Nonlinear DID:

Lessons from Staggered Linear Differences in Differences

Fernando Rios-Avila

Introduction

- **Differences in Differences** (DiD) design is one of the most popular methods in applied microeconomics, because it requires relatively few assumptions to identify treatment effects.
  - No anticipation,
  - Parallel trends,
  - No spillovers
- The canonical DiD, a 2x2 design, simply compares means (or conditional means) of the outcome variable (before after x treated non-treated) to identify treatment effects.
  - Thus it can be used even if outcome is a limited dependent variable (binary, count, etc) (parallel to the linear regression case)

- Because the Canonical design is rather limited, many extensions have been proposed to handle more complex scenarios: Staggered Treatment with **GxT DID**.
  - Early Extensions (infamous TWFE) have been shown to be problematic. (negative weights and bad controls)
  - but more recent approaches (See Roth et al. (2023)) have shown how can one better use these designs to identify treatment effects, avoiding the simple-TWFE problems.
- Linear models, however, have limitations:
  - Linear models do a poor job interpolating and predicting LDV outcomes
  - Parallel trends assumptions may only be credible under specific functional forms

Disclaimer:

who am I not?

Not Andrew Goodman-Bacon

- Among others, Andrew showed the problems of using TWFE in the presence of staggered adoption of the treatment.
- Because of treatment timing, later treated units are compared to **bad** controls (early treated ones), in potential violation of the parallel trends assumption.
- This also relates to negative weights.
- See Goodman-Bacon (2021)

Not Pedro Sant'Anna

- Pedro and Brantly proposed deconstructing the GxT problem. Consider only good 2x2 DD designs to identify Treatment effects in DID.
- Agregate them as needed to obtain the desired treatment effect (weighted Average). (dynamic, average, across time, across groups, etc)
- Along with **Jonathan Roth**, discuss the problem of PTA and functional forms. Not all may be valid.
- see Callaway and Sant'Anna (2021) and Roth and Sant'Anna (2023)

Not Jeffrey Wooldridge

- Jeff Wooldridge brought back life to the **TWFE**.
- The problem was not the **TWFE** part of the analysis, but the model specification.
  - ($post \times treated$ instead of $G \times T$)
- This insights, can be extended to nonlinear cases.
- See Wooldridge (2021) and Wooldridge (2023)

Fernando Rios-Avila

- I have followed some of the developments in DID with staggered adoption of the treatment.
  - Implemented few things (`drdid/csdid/csdid2/jwdid`)
  - Understood few others (comparison groups, efficiency, negative weights, nonlinear models)
- And today, I will be providing some of my insights regarding the empirical analysis of nonlinear DID.
  - I will rely heavily on Wooldridge (2023),

Basics: 2x2 DiD

- In the 2x2 DID design, we have 2 groups:

  - Control ($D = 0$) and treated ($D = 1$),

- Which are observed for two periods of time:

  - Before ($T = 0$) and after ($T = 1$) the treatment.

- For all groups and periods of time, we observe the *realized* outcome $Y_{i,t}$, but cannot observe all *potential* outcomes $Y_{i,t}(D)$.

- Realized outcomes are determined by the following equation:

$$Y_{i,t} = D_i Y_{i,t}(1) + (1 - D_i) Y_{i,t}(0)$$

If treatment occured at some point between T0 and T1, and we could observe all potential outcomes, the estimate of interested, Average Treatment effect, could be estimated as follows:

$$ATT = E(Y_{i,1}(1) - Y_{i,1}(0)|D_i = 1)$$

For the treated, we observe $Y_{i,1}(1)$, but cannot observe $Y_{i,t}(0)$ (counterfactual), thus, to identify Treatment Effects, we need to impose some assumptions.

- PTA:

$$\begin{aligned} E(Y_{i,1}(0) - Y_{i,0}(0)|D_i = 1) = E(Y_{i,1} - Y_{i,0}|D_i = 0) \\ E(Y_{i,1}(0)|D_i = 1) = E(Y_{i,0}(0)|D_i = 1) + E(Y_{i,1} - Y_{i,0}|D_i = 0) \end{aligned}$$

- No Anticipation:

$$Y_{i,0}(1) = Y_{i,0}(0) = Y_{i,0}$$

Thus, ATT can be estimated as follows:

$$\begin{aligned} ATT &= E(Y_{i,1}(1)|D_i = 1) - E(Y_{i,1}(0)|D_i = 1) \\ &= E(Y_{i,1}|D_i = 1) - \Big(E(Y_{i,0}|D_i = 1) + E(Y_{i,1} - Y_{i,0}|D_i = 0)\Big) \\ &= E(Y_{i,1} - Y_{i,0}|D_i = 1) - E(Y_{i,1} - Y_{i,0}|D_i = 0) \end{aligned}$$

- And the Same could be done via Regressions:

$$y_{i,t} = \beta_0 + \beta_1 T + \beta_2 D_i + \theta(D_i \times T) + \epsilon_{i,t}$$

- ATT identification relies on the Parallel trend assumption.

