Criminal Networks

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Road map / main questions

- Why networks matter for crime?
- Evidence on peer effects in crime.
- Peers as neighbors.
- Peers are criminals spending time together in prison.
- Theory of criminal networks.
- Key player: which criminal/area to remove to maximize crime reduction.
- Empirical tests of key players for juvenile crime in the US and adult co-offenders in Sweden.
- Key neighborhoods in London.

Is crime a group activity?

- Juvenile delinquency is primarily a group activity.
- A large share of serious crime is perpetrated by organized groups of criminals such as the Italian Mafia and street gangs in the US.
- High cost to society from these types of group activities.

Do social interactions affect delinquent and criminal behavior?

- Peer effects are important in criminal activities.
- The source of crime and delinquency is located in the intimate social networks of individuals.
- Delinquents often have friends who have themselves committed several offences, and social ties among delinquents are seen as a means whereby individuals exert an influence over one another to commit crimes.
- Peers can be defined as friends, family members, neighbors, people that serve time together in prison or juvenile jail, homeless in shelters, co-workers in the military, and co-offenders.
- Let us provide some evidence on peer effects in crime.

Impact of neighborhood on crime

Peer effects in crime: Peers as neighbors

- Does Growing Up in a High Crime Neighborhood Affect Youth Criminal Behavior?
- How early exposure to neighborhood crime affects subsequent criminal behavior of youth.
- Link individual records from all three registers and extract observations for refugee children who arrived in Denmark together with at least one parent between 1986 and 1998.
- Refugees from Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia.

Peer effects in crime: Peers as neighbors

- Sample of 4,425 children, 55 percent of them male.
- Refugee immigrants to Denmark were assigned to neighborhoods quasi-randomly.
- Measure individual criminal activity based on charges and convictions for offenses against the criminal code, which are recorded from the age of 15 onward.
- Observe all criminal convictions and charges between the ages of 15 and 21 and between 1986 and 1998.

Peer effects in crime: Peers as neighbors

	Refugee children		
	All	Men	Women
Panel A. Age range 15–21			
Charged with a criminal offense	0.376	0.545	0.165
	(0.484)	(0.498)	(0.372)
Convicted of a criminal offense	0.314	0.459	0.134
	(0.464)	(0.498)	(0.341)
Convicted of violent assault	0.104	0.180	0.009
	(0.305)	(0.384)	(0.093)
Convicted of a property offense	0.247	0.347	0.122
	(0.431)	(0.476)	(0.328)
Convicted of a drugs crime	0.054	0.092	0.006
	(0.225)	(0.289)	(0.075)
Convicted of another offense	0.090	0.154	0.011
	(0.286)	(0.361)	(0.103)
Charges	3.163	5.419	0.356
	(10.785)	(14.006)	(1.684)
Convictions	0.909	1.480	0.199
	(2.155)	(2.693)	(0.599)
Observations	4,425	2,453	1,972

Peer effects in crime: Peers as neighbors

- This table shows that 37.6 percent of all refugees who arrived in Denmark as children had been charged with a criminal offense by the age of 21.
- 31.4 percent have been convicted of a criminal offense at least once by the age of 21.
- This compares to about 13 percent (charged with a criminal offense) and 11 percent (convicted of a criminal offense) by the age of 21 for a 10 percent random sample of Danes born in 1980.

Peer effects in crime

Panel B. Age range 15–21			
Distribution of number of convictions:			
0 conviction	3,036	1,328	1,708
1 conviction	647	454	193
2 convictions	289	238	51
3 convictions	122	111	11
4 convictions	61	59	2
5 or more convictions	270	263	7
Observations	4,425	2,453	1,972
Panel C. Age range 15–17			
Charged with a criminal offense	0.251	0.374	0.098
	(0.408)	(0.464)	(.276)
Convicted of a criminal offense	0.211	0.314	0.083
	(0.408)	(0.464)	(0.276)
Charges	1.276	2.172	0.162
	(5.117)	(6.709)	(0.734)
Convictions	0.409	0.653	0.106
	(1.08)	(1.35)	(0.418)
Observations	4,425	2,453	1,972

Peer effects in crime

Panel D. Age range 18–21			
Charged with a criminal offense	0.279	0.432	0.090
	(0.449)	(0.495)	(0.286)
Convicted of a criminal offense	0.217	0.338	0.066
	(0.412)	(0.473)	(0.248)
Charges	1.886	3.247	0.192
	(6.935)	(9.018)	(1.259)
Convictions	0.500	0.827	0.093
	(1.32)	(1.65)	(0.438)
Observations	4,425	2,453	1,972

Peer effects in crime

- Equation to be tested:

$$y_{itr} = \alpha_1 + \alpha_2^M G_i C_{itr} + \alpha_2^F (1 - G_i) C_{itr} + \alpha_3 G_i + \mathbf{X}_{it}\alpha + \mathbf{T}_t + \epsilon_{itr}$$

- where the variable y_{itr} is an indicator that takes the value 1 if individual i assigned to location r in year t is convicted of a crime committed in the age range 15–21, 15–17, or 18–21.

- The key variable is C_{itr}: is the share of individuals aged 15–25 who were convicted for a crime committed in year t and who lived in municipality r to which individual i was randomly assigned in that year (the youth crime conviction rate).

- G_i, gender dummy, $G_i = 1$ if i is a male.

Effect of a Standard Deviation Increase in the Youth Crime Conviction Rate in the Municipality of Assignment in Year of Assignment on Convictions

Panel A. Men					
Convicted in age range					
15–21	0.019	0.017	0.023*	0.023*	0.043**
	(0.013)	(0.012)	(0.012)	(0.012)	(0.022)
15–17	0.017	0.015	0.014	0.014	0.027
	(0.013)	(0.012)	(0.013)	(0.013)	(0.019)
18–21	0.020*	0.019**	0.025**	0.023**	0.031
	(0.010)	(0.010)	(0.012)	(0.012)	(0.020)
Convictions in age range					
15–21	0.122**	0.113**	0.118*	0.106*	0.169*
	(0.058)	(0.052)	(0.062)	(0.063)	(0.097)
15–17	0.068**	0.061**	0.055*	0.050	0.098*
	(0.027)	(0.025)	(0.033)	(0.034)	(0.051)
18–21	0.054	0.052	0.063*	0.056	0.071
	(0.035)	(0.032)	(0.036)	(0.037)	(0.056)

Peer effects in crime: Effect on male refugees

- This table point to a positive effect of the share of convicted youth criminals in the area of first assignment at assignment date on the probability of later conviction.
- Males, Column (5): A one standard deviation higher youth crime rate in the assignment area increases the probability of a crime conviction by between 5 percent and 9 percent and the number of convictions by between 7 percent and 11 percent.
- This means that a 1 percentage point increase in the youth crime conviction rate in the assignment area increases the probability of a crime conviction by between 7 percent and 13 percent and the number of convictions by between 10 percent and 16 percent.

Peer effects in crime

Panel B. Women					
Convicted in age range					
15–21	−0.008	−0.004	0.002	0.001	0.031
	(0.007)	(0.007)	(0.010)	(0.010)	(0.020)
15–17	−0.005	−0.002	−0.002	−0.002	0.015
	(0.007)	(0.007)	(0.009)	(0.009)	(0.017)
18–21	−0.004	−0.001	0.005	0.003	0.018
	(0.005)	(0.006)	(0.008)	(0.008)	(0.018)
Convictions in age range					
15–21	0.001	0.018	0.022	0.008	0.095
	(0.014)	(0.021)	(0.033)	(0.035)	(0.084)
15–17	−0.004	0.003	−0.003	−0.009	0.048
	(0.008)	(0.011)	(0.018)	(0.019)	(0.044)
18–21	0.005	0.015	0.025	0.017	0.047
	(0.009)	(0.013)	(0.021)	(0.020)	(0.050)

Peer effects in crime: Effect on female refugees

- For females, the estimates are much smaller and in none of the specifications are they statistically significant, findings that stand in contrast to those for males.
- These estimates do not point to any systematic relation between area youth crime conviction rates at assignment and individual criminal behavior.
- They are in line with the criminology literature that suggests males and females react differently to detrimental neighborhood conditions

Peer effects in crime

	Convicted in age range					
	15–21		15–17		18–21	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Youth violent crime conviction rate	0.034***	0.045***	0.035***	0.046***	0.021**	0.024*
	(0.011)	(0.014)	(0.011)	(0.013)	(0.010)	(0.012)
Panel B						
Youth property crime conviction rate	0.016	0.029	0.008	0.009	0.017	0.019
	(0.012)	(0.021)	(0.013)	(0.019)	(0.011)	(0.019)
Panel C						
Youth drugs crime conviction rate	−0.011	−0.006	−0.015	0.005	0.003	0.002
	(0.013)	(0.018)	(0.012)	(0.016)	(0.013)	(0.017)
Panel D						
Youth conviction rate of other offenses	0.021*	0.011	0.017	0.005	0.022*	0.017
	(0.012)	(0.016)	(0.011)	(0.015)	(0.011)	(0.015)

Peer effects in crime: Peers as neighbors

- This table reports estimates for males only of the probability of conviction in age range 15–21 when neighborhood youth crime conviction rates are broken down by crime categories.
- It is mainly youth violent crime conviction rates that affect individual criminal behavior in each of the three age ranges.
- The effect of youth property crime conviction rates is somewhat smaller but not statistically significant.

