POLICE AND CRIME

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání

MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

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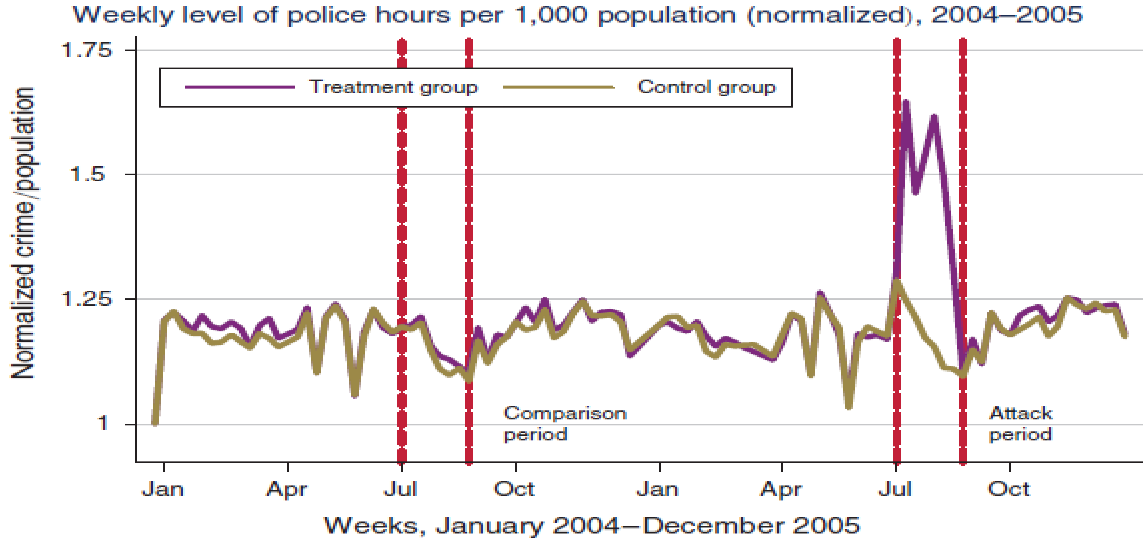
NÁRODOHOSPODÁŘSKÁ FAKULTA VŠE V PRAZE

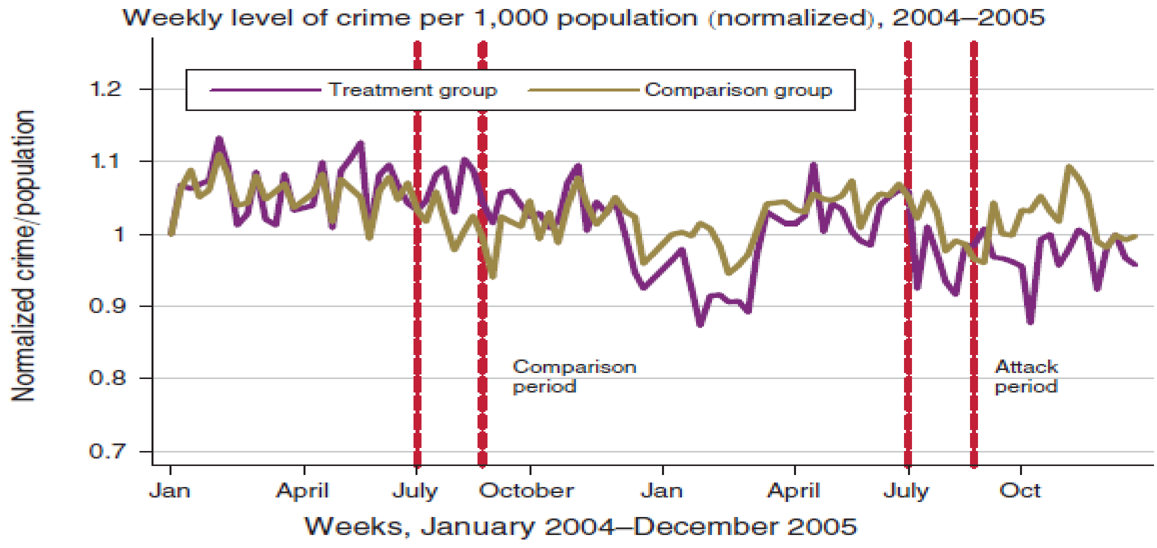
Event studies

- Short-term shock to police presence, typically due to some clearly exogenous event
- Draca, M., Machin, S., & Witt, R. (2011). Panic on the streets of London: Police, crime, and the July 2005 terror attacks. *The American Economic Review*, *101*(5), 2157-2181.

Panel A. Police hours (per 1,000 population)



Panel B. Total crimes (per 1,000 population)