How to test for PTA?

- PTA is a non-testable assumption, because we do not observe all potential outcomes.
- However, if we "move", from the 2x2 design, it may be possible to test if PTA hold Before treatment.
- Consider a case of T periods of time, and that treatment happen at period G.
- Say we estimate the ATT comparing periods T and T-1, for any T<G.

$$ATT(T) = E(Y_{i,T} - Y_{i,T-1}|D_i = 1) - E(Y_{i,T} - Y_{i,T-1}|D_i = 0)$$

- If there is no anticipation, and Parallel trends hold, then $ATT(T) = 0$ if $T < G$
  - This is what Callaway and Sant'Anna (2021) uses for PTA testing

How to test for PTA?

- Alternatively, one could simply estimate all ATT's using period G-1 as baseline period (`long2` differences):

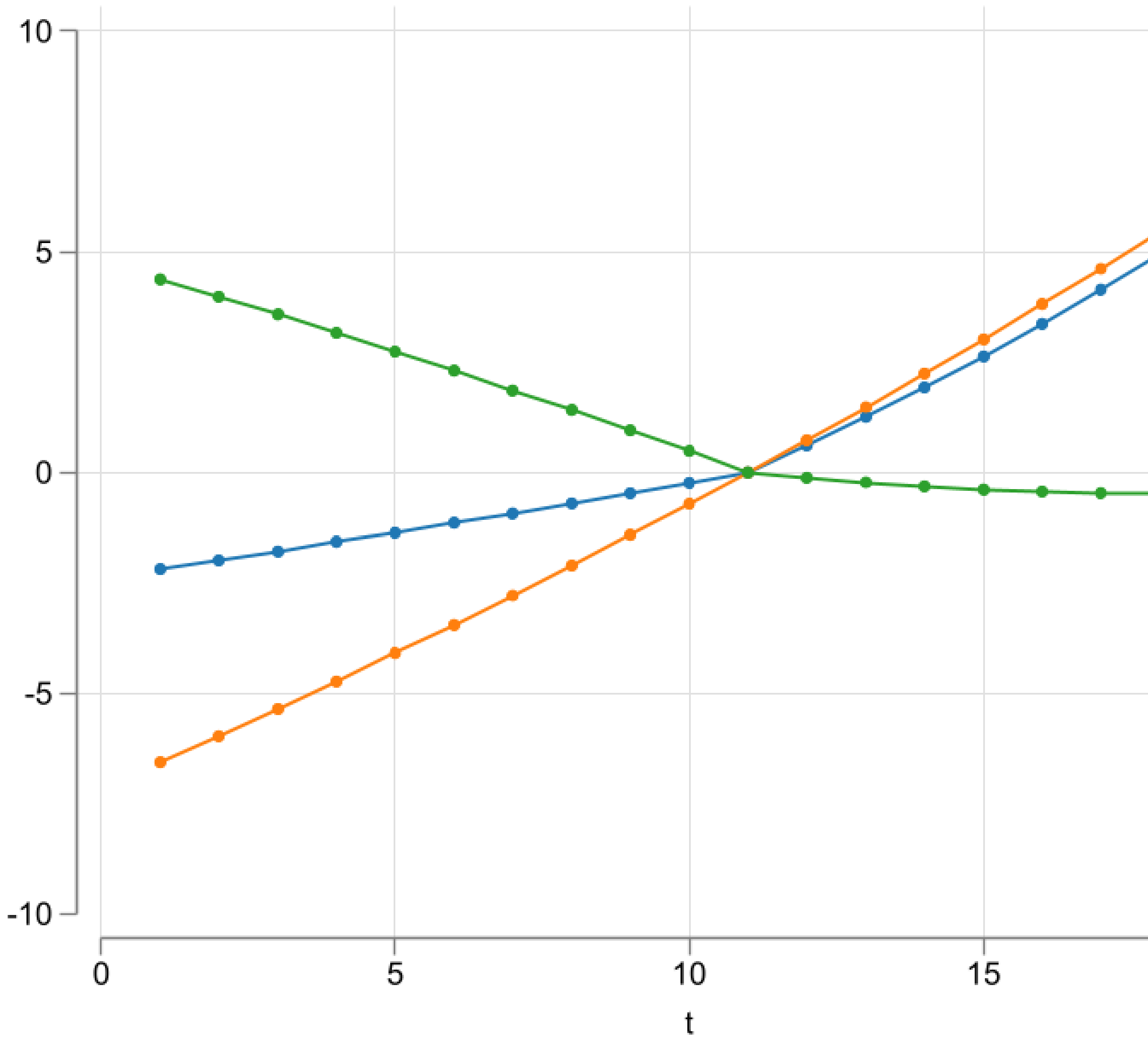
$$ATT^2(T) = E(Y_{i,T} - Y_{i,G-1}|D_i = 1) - E(Y_{i,T} - Y_{i,G-1}|D_i = 0)$$