Peer effects in crime: Peers as neighbors

- If social interaction is a main channel through which neighborhood crime affects criminal behavior later in life,
- then it is reasonable to expect that young men will be more affected by criminals from their own ethnic group with whom they have more communication and interaction opportunities.

Peer effects in crime

	Convicted in the 15–21 age range				
	(1)	(2)	(3)	(4)	(5)
Panel A. Youth crime conviction rate					
All	0.023*	0.028**	0.021*	0.022*	0.022*
	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)
Immigrants and descendants		–0.013			
		(0.012)			
Immigrants and descendants from refugee-sending countries			0.006		
			(0.010)		
Co-nationals				0.023**	0.023**
				(0.010)	(0.010)
Immigrants and descendants from other refugee-sending countries					–0.010
					(0.008)

Peer effects in crime: Summary

- It is the crime conviction rate of youth that affect criminal behavior later in life.
- Crime conviction rates of older individuals have no effect.
- The youth crime conviction rates of individuals from the same ethnic group, with whom contact and interaction is likely to be easier and more frequent, matter more for individual convictions.
- The age range in which assignees are most susceptible to neighborhood crime is between 10 and 14, an age at which young men are particularly vulnerable to delinquent peer influence.

Peers as criminals spending time together in jail

Peer effects in crime: Peers as criminals spending time together in jail

- Learning about crime.
- "Danbury" wasn't a prison. It was a crime school. I went in with a bachelor of marijuana and came out with a doctorate of cocaine." George Jung (Johnny Depp), describing his introduction to the cocaine industry in the motion picture Blow.
- Analyze the influence that juvenile offenders serving time in the same correctional facility have on each other's subsequent criminal behavior.
- The analysis is based on data on over 8,000 individuals serving time in 169 juvenile correctional facilities during a two-year period in Florida.

Peer effects in crime

- The assignment of juveniles to Florida facilities typically occurs in two steps:
- First, the judge decides the appropriate risk level of the youth,
- Second, the DJJ (Department of Juvenile Justice) assigns the youth to a particular program.
- Based on the probation officer's recommendation and assessment of the youth, the judge makes the final decision about the appropriate risk level (minimum, low, moderate, high, and maximum).
- These risk levels are also used to classify facilities.

Data

- The primary data source is the internal database maintained by the Florida DJJ for juvenile offenders under its care.
- Access to the DJJ's records on all youths (16,164 individuals) released from a Florida-based juvenile correctional facility between July 1, 1997, and June 30, 1999.
- For each of these individuals, the data detail whether or not the individual recidivates within the first year following release.
- Because the type of crime committed upon recidivating is only available if the individual is younger than age 18 at the date of re-arrest (i.e., still a juvenile in the Florida system), we restrict the sample to individuals age 17 and younger at the time of release.
- Data also on the youths' correctional facility assignments, criminal histories, personal characteristics, and home neighborhoods.

Peer effects in crime

Descriptive Statistics and Variable Definitions

Variable	N	Mean	Standard deviation: Overall	Standard deviation: Within	Definition
Recidivism					
Recidivism	8,216	0.67	0.47	0.45	1 if client recidivated within one year of release, 0 otherwise
R_felony drug	8,216	0.093	0.29	0.28	1 if client committed felony drug offense within one year of release, 0 otherwise
R_misd drug	8,216	0.090	0.29	0.28	1 if client committed misd. drug offense within one year of release, 0 otherwise
R_felony weapon	8,216	0.027	0.16	0.16	1 if client committed felony weapon offense within one year of release, 0 otherwise
R_agg assault	8,216	0.099	0.30	0.29	1 if client committed aggravated assault within one year of release, 0 otherwise
R_felony sex	8,216	0.013	0.11	0.11	1 if client committed felony sex offense within one year of release, 0 otherwise
R_auto theft	8,216	0.093	0.29	0.28	1 if client committed auto theft offense within one year of release, 0 otherwise

Peer effects in crime

R_burglary	8,216	0.14	0.34	0.33	1 if client committed burglary offense within one year of release, 0 otherwise
R_grand larceny	8,216	0.094	0.29	0.29	1 if client committed grand larceny offense within one year of release, 0 otherwise
R_petty larceny	8,216	0.12	0.32	0.32	1 if client committed petty larceny offense within one year of release, 0 otherwise
R_robbery	8,216	0.045	0.21	0.20	1 if client committed robbery offense within one year of release, 0 otherwise
Facility characteristics					
# Individuals in facility per day	14,421	48.7	73.5	0	Calculated as number of individuals released multiplied by avg. sentence length in the facility, divided by 729 (total number of sample days)

Peer effects in crime

- Within a year of release, 67% of the sample recidivates.
- 14% of the sample recidivates with a burglary offense,
- 12% with a petty larceny offense,
- and 9% with a felony drug offense, misdemeanor drug offense, auto theft, or a grand larceny offense.

Peer effects in crime

- Estimate each individual's exposure to peers who would have been released either before or after the sample period by using the characteristics of the individuals observed to be released from the facility during the full sample period.

- Form the peer measure used in the analysis by averaging:

  - (i) the characteristics of those peers actually observed to overlap with the individual;

  - (ii) a properly weighted measure of the estimated characteristics of the peers with whom this individual would have overlapped, but who were released outside the sample period.

Empirical Specification

- Equation to be tested:

$$
\begin{aligned}
R_{ijt}^{h} = {} & \beta_0 \left(\text{Offense}_{ijt}^{h} \times \text{PeerOffense}_{ijt}^{h} \right) \\
& + \beta_1 \left(\text{NoOffense}_{ijt}^{h} \times \text{PeerOffense}_{ijt}^{h} \right) \\
& + \mathbf{P}_{ijt}\alpha + \mathbf{X}_{ijt}\gamma + \lambda_j + \text{Offense}_{ijt}^{h} \times \mu_j + \eta_t + \epsilon_{ijt}^{h}
\end{aligned}
$$

- R_{ijt}^{h} indicates whether individual i in facility j, who is released in period t, recidivates with offense of type h.
- $\text{PeerOffense}_{ijt}^{h}$ describes an individual's exposure to peers with a history of offense type h.
- Offense_{ijt}^{h} equals 1 if individual i has a history of offense type h, while $\text{NoOffense}_{ijt}^{h}$ indicates no prior history of offense h.
- $\mathbf{P}_{ijt}$ vector of peer characteristics and $\mathbf{X}_{ijt}$ vector of individual demographic and criminal history variables.

Empirical Specification

- This equation focuses on crime-specific peer effects.
- For example, does the increased exposure to peers with a history of auto theft make an individual more likely to commit auto theft upon release?
- These crime-specific peer effects are captured by the parameters β_0 and β_1.

First results

SPECIALIZATION IN CRIME

	R_auto theft (1)	R_burglary (2)	R_grand larceny (3)	R_petty larceny (4)	R_robbery (5)	R_felony drug (6)	R_misd. drug (7)	R_felony weapon (8)	R_agg. assault (9)	R_felony sex (10)
Offense	0.096**	0.093**	0.055**	0.047**	0.065**	0.256**	0.125**	0.014	0.112**	0.050**
	9.78	*10.73*	*6.54*	*6.57*	*5.74*	*15.60*	*11.05*	*1.40*	*7.25*	*5.93*
Average of off-diagonal coefficients	0.013	0.014	0.001	0.002	0.014	0.015	0.012	0.008	0.025	0.000
Constant	0.029**	0.043**	0.041**	0.072**	0.008	0.029**	0.042**	0.013**	0.074**	0.008**
	4.68	*5.83*	*6.43*	*9.62*	*1.50*	*3.66*	*6.40*	*3.12*	*5.84*	*3.27*
Observations	8,216	8,216	8,216	8,216	8,216	8,216	8,216	8,216	8,216	8,216
R^2	0.03	0.04	0.03	0.01	0.02	0.11	0.04	0.01	0.02	0.01

Notes. Each column represents a different specification which is estimated by OLS, where the dependent variable is recidivism in the crime category at the top of the column. Offense varies across specifications, according to the crime category listed at the top of the column. Thus, in the first column, Offense is "Auto Theft" (individuals with a history of auto theft). Each specification also includes controls for whether the individual has any history of each of the other nine crime categories; for brevity, only the average of these off-diagonal coefficients is presented in the table. The absolute values of *t*-statistics are in italics. All standard errors are corrected for clustering at the facility level.

