

Williams College ECON 379:  
Program Evaluation for International Development

photo: Flore de Preneuf / World Bank



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Program Evaluation for International Development

## **Module 6: Diff-in-Diff in Panel Data**

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photo: Daniella Van Leggelo-Padilla / World Bank

## Testing Common Trends

# The Common Trends Assumption

Diff-in-diff does not identify treatment effect if treatment and comparison groups were on different trajectories pre-program

- This is the **common trends** assumption

Remember the assumptions underlying diff-in-diff estimation:

- Selection bias relates to fixed characteristics of individuals ( $\gamma_i$ )
- Time trend ( $\lambda_t$ ) same for treatment and control groups

These assumptions guarantee that the common trends assumption is satisfied, but they cannot be tested directly — we have to trust

- As with any identification strategy, important to think carefully about whether it checks out intuitively and econometrically

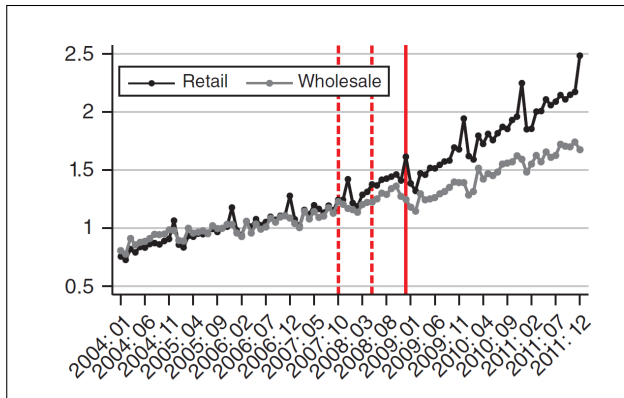
# How Can We Test the Common Trends Assumption?

A few approaches:

1. A compelling graph: were trends similar pre-program?
2. Test equality of (linear) pre-program trends in outcome variables
3. A **placebo experiment** (or **falsification test**)

Not possible with only two periods of data

# Approach #1: A Compelling Graph



source: Naritomi (2019)

## Approach #2: Testing Common Trends in a Regression

Godlonton and Okeke (2015) test for differences in pre-treatment trends:

$$Y_{ict} = \alpha + \beta HighExposure_c + \lambda Time_t + \gamma HighExposure_c \times Time_t + \varepsilon_{ict}$$

where:

- $Y_{it}$  = outcome variable in cluster  $i$  at time  $t$
- $HighExposure_c$  = indicator for (eventually) treated clusters
- $Time_t$  = (linear) measure of months from start of data set
- $\gamma$  = measures equality of time trends between treatment, control
- $\varepsilon_{it}$  = mean-zero error term

## Approach #2: Testing Common Trends in a Regression

**Table 2**

Test of parallel time trends.

Variables	(1)	(2)	(3)	(4)
	Birth attended by informal attendant	Birth attended by formal-sector provider	Child death within the first week	Child death within the first month
High exposure	0.566 (0.505)	− 0.419 (0.572)	0.0402 (0.0439)	0.0340 (0.0537)
Time trend	− 0.000558 (0.000349)	0.000560 (0.000442)	− 5.75e-05 (4.30e-05)	− 0.000110* (5.58e-05)
High exposure × time trend	− 0.000388 (0.000902)	0.000175 (0.00102)	− 6.52e-05 (8.21e-05)	− 5.12e-05 (9.83e-05)
Constant	0.401* (0.195)	0.459 − 0.247	0.0499** (0.0230)	0.0860*** (0.0301)
Observations	9277	9277	25,696	25,696
R-squared	0.171	0.100	0.002	0.002

Notes: sample is all births prior to the ban. All regressions include district dummies. The DHS collects data on type of birth attendant for only births within the preceding five years but collects mortality data for all births hence the larger sample size in Columns 3 and 4 (we restrict the sample to all births within the last ten years). Standard errors in parentheses are clustered at the district level (there are 27 districts).

\*\*\*  $p < 0.01$ .

\*\*  $p < 0.05$ .