- And use all post-treatment periods to estimate the ATT ($T \geq G$)
- and use all pre-treatment periods to test for PTA ($T < G$)

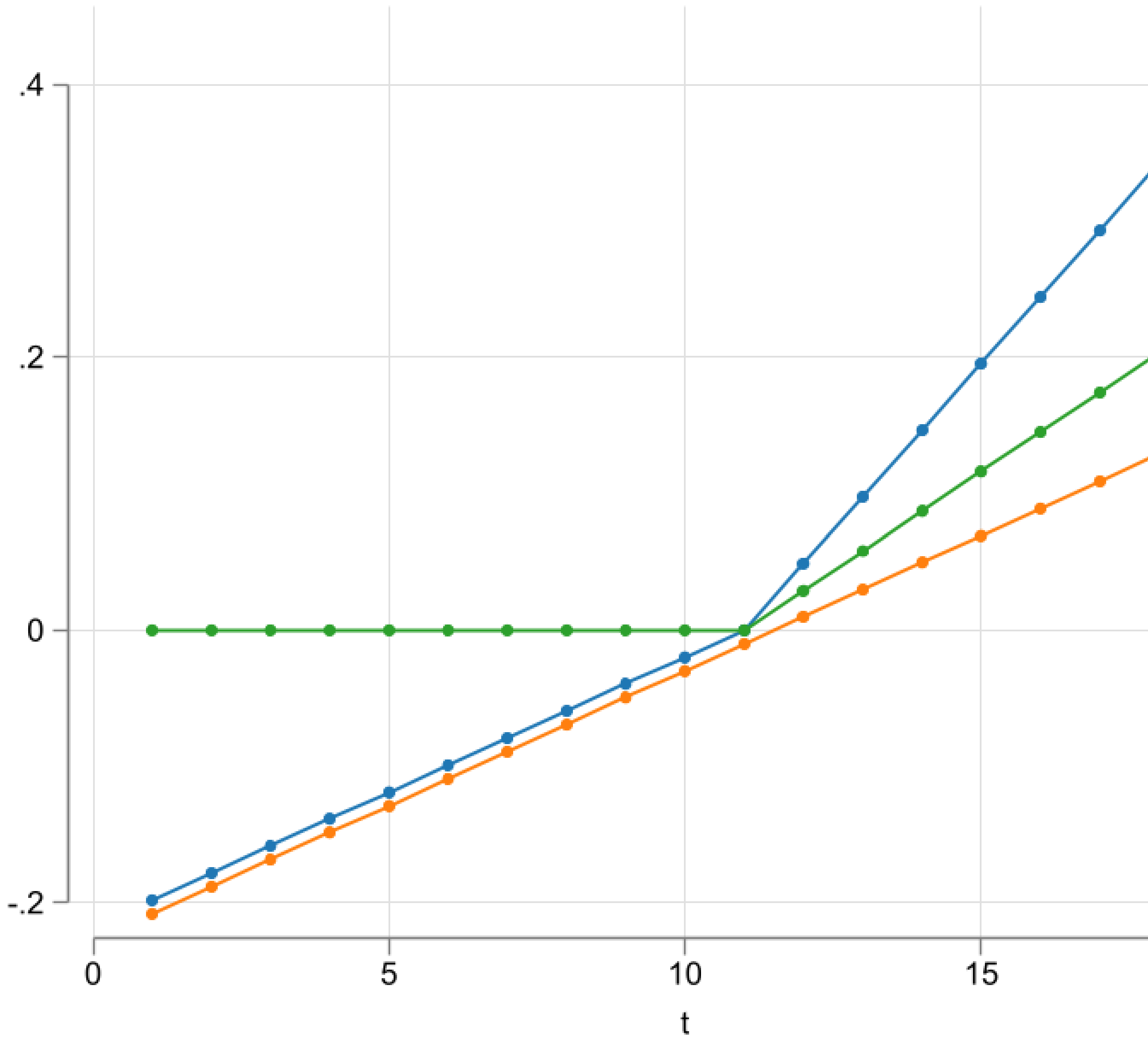
What if PTA does not hold?

- As suggested by Wooldridge (2023), one of the reasons PTA may not hold is because we may be analyzing the wrong model.
  - consider two groups of workers, high and low earners, that experience the same wage growth. (parallel trends in relative terms)
  - If we observe wages at levels, parallel trends would be violated
  - And Post treatment estimates will be missleading

Wage PTA in levels



Wage PTA in logs



PTA may hold for $G(\bar{Y})$

A similar story could be told about other types of transformations.