*Significant at 10%.

**Significant at 5%.

First results

- Table reports OLS estimates of regressing recidivism in each crime category (10) on whether the individuals had any history of each of the ten crimes.
- The first row presents the diagonal coefficients (e.g., the relationship between having a history of auto theft and recidivating with auto theft)
- while the second row presents the average of the off-diagonal coefficients.
- In every case but felony weapons, experience in a particular crime is a significant predictor of recidivating with that crime.

Main results

MAIN RESULTS: CRIME-SPECIFIC PEER EFFECTS IN FLORIDA JUVENILE CORRECTIONAL FACILITIES

	Dependent variable									
	R_auto theft	R_burglary	R_grand larceny	R_petty larceny	R_robbery	R_felony drug	R_misd. drug	R_felony weapon	R_agg. assault	R_felony sex
Offense*peer_offense (β_0)	−0.029	0.19**	−0.027	0.098*	0.079	0.31*	0.25**	−0.12	0.26*	0.34**
	0.31	*2.93*	*0.38*	*1.67*	*0.69*	*1.90*	*2.29*	*0.78*	*1.78*	*2.30*
No_offense*peer_offense (β_1)	0.032	−0.022	−0.00044	−0.11	0.084*	0.075	−0.045	0.049	0.090	0.043
	0.56	*0.29*	*0.01*	*1.52*	*1.70*	*1.18*	*0.82*	*0.88*	*0.91*	*1.27*
Recidivate with offense (%)	9.3	13.6	9.4	11.6	4.5	9.3	9.0	2.7	9.9	1.3
Observations	8,216	8,216	8,216	8,216	8,216	8,216	8,216	8,216	8,216	8,216
R^2	0.0970	0.0943	0.0712	0.0536	0.0942	0.1965	0.1002	0.0468	0.0724	0.0722
P-value on test of joint-significance-of-quarter dummies	.0328	.1075	.1557	.0575	.7902	.7817	.1463	.7371	.3827	.1096
H_0: $\beta_0^{\text{auto}} = \ldots = \beta_0^{\text{sex}} = 0$	$p = .0008$									
H_0: $\beta_1^{\text{auto}} = \ldots = \beta_1^{\text{sex}} = 0$	$p = .3694$									

Notes. This table presents the results of estimating equation (1) for the ten crime categories simultaneously via an SUR. Offense and Peer_offense vary across columns accordin to the crime category listed at the top of each column. In the first column, Offense is "Auto theft" (individuals with a history of auto theft) while Peer_offense in this specificatio is Peer_auto (exposure to peers with a history of auto theft). Each specification controls for facility-by-prior-offense fixed effects, quarter-of-release dummies, peer demographic an criminal history characteristics, and individual demographic and criminal history characteristics. The absolute values of t-statistics are in italics. The joint hypotheses that th coefficients are equal to 0 are evaluated using a Wald test.

*Significant at 10%.

**Significant at 5%.

Main results

- β_0 estimated crime-specific peer effect for those with a history of having committed the relevant offense.
- β_1 estimated peer effect for individuals without a history of having committed this offense. Mostly non-significant!
- β_0 estimates are positive in almost every case and statistically significant for burglary, petty larceny, felony and misdemeanor drug crimes, aggravated assault, and felony sex offenses.
- Thus, exposure to a greater percentage of peers with a history of having committed burglaries increases the likelihood that an individual with a prior record of burglary commits another burglary upon release. Individuals with a prior history of burglary recidivate with a burglary 13.6% of the time.
- No such effect exists for those without a prior history of burglary.

Summary

- Strong evidence of the existence of peer effects in juvenile correctional facilities.
- In almost all instances, these peer effects have a reinforcing nature,
- whereby exposure to peers with a history of committing a particular crime increases the probability that an individual who has already committed the same type of crime recidivates with that crime.
- Peer effects tend to reinforce existing criminal behavior.
- The matching of peers with common histories may lead to the creation and expansion of criminal networks.

The importance of social interactions in crime

- We have shown that social interactions matter in crime: Individual behaviors not only depend on the individual incentives but also on the behavior of peers and neighbors.

- An individual is more likely to commit crime if his peers commit than if they do not commit crime.

- In order to understand social interactions in crime, let us develop a simple model.

The importance of social interactions in crime

- Consider a society with two individuals.
- Let us start with a model without social interactions.

- Four cases are possible:

  - (a) both individuals are criminal,
  - (b) both individuals are noncriminal,
  - (c) individual 1 is a criminal but individual 2 is not,
  - (d) individual 2 is a criminal but individual 1 is not.

The importance of social interactions in crime

- No social interactions: If the individuals decide to become criminals by tossing a coin (probability 1/2), then each case occurs with probability 1/4.

- Expected number of criminals:

$$\mathbb{E}(C^{NS}) = \frac{1}{4} \times 2 + \frac{1}{4} \times 0 + \frac{1}{4} \times 1 + \frac{1}{4} \times 1 = 1,$$

  where C^{NS} is the number of criminals in the society when there are no social interactions NS.

- Variance:

$$\mathbb{V}(C^{NS}) = \frac{1}{4} \times (2-1)^2 + \frac{1}{4} \times (0-1)^2 + \frac{1}{4} \times (1-1)^2 + \frac{1}{4} \times (1-1)^2 = \frac{1}{2}.$$

The importance of social interactions in crime

- Let us introduce social interactions in this model.

- Two types of individuals but only individual 1 takes the decision to become a criminal while individual 2 only imitates 1.
- If 1 decides to become a criminal, then 2 is also a criminal.
- If 1 does not become a criminal, then 2 is not a criminal.

- Two cases are possible:

  - (a) both individuals are criminal,
  - (b) both individuals are noncriminal.

The importance of social interactions in crime

- With social interactions:

- Expected number of criminals:

$$\mathbb{E}(C^S) = \frac{1}{2} \times 2 + \frac{1}{2} \times 0 = 1.$$

  where C^S is the number of criminals in the society when there are social interactions S.

- Variance:

$$\mathbb{V}(C^S) = \frac{1}{2} \times (2-1)^2 + \frac{1}{2} \times (0-1)^2 = 1.$$

- Thus, $\mathbb{E}(C^{NS}) = \mathbb{E}(C^S) = 1$ but $\mathbb{V}(C^{NS}) = \frac{1}{2} < 1 = \mathbb{V}(C^S)$.

The importance of social interactions in crime

- Let us develop a more general model.

- Consider n individuals, where C are criminals and N are noncriminals: $n = C + N$
- The variance of crime without social interactions (i.e., each individual takes his crime decision independently of the decisions of the others) is:

$$\mathbb{V}(C^{NS}) = np(1-p)$$

where $p = \frac{C^{NS}}{C^{NS}+N}$ is the probability that a randomly chosen individual is a criminal.

The importance of social interactions in crime

- Social-interaction model (i.e., crime decisions are interdependent).
- n individuals, where C are criminals, N are noncriminals and I individuals imitate the others ($n = C + N + I$).

- The variance of crime with social interactions is (Glaeser et al., 1996):

$$\mathbb{V}(C^S) = np(1-p)f(\pi)$$

- $\pi = \frac{C^{NS}+N}{n} = \frac{n-I}{n}$ is the the probability that a randomly chosen individual is not someone that imitates the others,
- $f(\pi) = \frac{2-\pi}{\pi}$ indicates the covariance between agents and captures the degree of imitation of individuals.

The importance of social interactions in crime

- The variance of crime with social interactions is (Glaeser et al., 1996):

$$\mathbb{V}(C^S) = np(1-p)f(\pi)$$

- When $\pi = 1$, there is no imitation, i.e., crime decisions are independent, and we are back to the model without social interactions.
- When $\pi \to 0$, all individuals are imitating the others but there is nobody to imitate since nobody takes the decision to become criminal independently of the others. As a result, there is no specific pattern of crime (the variance becomes infinite).
- More generally, when $f(\pi)$ increases, there is more imitation and the variance of crime rises.

The importance of social interactions in crime

- This model allows us to explain why there is so much spatial variation in crime between and within cities.

- For example, East Point, Georgia has 0.092 crimes per capita while El Dorado, Arkansas, which has more unemployment, less education, more poverty, and lower per-capita income has 0.039 crimes per capita (between cities).

- The 51st precinct of New York City has 0.046 crimes per capita whereas the wealthier 49th has 0.116 crimes per capita (within cities).

