

Difference in Difference – Part 2

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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

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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,

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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

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- 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

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- Helmets are estimated to reduce the likelihood of death in a motorcycle crash by 37%. (Center for Disease Control)
- <http://www.cdc.gov/motorvehiclesafety/pdf/mc2012/MotorcycleSafetyBook.pdf>
- Where does this number come from?

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FARS

- Fatal Accident Reporting System
- Census of motor vehicle accidents that produce a fatality
- Produced since 1975
- Detail information about
 - Accident
 - Vehicles
 - Drivers

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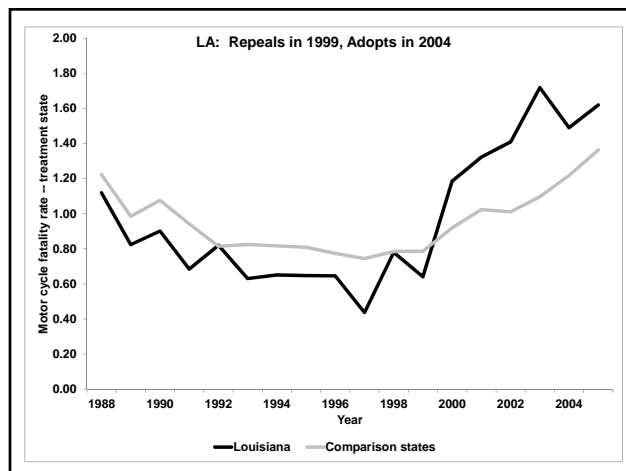
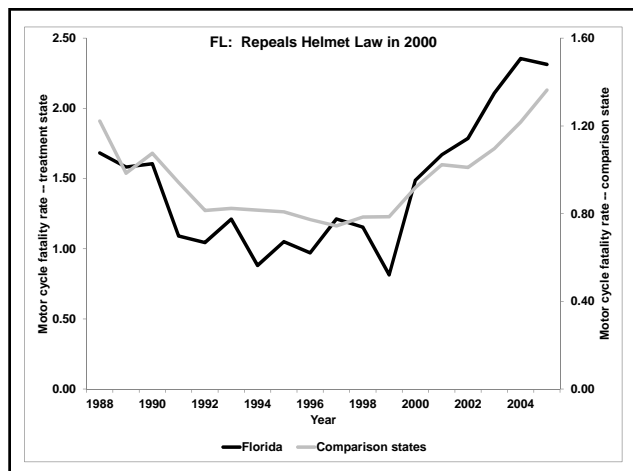
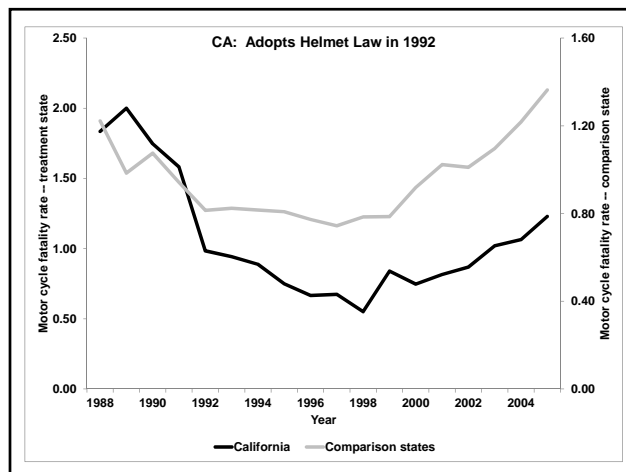
- Select sample from FARS, 1988-2005
- Unique sample
 - Two riders on motor cycle
 - At least one died (accident was severe enough to produce a death)
 - Where one of the riders used a helmet, the other did not

