Conditional No Anticipation, CNA)

For groups $g \in 1, 2, ..., \bar{g}$ and $t \in \{1, ..., c-1\}$,

$$E\left[Y_t(g) | R_1, ..., R_G, \mathbf{X}_t\right] = E\left[Y_t\left(\infty\right) | R_1, ..., R_G, \mathbf{X}_t\right].$$

- Rules out anticipatory changes in the potential outcomes prior to the intervention.
- Rules out treatment assignment on the basis of pre-treatment outcome.

Assumption CPT

- Let $R_g \in R_1, ..., R_{\bar{g}}, R_{\bar{g}+1}, ..., R_G$ denote a binary group-membership indicator.
- Let $\{R_g\}^c$ denote the subset of groups in cohort c.
- Let $P_t \in P_1, P_2, ..., P_T$ denote binary time-period indicators.

Assumption (Conditional Parallel Trends, CPT)

For $t = 1, 2, ..., T$,

$$E\left[Y_t(\infty) \,|R_1, ..., R_G, \mathbf{X}_t\right] = \sum_{g=1}^{G} \beta_g R_g + \sum_{g=1}^{G} (R_g \cdot \mathbf{X}_t)\, \mathbf{fl}_g + \mathbf{X}_t \mathbf{ß}_t + \eta_t.$$

- The CPT assumption assumes that, in the absence of treatment, the treated groups would change over time in the same way as the control groups.

Flexible Linear Estimator with X

Proposition (FLEX)

There is a linear-in-parameters regression specification that is identical to a consistent imputation estimator of the ATETs in a staggered Difference-in-differences design.

FLEX: Group-time Heterogeneity with Lags and Leads

$$E\left(Y_{it}|R_g, P_t, \boldsymbol{x}_{it}\right) =$$

$$\sum_{g=1}^{\bar{g}} \sum_{t=q}^{T} \tau_{gt} R_g P_t \qquad \textit{lags}$$

$$+ \sum_{g=1}^{G} \beta_t R_g + \sum_{t=2}^{T} \eta_t P_t$$

- A *lags only* specification sets all pre-treatment effects $= 0$

FLEX: Group-time Heterogeneity with Lags and Leads

$$
\begin{aligned}
&E\left(Y_{it} | R_g, P_t, \boldsymbol{x}_{it}\right) = \\
&\quad \sum_{g=1}^{\bar{g}} \sum_{t=q}^{T} \tau_{gt} R_g P_t && \textit{lags} \\
&+ \sum_{g=1}^{\bar{g}} \sum_{t=1}^{q-2} \tau_{gt} R_g P_t && \textit{leads} \\
&+ \sum_{g=1}^{G} \beta_t R_g + \sum_{t=2}^{T} \eta_t P_t
\end{aligned}
$$

- A *lags only* specification sets all pre-treatment effects $= 0$
- A *lags and leads* specification sets only one base-period pre-treatment effects $= 0$

FLEX: Group-time Heterogeneity with Lags and Leads

$$
\begin{aligned}
&E\left(Y_{it} | R_g, P_t, \boldsymbol{x}_{it}\right) = \\
&\quad \sum_{g=1}^{\bar{g}} \sum_{t=q}^{T} \tau_{gt} R_g P_t && \textit{lags} \\
&+ \sum_{g=1}^{\bar{g}} \sum_{t=1}^{q-2} \tau_{gt} R_g P_t && \textit{leads} \\
&+ \sum_{g=1}^{G} \beta_t R_g + \sum_{t=2}^{T} \eta_t P_t + \boldsymbol{x}_{it}\boldsymbol{\zeta}
\end{aligned}
$$

- A *lags only* specification sets all pre-treatment effects $= 0$
- A *lags and leads* specification sets only one base-period pre-treatment effects $= 0$