The importance of social interactions in crime

- Main idea: social interactions amplify the effects of crime and if these interactions are localized, then it becomes easy to explain very high levels of crime in some areas of the city.
- If there are already a lot of criminals in a particular location, crime becomes contagious by spreading around like a virus and amplifies the number of criminals in this location.
- Crime is here viewed as a disease.
- Peer effects of crime are driven by individuals' behavior that can have social multiplier effects through a feedback loop

Social multiplier in crime: The dyad

- Games with **strategic complementarities**
- Dyad: $n = 2$. Utility:

$$u_i(\mathbf{x}, \mathbf{g}) = \alpha\, x_i - \frac{1}{2} x_i^2 + \phi x_i x_j$$

- **No social interactions** Unique Nash equilibrium:

$$x_1^* = x_2^* = \alpha$$

- **Social interactions** Unique Nash equilibrium: If $\phi < 1$:

$$x_1^* = x_2^* = \frac{\alpha}{1 - \phi} > \alpha.$$

- $1/(1-\phi) > 1$: social multiplier.

A more general model of crime with social networks

- Games on networks: Applications to crime.
- Following Becker (1968), assume that delinquents trade off the costs and benefits of delinquent activities.
- The expected delinquency gains to delinquent i are:

$$u_i(\mathbf{x},\mathbf{g}) = \underbrace{y_i(\mathbf{x})}_{benefits} - \underbrace{p_i(\mathbf{x},\mathbf{g})}_{prob.caught} \underbrace{f}_{fine}, \tag{1}$$

where

$$\begin{cases} y_i(\mathbf{x}) = \alpha_i'\, x_i - \frac{1}{2}x_i^2 - \gamma x_i \sum_{j=1}^{n} x_j \\ p_i(\mathbf{x},\mathbf{g}) = p_0 x_i \max\left\{1 - \phi' \sum_{j=1}^{n} g_{ij} x_j, 0\right\} \end{cases}$$

Crime and social networks

- The crucial assumption is that delinquents' activity has complementarities with their friends' criminal activity (positive spillovers),
- but a criminal also faces global competition as well as increased expected costs as he or she increases activity.

Positive spillovers: Mechanisms

- Individuals (or groups) may have complementary skill sets.
- To supply drugs, you may need a chemist, a transporter, a salesman, and an accountant to launder the criminal proceeds.
- Each individual specializes in a specific task and only by cooperating can they make a profit.

Positive spillovers: Mechanisms

- Since there is no official crime school, mentoring and/or role modelling may enable a more efficient accumulation of criminal human capital.
- Some individuals hold more information about criminal opportunities, while others are old enough to supply younger friends and siblings with alcohol and drugs.

Positive spillovers: Mechanisms

- Group ideologies and social norms may either encourage or discourage anti-social behaviour and crime.
- In some groups, crime may be seen as a legitimate activity and a violent act may be viewed as a badge of honor.
- Understanding which of these (or other) social mechanisms is at work in a specific case may help to design a more effective policy for that particular problem or crime type.

Crime and social networks

- By direct substitution:

$$u_i(\mathbf{x}, \mathbf{g}) = (\alpha_i' - p_0 f)\, x_i - \frac{1}{2} x_i^2 - \gamma \sum_{j=1}^{n} x_i x_j + p_0 f \phi' \sum_{j=1}^{n} g_{ij} x_i x_j .$$

- γ is the degree of competition between criminals.

- If $\alpha_i' - p_0 f = \alpha_i$ and $p_0 f \phi' = \phi$, then:

$$u_i(\mathbf{x}, \mathbf{g}) = \alpha_i x_i - \frac{1}{2} x_i^2 - \underbrace{\gamma \sum_{j=1}^{n} x_i x_j}_{congestion} + \underbrace{\phi \sum_{j=1}^{n} g_{ij} x_i x_j}_{spillovers} .$$

Crime and social networks

- First-order condition:

$$x_i = \alpha_i - \gamma \sum_{j=1}^{n} x_j + \phi \sum_{j=1}^{n} g_{ij} x_j$$

- In matrix form:

$$\mathbf{x} = \boldsymbol{\alpha} - \gamma \mathbf{x}^T \mathbf{1} + \phi \mathbf{G} \mathbf{x}.$$

- Thus,

$$\mathbf{x} = (\mathbf{I} - \phi \mathbf{G})^{-1} \left(\boldsymbol{\alpha} - \gamma \mathbf{x}^T \mathbf{1} \right).$$

Katz-Bonacich Network Centrality

- Let
$$\mathbf{M}(\mathbf{g}, \phi) = (\mathbf{I} - \phi \mathbf{G})^{-1} = \sum_{k=0}^{+\infty} \phi^p \mathbf{G}^p$$
- Katz (1953) and Bonacich (1987)
- Given $\boldsymbol{\alpha} \in \mathbb{R}_+^n$ and $\phi \geq 0$, the vector of *weighted Katz-Bonacich centralities* relative to a network $\mathbf{g}$ is:

$$\mathbf{b}_{\boldsymbol{\alpha}}(\mathbf{g}, \phi) = \mathbf{M}(\mathbf{g}, \phi) \boldsymbol{\alpha} = (\mathbf{I} - \phi \mathbf{G})^{-1} \boldsymbol{\alpha} = \sum_{p=0}^{+\infty} \phi^p \mathbf{G}^p \boldsymbol{\alpha}. \tag{2}$$

Katz-Bonacich Network Centrality

- In particular, when $\boldsymbol{\alpha} = 1$, the *unweighted* Katz-Bonacich centrality of node i is:

$$b_{1,i}(\mathbf{g}, \phi) = \sum_{j=1}^{n} M_{ij}(\mathbf{g}, \phi),$$

or, in matrix form,

$$\mathbf{b_1}(\mathbf{g}, \phi) = (\mathbf{I} - \phi\mathbf{G})^{-1} \mathbf{1}.$$

- It counts the *total* number of walks in $\mathbf{g}$ starting from i, discounted exponentially by ϕ.
- It is the sum of all loops $M_{ii}(\mathbf{g}, \phi)$ from i to i itself, and of all the outer walks $\sum_{j \neq i} M_{ij}(\mathbf{g}, \phi)$ from i to every other player $j \neq i$, that is:

$$b_{1,i}(\mathbf{g}, \phi) = M_{ii}(\mathbf{g}, \phi) + \sum_{j \neq i} M_{ij}(\mathbf{g}, \phi).$$

- By definition, $M_{ii}(\mathbf{g}, \phi) \geq 1$, and thus $b_i(\mathbf{g}, \phi) \geq 1$, with equality when $\phi = 0$.

Crime and social networks: Nash equilibrium

- For all vector $\mathbf{u} \in \mathbb{R}^n$, let $u = u_1 + ... + u_n$.

Proposition

Let $\alpha^{\max} = \max\{\alpha_i \mid i \in N\}$ *and* $\alpha_{\min} = \min\{\alpha_i \mid i \in N\}$, *with* $\alpha^{\max} > \alpha_{\min} > 0$. *If*

$$1 + \gamma > \phi\mu_1(\mathbf{g}) + n\gamma\left(\alpha^{\max}/\alpha_{\min} - 1\right),$$

then the game with congestion has a unique interior Nash equilibrium in pure strategies $\mathbf{x}^*$, *which is interior and given by:*

$$\mathbf{x}^* = \frac{1}{1+\gamma}\left[\mathbf{b}_{\boldsymbol{\alpha}}\left(\mathbf{g}, \frac{\phi}{(1+\gamma)}\right) - \frac{\gamma b_{\alpha}\left(\mathbf{g}, \phi/(1+\gamma)\right)}{1+\gamma+\gamma b_1\left(\mathbf{g}, \phi/(1+\gamma)\right)}\mathbf{b}_{\mathbf{1}}\left(\mathbf{g}, \frac{\phi}{1+\gamma}\right)\right]$$

- Equilibrium criminal effort proportional to Katz-Bonacich centrality.

Key players in crime

Targeting: Key players

- Key Player Policy: Aims at removing the player (criminal) who reduces total activity (crime) in a network the most.

- Denote by $X^*(\mathbf{g}) = \sum_{i=1}^{n} x_i^*$ the total equilibrium level of crime (activity) in network $\mathbf{g}$, where x_i^* is the Nash equilibrium effort.
- Denote by $\mathbf{g}^{[-i]}$ the network $\mathbf{g}$ without individual i.