\*  $p < 0.1$ .

source: Godlonton and Okeke (2015)



## Approach #3: A Falsification Test

A placebo or falsification test looks for effects that shouldn't be

- In Malawi: test whether  $HighExposure_c \times Post_t$  predicts outcomes not impacted by ban on traditional birth attendants
- In Indonesia: test whether more schools predicts increases in educational attainment, income among (much) older cohorts

# Approach #3: A Falsification Test

**Table 4**  
Is treatment correlated with observables?

Variables	(1) Twin birth	(2) Male birth	(3) First birth	(4) Young mother	(5) Number of children ever born	(6) Mother's age at first birth	(7) Mother is Christian	(8) No education (mother)	(9) No education (spouse)
High exposure	0.0089	0.00306	-0.0095	-0.000565	0.237***	-0.00518	0.0172	0.0362***	0.00916
Post	-0.00578	-0.0122	-0.00854	-0.00758	-0.07	-0.113	-0.015	-0.0113	-0.00889
	0.00852	0.00697	-0.0209*	-0.00985	-0.00716	-0.143	-0.00901	0.0228*	0.00111
	-0.00858	-0.0134	-0.0112	-0.00737	-0.0616	-0.0949	-0.00953	-0.0123	-0.00908
High exposure × Post	-0.00693	-0.00823	0.00431	0.00415	-0.0992	-0.0479	-0.00602	-0.0164	0.00414
	-0.00744	-0.0156	-0.0122	-0.00865	-0.0713	-0.0641	-0.00817	-0.00994	-0.00847
Constant	0.549***	0.935***	-0.187	0.477***	17.16***	15.01***	0.868***	0.479***	-0.0109
	-0.12	-0.17	-0.157	-0.104	-0.795	-1.294	-0.121	-0.163	-0.121
Observations	19,680	19,680	19,680	19,680	19,680	19,680	19,680	19,680	19,192
R-squared	0.009	0.003	0.005	0.008	0.03	0.021	0.355	0.068	0.039
Variables	(10) Unemployed	(11) Household head is female	(12) Household size	(13) Household has bicycle	(14) Household has electricity	(15) Household has radio	(16) Poorest wealth quintile	(17) Rural location	(18) Distance to nearest facility
High exposure	-0.0155	-0.00487	0.00358	0.0149	-0.0385***	-0.0479***	0.0627***	0.0580***	2.067***
Post	-0.0173	-0.014	-0.0679	-0.0246	-0.00998	-0.0113	-0.0143	-0.0159	-0.296
	-0.0227**	-0.0122	-0.0784	0.0122	-0.000171	-0.0200***	-0.0155	0.00227	-0.0321
	-0.00914	-0.0139	-0.0578	-0.0111	-0.00514	-0.00683	-0.0102	-0.00766	-0.1
High exposure × Post	-0.00356	-0.00421	-0.0965	-0.00649	-0.00296	0.00277	0.00149	-0.00327	-0.014
	-0.0116	-0.0119	-0.0629	-0.0151	-0.00567	-0.00755	-0.0148	-0.00607	-0.067
Constant	-0.929***	-0.259	10.56***	1.737***	-0.183***	-0.313***	-0.431***	0.971***	5.341***
	-0.137	-0.177	-0.765	-0.152	-0.0642	-0.0923	-0.134	-0.102	-1.293
Observations	19,680	19,680	19,680	19,680	19,680	19,680	19,680	19,680	19,211
R-squared	0.086	0.022	0.028	0.043	0.062	0.046	0.053	0.192	0.242

Notes: all columns include district and month × year fixed effects. Standard errors in parentheses are clustered at the district level (there are 27 districts).

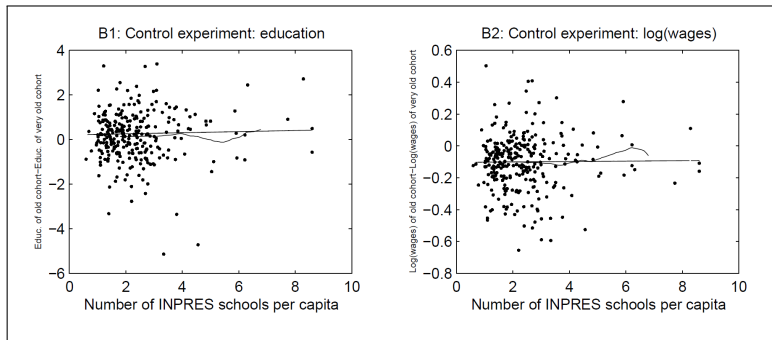
\*\*\* p < 0.01.

\*\* p < 0.05.

