Two-Period Difference-in-Differences with Panel Data

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1. Introduction and Overview
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1. Introduction and Overview

- Difference-in-Differences methods are increasingly popular for analyzing interventions.
  - Currie, Kleven, and Zwiers (2020, AER P&P).
- Observing units over at least two time periods allows controlling for unobserved heterogeneity.
  - Can also control for observed heterogeneity (covariates).
- Here we study panel data settings.

- Standard DiD methods use common or parallel trends assumptions.
  - Adding covariates can help.
- Also need “no anticipation” assumption.
- Common intervention date is relatively easy to handle.
  - $T = 2$ is the traditional special case.

2. The $T = 2$ Panel Data DiD Case

- Two periods, $t \in \{1,2\}$.
  - $t = 1$ is the control period.
  - Some units are "treated" just prior to $t = 2$.
- Treatment indicator $D_i \in \{0,1\}$ means treated in the second time period.
- For each i, we have four potential outcomes:

$$[Y_{i1}(0), Y_{i1}(1), Y_{i2}(0), Y_{i2}(1)]$$

- $Y_{i1}(0),\ Y_{i1}(1)$ are potential outcomes before the treatment is assigned.

- Common assumption:

$$Y_{i1}(1) = Y_{i1}(0)$$

  - Heckman, Ichimura, Todd (1997); Abadie (2005).
  - A strong form of "no anticipation."
  - Can relax it somewhat.
- Assume random sampling across i.

- Parameter of interest is the average treatment effect on the treated (ATT) in second period:

$$\tau_{2,att} \equiv E[Y_2(1) - Y_2(0)|D = 1]$$

- Stronger assumptions are needed to estimate

$$\tau_{2,ate} \equiv E[Y_2(1) - Y_2(0)]$$

- Henceforth, $\tau_2 \equiv \tau_{2,att}$.
- Missing data problem: We do not observe both $Y_{i2}(1)$ and $Y_{i2}(0)$ for any i.

- The data we observe are $\{(D_i, Y_{i1}, Y_{i2}) : i = 1, \ldots, N\}$, where

$$\begin{aligned} Y_{i1} &= (1 - D_i)Y_{i1}(0) + D_i Y_{i1}(1) \\ Y_{i2} &= (1 - D_i)Y_{i2}(0) + D_i Y_{i2}(1) \end{aligned}$$

- Suppose we only observe Y in $t = 2$.
  - ▸ Without additional information, we are stuck with the simple difference in means:

$$\hat{\tau}_{2,SDM} = N_1^{-1} \sum_{i=1}^{N} D_i Y_{i2} - N_0^{-1} \sum_{i=1}^{N} (1 - D_i) Y_{i2}$$

$$N_1 = \sum_{i=1}^{N} D_i, \;\; N_0 = N - N_1 = \sum_{i=1}^{N} (1 - D_i)$$

- Generally,

$$\begin{aligned} \text{plim}(\hat{\tau}_{2,SDM}) &= E[Y_2(1)|D=1] - E[Y_2(0)|D=0] \\ &= \tau_2 + \{E[Y_2(0)|D=1] - E[Y_2(0)|D=0]\} \\ &= \tau_2 + \text{selection bias} \end{aligned}$$

- Consistency of $\hat{\tau}_{2,SDM}$ requires no selection bias:

$$E[Y_2(0)|D=1] = E[Y_2(0)|D=0]$$

▸ Sufficient is assignment is independent of the outcome in the control state.

- How can we exploit the $T = 2$ panel structure?
- The difference-in-differences estimator is

$$\begin{aligned}\hat{\tau}_{2,DD} &= N_1^{-1} \sum_{i=1}^{N} D_i \Delta Y_i - N_0^{-1} \sum_{i=1}^{N} (1 - D_i) \Delta Y_i \\ &= \overline{\Delta Y}_{treat} - \overline{\Delta Y}_{control}\end{aligned}$$

$$\Delta Y_i = Y_{i2} - Y_{i1}$$

- **Question**: When does $\hat{\tau}_{2,DD}$ consistently estimate τ_2?
- Write TE_2 in a more complicated way:

$$
\begin{aligned}
TE_2 &= Y_2(1) - Y_2(0) = [Y_2(1) - Y_1(1)] - [Y_2(0) - Y_1(0)] \\
&\quad + [Y_1(1) - Y_1(0)] \\
&\equiv \Delta Y(1) - \Delta Y(0) + TE_1
\end{aligned}
$$

$$\Delta Y(d) \equiv Y_2(d) - Y_1(d),\ d \in \{0, 1\}$$

$$TE_2 = \text{[change in treated state]} - \text{[change in untreated state]}$$
$$+ \text{ [TE in pre-treatment period]}$$

