



Williams College ECON 523:

Program Evaluation for International Development

Lecture 4: Diff-in-Diff in a Panel Data Framework

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Panel Data

2×2 Diff-in-Diff in Panel Data

2×2 panel data diff-in-diff specification:

$$Y_{i,t} = \alpha + \beta \mathit{EverTreated}_i + \theta \mathit{Post}_t + \delta D_{i,t} + \varepsilon_{i,t}$$

where:

- $\mathit{EverTreated}_i$ = dummy for ever-treated unit(s)
- Post_t = dummy for post-treatment period(s)
- $D_{i,t}$ = treatment dummy, equal to one if unit i is treated in period t
- δ = diff-in-diff estimate of treatment effect

2×2 Diff-in-Diff in Panel Data

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Unit 1	0	0	0	0	0
Unit 2	0	0	0	0	0
Unit 3	0	0	0	1	1
Unit 4	0	0	0	1	1
Unit 5	0	0	0	1	1

OLS specification:

$$Y = \alpha + \beta \text{EverTreated}_i + \theta \text{Post}_t + \delta D_{i,t}$$

2×2 Diff-in-Diff in Panel Data

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Unit 1	0	0	0	0	0
Unit 2	0	0	0	0	0
Unit 3	0	0	0	1	1
Unit 4	0	0	0	1	1
Unit 5	0	0	0	1	1
\bar{D}_t		0		0.6	

OLS specification:

$$Y = \alpha + \beta \text{EverTreated}_i + \theta \text{Post}_t + \delta D_{i,t}$$

By Frisch-Waugh-Lovell:

equivalent to regression on normalized D_{it}

→ Subtract off mean $D_{i,t}$ in pre, post periods

2×2 Diff-in-Diff in Panel Data

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Unit 1	0	0	0	-0.6	-0.6
Unit 2	0	0	0	-0.6	-0.6
Unit 3	0	0	0	0.4	0.4
Unit 4	0	0	0	0.4	0.4
Unit 5	0	0	0	0.4	0.4
\bar{D}_t		0		0.6	

OLS specification:

$$Y = \alpha + \beta \text{EverTreated}_i + \theta \text{Post}_t + \delta D_{i,t}$$

By Frisch-Waugh-Lovell:

equivalent to regression on normalized D_{it}

→ Subtract off mean $D_{i,t}$ in pre, post periods

2×2 Diff-in-Diff in Panel Data

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Unit 1	0.24	0.24	0.24	-0.36	-0.36
Unit 2	0.24	0.24	0.24	-0.36	-0.36
Unit 3	-0.16	-0.16	-0.16	0.24	0.24
Unit 4	-0.16	-0.16	-0.16	0.24	0.24
Unit 5	-0.16	-0.16	-0.16	0.24	0.24
\bar{D}_t		0		0.6	

OLS specification:

$$Y = \alpha + \beta \text{EverTreated}_i + \theta \text{Post}_t + \delta D_{i,t}$$

By Frisch-Waugh-Lovell:

equivalent to regression on normalized D_{it}

→ Subtract off mean $D_{i,t}$ in pre, post periods

→ Subtract off mean of de-meanned $D_{i,t}$ in T, C

Diff-in-Diff with Time Fixed Effects

Panel data diff-in-diff specification including time fixed effects:

$$Y_{i,t} = \alpha + \gamma \text{EverTreated}_i + \delta D_{i,t} + \nu_t + \varepsilon_{i,t}$$

where:

- EverTreated_i = dummy for ever-treated unit(s)
- $D_{i,t}$ = treatment dummy, equal to one if unit i is treated in period t
- δ = diff-in-diff estimate of treatment effect
- ν_t = time-period fixed effects

Diff-in-Diff with Time Fixed Effects

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Unit 1	0	0	0	0	0
Unit 2	0	0	0	0	0
Unit 3	0	0	0	1	1
Unit 4	0	0	0	1	1
Unit 5	0	0	0	1	1
\bar{D}_t	0	0	0	0.6	0.6

OLS with fixed effects equivalent to a regression of:
normalized $\tilde{Y}_{i,t}$ on normalized $\tilde{D}_{i,t}$

To normalize $\tilde{D}_{i,t}$, we

→ Subtract off period-specific means, \bar{D}_t

Diff-in-Diff with Time Fixed Effects

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Unit 1	0	0	0	-0.6	-0.6
Unit 2	0	0	0	-0.6	-0.6
Unit 3	0	0	0	0.4	0.4
Unit 4	0	0	0	0.4	0.4
Unit 5	0	0	0	0.4	0.4
\bar{D}_t	0	0	0	0.6	0.6

OLS with fixed effects equivalent to a regression of:
normalized $\tilde{Y}_{i,t}$ on normalized $\tilde{D}_{i,t}$

To normalize $\tilde{D}_{i,t}$, we

→ Subtract off period-specific means, \bar{D}_t

Diff-in-Diff with Time Fixed Effects

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Unit 1	0.24	0.24	0.24	-0.36	-0.36
Unit 2	0.24	0.24	0.24	-0.36	-0.36
Unit 3	-0.16	-0.16	-0.16	0.24	0.24
Unit 4	-0.16	-0.16	-0.16	0.24	0.24
Unit 5	-0.16	-0.16	-0.16	0.24	0.24
\bar{D}_t	0	0	0	0.6	0.6

OLS with fixed effects equivalent to a regression of:
normalized $\tilde{Y}_{i,t}$ on normalized $\tilde{D}_{i,t}$

To normalize $\tilde{D}_{i,t}$, we

→ Subtract off period-specific means, \bar{D}_t

→ Subtract off mean of de-meaned $D_{i,t}$ in T, C

Diff-in-Diff with Time Fixed Effects

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Unit 1	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$
Unit 2	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$
Unit 3	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$
Unit 4	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$
Unit 5	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$	$\tilde{Y}_{i,t}$

OLS with fixed effects equivalent to a regression of:
normalized $\tilde{Y}_{i,t}$ on normalized $\tilde{D}_{i,t}$

To normalize $\tilde{D}_{i,t}$, we

→ Subtract off period-specific means, \bar{D}_t

→ Subtract off mean of de-meaned $D_{i,t}$ in T, C

Fixed effects absorb additional variation in Y

- Standard errors depend on the residuals

Diff-in-Diff with Fixed Effects

Why used fixed effects instead of dummies for post-treatment period and ever-treated group?