- To determine the key player, the planner will solve the following program:

$$\max\{X^*(\mathbf{g}) - X^*(\mathbf{g}^{[-i]}) \mid i = 1, ..., n\}.$$

Targeting: Key players

- When $\mathbf{g}$ is fixed, this is equivalent to:

$$\min\{X^*(\mathbf{g}^{[-i]}) \mid i = 1, ..., n\}.$$

Definition

Assume that $\phi\mu_1(\mathbf{g}) < 1$. The intercentrality or key-player centrality measure $d_i(\mathbf{g}, \phi)$ is defined as follows:

$$d_i(\mathbf{g}, \phi) = \frac{b_{\alpha_i}(\mathbf{g}, \phi) b_{1_i}(\mathbf{g}, \phi)}{m_{ii}} \tag{3}$$

- m_{ii} is a cell of the matrix

$$\mathbf{M}(\mathbf{g}, \phi) = (\mathbf{I} - \phi\mathbf{G})^{-1} = \sum_{k=0}^{+\infty} \phi^p \mathbf{G}^p.$$

Targeting: Key players

Proposition

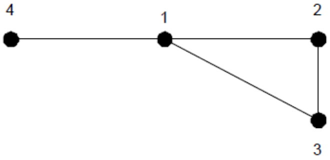
A player i^* is the key player if and only if i^* is a delinquent with the highest intercentrality in $\mathbf{g}$, that is, $d_{i^*}(\mathbf{g}, \phi_1) \geq d_i(\mathbf{g}, \phi_1)$, for all $i = 1, ..., n$.

- The intercentrality measure of delinquent i is the sum of i's centrality measures in $\mathbf{g}$, and i's contribution to the centrality measure of every other delinquent $j \neq i$ also in $\mathbf{g}$.

Key players: First Example

- Network of 4 delinquents with: $(\alpha_1, \alpha_2, \alpha_3, \alpha_4) = (0.1, 0.2, 0.3, 0.4)$, and $\phi = 0.3$. We have: $\mu_1(\mathbf{g}) = 2.17$, thus condition: $\phi < 1/\mu_1(\mathbf{g}) = 0.46$.

$$\mathbf{G} = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$$



Key players: First Example

- Nash equilibrium

$$\begin{pmatrix} x_1^* \\ x_2^* \\ x_3^* \\ x_4^* \end{pmatrix} = \begin{pmatrix} b_{\alpha,1}(\mathbf{g},\phi) \\ b_{\alpha,2}(\mathbf{g},\phi) \\ b_{\alpha,3}(\mathbf{g},\phi) \\ b_{\alpha,4}(\mathbf{g},\phi) \end{pmatrix} = \begin{pmatrix} 0.66521 \\ 0.60377 \\ 0.68068 \\ 0.59958 \end{pmatrix}$$

- Total crime effort:

$$X^*(\mathbf{g}) = x_1^* + x_2^* + x_3^* + x_4^* = b_{\boldsymbol{\alpha}}(\mathbf{g},\phi) = 2.549$$

- Delinquent 3 has the highest weighted Bonacich and thus provides the highest crime effort.

Key players: First Example

- Let us calculate the key player. Remove delinquent 1.

Key players: First Example

- We have now a network with three delinquents, with $(\alpha_2, \alpha_3, \alpha_4) = (0.2, 0.3, 0.4)$ and where

$$\mathbf{G} = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

- Using the same decay factor, $\phi = 0.3$, we obtain:

$$\begin{pmatrix} x_2^* \\ x_3^* \\ x_4^* \end{pmatrix} = \begin{pmatrix} b_{\alpha,2}(\mathbf{g}^{[-1]}, \phi) \\ b_{\alpha,3}(\mathbf{g}^{[-1]}, \phi) \\ b_{\alpha,4}(\mathbf{g}^{[-1]}, \phi) \end{pmatrix} = \begin{pmatrix} 0.31868 \\ 0.3956 \\ 0.4 \end{pmatrix}$$

- so that the total effort is now given by:

$$X^*(\mathbf{g}^{[-1]}) = x_2^* + x_3^* + x_4^* = b_{\boldsymbol{\alpha}}^{[-1]}(\mathbf{g}, \phi) = 1.114$$

Key players: First Example

- Thus, player 1's contribution is

$$X^*(\mathbf{g}) - X^*(\mathbf{g}^{[-1]}) := b_{\boldsymbol{\alpha}}(\mathbf{g}, \phi) - b_{\boldsymbol{\alpha}}^{[-1]}(\mathbf{g}, \phi) = 2.549 - 1.114 = 1.435$$

- Doing the similar exercise for individuals 2, 3, 4, we obtain:

$$b_{\boldsymbol{\alpha}}(\mathbf{g}, \phi) - b_{\boldsymbol{\alpha}}^{[-2]}(\mathbf{g}, \phi) = 1.244$$

$$b_{\boldsymbol{\alpha}}(\mathbf{g}, \phi) - b_{\boldsymbol{\alpha}}^{[-3]}(\mathbf{g}, \phi) = 1.146$$

$$b_{\boldsymbol{\alpha}}(\mathbf{g}, \phi) - b_{\boldsymbol{\alpha}}^{[-4]}(\mathbf{g}, \phi) = 0.988$$

Key players: First Example

- Let us show that we can obtain the same numbers with the intercentrality formula. Delinquent 1 intercentrality:

$$d_{1^*}(\mathbf{g},\phi) = \frac{b_{\boldsymbol{\alpha},1}(\mathbf{g},\phi)\sum_{j=1}^{j=4} m_{j1}(\mathbf{g},\phi)}{m_{11}(\mathbf{g},\phi)}$$

$$\mathbf{M} = (\mathbf{I} - \phi\mathbf{G})^{-1} = \begin{pmatrix} 1.5317 & 0.65646 & 0.65646 & 0.45952 \\ 0.65646 & 1.3802 & 0.61101 & 0.19694 \\ 0.65646 & 0.61101 & 1.3802 & 0.19694 \\ 0.45952 & 0.19694 & 0.19694 & 1.1379 \end{pmatrix}$$

where

$$m_{11}(\mathbf{g},\phi) = 1.5317$$

and

$$\begin{aligned} \sum_{j=1}^{j=4} m_{j1}(\mathbf{g},\phi) &= m_{11}(\mathbf{g},\phi) + m_{21}(\mathbf{g},\phi) + m_{31}(\mathbf{g},\phi) + m_{41}(\mathbf{g},\phi) \\ &= 1.5317 + 0.65646 + 0.65646 + 0.45952 = 3.3041 \end{aligned}$$

Key players: First Example

- Therefore,

$$
\begin{aligned}
d_{1^*}(\mathbf{g},\phi) &= \frac{b_{\boldsymbol{\alpha},1}\sum_{j=1}^{j=3} m_{j1}(\mathbf{g},\phi)}{m_{11}(\mathbf{g},\phi)} \\
&= \frac{0.66521 \times 3.3041}{1.5317} \\
&= 1.435
\end{aligned}
$$

$$
d_{1^*}(\mathbf{g},\phi) = b_{\boldsymbol{\alpha}}(\mathbf{g},\phi) - b_{\boldsymbol{\alpha}}^{[-1]}(\mathbf{g},\phi) = 1.435
$$

Key players: Second Example

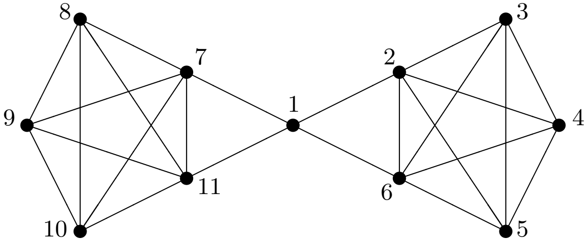


Figure: An example to illustrate the key player policy.

- Player 1 bridges together two fully intra-connected groups with five players each.
- Removing player 1 disrupts the network.
- Removing 2 decreases maximally the total number of network links.

Key players: Second Example

- Assume that $\alpha_1 = \cdots = \alpha_{11} = 1$, the intercentrality is:

$$d_i(\mathbf{g}, \phi) = \frac{[b_{1_i}(\mathbf{g}, \phi)]^2}{m_{ii}}.$$

- Here, the highest value for ϕ compatible with equilibrium is:

$$\phi < \frac{1}{\mu_1(\mathbf{g})} = \frac{1}{4.404} = 0.227.$$

ϕ	0.1		0.2	
Player Type	b_i	d_i	b_i	d_i
1	1.75	2.92	8.33	41.67
2	1.88	3.28	9.17	40.33
3	1.72	2.79	7.78	32.67

Table: Centrality measures for the key player policy.

- Player 2 has the highest Bonacich centrality.
- When ϕ is low, player 2 is also the key player.
- When ϕ is high, the most central player is not the key player.

Key players: Empirical test

- Dataset of friendship networks in the United States from the National Longitudinal Survey of Adolescent Health (AddHealth)
- Network is based upon actual friends nominations.
- Pupils were asked to identify their best friends from a school roster (up to five males and five females)
- The limit in the number of nominations is not binding.
- Less than 1% of the students in our sample show a list of ten best friends
- A link exists between two friends ($g_{ij} = 1$) if at least one of the two individuals has identified the other as his/her best friend (undirected networks)

Criminal activities

- Delinquency index: 15 delinquency items:

- 1) paint graffiti or signs on someone else's property or in a public place
- 2) deliberately damage property that didn't belong to you
- 3) lie to your parents or guardians about where you had been or whom you were with
- 4) take something from a store without paying for it
- 5) get into a serious physical fight
- 6) hurt someone badly enough to need bandages or care from a doctor or nurse
- 7) run away from home
- 8) drive a car without its owner's permission
- 9) steal something worth more than $50
- 10) go into a house or building to steal something;
- 11) use or threaten to use a weapon to get something from someone
- 12) sell marijuana or other drugs
- 13) steal something worth less than $50
- 14) take part in a fight where a group of your friends was against another group
- 15) act loud, rowdy, or unruly in a public place.