FLEX: Group-time Heterogeneity with Lags and Leads

$$
\begin{aligned}
&E\left(Y_{it} | R_g, P_t, \boldsymbol{x}_{it}\right) = \\
&\quad \sum_{g=1}^{\bar{g}} \sum_{t=q}^{T} \tau_{gt} R_g P_t + \sum_{g=1}^{\bar{g}} \sum_{t=q}^{T} R_g P_t \cdot \boldsymbol{x}_{it} \boldsymbol{\kappa}_{gt} && \textit{lags} \\
&+ \sum_{g=1}^{\bar{g}} \sum_{t=1}^{q-2} \tau_{gt} R_g P_t + \sum_{g=1}^{\bar{g}} \sum_{t=1}^{q-2} R_g P_t \cdot \boldsymbol{x}_{it} \boldsymbol{\kappa}_{gt} && \textit{leads} \\
&+ \sum_{g=1}^{G} \beta_t R_g + \sum_{t=2}^{T} \eta_t P_t + \boldsymbol{x}_{it} \boldsymbol{\zeta} + \sum_{g=1}^{G} R_g \cdot \boldsymbol{x}_{it} \boldsymbol{\gamma}_g + \sum_{t=1}^{T} P_t \cdot \boldsymbol{x}_{it} \boldsymbol{\pi}_t
\end{aligned}
$$

- A *lags only* specification sets all pre-treatment effects $= 0$
- A *lags and leads* specification sets only one base-period pre-treatment effects $= 0$

FLEX: Aggregating the Treatment Effects

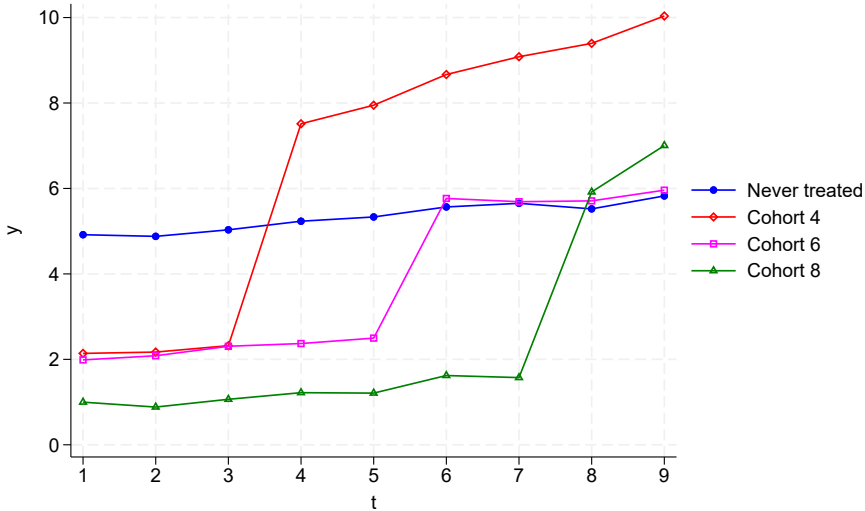
- Headline result is the grand aggregate

$$\tau = \frac{1}{N} \sum_{g=1}^{\bar{g}} \sum_{t=q}^{T} \sum_{i=1}^{n_{gt}} \left[\tau_{gt} \left(R_g P_t \right) + \left(R_g P_t \cdot \boldsymbol{x}_{it} \right) \boldsymbol{\kappa}_{gt} \right]$$

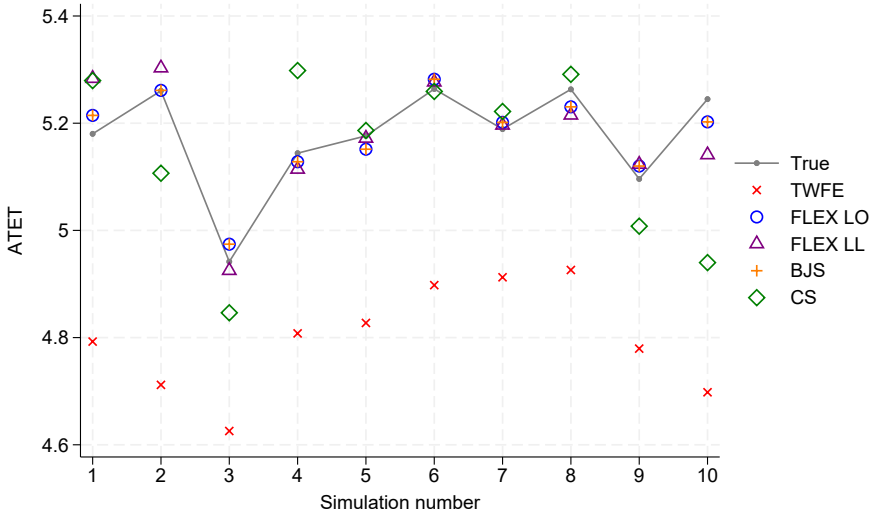
  where n_{gt} is the number of observations in the g^{th} treated group in the t^{th} time period and $N = \sum_{g=1}^{\bar{g}} \sum_{t=q}^{T} n_{gt}$.