In general, it is possible that PTA hold for some other monotonic transformation of the outcome variable.

$$G^{-1}\Big(E_1[Y_{i,1}(0)]\Big) - G^{-1}\Big(E_1[Y_{i,0}(0)]\Big) = G^{-1}\Big(E_0[Y_{i,1}]\Big) - G^{-1}\Big(E_0[Y_{i,0}]\Big)$$

This is very similar to the PTA assumption explored in Roth and Sant'Anna (2023).

$$E_1\Big[g(Y_{i,1}(0))\Big] - E_1\Big[g(Y_{i,0}(0))\Big] = E_0\Big[g(Y_{i,1})\Big] - E_0\Big[g(Y_{i,0})\Big]$$

Wooldridge idea: It may be possible to identify ATTs using correct functional forms, through the **latent index**.

How do things Change?

- Using this insight, we can go back to the 2x2 design, and see how things change.

Before:

$$E(y_{i,t}|D,T) = \beta_0 + \beta_1 T + \beta_2 D_i + \theta(D_i \times T)$$

After:

$$E(y_{i,t}|D,T) = G\Big(\beta_0 + \beta_1 T + \beta_2 D_i + \theta(D_i \times T)\Big)$$

- For the practitioner, the extended Nonlinear DID simply requires choosing a functional form that better fits the data.
  - Poisson, logit, ~~fractional regression~~, multinomial model, Linear model, etc

Extension I: Adding Covariates

- Many papers in the literature consider the use of covariates in the estimation of the ATT.
- The lessons from Sant'Anna and Zhao (2020):
  - The choosen covariates should be time fixed, to avoid contamination of the treatment effect.
  - Using covariates allows relaxing the parallel trends assumption: PTA hold for specific groups of individuals. (if not for the whole population due to compositional changes)
- In the 2x2 DID-Regression, covariates can be added with interactions:

$$\begin{aligned} y_{i,t} &= \beta_0 + \beta_1 D + \beta_2 T + \theta(D \times T) \\ &+ X\gamma + D \times X\gamma_d + T \times X\gamma_T + D \times T(X - \bar{X})\lambda + \epsilon_{i,t} \end{aligned}$$

- The same could be done in the nonlinear case

Extension II: GxT DiD

- The 2x2 design is rather limited, because often people have access to multiple periods of time, with differential treatment timing. (staggered adoption of the treatment)
  - I call this the GxT design (G groups, T periods of time)
- The majority of the papers that analyze this case impose an additional assumption:
  - Treatment is not Reversable: Once treated always treated

NOTE: Because of the interactions required, adding covariates would rapidily "consume" degrees of freedom. (may be a problem with nonlinear models).

How to see this? `--> tab tvar gvar`

The Problem

- Early extensions of the 2x2 design to the GxT design, relied on the **TWFE** estimator.

$$y_{i,t} = \delta_i + \delta_t + \theta^{fe} D_{i,t} + e_{i,t}$$

where $D_{i,t} = 1$ only after treatment is in place, and zero otherwise.

- This model has been shown to be problematic, because of How OLS estimates the θ^{fe} parameter.
  - θ^{fe} is a weighted average of all possible 2x2 DID designs. Goodman-Bacon (2021)
  - Some designs use early treated units as controls for late treated units, which might be a violation of the parallel trends assumption.
    * (treated units effectively receiving negative weights) Goodman-Bacon (2021), Chaisemartin and D'Haultfœuille (2020) and Borusyak, Jaravel, and Spiess (2023).

Avoiding the Problem

- Callaway and Sant'Anna (2021) proposes a simple solution: Deconstruct the problem into smaller pieces (2x2 DIDs), and aggregate them as needed.
- Wooldridge (2021), however, proposes a different solution: Use the correct functional form to estimate the ATTs.

$$\text{Instead of: } Y_{i,t} = \delta_i + \gamma_t + \theta^{fe} PT_{i,t} + \epsilon_{i,t}$$

$$\text{Use: } Y_{i,t} = \delta_i + \gamma_t + \sum_{g \in \mathbb{G}} \sum_{t=g}^{T} \theta_{g,t} \mathbb{1}(G = g, T = t) + \epsilon_{i,t}$$

- Their Message: Embrace heterogeneity across time and cohorts.

An added Insight

- The approach proposed by Wooldridge (2021), is more efficient than Callaway and Sant'Anna (2021), because it uses all pre-treatment data to estimate the ATTs. (Callaway and Sant'Anna (2021) uses only one pre-treatment period)
- However, doing this doesn't allow you to test for PTA directly, unless we use an alternative approach:

$$Y_{i,t} = \delta_i + \gamma_t + \sum_{g \in \mathbb{G}} \sum_{t=t_0}^{g-2} \theta_{g,t}^{pre} \mathbb{1}(G = g, T = t) + \sum_{g \in \mathbb{G}} \sum_{t=g}^{T} \theta_{g,t}^{post} \mathbb{1}(G = g, T = t) + \epsilon_{i,t}$$

- This specification is equivalent to Callaway and Sant'Anna (2021) and to Sun and Abraham (2021).
  - Its explicily a regression (Wooldridge)
  - and uses actual, instead of relative, time.