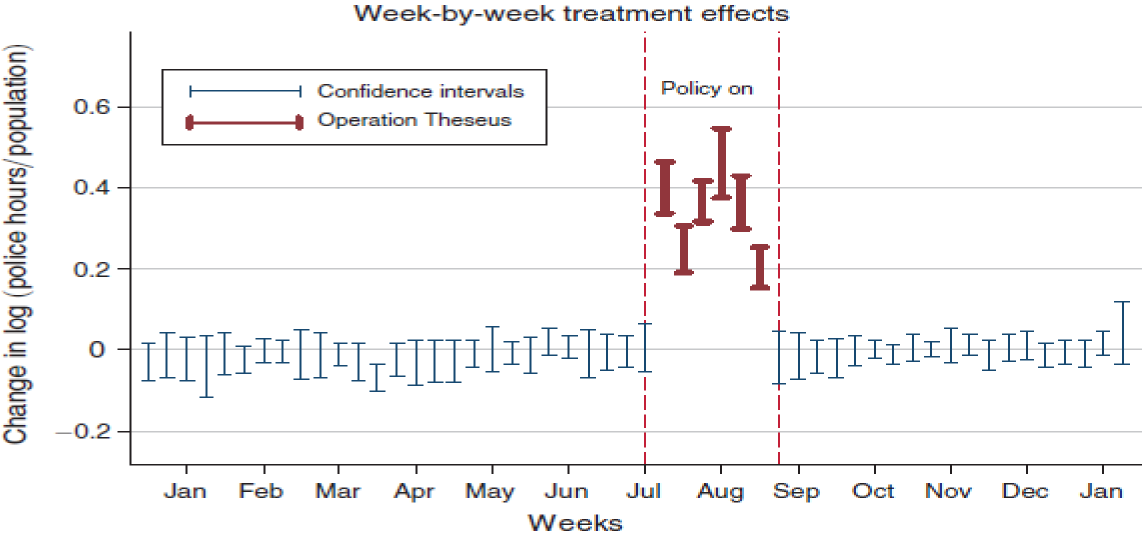
Change in police deployment after the attacks

	Full (1)	Split (2)	+Controls (3)	+Trends (4)
Panel A. Police deployment (Hours worked per 1,000 population)				
$T \times$ *Post-Attack*	0.081***			
	(0.010)			
$T \times$ *Post-Attack*1		0.341***	0.342***	0.356***
		(0.028)	(0.029)	(0.027)
$T \times$ *Post-Attack*2		−0.001	0.001	0.014
		(0.011)	(0.010)	(0.016)
Controls	No	No	Yes	Yes
Trends	No	No	No	Yes
Number of boroughs	32	32	32	32
Observations	1,664	1,664	1,664	1,664

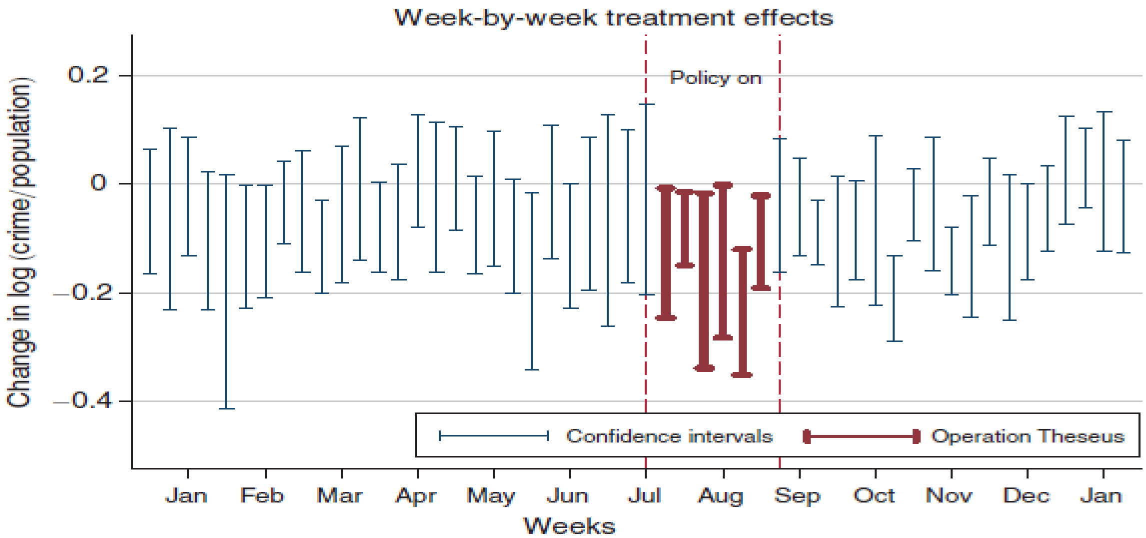
Change in crime after the attacks

	Full (1)	Split (2)	+Controls (3)	+Trends (4)
Panel B. Total crimes (Crimes per 1,000 population)				
$T \times$ *Post-Attack*	–0.052**			
	(0.021)			
$T \times$ *Post-Attack1*		–0.111***	–0.109***	–0.056*
		(0.027)	(0.027)	(0.030)
$T \times$ *Post-Attack2*		–0.033	–0.031	0.024
		(0.027)	(0.028)	(0.054)
Controls	No	No	Yes	Yes
Trends	No	No	No	Yes
Number of boroughs	32	32	32	32
Observations	1,664	1,664	1,664	1,664

Panel A. Year-on-year change in police hours (per 1,000 population)