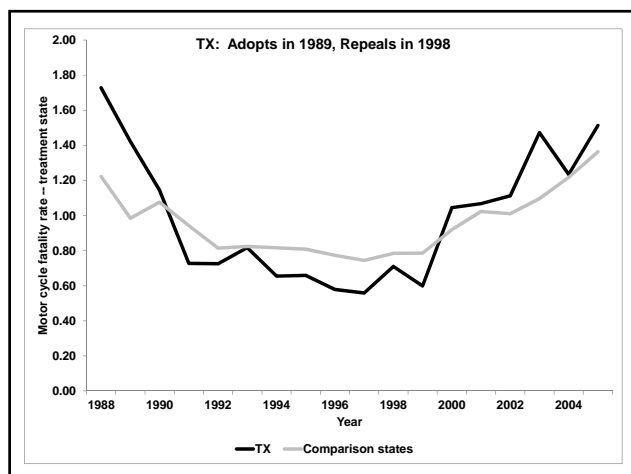
8

<div>Key</div> <div>frequency</div> <div>row percentage</div> <div>column percentage</div>				
helmet	fatal		Total	
	0	1		
0	240	511	751	
	31.96	68.04	100.00	Pr(Die no helmet) = 0.68
	36.31	61.64	50.40	
1	421	344	739	
	56.97	43.03	100.00	Pr(Die helmet) = 0.43
	63.69	36.36	49.60	
Total	661	829	1,490	
	44.36	55.64	100.00	
	100.00	100.00	100.00	

**Benefits of a helmet,
reduce prob. of death
by 37%**

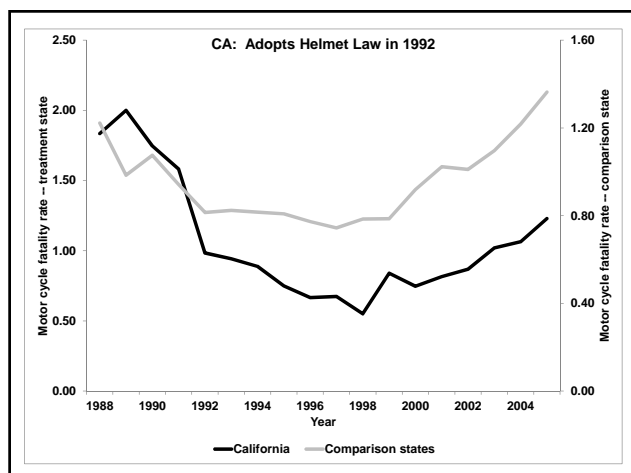
$(0.43-0.68)/0.68 = -0.37$





State group	Motor cycles registered per 100,000	Motor cycle death rate per 100,000
Never had helmet law	2366	1.18
Changed helmet law	1525	1.04
Always had helmet law	1224	0.77

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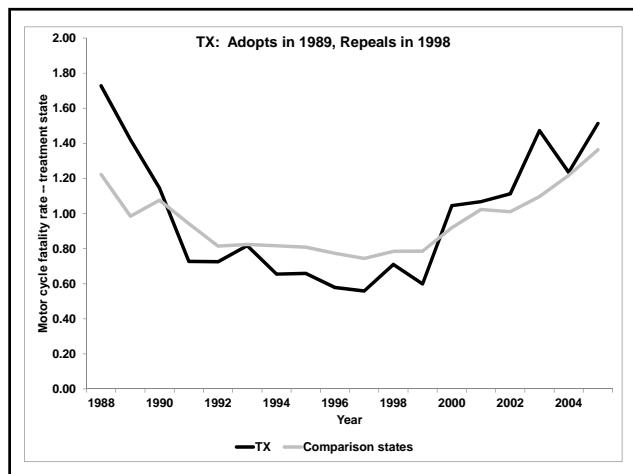
Results for CA alone

```
. reg modr1 speed65 unemp bac_10 trend helmet_law if state=="CA"
```