- But can also aggregate the effects to the cohort, or time or event-time level.

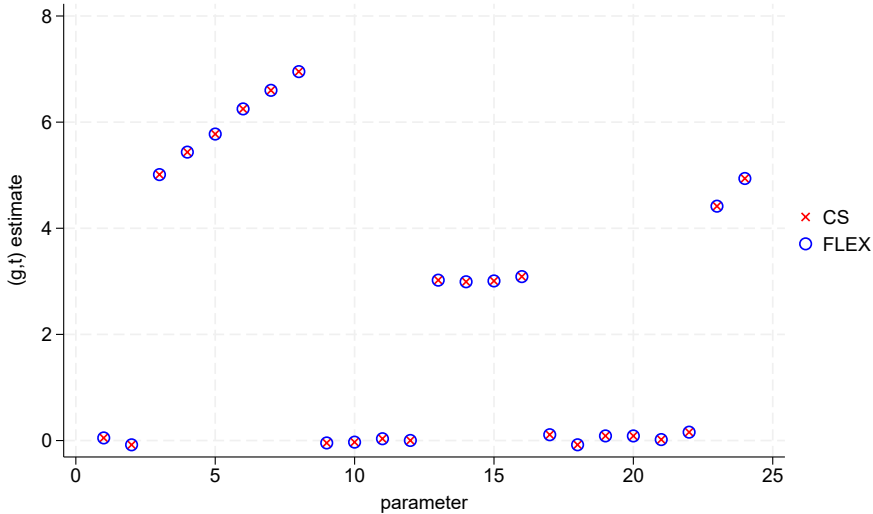
Simulation Evidence



Simulation Evidence



Simulation Evidence



FLEX Features

- FLEX(g,t) with lags only produces identical group-time ATETs as Borusyak et al. (2024).
- FLEX(c,t) with lags and leads and without covariates produces identical cohort-time ATETs as Callaway and Sant'Anna (2021).
- FLEX(c,t) with lags and leads and without covariates produces identical cohort-time ATETs as Sun and Abraham (2021).
- FLEX(c,t) with lags and leads and without covariates produces identical ATETs as **?**.
- FLEX(g,t) can produce estimates that are identical to Cengiz et al. (2019) "stacked".

Why Use FLEX

- Easy and transparent – one OLS regression.
- Can estimate models with (g, t) treatment coefficients – very important distinction if *treatment* is heterogeneous across g within c.
- Can estimate models with (c, t) treatment coefficients "mixed-and-matched" with g and t fixed effects.
- FLEX handles covariates in a very general (flexible) way
- Can choose whether to interact all or some Xs for flexibility – or be traditional and allow for only additive X.

Why Use FLEX

- Once the model is estimated, it's straightforward to calculate any ATET of interest
  - e.g., suppose one believes that ATET might vary by gender.
  - FLEX specifies gender to be fully interaced.
  - Aggregate up to an ATET for each value of gender.
- Can handle "unbalanced" data – missing geographic units in some time periods or some missing time periods.
- FLEX can be extended to allow for multiple staggered treatments.
- FLEX can be extended to allow for non-absorbing treatment (theory needs development).

FLEX Implementation

- It's really just an OLS regression `regress` in Stata
- Then, if you are a Stata user, `margins` is your friend.
- Implementation: Stata package `flexdid`
- `flexdid bmi, tx(hhabit) group(schools) time(year)`
- `estat atet, byexposure`

Empirical Example: Medicaid Expansion

- Question: What is the effect of Medicaid expansions on earnings of low income / low education Americans?
- Before the Patient Protection and Affordable Care Act (ACA), millions of Americans lacked access to health insurance.
- The ACA was designed to reduce the number of uninsured Americans.
- One of the ACA's provisions was to expand Medicaid eligibility.

Empirical Example: Medicaid Expansion

- Medicaid is a government program that provides health insurance to:
  - low income adults (below the poverty line)
  - pregnant women
  - children
- The expansion increased Medicaid coverage eligibility to include nearly all adults with income up to 138% of the federal poverty level.
- Following a 2012 Supreme Court ruling, states could decide whether to implement the, formerly required, expansion.

