Differences in Differences

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These slides are part of the set of slides
A. Colin Cameron, Introduction to Causal Methods
https://cameron.econ.ucdavis.edu/causal/

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Introduction

- These slides give an introductory example of differences-in-differences (DID) estimation
  - DID is a method for causal inference
  - it is a general method for when an exogenous policy comes into being that effects one group more than another
  - it is often used with repeated cross-section data over time
  - but can also be used by comparing subgroups.
- DID relies crucially on an assumption called parallel trends
  - in the absence of treatment the trends for treated and untreated groups are equal.

- Separately the Stata file `dind.do` implements these methods
  - using dataset AED_HEALTHACCESS.DTA
- The data are from chapter 13.6 of A. Colin Cameron (2022) *Analysis of Economics Data: An Introduction to Econometrics* https://cameron.econ.ucdavis.edu/.
- Data are originally from Shinsuke Tanaka (2014), "Does Abolishing User Fees Lead to Improved Health Status? Evidence from Post-Apartheid South Africa", *American Economics Journal: Economic Policy*, 6(3), pages 282-312.

Outline

Differences in differences: Two Time Periods

- Consider a "natural" experiment where an exogenous policy (called a treatment) comes into being that effects one group more than another.
- Let y denote the outcome and d denote the treatment
  - with $d = 1$ if treated and $d = 0$ if not treated.
- 1. Method 1: Treatment-control comparison (at a point in time)
  - Treatment effect = ($\bar{y}$ for treated) - ($\bar{y}$ for not treated)$= \bar{y}_{d=1} - \bar{y}_{d=0}$.
  - Problem: This is misleading if the treated and untreated groups differ in their characteristics
    - ★ e.g. if the policy was targeted towards poor people.
- 2. Method 2: Before-after comparison over time for treated only
  - Treatment effect = ($\bar{y}$ for treated after treatment) - ($\bar{y}$ for treated before treatment)
  - Problem: Misleading if other things also effect the treated over time.
- 3. Differences-in-differences combines methods 1. and 2.
  - it uses change over time for the untreated to control for nontreatment changes over time (assuming both groups have the same time trend).

Differences in differences formula

- Introduce time before (pre) and after (post) the policy comes into effect
  - $t = 0$ is a time period before and $t = 1$ is a time period after.
- Then the difference in difference estimate of the effect of treatment is
  - DinD= $\Delta\bar{y}$ for those treated $-$ $\Delta\bar{y}$ for those not treated
  - $= (\bar{y}_{d=1,\text{post}} - \bar{y}_{d=1,\text{pre}}) - (\bar{y}_{d=0,\text{post}} - \bar{y}_{d=0,\text{pre}})$.
- Equivalently we can use
  - DinD= $(\bar{y}_{d=1,\text{post}} - \bar{y}_{d=0,\text{post}}) - (\bar{y}_{d=1,\text{pre}} - \bar{y}_{d=0,\text{pre}})$
  - the post-period difference in the two groups less that in the pre-period.
- DinD can be estimated by computing the four separate means and then computing the differences.

Regression computation

- The same difference-in-difference estimate can be obtained as the coefficient of $t \times d$ in the OLS regression

$$y_i = \beta_1 + \beta_2 t_i + \beta_3 d_i + \beta_4 t_i \times d_i + u_i.$$

  - where $t_i = 1$ in the post-period and $t_i = 0$ in the pre-period
  - and $d_i = 1$ if treated and $d_i = 0$ if not treated
  - $t_i \times d_i = 1$ if treated and in the post-period and $= 0$ otherwise.

- Proof: The model implies that y equals the following

	Treated ($d = 1$)	Not Treated ($d = 0$)	Difference over treatment
Pre ($t = 0$)	$\beta_1 + \beta_3$	β_1	β_3
Post ($t = 1$)	$\beta_1 + \beta_2 + \beta_3 + \beta_4$	$\beta_1 + \beta_2$	$\beta_3 + \beta_4$
Change over time	$\beta_2 + \beta_4$	β_2	

Diff in diff = β_4!

Differences in differences regression computation

- So suppose we have data on each individual, not just the means.
- The OLS regression is

$$y_i = \beta_1 + \beta_2 t_i + \beta_3 d_i + \beta_4 t_i \times d_i + u_i.$$

- This is often written as

$$y_i = \beta_1 + \beta_2 Post_i + \beta_3 Treat_i + \beta_4 Post_i \times Treat_i + u_i.$$

- The difference-in-differences estimate is β_4.
- The advantages of using an OLS regression are
  - 1. A t-test of $H_0 : \beta_4 = 0$ is a test of statistical significance of the treatment
  - 2. We can add control variables as additional regressors.
  - 3. We can compute robust standard errors of $\widehat{\beta}_4$.