Criminal activities

- Each response is coded using an ordinal scale ranging from 0 (i.e. never participate) to 1 (i.e. participate 1 or 2 times), 2 (participate 3 or 4 times) up to 3 (i.e. participate 5 or more times).

- The delinquency index is a composite score: It ranges between 0.09 and 9.63.
- Exclude individuals who report never participating in any delinquent activity (roughly 40% of the total).

- Final sample: 1,297 criminals distributed over 150 networks.

- Minimum number of individuals in a delinquent network: 4, max 77.

- Mean and the standard deviation of network size: roughly 9 and 12 pupils.

- On average, delinquents declare having 2.26 friends with a standard deviation of 1.52.

Empirical strategy

- Theory (first-order conditions) (denote effort by y instead of x):

$$y_i = \phi \sum_{j=1}^{n} g_{ij} y_j + \sum_{m=1}^{M} \beta_m x_i^m + \frac{1}{g_i} \sum_{m=1}^{M} \sum_{j=1}^{n} \gamma_m g_{ij}\, x_j^m - pf + \eta_k + \varepsilon_i$$

- Econometric counterpart:

$$y_{i,r} = \phi \sum_{j=1}^{n_r} g_{ij,r} y_{j,r} + x'_{i,r}\beta + \frac{1}{g_{i,r}} \sum_{j=1}^{n_r} g_{ij,r} x'_{j,r}\gamma + \eta_r^* + \epsilon_{i,r},$$

- r denotes network.

Results

- The estimated effect of ϕ, which measures the intensity of peer effects is positive and highly statistically significant.
- The impact is not negligible in magnitude.
- A one-standard deviation increase in the aggregate level of delinquent activity of the peers translate into a roughly 11 percent increase of a standard deviation in the individual level of activity.
- Stronger peer effects for directed networks.

Different types of crime

- The literature on local interactions has uncovered some interesting differences between different types of crime
- For instance, Ludwig et al. (2000) find that neighborhood effects are large and negative for violent crime but have a mild positive effect on property crime.
- In contrast, Glaeser et al. (1996) find instead that social interactions seem to have a large effect on petty crimes, a moderate effect on more serious crime and a negligible effect on very violent crimes.

Different types of crime

- Split the reported offences between petty crimes and more serious crimes.
- The first group (type-1 crimes or petty crimes) encompasses the following offences:
- (i) paint graffiti or sign on someone else's property or in a public place;
- (ii) lie to the parents or guardians about where or with whom having been;
- (iii) run away from home;
- (iv) act loud, rowdy, or unruly in a public place;
- (v) take part in a group fight;
- (vi) damage properties that do not belong to you;
- steal something worth less than $50.

Different types of crime

- The second group (type-2 crimes or more serious crimes) encompasses the following offences:
- (i): taking something from a store without paying for it;
- (ii) hurting someone badly enough to need bandages or care from a doctor or nurse;
- (iii) driving a car without its owner's permission;
- (iv) stealing something worth more than \$50;
- (v) going into a house or building to steal something;
- (iv) using or threatening to use a weapon to get something from someone;
- (vii) selling marijuana or other drugs;
- $(viii)$ getting into a serious physical fight.

Different types of crime

- We obtain a sample of 1,099 petty criminals distributed over 132 networks and a sample of 545 more serious criminals distributed over 75 networks.

- Petty crime networks have a minimum of 4 individuals and a maximum of 73 (with mean equals to 8.33 and standard deviation equals to 10.74),

- whereas the range for more serious crime networks is between 4 and 38 (with mean equals to 7.27 and standard deviation equals to 6.64).

Different types of crime

- The impact of peer effects on crime are much higher for more serious crimes than for petty crimes.
- A standard deviation increase in the aggregate level of delinquent activity of the peers translate into a roughly 8 percent increase of a standard deviation in the individual level of activity for petty crimes.
- A standard deviation increase in the aggregate level of delinquent activity of the peers translate into a roughly 14.5 percent increase of a standard deviation in the individual level of activity for more serious crimes.

Differences between Key players and criminals: All crimes

	All Criminals		Key Player Criminals		
	Mean	St. dev	Mean	St. dev	t-test
Individual characteristics					
Female	0.53	0.50	0.23	0.42	0.0000
Religion practice	3.65	1.41	3.28	1.57	0.0078
Parent education	3.23	1.06	3.01	1.14	0.0279
Mathematics score	2.18	1.00	2.53	1.05	0.0003
Parental care	0.93	0.26	0.80	0.40	0.0002
School attachment	4.12	0.87	3.71	1.07	0.0000
Relationship with teachers	0.99	0.92	1.79	1.22	0.0000
Social inclusion	4.47	0.74	4.23	0.86	0.0018
Residential building quality	1.51	0.79	1.70	0.96	0.0226
Two married parent families	0.74	0.44	0.61	0.49	0.0020
Single parent family	0.22	0.42	0.30	0.46	0.0706
Parent occupation manager	0.11	0.31	0.17	0.38	0.0704
Parent occupation military or security	0.02	0.14	0.00	0.00	0.0000
Parent occupation other	0.16	0.37	0.11	0.31	0.0673

Differences between Key players and criminals: All crimes

	All Criminals		Key Player Criminals		
	Mean	St. dev	Mean	St. dev	t-test
Friends' characteristics					
Religious practice	2.52	1.98	3.02	1.80	0.0025
Student grade	6.42	4.33	7.64	3.85	0.0006
Parental education	2.30	1.66	2.61	1.54	0.0279
Mathematics score	1.54	1.24	1.87	1.24	0.0033
Self esteem	2.84	1.99	3.28	1.76	0.0066
Physical development	2.44	1.76	2.69	1.52	0.0810
Parental care	0.65	0.46	0.75	0.42	0.0152
School attachment	2.90	1.99	3.35	1.74	0.0055
Social inclusion	3.12	2.09	3.65	1.83	0.0019
Residential building quality	1.05	0.89	1.19	0.83	0.0621
Residential area urban	0.43	0.48	0.55	0.48	0.0033
Household size	3.13	2.22	3.48	1.97	0.0474
Single parent families	0.14	0.31	0.23	0.39	0.0105

Differences between Key players and criminals: Petty crimes

Petty crimes

	All Criminals		Key Player Criminals		
	Mean	St. dev	Mean	St. dev	t-test
Individual characteristics					
Female	0.54	0.50	0.24	0.43	0.0000
Mathematics score	2.17	1.00	2.44	1.01	0.0049
Physical development	3.33	1.09	3.55	1.06	0.0325
Parental care	0.93	0.25	0.74	0.44	0.0000
School attachment	4.11	0.88	3.69	1.09	0.0001
Relationship with teachers	0.99	0.94	1.62	1.16	0.0000
Social inclusion	4.48	0.73	4.14	0.88	0.0001
Residential area urban	0.56	0.50	0.65	0.48	0.0523
Parent occupation manager	0.11	0.31	0.18	0.38	0.0463
Parent occupation manual	0.33	0.47	0.22	0.41	0.0065
Friends' characteristics					
Student grade	6.53	4.39	7.66	3.95	0.0034
Religion practice	2.29	1.65	2.69	1.57	0.0086
Mathematics score	1.52	1.21	1.81	1.17	0.0108
Self esteem	2.85	2.00	3.24	1.76	0.0224
Parental care	0.65	0.46	0.75	0.42	0.0170
School attachment	2.90	1.99	3.29	1.76	0.0251
Social inclusion	3.12	2.09	3.62	1.86	0.0063
Residential area urban	0.41	0.47	0.54	0.47	0.0047
Single parent family	0.15	0.31	0.23	0.38	0.0181
Parent occupation professional/technical	0.14	0.31	0.20	0.36	0.0646

Differences between Key players and criminals: More serious crimes

More serious crimes

	All Criminals		Key Player Criminals		
	Mean	St. dev	Mean	St. dev	t-test
Individual characteristics					
Female	0.44	0.50	0.23	0.42	0.0004
Physical development	3.25	1.11	3.69	1.04	0.0023
School attachment	3.98	0.95	3.68	1.05	0.0271
Relationship with teachers	1.16	1.04	1.97	1.35	0.0000
Parent occupation manager	0.11	0.31	0.03	0.17	0.0022
Parent occupation military or security	0.01	0.09	0.00	0.00	0.0833
Friends' characteristics					
School attachment	2.74	1.95	3.17	1.78	0.0721
Social inclusion	3.07	2.11	3.53	1.96	0.0828
Parent occupation military or security	0.01	0.07	0.00	0.00	0.0718
Parent occupation farm or fishery	0.02	0.13	0.00	0.00	0.0115