Panel B. Year-on-year change in susceptible crime rate



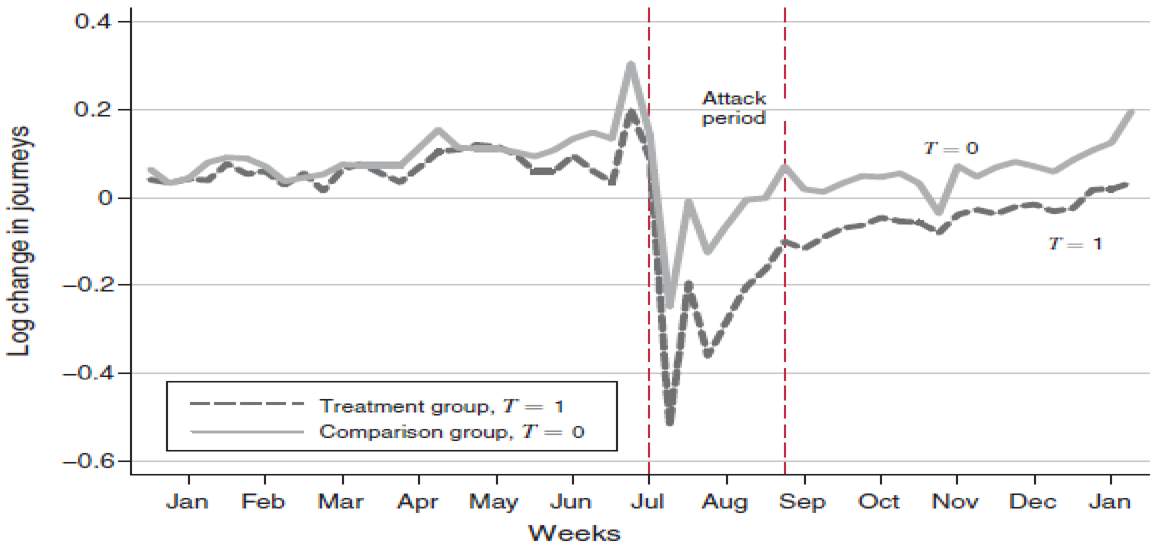


FIGURE 4. YEAR-ON-YEAR CHANGES IN NUMBER OF TUBE JOURNEYS, JANUARY 2004–JANUARY 2006

Instrumental variables

- External factors that affect the size of the police, but are not correlated with crime
- Levitt, S. D. (1997). Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime. *American Economic Review*, *87*(3), 270-90.
- Evans, W. N., & Owens, E. G. (2007). COPS and Crime. *Journal of Public Economics*, *91*(1), 181-201.

1st stage regression:
the effect of elections on the number of police officers per capita

	Gubernatorial election year ($N = 302$)	Mayoral election year ($N = 391$)	No election ($N = 621$)
Δln Sworn police officers per capita	0.021 (0.006)	0.020 (0.007)	0.000 (0.006)

TABLE 3—ESTIMATES OF THE ELASTICITY OF VIOLENT CRIME RATES WITH RESPECT TO SWORN POLICE OFFICERS

Variable	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) LIML
ln Sworn officers per capita	0.28 (0.05)	−0.27 (0.06)	−1.39 (0.55)	−0.90 (0.40)	−0.65 (0.25)	−1.16 (0.38)
State unemployment rate	−0.65 (0.40)	−0.25 (0.31)	−0.00 (0.36)	−0.19 (0.33)	−0.13 (0.32)	−0.02 (0.33)
ln Public welfare spending per capita	−0.03 (0.02)	−0.03 (0.02)	−0.03 (0.02)	−0.03 (0.02)	−0.02 (0.02)	−0.03 (0.02)
ln Education spending per capita	0.04 (0.07)	0.06 (0.06)	0.02 (0.07)	0.03 (0.07)	0.05 (0.06)	0.03 (0.06)
Percent ages 15–24 in SMSA	1.43 (1.00)	−2.61 (3.71)	−1.47 (4.12)	−2.55 (3.88)	−2.02 (3.76)	−1.50 (3.86)
Percent black	0.010 (0.003)	−0.017 (0.011)	−0.034 (0.015)	−0.025 (0.013)	−0.022 (0.012)	−0.031 (0.013)
Percent female-headed households	0.003 (0.006)	0.007 (0.023)	0.040 (0.030)	0.023 (0.027)	0.018 (0.025)	0.033 (0.027)
Data differenced?	No	Yes	Yes	Yes	Yes	Yes
Instruments:	None	None	Elections	Election * city-size interactions	Election * region interactions	Election * region interactions

The mechanism: police presence

- Through which mechanism does police cut crime?
  - Proactive policing (deterring crime from happening in the first place => prevention)
  - Reactive policing (ultimately increasing p => deterrence, incapacitation)
  - Investigation (ultimately increasing p => deterrence, incapacitation)
- Weisburd, Sarit (2015). Does Police Presence Create Deterrence? Working paper, Tel Aviv University

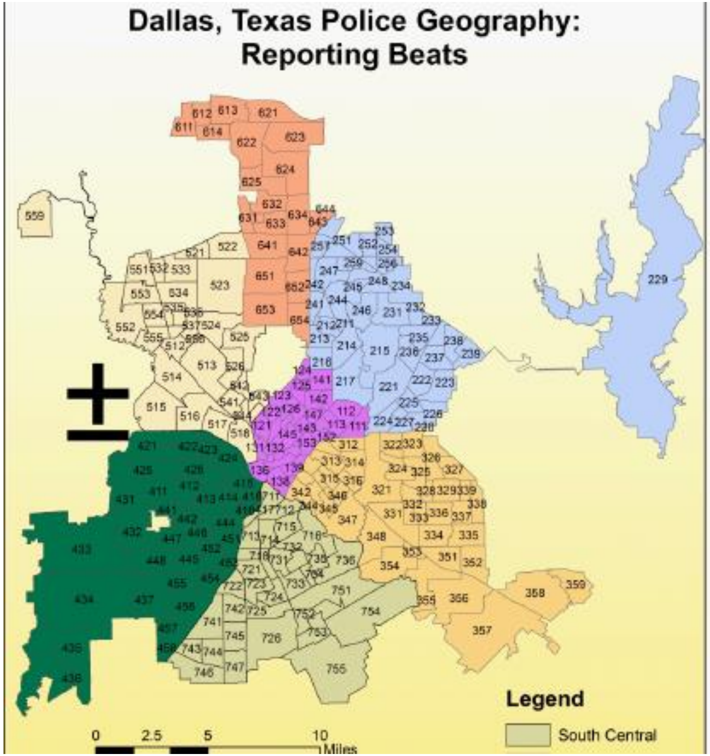

Dallas, Texas Police Geography:
Reporting Beats
Legend
South Central
0 2.5 5 10
Miles