Implementing NL-DID the `JW` way

- One of the advantages of the approaches proposed by Wooldridge (2021) and Wooldridge (2023), is that they can be directly estimated using regressions.
- The hard part is to construct all the interactions required for the model to work.
- And a second challenge is to aggregate the results.

`jwdid`

- `jwdid` is a simple command that helps with the construction of all required interactions that could be used to implement Wooldridge approach.

- It is flexible enough, in that it allows you to choose different estimators that would better fit your data.

- it comes with its own post estimation commands that can help you aggregate the results into simple ATT, dynamics effects, across periods, across years, etc.

- Lets take it for a spin

Command Syntax

- `jwdid` - Command Name. In charge of getting all interactions -right-
  - `depvar [indepvar]` - Declare the dependent variables. Independent variables are optional. They should be time fixed.
  - `[if] [in] [weight]`, Declares sample and weights. Only `PW` is allowed.

Command Main Options

- `jwdid`: main options
  - `ivar(varname)`: Panel indicator. If not declared, command assumes one is using repeated cross sections.
  - `cluster(varname)`: Cluster variable. To request a clustered standard error other than at `ivar` level. Recommended with RC.
  - `tvar(varname)` or `time(varname)`: Required, Time variable. There are two ways to call it for compatability with `csdid`.

- gvar(varname): Group variable. Indicates the timing of when a unit has ben treated.
- trtvar(varname): If using Panel data, one could instead provide the post-treatment dummy.
    - If data is repeated crossection, one requires using trgvar(varname) (Pseudo panel indicator).

Extra Options

- group: Requests using group fixed effects, instead of individual fixed effects (default)
- never: Request to use alternative specification that allows to test for PTA. (default is to use the standard specification)
- Linear and Nonlinear models:
    - method(command, options): Request to use a specific method to model the data. Default is using linear regression via reghdfe.
    - the option part allows you do include specific options for the method. (e.g. method(glm, link() family()))

