2

# Difference-in-Difference Models

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1

#### Florida

- 8/25/1997, State of Florida settles out of court in their suits against tobacco manufacturers
- Awarded \$13 billion over 25 years
- Use \$200m to run anti-smoking campaign aimed at kids
- Florida Tobacco Pilot Program (FTPP)
- Precursor to the national 'truth' campaign

• Florida's edgy "Truth" advertising campaign continues to have a significant impact in reducing teen smoking, a team of researchers concluded from a new study that examines the impact of the state's anti-tobacco advertising.

- in 1998, when surveillance began for tobacco use among Florida youth, 27.4 percent of high school students were current cigarette smokers. by 2000, this rates had declined to 22.6 among high school students.
- 4.8 percentage point decline or a 17.5% reduction in teen smoking









- Teen smoking rates fell from 36.5 to 31.4%
- A 5.1 percentage point decline or roughly 14%
- Rates in Florida fell by 4.8 percentage points similar to what was happening in the nation as a whole

10

# Difference in difference models

- Maybe the most popular "identification strategy" in applied statistical work in economics
- Attempts to mimic random assignment with treatment and "comparison" sample

# Simple problem set up

- One group is 'treated' with intervention
- Have pre & post treatment data for group receiving intervention
- Can examine time-series changes but,
- Unsure how much of the change is due to secular changes

• If the outcome of interest is trending over time, before/after comparisons will provide a biased estimate of the law

11

• Look at this graphically





• True effect of law

 $-Y_b - Y_a$ 

Only have data at t<sub>1</sub> and t<sub>2</sub>
 If using time series, estimate of the effectiveness of the law is Y<sub>t1</sub> - Y<sub>t2</sub>

13

• Solution?

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# Difference-in-difference models

- Pool cross-sectional and time series data
- Use time series of "untreated" group to establish "trends"
- What would have occurred in the treatment states in the absence of the intervention?

	Before Change	After Change	Difference
Group 1 (Treat)	Y <sub>t1</sub>	Y <sub>t2</sub>	$\Delta Y_t$ = $Y_{t2}$ - $Y_{t1}$
Group 2 (Control)	Y <sub>c1</sub>	Y <sub>c2</sub>	$\Delta Y_{c} = Y_{c2} - Y_{c1}$
Difference			$\begin{array}{c} \Delta \Delta Y \\ \Delta Y_t - \Delta Y_c \end{array}$

# Motor Voter Example

- Federal law change in 1993 allows people to register when they get theior driver's license
- Designed to increase voter registration
- Some states had motor voter before 1993
- Data on voting rates in in two years

   1992 Presidential (before MV)
   1996 Presidential (after)
- Two groups of states
  - Treated group (states that got MV through federal law in 1993)
  - Control group (states that had MV laws already)







# Basic Econometric Model

- Data varies by
  - state (i)
  - time (t)
  - Outcome is  $Y_{it}$
- Only two periods
- Intervention will occur in a group of observations (e.g. states, firms, etc.)



- T<sub>it</sub> =1 if obs i belongs in the state that will eventually be treated
- $-A_{it} = 1$  in the periods when treatment occurs
- $T_{it} A_{it}$  interaction term, treatment states after the intervention
- $Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 A_{it} + \beta_3 T_{it} A_{it} + \epsilon_{it}$

# $Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 A_{it} + \beta_3 T_{it} A_{it} + \epsilon_{it}$

	Before Change	Afte <del>r</del> Change	Difference
Group 1 (Treat)			
Group 2 (Control)			
Difference			
			22

#### Making the model more complicated

- So far, a very simple model
  - Two groups
  - Two periods
- However, the "treatment" may cover more than 1 group
- The treatment may happen at very different time periods across groups
- How to generalize this type of model for
  - Many treatments
  - Multiple groups being treated

23

21

# Example: States as laboratories

- Tremendous variation across states in their laws
  - Variation across states in any given year
  - Variation over time within a state
- Examples
  - Minimum wages, welfare policy, Medicaid coverage, traffic safety laws, use of death penalty, drinking age, cigarette taxes

# Panel Data at the State Level

- Data is in two dimensions
- $y_{it}$  outcome for state i in year t

- *i*=1,2,...*n* 

- **−** *t*=1,2,...T
- Example: all states from 1990-2019
  - 30 years
     51 states
  - 1530 obs.