Empirical Example: Medicaid Expansion

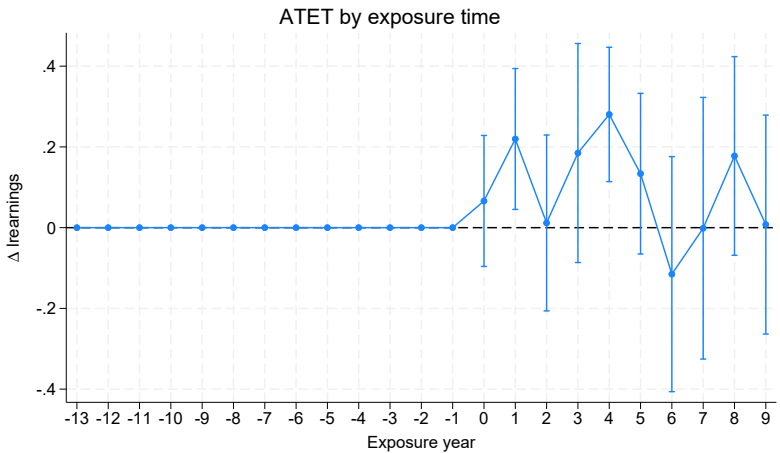
chrt	Freq.	Percent	Cum.
0	10	19.61	19.61
2014	27	52.94	72.55
2015	3	5.88	78.43
2016	2	3.92	82.35
2019	2	3.92	86.27
2020	3	5.88	92.16
2021	2	3.92	96.08
2023	2	3.92	100.00
Total	51	100.00	

Default Specification: Overall ATET

```
. flexdid lrearnings, tx(expansion) group(statefips) time(year)
Note: Variables _Cohort containing cohort identifiers and _Tx containing lags
      and leads treatment indicators, were added to the dataset.

Estimating lags only regression parameters
Aggregating estimates

Overall ATET                                          Number of obs   = 150,029
                                                      Subpop. no. obs =  60,279

                            (Std. err. adjusted for 51 clusters in statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .1069776    .075091     1.42   0.160     -.043847    .2578022
------------------------------------------------------------------------------
Note: Linearization is used to calculate the standard error of ATET
```

Default Specification: ATET By Exposure Time

```
. estat atet, byexposure
```



Default Specification: Overall ATET(0–5)

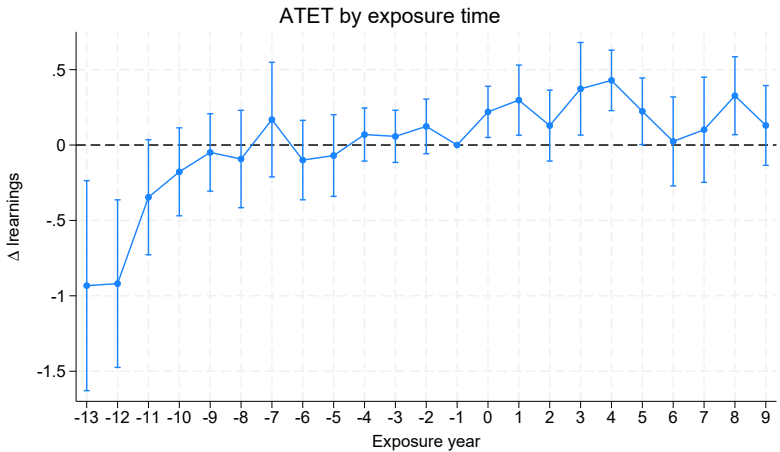
```
. estat atet, overall(0/5)

Overall ATET                                          Number of obs    = 150,029
                                                      Subpop. no. obs =  42,640

                              (Std. err. adjusted for 51 clusters in statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .1445832   .0672767     2.15   0.036     .0094539    .2797125
------------------------------------------------------------------------------
Note: Linearization is used to calculate the standard error of ATET
```

Lags and Leads Specification: Overall ATET

```
. flexdid lrearnings, tx(expansion) group(statefips) time(year) specification(lagsandleads)

Estimating lags and leads regression parameters
Aggregating estimates

Overall ATET                                          Number of obs   = 150,029
                                                      Subpop. no. obs =  60,279

                              (Std. err. adjusted for 51 clusters in statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .2368825    .077851     3.04   0.004     .0805141    .3932508
------------------------------------------------------------------------------
Note: Linearization is used to calculate the standard error of ATET
```