Example 1: Min Wages on Employment CS data

```
clear all
qui:ssc install frause
qui:frause mpdta, clear
frause mpdta, clear
jwdid lemp, ivar(county) tvar(year) gvar(first)
```

```
(Written by R.                )
WARNING: Singleton observations not dropped; statistical significance is biased
>  (link)
(MWFE estimator converged in 2 iterations)

HDFE Linear regression                            Number of obs   =      2,500
Absorbing 2 HDFE groups                           F(   7,    499) =       3.82
Statistics robust to heteroskedasticity           Prob > F        =     0.0005
                                                  R-squared       =     0.9933
                                                  Adj R-squared   =     0.9915
                                                  Within R-sq.    =     0.0101
Number of clusters (countyreal) =        500      Root MSE        =     0.1389
```

```
                              (Std. err. adjusted for 500 clusters in countyreal)
-------------------------------------------------------------------------------
             |               Robust
        lemp | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+-----------------------------------------------------------------
 first_treat#|
       year#|
    c.__tr__ |
  2004 2004  |  -.0193724   .0223818    -0.87   0.387    -.0633465    .0246018
  2004 2005  |  -.0783191   .0304878    -2.57   0.010    -.1382195   -.0184187
  2004 2006  |  -.1360781   .0354555    -3.84   0.000    -.2057386   -.0664177
  2004 2007  |  -.1047075   .0338743    -3.09   0.002    -.1712613   -.0381536
  2006 2006  |   .0025139   .0199328     0.13   0.900    -.0366487    .0416765
  2006 2007  |  -.0391927   .0240087    -1.63   0.103    -.0863634     .007978
  2007 2007  |   -.043106   .0184311    -2.34   0.020    -.0793182   -.0068938
             |
       _cons |    5.77807    .001544  3742.17   0.000     5.775036    5.781103
-------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
  countyreal |       500         500           0    *|
        year |         5           0           5     |
-----------------------------------------------------+
* = FE nested within cluster; treated as redundant for DoF computation
```

```
gen emp = exp(lemp)
jwdid emp, ivar(county) tvar(year) gvar(first) method(poisson)
```

```
Iteration 0:   log pseudolikelihood = -2980537.4
Iteration 1:   log pseudolikelihood = -2980526.5
Iteration 2:   log pseudolikelihood = -2980526.5

Poisson regression                                      Number of obs =  2,500
                                                        Wald chi2(14) = 225.38
Log pseudolikelihood = -2980526.5                       Prob > chi2   = 0.0000

                              (Std. err. adjusted for 500 clusters in countyreal)
-------------------------------------------------------------------------------
```

```
             |               Robust
         emp | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
 first_treat#|
        year#|
    c.__tr__ |
  2004 2004  |  -.0080499   .0100858    -0.80   0.425    -.0278177    .0117178
  2004 2005  |  -.0252131   .0176754    -1.43   0.154    -.0598562    .0094299
  2004 2006  |   -.051965   .0197745    -2.63   0.009    -.0907222   -.0132077
  2004 2007  |  -.0672208   .0192207    -3.50   0.000    -.1048926    -.029549
  2006 2006  |    .055212   .0330023     1.67   0.094    -.0094714    .1198954
  2006 2007  |   .0109993     .04294     0.26   0.798    -.0731617    .0951602
  2007 2007  |   -.060675   .0149793    -4.05   0.000    -.0900339   -.0313161
             |
 first_treat |
       2004  |   .4789133   .4347691     1.10   0.271    -.3732184    1.331045
       2006  |   .6010118   .3248861     1.85   0.064    -.0357532    1.237777
       2007  |   .1269293   .2472938     0.51   0.608    -.3577576    .6116163
             |
        year |
       2004  |  -.0459369   .0064592    -7.11   0.000    -.0585966   -.0332771
       2005  |  -.0301284   .0094457    -3.19   0.001    -.0486416   -.0116152
       2006  |  -.0030985   .0122001    -0.25   0.800    -.0270104    .0208133
       2007  |   .0350031   .0118264     2.96   0.003     .0118238    .0581824
             |
       _cons |    6.84775   .1555219    44.03   0.000     6.542932    7.152567
------------------------------------------------------------------------------
```

```
jwdid emp, ivar(county) tvar(year) gvar(first) method(poisson) never
```

```
Iteration 0:   log pseudolikelihood = -2980450.1
Iteration 1:   log pseudolikelihood = -2980438.8
Iteration 2:   log pseudolikelihood = -2980438.8

Poisson regression                                      Number of obs =  2,500
                                                        Wald chi2(19) = 262.50
Log pseudolikelihood = -2980438.8                       Prob > chi2   = 0.0000

                           (Std. err. adjusted for 500 clusters in countyreal)
------------------------------------------------------------------------------
             |               Robust
```

```
         emp | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
 first_treat#|
       year#|
    c.__tr__ |
  2004 2004  |  -.0063802   .0111509    -0.57   0.567    -.0282356    .0154752
  2004 2005  |   -.027483   .0190781    -1.44   0.150    -.0648753    .0099094
  2004 2006  |  -.0641446   .0224733    -2.85   0.004    -.1081913   -.0200978
  2004 2007  |  -.0704859   .0204208    -3.45   0.001    -.1105099   -.0304619
  2006 2003  |  -.0081647   .0366458    -0.22   0.824     -.079989    .0636597
  2006 2004  |  -.0289763   .0258763    -1.12   0.263    -.0796929    .0217403
  2006 2006  |   .0310817   .0186723     1.66   0.096    -.0055153    .0676788
  2006 2007  |  -.0042165   .0335939    -0.13   0.900    -.0700593    .0616263
  2007 2003  |   .0358582   .0236868     1.51   0.130    -.0105671    .0822835
  2007 2004  |   .0517571   .0164417     3.15   0.002      .019532    .0839822
  2007 2005  |   .0237174   .0112134     2.12   0.034     .0017395    .0456952
  2007 2007  |  -.0329817    .009941    -3.32   0.001    -.0524657   -.0134976
             |
 first_treat |
       2004  |   .4821784   .4354246     1.11   0.268    -.3712381    1.335595
       2006  |   .6162276   .3252255     1.89   0.058    -.0212028    1.253658
       2007  |    .099236    .244468     0.41   0.685    -.3799124    .5783844
             |
        year |
       2004  |  -.0476066   .0080213    -5.94   0.000     -.063328   -.0318852
       2005  |  -.0278586   .0118649    -2.35   0.019    -.0511134   -.0046038
       2006  |    .009081    .016213     0.56   0.575    -.0226959     .040858
       2007  |   .0382682   .0136908     2.80   0.005     .0114347    .0651017
             |
       _cons |   6.844485   .1573451    43.50   0.000     6.536094    7.152875
------------------------------------------------------------------------------
```