Source	SS	df	MS		Number of obs =
Model	2.14855814	5	.429711628		18
Residual	.225732886	12	.018811074		F(5, 12) = 22.84
Total	2.37429102	17	.139664178		Prob > F = 0.0000
					R-squared = 0.9049
					Adj R-squared = 0.8653
					Root MSE = .13715

modr1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
speed65	.4358863	.1725389	2.53	0.027	.0599564 .8118163
unemp	.0340391	.0485866	0.70	0.497	-.0718221 .1399003
bac_10	.3175567	.157151	2.02	0.066	-.0248439 .6599612
trend	.065022	.0149018	4.36	0.001	.0325538 .0974902
helmet_law	-.8972242	.168596	-5.32	0.000	-1.264563 -.5298851
_cons	-.3775448	.2939159	-1.28	0.223	-1.017931 .2628414

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Results for TX alone

```
* run a model for Texas
. reg mcdrl speed65 unemp bac_08 trend helmet_law if state=="TX"
```

Source	SS	df	MS	Number of obs =
Model	1.86115335	5	.37223067	18
Residual	.473677129	12	.039473094	F(5, 12) = 9.43
Total	2.33483048	17	.137342969	Prob > F = 0.0008
				R-squared = 0.7971
				Adj R-squared = 0.7126
				Root MSE = .19868

mcdrl	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
speed65	.1689669	.2624034	0.64	0.532	-.4027609 .7406947
unemp	.1301635	.0747096	1.74	0.107	-.0326147 .2929418
bac_08	.6692796	.2457196	2.72	0.018	.1339026 1.204657
trend	-.0405022	.0281575	-1.42	0.180	-.1025494 .021545
helmet_law	-.4592142	.1645968	-2.79	0.016	-.8178398 -.1005887
_cons	-.5765997	.464616	-1.24	0.238	-1.588911 .4357116

Purely Cross Sectional Model (1990)

```
* run basic OLS model for 1990
. reg mcdrl speed65 unemp bac_08 bac_10 helmet_law if year==1990
```

Source	SS	df	MS	Number of obs =
Model	2.59400681	5	.518801363	48
Residual	4.86098775	42	.115737804	F(5, 42) = 4.48
Total	7.45499457	47	.158616906	Prob > F = 0.0023
				R-squared = 0.3480
				Adj R-squared = 0.2703
				Root MSE = .3402

mcdrl	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
speed65	.1692481	.1357937	1.25	0.220	-.1047947 .4432909
unemp	.0524134	.0490639	1.07	0.292	-.0466015 .1514283
bac_08	-.0944842	.2372792	-0.40	0.693	-.573333 .3843645
bac_10	-.0133734	.1658892	0.08	0.936	-.3213985 .3481573
helmet_law	-.4684841	.1039582	-4.51	0.000	-.6780784 -.2588898
_cons	-.0642498	.3042114	-0.21	0.833	-.6782726 .5495743

define:

$$i = 1, 2, \dots, n; \quad t = 1, 2, \dots, T$$

$$S_i = 1 \text{ if state } i, = 0 \text{ otherwise}$$

$$W_t = 1 \text{ if year } t, = 0 \text{ otherwise}$$

$$Law_{it} = 1 \text{ if state } i \text{ has helmet law in year } t, = 0 \text{ otherwise}$$

$$y_{it} = \beta_0 + REFORM_{it}\beta_1 + x_i\beta_2 +$$

$$\sum_{j=2}^n S_j \alpha_j + \sum_{k=2}^T W_k \lambda_k + \varepsilon_{it}$$

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- Why $k=2$ to N and $j=2$ to T ?
- What does α measure?
- What does λ measure?

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

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```
Contains data from motorcycles.dta
obs:      864
vars:      12
size:      49,248 (99.6% of memory free)
10 Nov 2012 09:27
```

variable name	storage type	display format	value label	variable label
year	int	%9.0g		year
mcfatals	double	%9.0g		total motor cycle fatalities
state	str2	%2s		2 digit postal code, AL, CA, etc.
fips	byte	%8.0g		2 digit numeric fips code
helmet_law	float	%9.0g		=1 if motorcycle helmet law, =0 otherwise
speed65	float	%9.0g		=1 if speed limit is 65, 0 otherwise
speed70p	float	%9.0g		=1 if speed limit is 70 plus, 0 otherwise
bac_10	float	%9.0g		drunk driving defined as bac>=0.1, =0 otherwise
bac_08	float	%9.0g		drunk driving defined as bac>=0.08, =0 otherwise
unemp	float	%9.0g		state unemployment rate, 5 is 5%
population	float	%9.0g		state population
mregs	double	%10.0g		motor cycle registrations

Sorted by:

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```
.* construct dummy variables for state and year
. xi i.state i.year
i.state      _Istate_1-48      (_Istate_1 for state==AL omitted)
i.year       _Iyear_1988-2005  (naturally coded; _Iyear_1988 omitted)
```