- Take expectation conditional on $D = 1$:

$$\tau_2 = E(TE_2|D = 1) = E[\Delta Y(1)|D = 1] - E[\Delta Y(0)|D = 1] + \tau_1$$

- More precisely,

$$\tau_{2,att} = E[\Delta Y(1)|D = 1] - E[\Delta Y(0)|D = 1] + \tau_{1,att}$$

Assumption NA (No Anticipation): With D the treatment indicator,

$$E[Y_1(1) - Y_1(0)|D = 1] = 0. \square$$

- $E[Y_1(1) - Y_1(0)|D = 1]$ is the ATT before the intervention.
- Units cannot change behavior in anticipation in ways that would affect pre-treatment potential outcomes.
- Sufficient is the strongest form of no anticipation:

$$Y_1(1) = Y_1(0)$$

- Under Assumption NA,

$$\tau_{2,att} = E[\Delta Y(1)|D = 1] - E[\Delta Y(0)|D = 1]$$

- We can always estimate $E[\Delta Y(1)|D = 1]$ because, for each i,

$$\Delta Y_i = \Delta Y_i(1) \text{ when } D_i = 1$$

- Use the average change over the treated units:

$$N_1^{-1} \sum_{i=1}^{N} D_i \Delta Y_i = N_1^{-1} \sum_{i=1}^{N} D_i \Delta Y_i(1) \overset{p}{\to} E[\Delta Y(1) | D = 1]$$