#### Empirical example: Motorcycle Helmet laws

- 1967, Feds require states to have helmet law to get all federal highway money
- By 1975, all states have qualifying law
- 1976, Congress responds to state pressure and eliminate penalties
  - 20 states weaken their law and only require coverage for teens
  - 8 states repeal law completely

#### 26

28

• 1991 Federal law again provides incentives for laws covering everyone

- A bunch of states pass universal laws

- Congress changes its mind and in 1995 eliminate penalties
  - Again many states drop the law
- Currently
  - 20 states have universal law
  - 27 have teen coverage only

- Helmets are estimated to reduce the likelihood of death in a motorcycle crash by 37%. (Center for Disease Control)
- <u>http://www.cdc.gov/motorvehiclesafety/pdf/m</u> <u>c2012/MotorcycleSafetyBook.pdf</u>

#### Problem

• Time series correlation

- many laws came into effect during a boom/recession
- Motorcycle fatalities are pro-cyclic
- Need to control for the time series
- Motorcycle drivers HATE helmet laws
  - Laws are much less prevalent in states with lots of motorcyclists
  - Simple political economy

# $\begin{aligned} define: \\ i = 1, 2, \dots n; \quad t = 1, 2, \dots T \\ S_i = 1 \ if \ state \ i, = 0 \ otherwise \\ W_t = 1 \ if \ year \ t, = 0 \ otherwise \\ x_{it} = some \ controls \\ Law_{it} = 1 \ if \ state \ i \ has \ helmet \ law \\ in \ year \ t, = 0 \ otherwise \\ y_{it} = \beta_0 + LAW_{it}\beta_1 + x_i\beta_2 + \\ \sum_{j=2}^n S_j\alpha_j + \sum_{k=2}^T W_k\lambda_k + \varepsilon_{it} \end{aligned}$

- Why k=2 to N and j=2 to T?
- What does  $\alpha$  measure?
- What does  $\lambda$  measure?

- Question: impact of MC helmet laws on motorcycle fatalities
- Data: 48 states, 18 years (1988-2005), 864 observations
- Outcome ln(motor cycle death rate)
   Death rates = deaths/100,000 population
- Treatment variable: =1 if state i has a motor cycle law in year t, =0 otherwise

31

vars:	12			10 Nov 2012 09:27
size:	49,248 (9	99.6% of me	emory free)	
		display		
ariable name	type	format	label	variable label
	int	*0 0 <i>a</i>		vear
vear ncfatals				year total motor cycle fatalities
	str2			2 digit postal code, AL, CA,
tate	SULZ	*Z3		2 digit postal code, AL, CA, etc.
ips	byte	\$8.0a		2 digit numeric fips code
nelmet law				=1 if motorcycle helmet law, =0
leimet_iaw	LIGAC	89.0g		otherwise
peed65	float	%9.0g		=1 if speed limit is 65, 0
				otherwise
peed70p	float	%9.0q		=1 if speed limit is 70 plus, 0
				otherwise
ac_10	float	%9.0g		drunk driving defined as
				bac>=0.1, =0 otherwise
ac_08	float	%9.0q		drunk driving defined as
				bac>=0.08, =0 otherwise
nemp	float	%9.0q		state unemployment rate, 5 is 5%
opulation				state population
iregs				motor cycle registrations
-		-		
Sorted by:				



Source	SS	df		MS		Number of obs F( 70, 793)	
	139.812929 51.8558902				<	Prob > P R-squared	= 0.7295
Total	191.66882	863	. 2220	95967		Adj R squared Root MSE	- 0.7058 25572
mcdrl	Coef.	Std.	Err.	t	P> t	[95% Conf.	Interval]
speed65	0577686	.0552	537	-1.05	0.296	1662293	.0506922
speed70p	0855586	.0815	308	-1.05	0.294	2456004	.0744831
unemp	0117339	.0118	625	-0.99	0.323	0350195	.0115517
	.1423512					.0000241	
bac_10						0069859	
_Istate_2				-0.43	0.668	2126606	.1363826
	delete som						
	.2392712			2.67	0.008	.0632391	
Istate_48	.3987819			4.07		.2066474	.5909164
year_1989	2367341	.052		-4.52	0.000	3395401	1339281
	delete som						
year_2005				1.47			
elmet_law				-8.12			
cons	.5393718	.1275	965	4.23	0.000	.2889049	.7898387