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```

. * run the difference in difference model
. reg mcdrl speed65 speed70p unemp bac_08 bac_10 _I* helmet_law

```

Source	SS	df	MS	
Model	139.812929	70	1.99732756	
Residual	51.8558902	793	.065392043	
Total	191.66882	863	.222095967	

Number of obs = 864
F(70, 793) = 30.54
Prob > F = 0.0000
R-squared = 0.7295
Adj R-squared = 0.7258
Root MSE = .25572

mcdrl	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
speed65	-.0577686	.0552537	-1.05	0.296	-.1662293 .0506922
speed70p	-.0855586	.0815308	-1.05	0.294	-.2456004 .0744831
unemp	-.0117339	.0118625	-0.99	0.323	-.0350195 .0115517
bac_08	.1423512	.0725064	1.96	0.050	.0000241 .2846783
bac_10	.1163134	.0628129	1.85	0.064	-.0069859 .2396127
_Istate_2	-.038139	.0889074	-0.43	0.668	-.2126606 .1363826
delete some results					
_Istate_47	.2392712	.0896769	2.67	0.008	.0632391 .4153033
_Istate_48	.3987819	.09788	4.07	0.000	.2066474 .5909164
_Iyear_1989	-.2367341	.052373	-4.52	0.000	-.3395401 -.1339281
delete some results					
_Iyear_2005	.1032264	.0703676	1.47	0.143	-.0348778 .2413796
helmet_law	-.3728078	.0458932	-8.12	0.000	-.4628943 -.2827213
_cons	5.383748	.1275965	4.23	0.000	.2889049 .7898387

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Lojack

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Background

- Transponder installed in cars that is turned on when car is stolen
- Recover 95% of stolen cars, compared to 60% for cars without Lojack
- One-time cost at installation
- Requires working in unison with local police authorities, so market entrance is city-by-city

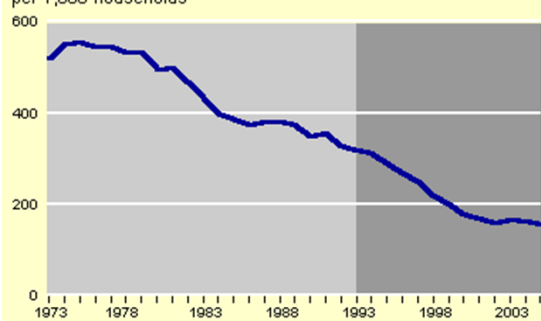
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- Starts in MA in 1986 and spreads to 12 cities by 1994
- Model: examine changes in crime before/after Lojack is introduced to cities without Lojack
- Time trends are key in this analysis

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Property crime rates

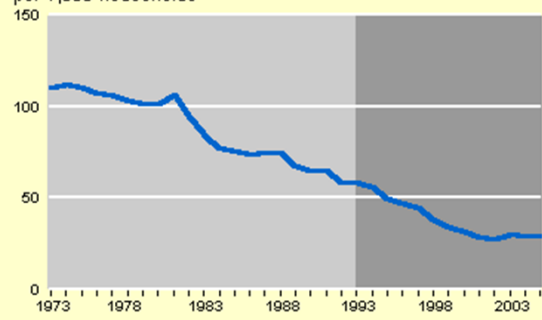
Adjusted victimization rate
per 1,000 households



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Burglary rates

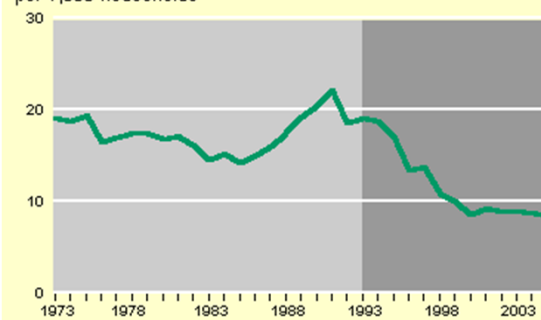
Adjusted victimization rate
per 1,000 households



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Motor vehicle theft rates

Adjusted victimization rate
per 1,000 households



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TABLE I
MARKETS SERVED BY LOJACK AS OF DECEMBER 1994

Market	Cities > 250,000 covered	Date of entry
Massachusetts	Boston	July 1986
South Florida	Miami	December 1988
New Jersey	Newark	March 1990
Los Angeles County	Los Angeles	July 1990