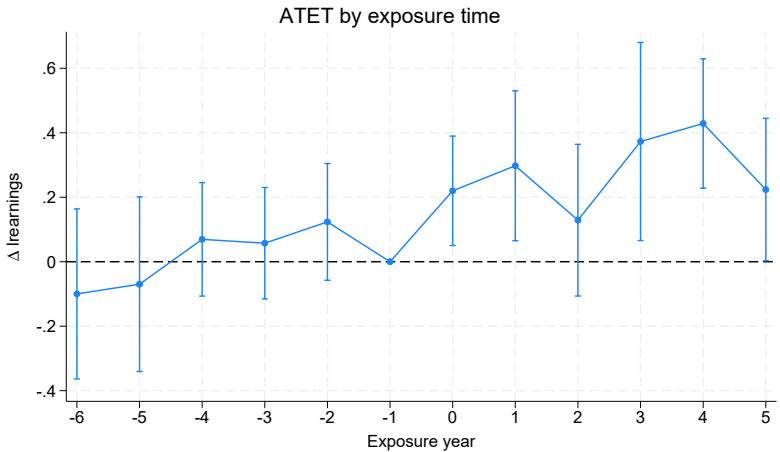
Lags and Leads Specification: ATET By Exposure Time

```
. estat atet, byexposure
```



Lags and Leads Specification: ATET By Exposure Time (-6 – 5)

```
. estat atet, byexposure(-6(1)5)
```



Cohorts As Groups

- Sometimes there might be too many treated groups.
- Users can legitimately combine groups into cohorts.

```
. egen chrt = min(year/expansion), by(statefips)
. replace chrt = 0 if chrt==.
. egen unique = tag(statefips)
. tab chrt if unique
```

chrt	Freq.	Percent	Cum.
0	10	19.61	19.61
2014	27	52.94	72.55
2015	3	5.88	78.43
2016	2	3.92	82.35
2019	2	3.92	86.27
2020	3	5.88	92.16
2021	2	3.92	96.08
2023	2	3.92	100.00
Total	51	100.00	

Cohorts As Groups

```
. flexdid lrearnings, tx(expansion) group(chrt) time(year) specification(lagsandleads)
 vce(cluster statefips)

Estimating lags and leads regression parameters
Aggregating estimates

Overall ATET                                          Number of obs    = 150,029
                                                      Subpop. no. obs =  60,279

                            (Std. err. adjusted for 51 clusters in statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .2287087   .0721785     3.17   0.003     .0837339    .3736834
------------------------------------------------------------------------------
Note: Linearization is used to calculate the standard error of ATET
```

Incorporating Covariates: Fully Interacted

```
. flexdid lrearnings age i.female i.black i.hisp, tx(expansion) group(chrt) time(year)
 specification(lagsandleads) vce(cluster statefips)

Estimating lags and leads regression parameters
Aggregating estimates

Overall ATET                                          Number of obs    = 150,029
                                                      Subpop. no. obs =  60,279

                            (Std. err. adjusted for 51 clusters in statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .1665959   .0763445     2.18   0.034     .0132534    .3199383
------------------------------------------------------------------------------
Note: Linearization is used to calculate the standard error of ATET
```

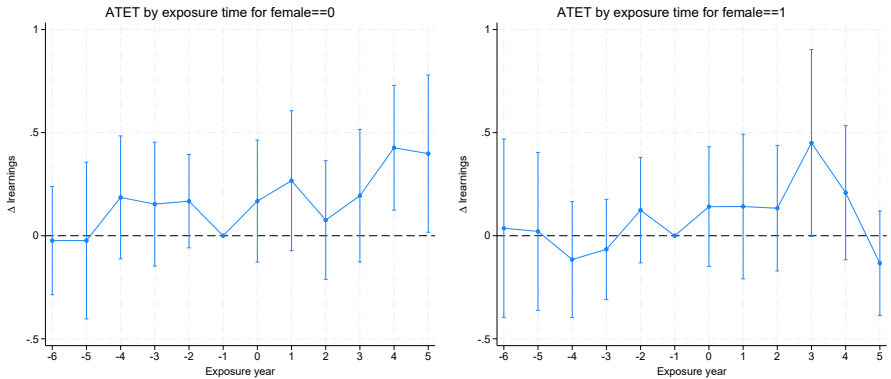
Moderating Effects of Covariates

```
. estat atet, overall for(female==0)

Overall ATET for female==0                          Number of obs    = 150,029
                                                    Subpop. no. obs =  31,053

                              (Std. err. adjusted for 51 clusters in statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .2600832   .1248745     2.08   0.042      .0092655     .510901
------------------------------------------------------------------------------
Note: Linearization is used to calculate the standard error of ATET
```