Differences between Key players petty crimes and Key players more serious crimes

	Key Player Petty Crime		Key Player More Serious Crime		
	Mean	St. dev	Mean	St. dev	t-test
Individual characteristics					
Black or African American	0.17	0.38	0.31	0.47	0.0308
Self esteem	4.04	1.08	3.73	1.11	0.0542
Parental care	0.74	0.44	0.90	0.30	0.0033
Relationship with teachers	1.62	1.16	1.97	1.35	0.0723
Social inclusion	4.14	0.88	4.47	0.70	0.0041
Parent occupation manager	0.18	0.38	0.03	0.17	0.0002
Parent occupation military or security	0.03	0.17	0.00	0.00	0.0451
Friends' characteristics					
Female	0.40	0.43	0.26	0.40	0.0315
Black or African American	0.13	0.32	0.24	0.43	0.0539
Relationship with teachers	0.70	0.71	1.05	1.03	0.0132
Parent occupation manager	0.11	0.29	0.05	0.19	0.0825
Parent occupation military or security	0.02	0.14	0.00	0.00	0.0575
Parental occupation farm or fishery	0.02	0.11	0.00	0.00	0.1027

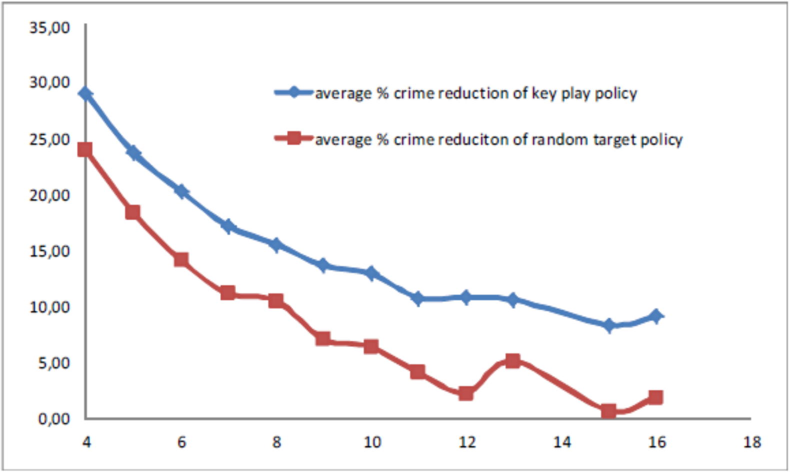
Policy implications

- Punishment should not be random but targeted to individuals that generate the highest multiplier effects.
- The way a key player is calculated is precisely using the multiplier effects due to endogenous peer effects.
- Key player removal policy: When a delinquent is removed from network r, the intercentrality measures of all the delinquents that remain active are reduced, which triggers a decrease in delinquency involvement for all of them.

Policy implications

- When delinquent i^* (KP) is removed from the delinquency network, the corresponding ratio of aggregate delinquency reduction with respect to the network centrality reduction is an increasing function of the intercentrality measure $d_{i,r}(\mathbf{g}, \phi)$ of this delinquent i in network r.
- This means that the target policy displays amplifying effects,
- and the gains following the judicious choice of the key player go beyond the differences in intercentrality measures between this player and any other delinquent in the network.

Crime reduction: Key Player vs Random player



Another analysis of KP: Co-offenders in Sweden

- Data: All persons born from 1932 onwards who have lived in Sweden at any time since 1961.
- Mothers and fathers, brothers and sisters, and children of each person in the 25 percent random sample were matched onto the sample. This resulted in a sample which includes approximately 70% of the Swedish population.
- Co-offenses account for 24% of all crimes in our suspects data and 42% of all offenders have at least one co-offender.
- In total, this group of crime suspects is responsible for 74% of all of the crimes in our data set.

Individual level descriptive statistics

	Period 1 2000 - 2002		Period 2 2003 - 2005	
	Mean	*(s.d.)*	*Mean*	*(s.d.)*
Crime	5.92	(5.53)	5.92	(5.62)
Lagged crime	4.69	(7.04)	3.79	(5.36)
Age	29.6	(11.2)	30.1	(11.7)
Log average income	8.35	(4.25)	8.14	(4.49)
Months on welfare	9.03	(10.8)	8.50	(10.8)
Years of schooling	9.86	(1.40)	9.84	(1.51)
Missing school info	0.10	(0.30)	0.08	(0.27)
Employed in November	0.20	(0.40)	0.20	(0.40)
Sick days	40.0	(139)	35.2	(132)
Immigrant	0.24	(0.42)	0.26	(0.44)
Male	0.84	(0.37)	0.82	(0.38)
Married or cohabitating	0.30	(0.46)	0.30	(0.46)
Child living at home	0.53	(0.50)	0.54	(0.50)
Nr of individuals	15,205		15,144	
Nr of networks	1,187		1,185	

Network level descriptive statistics (Unweighted)

	Period 1 2000-2002	Period 2 2003-2006
Number of co-offenders	15,205	15,144
Number of networks	1,187	1,185
Degree:		
Average, $\Gamma(g)$	2.88	2.99
standard deviation	(2.18)	(2.38)
Largest network:		
Size	7,830	7,592
Percentage of co-offenders	51%	50%
Size of second largest network:	49	45
Size of smallest networks	4	4
Distance in largest network:		
Average, $\Delta(g)$	16.25	17.00
standard deviation	(3.00)	(3.40)
Clustering coefficient, $c(g)$	0.52	0.55

Peer effects results

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	2SLS (5)
Local aggregate peer effect, $\widehat{\phi}$	0.189***	0.165***	0.130***	0.129***	0.137***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)
Lagged crime			0.328***	0.291***	0.288***
			(0.008)	(0.008)	(0.008)
Male				1.287***	1.287***
				(0.081)	(0.081)
Age				-0.022***	-0.022***
				(0.004)	(0.004)
Log average income				-0.089***	-0.087***
				(0.012)	(0.012)
Years of schooling				-0.033	-0.032
				(0.026)	(0.027)
Missing school info				0.964***	0.959***
				(0.144)	(0.145)
Immigrant				-0.212**	-0.212**
				(0.094)	(0.095)

Finding the key player

- What is the predicted reduction in crime achieved after removing the key player?
- We calculate the percentage decrease in crime obtained in each network after removing the key player.
- This is equal to 100 times the intercentrality of the key player in each network divided by the total Bonacich of that network: $\frac{100 \times d_i(\mathbf{g}_r, \widehat{\phi})_{max}}{b(\mathbf{g}_r, \widehat{\phi})}$

Finding the key player

- First, the key player model predicts that the population weighted average reduction in crime for the mean network (with size = 62) is equal to 34%.
- Second, it tells us that this reduction in crime is negatively related to network size.
- If we look at a network that is twice as large as the mean network (i.e., with size = 124), then the predicted % reduction in crime is equal to 23%.
- The predicted decrease for our smallest networks (with size = 4) is equal to 44%.
- How much does the key player policy outperform other reasonable policies?

Key players vs other centrality players

Dependent variable	Average Reduction	Network Size	Mean network size	Sample
Key Player: $\frac{100 * d_i(g_r,\widehat{\phi})_{max}}{B(g_r,\widehat{\phi})}$	33.83% (0.135)	-0.167% (0.001)	62	All N =14,009
$\frac{100 * d_i(g_r,\widehat{\phi})_{max}}{B(g_r,\widehat{\phi})} - \frac{100 * d_i(g_r,\widehat{\phi})_{random}}{B(g_r,\widehat{\phi})}$	13.70% (0.134)	-0.041% (0.001)	63	Key player $\neq$ random player N = 12,538
$\frac{100 * d_i(g_r,\widehat{\phi})_{max}}{B(g_r,\widehat{\phi})} - \frac{100 * d_i(g_r,\widehat{\phi})_{most\ active}}{B(g_r,\widehat{\phi})}$	10.91% (0.161)	-0.036% (0.001)	80	Key player $\neq$ most active N = 10,317
$\frac{100 * d_i(g_r,\widehat{\phi})_{max}}{B(g_r,\widehat{\phi})} - \frac{100 * d_i(g_r,\widehat{\phi})_{highest\ betweenness}}{B(g_r,\widehat{\phi})}$	8.33% (0.178)	-0.027% (0.002)	91	Key player $\neq$ highest betweenness N = 7,521
$\frac{100 * d_i(g_r,\widehat{\phi})_{max}}{B(g_r,\widehat{\phi})} - \frac{100 * d_i(g_r,\widehat{\phi})_{highest\ eigenvector}}{B(g_r,\widehat{\phi})}$	3.26% (0.053)	-0.013% (0.000)	76	Key player $\neq$ highest eigenvector N = 4,750

Key players vs other centrality players

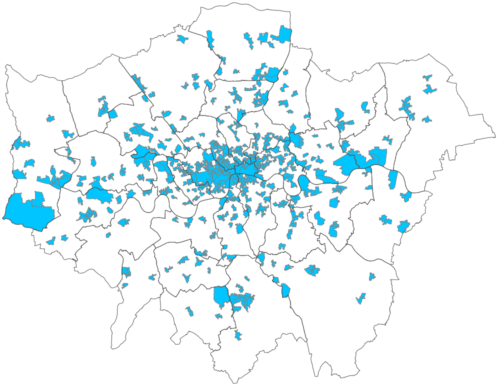
- Our results apply to the cases when the key player and the other player type are not the same individual.
- The key player policy outperforms the policy of removing one random individual from each network by 14% (on average).
- The key player policy outperforms the policy of removing the most active person from each network by an average of 11%.
- The key player policy outperforms will outperform more traditional measures of network centrality such as betweenness and eigenvector centrality by 8% and 3%, respectively.