	Long Beach	
Illinois	Chicago	November 1990
Georgia	Atlanta	August 1992
Virginia	Norfolk	August 1993
	Virginia Beach	
Michigan*	Detroit	February 1994
New York	New York City	June 1994
Rhode Island	None	June 1994
Tampa/St. Petersburg	Tampa	July 1994
District of Columbia	Washington, DC	September 1994

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Dynamics

- Lojack installed in new cars, so market penetration is a function of
 - New car sales
 - Fraction of new cars w/ Lojack
- After 5 yrs, only 2% of all cars have Lojack once it enters an area

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Potential benefits

- Does not reduce your chance of having your car stolen, but
- Reduces your costs, given that your car is stolen
- Given previous point, will reduce your insurance costs

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- Chance any car will have Lojack is low.
- If high volume chop shop, will encounter Lojack
- 50 cars annually, 3% market penetration, 78% chance get at least one car with Lojack
- With 100 cars, this rises to 95%

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- Prob(at least one Lojack car) = $1 - \text{Prob}(\text{no Lojack cars})$
- Prob car does not have Lojack = 0.97
- All probs are independent
- Prob (non have Lojack) = $0.97^{50} = 0.22$

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Externality

- What is externality?
- How does Lojack generate externalities?
- What does this imply about whether Lojack penetration is too high or low?

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Data

- 57 cities with pop > 250,000
 - Why only larger cities?
- 1981-1994
- Collect data on local economic conditions, police, age distribution

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Crime Rates in the US, 2005

	All areas	Metro Areas	Non-Metro
Violent	469	510	374
Property	3,430	3,599	3,998
Auto theft	417	467	195

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TABLE II
SUMMARY STATISTICS

Variable	Mean	Standard deviation	Minimum	Maximum
<u>All cities in sample:</u>				
Lojack share				
(% of all vehicles)	.05	.33	0	4.95
Years of Lojack	.17	.85	0	9
City population	764,268	1,045,791	250,720	7,375,097
Auto theft per capita	.012	.008	.002	.054
Robbery, burglary, larceny per capita	.078	.021	.033	.156
Assault, rape, murder per capita	.008	.004	.001	.025
SMSA unemp.	6.3	2.1	2.2	15.9
State per capita real income (\$1994)	19,911	2,821	13,720	31,228
% Black	26.0	18.7	1.2	80.7
% Aged 0-17	26.3	2.0	19.7	31.7
% Aged 18-24	11.5	1.3	8.4	15.1
% Aged 25-44	31.4	2.1	26.1	36.4
Sworn officers per capita (×1000)	2.47	.96	1.32	7.81