Moderating Effects of Covariates

```
. estat atet, overall for(female==1)

Overall ATET for female==1                          Number of obs    = 150,029
                                                    Subpop. no. obs =  29,226

                              (Std. err. adjusted for 51 clusters in statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .0672643   .1062511     0.63   0.530    -.1461472    .2806758
------------------------------------------------------------------------------
Note: Linearization is used to calculate the standard error of ATET
```

Moderating Effects of Covariates: Exposure by Gender



Incorporating Some Covariates Additively

```
. flexdid lrearnings i.female age i.black i.hisp, tx(expansion) group(chrt) time(year)
> specification(lagsandleads) vce(cluster statefips) xnotinteracted(i.statefips)

Estimating lags and leads regression parameters
Aggregating estimates

Overall ATET                                          Number of obs    = 150,029
                                                      Subpop. no. obs =  60,279

                            (Std. err. adjusted for 51 clusters in statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .1727859   .0782796     2.21   0.032     .0155568    .3300151
------------------------------------------------------------------------------
Note: Linearization is used to calculate the standard error of ATET
```

Testing: Parallel Trends

```
. estat atet, byexposure(-10/-2) test(zero) nograph
------------------------------------------------------------------------------
             |            Unconditional
    Exposure |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         -10 |   .1266767    .139007     0.91   0.367    -.1525271    .4058806
          -9 |   .1442811    .131073     1.10   0.276    -.1189868     .407549
          -8 |    .040485   .1599236     0.25   0.801    -.2807309     .361701
          -7 |   .2489863   .2193707     1.14   0.262    -.1916326    .6896052
          -6 |    .004129   .1500828     0.03   0.978    -.2973212    .3055793
          -5 |  -.0021978   .1540734    -0.01   0.989    -.3116633    .3072676
          -4 |   .0369063   .1113521     0.33   0.742     -.186751    .2605636
          -3 |   .0460204   .0981213     0.47   0.641    -.1510621     .243103
          -2 |   .1466701   .0962412     1.52   0.134    -.0466361    .3399762
------------------------------------------------------------------------------
Test of zero ATET by exposure time
H0: All effects are equal to zero
    F(9,50) =    0.941
    Prob > F = 0.4990
```

Testing: All Exposure-Time Effects Equal Zero

```
. estat atet, byexposure(0/5) test(zero) nograph
------------------------------------------------------------------------------
             |            Unconditional
    Exposure |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
           0 |   .1550539   .0931411     1.66   0.102    -.0320256    .3421333
           1 |   .2066248   .1093272     1.89   0.065    -.0129654     .426215
           2 |   .1036512   .1093589     0.95   0.348    -.1160027     .323305
           3 |   .3178993   .1476945     2.15   0.036     .0212462    .6145524
           4 |   .3210538   .1081205     2.97   0.005     .1038874    .5382201
           5 |   .1364478   .1163792     1.17   0.247    -.0973067    .3702023
------------------------------------------------------------------------------

Test of zero ATET by exposure time
H0: All effects are equal to zero
    F(6,50) =    2.094
    Prob > F = 0.0704
```

Testing: All Exposure-Time Effects Equal to Each Other

```
. estat atet, byexposure(0/5) test(equal) nograph
------------------------------------------------------------------------------
             |            Unconditional
    Exposure |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
           0 |   .1550539   .0931411     1.66   0.102    -.0320256    .3421333
           1 |   .2066248   .1093272     1.89   0.065    -.0129654     .426215
           2 |   .1036512   .1093589     0.95   0.348    -.1160027     .323305
           3 |   .3178993   .1476945     2.15   0.036     .0212462    .6145524
           4 |   .3210538   .1081205     2.97   0.005     .1038874    .5382201
           5 |   .1364478   .1163792     1.17   0.247    -.0973067    .3702023
------------------------------------------------------------------------------

Test of equal ATET by exposure time
H0: Effects are equal to each other
    F(5,50) =    1.726
    Prob > F = 0.1458
```