- The difficult term to estimate is

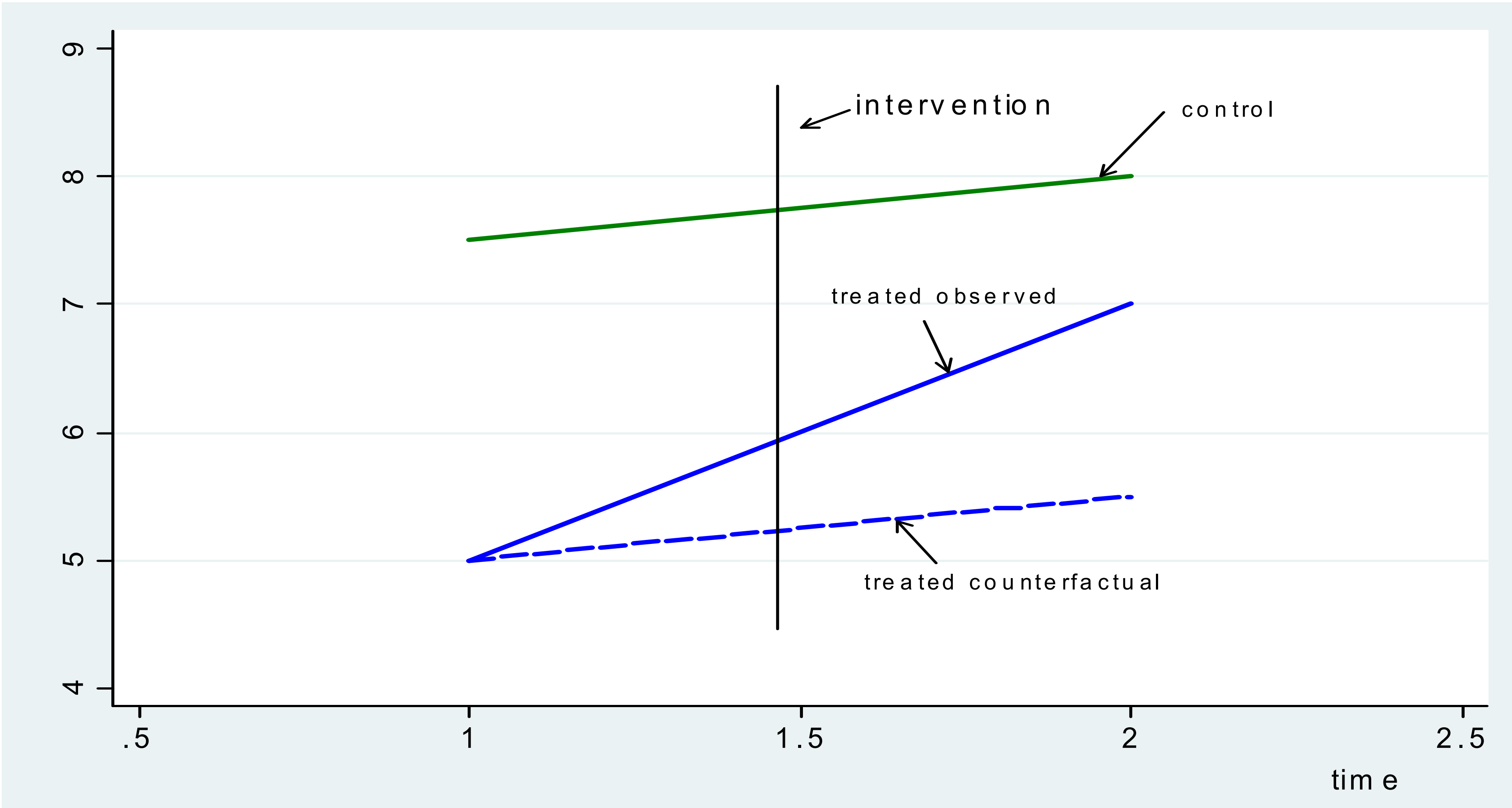
$$E[\Delta Y(0) | D = 1]$$

  - We do not observe $\Delta Y_i(0)$ when $D_i = 1$.

Assumption CT (Common or Parallel Trends): With D the treatment indicator,

$$E[\Delta Y(0)|D = 1] = E[\Delta Y(0)|D = 0]. \ \square$$

- In the untreated state, the average change is the same for treated and control.
  - ▸ No selection bias in the *trend* in the control state.
- Importantly, D can be correlated with $Y_1(0)$.
- D can be correlated with the change in the treated state, $\Delta Y(1) = Y_2(1) - Y_1(1)$.



$$E[Y_2(0)|D=1] = E[Y_2(0)|D=0] + \{E[Y_1(1)|D=1] - E[Y_1(0)|D=0]\}$$

- Under Assumption CT,

$$N_0^{-1}\sum_{i=1}^{N}(1-D_i)\Delta Y_i = N_0^{-1}\sum_{i=1}^{N}(1-D_i)\Delta Y_i(0) \xrightarrow{p} E[\Delta Y(0)|D=0]$$
$$= E[\Delta Y(0)|D=1]$$

- Conclusion: Under Assumptions NA and CT,

$$\text{plim}(\hat{\tau}_{2,DD}) = \text{plim}(\overline{\Delta Y}_{treat} - \overline{\Delta Y}_{control}) = \tau_{2,att}$$

Equivalent Methods for Obtaining $\hat{\tau}_{2,DD}$

1. Cross-Sectional OLS on Differences

- Run the regression

$$\Delta Y_i \text{ on } 1, D_i, \; i = 1, \ldots, N$$

and then $\hat{\tau}_{2,DD}$ is the coefficient on D_i.

  - ▸ Heteroskedasticity-robust inference.

- Contrast the difference-in-means regression for $t = 2$:

$$Y_{i2} \text{ on } 1, D_i, \; i = 1, \ldots, N$$

  - ▸ This produces $\hat{\tau}_{2,SDM}$.

2. Pooled OLS on Levels

- Define a second period dummy:

$$f2_t = 0 \text{ if } t = 1$$

$$f2_t = 1 \text{ if } t = 2$$

- The time-varying treatment indicator is

$$W_{it} = D_i \cdot f2_t$$

  - ▸ In both simple and complicated settings, useful to have W_{it}.

```
. * w = train

. list id year lwage train d d92 in 19/34, sep(2)

     +----------------------------------------+
     |  id   year      lwage   train   d   d92 |
     |----------------------------------------|
 19. | 166   1991   .9376874       0   1     0 |
 20. | 166   1992   1.432148       1   1     1 |
     |----------------------------------------|
 21. | 189   1991    .836248       0   0     0 |
 22. | 189   1992    1.46736       0   0     1 |
     |----------------------------------------|
 23. | 193   1991   2.493875       0   0     0 |
 24. | 193   1992   1.822662       0   0     1 |
     |----------------------------------------|
 25. | 209   1991   .7654077       0   0     0 |
 26. | 209   1992   1.978185       0   0     1 |
     |----------------------------------------|
 27. | 212   1991   2.179983       0   1     0 |
 28. | 212   1992   2.048526       1   1     1 |
     |----------------------------------------|
 29. | 218   1991   1.962152       0   0     0 |
 30. | 218   1992   2.275641       0   0     1 |
     |----------------------------------------|
 31. | 243   1991   1.683546       0   0     0 |
 32. | 243   1992   1.690503       0   0     1 |
     |----------------------------------------|
 33. | 259   1991   2.089011       0   1     0 |
 34. | 259   1992   2.147384       1   1     1 |
     |----------------------------------------|
```

- Can show $\hat{\tau}_{2,DD}$ is the coefficient on W_{it} in the regression

$$Y_{it} \text{ on } 1, D_i, f2_t, W_{it}, t = 1,2;\ i = 1,\ldots,N$$

▸ Cluster standard errors to account for serial correlation and heteroskedasticity.

- More traditional is to use:

$$Y_{it} \text{ on } 1, D_i, f2_t, D_i \cdot f2_t, t = 1,2;\ i = 1,\ldots,N$$

▸ In more complicated settings (adding covariates, nonlinear models), better to use W_{it}.

▸ Sometimes have to compute an average partial (marginal) effect with respect to W_{it}, not D_i.

3. Two-Way Fixed Effects

- Think of an equation for random draw i:

$$Y_{it} = \tau_2 W_{it} + \theta_2 f2_t + C_i + U_{it}, \; t = 1,2$$

- Estimate by fixed effects. Inclusion of $f2_t$ means TWFE.
- $\hat{\tau}_{2,DD}$ is the coefficient on W_{it}.
  - Cluster standard errors to account for serial correlation.
- Recall the TWFE dummy variable regression where $ch_i = 1[h = i]$:

$$Y_{it} \text{ on } W_{it}, c1_i, c2_i, ..., cN_i, f2_t, \; t = 1,2; \; i = 1,\ldots,N$$

- Equivalence of POLS and TWFE: It is enough to control for D_i rather than N unit dummies.

Stata Commands

```
xtset cid tid

reg D.y w, vce(robust)

reg y w d f2, vce(cluster cid)

xtreg y w f2, fe vce(cluster cid)
```

- Standard errors allow for heteroskedasticity and serial correlation.

3. Adding Covariates: Linear Regression Adjustment

- Common to include controls (covariates) in DiD settings.
  - Can help with failure of the CT Assumption.
- Current thinking: Only use pre-treatment controls.
  - Can ruin the CT assumption by conditioning on controls affected by intervention.
- Let $\mathbf{X}_i$ be a $1 \times K$ vector of pre-intervention covariates.

Adding Covariates in Levels has No Effect

- The POLS regressions

$$Y_{it} \text{ on } 1, W_{it}, D_i, f2_t, \; t = 1,2; i = 1,\ldots,N$$

and

$$Y_{it} \text{ on } 1, W_{it}, D_i, f2_t, \mathbf{X}_i, \; t = 1,2; i = 1,\ldots,N$$

give *identical* estimates on W_{it}, $\hat{\tau}_2$.

- Follows from Wooldridge (2021, Working Paper).

```
reg y w d f2, vce(cluster id)
reg y w d f2 x1 ... xK, vce(cluster id)
```

- Equivalence makes sense.
- If we write

$$Y_{it} = \tau_2 W_{it} + \theta_2 f2_t + \mathbf{X}_i \boldsymbol{\beta} + C_i + U_{it},\ t = 1,2$$

then using FE eliminates $\mathbf{X}_i$.