\* p < 0.1.

source: Godlonton and Okeke (2015)

## Approach #3: A Falsification Test



source: Duflo (2000)

## Approach #3: A Falsification Test

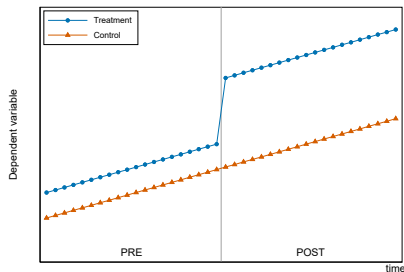
### Dependent Variable: Years of Education

	Obs.	OLS (1)	OLS (2)	OLS (3)
<i>Panel A: Entire Sample</i>				
<i>Intensity<sub>j</sub> * Younger<sub>i</sub></i>	78,488	0.009 (0.026)	0.018 (0.027)	0.008 (0.030)
<i>Panel B: Sample of Wage Earners</i>				
<i>Intensity<sub>j</sub> * Younger<sub>i</sub></i>	30,255	0.012 (0.048)	0.024 (0.048)	0.079 (0.056)
<i>Controls Included:</i>				
YOB*enrollment rate in 1971		No	Yes	Yes
YOB*other INPRES programs		No	No	Yes

Sample includes individuals aged 12 to 24 in 1974. All Specifications include region of birth dummies, year of birth dummies, and interactions between the year of birth dummies and the number of children in the region of birth (in 1971). Standard errors are in parentheses.

## Event Studies

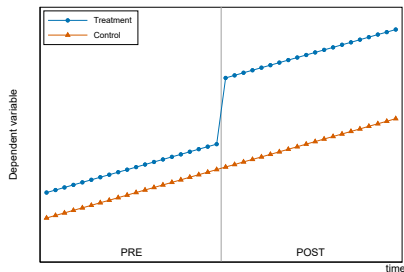
# The Difference-in-Differences Estimator



Diff-in-diff estimator is a linear combination four cell means

- In panel data, cell means average across periods

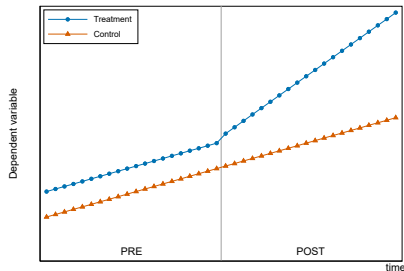
# The Difference-in-Differences Estimator



Clear interpretation when treatment effect is constant

$$\Rightarrow E[Y_{it}] = \gamma_i + \lambda_t + \delta_i D_{it}$$

# When Treatment Effect Changes Over Time



When treatment alters time trend (ie slope and not just level)

- DD estimand depends on chosen evaluation window



# The Event Study Approach

Always plot your data (and look for a plot in papers)!

- When common trends holds, diff-in-diff estimator is still unbiased measure of average treatment effect on treated units
- Which treatment effect? Answer: “impact of  $X$  over  $\tau$  years”

Alternative is to estimate treatment effect separately for each period

- Include treatment variable interacted with leads and lags
- Allows for statistical tests of functional form of effect
- Requires more data (statistical power) than pooled diff-in-diff

# The Event Study Approach

Let  $Z_{i,1}$  be an indicator for first observation after unit is treated

$\Rightarrow Z_{i,1} = 1$  when  $D_{i,t} = 1$  AND  $D_{i,t-1} = 0$

$\Rightarrow Z_{i,k} =$  indicator for the  $k^{\text{th}}$  period after treatment (starts)

$\Rightarrow Z_{i,-k} =$  indicator for  $k^{\text{th}}$  period before treatment starts

Event study specification:

$$Y_{i,t} = \alpha + \eta_i + \phi_t + \\ \dots + \beta_{-2}Z_{i,-2} + \beta_1Z_{i,1} + \beta_2Z_{i,2} + \dots + \epsilon_{i,t}$$

(notice we've omitted dummy for last pre-treatment period)

# The Event Study Approach in Stata

```
reg y minus3 minus2 minus1 plus1 plus2 plus3 i.time i.id
```



post-treatment dummies

# The Event Study Approach in Stata

```
reg y minus3 minus2 minus1 plus1 plus2 plus3 i.time i.id
```

↑  
post-treatment dummies

Treatment effects relative to omitted “period zero”

⇒ Exact moment of treatment or last pre-treatment observation

# The Event Study Approach in Stata

```
. reg y minus3 minus2 minus1 plus1 plus2 plus3 i.time i.id
```

Source	SS	df	MS	Number of obs	=	1,400
Model	191855.501	13	14758.1154	F(13, 1386)	=	146.64
Residual	139492.358	1,386	100.643837	Prob > F	=	0.0000
				R-squared	=	0.5790
				Adj R-squared	=	0.5751
Total	331347.858	1,399	236.846218	Root MSE	=	10.032