Figure 1: The Endogenous Relationship Between Policing and Crime

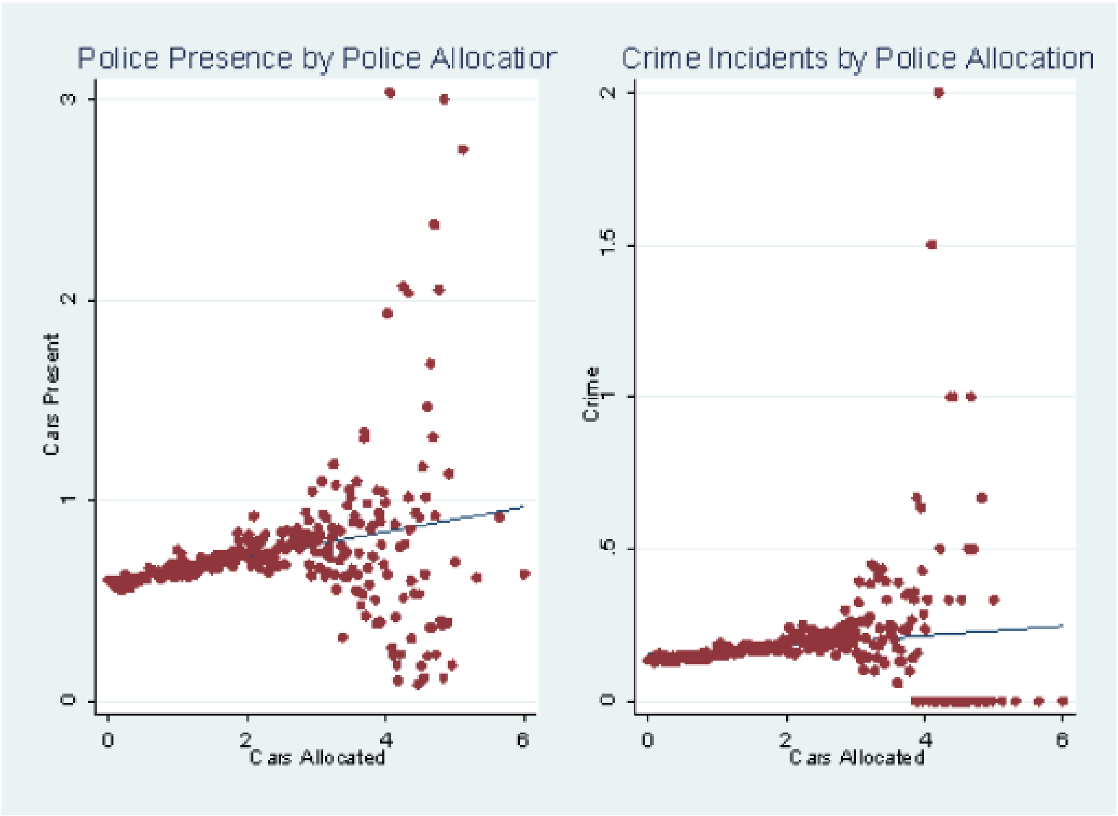


Figure 2: Instrumenting for Police Presence Using the Response Ratio

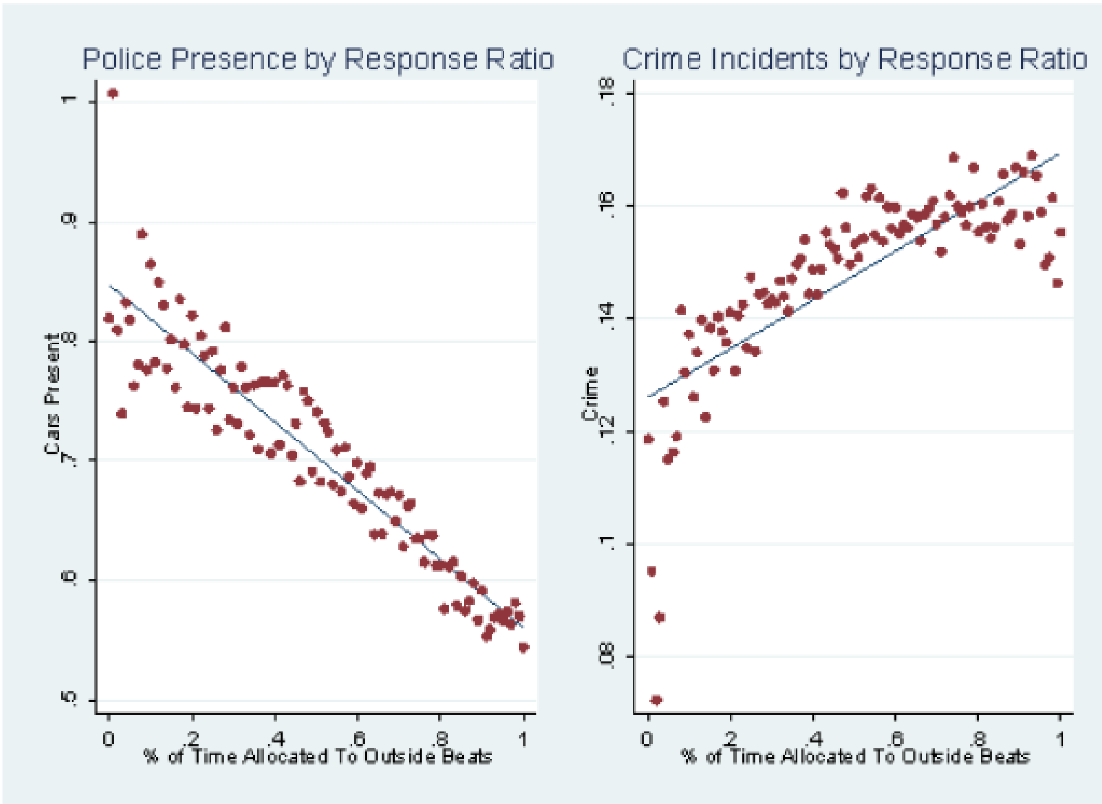


Table 3: Response Ratio as a Predictor of Police Presence

	(i)	(ii)[2]	(iii)
Response Ratio[1]	-0.280***	-0.253***	-0.176***
	(0.032)	(0.028)	(0.012)
Individuals in HH		-0.236	
		(0.185)	
Percent Hispanic		0.281	
		(0.446)	
Percent Asian		-0.132	
		(1.377)	
Percent Teens		8.024	
		(7.066)	
Temperature			0.000
			(0.000)
Precipitation			-0.000
			(0.001)
Twilight			0.000
			(0.003)
Dark			0.005
			(0.006)
Holiday			-0.094***
			(0.011)
Weekend			-0.100***
			(0.013)
Time Fixed Effects	No	Yes	Yes
Location Fixed Effects	No	No	Yes
Observations	2026298	2026298	2026298

Table 5: The Effect of Police Presence on Crime

	OLS		IV =RR		IV =ERR	
	(i)[2]	(ii)	(iii)[2]	(iv)	(v)[2]	(vi)