Example 1: Aggregations

```
estat event
```

```
------------------------------------------------------------------------------
             |            Delta-method
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
   __event__ |
```

```
          -4  |   37.84578   27.92442     1.36   0.175    -16.88508    92.57665
          -3  |   36.91665   23.13761     1.60   0.111     -8.43224    82.26554
          -2  |   7.462364   14.88422     0.50   0.616    -21.71018    36.63491
          -1  |          0  (omitted)
           0  |  -13.33389   12.32746    -1.08   0.279    -37.49527    10.82749
           1  |  -18.42686   40.35552    -0.46   0.648    -97.52222     60.6685
           2  |   -95.3188   36.54186    -2.61   0.009    -166.9395   -23.69806
           3  |  -107.5067   44.45653    -2.42   0.016    -194.6399   -20.37347
------------------------------------------------------------------------------
```

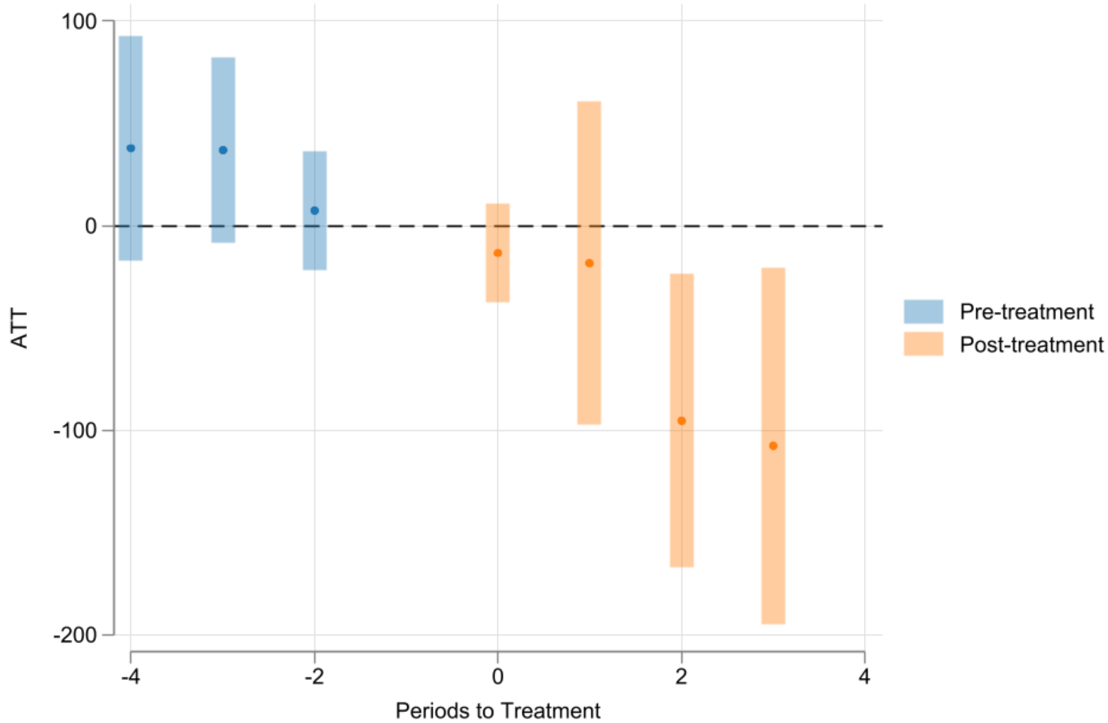
```
estat group
```

```
------------------------------------------------------------------------------
             |            Delta-method
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
   __group__ |
        2004 |  -63.03151   28.14208    -2.24   0.025     -118.189   -7.874052
        2006 |   23.89072   46.37715     0.52   0.606    -67.00682    114.7883
        2007 |  -34.94374   13.54265    -2.58   0.010    -61.48686   -8.400625
------------------------------------------------------------------------------
```

```
estat calendar
```

```
------------------------------------------------------------------------------
             |            Delta-method
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
__calendar__ |
        2004 |  -9.219455   15.81277    -0.58   0.560    -40.21192    21.77301
        2005 |  -40.08113   29.74368    -1.35   0.178    -98.37767    18.21541
        2006 |   5.147843   33.13277     0.16   0.877     -59.7912    70.08689
        2007 |  -36.81546   16.84608    -2.19   0.029    -69.83316   -3.797752
------------------------------------------------------------------------------
```

```
qui:estat event, plot
graph export event.png, replace width(1000)
```