- Fixed effects “soak up” period-specific shocks, unit-specific variation better
 - ▶ Smaller residuals \Rightarrow smaller standard errors \Rightarrow statistical power
- Inclusion of time fixed effects yield should not lead to substantial changes in coefficients
 - ▶ Coefficients mechanically identical in balanced panels

Two-way fixed effects specification:

$$Y_{i,t} = \alpha + \eta_i + \nu_t + \delta D_{i,t} + \varepsilon_{i,t}$$

where η_i is an individual FE, ν_t is a time FE, and δ is DD estimator

Example: Malawi's Ban on Traditional Birth Attendants

Does a ban on informal health providers save lives? Evidence from Malawi[☆]

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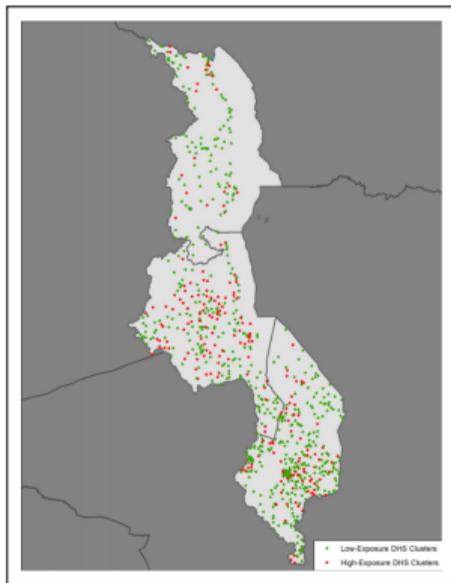
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ABSTRACT

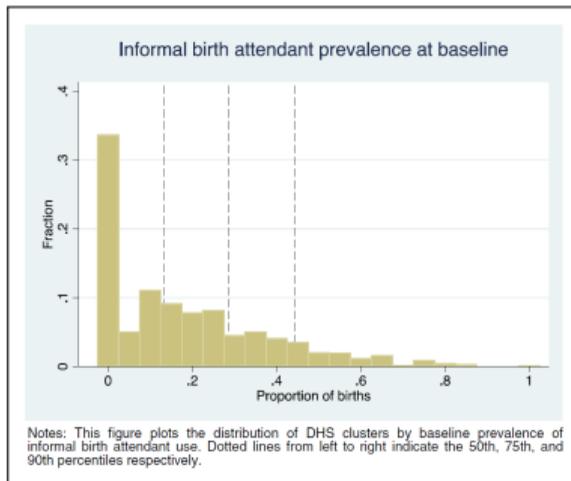
Informal health providers ranging from drug vendors to traditional healers account for a large fraction of health care provision in developing countries. They are, however, largely unlicensed and unregulated leading to concern that they provide ineffective and, in some cases, even harmful care. A new and controversial policy tool that has been proposed to alter household health seeking behavior is an outright ban on these informal providers. The theoretical effects of such a ban are ambiguous. In this paper, we study the effect of a ban on informal (traditional) birth attendants imposed by the Malawi government in 2007. To measure the effect of the ban, we use a difference-in-difference strategy exploiting variation across time and space in the intensity of exposure to the ban. Our most conservative estimates suggest that the ban decreased use of traditional attendants by about 15 percentage points. Approximately three quarters of this decline can be attributed to an increase in use of the formal sector and the remainder is accounted for by an increase in relative/friend-attended births. Despite the rather large shift from the informal to the formal sector, we do not find any evidence of a statistically significant reduction in newborn mortality on average. The results are robust to a triple difference specification using young children as a control group. We examine several explanations for this result and find evidence consistent with quality of formal care acting as a constraint on improvements in newborn health.

source: Godlonton and Okeke (2015)

Example: Malawi's Ban on Traditional Birth Attendants

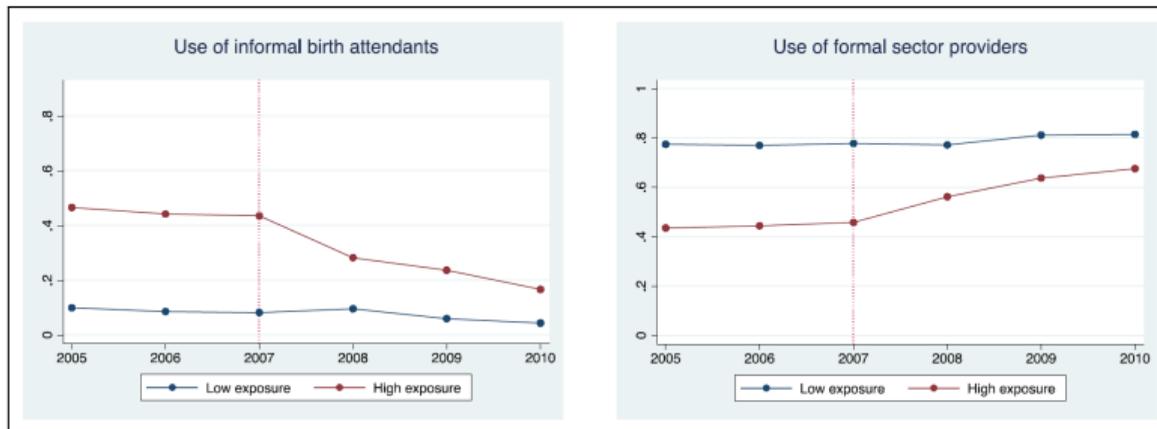


source: Godlonton and Okeke (2015)



source: Godlonton and Okeke (2015)

Example: Malawi's Ban on Traditional Birth Attendants



source: Godlonton and Okeke (2015)

Example: Malawi's Ban on Traditional Birth Attendants

Godlonton and Okeke (2015) estimate regression specification:

where:
$$Y_{ict} = \alpha + \theta HighExposure_c + \delta (HighExposure_c \times Post_t) + X_{ict}\beta + \tau_t + \varepsilon_{ict}$$

- $HighExposure_c$ = indicator for (more) treated clusters (pre-ban use of TBAs above 75th percentile)
- $HighExposure_c \times Post_t$ = indicator for treated cluster-months
- δ = diff-in-diff estimate of treatment effect
- X_{ict} = set of control variables (e.g. household size, etc.)
- τ_t = fixed effect for month of birth (e.g. January 2007)
- ε_{ict} = mean-zero error term

Example: Malawi's Ban on Traditional Birth Attendants

Table 5

What was the effect of the ban on the use of formal and informal sector providers?