- Moreover, if we use FD (equivalent to FE with $T = 2$),

$$\Delta Y_i = \tau_2 D_i + \theta_2 + \Delta U_i$$

Adding Covariates to Relax Common Trends

- How can we use time-constant covariates to adjust the basic DiD estimator?
- Recall under no anticipation:

$$\tau_2 = E[\Delta Y(1)|D = 1] - E[\Delta Y(0)|D = 1]$$

- $E[\Delta Y(1)|D = 1]$ is estimable as before.
- $E[\Delta Y(0)|D = 1]$ is still the problem.
- Want to relax Assumption CT:

$$E[\Delta Y(0)|D = 1] = E[\Delta Y(0)|D = 0]$$

Assumption CCT (Conditional Common Trends): For D the treatment indicator and covariates $\mathbf{X}$,

$$E[Y_2(0) - Y_1(0)|D, \mathbf{X}] = E[Y_2(0) - Y_1(0)|\mathbf{X}]. \; \square$$

- CT holds within each subpopulation determined by values of $\mathbf{X}$.
  - Think of partitioning population by values $\mathbf{x} \in \mathcal{X}$.
- Assumption CCT simply says: D is unconfounded for $\Delta Y(0)$ conditional on $\mathbf{X}$.
  - Cross sectional case: D is unconfounded for $Y(0)$ conditional on $\mathbf{X}$.

- Recall how unconfoundedness implies identification:

$$
\begin{aligned}
E[\Delta Y(0)|D=1] &= E\{E[\Delta Y(0)|D=1,\mathbf{X}]|D=1\} \text{ (iterated expectations)} \\
&= E\{E[\Delta Y(0)|D=0,\mathbf{X}]|D=1\} \text{ (CCT)}
\end{aligned}
$$

- The function

$$
m_0(\mathbf{x}) \equiv E[\Delta Y(0)|D=0,\mathbf{X}=\mathbf{x}] = E[\Delta Y(0)|\mathbf{X}=\mathbf{x}]
$$

is estimable using data on $D_i = 0$ (control group) because

$$
\Delta Y_i = \Delta Y_i(0) \text{ when } D_i = 0
$$

  - Generally, can only estimate $m_0(\mathbf{x})$ for $\mathbf{x} \in \text{Support}(\mathbf{X}|D=0)$.

Assumption OV (Overlap): For all $\mathbf{x} \in \text{Support}(\mathbf{X})$,

$$p(\mathbf{x}) \equiv P(D = 1|\mathbf{X} = \mathbf{x}) > 0. \ \square$$

- Overlap means that

$$\text{Support}(\mathbf{X}|D = 1) \subset \text{Support}(\mathbf{X}|D = 0)$$

- CCT + Overlap means we nonparametrically identify

$$E[\Delta Y(0)|D = 1] = E[m_0(\mathbf{X})|D = 1]$$

- Natural starting point: Apply linear regression adjustment to the cross-sectional data set

$$\{(\Delta Y_i, D_i, \mathbf{X}_i), i = 1, \ldots, N\}$$

- Let $\hat{\alpha}_0, \hat{\boldsymbol{\beta}}_0$ be from

$$\Delta Y_i \text{ on } 1, \mathbf{X}_i \text{ using } D_i = 0$$

- The RA estimate of τ_2 is

$$\begin{aligned}\hat{\tau}_{2,RA} &= N_1^{-1} \sum_{i=1}^{N} D_i \Delta Y_i - N_1^{-1} \sum_{i=1}^{N} D_i \left(\hat{\alpha}_0 + \mathbf{X}_i \hat{\boldsymbol{\beta}}_0\right) \\ &= \overline{\Delta Y}_{treat} - \left(\hat{\alpha}_0 + \bar{\mathbf{X}}_1 \hat{\boldsymbol{\beta}}_0\right)\end{aligned}$$

$$\bar{\mathbf{X}}_1 \equiv N_1^{-1} \sum_{i=1}^{N} \mathbf{X}_i$$

▸ Interpretation as imputation estimator.

- Same as the coefficient on D_i in the pooled regression

$$\Delta Y_i \text{ on } 1, D_i, \mathbf{X}_i, D_i \cdot (\mathbf{X}_i - \bar{\mathbf{X}}_1), i = 1, \ldots, N$$

  - Need to center around $\mathbf{X}_i$ around $\bar{\mathbf{X}}_1$.
- Some interest in coefficients on the interactions, $D_i \cdot (\mathbf{X}_i - \bar{\mathbf{X}}_1)$.
  - Moderating effects of the X_j.
- Słoczyński (2021, REStat): Bias in estimating τ_{ate} when dropping $D_i \cdot (\mathbf{X}_i - \bar{\mathbf{X}})$ when $P(D_i = 1)$ is far from 1/2.

