### Basic DiD

- Notation:
  - $T = \mathbf{1}\{\text{Post Treatment Period}\}.$
  - $G = \mathbf{1}\{\text{In the Treatment Group}\}.$
  - D = GT.
- Question: Can we identify ATT?
- What is ATT:  $E[Y_1 Y_0|D = 1] = E[Y_1 Y_0|T = 1, G = 1]$ .
- What we can identify:
  - $E[Y_1|T=1, G=1]$
  - $E[Y_0|T=0, G=0]$
  - $E[Y_0|T=1, G=0]$
  - $E[Y_0|T=0, G=1].$
- But no  $E[Y_0|T=1, G=1]$

## Time Trend and Regression

- Need additional assumption to identify the ATT
- Most common one: Parallel Trend Assumption
- Time trend for G = 0:  $E[Y_0|G = 0, T = 0]$  equals to time trend for G = 1:  $E[Y_0|G = 1, T = 1] E[Y_0|G = 1, T = 0]$ .
- Note: Only  $E[Y_0|G=1, T=1]$  not directly observed. Identified with assumption.
- In regression, people regress Y on 1, G, T, GT = D.

### Pre-Trend Evaluation

- To evaluate the parallel trend assumption, people look at pre-period trends
  - If in pre-period treatment and control evolve similarly
  - then the counterfactual will hopefully be the same
- Eye-ball tests are the most common
- In theory no reason to require the trend to be flat at 0
- Logically a straight trend should also be acceptable
- But in practice most people want things to be flat

### **Implementation**

- Let post period dummy be  $P_t$
- Let treatment group dummy be  $T_i$
- $Y_{it} = \beta_0 + \beta_1 P_t + \beta_2 T_i + \beta_3 P_t \times T_i + \epsilon_{it}$
- Parameter of interest is  $\beta_3$
- Usually people put control variables as well
- $Y_{it} = \beta_0 + \beta_1 P_t + \beta_2 T_i + \beta_3 P_t \times T_i + \gamma X_{it} + \epsilon_{it}$
- · With multiple periods, put time and individual fixed effects instead
- $Y_{it} = \delta_t + \delta_i + \beta^{DD} P_t \times T_i + \gamma X_{it} + \epsilon_{it}$

#### Remark

- DiD fundamentally relies on parametric assumption
- eg., Parallel trend for y and log(y) will not hold at the same time
- No pre-period trends do not guarantee the identification of ATT
- Treatment should still not be a result of selection

### Extension to Multiple Treatment

- Usually multiple periods e.g., staggered difference-in-difference
- Many people used to run two-way fixed effects
  - $y_{it} = \alpha_i + \alpha_t + \beta^{DD} D_{it} + \epsilon_{it}$ .
  - $y_{it} = \alpha_i + \alpha_t + \sum_r \beta_r \mathbf{1}\{R_{it} = r\} + \epsilon_{it}$  where  $R_{it}$  is relative time.
- Econometricians find problems on this around 2020

### **Assumptions Extensions**

#### Parallel Trend

• If treatment had not occurred, avg. outcome for all groups would evolve in parallel

#### No Anticipation

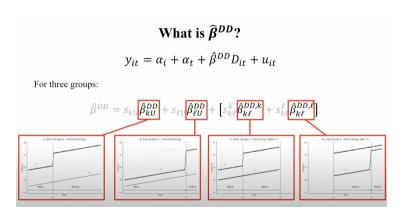
Units don't act on the knowledge of future treatment dates before treatment starts

### Does TWFE Work?

$$Y_{it} = \alpha_i + \alpha_t + \beta^{DD} D_{it} + u_{it}$$

- Suppose there is only heterogeneous treatment effect in time (denoted  $\tau_s$ )
- i.e., the effect 1 year after v.s. 2 years after are different  $(\tau_1 \neq \tau_2)$
- $\beta^{DD} = \sum_s \omega_s \tau_s$ , where  $\omega_s$  could be negative
- Issue:  $\tau_s$  could be all positive but  $\beta_{post} < 0$
- Source of problem: using the treated as control
- So TWFE does not work!

## Illustrations (Baker 2019)



## Illustrations continued (Baker 2019)

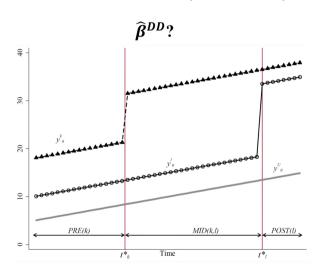
### What is $\widehat{\boldsymbol{\beta}}^{DD}$ ?

$$y_{it} = \alpha_i + \alpha_t + \hat{\beta}^{DD} D_{it} + u_{it}$$

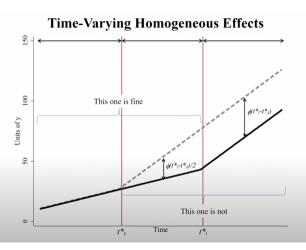
For three groups:

$$\begin{split} \hat{\beta}^{DD} &= s_{kU} \hat{\beta}^{DD}_{kU} + s_{\ell U} \hat{\beta}^{DD}_{\ell U} + \left[ s_{k\ell}^{k} \hat{\beta}^{DD,k}_{k\ell} + s_{k\ell}^{\ell} \hat{\beta}^{DD,\ell}_{k\ell} \right] \\ s_{kU} &= \frac{(n_{k} + n_{U}) \left[ n_{kU} (1 - n_{kU}) \overline{D}_{k} (1 - \overline{D}_{k}) \right]}{V(\overline{D}_{lt})} \\ s_{k\ell}^{k} &= \frac{((n_{k} + n_{\ell})(1 - \overline{D}_{\ell})) \left[ n_{k\ell} (1 - n_{k\ell}) \frac{\overline{D}_{k} - \overline{D}_{\ell}}{1 - \overline{D}_{\ell}} \frac{1 - \overline{D}_{k}}{1 - \overline{D}_{\ell}} \right]}{V(\overline{D}_{lt})} \\ s_{k\ell}^{\ell} &= \frac{((n_{k} + n_{\ell})\overline{D}_{k}) \left[ n_{k\ell} (1 - n_{k\ell}) \frac{\overline{D}_{k} - \overline{D}_{\ell}}{\overline{D}_{k}} \frac{\overline{D}_{\ell}}{\overline{D}_{k}} \frac{\overline{D}_{\ell}}{\overline{D}_{k}} \right]}{V(\overline{D}_{lt})} \end{split}$$

# Illustrations continued (Baker 2019)



## When things go wrong (Baker 2019)



## Does Dynamic TWFE Work?

$$Y_{it} = \alpha_i + \alpha_t + \sum_{r \neq 0} \mathbf{1} \{ R_{it} = r \} \beta_r + u_{it}$$

- where  $R_{it}$  is the relative event time
- This would work if only heterogeneity in time
- But not if different cohort has different cohort effect
- Again use the treated as control
- Does not work!

#### What to Do?

- Two Approaches
  - Diagnosis: Check if any weights are negative
  - New Estimators: Avoid using the treated as controls

#### **New Estimators**

- Idea: we still know how to do cohort-specific simple DiD
- Pick the valid comparisons and use those only
- A never-treated group could be useful
- Can also use later-treated groups
- Many packages now available

## Parallel Trends Assumptions

- Potentially you need to control for observables to make trends parallel
- Assess your pre-period trends with a plot
- The common pre-trend tests have low power though, need to be careful
- Many sensitivity methods available now