Police Vehicles[1]	0.009***	0.013***	-0.034***	-0.030***	-0.068***	-0.062***
	(0.003)	(0.002)	(0.008)	(0.006)	(0.017)	(0.013)
Individuals in HH	-0.025*		-0.036**		-0.044**	
	(0.013)		(0.015)		(0.019)	
Percent Hispanic	0.048*		0.059*		0.068	
	(0.026)		(0.032)		(0.043)	
Percent Asian	-0.220***		-0.229**		-0.236*	
	(0.077)		(0.101)		(0.137)	
Percent Teens	0.395**		0.741**		1.024*	
	(0.200)		(0.336)		(0.547)	
Time FE's	Yes	Yes	Yes	Yes	Yes	Yes
Location FE's	No	Yes	No	Yes	No	Yes
Observations	2026298	2026298	2026298	2026298	2026298	2026298

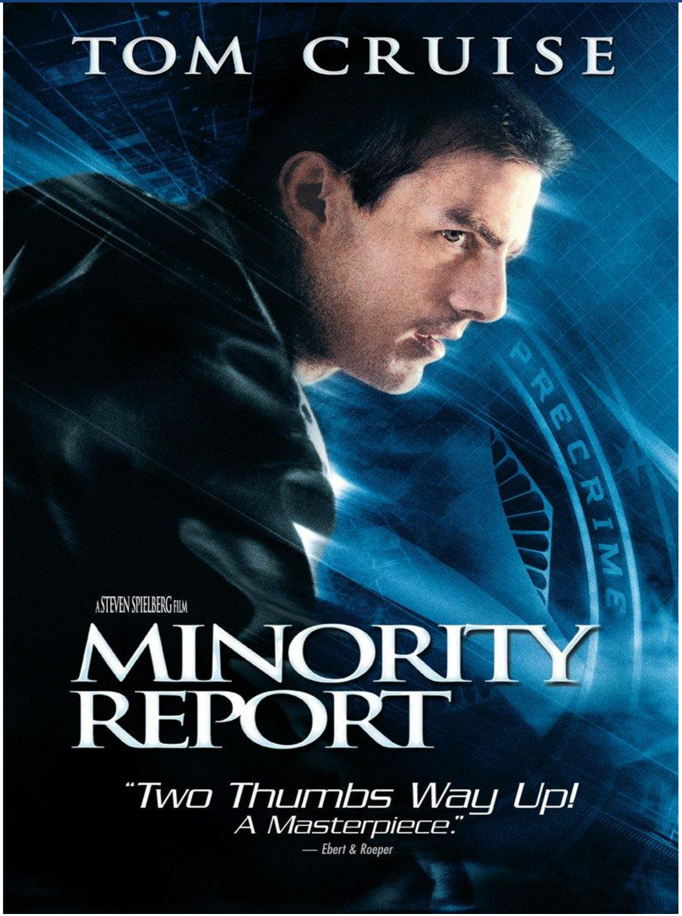
Table 11: The Deterrence Effect of Police by Crime Category (IV=Car Accident Expected Response Ratio)

	All Crimes	Violent crimes	Public Disturbances	Theft	Burglary
	(i)	(ii)	(iii)	(iv)	(v)
Police Vehicles[1]	-0.101***	-0.052***	-0.038***	-0.007**	-0.004
	(0.017)	(0.009)	(0.009)	(0.003)	(0.004)

Table 14: The Impact of Previous Police Presence on Crime (Instrument=ERR)