Variables	(1)	(2)	(3)	(4)	(5)	(6)
<i>A. Birth attendant is informal attendant</i>						
High exposure × Post	-0.189*** (0.0146)	-0.190*** (0.0130)	-0.184*** (0.0141)	-0.187*** (0.0144)	-0.154*** (0.0126)	-0.188*** (0.0146)
High exposure	0.344*** (0.0143)	0.321*** (0.0131)	0.318*** (0.0123)	0.320*** (0.0127)	0.267*** (0.0110)	
Post				0.0134 (0.0667)	-0.0655 (0.0908)	-0.000915 (0.0679)
Constant	0.0411*** (0.00204)	0.0537 (0.0415)	0.0512 (0.0410)	1.848*** (0.284)	3.525*** (0.440)	0.265*** (0.0637)
Observations	19,607	18,673	18,673	18,673	12,491	18,673
R-squared	0.138	0.149	0.150	0.148	0.113	0.209
<i>B. Birth attendant is formal sector provider</i>						
High exposure × Post	0.145*** (0.0157)	0.144*** (0.0136)	0.143*** (0.0153)	0.146*** (0.0152)	0.109*** (0.0152)	0.150*** (0.0165)
High exposure	-0.317*** (0.0177)	-0.279*** (0.0150)	-0.269*** (0.0152)	-0.271*** (0.0149)	-0.206*** (0.0155)	
Post				0.0660 (0.0794)	0.132 (0.0889)	0.00746 (0.0974)
Constant	0.808*** (0.00257)	0.726*** (0.0431)	0.730*** (0.0429)	-1.668*** (0.391)	-2.433*** (0.479)	0.446*** (0.0995)
Controls	No	Yes	Yes	Yes	Yes	Yes
Controls × Post	No	No	Yes	Yes	Yes	Yes
District-specific trend	No	No	No	Yes	Yes	No
Trimmed data	No	No	No	No	Yes	No
Cluster fixed effects	No	No	No	No	No	Yes
Observations	19,607	18,673	18,673	18,673	12,491	18,673
R-squared	0.088	0.132	0.134	0.131	0.104	0.218

Notes: for Panel A the dependent variable is an indicator for a birth attended by an informal birth attendant. For Panel B the dependent variable is an indicator for a birth attended by a formal-sector provider. Controls include an indicator for male births, an indicator for a multiple birth, birth order, dummies for mother's level of schooling, dummies for mother's age at birth, an indicator for women who are married or living with a partner, dummies for ethnicity and religion, dummies for the partner's educational attainment, distance to the nearest health facility, wealth quintile dummies, and a rural-urban indicator. Each column includes district and year × month fixed effects. Full set of coefficients is not shown to conserve space (see Table A.1). In Column 5, we exclude villages with baseline prevalence of 0 or 1 to account for 'floor' and 'ceiling' effects. Column 6 is equivalent to Column 3 except that district fixed effects have been replaced with cluster fixed effects. Post = 1 if birth occurs after December 2007. 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)

Example: Malawi's Ban on Traditional Birth Attendants

Table 6

What was the effect of the ban on the use of other substitutes?

Variables	(1)	(2)	(3)	(4)	(5)	(6)
<i>A. Birth attendant is a relative or friend</i>						
High exposure × Post	0.0414*** (0.00694)	0.0417*** (0.00725)	0.0364*** (0.00863)	0.0366*** (0.00918)	0.0389*** (0.0110)	0.0351*** (0.00962)
High exposure	-0.0256*** (0.00836)	-0.0424*** (0.00933)	-0.0396*** (0.00982)	-0.0399*** (0.0101)	-0.0496*** (0.0123)	
Post				-0.0476 (0.02543)	-0.0367 (0.0812)	0.121 (0.202***)
Constant	0.105*** (0.00151)	0.186*** (0.0542)	0.184*** (0.0536)	0.730*** (0.236)	0.251 (0.329)	0.0642 (0.0642)
Observations	19,607	18,673	18,673	18,673	12,491	18,673
R-squared	0.022	0.041	0.042	0.039	0.042	0.133
<i>B. Birth was unattended</i>						
High exposure × Post	0.00281 (0.00512)	0.00322 (0.00491)	0.00334 (0.00493)	0.00247 (0.00557)	0.00541 (0.00543)	0.00116 (0.00518)
High exposure	0.000257 (0.00338)	-0.00614* (0.00339)	-0.00622 (0.00369)	-0.00629 (0.00393)	-0.00931* (0.00493)	
Post				0.0110 (0.0474)	0.00680 (0.0572)	-0.0164 (0.0513)
Constant	0.0306*** (0.000623)	0.0184 (0.0267)	0.0173 (0.0265)	-0.0440 (0.158)	-0.234 (0.200)	0.0319 (0.0346)
Controls	No	Yes	Yes	Yes	Yes	Yes
Controls × Post	No	No	Yes	Yes	Yes	Yes
District-specific trend	No	No	No	Yes	Yes	No
Trimmed data	No	No	No	No	Yes	No
Cluster fixed effects	No	No	No	No	No	Yes
Observations	19,607	18,673	18,673	18,673	12,491	18,673
R-squared	0.009	0.033	0.034	0.033	0.038	0.097

Notes: In Panel A (top) the dependent variable is an indicator for a birth attended by a relative or friend while in Panel B (bottom) the dependent variable is an indicator for an unattended birth. Controls include an indicator for male births, an indicator for a multiple birth, birth order, dummies for mother's level of schooling, dummies for mother's age at birth, an indicator for women who are married or living with a partner, dummies for ethnicity and religion, dummies for the partner's educational attainment, distance to the nearest health facility, wealth quintile dummies, and a rural-urban indicator. Each column includes district and year × month fixed effects. Full set of coefficients not shown to conserve space (see Table A.1). In Column 5, we exclude villages with baseline prevalence of 0 or 1 to account for 'floor' and 'ceiling' effects. Column 6 is equivalent to Column 3 except that district fixed effects have been replaced with cluster fixed effects. Post = 1 if birth occurs after December 2007. 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)

Example: Malawi's Ban on Traditional Birth Attendants

Table 7
What was the effect of the ban on newborn deaths?