- Also same as running separate regressions:

$$\Delta Y_i \text{ on } 1, \mathbf{X}_i \text{ with } D_i = 0 \ \ (\hat{\alpha}_0, \hat{\boldsymbol{\beta}}_0)$$
$$\Delta Y_i \text{ on } 1, \mathbf{X}_i \text{ with } D_i = 1 \ \ (\hat{\alpha}_1, \hat{\boldsymbol{\beta}}_1)$$

$$\hat{\tau}_{2,RA} = (\hat{\alpha}_1 - \hat{\alpha}_0) + \bar{\mathbf{X}}_1\left(\hat{\boldsymbol{\beta}}_1 - \hat{\boldsymbol{\beta}}_0\right)$$

because, by the algebra of OLS,

$$\overline{\Delta Y}_{treat} = \hat{\alpha}_1 + \bar{\mathbf{X}}_1\hat{\boldsymbol{\beta}}_1$$

- $\hat{\tau}_{2,RA}$ is also the coefficient on $W_{it} = D_i \cdot f2_t$ in the POLS regression

$$Y_{it} \text{ on } 1, W_{it}, W_{it} \cdot (\mathbf{X}_i - \bar{\mathbf{X}}_1), D_i, f2_t, \mathbf{X}_i, D_i \cdot \mathbf{X}_i, f2_t \cdot \mathbf{X}_i$$

across $t = 1,2; i = 1,\ldots,N$.

- Fixed effects applied to

$$Y_{it} = \tau_2 W_{it} + W_{it} \cdot (\mathbf{X}_i - \bar{\mathbf{X}}_1)\boldsymbol{\delta}_2 + \theta_2 f2_t + (f2_t \cdot \mathbf{X}_i)\boldsymbol{\xi}_2 + C_i + U_{it},\ t = 1,2$$

also gives $\hat{\tau}_{2,RA}$ as coefficient on W_{it}.

  - Extended TWFE.

- The basic TWFE analysis drops

$$W_{it} \cdot (\mathbf{X}_i - \bar{\mathbf{X}}_1),\ f2_t \cdot \mathbf{X}_i$$

- Equivalence of POLS and ETWFE: Special case of Wooldridge (2021, working paper).

• Robust or cluster-robsust standard errors do not account for sampling error in $\bar{\mathbf{X}}_1$.

• In Stata, at least two possibilities.

1. Use `teffects ra` with ΔY_i as the outcome variable.

2. Use POLS, do *not* center $\mathbf{X}_i$ about $\bar{\mathbf{X}}_1$, and use `vce(uncond)` with `margins`.

  ▸ Useful in more complicated settings.

• Adjusting for sampling error in $\bar{\mathbf{X}}_1$ often has practically small effects.

- Stata commands:

```
sum x1 if d
gen x1_dm = x1 - r(mean)
sum x2 if d
gen x2_dm = x2 - r(mean)
...
sum xK if d
gen xK_dm = xK - r(mean)
```

- Get the ATT directly (not quite the correct standard errors):

```
reg d_y i.d x1 ... xK i.d#c.x1_dm ...
   i.d#c.xK_dm, vce(robust)
reg y i.w i.w#x1_dm ... i.w#xK_dm
   d f2 x1 ... xK i.d#x1 ... i.d#xK
   i.f2#x1 ... i.f2#xK, vce(cluster cid)
xtreg y i.w i.w#c.x1_dm ... i.w#c.xK_dm
   i.f2 i.f2#c.x1 ... i.f2#c.xK,
   fe vce(cluster cid)
```