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TABLE II
SUMMARY STATISTICS

Variable	Mean	Standard deviation	Minimum	Maximum
Cities with Lojack coverage by 12/94				
Lojack share (% of all vehicles)	.21	.67	0	4.95
Years of Lojack	.83	1.71	0	9
City population	1,402,239	1,959,315	257,617	7,375,097
Auto theft per capita	.018	.011	.002	.05
Robbery, burglary, larceny per capita	.0881	.025	.044	.156
Assault, rape, murder per capita	.011	.006	.001	15.9
SMSA unemp.	6.5	2.1	2.7	15.9
State per capita real income (\$1994)	20,843	3,370	13,932	31,228
% Black	37.5	21.0	10.4	80.7
% Aged 0-17	24.9	2.2	19.7	31.7
% Aged 18-24	11.5	1.5	8.4	15.1
% Aged 25-44	32.0	2.3	26.1	36.4
Sworn officers per capita ($\times 1000$)	3.20	1.33	1.40	7.81

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Mean Values

	All cities	W/ Lojack
Population	764,268	1,402,239
Car theft/pop	0.012	0.018
Unemp rate	6.3	6.5
Per capita inc	\$19,911	\$20,843
% black	26.0%	37.5%
%18-24	11.5	11.5

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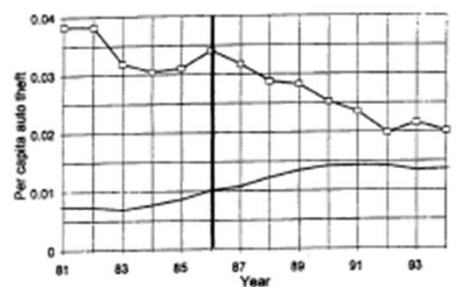
The form of the equations estimated in the basic specifications is as follows:

$$(1) \ln(AUTO_THEFT)_{it} = \beta LOJACK_{it} + X'_{it}\Gamma + \lambda_t + \theta_i + \epsilon_{it},$$

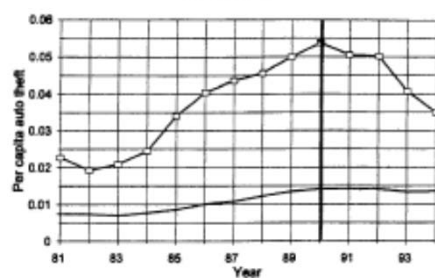
where i indexes cities and t corresponds to years. $AUTO_THEFT$ is the auto theft rate per capita, $LOJACK$ is one of the two Lojack proxies described earlier, and X is a vector of controls for SMSA

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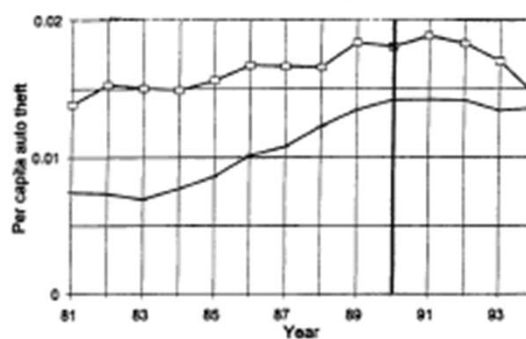
Boston



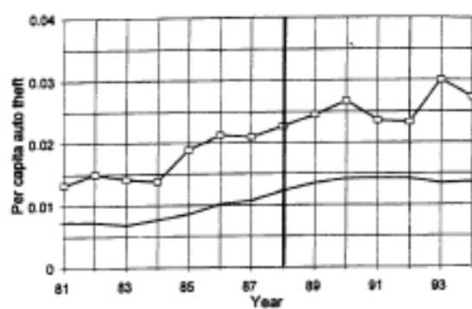
44

Newark

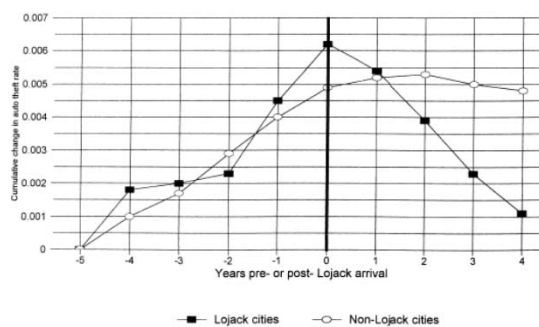
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Los Angeles/Long Beach

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Miami

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TABLE III
IMPACT OF LOJACK ON CITY AUTO THEFT RATES

Variable	(1)	(2)	(3)	(4)
Years of Lojack availability	-.109 (.013)	-.157 (.021)	—	—
Lojack share	—	—	-.242 (.031)	-.463 (.065)
Unemployment rate	.019 (.009)	.026 (.010)	.017 (.009)	.028 (.010)
State real per capita income (×1000)	.022 (.014)	.028 (.015)	.016 (.014)	.022 (.016)

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Linden and Rockoff

- Megan Kanka
 - 7 year old girl
 - Raped and murdered by neighbor who was convicted sex offender
- No one in the neighborhood knew about neighbor's history
- Lead to passage of "Megan's Law"

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Megan's Law

- Sexual Offender (Jacob Wetterling) Act of 1994
 - Sexual offenders required to notify state of change of address