	All Crimes			Violent Crimes		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Police Vehicles[1]	-0.056**	-0.062***	-0.055***	-0.025*	-0.032***	-0.029***
	(0.024)	(0.018)	(0.016)	(0.013)	(0.010)	(0.009)
Police Vehicles In Previous Hour[2]	0.009			0.004		
	(0.025)			(0.014)		
Police Vehicles In Previous 2 Hours[3]		0.021			0.016*	
		(0.018)			(0.009)	
Police Vehicles In Previous 3 Hours[4]			0.010			0.014
			(0.017)			(0.008)
Location & Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2026065	2025832	2025599	2026065	2025832	2025599

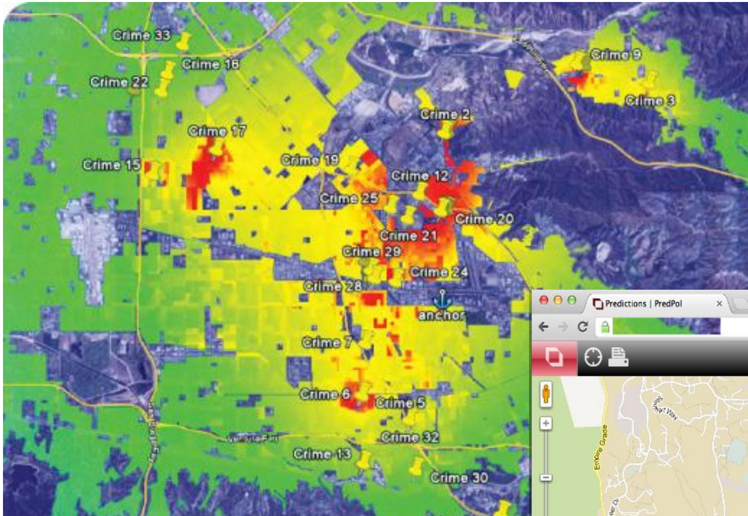
Policy topic: Predictive policing

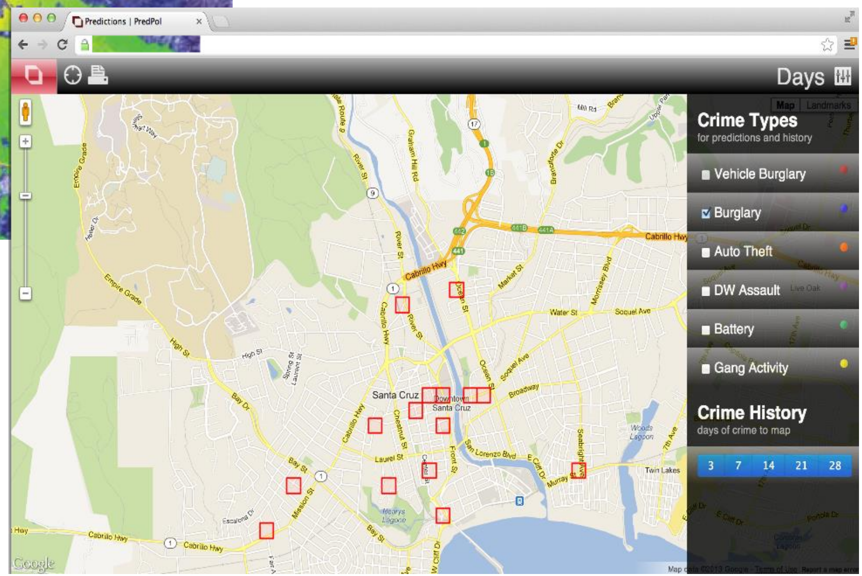


Policy topic: Predictive policing

- Predicting where and when the crime will happen
- In reality: Predicting the likelihood of a crime happening based on (potentially very rich) data
- Benefits:
    - More efficient allocation of the police force
    - Crime prevention

Policy topic: Predictive policing





Policy topic: Predictive policing

Social Network Analysis in Predictive Policing: Mohammad A. Tayebi, Uwe Glässer; Published in Lecture Notes in Social Networks 2016DOI:10.1007/978-3-319-41492-8

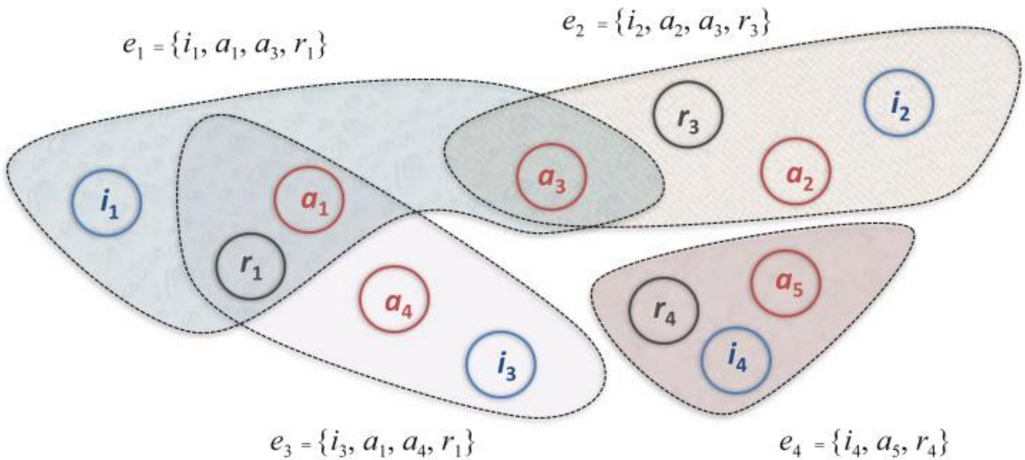


Fig. 3.1 Hypergraph $\mathscr{H}$ (without attributes) for a simple crime data model $\mathscr{C}$