Variables	(1)	(2)	(3)	(4)	(5)	(6)
A Child death within the first week						
High exposure × Post	-2.939 (3.600)	-2.742 (3.530)	0.319 (3.669)	-0.645 (3.706)	1.712 (4.121)	-0.344 (3.508)
High exposure	5.311** (2.465)	5.383* (2.812)	4.528 (2.854)	4.661 (2.912)	2.850 (3.380)	
Post				-25.62 (15.377)	-33.96 (20.75)	-13.10 (27.30)
Constant	21.39*** (0.414)	8.271 (0.116)	8.075 (0.053)	133.3*** (34.58)	110.7*** (58.83)	5.029 (14.15)
Observations	35,246	33,748	33,748	33,748	22,317	33,748
R-squared	0.005	0.010	0.010	0.008	0.009	0.037
B Child death within the first month						
High exposure × Post	-4.150 (4.242)	-4.414 (4.274)	-1.316 (4.369)	-1.808 (4.515)	-0.211 (4.603)	-2.760 (4.337)
High exposure	6.659** (3.142)	6.292* (3.395)	5.405 (3.472)	5.428 (3.531)	3.899 (3.994)	
Post				-35.98 (26.75)	-54.18 (35.46)	-7.289 (44.58)
Constant	31.90*** (0.543)	22.13* (11.61)	21.72* (11.49)	208.7*** (41.97)	231.5*** (54.47)	21.07 (15.41)
Controls	No	Yes	Yes	Yes	Yes	Yes
Controls × Post	No	No	Yes	Yes	Yes	Yes
District-specific trend	No	No	No	Yes	Yes	No
Trimmed data	No	No	No	No	Yes	No
Cluster fixed effects	No	No	No	No	No	Yes
Observations	35,246	33,748	33,748	33,748	22,317	33,748
R-squared	0.005	0.012	0.012	0.010	0.012	0.038

Notes: In Panel A the dependent variable is an indicator for a newborn death within a week of being born. In Panel B the dependent variable is an indicator for a newborn death within a month of being born. Both variables have been scaled to allow coefficients to be interpretable as X per 1000 live births. Controls include indicators for male births, first births and young mothers (age < 18), dummies for mother's level of schooling, an indicator for women who are married or living with a partner, dummies for ethnicity and religion, dummies for the partner's educational attainment, distance to the nearest health facility, wealth quintile dummies, and a rural-urban indicator. Each column includes district and year × month fixed effects. Full set of coefficients is not shown to conserve space (see Table A.1). In Column 5, we exclude villages with baseline prevalence of 0 or 1 to account for "floor" and "ceiling" effects. Column 6 is equivalent to Column 3 except that district fixed effects have been replaced with cluster fixed effects. Post = 1 if birth occurs after December 2007. 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)

Example: Malawi's Ban on Traditional Birth Attendants

Table A.2

Was there an offsetting effect of relative/friend-attended births?

Variables	(1)	(2)
	High travel costs	Low travel costs
Relative/friend-attended births	0.0430*** (0.0140)	0.0267 (0.0190)
Child death within one week	-0.00244 (0.00499)	0.00776 (0.00840)
Child death within one month	-0.00403 (0.00659)	0.00467 (0.00836)
N	(0.00659)	(0.00836)

Notes: the sample in Column 1 is women who answered 'yes' when asked whether distance was a 'big problem' in accessing medical services. The sample in Column 2 is women who answered 'no'. The estimates are from the regression specification in Column 5 of Tables 6 and 7. Standard errors in parentheses are clustered at the district level (there are 27 districts).

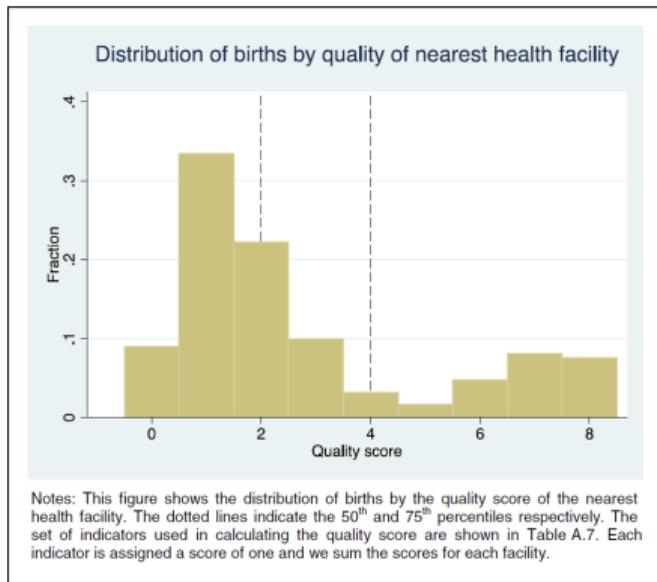
*** p < 0.01.

** p < 0.05.

* p < 0.1.

source: Godlonton and Okeke (2015)

Example: Malawi's Ban on Traditional Birth Attendants



source: Godlonton and Okeke (2015)

Example: Malawi's Ban on Traditional Birth Attendants

Table 10

Is the quality of formal care a constraint?

Variables	Nearest health facility is in the top quartile of quality distribution						Nearest health facility is in the bottom three quartiles of quality distribution					
	Child death within the first week						Child death within the first week					
High exposure × Post	-14.70** (6.725)	-14.32* (7.100)	-12.59 (8.439)	-14.42 (8.651)	-13.12 (9.448)	-12.84 (8.425)	-0.679 (4.418)	-0.333 (4.586)	2.491 (4.633)	2.377 (4.656)	5.432 (5.253)	1.653 (4.420)
High exposure	8.537* (4.738)	10.96* (5.745)	10.44* (6.006)	10.61* (5.969)	8.673 (6.034)		4.950 (3.185)	4.942 (3.470)	4.188 (3.489)	4.094 (3.549)	2.445 (4.092)	
Post			-26.32 (15.79)	-47.46* (24.46)	24.64 (46.70)					-29.31 (22.08)	-29.31 (26.48)	-44.60 (27.03)
Constant	21.16*** (0.976)	-13.68 (10.40)	-17.15 (10.19)	103.3** (41.39)	-4.514 (48.35)	13.77 (13.77)	30.46*** (0.566)	19.42 (12.07)	19.71 (11.97)	237.3*** (35.30)	296.6*** (34.60)	2.268 (16.85)
Observations	8735	8570	8570	8570	4764	8570	25,666	25,178	25,178	25,178	17,553	25,178
R-squared	0.015	0.023	0.027	0.017	0.023	0.053	0.007	0.012	0.013	0.009	0.010	0.039
	Child death within the first month						Child death within the first month					
High exposure × Post	-17.33** (7.479)	-17.02** (8.067)	-16.00 (10.04)	-17.73* (10.19)	-12.76 (10.22)	-17.69* (10.14)	-1.482 (5.376)	-1.899 (5.577)	1.340 (5.666)	1.459 (5.668)	2.604 (6.127)	-0.0690 (5.658)
High exposure	9.091 (5.670)	11.65* (6.633)	11.25 (7.109)	11.64 (7.070)	8.405 (6.658)		6.391 (3.934)	5.658 (4.172)	4.839 (4.254)	4.584 (4.288)	3.835 (4.869)	
Post			-33.89 (34.30)	-45.00* (25.51)	60.43 (89.20)					-41.40 (34.54)	-62.67 (45.67)	-60.54 (35.73)
Constant	31.91*** (1.009)	13.77 (25.26)	11.46 (26.43)	122.1** (51.73)	125.2 (77.49)	29.74 (36.08)	36.17*** (0.599)	23.61 (13.94)	23.38 (13.69)	227.9*** (37.19)	351.2*** (41.04)	19.69 (18.61)
Controls	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Controls × Post	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
District-specific trend	No	No	No	Yes	Yes	No	No	No	Yes	Yes	Yes	No
Trimmed data	No	No	No	Yes	Yes	No	No	No	No	Yes	No	No
Cluster fixed effects	No	No	No	No	No	Yes	No	No	No	No	No	Yes
Observations	8735	8570	8570	8570	4764	8570	25,666	25,178	25,178	25,178	17,553	25,178
R-squared	0.019	0.028	0.030	0.019	0.024	0.054	0.007	0.013	0.014	0.011	0.013	0.039

