From Diff in Diff to Panel Data

Econ 140, Section 11

Jonathan Old

Roadmap

1. Recap: DiD
2. Making DiD more general: Panel Data estimation
3. Section Assignment

Recap: DiD

How to get the causal effect of a treatment: DiD

	2020	2022
Free Mental Health: Treated	6	6
No Free Mental Health: Untreated	4	5

We can do several comparisons:

- Comparison 3: Compare treated to untreated group, before and after the intervention. **Differences in differences!**

How to get the causal effect of a treatment: DiD

	2020	2022
Free Mental Health: Treated	6	6
No Free Mental Health: Untreated	4	5

We can do several comparisons:

- Comparison 3: Compare treated to untreated group, before and after the intervention. **Differences in differences!**
- Estimated treatment effect?
  $(6-6)-(5-4)=(6-5)-(6-4)=-1$

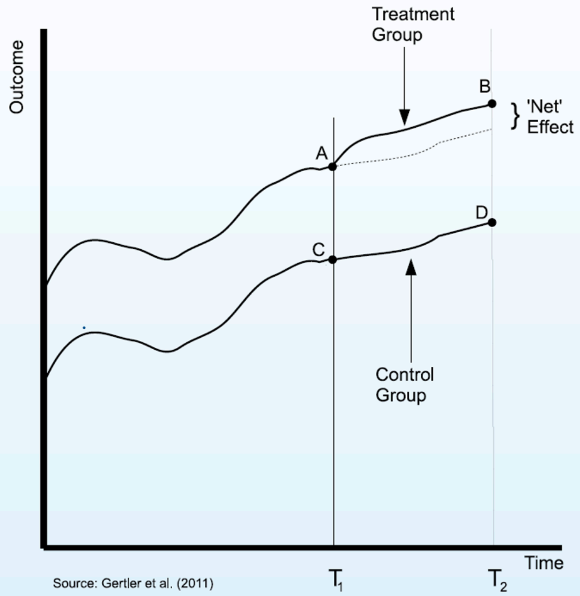
How to get the causal effect of a treatment: DiD

	2020	2022
Free Mental Health: Treated	6	6
No Free Mental Health: Untreated	4	5

We can do several comparisons:

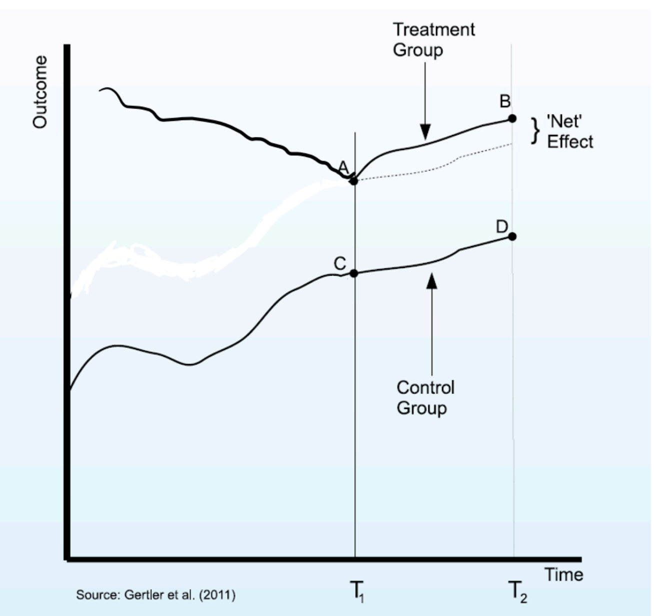
- Comparison 3: Compare treated to untreated group, before and after the intervention. **Differences in differences!**
- Estimated treatment effect?
  $(6-6)-(5-4)=(6-5)-(6-4)=-1$
- Identifying assumption: Parallel trends: Without the treatment, the average increase in the outcome of the treated would have been the same as the average increase in the outcome of the untreated.