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
minus3	1.071835	2.006428	0.53	0.593	-2.864129	5.007798
minus2	2.59693	2.006428	1.29	0.196	-1.339034	6.532894
minus1	.9845017	2.006428	0.49	0.624	-2.951462	4.920466
plus1	20.62988	2.006428	10.28	0.000	16.69392	24.56585
plus2	21.73297	2.006428	10.83	0.000	17.79701	25.66893
plus3	21.9125	2.006428	10.92	0.000	17.97654	25.84847
time						
18	-1.02448	1.418759	-0.72	0.470	-3.807626	1.758667
19	.958879	1.418759	0.68	0.499	-1.824268	3.742026
20	1.377901	1.418759	0.97	0.332	-1.405246	4.161047
21	2.864637	1.418759	2.02	0.044	.0814899	5.647783
22	2.970014	1.418759	2.09	0.036	.1868673	5.753161
23	4.825515	1.418759	3.40	0.001	2.042369	7.608662
2.id	-6.570828	1.418759	-4.63	0.000	-9.353975	-3.787682
_cons	33.30636	1.737618	19.17	0.000	29.89771	36.715

# The Event Study Approach: Hypothesis Testing

Hypotheses one might test in event studies:

- Individual coefficients (e.g. specific treatment effects) are zero
- A group of coefficients are all (jointly) equal to zero
- A group of coefficients are equal to each other (but not zero)
- A group of coefficients are related to each other linearly

In Stata, we can test hypotheses after estimation using `test`:

```
reg y x1 x2 x3 x4
```

```
test x1 x2 x3 x4 (list of coefficients)
```

```
test x1=x2 (test of equality)
```

# The Event Study Approach: Hypothesis Testing

```
. reg y minus3 minus2 minus1 plus1 plus2 plus3 i.time i.id
```

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# The Event Study Approach: Hypothesis Testing

```
test minus1 minus2 minus3
```

```
( 1) minus1 = 0
```

```
( 2) minus2 = 0
```

```
( 3) minus3 = 0
```

```
F(3,1386) = 0.57
```

```
Prob > F = 0.6341
```

⇒ Particularly useful in testing for pre-treatment common trends



# The Event Study Approach: Hypothesis Testing

```
. reg y minus3 minus2 minus1 plus1 plus2 plus3 i.time i.id
```

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# The Event Study Approach: Hypothesis Testing

```
test plus1 = plus2 = plus3
```

```
( 1) plus1 - plus2 = 0
```

```
( 2) plus1 - plus3 = 0
```

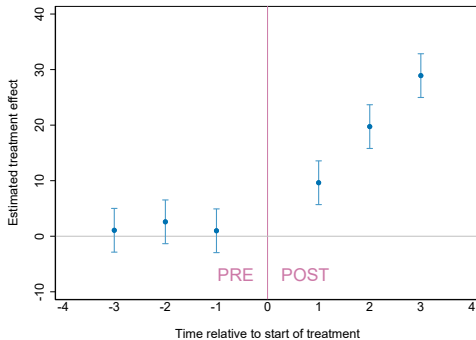
```
F( 2, 1386) = 0.24
```

```
Prob > F = 0.7869
```

⇒ Each coefficient statistically significantly different from zero

⇒ Coefficients not significantly different from each other

# The Event Study Approach: Hypothesis Testing



# The Event Study Approach: Hypothesis Testing

```
. reg y minus3 minus2 minus1 plus1 plus2 plus3 i.time i.id
```

Source	SS	df	MS	Number of obs	=	1,400
Model	188880.541	13	14529.2724	F(13, 1386)	=	144.36
Residual	139492.358	1,386	100.643837	Prob > F	=	0.0000
				R-squared	=	0.5752
				Adj R-squared	=	0.5712
Total	328372.899	1,399	234.719727	Root MSE	=	10.032

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
minus3	1.071835	2.006428	0.53	0.593	-2.864129	5.007798
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_cons	33.30636	1.737618	19.17	0.000	29.89771	36.715

# The Event Study Approach: Hypothesis Testing

Coefficients on `plus1` and `plus2` are not equal:

```
test plus1 = plus2
```

```
( 1) plus1 - plus2 = 0
```

```
      F( 1, 1386) = 25.35
```

```
      Prob > F = 0.0000
```

Can we reject hypothesis that `plus2` is twice as large as `plus1`?

```
test 2*plus1 = plus2
```

```
( 1) 2*plus1 - plus2 = 0
```

```
      F( 1, 1386) = 0.02
```

```
      Prob > F = 0.8917
```

The end!