Notes: coefficients have been scaled to allow them to be interpreted as X per 1000 live births. The sample in Panel A (left) consists of births to households with access to high-quality formal care (equal to one if the nearest health facility is within the top quartile of the quality distribution) while the sample in Panel B (right) consists of births to households where the nearest health facility is in the bottom three quartiles of the quality distribution. The dependent variables are shown at the top of each set of results. Controls include indicators for male births, first births and young mothers (age < 18), dummies for mother's level of schooling, an indicator for women who are married or living with a partner, dummies for ethnicity and religion, dummies for the partner's educational attainment, distance to the nearest health facility, wealth quintile dummies, and a rural-urban indicator. Each column includes district and year × month fixed effects. In Column 5, we exclude villages with baseline prevalence of 0 or 1 to account for "floor" and "ceiling" effects. Column 6 is equivalent to Column 3 except that district fixed effects have been replaced with cluster fixed effects. Post = 1 if birth occurs after December 2007. 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)

Choosing a Regression Specification

2 × 2 Diff-in-Diff Specifications

Godlonton and Okeke (2015) estimate regression specification:

where:
$$Y_{ict} = \alpha + \theta \text{HighExposure}_c + \delta (\text{HighExposure}_c \times \text{Post}_t) + \beta X_{ict} + \tau_t + \varepsilon_{ict}$$

- HighExposure_c = indicator for (more) treated clusters (pre-ban use of TBAs above 75th percentile)
- τ_t = fixed effect for month of birth (e.g. January 2007)
- X_{ict} includes district (not DHS cluster) fixed effects

Comparing 2×2 Diff-in-Diff Specifications

	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
High exposure \times Post	-0.189 (0.014)	-0.189 (0.015)	-0.192 (0.014)	-0.192 (0.015)
High exposure	0.344 (0.015)	0.344 (0.014)		
Post	-0.016 (0.005)		-0.016 (0.005)	
Month fixed effects	No	Yes	No	Yes
DHS cluster fixed effects	No	No	Yes	Yes

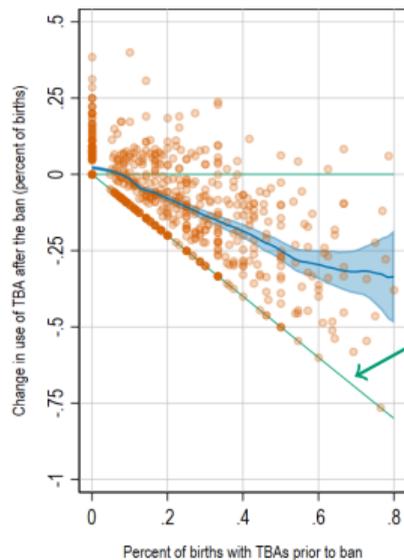
Continuous Variation in Treatment Intensity

Alternative regression specification (that Godlonton and Okeke don't use):

where:
$$Y_{i,t} = \alpha + \lambda PreMeanTBA_c + \gamma (PreMeanTBA_c \times Post_t) + \beta X_{ict} + \tau_t + \varepsilon_{ict}$$

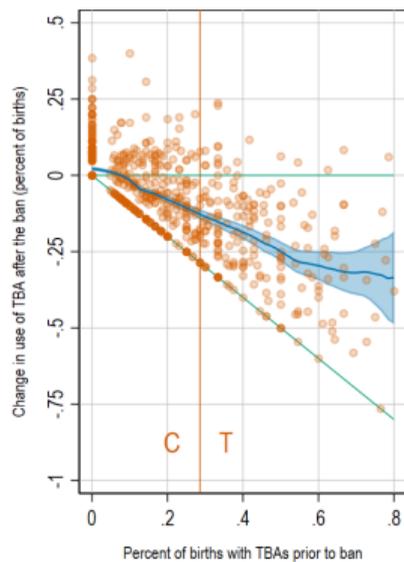
- $PreMeanTBA_c$ = level of TBA use in cluster c before TBA ban
- γ = diff-in-diff estimate of treatment effect
- X_{ict} = set of control variables (eg household size, etc.)
- τ_t = fixed effect for month of birth (eg January 2007)
- ε_{ict} = mean-zero error term

Long Differences

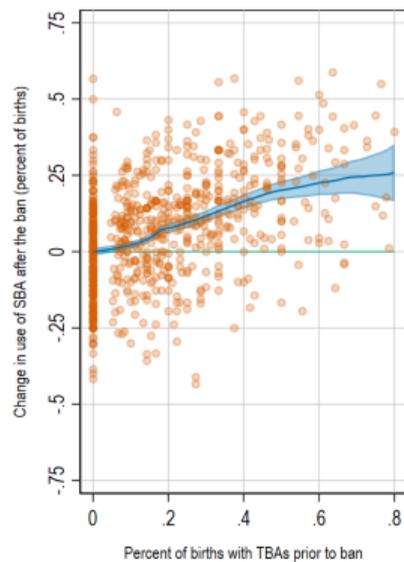
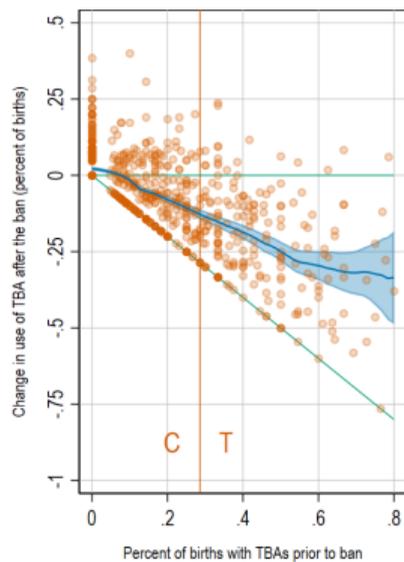