Key neighborhoods instead of key players: The case of London

- What is the most efficient way to reduce crime when areas are connected, that is, there is a network of neighborhoods?
- London: A Case Study.
- Police forces have limited resources to target crime, so need to focus on subsets of areas.

Key neighborhoods in London

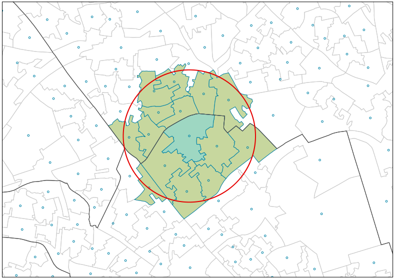
- Example of Hot Spot Policing (HSP) in London's neighborhoods: Target 500 Lower Super Output Areas (LSOAs) (10% of all LSOAs) with highest crime levels.



Source: Features of 2011 Census LSOAs are obtained from https://geoportal.statistics.gov.uk
The colored areas represent the 500 LSOAs with highest crime levels (year 2016).

Key neighborhoods in London

1. Collect LSOA data from police.co.uk from 2013 to 2019
2. Construct a network model: Crime in my LSOA is related to crime in neighbouring LSOAs (within 800m radius)

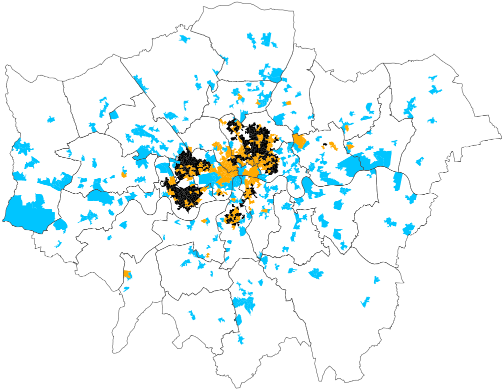


Source: Features of 2011 Census LSOAs are obtained from https://geoportal.statistics.gov.uk

3. Do this for all 4,835 LSOAs in London
4. Estimate an econometric model that measures spatial dependence
5. Identify the key players. They are "key" not just because they are central in the network but because they are connected with other well-connected LSOAs

Key neighborhoods in London

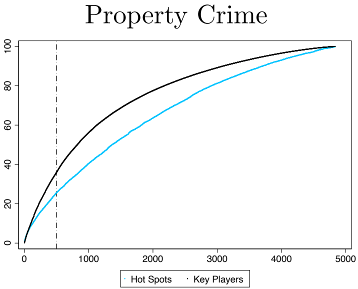
- Targeting KPs means moving from HS (blue) to KP (black). Overlapping areas (gold) can be ignored.
- *Any* such re-targeting is efficient, i.e., leads to total crime decrease



Source: Own analysis. Features of 2011 Census LSOAs are obtained from https://geoportal.statistics.gov.uk

Property vs Violent crime

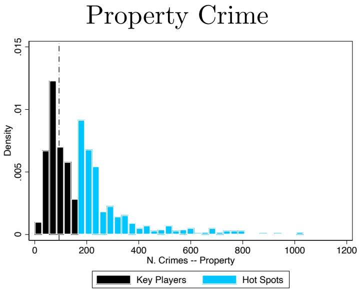
- Crime reduction “gains” would be particularly large in terms of property crime (up to 37%, figure on the left)
- For violent crime, instead, the two policies would produce nearly identical results. Violent crime does not propagate through spatial networks.

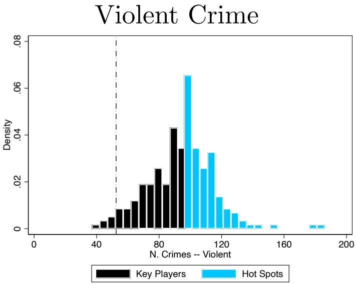


Source: Own calculations
The Y-axis represents the cumulative reduction in crime (measured as % of the total Bonachich). The X-axis is the ranking of Key Players and Hot Spots.

Key neighborhoods in London: Hiding in plain sight

- Some of the Key Players that have large influence on total crime:
  - are not high crime areas (black bins in figures below)
  - have a share of ethnic minority that is lower than Hot Spots





Source: Own analysis.
The figure represents the top 500 LSOAs in terms of intercentrality measure (Key Players) and in terms of crime rates (Hot Spots). Data refer to total crime for year 2016.
Features of 2011 Census LSOAs are obtained from https://geoportal.statistics.gov.uk

Policy implications

- Do we have access to network data in crime?
- Adult crime (police data): the police has in fact quite a lot of information on criminal networks.
- Sarnecki (2001) was able to construct the network of all criminals in Stockholm.
- Each time two (or more) persons are suspected about a crime (co-offenders), the police in Sweden registers this information.
- A link in a network is then created between individuals i and j, i.e. $g_{ij} = 1$, whenever individuals i and j are suspected of committing a crime together.

Policy implications

- This type of information can be obtained from the police in many countries.
- In the United States, there is also similar data.
- For example, Coplink was one of the first large scale research projects in crime data mining, and an excellent work in criminal network analysis.
- Colink has information about the perpetrators' habits and close associations in crime to capture the connections between people, places, events, and vehicles, based on past crimes.

Policy implications

- How to implement a key-player policy in the real-world?
- The characteristics of key players can be used to target some criminals if the information on networks is not known.
- However, several characteristics that can be used by the government to identify the key-player can be endogenous to the teenager (e.g., religious practice, social inclusion,...).
- Therefore, as long as he/she has some information regarding these characteristics, the teenager can change his/her behavior in order not to be targeted as a key player.

Policy implications

- Operation Ceasefire was designed as a focused deterrence strategy that placed extraordinary legal attention on a smaller number of gang members who were believed to be involved with (or connected to) a large share of the youth homicides in Boston.
- Researchers (Kennedy et al., 1997) aided the design of this policy:
- They aided the police in identifying a small number of key gangs on which the police could then focus their attention. accomplished this using a group-audit method together.
- A key component of the focused deterrence strategy used in the Boston Ceasefire programme was that the message and actions of deterrence were focused on groups (not individuals).
- The key gangs who were subject to extraordinary attention by the Boston police were told that they would be held collectively accountable for the violence perpetrated by any fellow gang member.

Policy implications

- Operation Ceasefire: first launched in Boston and youth homicide fell by two-thirds after the Ceasefire strategy was put in place in 1996.
- It was then implemented in Los Angeles in 2000: Strong effects.

Finding the key player: Summary

- What did we learn?
- Can apply the methodology of KP to many other problems.
- Development economics: Targeting individuals to increase adoption of new technology or microfinance program.
- Macroeconomics and financial markets: Which bank should be bailed out? Which sectors are critical for the economy?
- Urban and regional economics, and IO: Which region should be helped? Which firm should be subsidized?

Summary

- Social network analysis can help us understand the root causes of delinquent behavior and crime.

- Social network analysis provides practical guidance for the design of crime prevention policies

- Key players could be an effective policy when resources are limited.

Overviews of the literature

- Faust, K. and G.E. Tita (2019), "Social Networks and Crime: Pitfalls and Promises for Advancing the Field," *Annual Review of Criminology* 2, 99–122.

- Lindquist, M. and Y. Zenou (2019), "Crime and networks: Ten policy lessons," *Oxford Review of Economic Policy* 35(4), 746–771.

- Carrington, P.J. (2011), "Crime and Social Network Analysis," in J. Scott and P.J. Carrington (Eds), *Sage Handbook of Social Network Analysis*, London, SAGE Publications, pp. 236–255.

- van der Weele, J. (2012), "Beyond the state of nature: Introducing social interactions in the economic model of crime," *Review of Law and Economics* 8(1), 401–432.