- Job training data set; use only 1991 (pre) and 1992 (post).
- Outcome variable is *lwage* $= \log(wage)$.

```
. use wagepan_did, replace

. xtset id year

Panel variable: id (strongly balanced)
 Time variable: year, 1990 to 1992
         Delta: 1 unit

. sort id year

. * Three years, 1990, 1991, 1992. 1992 is the single post treatment period.
. * Here, two-period DID.
.
. drop if year == 1990
(545 observations deleted)

. egen d = sum(train), by(id)
```

```
. list id year lwage train d d92 in 19/34, sep(2)

     +----------------------------------------------+
     |  id   year       lwage   train   d   d92 |
     |----------------------------------------------|
 19. | 166   1991    .9376874       0   1     0 |
 20. | 166   1992    1.432148       1   1     1 |
     |----------------------------------------------|
 21. | 189   1991     .836248       0   0     0 |
 22. | 189   1992     1.46736       0   0     1 |
     |----------------------------------------------|
 23. | 193   1991    2.493875       0   0     0 |
 24. | 193   1992    1.822662       0   0     1 |
     |----------------------------------------------|
 25. | 209   1991    .7654077       0   0     0 |
 26. | 209   1992    1.978185       0   0     1 |
     |----------------------------------------------|
 27. | 212   1991    2.179983       0   1     0 |
 28. | 212   1992    2.048526       1   1     1 |
     |----------------------------------------------|
 29. | 218   1991    1.962152       0   0     0 |
 30. | 218   1992    2.275641       0   0     1 |
     |----------------------------------------------|
 31. | 243   1991    1.683546       0   0     0 |
 32. | 243   1992    1.690503       0   0     1 |
     |----------------------------------------------|
 33. | 259   1991    2.089011       0   1     0 |
 34. | 259   1992    2.147384       1   1     1 |
     |----------------------------------------------|
```

```
. * Basic DiD. Estimates are all the same:
.
. reg D.lwage train, vce(robust)

Linear regression                               Number of obs     =        545
                                                F(1, 543)         =       4.09
                                                Prob > F          =     0.0435
                                                R-squared         =     0.0085
                                                Root MSE          =     .45454

------------------------------------------------------------------------------
             |               Robust
     D.lwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
       train |   .0960654     .04748     2.02   0.044     .0027985    .1893324
       _cons |   .0599069   .0217649     2.75   0.006     .0171532    .1026605
------------------------------------------------------------------------------

. reg D.(lwage train d92), nocons vce(robust)

------------------------------------------------------------------------------
             |               Robust
     D.lwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
       train |
         D1. |   .0960654     .04748     2.02   0.044     .0027985    .1893324
             |
         d92 |
         D1. |   .0599069   .0217649     2.75   0.006     .0171532    .1026605
------------------------------------------------------------------------------
```

```
. * Pooled OLS:

. reg lwage train d d92, vce(cluster id)

Linear regression                               Number of obs     =      1,090
                                                F(3, 544)         =      20.23
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0547
                                                Root MSE          =     .50746

                                  (Std. err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
       lwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
       train |   .0960654   .0475018     2.02   0.044      .002756    .1893748
           d |   .2091146     .05122     4.08   0.000     .1085014    .3097278
         d92 |   .0599069   .0217749     2.75   0.006     .0171338      .10268
       _cons |    1.45915   .0260405    56.03   0.000     1.407997    1.510302
------------------------------------------------------------------------------
```

```
. * Fixed Effects:

. xtreg lwage train d92, fe vce(cluster id)

Fixed-effects (within) regression               Number of obs     =      1,090
Group variable: id                              Number of groups  =        545

R-squared:                                      Obs per group:
     Within  = 0.0415                                         min =          2
     Between = 0.0580                                         avg =        2.0
     Overall = 0.0290                                         max =          2

                                                F(2,544)          =      10.62
corr(u_i, Xb) = 0.0803                          Prob > F          =     0.0000

                                   (Std. err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
       lwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
       train |   .0960654   .0474799     2.02   0.044      .002799    .1893319
         d92 |   .0599069   .0217648     2.75   0.006     .0171535    .1026603
       _cons |   1.512867   .0097352   155.40   0.000     1.493744     1.53199
-------------+----------------------------------------------------------------
     sigma_u |  .46243458
     sigma_e |   .3214084
         rho |   .6742751   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. * Adding time constant controls, educ and exper (in 1990) to the pooled
. * regression does nothing except for changing the degrees-of-freedom used
. * to construct standard errors. And the R-squared increases a lot:
.
. reg lwage train d d92 educ exper, vce(cluster id)

Linear regression                               Number of obs     =      1,090
                                                F(5, 544)         =      28.48