Parallel trends assumption



Source: Gertler et al. (2011)

(Potential) violation of a parallel trends assumption



Estimating DiD with regressions

We can set up a simple linear regression to estimate a DiD model:

$$Y_{it} = \alpha + \beta \text{ Treated }_i + \gamma \text{ Post }_t + \delta \text{ Treated }_i \cdot \text{ Post }_t + u_{it}$$

	2020	2022
Free Mental Health: Treated	$\alpha + \beta$	$\alpha + \beta + \gamma + \delta$
No Free Mental Health: Untreated	α	$\alpha + \gamma$

Any questions?

... Remember – Every question is useful!

Making DiD more general: Panel Data estimation

Limitations of the 2x2 DiD framework

In the simple 2x2 framework, we estimated:

$$Y_{it} = \alpha + \beta \text{ Treated }_i + \gamma \text{ Post }_t + \delta \text{ Treated }_i \cdot \text{ Post }_t + u_{it}$$

What are some potential limitations in this approach?

A panel dataset may look like this:

	country	iso2c	iso3c	year	oda_per_cap	perc_below_pov_line	gdp_per_cap	inflation
316	Chile	CL	CHL	2015	3.0402700	0.4	13569.9478	4.34877353
317	Chile	CL	CHL	2016	9.8673522	NA	13785.6883	3.78619356
318	Chile	CL	CHL	2017	3.8277324	0.3	15045.5277	2.18271847
319	Chile	CL	CHL	2018	NA	NA	15795.7085	2.43488981
320	Chile	CL	CHL	2019	NA	NA	14631.9469	2.55754476
321	Chile	CL	CHL	2020	NA	0.7	13094.4595	3.04549085
322	Chile	CL	CHL	2021	NA	NA	16265.0960	4.52456838
323	China	CN	CHN	2015	-0.2219718	1.2	8016.4314	1.43702381
324	China	CN	CHN	2016	-0.5702808	0.8	8094.3634	2.00000182
325	China	CN	CHN	2017	-0.7090169	0.7	8816.9869	1.59313600
326	China	CN	CHN	2018	-0.5027731	0.4	9905.3420	2.07479040
327	China	CN	CHN	2019	-0.4323084	0.1	10143.8382	2.89923416
328	China	CN	CHN	2020	-0.4059315	NA	10408.6698	2.41942189
329	China	CN	CHN	2021	-0.4002945	NA	12556.3331	0.98101514
330	Colombia	CO	COL	2015	28.7760584	4.9	6228.4263	4.98983116
331	Colombia	CO	COL	2016	23.2331299	4.9	5938.4639	7.51346025
332	Colombia	CO	COL	2017	17.5871894	4.3	6450.3196	4.31431326
333	Colombia	CO	COL	2018	36.1416353	4.5	6782.0379	3.24056933
334	Colombia	CO	COL	2019	17.4085507	5.3	6438.0602	3.52301933

It may also look like this:

	Crime_2006	Crime_2007	Crime_2008	Crime_2009	Crime_2010	Crime_2011	Crime_2012	Crime_2013	Crime_2014	Crime_2015	Crime_2016	Crime_2017
New York	0,74075276	0,80312483	0,57854938	0,58480987	0,20097276	0,80826596	0,97070048	0,02437202	0,07831943	0,84572914	0,75749919	0,98948363
Los Angeles	0,81840795	0,63440595	0,75200179	0,45218138	0,54532883	0,0015679	0,39512876	0,41847691	0,66467241	0,01946605	0,55885996	0,27521867
Chicago	0,81682982	0,00089416	0,74575534	0,5521186	0,60461758	0,34694645	0,47874246	0,15925374	0,34667588	0,83944993	0,44825934	0,58746291
Houston	0,05885616	0,79349661	0,18033028	0,51317119	0,79642654	0,50269029	0,56157808	0,77173283	0,60797558	0,40461519	0,785332	0,6477959
Phoenix	0,2568483	0,28097691	0,82722175	0,11994755	0,884851	0,83800072	0,08978678	0,21613254	0,97306225	0,57291156	0,27341507	0,20641572
Philadelphia	0,86364857	0,30478317	0,07818559	0,82930161	0,28324875	0,60204952	0,4467311	0,1165021	0,15597767	0,36430802	0,38034388	0,37091781
San Antonio	0,98256294	0,13215208	0,55220195	0,25274349	0,22117177	0,63049228	0,74109619	0,17937274	0,50914785	0,68773119	0,17854372	0,50634586
San Diego	0,26052609	0,90551179	0,96145068	0,04932108	0,55859179	0,57753748	0,38254621	0,36728436	0,39429268	0,40312699	0,55506545	0,51665312
Dallas	0,85045327	0,33482019	0,15361924	0,74231968	0,55762722	0,05057305	0,57960707	0,71774087	0,63565644	0,04305477	0,06451316	0,27719973
San Jose	0,75452737	0,21462214	0,24820183	0,2727016	0,00127307	0,36822105	0,32304996	0,9116018	0,86006177	0,05904204	0,1124391	0,83247218
Austin	0,45398495	0,27082977	0,89920786	0,82480029	0,52877813	0,9452614	0,82578514	0,828743	0,20606871	0,4439492	0,38857348	0,8154967
Jacksonville	0,18638302	0,66744344	0,38392491	0,83800597	0,30374371	0,16785163	0,53614039	0,15558203	0,14260844	0,51748284	0,07054862	0,70962828
Fort Worth	0,13254183	0,78355507	0,83321159	0,33460775	0,00772913	0,78127289	0,61026409	0,25552213	0,27373821	0,78588972	0,80784366	0,1307398
Columbus	0,21457262	0,59542339	0,65347292	0,16532587	0,35580394	0,7113844	0,72036005	0,39323372	0,73022336	0,32649945	0,95442814	0,44923343
Indianapolis	0,97993863	0,2017115	0,58883837	0,54914541	0,22495244	0,58047281	0,01984661	0,88891756	0,34920826	0,326581	0,11407985	0,76592867
Charlotte	0,13043704	0,44544929	0,13581143	0,32176217	0,06451777	0,60708331	0,24805805	0,91489751	0,39053247	0,36409354	0,94249222	0,12812588

Estimating FE regressions

[SA12-Q2b]

Recall from the lecture:

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \ldots + \beta_k X_{k,it} + \alpha_i + u_{it}$$

We take averages (by i or by t - both are possible):

$$\bar{Y}_i = \beta_0 + \beta_1 \bar{X}_{1,i} + \ldots + \beta_k \bar{X}_{k,i} + \alpha_i + \bar{u}_i$$

We subtract the two equations from each other and get:

$$\left(Y_{it} - \bar{Y}_i\right) = \beta_1 \left(X_{1,it} - \bar{X}_{1,i}\right) + \ldots + \beta_k \left(X_{k,it} - \bar{X}_{k,i}\right) + \left(u_{it} - \bar{u}_i\right)$$

Interpreting FE regressions [SA12-Q2c]

Suppose we estimate this model with fixed effects:

$$\text{Sales}_{it} = \beta_0 + \beta_1 \text{Price}_{it} + \alpha_i + \varepsilon_{it}$$

How do we interpret β_1?

Interpreting FE regressions [SA12-Q2c]

Suppose we estimate this model with fixed effects:

$$\text{Sales}_{it} = \beta_0 + \beta_1 \text{Price}_{it} + \alpha_i + \varepsilon_{it}$$

How do we interpret β_1?

The same way as in an OLS regression!

β_1, is the effect of changes in price on changes in sales, holding constant all other firm-specific factors that do not change over time. In other words, β_1 represents the average effect of a one-unit increase in price on sales within each firm over time, after controlling for the firm-specific fixed effect.

Visualization

See separate gif!

Limitations of fixed effects

- Imagine we want to estimate the effect of annual income on happiness and we have a panel following 1,000 individuals over 10 years. You think there are many omitted variables and include individual-level fixed effects. You are **also** interested in the effect of parental income on happiness. What's the problem?
- We want to estimate the effect of democracy on economic growth in a panel of 180 countries over 60 years. We can include country-fixed effects to account for any effect coming from different countries having a different climate, terrain, access to the sea, culture, etc. Are you satisfied with this approach?

Any questions?

… Remember – Every question is useful!

Section Assignment

See you on R!