Post-ban mean must be positive
⇒ Decline ↑ with pre-ban mean

Long Differences



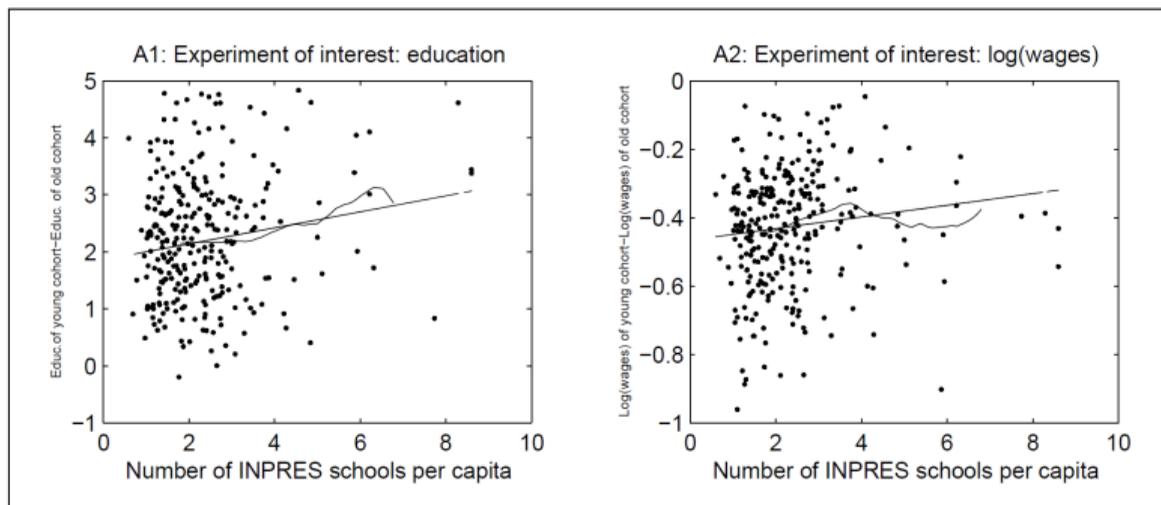
Long Differences



Continuous Variation in Treatment Intensity

	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Mean Pre-Ban TBA \times Post	-0.531 (0.036)	-0.532 (0.036)	-0.528 (0.036)	-0.5295 (0.036)
Mean Pre-Ban TBA	0.984 (0.008)	0.984 (0.007)		
Post	0.0296 (0.005)		.0287 (0.005)	
Month fixed effects	No	Yes	No	Yes
DHS cluster fixed effects	No	No	Yes	Yes

Long Differences: School Construction in Indonesia



source: Duflo (2000)

Example: School Construction in Indonesia

Main empirical specification in Duflo (2001):

where:
$$S_{ijk} = \alpha + \eta_j + \beta_k + \gamma (\text{Intensity}_j * \text{Young}_i) + \mathbf{C}_j\delta + \varepsilon_{ijk}$$

- S_{ijk} = education of individual i born in region j in year k
- η_j = region of birth fixed effect
- β_k = year of birth fixed effect
- Young_i = dummy for being 6 or younger in 1974 (treatment group)
- Intensity_j = INPRES schools per thousand school-aged children
- \mathbf{C}_j = a vector of region-specific controls (that change over time)

Example: School Construction in Indonesia

Dependent Variable: Years of Education

	Obs.	OLS (1)	OLS (2)	OLS (3)
<i>Panel A: Entire Sample</i>				
<i>Intensity_j * Young_i</i>	78,470	0.124 (0.025)	0.150 (0.026)	0.188 (0.029)
<i>Panel B: Sample of Wage Earners</i>				
<i>Intensity_j * Young_i</i>	31,061	0.196 (0.042)	0.199 (0.043)	0.259 (0.050)
<i>Controls Included:</i>				
YOB*enrollment rate in 1971		No	Yes	Yes
YOB*other INPRES programs		No	No	Yes

Sample includes individuals aged 2 to 6 or 12 to 17 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.

Example: School Construction in Indonesia

Dependent Variable: Log Hourly Wages (as Adults)

	Obs.	OLS (1)	OLS (2)	OLS (3)
<i>Panel A: Sample of Wage Earners</i>				
<i>Intensity_j * Young_i</i>	31,061	0.0147 (0.007)	0.0172 (0.007)	0.027 (0.008)
<i>Controls Included:</i>				
YOB*enrollment rate in 1971		No	Yes	Yes
YOB*other INPRES programs		No	No	Yes

Sample includes individuals aged 2 to 6 or 12 to 17 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.

Testing Common Trends

How Can We Test the Common Trends Assumption?

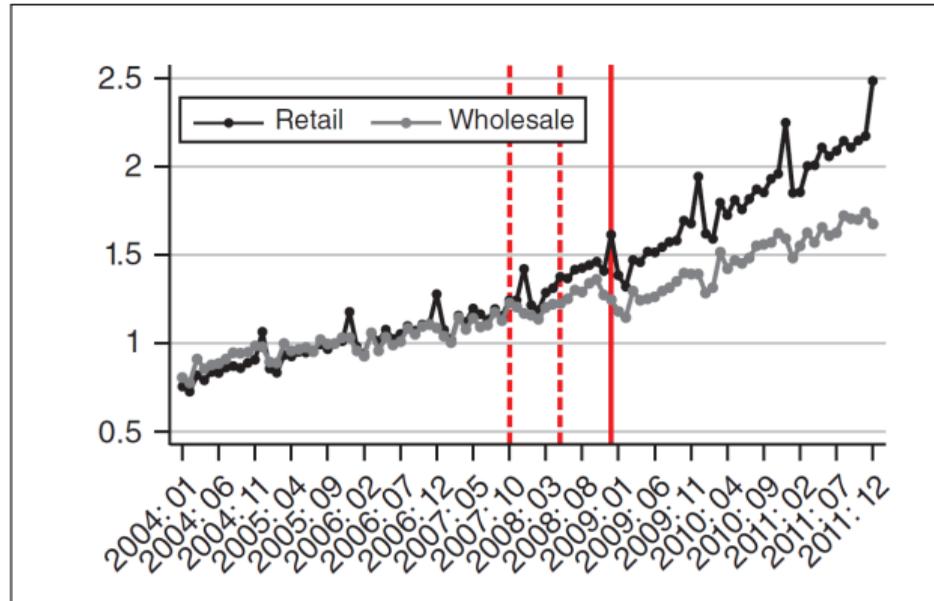
The **common trends** assumption: in the absence of treatment, outcomes in the treatment (i.e. ever-treated) group and the comparison group would have evolved along similar trajectories