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1361
                                                Root MSE          =     .48557

                                   (Std. err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
       lwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
       train |   .0960654   .0475456     2.02   0.044       .00267    .1894609
           d |   .2048787   .0489374     4.19   0.000     .1087493    .3010081
         d92 |   .0599069   .0217949     2.75   0.006     .0170943    .1027194
        educ |    .104157   .0127503     8.17   0.000     .0791112    .1292028
       exper |   .0568412   .0142865     3.98   0.000     .0287778    .0849046
       _cons |   .0632674   .1845499     0.34   0.732    -.2992502    .4257851
------------------------------------------------------------------------------
```

```
. * Full regression adjustment. Demean educ and exper using treated subsample:
.
. qui sum educ if d
. gen educ_dm = educ - r(mean)
. qui sum exper if d
. gen exper_dm = exper - r(mean)

. reg D.lwage train c.train#c.educ_dm c.train#c.exper_dm ///
>         d92 educ exper, nocons vce(robust)

Linear regression                               Number of obs     =        545
                                                F(6, 539)         =       4.36
                                                Prob > F          =     0.0003
                                                R-squared         =     0.0461
                                                Root MSE          =     .45514

------------------------------------------------------------------------------------
                   |               Robust
           D.lwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------------+----------------------------------------------------------------
             train |    .095888   .0472991     2.03   0.043     .0029748    .1888012
                   |
  c.train#c.educ_dm |  -.0281286   .0364286    -0.77   0.440    -.0996881    .0434309
                   |
c.train#c.exper_dm |   -.044728   .0355761    -1.26   0.209    -.1146128    .0251568
                   |
               d92 |  -.0245192   .2273547    -0.11   0.914     -.471129    .4220906
              educ |    .007221   .0150001     0.48   0.630    -.0222448    .0366868
             exper |  -.0001651    .017045    -0.01   0.992     -.033648    .0333177
------------------------------------------------------------------------------------
```

```
. * POLS version:

. reg lwage train c.train#c.educ_dm c.train#c.exper_dm ///
>         d d92 educ exper c.d#c.educ c.d#c.exper c.d92#c.educ c.d92#c.exper, ///
>         vce(cluster id)

Linear regression                               Number of obs     =      1,090
                                                F(11, 544)        =      14.20
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1383
                                                Root MSE          =      .4863

                                   (Std. err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
                  |               Robust
            lwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
------------------+-----------------------------------------------------------
            train |    .095888   .0473209     2.03   0.043      .002934    .188842
                  |
c.train#c.educ_dm |  -.0281286   .0364454    -0.77   0.441    -.0997195   .0434623
                  |
c.train#c.exper_dm |  -.044728   .0355924    -1.26   0.209    -.1146435   .0251875
                  |
                d |  -.4698976   .5744642    -0.82   0.414    -1.598337   .6585423
              d92 |  -.0245192   .2274591    -0.11   0.914     -.471325   .4222866
             educ |   .0954815   .0163737     5.83   0.000      .063318    .127645
            exper |   .0545992   .0186165     2.93   0.004     .0180302   .0911682
```

```
                |
    c.d#c.educ  |   .0504608   .0408213     1.24   0.217    -.0297259    .1306476
                |
   c.d#c.exper  |   .0264654   .0369413     0.72   0.474    -.0460997    .0990305
                |
  c.d92#c.educ  |    .007221    .015007     0.48   0.631    -.0222577    .0366998
                |
 c.d92#c.exper  |  -.0001651   .0170529    -0.01   0.992    -.0336627    .0333324
                |
          _cons |   .1720381   .2396264     0.72   0.473    -.2986682    .6427445
---------------------------------------------------------------------------------
```

```
. xtreg lwage train c.train#c.educ_dm c.train#c.exper_dm ///
>         d92 c.d92#c.educ c.d92#c.exper, fe vce(cluster id)

Fixed-effects (within) regression               Number of obs     =      1,090
Group variable: id                              Number of groups  =        545

                                     (Std. err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
                 |               Robust
           lwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-----------------+------------------------------------------------------------
           train |    .095888   .0472115     2.03   0.043     .0031488    .1886272
                 |
c.train#c.educ_dm |  -.0281286   .0363611    -0.77   0.440     -.099554    .0432968
                 |
c.train#c.exper_dm |  -.044728   .0355102    -1.26   0.208    -.1144819    .0250259
                 |
             d92 |  -.0245192   .2269334    -0.11   0.914    -.4702924     .421254
                 |
     c.d92#c.educ |    .007221   .0149723     0.48   0.630    -.0221896    .0366316
                 |
    c.d92#c.exper |  -.0001651   .0170135    -0.01   0.992    -.0335853     .033255
                 |
           _cons |   1.512867     .00973   155.49   0.000     1.493754     1.53198
-----------------+------------------------------------------------------------
         sigma_u |  .46266869
         sigma_e |   .3218322
             rho |   .6739185   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```