 - Time limits vary across states (10 years after conviction or life)
 - Required of all child sex offenders, some states require of all offenders

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Megan's Law

- 1996 Amendment to original law required states to publicly announce location and type of offense of sex offenders
- Indiana site
- <http://www.icrimewatch.net/indiana.php>

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Economic question

- Crime negatively impacts property values
- Problem: crime is not random and neither are home purchases
- Therefore, getting an estimate of the impact of crime on housing prices is tough
- Megan's law
 - Sex offenders will most likely live in poorer areas
 - How to separate this fact from their impact on house prices?

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Methodology

- Compare house sales in neighborhoods before and after arrival of sex offender
- Impact should be "local" so comparison sample included homes in the same neighborhood but not near the offender

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Data: NC Megan's Law Registry

- Between 1/1/1996 – 3/9/2003
- A total of 8287 released offenders required to register
- 1007 left the state
- Of the remaining, 103 (1.4 percent) failed to register

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Data

- Location of sex offender's address
- Timing of when they moved in
- Matched to home sales data – Charlotte/Mecklenburg county
 - 1994-2004
- Detailed characteristics of home sales
 - 170,000 homes
 - 9,000 within 1/3 miles of a sex offender

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Consider a simple OLS model

- Cross section of homes ($i=1,2,...n$)
- p_i =sales price of home i
- $x_{1i}, x_{2i}, ..., x_{ki}$ characteristics of home
– (rooms, sq feet, brick exterior, Jacuzzi)
- $s_i = 1$ if sex offender lives nearby, $=0$ otherwise

$$\ln(p_i) = \beta_0 + x_{1i}\beta_1 + \dots + x_{ki}\beta_k + s_i\alpha + \varepsilon_i$$

TABLE 1—CHARACTERISTICS OF HOMES SOLD IN MECKLENBURG COUNTY, 1994–2004

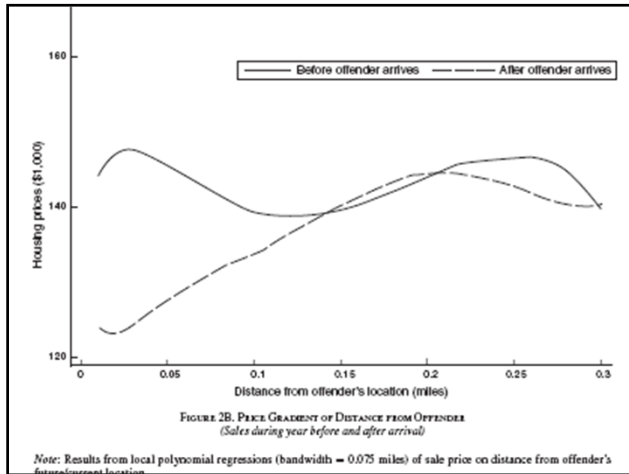
	All parcels	Within 1/3 mile of offender	Marginal effect in price regression ¹
	Mean (Standard deviation)	Mean (Standard deviation)	
Sale price (\$100,000)	2.048 (1.324)	1.438 (0.848)	
Square footage (1,000 square feet)	2.075 (0.880)	1.620 (0.595)	0.266 (0.012) ^a
Quality rating (1 to 6)	3.251 (1.208)	3.066 (0.979)	0.047 (0.006) ^a
Age (in years)	10.347 (12.090)	16.322 (12.815)	−0.008 (0.001) ^a
Bedrooms	3.327 (0.648)	3.061 (0.566)	0.028 (0.010) ^a
Bathrooms	2.018 (0.592)	1.737 (0.539)	0.028 (0.008) ^a