- Common trends relates to potential outcomes without treatment
 - ▶ We can never observe the (treatment group) counterfactual
- It is fundamentally impossible to test the common trends assumption

Approaches to defending (or perhaps evaluating) the common trends assumption:

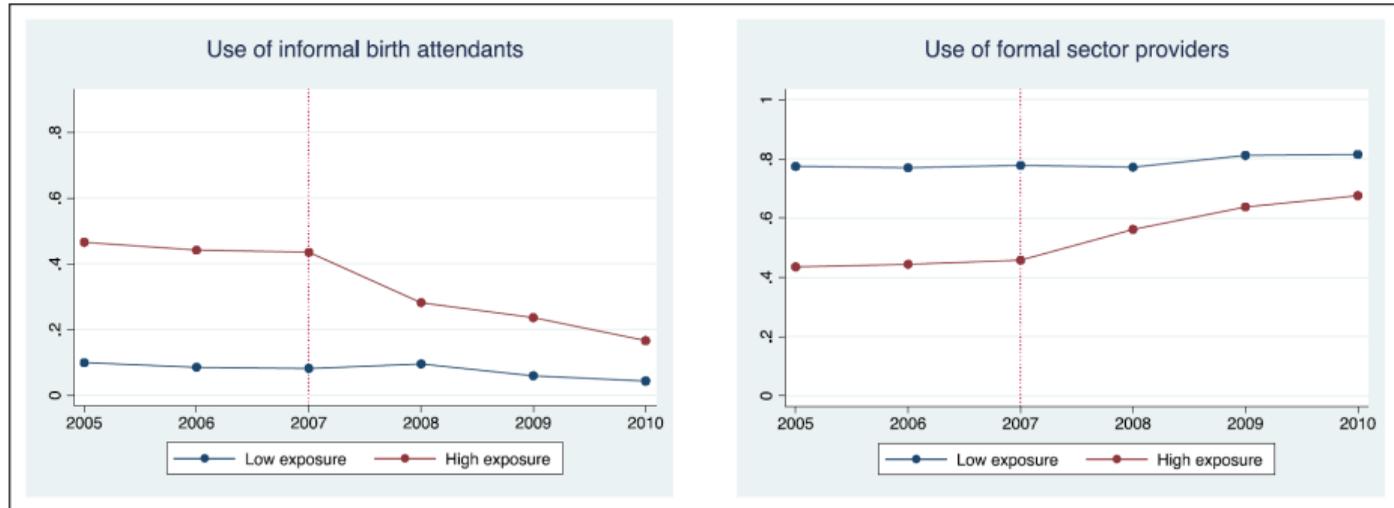
1. Comparing pre-treatment trends in the treatment and comparison groups
2. Conducting a **falsification test** (sometimes called a **placebo test**)

Pre-Trends: A Picture Is Worth a Thousand Words



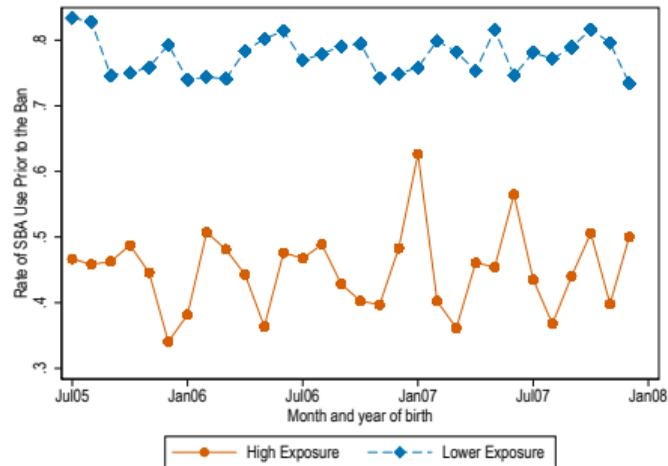
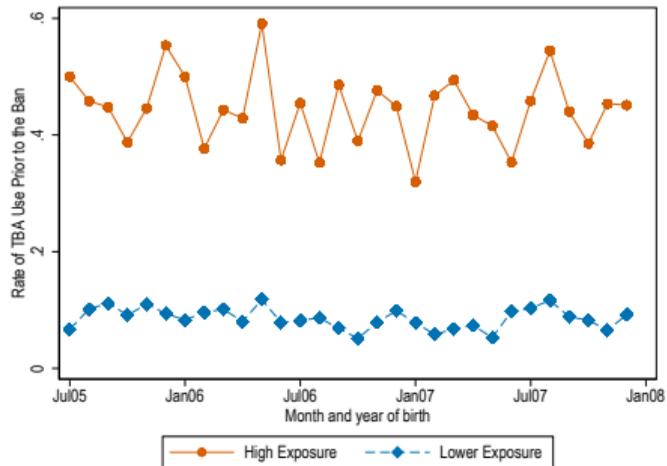
source: Naritomi (2019)

Pre-Trends: A Picture Is Worth a Thousand Words



source: Godlonton and Okeke (2015)

Pre-Trends: A Picture Is Worth a Thousand Words



Testing Pre-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
- λ = captures the time trend (slope) in low exposure DHS clusters
- γ = measures equality of time trends between treatment, control

Sample is restricted to observations from before the ban on traditional birth attendants

Testing Pre-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

source: Godlonton and Okeke (2015)

Testing Pre-Trends: Implications for Practice

- A compelling test of the equality of pre-trends requires lots of pre-treatment data
 - ▶ At a minimum, you need two pre-treatment periods
 - ▶ With only two periods, implement a falsification/placebo test
 - ▶ Statistical power can be a serious issue with limited pre-treatment data
- Often makes sense to disaggregate data as much as possible (e.g. months instead of years)
 - ▶ Treatment and comparison groups should be impacted by the same period-specific shocks
- Whenever possible, graph your data **and** conduct a statistical (i.e. regression) test

Falsification Tests

A placebo or **falsification test** looks for effects that shouldn't be there using:

- A different outcome (that should not be impacted)
- A different (i.e. not real) definition of treatment (a placebo)
- A different sample (i.e. one not impacted by treatment, or where treatment didn't happen)

Unlike tests of pre-trends, falsification tests typically use the same diff-in-diff regression specifications as the main analysis (but with a different outcome and/or sample)

Falsification Test Example 1: Alternative Outcomes

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	-0.00849	-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).