Example: Access to health care and health outcomes

- Does better access to health care lead to better health outcomes?
- Dataset AED_HEALTHACCESS has data on 1,071 South African children aged 1 to 4 years in 54 communities.
- In 1993 26 of 54 communities had access to a health care clinic.
- In 1998 all 54 communities had access to a health care clinic.
- Outcome y is `waz` is a weight-for-age $z-$score
- Treatment $d = 1$ if have access to a health care clinic.
- Time $t = 0$ in 1993 (pre-period) and $t = 1$ in 1998 (post-period).

Example (continued)

- Summary statistics for key variables

```
Variable      Storage   Display    Value
    name         type    format    label      Variable label
------------------------------------------------------------------------------
waz             double  %6.2f                 Weight for age z Score
hightreat       float   %9.0g                 = 1 if community has clinic in 1993
post            float   %9.0g                 = 1 if year==98 and =0 if year==93
postXhigh       float   %9.0g                 = post times hightreat
waz             double  %6.2f                 Weight for age z Score
whz             double  %6.2f                 Weight for height z Score
```

```
. summarize waz hightreat post postXhigh waz whz
```

Variable	Obs	Mean	Std. dev.	Min	Max
waz	1,071	-.205873	1.587432	-5.88	4.94
hightreat	1,071	.4276377	.4949671	0	1
post	1,071	.4668534	.4991332	0	1
postXhigh	1,071	.1979458	.3986373	0	1
waz	1,071	-.205873	1.587432	-5.88	4.94
whz	1,071	.6390009	2.199942	-9.89	9.99

Results: Manual computation

- The following table gives the mean values of `waz`
  - for the high treated and low treated children
  - before and after the expansion in free health care.

	High treated	Low treated
Before (1993)	-0.545 $(n = 246)$	-0.414 $(n = 325)$
After (1998)	0.321 $(n = 212)$	-0.069 $(n = 288)$
Change over time	0.867	0.345
Difference in differences	0.521	

- High treated: `waz` increased by 0.867, from -0.545 to 0.321.
- Low treated: waz increased by 0.345, from -0.414 to -0.069.
- DID estimate is $0.867 - 0.345 = 0.521$.
- This is a very substantial effect
  - a third of a standard deviation change in `waz` for this sample.

Results: Regression computation

- Again greater access to health clinics increased `waz` by 0.521
- Since the treatment was at the community level, use cluster-robust standard errors with clustering on community
  - the standard error is 0.236 whereas heteroskedastic-robust s.e. is 0.194.

```
. * Diff-in-diff - no controls and cluster-robust standard errors
. reg waz postXhigh post hightreat, vce(cluster idcommunity) noheader
                          (Std. err. adjusted for 54 clusters in idcommunity)
```

waz	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
postXhigh	.5216188	.2352991	2.22	0.031	.0496685	.993569
post	.3450874	.1371018	2.52	0.015	.070096	.6200788
hightreat	-.1310593	.1968084	-0.67	0.508	-.525807	.2636884
_cons	-.4141846	.1151423	-3.60	0.001	-.6451308	-.1832384

Further analysis

- A richer and better model
  - controls for community by adding fixed effects for each community
  - controls for each individual by adding regressors such as parental education and household income
- For child i in community c
  - $y_{ic} = \beta_1 + \beta_2 t_i + \beta_3 d_i + \beta_4 t_i \times d_i + \gamma_c + \beta_5 x_{ic} + \cdots + u_i$.

```
. * D in D with fixed effects for community and individual controls
. reg waz postXhigh post hightreat i.idcommunity      ///
>     fedu medu hhsizep lntotminc immuniz nonclinic,  ///
>     vce(cluster idcommunity) noheader
note: 242.idcommunity omitted because of collinearity.
                          (Std. err. adjusted for 54 clusters in idcommunity)
```

waz	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
postXhigh	.6428807	.2710993	2.37	0.021	.0991243	1.186637
post	-.6807024	.3487963	-1.95	0.056	-1.380299	.0188944
hightreat	-.2911247	.2360665	-1.23	0.223	-.7646142	.1823648

Further Details

- Differences-in-differences analysis is not restricted to one with time.
  - e.g. we might have a policy that affected only single women.
  - then compare the difference between married and single women with the difference between married and single men
    - ★ assuming that without the policy the change from married to single would be the same for men and women.