Example 2: Wooldridge Simulation data

```
clear all
use nonlinear_did/did_common_6_binary, clear
qui {
reg y i.w#c.d#c.f04 i.w#c.d#c.f05 i.w#c.d#c.f06 ///
    i.w#c.d#c.f04#c.x i.w#c.d#c.f05#c.x i.w#c.d#c.f06#c.x ///
    f02 f03 f04 f05 f06 ///
    c.f02#c.x c.f03#c.x c.f04#c.x c.f05#c.x c.f06#c.x ///
    d x c.d#c.x, noomitted vce(cluster id)
  est sto m1
}
qui:margins, dydx(w) at(f02 = 0 f03 = 0 f04 = 1 f05 = 0 f06 = 0) ///
    subpop(if d == 1) noestimcheck vce(uncond)  post
ereturn display
est restore m1
qui:margins, dydx(w) at(f02 = 0 f03 = 0 f04 = 0 f05 = 1 f06 = 0) ///
    subpop(if d == 1) noestimcheck vce(uncond) post
```

```
ereturn display
est restore m1
qui:margins, dydx(w) at(f02 = 0 f03 = 0 f04 = 0 f05 = 0 f06 = 1) ///
    subpop(if d == 1) noestimcheck vce(uncond) post
ereturn display
```

```
                                 (Std. err. adjusted for 1,000 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         1.w |   .0462206   .0367939     1.26   0.209    -.0259816    .1184228
------------------------------------------------------------------------------
(results m1 are active now)
                                 (Std. err. adjusted for 1,000 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         1.w |   .0755069   .0376124     2.01   0.045     .0016985    .1493153
------------------------------------------------------------------------------
(results m1 are active now)
                                 (Std. err. adjusted for 1,000 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         1.w |   .0445457   .0379857     1.17   0.241    -.0299952    .1190866
------------------------------------------------------------------------------
```

Using jwdid:

```
clear all
use nonlinear_did/did_common_6_binary, clear
qui: jwdid y x, ivar(id) tvar(year) trtvar(w) method(regress)
estat event, vce(unconditional)
```

```
                                 (Std. err. adjusted for 1,000 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
```

```
-------------+----------------------------------------------------------------
   __event__ |
           0 |   .0462206   .0367939     1.26   0.209    -.0259816    .1184228
           1 |   .0755069   .0376124     2.01   0.045     .0016985    .1493153
           2 |   .0445457   .0379857     1.17   0.241    -.0299952    .1190866
------------------------------------------------------------------------------
```

Using Logit

```
clear all
use nonlinear_did/did_common_6_binary, clear
qui {
logit y i.w#c.d#c.f04 i.w#c.d#c.f05 i.w#c.d#c.f06 ///
    i.w#c.d#c.f04#c.x i.w#c.d#c.f05#c.x i.w#c.d#c.f06#c.x ///
    f02 f03 f04 f05 f06 c.f02#c.x c.f03#c.x c.f04#c.x c.f05#c.x c.f06#c.x ///
    d x c.d#c.x, noomitted vce(cluster id)
  est store m1
}

qui:margins, dydx(w) at(f02 = 0 f03 = 0 f04 = 1 f05 = 0 f06 = 0) ///
    subpop(if d == 1) noestimcheck vce(uncond)  post
ereturn display
est restore m1
qui:margins, dydx(w) at(f02 = 0 f03 = 0 f04 = 0 f05 = 1 f06 = 0) ///
    subpop(if d == 1) noestimcheck vce(uncond) post
ereturn display
est restore m1
qui:margins, dydx(w) at(f02 = 0 f03 = 0 f04 = 0 f05 = 0 f06 = 1) ///
    subpop(if d == 1) noestimcheck vce(uncond) post
ereturn display
```

```
                                 (Std. err. adjusted for 1,000 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         1.w |   .0886639   .0326848     2.71   0.007     .0246029    .1527249
------------------------------------------------------------------------------
(results m1 are active now)
                                 (Std. err. adjusted for 1,000 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
```

```
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         1.w |   .1217999   .0355845     3.42   0.001     .0520556    .1915441
------------------------------------------------------------------------------
(results m1 are active now)
                                 (Std. err. adjusted for 1,000 clusters in id)
------------------------------------------------------------------------------
             |           Unconditional
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         1.w |   .1073639   .0371242     2.89   0.004     .0346018    .1801261
------------------------------------------------------------------------------
```

Using `jwdid`:

```
clear all
use nonlinear_did/did_common_6_binary, clear
qui: jwdid y x, ivar(id) tvar(year) trtvar(w) method(logit)
estat event, vce(unconditional)
```

```
                                 (Std. err. adjusted for 1,000 clusters in id)
------------------------------------------------------------------------------
             |           Unconditional
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
   __event__ |
          0  |   .0886639   .0326848     2.71   0.007     .0246029    .1527249
          1  |   .1217999   .0355845     3.42   0.001     .0520556    .1915441
          2  |   .1073639   .0371242     2.89   0.004     .0346018    .1801261
------------------------------------------------------------------------------
```

Conclusion

- DID is a popular method for analyzing policy interventions.
- Thanks to the contributions of Wooldridge, Roth and Sant'Anna among others, we have a better understanding of how to implement DID in more complex scenarios.
- One of this important extensions is the use of nonlinear models to better fit the data, and better estimate treatment effects.
- The `jwdid` command is a simple tool that can help you implement the Wooldridge approach to nonlinear DID.

Thank you

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