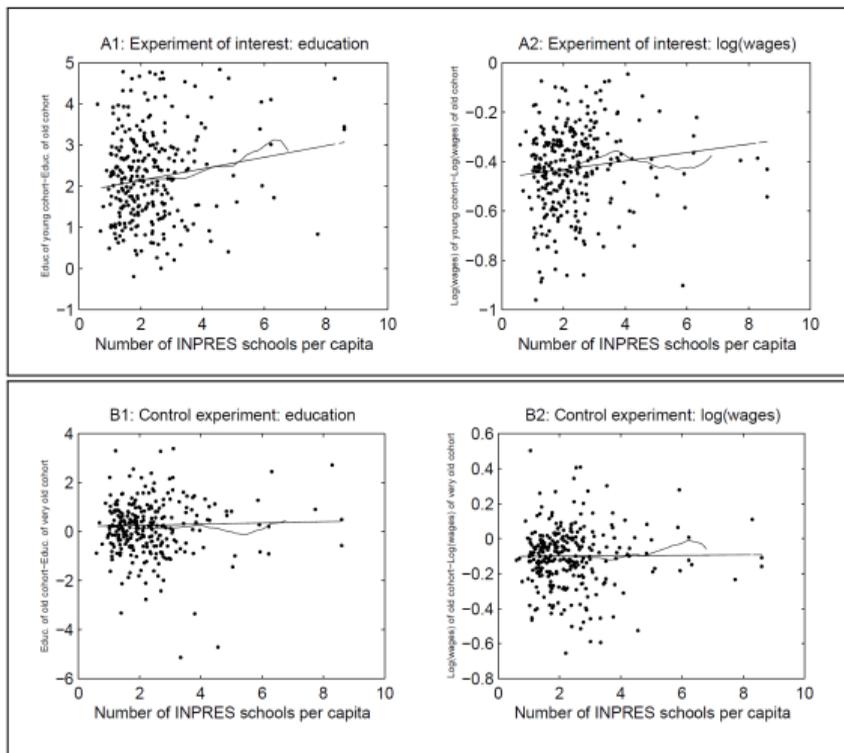
*** p < 0.01.

** p < 0.05.

* p < 0.1.

source: Godlonton and Okeke (2015)

Falsification Test Example 2: Alternative Sample / Placebo Treatment



source: Duflo (2000)

Falsification Test Example 2: Alternative Sample / Placebo Treatment

Dependent Variable: Years of Education

	Obs.	OLS (1)	OLS (2)	OLS (3)
<i>Panel A: Entire Sample</i>				
$Intensity_j * Younger_i$	78,488	0.009 (0.026)	0.018 (0.027)	0.008 (0.030)
<i>Panel B: Sample of Wage Earners</i>				
$Intensity_j * Younger_i$	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.

Falsification Tests: Implications for Practice

Falsification tests are fundamentally context-specific:

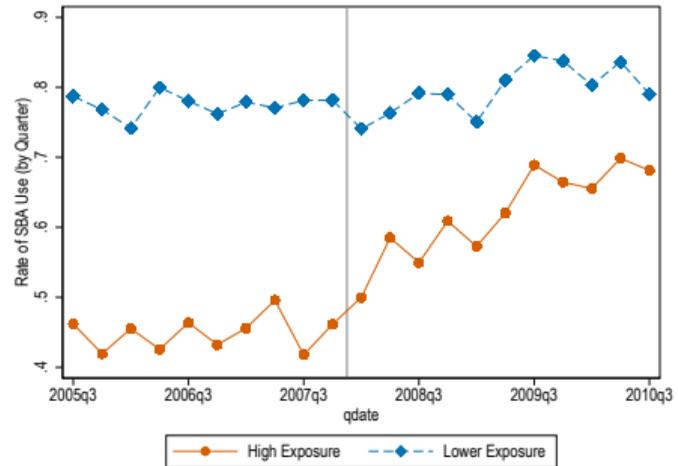
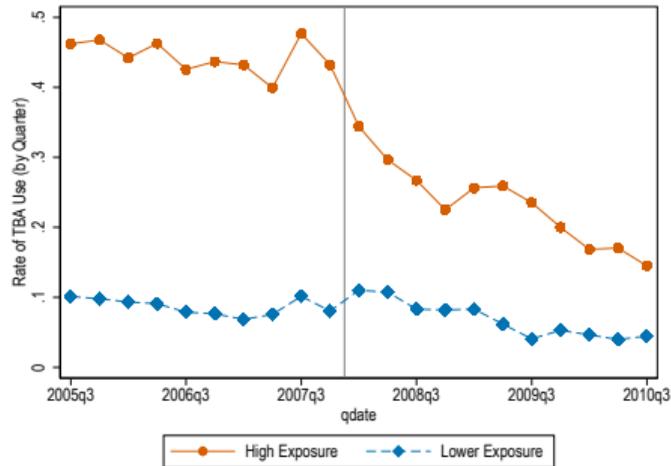
- Which outcomes and/or groups should not be impacted?
 - ▶ Could there be spillovers onto groups that weren't directly treated?
 - ▶ Could treatment have unintended consequences?
 - ▶ Example: impacts of maternity leave on attitudes toward LGBTQ issues

There is not a one-size-fits-all approach to coming up with a good falsification test

- You need to know your setting and your data, and framing matters

Event Studies

Treatment Effects Evolve Over Time



Allowing Treatment Effects to Vary Over Time

<u>Year</u>		<u>Relative Time</u>		<u>Dummy</u>
2005		-3		minus_3
2006		-2		minus_2
2007		-1		minus_1
2008	⇒	0	⇒	plus_0
2009		1		plus_1
2010		2		plus_2

The Event Study Specification

Extend benchmark diff-in-diff specification to include

$$\begin{aligned} Y_{ict} = & \alpha + \theta \text{HighExposure}_c \\ & + \gamma_{-3} (\text{HighExposure}_c \times \text{Minus}_3) + \gamma_{-2} (\text{HighExposure}_c \times \text{Minus}_2) \\ & + \delta_0 (\text{HighExposure}_c \times \text{Plus}_0) + \delta_1 (\text{HighExposure}_c \times \text{Plus}_1) + \delta_2 (\text{HighExposure}_c \times \text{Plus}_2) \\ & + \beta X_{ict} + \tau_t + \varepsilon_{ict} \end{aligned}$$

where:

- Minus_τ = variables capture violations of common trends
 - ▶ Minus_{-1} = is the omitted category
- Plus_τ = captures treatment effect τ periods after the start of treatment

Event Study Results