Differences in Differences: Multiple Time Periods

- A more general model has several periods of data.
- Suppose we have individual i in state s in year t, and the treatment of interest d_{st} occurs at the state-year level.
- Then we estimate the two-way fixed effects model
  - $y_{ist} = \phi_s + \gamma_t + \alpha d_{st} + \beta_1 x1_{ist} + \cdots + u_{ist}$
  - here ϕ_s and γ_t are state-specific and time-specific fixed effects.
- The key assumption is that of "parallel trends"
  - the time trend each period is the same for each state
    - ★ γ_t is the same for each state
  - this is partly testable in some applications using pretreatment data.
- Inference is based on standard errors clustered at the state (s) level
  - this leads to the "few clusters" problem if there are few clusters.
- While estimation by OLS is straightforward, interpretation is difficult if the treatment is binary $(d_{st} = 1 \text{ or } 0)$ and treatment is staggered, occurring at different times for different states.
  - this is an area of current academic research.

Example: From Stata Documentation

- Example
  - y outcome is `satis` (Patient satisfaction score)
  - d treatment is `procedure = 1`
  - s group is hospital (there are 46)
  - t time is month (there are 7 months: January to July)
  - i is individual
- Treatment begins in April at 18 of the 46 hospitals

- Summary statistics

```
. summarize
```

Variable	Obs	Mean	Std. dev.	Min	Max
hospital	7,368	22.83822	13.57186	1	46
frequency	7,368	2.473398	1.163957	1	4
month	7,368	3.625	2.117778	1	7
procedure	7,368	.2079262	.4058512	0	1
satis	7,368	3.619074	1.05576	.5467862	9.712885

- Stata `didregress` command: Treatment effect is 0.84789

```
. didregress (satis)(procedure), group(hospital) time(month)

Treatment and time information

Time variable: month
Control:       procedure = 0
Treatment:     procedure = 1
```

	Control	Treatment
Group		
hospital	28	18
Time		
Minimum	1	4
Maximum	1	4

```
Difference-in-differences regression                 Number of obs = 7,368
Data type: Repeated cross-sectional

                                  (Std. err. adjusted for 46 clusters in hospital)
```

satis	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ATET						
procedure (New vs Old)	.8479879	.0321121	26.41	0.000	.7833108	.912665

```
Note: ATET estimate adjusted for group effects and time effects.
```

- Following gives the same estimate using `regress`

```
. * The following gives the same results as didregress
. regress satis procedure i.hospital i.month, vce(cluster hospital)

Linear regression                               Number of obs     =      7,368
                                                F(6, 45)          =          .
                                                Prob > F          =          .
                                                R-squared         =     0.5333
                                                Root MSE          =     .72384

                                    (Std. err. adjusted for 46 clusters in hospital)
------------------------------------------------------------------------------
             |               Robust
       satis |      Coef.   Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
   procedure |   .8479879   .0321121    26.41   0.000     .7833108    .912665
```

- Visual test of parallel trends assumption
  - `estat trendplots`
- Formal test of parallel trends assumption
  - `estat ptrends`
- For more read the Stata pdf documentation.

References for DID

- These books are given in approximate order of increasing difficulty.
- A. Colin Cameron (2022), Analysis of Economics Data: An Introduction to Econometrics, chapter 13.6.
- Joshua D. Angrist and Jörn-Steffen Pischke (2015), Mastering Metrics, ch. 5.
- Cunningham, Scott (2021), Causal Inference: The MixTape, Yale UP, chapter 9.
- A. Colin Cameron and Pravin K. Trivedi (2022), Microeconometrics using Stata: Volumes 1 and 2, Second Edition, Stata Press, chapter 25.6.
- Joshua D. Angrist and Jörn-Steffen Pischke (2009), Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, chapter 5.
- A. Colin Cameron and Pravin K. Trivedi (2005), Microeconometrics: Methods and Applications, Cambridge University Press, chapter 22.6.
- Jeffrey M. Wooldridge, (2010), Econometric Analysis of Cross Section and Panel Data, Second Edition, MIT Press, chapter 6.5.

References for DID (continued)

- These books by non-economists are similar to *Mastering Metrics* in accessibility.
- Stephen L. Morgan and Christopher Winship (2015), Counterfactuals and Causal Inference: Methods and Principles for Social Research, Second edition, Cambridge University Press, chapter 11.3.
- Andrew Gelman, Jennifer Hill and Aki Vehtari (2022), Regression and Other Stories, Cambridge University Press, especially chapters 21.4.
- These are current more advanced econometrics articles
- B. Callaway and P.H.C. Sant'Anna (2021), "Difference-in-Differences with multiple time periods," Journal of Econometrics, 225, pages 200–230.
- Jeffrey M. Wooldridge (2021), "Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators," http://doi.org/10.2139/ssrn.3906345.