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Table 3.1 Statistical properties of the BC co-offending network

Metric	All crimes	Serious	Property	Drugs	Moral
Number of offenders	157,274	31,132	44,321	54,286	35,266
Average degree	4	1.85	1.95	2.15	4.8
Average distance	12.2	1.69	8.45	22.17	3.41
Diameter	36	13	24	56	19
Effective diameter	16.87	4.1	14.36	36.14	5.68
Clustering coefficient	0.39	0.28	0.33	0.39	0.49
Largest component percentage	25 %	10 %	32 %	23 %	21 %

$$P(k) = k^{-\lambda}$$

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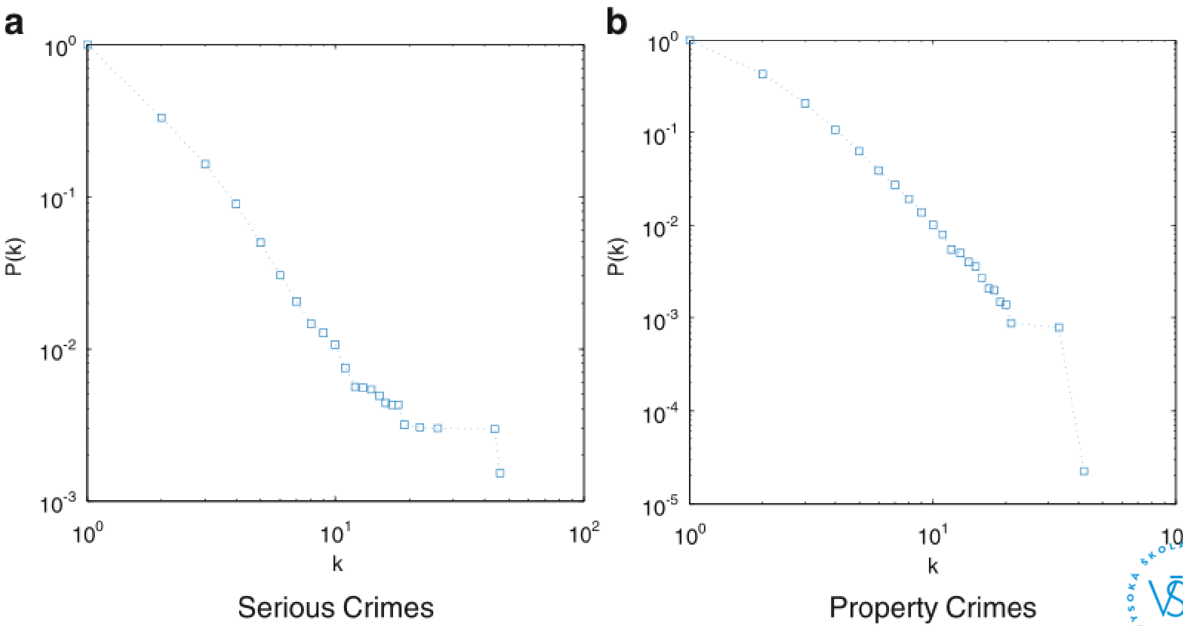

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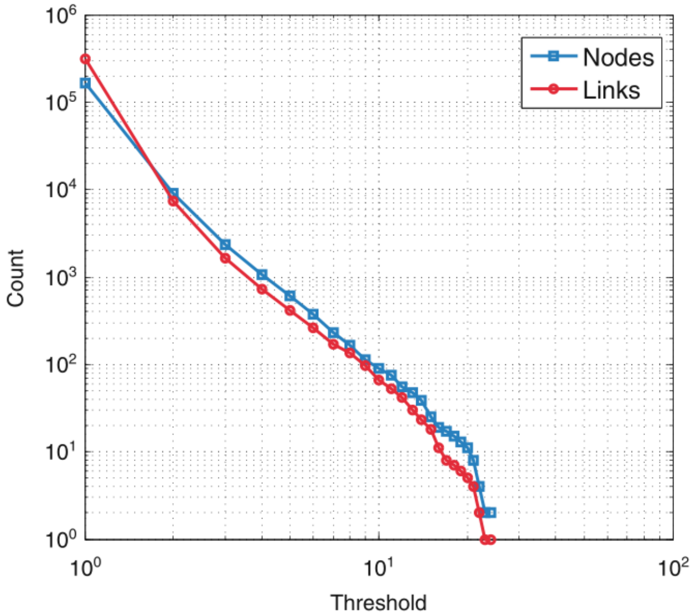

Fig. 3.3 Co-offending strength distribution

Policy topic: Predictive policing

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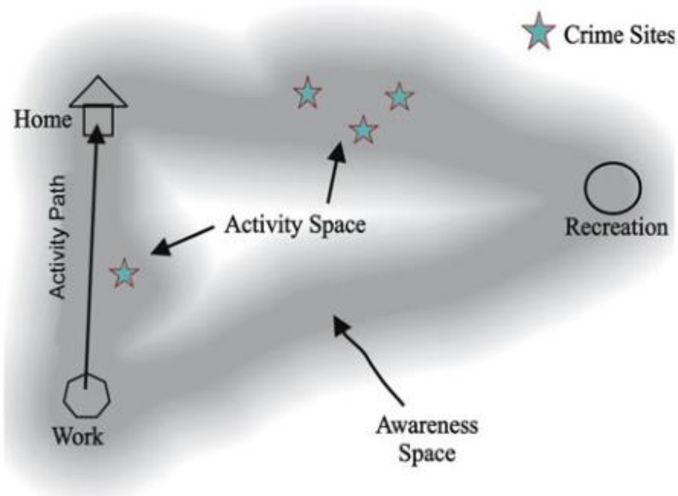