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Data set design

- Identify home that eventually get a sex offender resident
- Two types of homes
 - Treated: homes within 1/10th of a mile
 - Control: homes within 0.1 – 0.3 miles
- Two periods – before and after offender moves in
- Why just 0.1 miles?
- Why not all homes – why just 0.1 – 0.3 miles?





The Difference-in-Difference model

- Data varies cross homes (i) neighborhoods (j) and time (t)
- $D^{0.1} = 1$ if home within 0.1 of sex offender
- $D^{0.3} = 1$ if home within 0.1-0.3 of sex offender
- $Post = 1$ if after SO arrives in a neighborhood, =0 otherwise
- $\alpha_{ji} = 1$ if home is from neighborhood j in year t , =0 otherwise

$$\ln(p_{ijt}) = \alpha_{jt} + x_{ijt}\beta_1 + \dots + x_{kijt}\beta_k + D_{ijt}^{0.1}\gamma + D_{ijt}^{0.3} * POST_{ijt}\theta + D_{ijt}^{0.1} * POST_{ijt}\pi + \varepsilon_i$$

What does α_{jt} capture?

What does $D_{ijt}^{0.1}\gamma$ capture?

What does $D_{ijt}^{0.1} * POST_{ijt}\pi$ capture?

What does $D_{ijt}^{0.3} * POST_{ijt}\theta$ capture?

TABLE 2.—PRE- AND POST-ARRIVAL DIFFERENCES IN AVERAGE CHARACTERISTICS OF HOMES SOLD CLOSE TO OFFENDERS' LOCATIONS

Panel A: Pre-arrival differences in sales	Log price	Built in year sold	Age in years	Square feet (1,000s)	Number of bedrooms	Number of bathrooms
Within 0.1 miles of offender	0.007 (0.034)	0.062 (0.035)+	-1.081 (1.117)	0.059 (0.047)	0.022 (0.034)	< 0.001 (0.036)
Constant	11.745 (0.036)*	0.136 (0.030)*	16.616 (1.153)*	1.589 (0.039)*	3.050 (0.028)*	1.717 (0.034)*
Sample size	4,497	4,497	4,497	4,497	4,497	4,497
R ²	0.05	0.03	0.04	0.03	0.03	0.03

Sample: homes within of 0.3 of where a sex offender will eventually move

$$x_{ijt} = \delta_0 + D_{ijt}^{0.1}\delta_1 + \xi_i$$

TABLE 3.—IMPACT OF SEX OFFENDERS' LOCATIONS ON PROPERTY VALUE AND SALE PROBABILITY

	Pre- and post-arrival		Probability of sale [†]
	(5)	(6)	(7)
Within 0.1 miles of offender	-0.006 (0.012)	-0.006 (0.012)	-0.029 (0.035)
Within 0.1 miles × post-arrival	-0.036 (0.021)+	-0.116 (0.059)+	0.126 (0.059)*
Dist [‡] ≤ 0.1 miles × post-arrival (0.1 Miles = 1)		0.107 (0.064)+	
Within 1/3 miles of offender			
Within 1/3 miles × post-arrival	0.003 (0.016)	0.004 (0.016)	-0.055 (0.040)
H ₀ : within 0.1 miles × post-arrival = 0	<i>p</i> -value = 0.0828 ✓	<i>p</i> -value = 0.0502 ✓	<i>p</i> -value = 0.0361 ✓
Sample size	9,086	9,086	1,519,364
R ²	0.75	0.75	0.01

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Questions:

- How is identification achieved?
- What is the key assumption necessary for identification?
- Why might the estimates be an under/over estimate?

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