Model Comparisons: FLEX v BJS

```
. flexdid lrearnings, tx(expansion) group(chrt) time(year) vce(cluster statefips)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .0997027   .0704622     1.41   0.163    -.0418248    .2412302
------------------------------------------------------------------------------

. generate bjs_cohort = chrt if chrt>0
. did_imputation lrearnings chrt year bjs_cohort, autosample nose
------------------------------------------------------------------------------
  lrearnings | Coefficient
-------------+----------------------------------------------------------------
         tau |   .0997028
------------------------------------------------------------------------------
```

Model Comparisons: FLEX v CS

```
. estat atet, byget
------------------------------------------------------------------------------
             |            Unconditional
      G X ET |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     2014 -4 |   .0761119   .1031356     0.74   0.464    -.1310421    .2832659
     2014 -3 |   .0856383   .1002264     0.85   0.397    -.1156724    .2869489
     2014 -2 |   .1868649   .1112851     1.68   0.099    -.0366579    .4103876
      2014 0 |     .23539   .1273022     1.85   0.070     -.020304    .4910841
      2014 1 |   .3248227   .1341705     2.42   0.019     .0553334     .594312
      2014 2 |   .0804945   .1290368     0.62   0.536    -.1786836    .3396727
...
      2014 7 |   .0529823   .1799295     0.29   0.770    -.3084167    .4143813
      2014 8 |   .3678854    .143674     2.56   0.014     .0793077     .656463
      2014 9 |    .127444   .1245521     1.02   0.311    -.1227264    .3776143
------------------------------------------------------------------------------
```

Model Comparisons: FLEX v CS

```
. hdidregress ra (lrearnings) (expansion), group(statefips) time(year) basetime(common)
------------------------------------------------------------------------------
             |               Robust
Cohort       |       ATET   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
2014         |
        year |
        2010 |   .0761119   .1020817     0.75   0.456    -.1239645    .2761883
        2011 |   .0856383   .0992022     0.86   0.388    -.1087945     .280071
        2012 |   .1868649   .1101479     1.70   0.090    -.0290211    .4027509
        2014 |     .23539   .1260014     1.87   0.062    -.0115681    .4823481
        2015 |   .3248227   .1327994     2.45   0.014     .0645407    .5851048
        2016 |   .0804945   .1277182     0.63   0.529    -.1698286    .3308177
        2017 |   .3659197    .173268     2.11   0.035     .0263207    .7055186
...
        2021 |   .0529823   .1780908     0.30   0.766    -.2960693    .4020339
        2022 |   .3678854   .1422058     2.59   0.010     .0891671    .6466036
        2023 |    .127444   .1232794     1.03   0.301    -.1141791    .3690671
-------------+----------------------------------------------------------------
```

Model Comparisons: FLEX v CS

```
. flexdid lrearnings, tx(expansion) group(chrt) time(year) vce(cluster statefips) specif
> ication(lagsandleads)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .2287087   .0721785     3.17   0.003     .0837339    .3736834
------------------------------------------------------------------------------

. hdidregress ra (lrearnings) (expansion), group(statefips) time(year) basetime(common)
. estat aggregation
------------------------------------------------------------------------------
             |              Robust
  lrearnings |       ATET   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
   expansion |
   (1 vs 0)  |   .2236172   .0730612     3.06   0.002     .0804198    .3668146
------------------------------------------------------------------------------
Note: Aggregation weights vary across times and cohorts.
```

Model Comparisons: FLEX v dCdH

```
. flexdid lrearnings, tx(expansion) group(chrt) time(year) vce(cluster statefips) specif
> ication(lagsandleads)
------------------------------------------------------------------------------
             |            Unconditional
  lrearnings |       ATET   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     Overall |   .2287087   .0721785     3.17   0.003     .0837339    .3736834
------------------------------------------------------------------------------

. did_multiplegt (dyn) lrearnings chrt year expansion, effects(10) graph_off only_never_
> switchers
-------------------------------------------------------------------------------------
              Average cumulative (total) effect per treatment unit
-------------------------------------------------------------------------------------
             |  Estimate          SE      LB CI      UB CI          N     Switch
-------------+-----------------------------------------------------------------------
  Av_tot_eff |  .2287088    .2132257  -.1892058    .6466234      86787      60279
```

Thank you