Fig. 7.1 Activity space

Policy topic: Predictive policing

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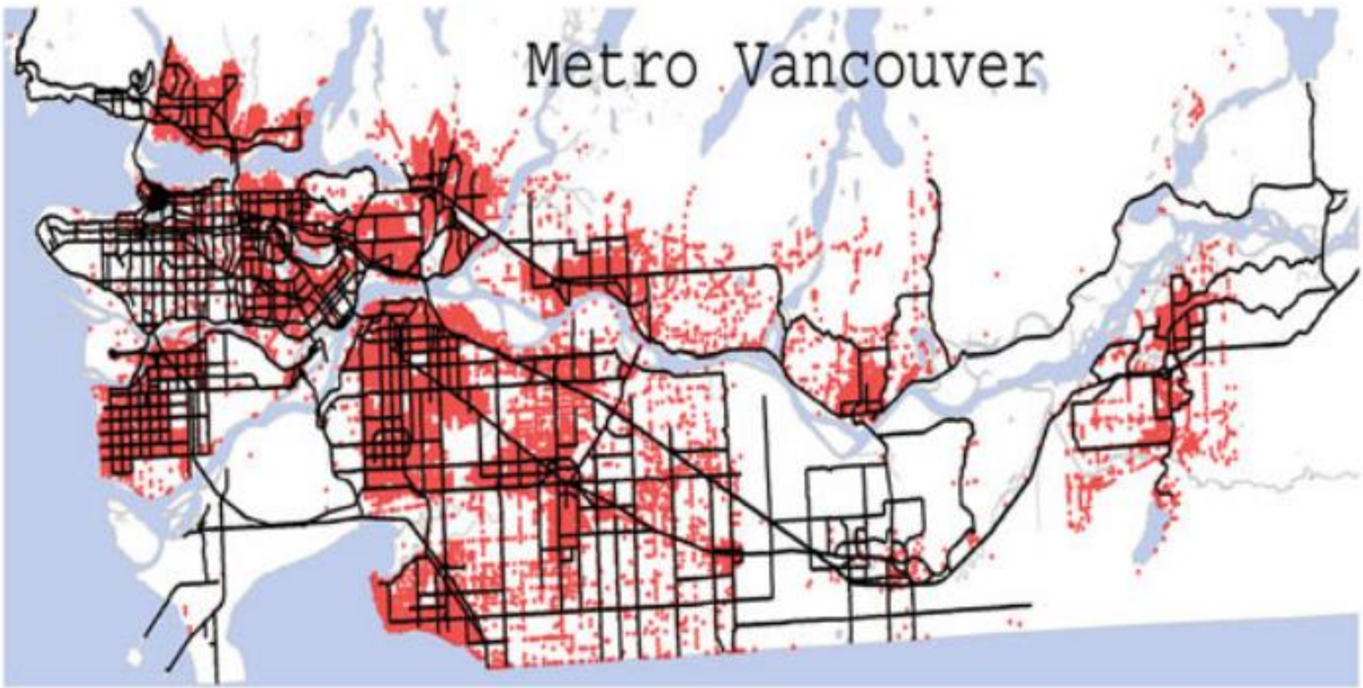

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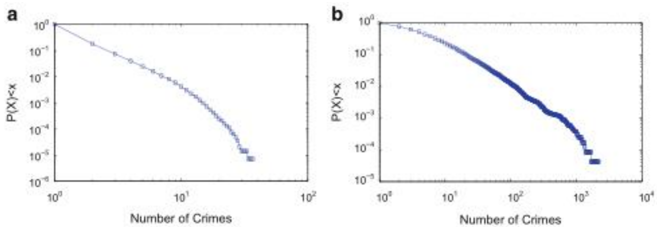

Fig. 7.3 Distribution function: (**a**) Crimes per offender; (**b**) Crimes per road segment

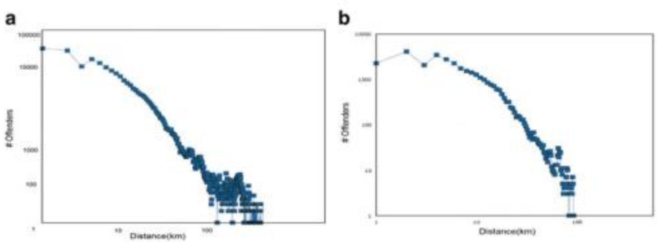

Fig. 7.4 Avg. distance (**a**) home–crime locations; (**b**) crime–crime locations

Predictive policing: design issues

- Predicting crime or offenders or victims?
- Which data enter the calculation? (there could be too much of a good thing)
- Could be self-fulfilling
- Unstable model (cat-and-mouse game with criminals)

Predictive policing: public management

- SW typically developed by private sector
  - The algorithm is typically secret
- Quality of the predictive algorithm:
  - is it publicly verifiable?
- Algorithm
  - Can the public agency control the algorithm?
  - Risk of biases against disadvantaged groups/locations

Summary

- Effect on more police on crime can be ambiguous, its hard to find causality
- Instrumental Variables (IV)
- Predictive policing

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